Social mobility and cohesion in post-apartheid South Africa

by

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Declaration

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Abstract

Twenty years after the end of apartheid, South Africa remains one of the most unequal countries in the world. Socio-economic polarisation is entrenched by the lack of social capital and interactions across racial and economic divides, blocking pathways out of poverty. This dissertation examines social mobility and cohesion in post-apartheid South Africa by considering three related topics.

Chapter 2 of the dissertation examines the impact of school quality on the academic performance of disadvantaged learners as one of the most important enforcing factors perpetuating the social and economic divides. Given the historic racial and economic stratification of the South African public school system, many black children are sent to historically white public schools as a way to escape poverty. Using longitudinal data, this chapter estimates the effect of attending a historically white school on the numeracy and literacy scores of black children. The main challenge is to address the selection bias in the estimates, for which a value-added approach is implemented in order to control for unobserved child-specific heterogeneity. In addition, various household covariates are used to control for household-level differences among children. The results indicate that the attendance of a former white school has a large and statistically significant impact on academic performance in both literacy and numeracy which translates into more than a year's worth of learning. The main finding is robust to various robustness checks.

In Chapter 3 the dissertation examines social cohesion by considering the concept of reference groups used in the evaluation of relative standing in utility functions. The chapter develops a model in which various parameters are allowed to enter the utility function without linearity constraints in order to determine the weight placed on the well-being of individuals in the same race group as the respondent versus all the other race groups living in one of three specified geographic areas. The findings suggest that reference groups have shifted away from a purely racial delineation to a more inclusive one subsequent to the country's first democratic elections in 1994. Although most of the weight is still placed on same-race relative standing, the estimates suggest that individuals from other race groups also enter the utility function. The chapter also examines the spatial variation of reference groups and finds evidence that the relative standing of close others (such as neighbours) enter the utility function positively while individuals who live further away (strangers) enter the utility function negatively.

Finally, Chapter 4 provides a summary of the dynamics of income in South Africa, using longitudinal household data. Chapter 4 is aimed at separating structural trends in income from stochastic shocks and measurement error, and makes use of an asset-based approach. It first estimates the percentage of individuals who were in chronic poverty between 2010 and 2012 and then estimates the shape of structural income dynamics in order to test for the existence of one or more dynamic equilibrium points, which would be indicative of the existence of a poverty trap. The findings do not provide any evidence for the existence of a poverty trap. In addition, contrary to earlier findings, the results do not provide evidence for the existence of an asset-based threshold at which the structural income accumulation paths of households bifurcate. Instead, the results seem to indicate the existence of a threshold beyond which structural income remains persistent with very little upward mobility. The robustness of the results is confirmed by making use of control functions in order to correct for any measurement error which may exist in the data on assets.

Opsomming

Twintig jaar nadat apartheid beëindig is word Suid-Afrika steeds as een van die wêreld se mees ongelyke lande gekenmerk. Sosio-ekonomiese polarisasie word verskans deur die gebrek aan sosiale kapitaal en interaksies tussen rassegroepe en ekonomiese klasse, wat lei tot die versperring van roetes uit armoede. Hierdie proefskrif bestudeer sosiale mobiliteit en samehorigheid in post-apartheid Suid-Afrika deur middel van drie verwante onderwerpe.

Hoofstuk 2 van hierdie proefskrif ondersoek die impak van skoolkwaliteit op die akademiese prestasie van benadeelde leerders as een van die belangrikste faktore wat huidige sosiale en ekonomiese skeidings afdwing. Gegewe die historiese verdeling van die openbare skoolstelsel volgens ras en ekonomiese status, word heelwat swart kinders na historiese blanke skole gestuur ten einde armoede te ontsnap. Deur gebruik te maak van paneeldata word die impak van skoolbywoning van 'n historiese blanke skool op die geletterheid van swart kinders - in beide wiskunde en Engels - beraam. Die grootste uitdaging is om enige sydigheid in die beramings aan te spreek, waarvoor daar van 'n waarde-toevoegings inslag gebruik gemaak word ten einde te kontroleer vir enige individuele heterogeniteit. 'n Verskeidenheid kontroles op die vlak van die huishouding word gebruik ten einde te kontroleer vir verskille tussen kinders uit verkillende huishoudings. Die resultate dui daarop dat bywoning van 'n historiese wit skool 'n groot en statisties beduidende impak op die akademiese prestasie van beide wiskundige asook litterêre geletterdheid het, wat omgeskakel kan word in meer as 'n jaar se leerwerk. 'n Verskeidenheid verifikasie toetse bevestig die geldigheid van die resultate.

Hoofstuk 3 van die proefskrif bestudeer sosiale samehorigheid deur die samestelling van verwysingsgroepe in die evaluasie van relatiewe posisionering in nutsfunksies te oorweeg. Die hoofstuk ontwikkel 'n model waarin verskeie parameters sonder liniêre beperkings in die nutsfunksie toegelaat word ten einde die gewig te beraam wat geplaas word op die welstand van individue in dieselfde rasgroep as die respondent teenoor al die ander rasgroepe wat in een van drie gespesifiseerde geografiese areas woon. Die bevindings dui daarop dat, na die land se eerste demokratiese verkiesings in 1994, die definiering van verwysingsgroepe weggeskuif het van 'n verdeling volgens ras na 'n meer inklusiewe definisie. Alhoewel meeste van die gewig steeds geplaas word op relatiewe posisionering teenoor individue van dieselfde ras, dui die beramings daarop dat individue van ander rassegroepe ook ingesluit word in die nutsfunksie. Die hoofstuk beoordeel ook die ruimtelike variasie van verwysingsgroepe en bevind dat die relatiewe posisionering van nabye individue (soos byvoorbeeld bure) die nutsfunksie positief beïnvloed terwyl individue wat vêr weg woon (vreemdelinge) die nutsfunksie negatief beïnvloed.

Hoofstuk 4 van die proefskrif sluit af met 'n opsomming van die inkomste dinamika in Suid-Afrika, deur gebruik te maak van paneelhuishoudingdata. Die laaste hoofstuk mik om die strukturele tendens in inkomste van enige stogastiese skokke en metingsfoute te isoleer en maak gebruik van 'n bate-gebasseerde inslag. Dit beraam eerstens die persentasie van individue wat in kroniese armoede verkeer het tussen 2010 en 2012 en beraam dan die vorm van die strukturele inkomste dinamika. Dit word gedoen ten einde vir die bestaan van een of meer dinamiese ekwilibrium punte te toets, wat aanduidend sou wees van die bestaan van 'n armoedestrik. Die bevindings bied nie enige bewyse vir die bestaan van 'n armoedestrik nie. Ook bied die resultate geen bewyse vir die bestaan van 'n bate-gebasseerde drempel waar die strukturele inkomste akkumulasieroetes van huishoudings vertak nie, in teenstelling met vorige resultate. In plaas daarvan, blyk die resultate te dui op die bestaan van 'n drempel waarna strukturele inkomste volhardend bly met baie min opwaardse mobiliteit. Die geldigheid van die resultate word bevestig deur gebruik te maak van kontrolefunksies ten einde te korrigeer vir enige metingsfoute wat moontlik in die data van bates mag bestaan.

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Almost six years ago I made one of the biggest decisions of my life when I resigned from my job as attorney in Johannesburg and moved back with my parents to start with my masters' degree as a full-time student. This step, and what followed, would not have been possible if it were not for my parents, Marianne and Abrie Coetzee, as well as my sister and brother-in-law Annemarie and Johan Viljoen, who are and have always been my greatest supporters. Thank you for your love and encouragement.

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Chapter 1

Introduction and overview of research questions

> *We can constructively build on the shared desire to unite and move forward from apartheid. To do so, however, South Africans of all races need to come together on the same page about the pressing need to rectify the economic, cultural and psychological imbalance which pervades our society (Wale, 2013, p. 41).*

Twenty years after the first democratic elections and the end of the apartheid regime, South Africa remains one of the most unequal societies in the world, with a Gini coefficient which has recently been estimated to be in the region of 0.7 (Leibbrandt, Finn and Woolard, 2012).

Given South Africa's history of apartheid, it is not surprising that the divide between rich and poor also remains a division along racial lines. Although the emergence of a black middle class is slowly changing the traditional racial income divides, for the most part the racial patterns entrenched by the apartheid policies remain, with black individuals still making up the overwhelming majority of South Africa's poor (as illustrated in Chapter 4 of this dissertation). This racial and socio-economic divide is further entrenched by the historic legacy of geographical division imposed by the apartheid regime. Given the high correlation between income inequality and race, ethnicity and language, economic inequality in South Africa is not a transitory phenomenon, but is greatly persistent and socially embedded (Mogues and Carter, 2005).

This socially embedded inequality has contributed to the polarisation of society in South Africa through the depletion of social networks, specifically those across socio-economic and racial divides which would otherwise have provided a potential escape route out of poverty for households in poverty (Mogues and Carter, 2005; Adato, Carter and May 2006 and Burger, Coetzee and Van der Watt, 2013).

Evidence of this break-down has been recorded in the Institute for Justice and Reconciliation's Reconciliation Barometer Survey, in which recorded inter-racial contact (in the form of conversations or socialising) has been increasing year-on-year but remains low. This is especially true among the poorest and most deprived, where only approximately 10% of the individuals interviewed indicated that they had any contact with someone from another race group on a daily basis (Wale, 2013).

Against the background of high inequality and subsequent social exclusion, the question of social mobility is of importance to ascertain which individuals are able to escape poverty and which individuals are left behind, being excluded from any social links or financial means to escape poverty. There has been a large body of literature developing around the issue of social mobility in South Africa. Maluccio, Haddad and May (2000) highlight the existence of a polarised society which is racially divided and in which poverty is persistent and is entrenched because the necessary social capital (and the accompanying linking ties necessary for social mobility) is often absent in the lives of the poor.

Carter and May (2001) and Adato, Carter and May (2006) evaluate the question of social mobility of black individuals post apartheid by using the 1994 and 1998 KwaZulu Natal Income Dynamics Study. They show that, although many individuals have been able to move out of poverty during this period, many of the most vulnerable have remained trapped in poverty, with inequality within this group of poor individuals increasing.

This finding is supported by Woolard and Klasen (2005) who, using the same data, identify four types of poverty traps, namely: a large household size, below average education in the initial period, below average asset endowment in the initial period and a lack of employment access. Louw, Van der Berg and Yu (2006) find supportive evidence for this conclusion. They evaluate the inter-generational social mobility between parents and their children in the period 1970-2001 using census data. They find that, although mobility has improved during this period, children's potential to access high-earning labour market opportunities is still to a large extent a function of their parents' educational attainment, forming a barrier to any economic progress to be made by these children.

The aim of this dissertation is to focus on three topics within the broader literature of social mobility and cohesion. The three topics are all either mechanisms enforcing the current polarisation and economic inequality or are vital for understanding the existence of the current divisions.

I set out the analysis of these three topics in three corresponding chapters, each examining a different facet of this complex issue. The first topic, in Chapter 2, examines the impact of school quality on the academic performance of poor children. The stratification of the South African public school system is undoubtedly one of the most indelible legacies of the apartheid regime, entrenching the current social and economic divides. Second, in Chapter 3, the dissertation touches on the concept of social cohesion by looking at the formation of reference groups used in the subjective assessment by South Africans of their well-being. The last topic, set out in Chapter 4, looks at income mobility and tests for the existence of poverty traps.

1.1 School quality

The lack of social cohesion and mobility in the South African economy originates in a perverse cycle of poverty, in which a child who is born into a poor household has little if any chance of moving out of poverty during her lifetime. Possibly the most important component of this re-inforcing cycle is the large differences in school quality which are observed in the public school system. It therefore makes sense that the second chapter of this dissertation should consider the impact of school quality on the performance of disadvantaged children.

In South Africa, the quality of schools within the public school system is heterogeneous and highly stratified along the lines of race, socio-economic status and geographic location; a result which emanates from at least two policies which were implemented during the apartheid period. First, the policy of geographic segregation of population groups legally imposed by apartheid legislation caused the spatial distribution of households within the country to be racially determined and limited the economic opportunities available to black adults. Second, the policy of institutional segregation under apartheid translated into racially segregated education departments administering schools. The non-white education departments received considerably less funding (Case and Deaton, 1999; Fiske and Ladd, 2006 and Bhorat and Oosthuizen, 2008), and the schools under their management were of inferior quality compared to the schools administered by the white education department.

Because of the racial, economic and geographic polarisation which exists, the parents of black children who often reside in poor neighbourhoods with corresponding poor schools of inferior quality, are often restricted in their choice of school for their children. However, as is set out in Chapter 2, some parents are able to send their children to historically white schools which are often situated outside of their neighbourhoods in the hope of securing a better future for their children.

The aim of Chapter 2 is to answer the question of what the impact is of attending one of these historically white schools on the academic performance of black children. For this purpose, I make use of a panel dataset containing data on a representative sample of 266 schools in South Africa, collected as part of the National School Effectiveness Study. The National School Effectiveness Study conducted standardised tests testing children's skills in English and mathematics when they were in grade 3 (2007), grade 4 (2008) and grade 5 (2009). It also collected background information on the learners, their households and the schools that they attended.

The main challenge in estimating the impact is addressing the selection bias which may be introduced as a result of various unobserved factors which influence the choice of school and which are correlated with academic performance. In order to control for selection bias, I make use of various household and individual child covariates. In addition, I implement a value-added approach in which lagged test scores are used as a proxy of unobserved learner heterogeneity in the form of past endowment and ability which would otherwise bias the estimates of the effect of attending a former white school.

After estimating the impact of school quality, I consider the fact that the results may still be biased and that the value-added technique may not have been able to successfully deal with the issue of selection bias. I therefore conduct various robustness checks. First, I consider the potentially confounding influence of the language policy implemented in primary schools in South Africa. Second, I control for biases arising from selective attrition. Last, I control for measurement error in the test scores. I also address the issue of remaining unobserved individual child ability by using an instrumental variable and discuss the validity of this approach. The initial results are to a great extent confirmed by these robustness checks.

1.2 Subjective well-being and reference groups

The second topic to be discussed in this dissertation relates to social cohesion. The South African government has highlighted a broadening of social cohesion and unity as part of the process of redressing the inequities of the past, as set out in the National Development Plan for 2030. The absence of social cohesion can be seen as another way in which the racial and economic divisions of the past are sustained, although more subtle than the enforcement of racial and socio-economic divides through differential school quality.

In the third chapter of the dissertation, I consider the concept of social cohesion in a very specific way - by examining the reference groups which are used by South Africans when considering the impact of their relative standing on their reported well-being, using data from the first wave of the National Income Dynamics Study from 2008.

The analysis in Chapter 3 commences with an overview of various descriptive statistics which are aimed at highlighting the differences in household characteristics as well as neighbourhood circumstances of households of various race groups. The descriptive statistics highlight the fact that black households are more likely to be poor and to be located in poor residential clusters (as a proxy for neighbourhoods) and districts than their white counterparts, who are very likely to be residing in affluent residential clusters and districts. In addition, black households are more likely than white households to be residing in areas where there is greater racial homogeneity.

I then move on to a replication of some of the results from Kingdon and Knight (2006, 2007) who employed data from 1993, prior to the first democratic elections on 27 April 1994. The aim of this exercise is to revisit their result that same-race relative income is an important input into the utility function. In addition, the analysis is also aimed at updating the previous results regarding spatial variation of the reference group and the evidence that households in closer proximity enter the individual's utility function positively while more far-off individuals enter the utility function negatively.

However, my analysis also adds to the current literature on reference groups and relative standing by developing a more flexible model which allows for various parameters to enter the utility function without linear restrictions. The model estimates the weight placed on others of the same race versus those of a different race, while simultaneously estimating the weight placed on the geographic distance of others.

Last, I consider various alternative specifications in order to take into consideration area fixed effects in the form of provincial and district controls. In addition, I include alternative transformations of the income variable. The main results remain robust to these alternative specifications.

1.3 Poverty traps

The final topic examined in the dissertation is one of income mobility, which is aimed at testing for the existence of poverty traps in South Africa. A poverty trap is defined as any mechanism which causes an individual, household or geographic area to remain in persistent poverty over a period of time. The concept of poverty traps provides a useful way in which to consider the economic and social polarisation in South Africa from a policy perspective as it offers an explanation for the existence of these divides.

The analysis in this chapter brings together techniques from two literatures. In the first place I consider studies on income dynamics, which have focussed on ways in which the attenuation of income persistence as a result of measurement error in reported income data may be minimised. In the second place, I consider the asset-based approach followed by Carter and Barrett (2006) and subsequent studies in testing for poverty traps using nonparametric techniques. The essence of the asset-based approach is to identify the structural component of income and to separate this structural component from the stochastic (random) shocks which may influence income data as well as any measurement error which may be present in reported income.

In order to facilitate this separation, the analysis in Chapter 4 makes use of a broad definition of assets, which includes all household characteristics which enable the household to earn a living, as well as any physical assets in order to estimate an asset-weighted livelihood index or structural income. The dynamics of structural income over time is then used to test for any non-linearities which may indicate the existence of a poverty trap.

In their seminal paper, Carter and Barrett (2006) postulate the existence of a specific type of poverty trap based on macroeconomic growth literature, according to which the existence of locally increasing marginal returns to wealth (level of assets) allows for a region in the growth path where households are able to switch from the low-level growth path to the higher-level growth path, thus leading to multiple dynamic equilibrium points and the bifurcation of the growth path.

Using data from the National Income Dynamics Study from 2010 and 2012, the analysis in Chapter 4 tests for the existence of these multiple equilibrium dynamic poverty traps by estimating the dynamics of structural income nonparametrically. The analysis then continues to also estimate the dynamics using parametric non-linear regressions. The findings provide no evidence for the existence of this type of poverty trap. Instead, the results seem to indicate the existence of a threshold beyond which structural income remains very persistent with little upward mobility. The location of the threshold is above the usual poverty line, indicating that upward mobility is possible for much of the population; however beyond a certain level, very little further mobility takes place, which accurately describes a country with high levels of income inequality.

1.4 Conclusion

The aim of this dissertation is to focus on three topics within the broader literature of social mobility and cohesion. It first considers one of the most important mechanisms through which social mobility is restricted and the current *status quo* of high inequality is entrenched within post-apartheid South Africa, namely school quality. It then introduces a new way of testing for the composition of reference groups used in comparisons of relative income in utility functions, as a way of examining the level of social cohesion in post-apartheid South Africa. Third, it tests for the existence of poverty traps, after examining the prevalence of chronic poverty in post-apartheid South Africa. The results from these three chapters allow for a better understanding of the existence of the current divisions in the country, which is essential for moving towards a more integrated society in which movements out of poverty are possible.

Chapter 2

School quality and the performance of disadvantaged learners

2.1 Introduction

School quality and its impact on individuals, both in terms of their immediate cognitive development as well as their future success in the labour market, have received substantial attention from economists. In countries where school quality is heterogeneous and unequally distributed within the education system, attending a school which performs better on observed measures of quality has been found to have a significant and substantial causal effect on the academic performance of children. Examples of studies capturing this effect include those estimating the private school effect in India and Pakistan (for example, Muralidharan and Kremer, 2009; Andrabi, Das, Khwaja and Zajonc, 2011; Muralidharan, 2012 and Singh, 2013); the impact of attending an elite public school in Kenya (Lucas and Mbiti, 2014); as well as the impact of attending a charter school in the context of the United States (for example, Hanuschek, Kain, Rivkin and Branch, 2007; Hoxby and Murarka, 2009 and Angrist, Pathak and Walters, 2012).

The aim of this study is to similarly estimate the impact of school quality on the academic performance of children within South Africa. For this purpose, I make use of a panel dataset containing data on a representative sample of 266 schools in South Africa, collected as part of the National School Effectiveness Study (NSES). The NSES conducted standardised tests testing children's skills in English and mathematics when they were in grade 3 (2007), grade 4 (2008) and grade 5 (2009). It also collected background information on the learners, their households and the schools that they attended.[1]

[1] Although the NSES did not directly ask children about their race, in the next section I indicate how I am able to identfy black children using the data on home language.

In South Africa, the quality of schools within the public school system is heterogeneous and highly stratified along lines of race, socio-economic status and geographic location. Large parts of the population live in geographic clusters of poverty or affluence, with access to neighbourhood schools that are of corresponding quality (Yamauchi, 2004). This emphasises the importance of school choice, especially for black children living in poor neighbourhoods (Van der Berg, 2007 and Yamauchi, 2011). The heterogeneity and stratification of school quality can be ascribed to the legacy of two historic policies. First, the policy of geographic segregation of population groups legally imposed by apartheid legislation, which caused the spatial distribution of households within the country to be racially determined and which limited the economic opportunities available to black adults. Second, the policy of institutional segregation under apartheid, which translated into racially segregated education departments administering schools.[2] The non-white education departments received considerably less funding[3] (Case and Deaton, 1999; Fiske and Ladd, 2006 and Bhorat and Oosthuizen, 2008), and the schools under their management were of inferior quality compared to the schools administered by the white education department.[4]

The result of this segregation is that the school choice of many black[5] parents living in poor neighbourhoods is limited to the low quality schools available to them by virtue of the area in which they live. Those parents who are not willing to send their children to one of the low quality local schools are forced to seek alternative schools in other areas in order to escape the low quality education that is available to them. As former department of education continues to remain a significant predictor of school quality (Van der Berg, 2007), this often involves sending children to schools that were historically reserved for white children. School surveys reveal that there is a growing sub-sample of black children attending these historically white schools.[6] However, as in the case of charter schools and private schools, there is a selection issue in the choice of these schools and these children typically

[2]The department for white schools was the House of Assemblies (HOA); for coloured schools it was the House of Representatives (HOR); Indian schools were administered by the House of Delegates (HOD) and black schools were administered by the Department of Education and Training (DET). In addition, each of the homelands had a separate education department.

[3]Bhorat and Oosthuizen (2008) report that during apartheid, *per capita* spending on black schools was equal to just 19% of the *per capita* spending on white schools, whereas Fiske and Ladd (2006) estimate that white schools received 10 times the amount of *per capita* funding that Black schools received.

[4]The view of the apartheid government regarding education is illustrated quite succinctly by this quote from Hendrik Verwoerd, who was the Minister of Native Affairs in the 1950's: "*What is the use of teaching a Bantu child mathematics when it cannot use it in practice? That is quite absurd. Education must train people in accordance with their opportunities in life, according to the sphere in which they live*" (as quoted in Timaeus, Simelane and Letsoalo, 2013 and Fiske and Ladd, 2006).

[5]With regards to the use of the terms "white" and "black" to distinguish between the two groups, I find it useful to quote Spaull (2012, footnote 2): "*The use of race as a form of classification and nomenclature in South Africa is still widespread in the academic literature with the four largest race groups being Black African, Indian, Coloured (mixed-race) and White. This serves a functional (rather than normative) purpose and any other attempt to refer to these population groups would be cumbersome, impractical or inaccurate*".

[6]Using 2009 administrative data, in approximately 40% of the historically white schools, over half of the school population was registered as being "African".

come from richer households than those black children who remain in schools that were historically part of the black part of the school system.

In previous studies aimed at estimating the causal effect of attending a higher-quality school, the main aim has been to deal with the non-random selection of children into these higher quality schools (be it private schools, charter schools or merely higher quality neighbourhood schools). Various strategies have been employed in this regard. Some studies have made use of instrumental variables such as religion (see, for example, Evans and Schwab, 1995 and Neal, 1997) to obtain unbiased estimates of the effect of private schools. Other researchers have made use of the over-subscription for charter schools and subsequent random allocation of places by way of lottery (Angrist, Bettinger and Kremer, 2006; Hoxby and Murarka, 2009 and Angrist, Pathak and Walters, 2012). An alternative identification strategy has been used to identify the effect of charter schools using dynamic panel techniques in order to eliminate or at least minimise the selection bias (Hanuschek, Kain, Rivkin and Branch, 2007). The results from these papers have been mixed, and seem to suggest a positive effect for some types of schools, but these studies find no conclusive evidence for the hypothesis that charter schools do have a positive effect on children's test scores.

In order to control for the selection bias inherent in the choice of school, I make use of the richness of the NSES data and control for a wide variety of child- and household-level characteristics. In addition, I make use of a value-added approach in which I include lagged test scores as a control for the unobserved learner heterogeneity in the form of past endowment and ability which would otherwise bias the estimates of the effect of attending a former white school. I find initial estimates of an increase of 0.7 of a standard deviation on English test scores and 0.5 of a standard deviation on mathematics test scores for black children attending a former white school. These initial estimates are slightly larger than what has been estimated for India and Pakistan[7] using the same estimation strategy. However, they should be seen within the context of South Africa having one of the most divided school systems in the world. I interpret these results by making use of empirical evidence on the learning that takes place on a year-to-year basis in South African schools. The results translate into more than a year's worth of learning.

In addition to these initial estimates, I also explore the heterogeneity of the impact of attending a former white school using only the grade 4 data and then only the grade 5 data. Results seem to indicate that the former white school impact becomes less important over time, as the lagged test score from the previous year (a measure capturing both inherent ability and past inputs) become more important.

I next address some of the concerns with the estimates that remain. First, I address the possibility that the estimates include a language effect which arises from the potentially confounding language policy implemented in primary schools in South Africa. Second, because of the high attrition rate in the NSES

[7] Where the impact was estimated to be in the region of 0.2 to 0.3 of a standard deviation.

data, I use inverse probability weighting to control for biases arising from selective attrition. Last, I am able to control for measurement error in the test scores by including the lagged scores of the other tested subject (under the assumption that the measurement errors in the English and mathematics test scores are not correlated). In addition, I address the issue of remaining unobserved individual child ability by using an instrumental variable and discuss the validity of this approach. I confirm the robustness of the estimates from the OLS value-added model in the same way that it has been confirmed for India and Pakistan by various authors. I therefore contribute to the literature on value-added models and school choice by applying this technique to the South African context. As far as I am aware, this technique has not been applied for this purpose within the South African context before.

The results have important implications for education policy in South Africa. Although it is not feasible to improve the school system by moving all children from historically black schools to historically white schools, a measure of the causal impact of attending these former white schools is necessary in the policy debate regarding the improvement of government schools which has been taking place on an on-going basis between policy makers and other interest groups. Estimating the causal effect of attending a former white school provides much-needed information on separating the effect of higher quality schools from the impact of living in a wealthier household.

The rest of the chapter is set out as follows. The next section provides further background on the quality of schools in South Africa and discusses some of the literature regarding school choice in the country. Section 2.3 describes the NSES dataset used in the chapter. The fourth section provides background on value-added models and reports the estimates from the data. The fifth section deals with some remaining issues which might bias the initial results and discusses several robustness checks I conducted in this regard. Section 2.6 concludes.

2.2 School quality and inequality in South Africa

As indicated in the introduction, the consequences of historical segregation under apartheid are still visible within the highly unequal school system which operates in South Africa today, with education quality and outcomes being highly correlated with race, socio-economic status and geographic location.

With the abolition of the apartheid system, the separate racially determined education departments were replaced by nine provincial education departments overseen by the national Department of Education.[8]

[8] Since 2009, the Department of Education has been operating as two separate departments – the Department of Basic Education (overseeing primary and secondary schools) and the Department of Higher Education and Training (overseeing all tertiary education).

Since 2007, the government has also exempted certain schools from charging school fees, based on the socio-economic status of households living in the catchment area (being the immediate geographic area) of the school. These schools are typically serving those learners in the bottom three quintiles of South Africa's income distribution.

In addition, the post-apartheid South African government has gone to great lengths to ensure a more equitable distribution of public funds in order to ensure that the legacy of unequal spending under apartheid is eliminated. Education funding has increased with every post-apartheid budget[9] and the funds have been allocated to the poorest schools (Fiske and Ladd, 2006). It has been estimated that the poorest 40% of households received 49% of the education spending in 2009 (Van der Berg, 2009). However, although the historical institutions enforcing the racial divide were abolished and public spending was targeted towards poor schools, the end of the apartheid system did not also herald the end of the quality divide between the former white and black parts of the system.

The result of these remaining differences in school quality can most clearly be seen in the differences in the performance of children within the two systems. Using the NSES data, I illustrate this point graphically in the figures included in the appendix to the chapter, where all of the tables and figures are set out. It should at this point be noted that the NSES data include test scores from a mathematics (numeracy) and English (literacy) test. The same two tests were administered in three subsequent school years - starting with grade 3 children in 2007, then grade 4 children in 2008 and finally grade 5 children in 2009. It is therefore possible to track the progress of the children in terms of their performance in these two tests over a three-year period. Looking at the kernel density curves of the distribution of the literacy and numeracy scores of black learners in the two school systems in Figure 2.1,[10] it is clear how, for both numeracy and literacy, black learners attending former black schools underperform. In fact, it would appear that, for the most part, black learners in the historically white part of the school system perform better in the standardised test, written by all grades, when they are in grade 3 than a large part of the learners in the historically black part of the school system when they are in grade 5. To emphasise this point, Figure 2.2 shows how the distribution of standardised test scores are almost undistinguishable for white and black children in the same (historically white) part of the school system.

It is this divide which has caused the South African education system to be described as bimodal (Fleisch, 2008 and Van der Berg, 2008) and to be treated as two separate data generating processes (Van der Berg, 2008 and Taylor, 2011). Van der Berg (2008) estimates the intraclass correlation coefficient (a measure of the variance between schools as a proportion of overall variance) in South Africa to be between 0.6 and 0.7, illustrating the large differences between schools. Spaull (2012) shows how

[9]The most recent budget (2013/2014) allocates R164 billion (approximately 16 US$ billion) to basic (i.e. primary and secondary) education (National Treasury of the Republic of South Africa, 2013).

[10]To be found in the appendix.

the bimodality of the South African system is not just a function of the two historic school systems, but also of school language and wealth quintiles. He also draws attention to the fact that this divide has been confirmed by all of the most recent studies conducted on South African education.[11] The ramifications of this divide extend into the labour market and create a poverty trap to those who are unlucky enough to attend a school in the wrong part of the system (see Van der Berg (2011) for further detail).

Although the existence of huge differences in school quality and academic performance exists, the causes of these differences in quality have not been easy to identify and rectify. It is clear that wide gaps still exist in terms of the resource allocation between these two systems. To illustrate this point using the schools within the NSES data, there are for example on average 33 students per teacher within the former black schools but only 22 students per teacher in the former white schools. In addition, there is a large difference in the motivation levels between these two groups of teachers. Taylor (2011) shows how over 75% of the teachers in the former white schools cover the prescribed minimum number of subjects in the curriculum, while only approximately 26% of the teachers in the former black schools cover the minimum number of prescribed topics in the curriculum. A summary of these differences is set out in Table 2.1.

However, there is widespread consensus among researchers that the differences in performance between the two school systems is not merely a result of the differences in school inputs and access to resources (Van der Berg, 2007, 2008; Bhorat and Oosthuizen, 2008 and Timaeus, Simelane and Letsoalo, 2013). Most of the empirical literature on the topic concludes that, even after controlling for school resources, a large and significant difference between the two school systems remains, which is difficult to measure explicitly and may only be ascribed to the lingering effect of many decades of discrimination between schools under apartheid (Van der Berg, 2007; Timaeus, Simelane and Letsoalo, 2013).

It is within this context that parents have to decide which school to send their children to. Officially, the choice of public school in South Africa is regulated by legislation, which determines the catchment area of each school and technically limits the choice of school to a geographic area (De Kadt, 2011).[12] However, these rules are not strictly implemented and many children currently attend schools outside their immediate neighbourhood (De Kadt, 2011). Given the bimodal nature of the school system described above as well as the situation of geographic and racial divide, many poor black parents exercise what Msila (2005) describes as the "exit option" by sending their children to a school that is

[11] Including the Trends in International Mathematics and Science Study (TIMSS) in 2002, the Progress in International Reading Literacy Study (PIRLS) in 2006, and the Southern and Eastern African Consortium for Monitoring Education Quality Survey in 2007 (SACMEQ III).

[12] School choice in South Africa is regulated primarily through the National Education Policy Act, the South Africa Schools Act, and the Employment of Educators Act. In addition, the introduction of no fee schools has also played a role (De Kadt, 2011).

not within their immediate geographic area (Lemon and Battersby-Lennard, 2010). For these parents, avoiding low quality education for their children leaves them with one of two options: first, parents can follow the route of entering their children into a low-fee private school (Centre for Development and Enterprise, 2010), and second, parents can attempt to enter their children into a former white public school.

The first choice has been studied most recently by Hofmeyr, McCarthy, Oliphant, Schimer and Bernstein (2013) and Schirmer, Johnston and Bernstein (Centre for Development and Enterprise, 2010), who report results from their study of private schools (or independent schools as they are referred to by the Department of Basic Education) in three of South Africa's provinces (Gauteng, Limpopo and the Eastern Cape). They conclude that the low fee private school sector in South Africa is growing rapidly, although it has not yet reached the proportions of these types of private schools elsewhere in the developing world (such as India).[13] It is estimated that approximately 6% of the schools in South Africa are private schools serving 4% of the school children in South Africa (Hofmeyr, McCarthy, Oliphant, Schimer and Bernstein, 2013). Although these low fee private schools in South Africa typically have access to fewer facilities, employ teachers who are on average less qualified and work for a lower salary, the Centre for Development and Enterprise (2010) found evidence to show that the learners in private schools performed much better in literacy and numeracy tests than the learners in public schools.[14]

Anecdotal evidence of the second option is numerous, and newspaper articles on the migration of children to other provinces for the sake of attending a former white school abound (see, for example, Gower, 2009 and Mail and Guardian, 2003). Lemon and Battersby-Lennard (2010) confirm these anecdotes with data from 10 schools in the Western Cape province where they conducted interviews with black school children who were sent away from their neighbourhood to historically coloured, Indian or white schools. From the data collected, it became clear that parental preference for higher school quality was the main impetus for movements to these other schools. These parents see access to a historically white school as a stepping stone into the middle class. Qualitative interviews conducted by Msila (2005) illustrate how most parents in poor black neighbourhoods would want to send their children to a better school, but are often not able to due to a shortage of cash to fund the transport to and from the school as well as pay for the school fees.

Almost 20 years after the political transition away from apartheid, South Africa's schools are more racially integrated and school-level data indicate a significant proportion of black children attending

[13] This is mostly attributed to the regulatory environment which complicates and subsequently inhibits the registration of private schools (Centre for Development and Enterprise, 2010), as well as the existence of historically white schools as an option.

[14] Although the robustness of these differences could not be tested, as the researchers were not able to obtain data on the background characteristics of learners in the public schools and accordingly, the study could not control or the differences in the backgrounds of the learners (Centre for Development and Enterprise, 2010).

what were previously white schools (although very little racial integration has occurred in the historically black schools). Although these black children in the historically white schools are often from household with a lower socio-economic status than the white children attending these schools, it is also the case that the sub-sample of black children attending these former white schools are on average from wealthier households than their peers in historically black schools (Lam, Ardington and Leibbrandt, 2011), as will be illustrated later in this chapter.

The question I wish to answer in this study is to what extent these black children in the historically white part of the school system perform better because of the improved quality of the former white schools they attend. This can only be estimated accurately if controlling for the fact that their performance is driven, to a large extent, by the fact that they come from more affluent households. In addition, and more importantly, it is necessary to note that children attending these former white schools might not only be different based on observable characteristics, but may also differ in terms of characteristics not observed in the data, for example these children might have parents who are more likely to value education and be more motivated to ensure that their children succeed in life. In addition, these might be more motivated and more able children. In this chapter, I refer to these factors collectively as "unobserved ability".

The main advantage of using the NSES data is that it provides information on outcomes and household circumstances for the same children for three years, allowing for a large number of controls and for the use of a value-added model specification. As will be discussed in Section 2.4 below, value-added models have in many instances been shown to provide unbiased estimates of the effect of attending a private or charter school. In addition, using such rich data allows me to estimate the heterogeneous effects of attending a former white school for different years. Using the same technique which has been used in other developing countries also provides an opportunity to view the South African estimates within an international context.

2.3 Description of the data used

The data used here are from the NSES, which constitutes a panel dataset with three waves collected in 2007, 2008, and 2009. Students in 266 schools, in eight of the nine provinces of South Africa[15] were tested in literacy and numeracy at the end of the school year in grade 3 (2007), grade 4 (2008) and grade 5 (2009).[16] The median ages of sampled children in the three grades were 9, 10 and 11 years respectively. Because I am only interested in former black and former white schools, i.e. schools

[15] Unfortunately, the province of Gauteng (which includes Johannesburg and Pretoria) was excluded from the survey due to other testing that was being administered in that province at the same time.

[16] In South Africa, learners attend primary school from grade R (the inception year) to grade 7.

which existed prior to 1994, only 236 schools remain in the sample. Of these, 19 schools are former white schools and 217 are former black schools. In the estimations, I lose a further number of schools as a result of missing data. My final estimation sample therefore includes only 223 schools, of which 14 are former white schools.

The NSES was designed so as to include a nationally representative sample of schools. The sampling of the schools was done using a one-stage stratification design. Schools were selected randomly from within each of the provinces, ensuring a nationally representative sample of schools. Within each randomly selected school, the entire population of grade-specific children were included in the survey.[17] A breakdown of the provincial distribution of the schools in the sample is set out in the appendix in Table 2.2.

Questionnaires regarding data at the level of the child, household and school were administered. The child and household questionnaires were answered by the children themselves. The school-level questionnaires were completed by principals and included questions on classroom size and school management practices (frequency of grade meetings, availability of lesson plans and text books). In the second and third waves, questionnaires on classroom-level characteristics were also distributed to teachers.[18] These were mostly concerned with teacher knowledge and curriculum coverage. In addition, both the literacy and numeracy tests were administered in English to all learners in all three years. In order to facilitate comparisons over time, the same tests were administered each year.

The scores used in this study were generated from the raw scores after implementing a Rasch model, a type of Item Response Theory (IRT) model. IRT models such as the Rasch model are regularly used to standardise test scores for studying the results from education assessments. The Rasch model takes into account the variation in the level of difficulty within the test (some items were more difficult than others).[19] In addition, standardising test scores using this method allows for the detection and removal of items that were uninformative in the sense that they did not fit the model as specified, and accordingly did not provide information on children's ability.[20] Since the same test was written in each year, an additional advantage of using IRT is that the items can be combined across years and therefore items can be ordered on one scale. The scores generated by the Rasch model were then standardised to have a mean of zero and a standard deviation of one.[21]

[17]The largest number of children per grade included in the survey is 256 and the smallest number of children per grade included is 4

[18]For the interested reader, Taylor (2011) includes a comprehensive discussion regarding the quality of the data collected as part of the NSES.

[19]In the Rasch model, the probability of answering any item from the test correctly is modelled as a function of the individual child's ability and the item difficulty of the specific question.

[20]In the literacy test, three "misfitting" items were removed, while in the numeracy test, only one was removed.

[21]In order to be consistent with the fact that the same tests were repeated every year, the standardisation was done using the scores from the Rasch model for 2007 for numeracy and literacy separately. This approach is suggested by Rothstein (2010).

The historical categorisation for each school was obtained using the master list data from the Department of Basic Education website. One of the main drawbacks of the NSES survey is that it did not directly ask about the race of each of the learners. Therefore, another method had to be employed in order to identify which learners in the sample could be classified as black and white. This process involved using the home language spoken by each of the learners as an indicator of the race of the learner. In South Africa, there is a strong correlation between race and language. More precisely, the home language speakers of the indigenous African languages are almost exclusively black individuals (in the 2011 census, 99.1% of the indigenous African language speakers were black and only 0.9% were from a different race group). There are, however, an increasing number of black individuals who speak English as their home language (in the 2011 census, this group made up approximately 2.9% of the black population). In order to maximise homogeneity between the two groups of black learners being compared in this study, I restricted the identification of black children in the sample to children who indicated their home language to be one of the indigenous African languages spoken in South Africa. In this way, I minimised the chance of incorrectly identifying non-black children as black.[22] On the other hand, this approach opens up the possibility of missing black children who speak English or Afrikaans at home. Since this group would most likely be from more affluent households and more likely to attend former white schools, their presence in the sample would most likely increase the size of the estimated differences between the two groups of children. Their omission does therefore not pose a significant problem to my analysis. At worst their omission would lead me to estimate smaller effect sizes, which may be interpreted as a lower bound.

Table 2.3 in the appendix sets out the structure of the data and specifies the total number of children appearing in the sample in each wave. Since the aim of this study is to compare black children in the two different school systems, the table also specifies the number of black children in historically white schools and historically black schools.

The attrition in the sample from year-to-year is high, with just over half of the original sample (8 383 children out of an original 16 503) remaining in the sample in all three waves. The attrition for the smaller sample of black children in historically white schools seems to be somewhat lower than this, with approximately 63% of the original sample remaining at the end of the three years (225 children out of an original number of 358). The high attrition rate is not entirely unsurprising, given the frequency of drop-outs and grade repetition among black children (Branson and Lam, 2010 and Lam, Ardington and Leibbrandt, 2011) as well as the frequency of movements in between schools, specifically former black schools.[23] Since the survey did not follow children but schools, I am not able to distinguish

[22] An additional sanity check reveals that this criterion to identify black children seems to be successful. Comparing the distribution of the home languages spoken by children identified as being black in the NSES with the home languages spoken by children recorded as being black and of the same age in the national census of 2011 reveals only small differences in the two distributions.

[23] Unfortunately, administrative data of the movement of children between specific schools do not exist outside the West-

between drop-outs and repeaters on the one hand and movers on the other.

For the purpose of this study, there are two distinct groups of interest in the data, namely the black children attending historically black schools and black children attending historically white schools. However, it is also useful to consider white[24] children attending historically white schools as a third group in order to provide some context.

One would expect these three sub-samples to exhibit significant differences in observable characteristics. Table 2.4 in the appendix contains the mean values of the most important covariates for each of these sub-samples. What is clear from the statistics in Table 2.4 is that, although black children attending historically white schools are on average from wealthier households than their black counterparts in historically black schools, these children are also from households which are significantly poorer than the white children attending these historically white schools.[25] In addition, on average, black children attending these historically white schools are also at a disadvantage in terms of the extent of their exposure to English (measured here in terms of whether they speak it at home and how often they watch English television programmes). If one uses the number of books available in the learner's home as well as parental assistance with homework as proxies of parents' education and their motivation for ensuring their children's education, the group of white children in historically white schools are on average significantly better off than the other two groups.

In terms of academic performance, black children in historically black schools perform significantly worse on average compared with the sample of black children in former white schools. White children in the former white schools however perform significantly better in both literacy and numeracy than both samples of black children.

The mean unconditional difference in test scores for the two samples of black children in both numeracy and literacy as well as the difference across years are summarised graphically in Figures 2.3 and 2.4. Without controlling for any of the differences in these two groups, the raw difference in mean test scores between black children in former white and black schools is close to 1.4 standard deviations of the pooled sample for both numeracy and literacy in all three years. The rest of the chapter aims

ern Cape province, where previous studies have found large movements into and out of schools (Van der Berg, 2007). Interestingly, these movements were not found to be systematic in the sense that they were in response to school performance or quality.

[24]These would also include a number of black children who are classified as being white because they speak English or Afrikaans as their home language. As indicated in the table, home language and socio-economic status are positively correlated and I would therefore expect the black children in this group to be from households that are significantly wealthier than their counterparts who speak one of the African languages at home. However, this is not testable since I do not have any indication of actual race in the data.

[25]In this chapter, the terms "black" and "disadvantaged" are often used interchangeably. Although black children in historically white schools are not disadvantaged compared to their peers in historically black schools, I argue that the term "disadvantaged" remains applicable to their situation insofar as they are relatively disadvantaged compared to their white peers who are also attending the historically white schools, as set out in Table 2.4.

to ascertain whether this difference can causally be attributed to the impact of better school quality in former white schools.

2.4 Value-Added Models

2.4.1 Background

Value-added models of learning have frequently been used to estimate the impact of teacher[26] and school quality on the academic outcomes of children. Employing these models allow for the decomposition of academic performance into attributes related to child ability[27] and school or teacher quality. Several studies which compare the estimates of teacher and school quality using value-added models to the estimates from experimental data on the same sample have recently emerged. A number of these studies find limited bias in the school quality estimates from using value-added models.

Using experimental data on assignment of teachers to classrooms in Los Angeles, Kane and Staiger (2008) test the estimates from value-added models against those using random assignment of teachers. They find that value-added models controlling for lagged student test scores and classroom characteristics produce unbiased estimates of the impact of being assigned a high quality *versus* low quality teacher. Similarly, Deming, Hastings, Kane and Staiger (2011) find that their estimates of the impact of attending a good quality neighbourhood school by using value-added models are not significantly different from the results using public school choice lottery data.

Andrabi, Das, Khwaja and Zajonc (2011) estimate the impact of private schools on test scores using first a value-added model and thereafter also employing the panel dimension of their data by specifying a dynamic GMM panel model (of the type set out in Arellano and Bond, 1991) so as to simultaneously control for measurement error in the lagged test score as well as any unobserved ability.[28] In estimating the private school effect in Pakistan, Andrabi, Das, Khwaja and Zajonc (2011) find estimates using the value-added approach and the dynamic panel GMM approach (assuming strictly exogenous inputs) that are statistically indistinguishable.

Singh (2013) estimates the private school premium in Andhra Pradesh in India using a value-added model and finds that his estimates corresponded almost exactly with the estimates by Muralidharan

[26] I apply the literature on classroom or teacher assignment directly to the case of school choice as the fundamental selection mechanism and accordingly the potential resulting bias would be exactly the same.

[27] Used here, as described earlier, to refer to both parental input and motivation as well as the child's own ability and motivation.

[28] Since the NSES data followed schools and not individual children, I cannot make use of these dynamic panel models.

(2012), which were estimated using experimental data from the same cohort of children within the same geographic area.

Chetty, Friedman and Rockoff (2014a,b) ask two related questions. First, do value-added models provide estimates of the impact of teachers on the academic performance of students which are unbiased by student sorting? Second, what are the long-term impacts of teacher quality? They use US district-level data on school outcomes and teacher assignment and match these with parent characteristics and tax records of the earnings of these children after school completion to create a panel dataset covering the school and earnings history of individuals. Using data on more than 2 million US children, Chetty, Friedman and Rockoff (2014b) answer the second question in the affirmative, showing that students who were taught by better teachers, as identified by value-added models, are financially more successful later in their lives.

To answer the first question, Chetty, Friedman and Rockoff (2014a) test for bias in the value-added models by making use of parental controls as well as the exogenous changes in teaching staff. First, the authors create a measure of forecasting error by comparing predictions from the traditional value-added model to predictions from two models which are assumed to be estimated with less bias - one including parental controls and one estimated from the movements of teachers between schools. Chetty, Friedman and Rockoff (2014a) find that the bias included in traditional value-added models is small; they obtain point estimates of the bias which are indistinguishable from zero. Most importantly, Chetty, Friedman and Rockoff (2014a) single out the lagged test score as the most important control to be included in value-added models in order to reduce bias. They find that the inclusion of the lagged test score reduces the forecast bias to approximately 5%, which is statistically insignificant from zero.

However, Rothstein (2010) warns that selection into classrooms, based on unobservable factors, may lead value-added estimates of teacher quality to produce biased results. Rothstein (2010) cautions that the bias resulting from selection of children into classrooms (or schools) could be significant. Including as many observed factors which may influence the selection into these schools are found to significantly reduce the bias.[29]

In this study, I address the issue of selection by including a rich set of covariates of the home background of children in the sample. Seeing that selection into these former white schools is highly correlated with the socio-economic status of the children, this approach should address some of the issues raised by Rothstein (2010).

[29] As indicated above, both Chetty, Friedman and Rockoff (2014a) and Kane and Staiger (2008) do not find evidence of this bias in their estimates.

2.4.2 Estimation framework

Based on these findings, this study employs a value-added model. Starting with a simple model of learning based on the education production function approach in which outcomes are a function of learning in previous time periods, inherent ability and various child and household characteristics (see for example Todd and Wolpin, 2003), the following model is specified:

$$y_{it}^* = \alpha_1^{'}\mathbf{x_{it}} + \alpha_2^{'}\mathbf{x_{i,t-1}} + \alpha_3^{'}\mathbf{x_{i,t-2}} + \ldots + \alpha_t^{'}\mathbf{x_{i1}} + \delta T_{it} + \sum_{s=1}^{s=t} \theta_{t+1,s}\mu_{is}. \tag{2.1}$$

In Equation 2.1, true (unobserved) achievement of learner i in grade (or time) t is y_{it}^*, and it is a function of all past and present inputs aggregated as vector x and the cumulative shocks to learner productivity, represented by the summed μ_{is}. For the purpose of estimating the former white school premium, I also wish to include T_{it},[30] which is a dummy equal to one if child i attended a former white school in period (or grade) t.

In practice, it is not possible to include controls for all past and present inputs, since these are unobserved in even the richest available data. However, omitting any of these controls would cause bias in the estimation of the treatment parameter δ, as the model would not be controlling for individual child ability. In order to get around this problem, a value-added model can be specified which includes lagged test scores as a catch-all variable to control for unobserved inputs or endowments, including ability, as well as unobserved past shocks. Following Andrabi, Das, Khwaja and Zajonc (2011), the model in Equation 2.2 can be specified by adding and then subtracting $y_{i,t-1}^*$; assuming that $\theta_1 = 1$ and assuming that the coefficients β and θ are geometrically decreasing.

$$y_{it}^* = \alpha'\mathbf{x_{it}} + \beta y_{i,t-1}^* + \delta T_{it} + \mu_{it}. \tag{2.2}$$

The error comprises two separate components, namely $\mu_{it} = \eta_i + \nu_{it}$. The first, η_i, is learner-specific ability which includes all unobserved characteristics of the child influencing her performance in the tests, as well as her speed of learning since it is plausible that children that come from wealthier households learn faster (Van der Berg, 2008; Timaeus, Simelane and Letsoalo, 2013). The second, ν_{it}, is the time-varying child-specific error component. As is common in the literature, I will assume that this variable is independently and identically distributed. In this model, α is referred to as the input coefficient. The parameter β is referred to in the literature as the persistence parameter and links performance across years. This is sometimes estimated as a "restricted value-added model",

$$y_{it}^* - y_{i,t-1}^* = \alpha'\mathbf{x_{it}} + \delta T_{it} + \mu_{it}, \tag{2.3}$$

[30] I define T_{it} to not be cumulative, as it only represents the current period impact of attending a former white school.

where β is assumed to be equal to one (see, for example, Hanuschek, Kain, Rivkin and Branch (2007)). However, this assumption has been shown to be untrue empirically (Andrabi, Das, Khwaja and Zajonc, 2011).

In estimating β in Equation 2.2 using pooled OLS, there are two opposing biases that work against each other. On the one hand, omitted heterogeneity or ability, captured by η_i, could potentially bias estimates of β upwards if $cov(y^*_{i,t-1}, \mu_{it}) > 0$. On the other hand, measurement error in the test scores could potentially cause attenuation bias in the estimation of the persistence coefficient. To see why this is the case, one can write observed achievement as a function of true achievement and measurement error, as in $y_{it} = y^*_{it} + \varepsilon_{it}$ and $y_{i,t-1} = y^*_{i,t-1} + \varepsilon_{it}$, with $\varepsilon_{it} \sim_{iid} N(0, \sigma^2_\varepsilon)$. I assume that measurement error is not serially correlated between years. The term ε_{it} therefore captures random guessing and marking mistakes as well as errors in data capturing, but nothing more systematic than that.

Equation 2.2 then becomes:

$$y_{it} = \alpha^{'}\mathbf{x_{it}} + \beta y_{i,t-1} + \delta T_{it} + (\eta_i + \nu_{it} + \varepsilon_{it} - \beta\varepsilon_{i,t-1}). \tag{2.4}$$

For simplicity sake, I assume that $\alpha = 0$. Now, considering only the persistence parameter, the bias associated with the measurement error, as well as the correlation between y^*_{it} and the error term can be expressed as follows:

$$\begin{aligned} plim\hat{\beta}_{OLS} &= \frac{cov(y_{it}, y_{i,t-1})}{var(y_{i,t-1})} \\ &= \frac{cov(\beta y_{i,t-1} + \delta T_{it} + \eta_i + \nu_{it} + \varepsilon_{it} - \beta\varepsilon_{i,t-1}, y_{i,t-1})}{var(y_{i,t-1})} \\ &= \beta - \beta\frac{cov(\varepsilon_{i,t-1}, y_{i,t-1})}{var(y_{i,t-1})} + \frac{cov(\eta_i, y_{i,t-1})}{var(y_{i,t-1})} \\ &= \beta + \left(\frac{cov(\eta_i, y^*_{i,t-1})}{\sigma^2_y + \sigma^2_\varepsilon}\right) - \left(\frac{\sigma^2_\varepsilon}{\sigma^2_y + \sigma^2_\varepsilon}\right)\beta. \end{aligned} \tag{2.5}$$

In Equation 2.5 I assume that ν_{it} and ε_{it} are both uncorrelated with the lagged test scores, $y_{i,t-1}$, since ν_{it} represents the random error component and I assume measurement error ε_{it} is not serially correlated.

The estimate of the persistence parameter will be biased upwards by the correlation between unobserved ability and downward by the measurement error. As pointed out by Andrabi, Das, Khwaja and Zajonc (2011), these two opposing sources of bias only cancel out directly if $cov(\eta_i, y^*_{i,t-1}) = \sigma^2_\varepsilon\beta$. Andrabi, Das, Khwaja and Zajonc (2011) show how controlling only for the measurement error in the persistence parameter without also controlling for the unobserved ability could do more harm than good. In their estimates, controlling for measurement error without a contemporaneous control for unobserved ability leads to upward bias in the estimates of the persistence parameters and attenuation bias in the estimates of the treatment variable (they also show that the pure value-added model estimation without controlling for either measurement error or unobserved ability provides unbiased estimates).[31] I will now show how this finding may be explained within the current framework by exploring the potential bias in estimates of δ.

Although the persistence parameter is of interest, the main interest of this study is in estimating δ, the treatment effect. If $\hat{\beta}$ is however biased, then $\hat{\delta}$ will also be biased. In order to break down the bias in $\hat{\delta}$, it is useful to consider imposing a biased $\hat{\beta}$ in the value-added model (Andrabi, Das, Khwaja and Zajonc, 2011). I assume that $\hat{\beta} \neq \beta$ and that the bias may be positive or negative, as set out above in Equation 2.5.

$$\begin{aligned} y_{it} &= (\beta - \hat{\beta}) y_{i,t-1} + \delta T_{it} + \eta_i + \nu_{it} + \varepsilon_{it} - \beta \varepsilon_{i,t-1} \\ y_{it} &= \beta y_{i,t-1} + \delta T_{it} + \left[\eta_i + \nu_{it} + \varepsilon_{it} - \beta \varepsilon_{i,t-1} - \hat{\beta} y_{i,t-1} \right] \end{aligned} \tag{2.6}$$

The error term now contains $\hat{\beta} y_{i,t-1}$. The bias in the coefficient on the treatment variable can be broken down as follows:

$$\begin{aligned} plim \hat{\delta}_{OLS} &= \frac{cov(y_{it}, T_{it})}{var(T_{it})} \\ &= \frac{cov(\beta y_{i,t-1} + \delta T_{it} + \left[\eta_i + \nu_{it} + \varepsilon_{it} - \beta \varepsilon_{i,t-1} - \hat{\beta} y_{i,t-1} \right], T_{it})}{var(T_{it})} \\ &= \delta + \beta \frac{cov(y_{i,t-1}, T_{it})}{\sigma_T^2} + \frac{cov(\eta_i, T_{it})}{\sigma_T^2} + \frac{cov(\varepsilon_{it}, T_{it})}{\sigma_T^2} - \beta \frac{cov(\varepsilon_{it-1}, T_{it})}{\sigma_T^2} - \hat{\beta} \frac{cov(y_{it-1}, T_{it})}{\sigma_T^2} \\ &= \delta + \frac{cov(\eta_i, T_{it})}{\sigma_T^2} + (\beta - \hat{\beta}) \frac{cov(y_{i,t-1}, T_{it})}{\sigma_T^2} \end{aligned} \tag{2.7}$$

There are three things of interest here. First, estimates of attending a former white school will be upwardly biased by the fact that selection into a former white school and ability, η_i, are positively correlated with each other.

Second, since I assume that measurement error captures mostly random guessing, there is no influence on the estimates of δ arising from the presence of measurement error in test scores and lagged test scores. Although it is likely that $var(\varepsilon_{it})$ would be smaller in historically white schools than in historically black schools (as one would expect children in higher quality schools to be less likely to rely on

[31] As I show in the next section, this result holds for the NSES data as well.

random guessing), there is no reason to expect measurement error ε_{it} to be systematicallly correlated with T_{it}.

Third, the term $(\beta - \hat{\beta})\frac{cov(y_{i,t-1},T_{it})}{\sigma_T^2}$ could be positive or negative, depending on whether $\hat{\beta}$ is biased downward (i.e. $\beta > \hat{\beta}$) or upwards (i.e. $\beta < \hat{\beta}$). This will depend on the size of the terms in Equation 2.5 above.

Summarising, any estimate of δ would be biased (i) upward by individual child ability, and (iii) upward or downward by the bias in the estimate of the persistence parameter.

As discussed in the previous section, multiple studies have confirmed that the remaining bias in the OLS estimates of δ is not substantial, in other words that these biases do cancel out in practice provided the set of household and child controls in the model are rich enough (Evans and Schwab (1995); Andrabi, Das, Khwaja and Zajonc (2011); Deming, Hastings, Kane and Staiger (2011) and Singh (2013)). In the rest of the chapter, I estimate the impact of attending a former white school using a value-added model first without controlling for measurement error and potential omitted variable bias and thereafter I use an instrumental variables approach to try and control for both measurement error and unobserved ability. I then discuss the impact of these approaches with reference to this section.

2.4.3 Results

I start by estimating the value-added model specified in Equation 2.2, with a set of controls at the level of the individual child, household and provincial fixed effects. Detailed descriptions of the covariates are included in the appendix as Table 2.5. In my discussion I focus on the former white school coefficient, as this is the variable I am interested in estimating. However, throughout I also report the persistence parameter.

The output from the estimation of this baseline model is included in the appendix as Table 2.6. The estimated effect of attending a former white school varies with the inclusion of different controls. However including all three levels of controls (probably the most desirable specification) produces a coefficient of 0.7 for literacy and 0.5 for numeracy, being the magnitude of the premium derived by black children attending a former white school.

The sizes of these coefficients are large, and should be viewed in the light of previous findings in the literature dealing with the impacts of education interventions. According to Cohen (1988), an effect size of approximately 0.2 of a standard deviation should be interpreted as being small; approximately 0.5 as being medium; and in the region of 0.8 as being a large effect.

Hill, Bloom, Black and Lipsey (2008) indicate that effect sizes in educational interventions should be interpreted within the context of the intervention and in relation to empirical benchmarks such as normative expectations of what students may be expected to learn as well as empirical evidence on the speed of learning. Referring back to Figure 2.3 provides an indication of the size of learning for children in grades 3 to 5 - between 0.4 and 0.5 of a standard deviation on a year-to-year basis. An effect size of approximately 0.4 to 0.5 of a standard deviation would therefore approximately equal a year's worth of learning.

Taking this approach, the baseline results in the third specification of Table 2.6 seem to indicate more than a year's worth of learning differences between black children in former black schools and black children in former white schools, after controlling for observed household differences as well as lagged performance as a proxy of ability.

For interest sake, I also split the sample so as to estimate the impact for the children in the sample separately when they are 10 years old in grade 4 and again when they are 11 years old and in grade 5, instead of pooling the data. This has some interesting results which are reported in Table 2.7. In the first place, the impact of attending a former white school seems to diminish with time, with the persistence parameter becoming larger. This seems to indicate the divergence which takes place between the two groups of children, and the contemporaneous impact of being observed in a former white school becomes less important in determining children's test scores and the accumulation of previous input becomes more important. However, this interpretation is of course at most tentative in light of the fact that only 3 waves of data are available.

Another way of thinking about this is to view the white school effect as the intercept, with the persistence parameter as the slope of the learning curve of children in these two school systems. Table 2.8 reports the results from value-added models where the former white school dummy has been interacted with the persistence parameter, indicating this difference in slope between the learning curves of children in the two systems. Although the coefficient on the interaction term is statistically significant for the 2008 regression, it becomes small and statistically insignificant in the 2009 regression. There does not therefore seem to be persuasive evidence (at least for the duration of the NSES panel) of a steeper slope of learning in former white schools pointing to the fact that children in former white schools are persistently able to retain more knowledge from year to year. Evidence of this result has already been seen in the trends graphically depicted in Figure 2.4.

2.5 Remaining issues and robustness checks

Various concerns with the estimation strategy and the robustness of the results set out in the previous section can still be raised. This section is dedicated to discussing the most important of these concerns and trying to address these concerns by conducting various robustness checks.

2.5.1 Language policy

The first concern that I discuss here is the fact that the language policy of teaching in South African primary schools could potentially bias the results set out above. Within the current policy framework, schools have a choice to teach in the home language of the majority of the children in the school until the end of grade 3, whereafter schools mostly switch to English as language of instruction (Vorster, Mayet and Taylor, 2013).[32] The exceptions are Afrikaans schools, which are allowed to continue teaching in Afrikaans even after the end of grade 3. In the estimation sample, there are 26 schools who selected to start teaching in English from grade 1 (referred to as "straight for English" schools). Within this sub-sample of 26 straight for English schools, there are 10 former white schools and 16 former black schools. The remaining 197 schools are schools which have selected to teach in the home language of the majority of the learners in the school during grades one to 3, and then switch to English at the beginning of grade 4 (these schools are referred to as "home language" schools). Included in this sub-sample are the 4 former white Afrikaans schools.

Since the tests used as part of the NSES were conducted in English in all three years, the concern is that this discrepancy in the language of teaching will have an effect on the performance of non-English speaking children. The former white school effect estimated in the previous section could therefore just be picking up the fact that certain non-English speaking black children in former black schools were disadvantaged by the fact that they had to write the test in a language which was less familiar to them, while those black children in former white schools were advantaged because they were taught in English. This would bias the size of the former white school premium as it would include both a school quality effect as well as a language effect. In order to obtain a cleaner estimate of the effect of these former white schools on the performance of black learners, I limit the sample so that only children who have been educated in English from grade 1 are included in the estimation.

Table 2.9 in the appendix contains the results from these regressions which only include straight for English schools. Unfortunately, the sample of black children in such schools is very small (only 1 431 children). However, the estimated coefficients for the impact of attending a former white school from this smaller sample are not statistically different from the original point estimates reported in Table 2.6. The p-value from a Wald test for the former white school coefficient being statistically significantly

[32] Although schools are allowed to formulate their own language policies in terms of the South African Schools Act of 1996, the final school-leaving exam is only available in either English or Afrikaans, and so all schools opt for either of these languages, with the vast majority of former black schools opting to teach in English (rather than Afrikaans) from grade 4 onward.

different from the coefficients estimated in the final specification in Table 2.6 is 0.4 for literacy and 0.6 for numeracy.[33]

2.5.2 Attrition

The next robustness check I conduct is to consider the high rate of attrition in the data. As discussed in Section 2.3, the survey was designed to follow schools and not individual children, and there is therefore no way of tracking children from one wave to the next. Without further information on why children move between schools, it is unclear which of the numerous possible reasons why children would drop out of and drop into the sample from one year to the next is the correct explanation. Explanations for the high levels of attrition could include the fact that children leave weak schools to attend better schools (i.e. movement related to school choice), or because some students repeat grades and are therefore not observed in the sample in later years. However, it could also be driven by absenteeism. Overall attrition in the sample is 45%. For black children in former white schools it is 36% and for black children in former black schools it is 45%. In Table 2.3, attrition per wave is set out in further detail.

There seems to be selective attrition based on certain characteristics, as set out in Table 2.10, which summarises the mean characteristics per group of attriters (i.e. children who are only observed in the data for one or two periods) versus children who remain in the data for all three years of the survey. It would appear that attriters are on average more likely to come from poorer households, attend former black schools and perform worse in both tests. This is true for the entire sample of children as well as only the sample of black children in former white schools. Using these as well as other characteristics,[34] I estimate a probit model in order to predict the propensity of attriting for all children in the sample. I then use inverse probability weighting[35] and re-estimate the baseline regression, as reported in Table 2.11 in the appendix. Again, the results for the former white school effect are very close to the initial baseline results and I am unable to reject the hypothesis that the coefficient on the former white school dummy is equal to the initial estimates in the third column of Table 2.6.

[33] I do not estimate the same regression for the sub-sample of home language schools, as the only former white home language schools are the Afrikaans schools and there are only 4 such schools in the estimation sample, with only 63 black children in these schools.

[34] I include both test scores and lagged test scores for both subjects, whether the child is male, the child's age, socio-economic status, household size, exposure to English and help with homework from adults at home as controls.

[35] Inverse probability weighting involves using the inverse of the predicted propensities from the probit model as weights in a weighted least squares regression in order to control for attrition (see, for example, Andrabi, Das, Khwaja and Zajonc, 2011).

2.5.3 Measurement error and unobserved heterogeneity

Finally, I address the two issues discussed in Andrabi, Das, Khwaja and Zajonc (2011) as set out in Section 2.4 above, namely measurement error and unobserved child ability. As discussed above, both these issues could bias the estimates of the former white school effect. The direction of bias from the unobserved ability is clearly upwards, however the impact of the bias in the persistence parameter (through selection bias and measurement error) is not clearly upwards or downwards and therefore it is not quite clear what the overall effect would be. As discussed in detail in Section 2.4, there is convincing evidence to believe that the baseline value-added estimation strategy will produce unbiased estimates of the former white school effect, as long as the covariates included in the estimation are sufficiently rich. There is therefore reason to believe that the initial results are a good indication of the impact of white schools on academic performance.

However, I also make use of two instrumental variables in order to conduct a last robustness check on the initial estimates. In the first place, I use the lagged score of the alternative subject (i.e. numeracy in the literacy regression and literacy in the numeracy regression) as an instrumental variable for measurement error in the persistence parameter. The lagged scores are highly correlated across the two subjects, making this a relevant instrument. In addition, given the nature of the measurement error I am envisaging, as described in the previous section, it is highly likely that the measurement errors in the test scores are not systematically correlated across subjects.[36] This approach therefore seems to provide a valid instrument. Using 2SLS to correct only for the measurement error in the baseline regression, I re-estimate the initial value-added model with all of the controls and report the results in the first three columns of Table 2.12. As discussed in Andrabi, Das, Khwaja and Zajonc (2011), the use of an instrument to correct for the measurement error alone increases the size of the persistence parameter by correcting for the attenuation bias. However, it causes the treatment estimates to decrease, possibly leading to an under-estimation of the true size of this effect.

Looking back at Section 2.4, the attenuation in the treatment estimates when only controlling for measurement error in the persistence parameter is in line with what is set out in Equations 2.5 and 2.7. Correcting for the attenuation in $\hat{\beta}$ without correcting for the selection bias as a result of individual child ability would lead to $\hat{\beta} > \beta$, as set out in Equation 2.5. This would feed into Equation 2.7 to lead to a negative second term, resulting in attenuated estimates of the treatment effect, $\hat{\delta}$.

In order to correct for this bias, I also make use of an instrument to control for unobserved child ability. Since there is clear selection into the former white schools by children from wealthier households, it is easy to imagine that there could be unobserved characteristics of parents and children influencing

[36] Although there would be greater variation in the measurement error of weaker students, this would merely lead to a correlation between the variation in the error and the school choice of black learners, and not to a correlation between the measurement error associated with the two subjects.

the choice of school as well as the performance of the individual child. Since the information in the NSES data is limited, it is possible that these unobserved characteristics are not controlled for merely by including covariates in the regression as in the baseline estimation.

As indicated previously, in the current circumstances, unobserved ability could bias estimates through the effect it has on the choice of school in the following two ways. In the first place, unobserved heterogeneity at the level of the child in the form of unobserved signals of the child's inherent ability could be correlated with both the choice of school and the child's academic outcomes. More specifically, because some children have higher ability than others, it might be that parents or caregivers have high aspirations for some children and therefore send these children to former white schools. Since I do not have baseline test scores or information on the aspirations of parents for their children, I cannot control for this explicitly in the regression.[37] In the second place, bias could enter the estimation framework because of parental heterogeneity that is correlated with school choice and academic outcomes, in other words some parents or caregivers may just be more motivated than others and value education much more than other parents, irrespective of the inherent ability of their child.

Using administrative data on the exact location of each of the schools in South Africa, I am able to identify whether there are any former white schools in the neighbourhood of the children in the sample. Using the administrative data, I identify the number of former white primary schools in a 10 km radius around each of the schools in the NSES data. For most of the former black schools in the sample, there are none such alternatives in the neighbourhood. However, for 44 former black schools in the sample, there is at least one former white primary school in a 10 km radius around the school.

I restrict the sample to only include children observed in schools where there is at least one former white primary school as an alternative in the 10 km radius around the school and then re-estimate the original value-added model with all controls using 2SLS with two instruments - the lagged test score of the alternative subject for measurement error (as discussed above) and the number of former white primary schools in the 10 km radius around the school as the second instrument to control for unobserved ability. The choice of including only children in areas where there is at least one former white school in a 10 km radius is aimed at making the sample more homogenous by only taking into consideration those children who live in an area where there is a former white school close by. In other words, the parents of these children have already taken the decision to migrate or send their children to areas where there is a former white school (whereas, for the rest of the sample, there are no former white schools available in the immediate area). It should also be noted that for the current sample, the presence of a former white school in a 10 km radius is also positively correlated with socio-economic status. In other words, the sample of children living in one of the areas where there is a former white school are generally from wealthier households than those who are not (leading to a more homogenous sample, as indicated previously).

[37] This is the concern raised by Rothstein (2010).

The results are set out in the last two columns in Table 2.12. The persistence parameters are unchanged, but the use of the second instrument increases the value of the former white school coefficient by approximately 0.1 of a standard deviation for literacy and numeracy, in line with what is set out in Equations 2.5 and 2.7. These estimates are not statistically significantly different from the original baseline estimates of 0.7 of a standard deviation for literacy and 0.5 of a standard deviation for numeracy.[38]

The number of former white primary schools in the 10 km radius around the NSES school is highly correlated with whether a specific child was observed in a former white school. This makes sense intuitively, as one would expect that it would be more likely for a black child to attend a former white school if there were many alternatives within driving distance from where the child lives.[39] Using this instrument I am assuming that, after controlling for socio-economic status and other proxies of household wealth and parental involvement and education, the number of white schools in the 10 km radius would not be correlated with unobserved child- and parental characteristics. This would only be violated if it is plausible that parents/households migrate specifically to an area with numerous former white schools because they value education and want their child to attend a former white school. However, since I am only including children in the sample who have been observed in areas where there is at least one alternative former white primary school as well as the fact that school choice in South Africa is not strictly regulated according to the neighbourhood in which one lives, I propose that this is a valid instrument.

It is useful at this point to consider the validity for the South African context of the conclusion by other authors (Evans and Schwab, 1995; Andrabi, Das, Khwaja and Zajonc, 2011 and Deming, Hastings, Kane and Staiger, 2011) that value-added models estimated using OLS provide unbiased estimates. For this purpose, I re-estimate the impact of attending a former white school on the limited sample of 3 621 children included in the 2SLS estimates controlling for both measurement error and unobserved heterogeneity. These results are reported in Table 2.13.

In the first two columns, I re-estimate Equation 2.2. It is clear that this sub-sample of children is better performing than the full sample of children. Although the persistence parameter remains in the same range as the original OLS estimates, the coefficient on the former white school dummy is significantly larger than estimated for the entire sample, at around 0.9 for literacy and 0.6 for numeracy. As expected from the discussion in Section 2.4, when I control for measurement error in the persistence parameter by including the lagged test score of the other subject, I find that the persistence parameter is no longer attenuated, but there is a marked decrease in the size of the coefficient on the white school dummy. In line with what previous authors have found, when controlling for individual ability as well

[38]The p-value from a Wald test on the coefficient for attending a former white school in the literacy regression is 0.697 and in the numeracy regression it is 0.730.

[39]Although I do not have data on where exactly these children live, this radius tries to cover the maximum distance that most black children would travel (De Kadt, 2011).

as measurement error, the white school coefficient increases back to its original OLS level. This result confirms the conclusions by Evans and Schwab (1995); Andrabi, Das, Khwaja and Zajonc (2011) and Deming, Hastings, Kane and Staiger (2011) in the South African context and provides additional evidence for the robustness of the original value-added estimates estimated using OLS.

2.6 Conclusion

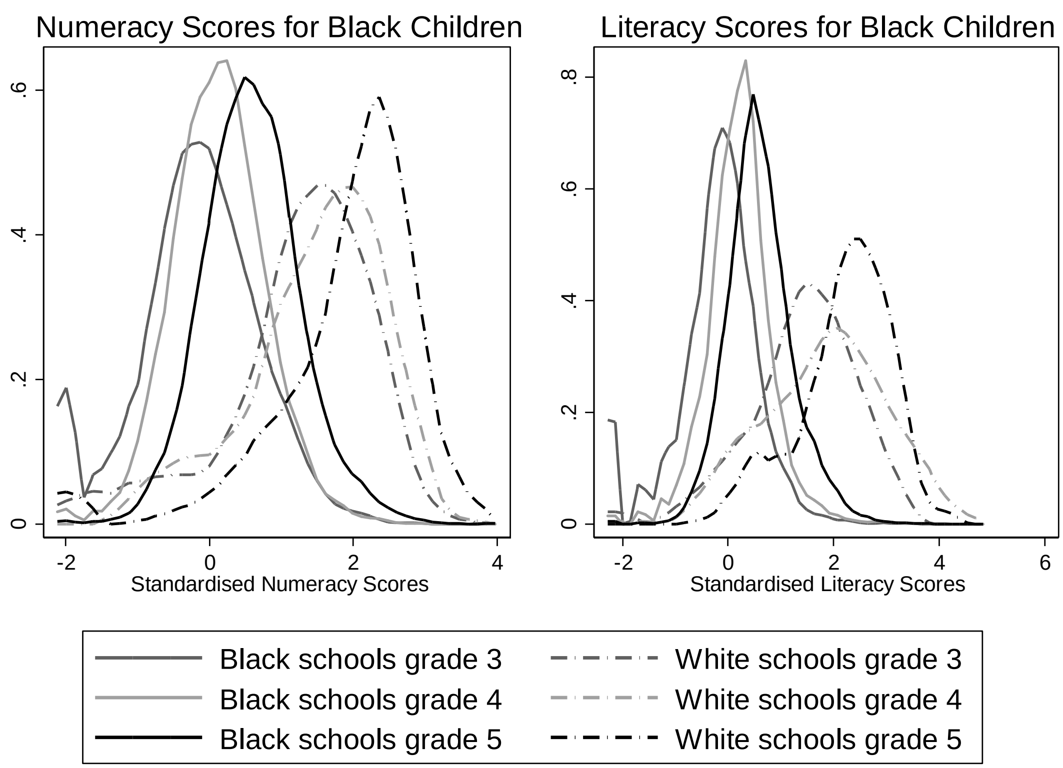
In South Africa, the quality of schools within the public school system is heterogeneous and highly stratified along the lines of race, socio-economic status and geographic location. Because of the lingering effect of apartheid, schools which historically served the white minority and accordingly received a much higher endowment of inputs and were subjected to different rules and regulations are still out-performing schools which historically served the black population. Attending one of these former black schools reduces the opportunity of poor black children to find employment after school and escape the poverty trap. In order to avoid these schools, many poor black parents send their children to former white schools situated outside of their immediate geographic area.

In this study I compare the difference in the performance between black learners who attend the historically white schools and those black learners who remain behind in the historically back part of the school system in order to obtain an estimate of the former white school premium. For this purpose, I have made use of the NSES longitudinal dataset which contains data on learner, household and school level characteristics of learners in both school systems in grades 3, 4 and 5. In order to estimate this effect, I make use of a value-added model and find an impact of 0.5 of a standard deviation for numeracy and 0.7 of a standard deviation for literacy. I conduct a number of robustness checks and discuss some of the factors which may potentially be biasing the results, including the language policy in these primary schools, attrition in the data, measurement error in the test scores and unobserved ability which may be biasing the results. In all of the robustness checks, I find estimates that are within the same range as the estimates in the baseline regression. Although the size of these effects are somewhat larger than what has been estimated for other developing countries such as Pakistan and India, their size should be seen within the context of South Africa being one of the countries with the most unequal education system in the world.

I also find additional evidence for the fact that the original OLS estimates are unbiased in the South African context by confirming the results from Andrabi, Das, Khwaja and Zajonc (2011) and others. I show that the original estimates from the value-added model using OLS are almost identical to the estimates from the 2SLS model where both measurement error (which attenuates the coefficients) and unobserved heterogeneity (which biases the coefficients upward) are controlled for.

Appendix to Chapter 2

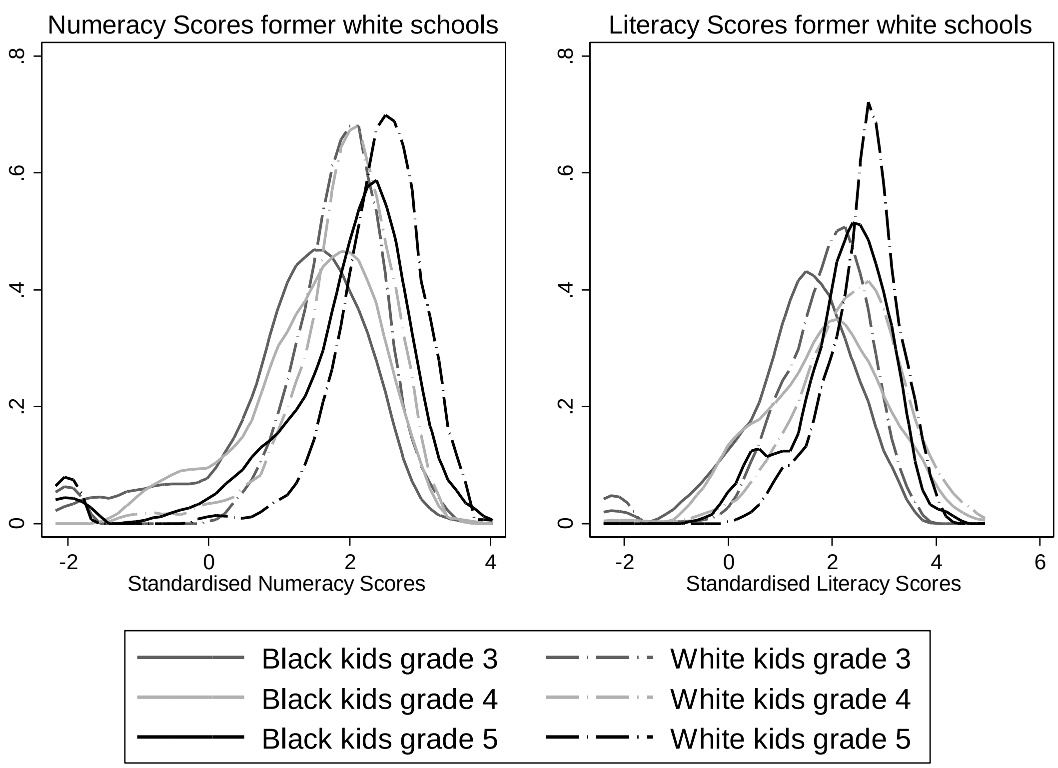
Figure 2.1: The performance of black children in the two school systems



Source: NSES data (2007, 2008, 2009).

Notes: Includes all black children who remained in the sample for all three waves.

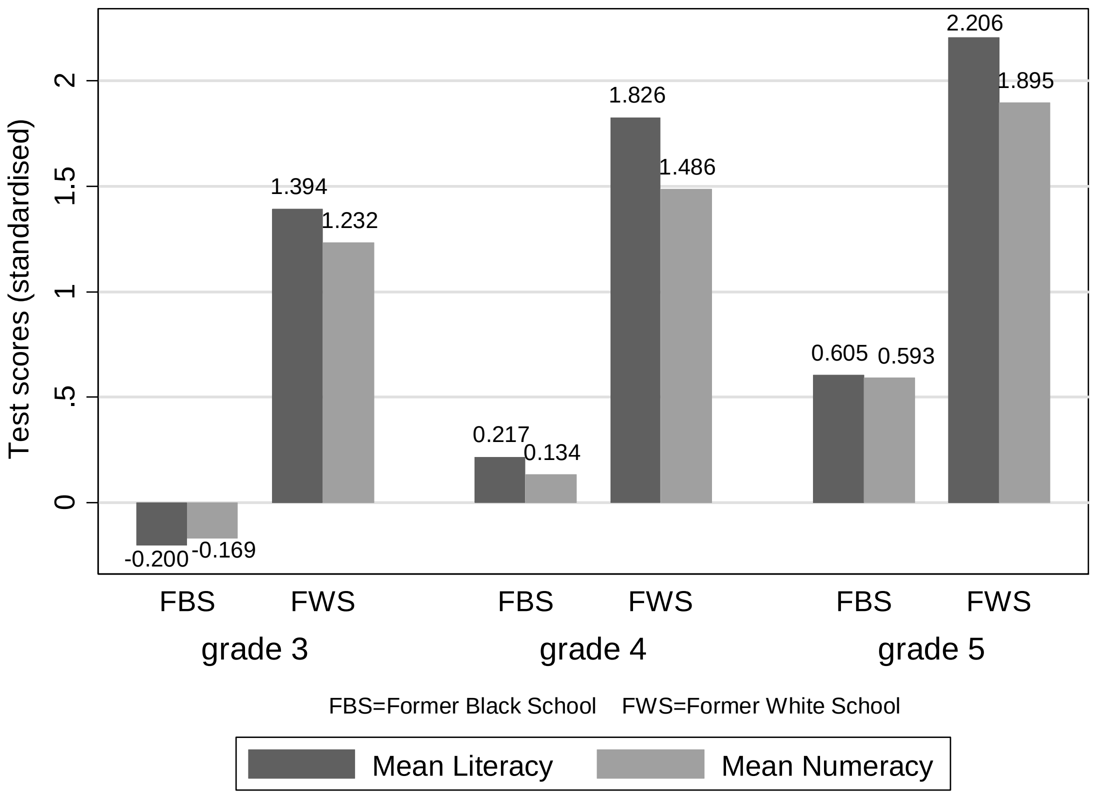
Figure 2.2: The performance of all children in the former white schools



Source: NSES data (2007, 2008, 2009).

Notes: Sample includes only black children who remained in the sample for all three waves.

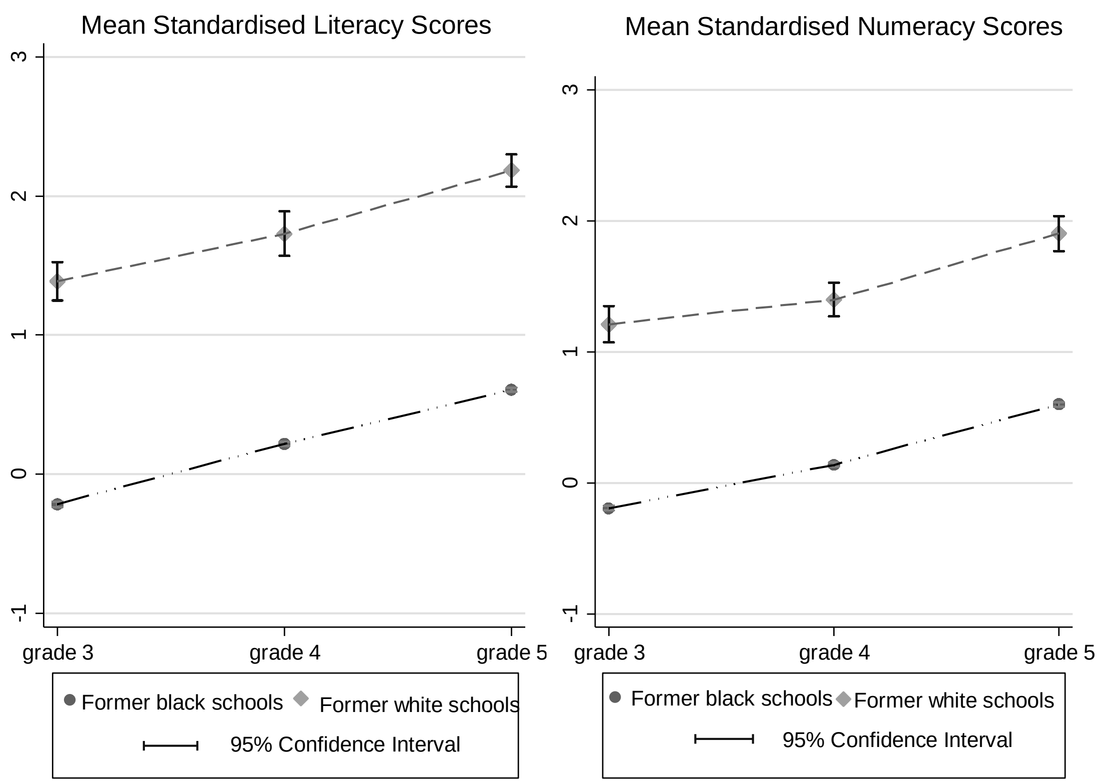
Figure 2.3: Unconditional differences in standardised test scores of black children (I)



Source: NSES data (2007, 2008, 2009).

Notes: Sample includes only black children who remained in the sample for all three waves. Weighted mean standardised test scores (mean=0, standard deviation=1).

Figure 2.4: Unconditional differences in standardised test scores of black children (II)



Source: NSES data (2007, 2008, 2009).

Notes: Sample includes only black children who remained in the sample for all three waves. Weighted mean standardised test scores (mean=0, standard deviation=1). 95% Confidence intervals reported (not visible for sample of former black schools).

Table 2.1: Differences in schools by ex-departments - mean value per school type

	Historically black schools Mean value with standard deviation in parentheses	Historically white schools Mean value with standard deviation in parentheses
Percentage of teachers absent on day of interview	13.021 (11.682)	8.698 (13.028)
Proportion of schools with functional electricity	0.663 (0.354)	0.991 (0.016)
Proportion of schools with functional running water	0.556 (0.421)	0.976 (0.107)
Proportion of schools with functional toilet facilities	0.568 (0.391)	0.880 (0.289)
Proportion of schools with functional box library	0.238 (0.341)	0.801 (0.371)
Proportion of schools with functional landline	0.327 (0.463)	0.9651 (0.221)
Pupil-teacher ratio	32.701 (6.0225)	22.464 (5.246)
Number of schools°	217	19

Source: NSES data (2007, 2008, 2009).

Notes: Sample includes only black children who remained in the sample for all three waves. ° Number of schools excludes 30 schools which were started subsequent to 1994 and therefore could not be classified as either former black or former white schools.

Table 2.2: Breakdown of schools in estimation sample per province

Province	Number of historically black schools in sample	Number of historically white schools in the sample
Eastern Cape	56	2
Free State	11	4
KwaZulu-Natal	48	2
Limpopo	37	1
Mpumalanga	29	2
North West	20	0
Northern Cape	7	1
Western Cape	1	2
Total number of schools°	209	14

Source: NSES data (2007, 2008, 2009).

Notes:° Number of schools excludes 30 schools which were started subsequent to 1994 and therefore could not be classified as either former black or former white schools, as well as 13 schools excluded from the estimation sample as a result of missing data.

Table 2.3: The number of children in the sample in each wave

Appearance in NSES	Type of observation	Grade 3 (9 years)	Grade 4 (10 years)	Grade 5 (11 years)	Total
	All children	4 583	0	0	4 583
2007	Black children in former white schools	79	0	0	79
	Black children in former black schools	3 061	0	0	3 061
	All children	0	1 535	0	1 535
2008	Black children in former white schools	0	30	0	30
	Black children in former black schools	0	1 188	0	1 188
	All children	0	0	3 612	3 612
2009	Black children in former white schools	0	0	54	54
	Black children in former black schools	0	0	2 954	2 954
	All children	3 458	3 458	0	6 916
2007&2008	Black children in former white schools	51	51	0	102
	Black children in former black schools	2 620	2 620	0	5 240
	All children	0	2 322	2 322	4 644
2008&2009	Black children in former white schools	0	53	53	106
	Black children in former black schools	0	1 740	1 740	3 480
	All children	79	0	79	158
2007&2009	Black children in former white schools	3	0	3	6
	Black children in former black schools	64	0	64	128
	All children	8 383	8 383	8 383	25 149
2007-2009	Black children in former white schools	225	225	225	675
	Black children in former black schools	6 642	6 642	6 642	19 926
	Total children	16 503	15 698	14 396	46 597
All	Total black children in former white schools	358	359	335	1 052
	Total black children in former black schools	12 387	12 190	11 400	35 977

Source: NSES data (2007, 2008, 2009).

Notes: All observations in NSES data included.

Table 2.4: Descriptive statistics - differences between three groups (pooled data from 2007 to 2009)

	Black children in former white schools$^{\circ}$	Black children in former black schools$^{\circ}$	White children in former white schools$^{\circ\circ}$
Mean home SES	0.973	-0.183*	1.424*
Proportion male	0.512	0.470	0.440*
Age in years	10.418	10.799*	9.830*
Proportion living in house with 4+ siblings	0.248	0.468*	0.054*
Proportion speaking English 4+ times per week at home	0.348	0.073*	0.444*
Proportion exposed to English on TV 4+ times per week	0.762	0.407*	0.770
Proportion receiving help with homework from parents	0.757	0.505*	0.792*
Proportion with >50 books in their home	0.306	0.083*	0.544*
Mean numeracy score	1.677	0.383*	1.948*
Mean literacy score	1.979	0.428*	2.149*
Number of observations	428	12 539	1 170

Source: NSES data (2007, 2008, 2009).

Notes: $^{\circ}$Descriptive statistics of children included in estimation sample. $^{\circ\circ}$ Descriptive statistics of children included in data (not in estimation sample).* Indicates that the difference between black learners in historically white schools and historically black schools is significant at the 5% level (3rd column) and the difference between black and white learners in historically white schools is significant at the 5% level (4th column).

Table 2.5: Description of covariates

Variable name	Description
Child level controls	
male	=1 if child is male and =0 if child ifs female.
actual_age	Age of the child in years.
actual_age2	Age of the child in years squared.
Household level controls	
ses	Household socio-economic status (SES). Using multiple correspondence analysis, the household socio-economic status was derived using data on a list of eight household amenities and assets which were either present in the household or not (based on the survey completed by each learner). These are: electricity, tap water, flush toilet in the dwelling, car, computer, daily newspaper, fridge, washing machine.
ses2	ses squared.
hhsize_big	Child lives in a household with four or more siblings.
read_adult_never	The child never reads with an adult at home.
read_adult_1to3	The child reads with an adult at home 1 to 3 times a week on average.
read_adult_4plus	The child reads with an adult at home 4 times or more per week on average.
speak_never	The child never speaks English at home.
speak_1to3	The child speaks English at home 1 to 3 times per week on average.
speak_4plus	The child speaks English at home 4 times or more per week on average.
tv_never	The child never watches English television at home.
tv_1to3	The child watches English television 1to 3 times per week on average.
tv_4plus	The child watches English television 4 times or more per week on average.
nohelp	The child receives no help from an adult at home with homework.
help_parents	The child receives help from parents at home with homework.
help_other	The child receives help from other adults(s) (not his/her parents) at home with homework.
books_0	No books at home.
books_1to10	One to ten books at home.
books_10to50	Ten to fifty books at home.
books_50plus	Fifty books or more at home.
Provincial controls	
prov1	Eastern Cape
prov2	Free State
prov3	KwaZulu Natal
prov4	Limpopo
prov5	Mpumalanga
prov6	North West
prov7	Northern Cape
prov8	Western Cape

Table 2.6: Baseline value-added model (pooled OLS)

	Literacy			Numeracy		
	1	2	3	1	2	3
Former White School	0.831***	0.693***	0.699***	0.574***	0.461***	0.465***
	(0.1507)	(0.145)	(0.133)	(0.115)	(0.113)	(0.104)
Persistence	0.474***	0.450***	0.437***	0.547***	0.535***	0.524***
	(0.025)	(0.023)	(0.021)	(0.019)	(0.017)	(0.017)
N	12 967	12 967	12 967	12 967	12 967	12 967
Clusters	223	223	223	223	223	223
R-squared	0.422	0.444	0.451	0.437	0.455	0.465
F-stat	154.263	65.001	59.646	226.51	90.803	94.052
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	No	Yes	Yes	No	Yes	Yes
Provincial Controls	No	No	Yes	No	No	Yes

Source: NSES data (2007, 2008, 2009).

Notes: OLS regression coefficients with standard errors (clustered at school level). Sample includes only black learners who were observed in all three waves and who attended one of 223 schools in estimation sample. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 2.7: Value-added model per grade

	Literacy		Numeracy	
	Grade 4 (10 years)	Grade 5 (11 years)	Grade 4 (10 years)	Grade 5 (11 years)
Former White School	0.925***	0.4881***	0.689***	0.226***
	(0.222)	(0.072)	(0.142)	(0.126)
Persistence	0.293***	0.574***	0.372***	0.709***
	(0.026)	(0.020)	(0.022)	(0.019)
N	6 620	6 347	6 620	6 347
Clusters	223	223	223	223
R-squared	0.366	0.549	0.391	0.577
F-stat	50.800	113.125	34.850	120.510
Individual controls	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Provincial controls	Yes	Yes	Yes	Yes

Source: NSES data (2007, 2008, 2009).

Notes: OLS regression coefficients with standard errors (clustered at school level). Sample includes only black learners who were observed in all three waves and who attended one of 223 schools in estimation sample. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 2.8: Value-added model per grade with interaction effects

	Literacy		Numeracy	
	Grade 4 (10 years)	Grade 5 (11 years)	Grade 4 (10 years)	Grade 5 (11 years)
Former White School	0.446*	0.610***	0.427***	0.180
	(0.231)	(0.171)	(0.144)	(0.2898)
Persistence	0.274***	0.581***	0.361***	0.707***
	(0.025)	(0.020)	(0.022)	(0.019)
Former White School*Persistence	0.378***	-0.073	0.236***	0.033
	(0.127)	(0.072))	(0.071)	(0.130)
N	6 620	6 347	6 620	6 347
Clusters	223	223	223	223
R-squared	0.375	0.549	0.394	0.577
F-stat	51.252	176.127	60.858	117.787
Individual Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Provincial Controls	Yes	Yes	Yes	Yes

Source: NSES data (2007, 2008, 2009).

Notes: OLS regression coefficients with standard errors (clustered at school level). Sample includes only black learners who were observed in all three waves and who attended one of 223 schools in estimation sample. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 2.9: Language policy estimating impact in straight for English schools

	Literacy	Numeracy
Former White School	0.519**	0.384**
	(0.203)	(0.161)
Persistence	0.460***	0.494***
	(0.049)	(0.047)
N	1 431	1 431
Clusters	26	26
R-squared	0.724	0.696

Source: NSES data (2007, 2008, 2009).

Notes: OLS regression coefficients and standard errors (clustered at school level). Specifications include all controls. Sample includes only black learners who were observed in all three waves and attended a straight for English school. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 2.10: Describing the attriters

	Full sample		Black children in former white schools	
Covariate	Observed in only one or two waves	Observed in all three waves	Observed in only one or two waves	Observed in all three waves
Mean home SES	-0.028	0.024*	1.001	0.945
In former white school	0.066	0.084*	-	-
Black	0.841	0.837	-	-
Age in years	10.591	10.270*	10.118	9.966
Mean numeracy score	0.203	0.532*	1.462	1.864*
Mean literacy score	0.391	0.755*	1.949	2.421*

Source: NSES data (2007, 2008, 2009).

Notes: Sample means per group. * indicates that the difference between the attriters and those children who remained in the panel is significant at the 5% level.

Table 2.11: Value-added model controlling for attrition using inverse probability weighting

	Literacy	Numeracy
Former White School	0.652***	0.419***
	(0.187)	(0.143)
Persistence	0.396***	0.491***
	(0.022)	(0.018)
N	12 967	12 967
Clusters	223	223
R-squared	0.402	0.427
F-stat	40.587	85.752

Source: NSES data (2007, 2008, 2009).

Notes: WLS regression coefficients with standard errors (clustered at school level) including all controls. Weights used are inverse probability of not remaining in the sample for all three waves. Sample includes only black learners who were observed in all three waves and attended one of the 223 schools in the estimation sample. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 2.12: Value-added model controlling for measurement error and unobserved heterogeneity

	Controlling for measurement error		Controlling for measurement error and unobserved heterogeneity	
	Literacy	Numeracy	Literacy	Numeracy
Former White School	0.441***	0.289***	0.835***	0.523***
	(0.100)	(0.089)	(0.338)	(0.243)
Persistence	0.628***	0.670***	0.626***	0.685***
	(0.031)	(0.029)	(0.096)	(0.072)
N	12 967	12 967	3 621	3 621
Clusters	223	223	44	44
R-squared	0.415	0.443	0.573	0.565
First stage F-statistic (persistence)	786.31	710.62	354.63	208.44
First stage F-statistic (former white school)	-	-	27.22	30.27

Source: NSES data (2007, 2008, 2009).

Notes: 2SLS regression coefficients with standard errors (clustered at school level). Instrument for persistence parameter is the lagged test score of the other subject. Instrument for unobserved heterogeneity is the number of former white primary schools in a 10km radius around the school in which the child is observed in the sample. The sample includes only black learners who were observed in all three waves and for second specification the sample is also limited to children in areas with at least one former white primary school in a 10 km radius. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 2.13: Value-added model controlling for measurement error and unobserved heterogeneity (limited sample)

	Pooled OLS (no instruments) on limited sample		2SLS Controlling for measurement error		2SLS Controlling for measurement error and unobserved heterogeneity	
	Literacy	Numeracy	Literacy	Numeracy	Literacy	Numeracy
Former White School	0.857***	0.577***	0.422***	0.230***	0.835***	0.523***
	(0.121)	(0.089)	(0.124)	(0.094)	(0.338)	(0.243)
Persistence	0.450***	0.523***	0.702***	0.743***	0.626***	0.685***
	(0.037)	(0.023)	(0.063)	(0.052)	(0.096)	(0.072)
N	3 621	3 621	3 621	3 621	3 621	3 621
Clusters	44	44	44	44	44	44
R-squared	0.599	0.586	0.557	0.552	0.573	0.565
First stage F-statistic (persistence)	-	-	233.16	289.69	354.63	208.44
First stage F-statistic (former white school)	-	-	-	-	27.22	30.27

Source: NSES data (2007, 2008, 2009).

Notes: 2SLS regression coefficients with standard errors (clustered at school level). Instrument for persistence parameter is the lagged test score of the other subject. Instrument for unobserved heterogeneity is the number of former white primary schools in a 10km radius around the school in which the child is observed in the sample. The sample includes only black learners who were observed in all three waves and for second specification the sample is also limited to children in areas with at least one former white primary school in a 10 km radius. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Chapter 3

Subjective well-being and reference groups

3.1 Introduction

The importance of subjective well-being as concept in economics has by now been firmly entrenched (Stutzer and Frey, 2010). Central to the understanding of subjective well-being and its correlates is the role of the individuals' relative well-being, or relative standing, compared to some well-defined reference group.

The relationship between relative standing and subjective well-being are important within economics for various reasons. First, it provides insight into the determinants of subjectively measured individual utility, which in turn challenges the traditional axiomatic revealed-preference models, in which individuals' utility is objective and only observable through their independent, rational, utility maximising choices (Kapteyn, Van Praag and Van Herwaarden, 1976; Frey and Stutzer, 2002; Dolan, Peasgood and White, 2008; Stutzer and Frey, 2010).[1] The relationship between relative income and subjective well-being has also challenged traditional views of utility that "more is always better" - increases in absolute income do not unequivocally lead to higher subjective well-being or utility (Ferrer-i-Carbonell, 2005). Furthermore, research on relative standing provides insight into the definition of poverty and how relative poverty may provide a more comprehensive measure of the number of people who are deprived in a specific country by constructing what Ravallion (2012) calls a "social subjective poverty line"[2] (Pradhan and Ravallion, 2000; Ravallion and Chen, 2011).[3] Last, it provides insights into the

[1]Instead, what is proposed by Kapteyn, Van Praag and Van Herwaarden (1976) is the "individual welfare function", which takes cognisance of the well-being of others.

[2]Ravallion (2012) explains how, although subjective well-being measures in themselves cannot be used as poverty lines, the relativeness of the subjective well-being measure may be used to calibrate multidimensional measures of poverty to find the point above which individuals stop feeling poor.

[3]The concept of a relative measure of poverty has come as least as far as Adam Smith, who commented on the differ-

impact of inequality on society, and reasons for why inequality is detrimental to society (Van Praag, 2011; Card, Mas, Moretti and Saez, 2012).

Although various studies have been conducted on the importance of relative well-being in developed economies, the literature regarding relative standing and reference groups in emerging and poor economies is still in its infancy. A few studies have focussed on ascertaining the importance of relative versus absolute income in countries such as India, Nepal, and Ethiopia.[4]

In the South African context, most of the research on subjective well-being has focussed on the apartheid era - the period prior to the first democratic elections on 27 April 1994 and subsequent new political dispensation.[5] Kingdon and Knight (2006, 2007) examine the question of reference groups and relative standing in South Africa in 1993. Two main conclusions arise from their studies. First, relative income is identified as a significant predictor of subjective well-being. Kingdon and Knight use two definitions of relative income, namely the mean income of individuals who are the same race as the respondent; and the position of the respondent in the income distribution of the respondent's own race group.[6] This leads to the conclusion that reference groups are divided along racial lines, a conclusion which is not surprising given the country's history of racial segregation. Second, Kingdon and Knight (2007) also find that relative income enters individuals' utility functions positively for individuals who are in the same residential cluster ("close neighbours") and negatively for more far-off individuals ("more distant others").[7] This phenomenon is ascribed to feelings of altruism which exist within small geographic areas such as the neighbourhood or village (of which the residential cluster is a proxy), while feelings of envy exist towards others in the same district, who are seen as being socially more distant.

Since 1994 South Africa has been introduced back into the world economy and has experienced unprecedented economic growth and large-scale racial integration. However, with high and persistent levels of inequality and poverty (both of which have a lingering racial undertone) remaining part of the South African economic landscape (Leibbrandt, Woolard, Finn and Argent, 2010; Finn, Leibbrandt and Levinsohn, 2012), a relevant question at this stage is whether the new political dispensation has caused any shifts in the definition of the reference group used in determining relative well-being. In other words, do individuals still compare their income with others of the same race group? And are these comparisons correlated with higher levels of subjective well-being if the reference group lives in the same cluster? Also, if reference groups are no longer solely divided along racial lines, how

ences in perceived deprivation among children in Scotland and England. In Scotland, children were not perceived to be deprived if they did not own a pair of shoes, while in England only the severely deprived did not own a single pair of shoes (Clark and Senik, 2011).

[4]An overview of this literature has been conducted by Stutzer and Frey (2010).

[5]There has been some work using 2008 data, for example Posel and Casale (2011) and Posel (2014).

[6]These definitions both assume a restrictive definition of the reference group; something which I will test in this study.

[7]This finding is confirmed by Bookwalter and Dalenberg (2010) for the non-white population.

much weight is placed on others from different race groups? The answers to these questions require some consideration. Although racial integration has taken place in many spheres of South Africans' everyday lives, interracial contact between individuals remains fragmented. In 2013, 41% of a representative sample of South Africans reported having no conversations with anyone who was not of their own race group (referred to as "interracial talk") on an average day, while only 31% reported taking part in interracial talk on a daily basis (Wale (2013), using the SA Reconciliation Barometer Survey).

The aim of this chapter is to attempt to answer questions about the racial and geographic definition of reference groups within South Africa using data from the first wave of the National Income Dynamics Study (NIDS) collected in 2008, 14 years after the first democratic elections. The data offers a unique opportunity to reassess the findings from 1993 and to add to the small body of evidence regarding reference groups in South Africa.

After providing an overview of the relevant literature, an overview of the data used in this chapter is provided. The empirical framework is explained next. In order to test the previous conclusions from the literature on the racial and geographic definition of reference groups in South Africa, I develop a more flexible way of estimating the relevant parameters. This is done by making use of a non-linear model which allows for the estimation of the weight placed on the relative standing of one's own race group compared with other race groups, while simultaneously estimating the weight placed on the geographic distance of others.

The results seem to broadly confirm the findings by Kingdon and Knight (2007) and Bookwalter and Dalenberg (2010) and indicate that households in closer proximity enter the individual's utility function positively while more far-off individuals enter the utility function negatively. More specifically, the spatial parameter is estimated as being positive for others in the same residential cluster, and negative for others living in the same district (although imprecisely estimated and therefore not statistically significant). However, the weight placed on national-level averages, as a proxy of all others in the country, are estimated to be negative and statistically significant. Some interpretations for these findings are explored.

The results also seem to broadly confirm the findings from Kingdon and Knight (2007) in terms of the racial delineation of reference groups. Allowing the parameters to be estimated non-linearly leads to estimates of the size of the own-race parameter that are between 70% and 90% of the total weight placed on others, depending on the specification. This suggests that although some racial integration has taken place, comparisons with own race weigh more than comparisons with other race groups (which, by way of definition, would be 10%-30% of the total weight). In fact, in none of the specifications can the hypothesis be rejected that the own-race parameter is not equal to 100% of the total weight, in other words where all of the weight is placed on individuals of the same race group. The chapter concludes by examining the robustness of the main findings by introducing fixed effects as well as alternative income measures.

The contribution of the empirical work is two-fold. First, it revisits the previous studies on reference groups in South Africa in 1993 and updates these findings using data from 2008. However, the main contribution of the study is that it develops a new way of estimating the various parameters which comprise the definition of reference groups in the utility function. This methodological innovation allows for these parameters to be estimated in a more flexible way, which allows for the testing of hypotheses which have formed the basis of previous studies, and which have not been tested before.

3.2 Subjective well-being and reference groups

3.2.1 A general overview of the literature

Given the large body of research on the determinants of subjective well-being, certain stylised facts have emerged in the literature. In the first place, there is general consensus that individuals with higher income are on average more likely to report higher levels of subjective well-being. In addition, the causation has been shown to run from income to happiness (Frey and Stutzer, 2002, and more recently Pischke, 2011). However, this positive relationship is limited to cross-sectional, and not time-series data. In explaining this paradox, Easterlin (1995) comes to the conclusion that it is not only absolute, but also relative income that matters - while own income is positively correlated with reported well-being, the income of all relevant others is negatively correlated. This confirmed the relative income hypothesis first proposed by Duesenberry (1949) decades earlier.

A large literature has developed around identifying and characterising the relevant reference group with whom people compare themselves. Definitions of reference groups are mostly centred around individuals who have similar attributes or have frequent social interaction with each other. Examples include parents (McBride, 2001); colleagues (Clark and Oswald (1996) using British data, Clark and Senik (2010) using data on 18 European countries, Schneider (2010) using German data and Card, Mas, Moretti and Saez (2012) using US data); an individual who is similar in age, education and gender (McBride, 2001; Ferrer-i-Carbonell, 2005); neighbours (Fafchamps and Shilpi, 2008; Dittmann and Goebel, 2010); an undefined "representative person" in society (Easterlin, 1995); and the individual at a different time period in their life (Easterlin, 2001, 2006).[8]

[8] Easterlin (2001, 2006) refer to this as life-cycle happiness and adaptation - the fact that individuals compare their present well-being to their well-being in the past.

Mostly, these studies have found that the income of the reference group enters the utility function negatively (Clark and Oswald, 1996; Clark and Senik, 2010; Schneider, 2010; Card, Mas, Moretti and Saez, 2012), seen as indicative of feelings of envy, rivalry, unfairness or relative deprivation. However, in specific settings there have also been findings that the relative standing enters the utility function positively. For example, Ferrer-i-Carbonell (2005) uses data from the German Socio-Economic Panel and finds that, for the West German sample, the results are as expected - the reference group income is negatively correlated to reported well-being. However, for the East German sample the negative effect of reference income is small (although the coefficient remains negative) and only statistically significant at the 10% level. These results are confirmed by Knies (2012), who finds a positive effect of reference income for the East German sample, although the coefficient is not statistically significant. Ferrer-i-Carbonell (2005) and Knies (2012) provide the explanation that it might be because the East German economy is more unstable, and therefore there is both a negative comparison effect (comparing oneself with better-off others and feeling worse about one's own situation) as well as a positive information effect (if others are doing well, then perhaps I will do better in the future as well). Senik (2004) finds evidence of this positive information effect for Russia, another economically unstable economy. Other reasons for the positive relationship between subjective well-being and relative income include feelings of altruism or, as will be discussed below, risk-sharing within a poor and vulnerable community.

Comparisons to reference groups are done in various domains, not only income. Frey and Stutzer (2002) and Stutzer and Frey (2010) discuss the literature on the negative impact of the general unemployment rate in a region (the country as a whole, or some smaller geographic area) on the subjective well-being of individuals. Various studies have also found that the negative impact of unemployment on subjective well-being is mitigated by high regional unemployment rates, providing evidence for reference-dependence (Grunow, 2014).

An independent though related body of research looking at the concept of social reference groups in a more structured way has also been developed by the Leyden school (including papers such as Kapteyn, Van Praag and Van Herwaarden, 1976; Van Praag, Kapteyn and Van Herwaarden, 1979; Kapteyn and Van Herwaarden, 1980; Van Praag, Frijters and i Carbonell, 2003). These authors define the concept of individuals' social reference spaces. In other words, the methodology assigns a weight to each individual within the reference group to take into account that certain individuals are more influential than others. Reference weights are estimated along a vector of social characteristics, including race, age, gender, geographic area, education, and employment status. Individuals with the same social characteristics vector are said to be of the same social type. The frequency of observing a specific social type is used along with the assumption that all individuals of the same social type will have the same social reference space, in order to estimate the weight attached to each individual in the reference space.

Apart from regression techniques, a few studies have utilised experiments to estimate the importance of relative well-being. One strand of research has made use of experiments to identify the importance of relative well-being (or "positional concerns") on overall well-being or utility, by asking participants to choose among a list of options, each containing information about the absolute and relative well-being of the participant in hypothetical future scenarios (Johansson-Stenman and Daruvala, 2002; Alpizar, Carlsson and Johansson-Stenman, 2005; Yamada and Sato, 2013). Participants clearly favour more equal societies, but choices indicate that relative standing within society remains important, and participant choices indicate a preference for a higher relative income. This holds true for income, but also consumption, especially for more visible items such as cars and houses (Alpizar, Carlsson and Johansson-Stenman, 2005). In a randomised experiment, Card, Mas, Moretti and Saez (2012) show how disclosing information on peer's salaries has an impact on workers' job satisfaction, with workers earning below the median in their occupation experiencing a decrease in job satisfaction, and an increased probability of looking for alternative employment subsequent to the information treatment.

Another approach has been to make use of functional magnetic resonance imaging (Fließbach, Weber, Trautner, Dohmen, Sunde, Elger and Falk, 2007). By varying the size of payment for correct answers in an estimation game, Fließbach, Weber, Trautner, Dohmen, Sunde, Elger and Falk (2007) show how participants' brain activity varies as the payment for correct answers changes relative to their comparison participant. This provides evidence that participants make use of social comparison in evaluating their payment.

Although the studies mentioned above have all been within the context of OECD countries, much research has also been conducted on answering similar questions for emerging economies. Clark and Senik (2011) provide an overview of the literature on subjective well-being and relative measures of well-being in various countries in Latin America, Asia and Africa. The results from these studies seem to depend on the context of the country where they were conducted and no consensus has emerged.

Fafchamps and Shilpi (2008) use data from Nepal to ascertain whether relative consumption is as important to individuals in poor, isolated countries as it is in developed countries. They find that, similar to the findings from more developed countries, Nepalese households' subjective assessment of the adequacy of their consumption[9] rises with own consumption but decreases with the higher levels of mean consumption in the ward (a proxy for neighbourhood) where the individuals live. Fafchamps and Shilpi (2008) reject the hypothesis that relative consumption only matters for individuals in developed countries.

Using a questionnaire-based choice experimental method following the design by Johansson-Stenman and Daruvala (2002) and Alpizar, Carlsson and Johansson-Stenman (2005), Carlsson, Gupta and

[9] In their paper, self-assessed adequacy of consumption is used instead of subjective well-being. The self-assessed adequacy questions ask household heads whether their household has been consuming adequate amounts of various consumer products. Fafchamps and Shilpi (2008) argue that this is a more accurate measure of utility than subjective well-being.

Johansson-Stenman (2008) asks Indian participants to choose between various fictitious future societies on behalf of an imaginary grandchild. Carlsson, Gupta and Johansson-Stenman (2008) find that there is a negative relative income effect overall, i.e. having a lower relative income in comparison to others in the same caste decreases subjective well-being. However, belonging to a caste with higher average income has a positive effect on subjective well-being. The findings suggest that the former effect dominates the latter, i.e. reported subjective well-being decreases as the relative income of the caste increases.

Ravallion and Lokshin (2010) examine the relative income hypothesis for individuals in Malawi. They find that, in contrast to the negative effect found in OECD countries, relative income of neighbours and friends (measured both objectively by taking the mean income of the enumeration area and subjectively through questions regarding perceived relative standing) enter the subjective well-being function positively for most of the sample. This positive impact may be as a result of risk-sharing agreements that would be more prevalent in poor rural areas where individuals have known their neighbours for many years.

In a related experiment, Akay, Martinsson and Medhin (2011) asks individuals in Ethiopia to choose between two fictitious villages to live in, where their own and others in the village receive different income packages, which are framed as aid packages. Akay, Martinsson and Medhin (2011) find a relatively low degree of positionality, indicating that individuals in their experiment cared less about relative income than what was generally found to be the case in richer countries. This leads Akay, Martinsson and Medhin (2011) to conclude that individuals in poorer countries care less about relative income than individuals in richer countries.

3.2.2 Subjective well-being and reference groups within the South African context

Within the South African context, quite a few studies have considered the determinants of subjective well-being generally. In earlier research, Møller and Saris (2001) examine the different domains that affect subjective well-being within each race group. Møller and Saris (2001) find that, while income is an important domain for the determination of subjective well-being for black and coloured individuals, white individuals and Asians are more influenced by other domains related to family and relationships. They also find that the determinants of subjective well-being are differentiated between the different provinces.

A similar conclusion is found in the research by Bookwalter and Dalenberg (2004) where they use the Southern African Labour and Development Research Unit (SALDRU) household survey administered in 1993 to examine the determinants of happiness for individuals in and out of poverty. They find that individuals below the poverty line view housing and transportation as the most important determinants of happiness, while those above the poverty line view sanitation, water, energy, education and health as more important. These results have important policy implications.

The structure of subjective well-being equations and the determinants of subjective well-being in South African data have been discussed in depth by Powdthavee (2003, 2005, 2006). In terms of the structure of subjective well-being equations, Powdthavee (2003) finds correlates with subjective well-being that are similar to those found in developed countries. These include reported as well as relative income, household living conditions as well as individual-level characteristics, such as whether an individual is unemployed as well as the age and race of the individual. Within the South African context, whether the individual has been a victim of a crime is also significantly (negatively) correlated with reported subjective well-being (Powdthavee, 2005).

Kingdon and Knight (2006) also use the 1993 SALDRU household survey to examine the determinants of subjective well-being in South Africa prior to the end of apartheid, and argue that subjective well-being may be used as an alternative measure of poverty.[10] They find that, although reported household income and subjective well-being are positively correlated, the effect of household income on the subjective well-being of the household is not very large. In addition, Kingdon and Knight (2006) find that absolute income seems to matter for individuals in households below the poverty line, while relative income matters for individuals in households above the poverty line. In their study, relative income is calculated using the household's race group as reference and generating race-specific income quintiles from the reported income data.

More recent studies have focussed on the changes in South Africans subjective well-being subsequent to the end of apartheid. In this regard, Møller (2007a,b) provides a detailed overview of the perceptions and attitudes of South Africans ten years subsequent to the 1994 democratic elections. She argues that, within a transitional economy such as South Africa (in which political liberation was introduced before economic reform), a large portion of the population were granted political rights without the necessary economic opportunities. According to Møller, this explains the increase in self-reported well-being among black individuals during the time of the 1994 elections, and the subsequent decrease as basic economic needs were not met, which may be interpreted as a reflection of the economic opportunities available to individuals. This decrease in hope and optimism (as evidenced by a decrease in subjective well-being) has also been ascribed to the increase in violent crime which affected thousands of South Africans in this post-apartheid period (Louw, 2007).

In terms of reference groups within the South African context, Kingdon and Knight (2007) specifically

[10] It should be noted that the SALDRU data only includes information on the perceived well-being of the household, as reported by the household head.

focus on the issue of reference groups within South Africa as a divided society. They find, again looking at 1993 SALDRU data, that although relative education and relative employment levels matter for subjective well-being, relative income is still the most significant determinant of subjective well-being. Relative income to other households in the same neighbourhood cluster is positively associated with subjective well-being, while relative income to more far-off others (i.e. other households in the district) is negatively associated with subjective well-being (Kingdon and Knight, 2007). Testing this hypothesis further, they come to the conclusion that the positive effect of others' income at the cluster level is altruistic. Kingdon and Knight (2007) use two definitions of relative income, namely the mean reported income of individuals who are the same race as the respondent; and the position of the respondent in the reported income distribution of the respondent's own race group. Finding that these two definitions are both significantly correlated with subjective well-being leads to the conclusion that reference groups also have a racial element in that individuals are more likely to compare themselves to others of the same race group. These definitions both assume a restrictive definition of the reference group, an assumption which I will relax and then test later in this chapter.

Bookwalter and Dalenberg (2010) confirm the findings of Kingdon and Knight (2007)[11] by finding that poorer households are more likely to perceive wealthier households as a positive, rather than a negative, impact on well-being. They also expand the definition of the reference group tested by Kingdon and Knight (2007) by also testing the significance of relative income in comparison to one's parents on subjective well-being. Bookwalter and Dalenberg (2010) find that relative income in comparison with one's parents has a large and significant impact on subjective well-being. Those individuals who perceived their own household to be wealthier than their parents were much more likely to report higher levels of subjective well-being.

One criticism against using reported mean income in the geographic area as the measure of relative standing comes from the work of Posel and Casale (2011), in which it was found that perceived relative income, rather than the position of the household in the income distribution based on reported income, influences the subjective well-being level of South Africans, specifically for the black sample. Posel and Casale (2011) show that this is mainly because of the large disconnect between where individuals actually are on the income distribution *versus* where they perceive themselves to be.

Although significant advances have been made in increasing the level of racial integration within South Africa subsequent to 1994, Du Toit and Kotzè (2011) point out the fact that post-apartheid affirmative action may have had the opposite effect, entrenching the racial divide brought about by apartheid legislation.[12] Some evidence of this break-down in society is found in the study by Posel and Hinks (2013) examining the levels of trust in South Africa. They find that South Africans have very low levels of reported trust compared with other countries, even when looking at trust among neighbours.

[11]Using the same data as Kingdon and Knight (2007).

[12]The authors refer to the "re-racialisation of society" in South Africa (Du Toit and Kotzè, 2011, p. 85).

Burns (2012) confirms this finding for high school children. She finds that in trust games played in high schools in South Africa, non-black students still display a greater measure of distrust towards black partners in the game. However, the results from the study do seem to indicate that students from more racially integrated schools are prone to more pro-social behaviour.

In recent work Kaus (2013) approaches the question of reference groups in South Africa from a different angle. Kaus, using Income and Expenditure Survey data from 1995, 2000 and 2005, examines the issue of conspicuous consumption within different race groups in South Africa. The hypothesis is that if conspicuous (visible) consumption is a form of status-seeking behaviour in line with Veblen's signalling model,[13] then the introduction of the relative standing of the individual compared to the reference group into the model should account for all differences in conspicuous spending between race groups. After finding large and significant differences in conspicuous consumption between white and black South Africans, Kaus sets out to test whether these differences can be explained by the signalling model. He does this by introducing a proxy of reference group income, using the mean provincial reported income of each race group as a rough proxy of reference groups. Introducing this proxy diminishes all differences in conspicuous spending in Kaus' models. Indirectly, Kaus' assumption that reference groups in South Africa remain divided along racial lines is therefore confirmed by the results.

However, Du Toit and Kotzè (2011) highlight the fact that recent data from the World Values Survey (2006) seem to signal an increased racial tolerance and inter-personal trust. Indications of racial integration seem to be borne out by the results of Hinks (2012) on the impact of fractionalisation within the South African context. Hinks (2012) finds that a higher level of ethnic and linguistic fractionalisation within the residential cluster is positively correlated with subjective well-being, which seems to indicate that there has been an increase in racial tolerance. Hinks (2012) even goes so far as describing these results as being "… *consistent with a nation that enjoys diversity*" (p. 261).

As indicated in the introduction, the question is therefore whether the new political dispensation had any effect on the way South Africans view their lives. In other words, did subjective well-being and the reference groups against which individuals compare themselves changed since 1993? The remainder of this chapter is aimed at answering this question.

[13] In other words individuals purchase certain assets purely to indicate their relative standing in the income distribution of their reference group. Therefore, the higher up one is in the reference group income distribution, the more conspicuous one's consumption will be.

3.3 Methodology

In this study, I test two hypotheses. First, I test whether the influence of reference groups is heterogeneous across space. More specifically, I test the earlier finding of Kingdon and Knight (2006, 2007) in which it was found that in apartheid South Africa, neighbours (i.e. others that live in close proximity) have a positive impact on subjective well-being (which is ascribed to altruism towards others living in close proximity) whereas others who live further away enter the utility function negatively (reflecting feelings of envy). This has also been referred to by Fafchamps and Shilpi (2008) as the convivial *versus* invidious village hypothesis. Second, I test whether earlier findings by Kingdon and Knight (2006, 2007) remain valid and test whether in post-apartheid South Africa reference groups are still racially delineated as they were found to be in 1993.

I conduct my analysis in two stages. I start by roughly replicating the approach followed by Kingdon and Knight (2007) to test whether these prior findings still hold. This approach involves the estimation of the utility function with the assumption that the parameters all enter the function linearly, and that the parameter which represents the weight placed on individuals of one's own race fully captures the relevant reference group; i.e. individuals from other race groups do not enter the utility function. This approach is restrictive in the sense that it does not allow the parameter capturing the weight placed on different race groups to vary, but rather assumes that all the weight is placed on others within the same race group, and none of the weight is placed on others from a different race group.

Therefore, to be able to get a real sense of whether the results from these previous studies still hold, it is necessary to relax these restrictions and to estimate a more flexible model, so that I am able to test both the size of the spatial parameters as well as the race parameter. For this reason, in the second stage of the analysis, I develop a more flexible model which allows the weighting parameters to enter non-linearly. With this model, I am able to estimate the weight placed on others within the same race group versus those of another race, while simultaneously estimating the spatial weights that individuals place on others in order to get to a better understanding of the correct definition of the appropriate reference group. I set out the two stages of my analysis below.

3.3.1 Testing spatial and racial variations in the reference group as per Kingdon and Knight (2007)

I start with the basic model used by Fafchamps and Shilpi (2008) in terms of which only own income, x_{ik}, and relative income, $\bar{x}_k = \frac{1}{n}\sum_{i=1}^{n} x_i$, which is just the mean income in the geographic area, are considered. The individual utility function U of individual i living in the geographic region k then takes the form:

$$U_{ik} = \alpha log(x_{ik}) + \beta log(\frac{x_{ik}}{\bar{x}_k}) + \gamma z_{ik}$$

Here utility is measured as the subjective well-being of the individual. It is modelled as a function of individual income, x_{ik} (defined as the monthly *per capita* household income); the income of the reference group, $\bar{x}_k$ (defined as the mean monthly *per capita* household income of others in the geographic area k), as well as a set of individual and household controls, z_{ik}. Typically, this is then estimated as:

$$U_{ik} = \kappa log(x_{ik}) - \beta log(\bar{x}_k) + \gamma z_{ik} \tag{3.1}$$

where $\kappa = \alpha + \beta$. The expectation is that the sign associated with the coefficient on the mean income of all others in the relevant geographic area would be negative, while the sign on the own income coefficient would be positive, reflecting the way in which the two variables enter the utility function.

In order to test the two hypotheses, I start by estimating ordered probit regressions. I include two definitions of the geographic area in which the mean income is measured: the cluster and the district. The choice of these two geographic areas is motivated by the aim of testing whether the conclusions by Kingdon and Knight (2007) remain valid. In Kingdon and Knight (2007), the residential cluster is taken as a proxy of those living in close proximity, who might be referred to as neighbours. The district is seen as a proxy of all others living a further distance away, who might be seen as strangers. In order to remain consistent with the approach by Kingdon and Knight (2007) I repeat these ordered probit regressions, not only for relative income, but also for relative education and relative employment.

I then estimate Equation 3.1, but now I use the average mean income of all others of the same race group in the cluster and then the district as the relative income measure, thereby testing the hypothesis of whether the correct reference group in South Africa is still defined in terms of race.

The robustness of this finding is tested by making use of a different measure of the reference group by including the position of the individual's household on the race-specific income distribution. This repeats the approach of Kingdon and Knight (2007), however the results can of course not be directly comparable to the results where the mean same-race income is used as a proxy of relative income. The main reason for this is that the use of the position in the race-specific income distribution makes the additional assumption that the individuals are aware of their position in relation to others of the same race, something which has been shown to rarely be true in South Africa, as discussed earlier (Posel and Casale, 2011). On the other hand, the use of mean income of all others in the same race group in the cluster and district acts merely as a proxy of the well-being of all others in the geographic area and does not assume any knowledge from the individual about where he or she ranks in the income distribution.

3.3.2 Testing spatial and racial variations in the reference group taking a more flexible approach

As indicated above, the approach above imposes some restrictions on how the parameters enter the utility function. In order to relax these assumptions, I make use of the concept of social reference spaces developed by the Leyden school (Kapteyn, Van Praag and Van Herwaarden, 1976), in the sense that I make provision for the inclusion of weights in the utility function, in order to estimate what preference is given to individuals of the same race *vis-à-vis* others of a different race in defining the relevant reference group with whom an individual compares themselves in evaluating their subjective well-being or utility.

For this purpose I define a race parameter, μ, representing the weight placed on an individual's own race group in the utility function. I define the weight placed on the other race groups in the individual's utility function as $1-\mu$, in order to capture the idea of a proportion - i.e. the sum of the two weights should be equal to one. [14]

This allows Equation 3.1 to be re-written as:

$$U_{ik} = \kappa log(x_{ik}) - \beta log(\mu \bar{x}_{1k} + (1-\mu)\bar{x}_{2k}) + \gamma z_{ik} \tag{3.2}$$

where $\bar{x}_{1k}$ is the mean income of all others in the geographic area k who are the same race as individual i and $\bar{x}_{2k}$ is the mean income of all others in the geographic area k who are a different race as individual i.

The implicit assumption made by Kingdon and Knight (2007) is that $\mu = 1$, in other words all of the weight is placed on individuals of the same race, and none on individuals of other race groups. In other words, Equation 3.2 above just simplifies back to:

$$U_{ik} = \kappa log(x_{ik}) - \beta log(\bar{x}_{1k}) + \gamma z_{ik}$$

with the only relevant comparison income being that of others in the same race group in area k.

In order to combine this race parameter with the hypothesis about spatial variation, I expand Equation 3.2 into a non-linear model which is able to test the two hypotheses described above; i.e. whether there

[14] However, in the estimations in the next section, the race parameter μ is not constrained to be between zero and one, which essentially allows it to take any value.

is spatial variation in the reference groups as well as estimating the weight or preference placed on own *versus* other race.

$$\begin{aligned} U_{icdn} &= \lambda_y log(x_{icdn}) + \lambda_y \theta_c log(\mu \bar{x}_{1cdn} + (1-\mu)\bar{x}_{2cdn}) \\ &\quad -\lambda_y \theta_d log(\mu \bar{x}_{1dn} + (1-\mu)\bar{x}_{2dn}) - \lambda_y \theta_n log(\mu \bar{x}_{1n} + (1-\mu)\bar{x}_{2n}) + \gamma z_{icdn} \end{aligned} \tag{3.3}$$

To be clear, Equation 3.3 sets out the utility function of individual i, living in residential cluster c, in district d, in nation n. The utility function includes essentially four sets of parameters or weights:

1. First, a set of preference parameters capturing the weight placed on or preference given to income λ_y in the utility function.
2. Second, a set of spatial parameters, capturing the weight or preference placed on the geographical reference group, is included. These are represented as θ's. There are 3 spatial parameters, namely θ_c (the weight placed on others living in the same residential cluster), θ_d (the weight placed on others living in the same district), and θ_n (the weight placed on all other South Africans).

   Following the conclusions of Kingdon and Knight (2007), I expect the signs of the spatial parameter associated with the cluster, θ_c, to be positive, as it captures the positive influence of the well-being of others in the same neighbourhood or village (the convivial village hypothesis). However, the signs of the spatial parameters associated with the district, θ_d and nation, θ_n, are expected to be negative in line with the invidious village hypothesis (i.e. others living further away invoke envy and have a negative impact on the individual's subjective well-being).
3. Third, the race parameter, μ, which captures the weight placed on the race group of the individual, with $1-\mu$ capturing the weight or preference placed on other race groups within the specific geographic area (cluster, district or nationally). The race parameter μ enters the utility function through the mean income variables for each of the geographic layers. In other words, μ is used to weight the mean income of the individual's own race group in the relevant geographic area, whereas $1-\mu$ is used to weight the mean income of all the other race groups in the relevant geographic area.

   An intuitive way of thinking about the interpretation of the race parameter μ is by considering the case where there is no preference given to any other individual on the basis of their race. In other words, where individual i is agnostic about the preference or weight placed on every individual in the cluster. In this instance, the size of μ would merely reflect the population weight attributed to a specific race group, and the second term in Equation 3.3 could be re-written as:

$$
\begin{aligned}
\lambda_y \theta_c log\left(\mu \bar{x}_{1cdn} + (1-\mu)\bar{x}_{2cdn}\right) &= \lambda_y \theta_c log\left(\mu(\frac{1}{n_1}\sum_{i=1}^{n_1} x_{icdn}) + (1-\mu)(\frac{1}{n_2}\sum_{i=1}^{n_2} x_{icdn})\right) \\
&= \lambda_y \theta_c log\left(\frac{n_1}{n_1+n_2}(\frac{1}{n_1}\sum_{i=1}^{n_1} x_{icdn}) + \frac{n_2}{n_1+n_2}(\frac{1}{n_2}\sum_{i=1}^{n_2} x_{icdn})\right) \\
&= \lambda_y \theta_c log(\bar{x}_{cdn})
\end{aligned}
$$

In other words, it would simplify back to the simplest case where the mean income of all individuals in the cluster, irrespective of their race, is taken as the correct measure of relative income.

4. Last, γ captures the weight placed on the individual and household controls included in the estimations as a way in which to ensure that other influences on the individual's subjective well-being has been taken into account.

3.4 Data

The data used in this analysis are from the first wave of NIDS. NIDS is conducted by SALDRU at the University of Cape Town. The survey, which was conducted by SALDRU and based on the initial 1993 SALDRU survey, was completed during 2008.[15] It incorporates data from just over 7 000 households, containing approximately 28 000 household members as well as data on approximately 18 600 "adults", defined as all individuals aged 15 years and older.[16]

The level of subjective well-being of all adults in the NIDS dataset is recorded by the inclusion of a variable measuring, on a scale from 1 to 10, the level of satisfaction with life experienced by each adult (with 1 signalling extreme dissatisfaction and 10 signalling extreme satisfaction). This differs from the SALDRU data discussed above where the question was posed to ascertain the household's subjective well-being (Posel, 2012, 2014).[17] Approximately 74% of adults who completed a questionnaire

[15] Although the second and third waves of NIDS are available, for this study it was decided to focus only on the first wave. The primary reason for this decision is the fact that there were such high levels of attrition among the white population. More specifically, attrition within the white population was 50.3% over the three waves, and was mostly as a result of refusal to complete a questionnaire. On the other hand, attrition in the black population group was much lower at 13.4%, mostly attributable to loss of contact. (De Villiers, Brown, Woolard, Daniels and Leibbrandt, 2013, p. 21-22)

[16] It should be noted that the sample worked with here is limited to individuals who were included in the adult questionnaire, which was aimed at individuals aged 15 years and older. However, as a result of inaccurate birth dates, 50 individuals aged 14 years were accidentally included in the adult questionnaire and accordingly also in the sample used in the current study. As a robustness check, I repeated the results without these individuals. The results remained unchanged up to the third decimal.

[17] One advantage of using the NIDS data is that it allows for the examination of self-reported subjective well-being per individual.

provided a response to this question.[18]

The distribution of the level of subjective well-being in the data is graphically depicted in Figure 3.1, while the summary statistics of the variable are broken down by race in Table 3.1 (all figures and tables are to be found in the appendix to the chapter). Although the mean level of subjective well-being for the entire sample is approximately 5.5, marked differences in the subjective well-being between black and white individuals are observed in the data. While the mean subjective well-being for the black population in the sample is just above 5 (with a standard deviation of 2.5), the mean for the white sample is much higher at a subjective well-being level of almost 7 (with a standard deviation of 1.8). This is in line with the differences in mean per capita income which are observed between the two race groups: the average *per capita* household income for white individuals in the data was approximately R6 448, while the average *per capita* household income for black individuals was approximately R878 (both in 2008 Rands). In addition, the distribution of subjective well-being for the white sample is much more skewed, indicating the higher levels of subjective well-being generally observed amongst white respondents (Hinks, 2012; Posel and Casale, 2011).[19]

For the current analysis, there are essentially four sets of variables used in the empirical analysis. Each of these will be discussed in turn below to provide an overview of the variables used in the empirical analysis.

In the first place, the analysis makes use of geographic variables. The NIDS data include 400 residential clusters that are all in the same district and urban or rural area. This is the smallest geographic unit of analysis within NIDS. These clusters together comprise the district councils or district municipalities, of which there are 53 in South Africa.[20] Within the district councils, households from different geographical areas are included. Since districts include a larger geographic area than the residential clusters, the district is therefore seen as a proxy for more distant others, while the cluster is seen as a proxy for closer others.

Second, the analysis relies on various individual and household-level controls which are included in the utility function. These include mean household monthly *per capita* income;[21] household size; the mean education of the household for all individuals aged 18 or older; and the proportion of individuals aged

[18] This calculation and all subsequent analyses exclude all adults for whom only a proxy questionnaire was completed.

[19] Although the significance of this difference disappears in some specifications, as indicated in the results set out in the next section.

[20] In this chapter, I refer to districts or district councils interchangeably. To be clear, I make use of the demarcation of the district and provincial boundaries at the time of the 2001 census. Although some changes have been made since 2001 in terms of the official district and provincial boundaries, these changes were small and should not have any impact on the results reported here. I have, however, also tested the robustness of my results using the boundaries of the 2011 census and there is no significant difference in the results.

[21] It should be noted that the income variable used includes the variable generated by SALDRU which includes all income brackets and a limited amount of imputations on the level of the household, but does not include a full set of imputations at the individual level.

between 16 and 64 (both inclusive) in the household who are employed. This employment variable is more preferable than the unemployment rate of the household, since a large proportion of households in the sample do not include any individuals who are economically active.[22] In calculating the mean unemployment rate, it is therefore not clear to know how to treat these cases. Setting the unemployment rate in these households equal to zero distorts the impact of the variable in the regressions. It was therefore decided to rather include the variable as an employment rate rather than an unemployment rate.

The individual-level controls included in the utility function are as follows: race; age in years; years of education; whether male or female; employment status; and marital status. These have all been shown to influence reported well-being in South Africa (see, for example, Powdthavee, 2003; Hinks and Gruen, 2007).

Differences in the subjective well-being of the four main race groups in South Africa should be seen in the light of the large differences in these covariates described above. Table 3.2 contains the descriptive statistics of variables describing the living conditions of individuals in the estimation sample, by race. It is clear that white individuals reside in smaller, wealthier households with more educated and employed adults than any of the other races, on average. As expected, individuals in the black population group remain more likely to be in poverty, live in households where individuals are less educated and are more likely to not be employed, on average. At the level of the individual, the descriptive statistics in Table 3.2 provide more evidence of the inequality that still remains between the four race groups, with much larger proportions of black individuals in the sample being discouraged or unemployed, and with a lower level of education, than white individuals, on average. Interestingly, in the sample we also see differences in the age of the individuals by race group (white individuals included in the sample are older on average), and in the marital patterns (black individuals are far less likely to be married than any of the other race groups), a phenomenon which has been researched by Posel, Rudwick and Casale (2011).

Third, the analysis also includes variables capturing the mean income, mean education and mean employment of individuals living in the same cluster and district who are from the same race group as the respondent or who are from a different race group. These variables are essentially weighted averages of the reported income (derived at the level of the household as described above) for various geographic levels - the residential cluster and the district - as the weighted mean of the respondent's own race group and as a weighted mean of all the other race groups residing in the geographic area. For individuals living in areas with complete racial homogeneity, the "other race group" variables take the value of zero. Table 3.3 sets out how the "other race group" variables differ per geographic level per race. From the table, it is clear that black individuals, when residing in neighbourhoods and villages

[22] This makes sense in the context of the findings of Leibbrandt, Woolard, Finn and Argent (2010), i.e. that approximately 30% of households reported that their main source of income was social grants.

(captured by the residential cluster) where there is racial heterogeneity (the likelihood of this occurring is discussed below), generally reside in poorer areas. This is in stark contrast to the other three race groups, but especially the white sample, who typically reside in more affluent neighbourhoods. Table 3.3 generally paints a picture of pockets of affluence and poverty which are highly correlated with the race of the households living there. This economic division raises the question whether there would be any racial integration in terms of the reference groups that individuals use to compare themselves to.

Finally, the fourth set of variables is included in order to control for the racial concentration in the various regions in South Africa. More specifically, since the utility function specified in Equation 3.3 above makes use of the division between own race and other race groups, it is necessary to control for the fact that the different geographic regions used in the analysis are not all equal in terms of racial concentration. In order to capture the extent of racial concentration a Herfindahl-Hirschman index (HHI) is calculated, in line with Hinks (2012), as follows: The HHI in area (cluster, district or province) j is calculated as follows: $H_j = 1 - \sum_{i=1}^{N=4} s_{ij}$ where s_{ij} is the proportion of race i residing in area j. More racially fractionalised or heterogeneous clusters or districts would therefore have a higher HHI.[23]

The distribution of the HHI for each race group in the cluster, district and province is reported in Table 3.4. Here it is clear to see that approximately 82% of all black individuals included in the NIDS data reside in residential clusters where there are no other race groups, i.e. neighbourhoods or villages of complete racial homogeneity. In order to control for this phenomenon, I include a control variable capturing the degree of racial concentration in the residential cluster.[24]

3.5 Empirical analysis

As discussed above, I conduct the empirical analysis by first implementing the approach followed by Kingdon and Knight (2006, 2007) and thereafter relaxing some of the restrictions of their approach so as to estimate the parameters in a more flexible way.

3.5.1 Spatial reference groups

The first hypothesis I wish to test is whether there are variations in how reference groups who live various distances from the individual enters the utility function, in line with what Kingdon and Knight

[23] According to this formulation, a HHI of zero is equal to having only a single race group in the geographic area, whereas if the four race groups were distributed equally, the HHI within the geographic area would be 0.75.

[24] The coefficient of this parameter is mostly insignificant and is therefore not reported in the next section.

(2007) have found. For this purpose, I estimate Equation 3.1 separately for each of income, education, and employment at both the cluster and district level. I include all individual and household controls described in Table 3.2 as well as provincial fixed effects. The results from these ordered probit regressions are reported in Table 3.5.

The regression output seems to provide evidence of a convivial village or neighbourhood, since the coefficient on the average well-being at the level of the residential cluster enters positively in each of the regressions (although not statistically significant in the case of the employment parameter). This confirms the findings by Kingdon and Knight (2007) where the positive coefficient was ascribed to the fact that the ties people have with their neighbours (or others in close proximity) mimic the ties with family members and that this "extended family" effect encourages feelings of altruism towards these close others rather than envy.

However, again in line with Kingdon and Knight (2007), the positive coefficients make way for negative coefficients on the relative income, education and employment of the district (although the coefficient is not significant in any of the specifications except when looking at relative education). This seems to provide evidence of a invidious district effect - i.e. the feelings of altruism that existed towards others in the same neighbourhood or village have been replaced by envy towards peers in further away areas such as the district.

3.5.2 Racial reference groups

Next, I test the finding of Kingdon and Knight (2007), namely that preference is given to the race group of the individual and less weight is placed on other race groups in the utility function when considering relative income. I follow their approach and make use of three specifications. The results from these estimations are reported in Table 3.6. All three specifications include individual and household controls as set out in Table 3.2 as well as provincial fixed effects. I estimate the results using an ordered probit model and report these coefficients.

In the first place, I create a variable which captures the position of the individual's household in the race-specific income distribution. More specifically, I specify the race-specific income quintile. Column (10) sets out the results from this specification. Unlike the results reported by Kingdon and Knight (2007) for 1993, none of these race-specific income variables are significant.

However, I also use the log of the mean income of all others residing in the same residential cluster who are the same race as the respondent to estimate the importance of same-race reference groups in the cluster. The results from this estimation are set out in Column (11). The coefficient on mean income of others of the same race is positive and significant in the regression, indicating that the income of others of the same race does seem to make a difference to the subjective well-being of individuals in a way which is consistent with the convivial village hypothesis set out above. However, although the sign of the coefficient on the mean income of others of the same race residing in the same district is negative, it is not significant.

Given the theoretical framework set out in Section 3.3, it is not clear exactly how these results should be interpreted. What is captured by the coefficients on the mean income of others of the same race (within the cluster and district) is a combination of the following three weights, which all enter the utility function: the weight placed on income, the weight placed on others within the same race group, and the weight placed on others within the cluster or district. It is not possible to separate the size of these three weights without allowing for a more flexible model, as discussed in Section 3.3.

As a first step, I allow μ to not be equal to one, by introducing variables which capture the mean income of others who are from different race groups alongside the mean income of others within the same race group, for the cluster, district and nationally. These results are reported in Table 3.7. Whereas the regression output in Table 3.6 assumed that $\mu = 1$, the approach in Table 3.7 allows μ to not be equal to one, however the approach does not allow for a separation of the weight associated with geographic distance from the weight associated with income or the weight associated with race. However, the results do provide some indication that both individuals within the race group as well as individuals from other race groups belong in the utility function.

3.5.3 Non-linear estimates

Next, I allow the parameters on income, geographic location and race to enter the utility function non-linearly.

To this end, I estimate Equation 3.3.[25] Since the preference parameters enter the utility function in a non-linear way, I make use of a non-linear least squares estimation. This estimation technique differs from the ordered probit or logit model that is generally used to model subjective well-being. Ordered probit or logit regressions allow an unobserved latent variable with unevenly spaced cut-points, in line with an ordinal utility function, whereas least squares assumes a cardinal utility function with evenly spaced categories. However, as indicated by Ferrer-i-Carbonell and Frijters (2004); Senik (2004) and Geishecker and Riedl (2012), least squares estimation remains useful in research regarding subjective well-being as an alternative to ordered probit or logit models where individual fixed effects are included, since including individual fixed effects to control for individual heterogeneity leads to biased

[25] For these estimations, I no longer include the education and employment variables in order to simplify the estimation of the race parameter and in line with the conclusions from the initial regressions which seemed to indicate that the parameters associated with employment and education were insignificant in most specifications.

ordered probit or logit estimates. In general, these authors have found their findings from least squares estimations to be very similar to the results where more flexible techniques were employed (for further detail, the reader is referred to Geishecker and Riedl, 2012). In addition, since I will not be using the fitted values from the regression, the objection of out-of-bound (i.e. below 1 or above 10) predictions is not a big concern (Angrist and Pischke, 2009).

The results from the non-linear regressions are set out in Table 3.8. Columns (16), (17) and (18) report the results from three different specifications. In the first specification in Column (16), only race is included as an additional control along with the parameters of interest. In Column (17), all of the the individual controls set out in Table 3.2 are included, whereas Column (18) report results from a regression which also includes the also includes the household-level controls described in Table 3.2. In the first specification, μ is estimated to be approximately one, indicating that individuals place all of the weight in making comparisons on their own race group, and almost nothing on other race groups. However with the inclusion of the other individual controls, the race parameter is estimated to be approximately 0.8. These point estimates seem to provide evidence that although most of the weight is still placed on individuals of the same race group, there is some comparison to others who are from the other race groups. However, importantly, none of the estimated race parameters are statistically different from 1 and I therefore cannot reject the conclusions made by Kingdon and Knight (2006, 2007); i.e. that the reference group for South Africans comprises only individuals from the same race group.

Another result from Table 3.8 is the fact that the weight placed on income is large and significant. As far as the spatial parameters are concerned, the signs of the parameters seem to confirm the findings from the ordered probit regressions - i.e. that closer others enter as positives. However, as with the ordered probit results, it is not clear what the influence of the district parameter is, since it is imprecicesly estimated and therefore statistically insignificant, although the sign of the coefficient is negative, in line with expectations. The national parameter, θ_n, is estimated to be negative and statistically significant. This seems to provide clearer evidence of the hypothesis that others living further away enter the utility function as negatives.

In order to try and ascertain the reason why the cluster parameter is positive, I test two hypotheses. First, the reason for the positive coefficient may be that the cluster-level income is a proxy for the improved service delivery which exists in richer neighbourhoods. In other words, one of the benefits of living in a wealthier neighbourhood is the fact that neighbours are more concerned about the quality of the service delivery in the neighbourhood and would make sure that basic amenities are in working condition. To test this hypothesis, I include three variables as proxies for service delivery, namely access to piped water; access to working electricity and access to a flush toilet. The results are set out in Table 3.9. Although the inclusion of these variables diminishes the size of θ_c, it remains positive and significant.

Next, I test whether the hypothesis of Kingdon and Knight (2007), namely that the positive sign of the cluster parameter is as a result of altruism existing among neighbours in the cluster. For this I re-estimate the main model for two sub-samples: the sub-sample of smaller clusters where there are less than 100 sampled individuals residing in the cluster and a separate regression for all of the larger samples where there are 100 or more sampled individuals residing in the cluster. These are reported in Table 3.9. If there are signs of altruism in the residential cluster, θ_c should be more significant for smaller clusters where individuals know each other better and the social distance between individuals is small. This is exactly what is seen from these regressions, with the estimated cluster parameter being positive and significant for the sub-sample of smaller clusters, but not for the larger clusters. This may be because the sample of larger clusters is too small to obtain an accurate estimate of θ_c. I therefore vary the cut-off for small and large clusters to be 80 and 90 individuals, and for both of these definitions, the same pattern remains. It therefore seems to indicate that there is evidence of altruism within the residential cluster.

I also examine variation in the size of the parameters. The most likely source of heterogeneity in these parameters would potentially be race. Indeed, previous studies have argued for the estimation of separate subjective well-being equations for the white and black (or non-white) population, given the large differences in the reported well-being between the race groups (Posel, 2012; Bookwalter and Dalenberg, 2010). In addition, one would expect the size of μ for the black population group to be different to that of the other population group, since (as has been shown in Table 3.4) black individuals in the sample are much more likely to live in residential clusters and districts where there is complete racial homogeneity. More precisely, 82% of black individuals in the sample live in these racially homogeneous residential clusters, while almost 19% of black individuals live in districts with complete racial homogeneity.[26] Generally, one would expect this to influence the weight that these individuals would attach to the relative well-being of individuals from other race groups.[27]

I therefore start by estimating the preference parameters using the non-linear model for two separate samples. First, I use only the black individuals in the sample. Then, I combine the sample of non-black individuals, as these three groups are all much more likely to be living in areas where there is racial heterogeneity. The findings are set out in Table 3.10. The results seem to indicate that the black sample places a greater weight on individuals in their own racial group than on individuals of another race, with an estimated size of 0.7 for μ for the black sample, whereas μ is estimated to be 1 for the non-black population. The results from the black sample also suggest a larger weight on income,[28] in

[26] As is clear from Table 3.4, the other race groups are living in areas that are much more racially integrated, and none of the other race groups live in completely homogenous districts.

[27] It is also clear how the racial concentration within a residential cluster influences the size of the race parameter μ - estimations on the sub-sample of black individuals who reside in racially integrated residential clusters report a much smaller coefficient on the race parameter - in the region of 0.571.

[28] In splitting the sample, Posel and Casale (2011) also found larger coefficients on the own income variable for the black sub-sample than for the white sub-sample.

comparison to the non-black sample.

These findings seem at first to be in contradiction to what was found by Posel and Casale (2011), i.e. that perceived relative standing is more important to the black sample than to the white sample. Posel and Casale (2011) suggest that this might be because white individuals are more likely to have access to information and would not rely solely on their own perceptions of the well-being of others in their immediate environment in order to make conclusions on their relative position in the income distribution. In contrast, many black individuals are in poverty, have less years of education on average, are more likely to live in rural areas and would accordingly be less likely to have access to accurate information regarding their relative standing. In other words, these black individuals are more likely to compare themselves to others of the same race, who live in close proximity. However, the results could also just be indicative of the fact that individuals always aspire to have more and therefore compare themselves to those who are on the same economic rank or on a higher rank than they are. This would explain why for black individuals this includes their own race as well as others of other race groups, while for the other race groups who are wealthier, this comparison is centred more around their own race group.

At this point it should be acknowledged that there has been criticism against estimating the impact of different spatial reference groups as was done above. Posel and Casale (2011) have shown, specifically with reference to the NIDS data, that perceived relative standing is a more important correlate of subjective well-being than relative standing based on reported income. However, given the framework used in this study, it would not be possible to use perceived relative standing for all of the hypotheses (most importantly, it would not have been possible to include perceived relative standing in the model used to estimate the race parameter or any of the parameters not related to income). This, along with the fact that it has been shown that relative standing based on repoted income remains an important input into the utility function, even after controlling for perceived relative standing (Posel and Casale, 2011), are the reasons why reported relative income is used in this study and not perceived relative income.

3.6 Alternative income measures and specifications

This section tests the robustness of the findings in the previous section in two ways. First by introducing geographic fixed effects and then by making use of three variations in the definition of income used in the utility function.

First, I extend the main specification set out in Equation 3.3 by introducing fixed effects at the level of the province, as well as at the level of the district council. The results from the fixed effects regressions are reported in Table 3.11. The introduction of the provincial-level fixed effects in the first column does not have any influence on the size or significance of the race parameter, while the estimation of the weight placed on others in South Africa remains negative (and somewhat larger than estimated in the baseline regressions). The cluster parameter also remains positive and significant. When the district controls are included, as reported in the second column of Table 3.11, the size of μ is increased from approximately 0.8 to 0.9. In addition, only the cluster parameter remains significant (and positive), as was the case with the introduction of the provincial fixed effects. The estimate of the weight placed on others within South Africa is diminished and the coefficient becomes insignificant. The increase in the estimated size of μ is not substantial and neither of the estimates of μ in Table 3.11 has a confidence interval which excludes one. It is therefore not possible to reject the hypothesis that μ is not equal to one. These results seem to confirm the main conclusion; i.e. that individuals place the bulk of the weight on others of their race group rather than those who are of a different race group in the construction of the reference group in their utility function. The relative standing enters the utility function positively for everyone residing in the same cluster and negatively for others who live further away - i.e. in the rest of South Africa.

The second set of robustness checks I conduct is to vary the way in which income enters the utility function. In the main specification, I have followed the convention of previous studies and have included relative income by taking the logarithm of the mean of the income in the relevant geographic area. However, this approach is susceptible to the influence of outliers. This is especially true in this particular study since I have only made use of the data available in NIDS in calculating the mean income of the various geographic areas.[29] For small geographic areas such as the residential cluster, the inclusion of outliers will almost definitely influence the size of the mean income. This could influence the size of the cluster parameter as well as the parameter associated with income. In order to ascertain whether this is the case, I propose two different ways in which income may be specified in the utility function, both of which have been suggested by Deaton (1997: 121).[30]

In the first place, I amend Equation 3.3 so that income is specified as the mean of the logarithm of individual incomes, in other words, where utility of individual i in cluster c, district d and country n was previously defined as in Equation 3.3, now it is defined as

[29] The GIS data in NIDS which would allow one to obtain census data for the geographic means became available too late to be included in this study. However, it is definitely an avenue worth exploring in the future.

[30] A related concern is the very high sampling variation which arises from the fact that the sample sizes for white and Indian populations are very small in certain clusters. In this regard, I check the robustness of the results by excluding all small clusters from the analysis, and find that the main results are robust to this exclusion.

$$
\begin{aligned}
U_{icdn} &= \lambda_y log(x_{icdn}) + \lambda_y \theta_c(\mu \bar{x}_{1cdn} + (1-\mu)\bar{x}_{2cdn}) \\
&\quad -\lambda_y \theta_d(\mu \bar{x}_{1dn} + (1-\mu)\bar{x}_{2dn}) - \lambda_y \theta_n(\mu \bar{x}_{1n} + (1-\mu)\bar{x}_{2n}) + \gamma z_{icdn}
\end{aligned} \tag{3.4}
$$

where $\bar{x}_{1cdn} = \frac{1}{n_1}\sum_{i=1}^{n_1} log(x_{icdn})$.

The results from the specification using the mean of the logarithms of individual incomes is set out in Table 3.12. The income and cluster parameters do not change substantially from the main specification, seeming to validate the conclusion from the main results that the cluster income enters the utility function positively. The race and South African parameters are estimated to be somewhat larger as in the main specification. This does not however invalidate the main conclusion that the size of μ is no longer equal to one, and that some weight is also placed on other race groups. The negative sign of θ_n remains and is somewhat larger using the mean of the log income. This again confirms the result from the main specification that others who live further away, and can be seen as strangers rather than neighbours, enter the utility function as a negative.

The second alteration to the definition of the income variable again makes use of the specification in Equation 3.4, however instead of mean income, the median is used. The results from this regression is reported in the second column in Table 3.12. The income parameter λ_y and the cluster parameter θ_c again do not significantly differ in size or significance from the main regression, seeming to again confirm the conclusion that the income in the cluster enters the utility function positively. However, μ is estimated to be slightly larger, at 0.92. The parameter associated with national income, θ_n is however statistically insignificant (and positive) in this specification.

One final robustness check which I conduct involves amending the composition of the income variable in order to remove the potential of double counting individuals in the utility function. More specifically, up to this point I have defined the own race cluster, district and national income averages to include individuals to whom these averages pertain. In the final robustness check, I amend this by creating the own race average cluster income variable by excluding own income; I create the own race average district income variable by excluding the average income of the individual's own cluster and I create the own race average national income by excluding the average income of the individual's district. The results from this regression are reported in the third column of Table 3.12. The estimated size of μ is slightly diminished, but confirms the main conclusion, as it is not possible to reject the hypothesis that it is equal to one. The size and significance of the income and cluster parameters remain, however the national parameter becomes insignificant.

3.7 Conclusion

This aim of this work was to update and expand the findings from previous authors, most notably Kingdon and Knight (2006, 2007) and Bookwalter and Dalenberg (2010) regarding the definition of reference groups for the purposes of subjective well-being or utility functions in the South African context. Being a country which remains highly unequal, and where this inequality has a lingering racial undertone, South Africa makes for an interesting case study of the formation of reference groups. Since 1994, much has been done to improve this inequality and the racial segregation which remains part of the South African landscape.

Using data from the NIDS survey in 2008, the study aims to investigate spatial and racial variation in the determination of the relevant reference group. It revisits previous findings by Bookwalter and Dalenberg (2010) and Kingdon and Knight (2007, 2006) for South Africa in 1993. First, the empirical methodology implemented in these previous studies is repeated in order to confirm the validity of the results on the 2008 data. However, in addition to this, I also expand these previous findings by relaxing the assumptions used in the estimation of the results by Kingdon and Knight (2007). More specifically, while Kingdon and Knight (2007) made use of a restrictive model in which the spatial parameters entered the utility function linearly, and the race parameter was not allowed to vary between different races, I relax these restrictions. For this purpose, I make use of a more flexible non-linear model in which the various spatial parameters are allowed to enter on-linearly and interact with the race and preference parameters. In addition, the race parameter is allowed to vary between zero and one, and may be interpreted as the weight placed on individuals of the same race group in the determination of the reference group.

The results for various specifications of the more flexible non-linear model suggest that for the sample, the relative well-being of others in the same residential cluster (a proxy for neighbours) enter the utility function positively whereas the relative well-being of others who live further away, more specifically in the rest of the country, enter the utility function negatively. This seems to confirm the hypothesis that while individuals are altruistic towards their neighbours or individuals living in the close vicinity, they view those living further away with envy. Similar conclusions by Fafchamps and Shilpi (2008) label the first as the convivial village hypothesis whereas the second is referred to as the invidious village hypothesis.

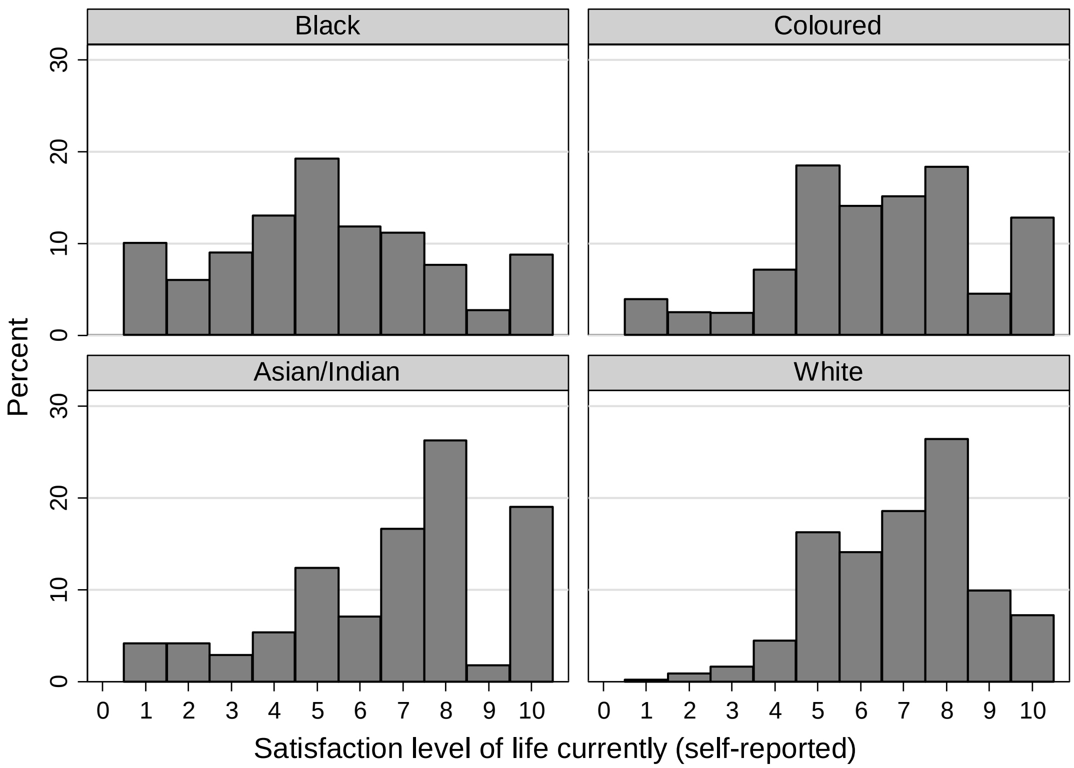
Furthermore, as far as the race parameter is concerned, the results seem to indicate that at least some racial integration has taken place in the 14 years subsequent to the end of apartheid, with reference groups shifting from being solely based on own race, to also include others from different races. However, the size of the own-race parameter remains larger than the weight placed on other race groups, and is estimated to be between 0.7-0.9,[31] depending on the specification. This suggests that although some racial integration has taken place, comparisons with own race weigh more than comparisons with other race groups.

The robustness of these results is tested by introducing provincial and district fixed effects. In addition, three alternative definitions of income are used to test for the effect of outliers. These robustness checks seem to confirm the main results.

[31] In none of the specifications could I reject the hypothesis that the race parameter is equal to one.

Appendix to Chapter 3

Figure 3.1: Subjective well-being level by race



Source: NIDS data (2008).

Notes: Weighted satisfaction levels of 13 777 adults who completed the question on subjective well-being, measuring, on a scale from 1 to 10, the level of satisfaction with life experienced by each adult (with 1 signalling extreme dissatisfaction and 10 signalling extreme satisfaction).

Table 3.1: Summary statistics of subjective well-being by race

	Mean	Standard deviation	Median	Mode	Number of observations
Black	5.229	2.553	5	5	10 690
Coloured	6.464	2.294	7	5	1 991
Asian & Indian	6.809	2.474	7	8	218
White	6.950	1.766	7	8	878
Total	5.567	2.536	5	5	13 777

Source: NIDS data (2008).

Notes: Weighted satisfaction levels of 13 777 adults who completed the question on subjective well-being, measuring, on a scale from 1 to 10, the level of satisfaction with life experienced by each adult (with 1 signalling extreme dissatisfaction and 10 signalling extreme satisfaction).

Table 3.2: Descriptive statistics of characteristics of estimation sample

Variable	Mean (standard deviation)				
	Black	Coloured	Asian & Indian	White	Entire sample
Mean household:					
Monthly pc hh inc (2008 Rands)	877.909	2231.740	3456.610	6448.484	1651.319
	(2166.175)	(9459.668)	(4204.452)	(7886.163)	(4613.861)
Size	4.864	4.631	4.886	3.079	4.656
	(3.370)	(2.611)	(2.695)	(1.236)	(3.181)
Education in years°	8.484	9.025	10.438	12.164	8.972
	(3.161)	(3.123)	(2.581)	(1.620)	(3.229)
Proportion of adults employed°°	0.427	0.537	0.585	0.659	0.465
	(0.383)	(0.370)	(0.360)	(0.383)	(0.389)
HHI in the cluster	0.043	0.234	0.327	0.325	0.0966
	(0.127)	(0.224)	(0.214)	(0.208)	(0.183)
Mean individual:					
Age in years	34.300	36.994	37.528	42.604	35.494
	(14.913)	(14.702)	(15.178)	(15.178)	(15.153)
Education in years	8.591	8.969	10.269	12.128	9.043
	(3.833)	(3.594)	(3.202)	(1.959)	(3.805)
Proportion male	0.448	0.423	0.417	0.444	0.444
	(0.497)	(0.494)	(0.494)	(0.497)	(0.467)
Not economically active	0.364	0.289	0.330	0.265	0.346
	(0.481)	(0.453)	(0.471)	(0.442)	(0.476)
Unemployed (discouraged)	0.051	0.071	0.064	0.034	0.051
	(0.220)	(0.257)	(0.245)	(0.182)	(0.221)
Unemployed (strict)	0.160	0.112	0.038	0.073	0.144
	(0.367)	(0.315)	(0.192)	(0.260)	(0.351)
Employed	0.425	0.528	0.568	0.628	0.459
	(0.494)	(0.499)	(0.497)	(0.484)	(0.498)
Married	0.251	0.404	0.586	0.614	0.312
	(0.434)	(0.491)	(0.494)	(0.487)	(0.463)
Living with partner	0.102	0.111	0.007	0.040	0.093
	(0.302)	(0.314)	(0.085)	(0.196)	(0.291)
Widowed	0.063	0.044	0.076	0.053	0.060
	(0.243)	(0.206)	(0.265)	(0.223)	(0.238)
Divorced or separated	0.021	0.059	0.062	0.107	0.034
	(0.143)	(0.236)	(0.242)	(0.310)	(0.182)
Never married	0.563	0.382	0.268	0.186	0.500
	(0.496)	(0.486)	(0.444)	(0.310)	(0.500)
Number of observations	9 774	1 802	202	727	12 505

Source: NIDS data (2008).

Notes: Descriptive statistics of 12 505 adults (aged 15 years and older) who are included in the estimation sample.°Education in the household is calculated only for individuals aged 18 years and older.°°Proportion of individuals aged between 16 and 64 (both inclusive) in the household who are employed.

Table 3.3: Distribution of income, education and employment in the residential cluster, district and province of the estimation sample

Variable	Mean (standard deviation)				
	Black	Coloured	Asian/Indian	White	Entire sample
Mean income of other race groups in:					
Cluster	1860.54 (2551.06)	2540.55 (3093.17)	2825.29 (2672.61)	5235.01 (4513.00)	2988.28 (3602.68)
District	3491.15 (2625.65)	2159.26 (1220.45)	1799.05 (774.52)	1367.84 (554.99)	3050.15 (2446.72)
Province	4801.13 (1915.29)	1981.19 (544.82)	1096.17 (462.74)	1206.52 (411.50)	4082.93 (2193.88)
Mean education of other race groups in:					
Cluster	8.114 (3.958)	10.029 (2.593)	10.575 (1.680)	11.398 (1.888)	9.546 (3.438)
District	10.247 (2.428)	9.883 (1.208)	8.964 (1.083)	9.212 (0.971)	10.046 (2.206)
Province	11.330 (0.947)	9.734 (1.072)	8.159 (0.975)	8.886 (0.789)	10.851 (1.334)
Mean employment of other race groups in:					
Cluster	0.482 (0.292)	0.575 (0.270)	0.595 (0.133)	0.723 (0.244)	0.574 (0.285)
District	0.511 (0.191)	0.495 (0.102)	0.456 (0.063)	0.481 (0.081)	0.504 (0.171)
Province	0.550 (0.093)	0.467 (0.078)	0.433 (0.032)	0.449 (0.060)	0.529 (0.096)
Sample size	9 774	1 802	202	727	12 505

Source: NIDS data (2008).

Notes: Mean income of other race group is calculated as the weighted average of the per capita monthly household income for households in the geographic area. Mean education of other race group is calculated as the weighted average of the mean education in each household for all individuals aged 18 or older in the geographic area. Mean employment of other race group is calculated as weighted proportion of individuals aged between 16 and 64 (both inclusive) in the household who are employed within each geographic area.

Table 3.4: Distribution of concentration of race groups

	Black	Coloured	Asian & Indian	White	Entire sample
% of sample living in residential cluster where:					
HHI=0°	82.38	29.91	16.06	13.07	69.37
0<HHI≤0.25	11.89	20.30	18.14	34.78	14.89
0.25<HHI≤0.5	3.92	34.11	40.90	24.43	9.54
0.5<HHI≤0.75	1.81	15.67	24.90	27.72	6.11
% of sample living in district where:					
HHI=0°	18.85	0	0	0	14.87
0<HHI≤0.25	41.14	8.05	7.77	13.75	34.70
0.25<HHI≤0.5	29.84	37.36	63.18	41.84	32.50
0.5<HHI≤0.75	10.17	54.59	29.06	44.42	17.93
% of sample living in province where:					
HHI=0°	0	0	0	0	0
0<HHI≤0.25	52.45	10.69	11.35	27.55	45.26
0.25<HHI≤0.5	42.62	18.84	85.41	44.79	41.74
0.5<HHI≤0.75	4.92	70.47	3.25	27.66	13.00

Source: NIDS data (2008).

Notes: °Regions where there is only a single race group. Statistics for entire sample included in NIDS (28 226 individuals). The HHI in area (cluster, district or province) j is calculated as follows:

$H_j = 1 - \sum_{i=1}^{N=4} s_{ij}$ where s_{ij} is the proportion of race i residing in area j.

Table 3.5: Subjective well-being and spatial reference groups (ordered probit model)

Dependent variable: SWB	Relative income			Relative education			Relative employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log pc monthly hh income	0.103***	0.131***	0.104***	0.112***	0.128***	0.113***	0.124***	0.127***	0.124***
	(0.026)	(0.024)	(0.026)	(0.025)	(0.024)	(0.025)	(0.024)	(0.024)	(0.024)
Mean education in hh	0.024***	0.027***	0.025***	0.014*	0.027***	0.013*	0.026***	0.026***	0.026***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Employment rate in hh	0.074	0.090	0.078	0.089	0.086	0.094	0.068	0.092	0.068
	(0.059)	(0.059)	(0.059)	(0.060)	(0.059)	(0.060)	(0.059)	(0.059)	(0.059)
Black	-0.179**	-0.282***	-0.178**	-0.197***	-0.274***	-0.196***	-0.263***	-0.275***	-0.270***
	(0.075)	(0.077)	(0.074)	(0.070)	(0.075)	(0.070)	(0.074)	(0.075)	(0.074)
Coloured	0.181*	0.113	0.181**	0.180*	0.117	0.180**	0.123	0.122	0.123
	(0.083)	(0.089)	(0.082)	(0.081)	(0.089)	(0.080)	(0.087)	(0.088)	(0.087)
Asian & Indian	0.332***	0.322**	0.368***	0.320**	0.307**	0.345**	0.301**	0.299**	0.302**
	(0.128)	(0.126)	(0.135)	(0.127)	(0.124)	(0.133)	(0.123)	(0.122)	(0.123)
Average in cluster	0.091**		0.055***	0.055***		0.065***	0.088		0.148
	(0.038)		(0.017)	(0.017)		(0.020)	(0.132)		(0.145)
Average in district		-0.071	-0.019		-0.019	-0.053*		-0.225	-0.329
		(0.046)	(0.025)		(0.025)	(0.029)		(0.278)	(0.306)
Number of observations	12 505	12 505		12 505	12 505	12 505	12 505	12 505	12 505
Number of clusters	400	400		400	400	400	400	400	400
Number of districts	53	53		53	53	53	53	53	53
F-statistic	23.238	23.120		23.788	22.705	23.338	22.468	22.774	21.890

Source: NIDS data (2008).

Notes: Ordered probit regression coefficients with standard errors (clustered at the district level). All controls described in Table 3.2 have been included, but not all reported. All specifications also include provincial fixed effects. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 3.6: Subjective well-being and racial reference groups (ordered probit model)

Dependent variable: SWB	Specification		
	(10)	(11)	(12)
Log pc monthly hh income	0.081	0.097***	0.127***
	(0.052)	(0.026)	(0.024)
Mean education in hh	0.025***	0.023***	0.026***
	(0.007)	(0.007)	(0.007)
Employment rate in hh	0.076	0.076	0.085
	(0.059)	(0.059)	(0.059)
Black	-0.379***	-0.164**	-0.283**
	(0.133)	(0.075)	(0.127)
Coloured	0.047	0.196**	0.114
	(0.120)	(0.085)	(0.110)
Asian & Indian	0.218	0.340***	0.298**
	(0.135)	(0.121)	(0.124)
Position in racial income distribution in SA^			
Quintile 2	-0.013		
	(0.059)		
Quintile 3	0.057		
	(0.082)		
Quintile 4	0.096		
	(0.109)		
Quintile 5	0.173		
	(0.164)		
Log of mean own race income in cluster		0.102***	
		(0.038)	
Log of mean own race income in district			-0.009
			(0.057)
Number of observations	12 505	12 505	12 505
Number of clusters	400	400	400
Number of districts	53	53	53
F-statistic	20.559	23.141	23.615

Source: NIDS data (2008).

Notes: ° As per reported income. Ordered probit regression coefficients with standard errors (clustered at the district level). All controls described in Table 3.2 have been included, but not all reported. All specifications also include provincial fixed effects. * Significant at the 10% level. **Significant at the 5% level ***Significant at the 1% level

Table 3.7: OLS estimates of preference parameters

Dependent variable: SWB	Specification		
	(13)	(14)	(15)
Log pc monthly hh income	0.213***	0.215***	0.217***
	(0.063)	(0.064)	(0.064)
Mean education in hh	0.059***	0.059***	0.059***
	(0.018)	(0.018)	(0.018)
Employment rate in hh	0.097	0.101	0.110
	(0.142)	(0.143)	(0.143)
Black	-0.261	-0.124	-
	(0.176)	(0.280)	
Coloured	0.667***	0.739***	-
	(0.197)	(0.237)	
Asian & Indian	0.315	0.341	-
	(0.240)	(0.244)	
Log of mean own race income in cluster	0.329***	0.291***	0.283***
	(0.075)	(0.112)	(0.112)
Log of mean other race income in cluster	0.014	0.014	0.014
	(0.026)	(0.026)	(0.027)
Log of mean own race income in district	-	0.104	0.109
		(0.169)	(0.169)
Log of mean other race income in district	-	-0.006	-0.006
		(0.021)	(0.021)
Log of mean own race income in SA	-	-	-1.361***
			(0.348)
Log of mean other race income in SA	-	-	-2.095***
			(0.409)
Number of observations	12 505	12 505	12 505
Number of clusters	400	400	400
Number of districts	53	53	53
R-squared	0.123	0.123	0.122

Source: NIDS data (2008).

Notes: OLS coefficients with standard errors (clustered at the district level). All controls described in Table 3.2 have been included, but not all reported. Race dummies for third specification not included because of perfect multicollinearity with mean income per race at national level. * Significant at the 10% level. **Significant at the 5% level ***Significant at the 1% level

Table 3.8: Non-linear estimation of preference parameters

Dependent variable: SWB	Specification		
	(16)	(17)	(18)
Weight on own race (μ)	1.022***	0.832***	0.757***
	(0.019)	(0.163)	(0.185)
Weight on income (λ_y)	0.193***	-0.166***	0.214***
	(0.053)	(0.053)	(0.063)
Weight on others in cluster (θ_c)	1.574*	2.183*	1.788**
	(0.860)	(1.185)	(0.896)
Weight on others in the district (θ_d)	0.953	-0.541	-0.523
	(0.787)	(0.967)	(0.684)
Weight on others in the country (θ_n)	-1.917***	-0.918	-0.806*
	(0.633)	(0.609)	(0.433)
African	-1.000***	-0.602***	-0.558***
	(0.113)	(0.179)	(0.195)
Coloured	0.225	0.395**	0.420**
	(0.178)	(0.160)	(0.165)
Asian/Indian	0.132	0.234	0.210
	(0.255)	(0.243)	(0.249)
Number of observations	12 506	12 505	12 506
Number of clusters	400	400	400
Number of districts	53	53	53
R squared	0.095	0.112	0.119
P-score from Wald test: $\mu = 1$	0.221	0.303	0.191
Additional individual controls	N	Y	Y
Household controls	N	N	Y

Source: NIDS data (2008).

Notes: Non-linear least squares regression coefficients with standard errors (clustered at the district level). * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 3.9: Non-linear estimation of preference parameters - testing for altruism

Dependent variable: SWB	Specification		
	Including access to services	Cluster size >= 100	Cluster size < 100
Weight on own race (μ)	0.684***	0.709***	1.022***
	(0.260)	(0.258)	(0.028)
Weight on income (λ_y)	0.210***	0.137	0.264***
	(0.061)	(0.176)	(0.060)
Weight on others in cluster (θ_c)	1.298*	9.069	0.750*
	(0.732)	(15.056)	(0.440)
Weight on others in the district (θ_d)	-0.820	-1.861	0.904
	(0.779)	(3.822)	(0.563)
Weight on others in the country (θ_n)	0.849	-2.428	-0.154
	(0.668)	(3.760)	(0.386)
Black	-0.271*	-0.908	-0.121
	(0.149)	(0.765)	(0.148)
Coloured	0.515***	-0.645	0.798***
	(0.175)	(0.642)	(0.172)
Asian & Indian	0.293	-0.528	0.045
	(0.255)	(0.430)	(0.434)
Access to piped water	0.152		
	(0.223)		
Access to working electricity	0.334**		
	(0.147)		
Access to flush toilet	0.478***		
	(0.160)		
Number of observations	12 505	3 374	9 131
Number of clusters	400	68	332
Number of districts	53	30	53
R squared	0.130	0.120	0.133

Source: NIDS data (2008).

Notes: Non-linear least squares regression coefficients with standard errors (clustered at the district level). All specifications include individual controls and household controls as set out in Table 3.2. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 3.10: Non-linear estimation of preference parameters by race

Dependent variable: SWB	Black sample	Non-black sample
Weight on own race (μ)	0.692***	0.994***
	(0.281)	(0.038)
Weight on income (λ_y)	0.218***	0.208*
	(0.073)	(0.123)
Weight on others in cluster (θ_c)	1.792*	2.212
	(1.030)	(1.875)
Weight on others in the district (θ_d)	-0.506	-1.485
	(0.705)	(1.147)
Weight on others in the country (θ_n)	-4.155	-1.492
	(1.294)	(1.136)
Coloured		-0.161
		(0.199)
Asian/Indian		-0.078
		(0.273)
Number of observations	9 774	2 731
Number of clusters	400	322
Number of districts	53	41
R squared	0.066	0.096
P-score from Wald test: $\mu = 1$	0.273	0.871
Individual controls	Y	Y
Household controls	Y	Y

Source: NIDS data (2008).

Notes: Non-linear ordinary least squares regression coefficients with standard errors (clustered at the district level). * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 3.11: Non-linear estimation of preference parameters with fixed effects

Dependent variable: SWB	Provincial level controls	District level controls
Weight on own race (μ)	0.751***	0.918***
	(0.188)	(0.167)
Weight on income (λ_y)	0.228***	0.216***
	(0.059)	(0.059)
Weight on others in cluster (θ_{ct})	1.323*	1.389*
	(0.686)	(0.712)
Weight on others in the district (θ_d)	-0.955	0.221
	(0.699)	(0.820)
Weight on others in the country (θ_n)	-2.981***	-0.739
	(0.772)	(0.575)
Number of observations	12 505	12 505
Number of clusters	400	400
Number of districts	53	53
R squared	0.140	0.168
P-score from Wald test: $\mu = 1$	0.186	0.624
Individual controls	Y	Y
Household controls	Y	Y
Fixed-effects	Y (provincial)	Y (district)

Source: NIDS data (2008).

Notes: Non-linear least squares regression coefficients with standard errors (clustered at the district level). * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 3.12: Non-linear estimation of preference parameters using alternative income measures

Dependent variable: SWB	Specification		
	Mean of log income	Median of log income	Income excluding own income°
Weight on own race (μ)	0.946***	0.922***	0.618**
	(0.095)	(0.105)	(0.262)
Weight on income (λ_y)	0.222***	0.233***	0.257***
	(0.062)	(0.065)	(0.063)
Weight on others in cluster (θ_c)	1.146*	1.133*	1.050*
	(0.677)	(0.661)	(0.563)
Weight on others in the district (θ_d)	0.526	0.119	-0.372
	(0.896)	(0.813)	(0.284)
Weight on others in the country (θ_n)	-2.888***	0.756	-0.072
	(0.900)	(0.745)	(2.625)
Number of observations	12 505	12 505	12 505
Number of clusters	400	400	400
Number of districts	53	53	53
R squared	0.117	0.116	0.117
P-score from Wald test: $\mu = 1$	0.573	0.461	0.145
Individual controls	Y	Y	Y
Household controls	Y	Y	Y

Source: NIDS data (2008).

Notes: Non-linear least squares regression coefficients with standard errors (clustered at the district level). ° Income excluding own income refers to the definition of income where: (i) own individual income is excluded in the calculation of the own race mean income in the cluster; (ii) own cluster income is excluded in the calculation of the own race mean income of the district; and (iii) own district income is excluded in the calculation of the own race mean income in South Africa. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Chapter 4

Income dynamics, assets and poverty traps

4.1 Introduction

The measurement of poverty in South Africa has a long history, dating back to the Carnegie Commission's report published in 1932, which investigated the poor white problem.[1] Although the direction of poverty trends in South Africa has been contested in the past, there seems to be some consensus that the rate of poverty has declined since the mid-2000s (Agüero, Carter and May, 2007; Van der Berg, 2007; Leibbrandt, Wegner and Finn, 2011 and Leibbrandt, Finn and Woolard, 2012). However, despite this decline in poverty I will illustrate in this chapter that there are many households who remain in chronic poverty, i.e. who are observed to be earning below the poverty line over multiple years with no indication of upward income mobility (Agüero, Carter and May, 2007).

The concept of a poverty trap provides an explanation for why chronic poverty exists - i.e. individuals (or geographic areas, such as regions within a country or countries themselves) are observed to earn below the poverty line in two or more consecutive periods because of the "*... self-reinforcing mechanism[s] which cause ... poverty to persist*" (Azardiadis and Stachurski, 2005, p. 326).[2] In addition, the concept of a poverty trap provides information regarding the types of policy interventions which may be implemented in order to decrease the number of individuals in chronic poverty, by addressing these self-reinforcing mechanisms. Various studies have focussed specifically on identifying these mechanisms, which are mostly centred around conditions which preclude the household from moving above

[1]For the most recent measures of poverty in South Africa, see Leibbrandt, Woolard, Finn and Argent (2010) and Finn, Leibbrandt and Levinsohn (2014). For a summary of the work on poverty measurement in South Africa, see May (2012) as well as the appendix in Posel and Hinks (2013).

[2]Although poverty traps can be examined from both a macro/growth perspective as well as on a micro level, i.e. from the perspective of the household, I exclusively focus on the micro level for the purpose of this chapter.

a critical level of asset holdings or investments which will allow it to increase its income and consumption above the poverty level. These include poor health, low levels of education, lack of collateral for loans, social exclusion and geographic location (i.e. living in a rural area).[3]

In testing for poverty traps, there are two sets of literature which are relevant. On the one hand are the studies which have focussed on the dynamics in income over time in order to test for the persistence of income as well as the existence of non-linearities in this process of income accumulation. A common theme in this literature is the awareness of the shortcomings of income data; most prominent is the existence of measurement error. Various approaches have been followed in order to minimise the impact of the measurement error on the estimates of income dynamics in order to obtain an idea of the persistence of income over time.

On the other hand there is the literature dealing with poverty traps explicitly. Framed within this literature, Carter and Barrett (2006) have developed an asset-based approach to evaluate the existence of poverty traps which aims at separating the structural (permanent) component of income from other influences on income dynamics, most notably (short-run) stochastic shocks and measurement error. In order to obtain an estimate of the structural component of income, Carter and Barrett (2006) propose the use of assets to predict the expected income level of each individual, which is viewed as an indication of their structural income.

In their seminal paper, Carter and Barrett (2006) postulate the existence of a specific type of poverty trap based on macroeconomic growth literature. Essentially, the approach allows for the existence of locally increasing marginal returns to wealth (level of assets),[4] which at the level of the household would be the case if certain livelihood activities required higher levels of initial asset endowments and resulted in a higher level steady state than other activities. In the region where households are able to switch from the low-level growth path to the higher-level growth path, there are locally increasing marginal returns to assets. This point is referred to by Carter and Barrett (2006) as the dynamic asset poverty threshold or the so-called Micawber threshold.[5] If households are able to accumulate sufficient assets by either borrowing or saving, they will be able to make the transition and move onto the higher-level growth path, beyond the Micawber threshold. However, because poor households are often not able to make this transition, they remain in poverty, on the low-level growth path - essentially trapped in poverty. In this sense, the asset growth path bifurcates at the point of the Micawber threshold, with certain households who are able to avoid poverty and remain on the high-level accumulation or growth path, while others remain in poverty. This theoretical framwork is set out in Figure 4.1 in the appendix

[3]For a detailed overview of the literature, see SAHRC and UNICEF (2014) and Kraay and McKenzie (2014).

[4]In contrast to the globally diminishing returns which are assumed in the case of convergent growth paths between rich and poor countries, locally increasing returns would lead to diverging growth paths - with poor countries converging to a lower steady state growth path than rich countries.

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

(all figures and tables referred to in this chapter are included in the appendix), where the Micawber threshold is labelled as A'_m.

Using this framework and data from the KwaZulu-Natal Income Dynamics Study (KIDS) dataset,[6] Adato, Carter and May (2006) confirm the existence of multiple equilibrium asset dynamics in South Africa between 1993 and 1998, with a Micawber threshold situated around twice the value of the poverty line.

The aim of this chapter is to make use of recently released panel data from NIDS, which was collected from a representative sample of households during 2008, 2010, and again in 2012 in order to test for the existence of a poverty trap arising from the South African income dynamics over this period. For this purpose, I make use of reported asset data in order to predict the structural component of income and separate it from the stochastic component of income, as defined in the context of Carter and Barrett (2006). However, I also address the possibility that the asset data may be reported with error. In addition, I make use of both a parametric and nonparametric approach when estimating the dynamics between structural income over the period 2010 to 2012.

The contribution of this chapter is that it updates the findings of Adato, Carter and May (2006) in the South African context, using more recent panel data from NIDS. In addition, this chapter also places the approach by Carter and Barrett (2006) within the greater literature on income dynamics by addressing one of the criticism raised by Antman and McKenzie (2007) against the asset-based approach to measuring poverty traps, namely that although it takes into account the fact that there may be measurement error in reported income, it does not take into consideration the potential measurement error in reported assets. Last, the chapter also adds to the literature on the measurement of income dynamics by offering an alternative technique to address the existence of measurement error in reported income data, using the framework developed by Carter and Barrett (2006). The chapter therefore brings together two related literatures - on the one hand the literature dealing with the treatment of measurement error in reported income; and on the other the literature dealing with asset-based estimations of poverty traps.

My findings provide no evidence for the existence of a poverty trap. In addition, contrary to earlier findings by Adato, Carter and May (2006) from 1993 and 1998, the results do not provide evidence for the existence of a Micawber threshold at which the structural income accumulation paths of households bifurcate - with certain households moving back into poverty while others are able to move out of poverty. Instead, the results seem to indicate the existence of a threshold beyond which structural income remains very persistent with very little upward mobility. The location of the threshold is above

[6] KwaZulu-Natal is one of the nine provinces in South Africa and KIDS was a precursor to NIDS. Prior to the existence of the NIDS dataset, there were no nationally representative household panel datasets.

the usual poverty line, indicating that upward mobility is possible for much of the population; however, after a certain level, very little further mobility takes place.

These findings should be viewed within the broader economic conditions prevalent during the period 2010 to 2012, during which time GDP growth was positive (albeit slow),[7] however overall inequality remained persistently high (Finn and Leibbrandt, 2013b).

I provide an overview of the literature on the topic in the next section and then conduct a general analysis of income dynamics over the period 2010 to 2012 using the NIDS data. After setting out the theoretical framework which I implement in the chapter, I test for the existence of a poverty trap. In order to also take into account the possibility of bias as a result of the correlation between measurement error in reported income and reported assets, I make use of control functions and instrumental variables. This does not change the results substantially. However it serves as a useful expansion of the current theoretical framework. Last, I test for the existence of poverty traps using a parametric approach.

4.2 Income dynamics and poverty traps

As indicated in the introduction, the chapter brings together two related literatures. First, there is the literature on income dynamics, which has to a large extent been aimed at estimating the persistence of income by minimising the influence of measurement error on the estimates. Second, there is the literature on asset-based poverty traps pioneered by Carter and Barrett (2006).

In terms of the literature on income dynamics, various techniques have been implemented. Some earlier studies made use of instrumental variables in order to instrument for the existence of measurement error in reported income. Jalan and Ravallion (2002) test for the existence of a geographic poverty trap in rural China by estimating a consumption growth model using a generalised methods of moments approach and lagged consumption as instrumental variables in order to minimise the impact of measurement error.

Fields, Cichello, Freije, Menéndez and Newhouse (2003) make use of an instrumental variable approach in order to eliminate the measurement error from reported income data, where household expenditure as well as a host of household living conditions and assets are used as instruments. Fields, Cichello, Freije, Menéndez and Newhouse (2003) apply this technique for four countries, including South Africa using data from the first two waves of KIDS, collected in 1993 and 1998. Their results illustrate how the use of instrumental variables removes some of the measurement error, pointing to higher levels of persistence in income over time.

[7] At an average rate of above 3% during 2010 and 2011, and 2.5% in 2012, when calculated as year-on-year growth Statistics South Africa (2012).

However, more recently there has been an acknowledgement that a simple strategy of instrumentation is not sufficient since it has been shown that there is positive autocorrelation in the measurement error (Bound and Krueger, 1991).[8] Antman and McKenzie (2007) therefore suggest making use of pseudo-panel data with an estimator which takes into account individual heterogeneity and accounts for measurement error in reported income which is serially correlated. The additional advantage of making use of pseudo-panel data is that they overcome the necessity of long panel data and avoid problems from attrition. Implementing this pseudo-panel technique on labour earnings data from Mexico leads Antman and McKenzie (2007) to the conclusion that no poverty trap exists for urban Mexico, although income from earnings is very persistent across years and any upward mobility would therefore occur very slowly.

Other approaches include using the predicted earnings from various specifications which include individual characteristics in the analysis of income dynamics. Fields and Puerta (2010) implement this technique and argue that these predictions capture long-run earnings which are not susceptible to measurement error in the same way as reported earnings data. Using panel data from Argentina, Fields and Puerta (2010) find evidence to indicate that earnings in Argentina seem to have been convergent over the period 1996-2003.

For South Africa, Lechtenfeld and Zoch (2014) make use of the lagged income value from the previous period as well as an asset index in order to estimate the persistence of income using the NIDS data. They find that the persistence of income is significantly under-estimated if measurement error is not controlled for, and estimate that income dynamics could have been over-estimated by as much as 77% for the period 2008-2010. Glewwe (2011), also making use of an instrumental variables approach, finds this figure to be between 15% and 42% for Vietnam during the 1990's.

In the second place, this chapter also draws from the literature on the development of the asset-based approach by Carter and Barrett (2006), as set out above. In essence, this approach has the same aim as the studies above - namely to obtain an estimate of income dynamics over time after removing any influence from measurement error or other random shocks which are prevalent in longitudinal data.

Prior to the seminal article by Carter and Barrett (2006), an earlier literature developed a single period asset poverty line in order to distinguish between structural and stochastic poverty (Carter and May, 2001). Using the KIDS data between 1994 and 1998, Carter and May (2001) could for the first time in South Africa's post-democratic history estimate earnings dynamics.[9] Carter and May (2001) develop a theoretical framework in terms of which predicted income, conditional on asset ownership, is interpreted as being the structural component of income, whereas any part of income changes not explained

[8] Although Gottschalk and Huynh (2010) illustrate that the impact of non-classical measurement error is largely eliminated in the estimation of income dynamics, using the same data as Bound and Krueger (1991).

[9] KIDS was only collected in one province, KwaZulu-Natal, and would therefore not have been representative of the entire country. This analysis was later expanded to also include a third wave collected in 2004 (May and Woolard, 2007).

by changes in predicted (asset-based) income is attributed to stochastic movements in reported income and is referred to as "entitlement failures" (negatives) and "entitlement windfalls" (positives).[10] Only when asset-based predicted income is estimated to have been below the poverty line and the household found itself in chronic poverty over time can one identify the household as being in a poverty trap. Implementing this framework, Carter and May (2001) identify approximately 92% of the chronically poor households in 1998 as being structurally poor and therefore stuck in an asset-based poverty trap.[11]

Taking this concept further, Carter and Barrett (2006) develop the dynamic analogue of the static asset poverty line. As set out in Figure 4.1, this approach interprets the non-linear asset dynamics (as proxy for structural income) between two periods as evidence of the existence of an unstable dynamic asset poverty threshold, or Micawber threshold (labelled A'_m), if the 45-degree line is crossed more than once. As set out in the introduction to the chapter, the underlying theory is that households stuck between the low-level poverty threshold, labelled A'_p and the Micawber threshold at A'_m will be stuck in a poverty trap if they are not assisted (through policy intervention) to move beyond this point onto the higher-level asset growth path.

Carter and Barrett (2006, p. 179) define assets broadly as including "*conventional, privately held productive and financial wealth, as well as social, geographic and market access positions that confer economic advantage*". The main motivation behind the use of assets instead of income or consumption data is that it is argued to be less prone to measurement error, and that it reflects the underlying ability of a household to earn an income in the long run (Barrett, Carter and Little, 2006). Assets are an indication of the household's ability to earn income in the future and endure adverse shocks. In therefore relying on asset dynamics rather than income dynamics, these studies attempt to identify the long-run growth path from stochastic shocks and measurement error. In this sense, the use of an asset-based approach to test for the existence of poverty traps is aligned with the broader literature around income dynamics and measurement error.

Apart from this core literature, there have been some expansions of the asset-based approach. Anderson (2012) expands on this by decomposing the correlation between assets and future earnings into direct effect (i.e. the income resulting from the ownership of the asset directly) and indirect effects (through the interaction with other assets and agency of the household - i.e. its ability to utilise the asset). The asset-based approach has also been implemented in various countries where the existence of an asset-based poverty trap has been confirmed, including South Africa (Adato, Carter and May, 2006, using the KIDS data from 1993 to 1998) and rural Kenya and Madagascar (Carter and Barrett, 2006). Giesbert and Schindler (2012) implement the technique on data from rural Mozambique and do find evidence of a low-level single poverty threshold, but no evidence of multiple equilibria.

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

[11] Chronic poverty in the South African context between 1993 and 1998 has been attributed to four factors, namely large household size; poor education; asset endowment; and the lack of access to employment (Woolard and Klasen, 2005).

Before setting out the empirical framework used to test for the existence of a poverty trap, I first discuss the data used in the study and provide an overview of poverty and income dynamics in the data in the next two sections.

4.3 The NIDS data

The data used in this chapter come from the latest release of NIDS which includes three waves of data collected in 2008, 2010 and 2012. NIDS includes information on individuals and households as well as detailed information on income over this four year period and is therefore very appropriate for examining trends in poverty over time.

As with any panel dataset, attrition is a problem, and was highest among individuals with certain characteristics. Within the white population group, attrition was 50.3%, mostly as a result of refusal to complete a questionnaire (De Villiers, Brown, Woolard, Daniels and Leibbrandt, 2013, pp. 21-22), whereas attrition in the black population group was much lower at 13.4%, mostly attributable to loss of contact. Table 4.1 in the appendix sets out the nature of the attrition observed in the data, and provides an indication of the number of individuals who completed interviews. For the current study, the focus is limited to individuals who were successfully interviewed in all three waves, which amounts to 18 818 individuals in total (56 454 observations over the three waves). In other words, unless stated otherwise, the estimates only include data from the balanced panel. In addition, I will limit my attention to the period from 2010 to 2012.

In order to explore the differences between attriters and those individuals who remain in the sample, I compare the means of certain key variables within each of these groups. Table 4.2 reports the means and standard deviations as well as the t-statistics. It is clear that there is a significant difference between attriters and non-attriters in that the group of attriters is wealthier and more educated. They also come from households with more employed individuals, fewer individuals of pension-recipient age (60 years for both males and females) and less likely to be black.

Before considering the income dynamics in the sample over the period of the NIDS panel, it is useful to clarify a few concepts that will be used in the analysis of income dynamics and poverty traps. First, in order to deal with the potential detrimental influence of non-random attrition, as illustrated by the differences in individuals who remained in the panel for all three waves and those who attrited in Table 4.2, which may potentially bias the results (Barrett and Carter, 2013), I make use of panel weights within NIDS in order to account for the potential impact of attrition on the estimates.

It should be noted that I make use of a *per capita* household measure of well-being, where the monthly income is divided by the number of members of the household, irrespective of what share of household consumption each member is actually responsible for.[12] There have been arguments for and against the use of equivalence scales in poverty measurement in the South African literature. While many studies have made use of adult equivalence scales, Streak, Yu and Van der Berg (2009) find that the main trends and conclusions from the measurement of child poverty are not significantly influenced by the use of adult equivalent income or expenditure compared to household *per capita* income or expenditure. In more recent work, Posel and Rogan (2013) have however shown how the use of adult equivalence scales may improve the measurement of poverty and indeed narrow the gap between objective and subjective (perceived) poverty. In order to increase comparability to the most recent studies which make use of NIDS data, and given that there is no consensus on the use of equivalence scales, I have decided not to make use of equivalence scales in the current study.

Last, I make use of a poverty line of R636 in 2012 Rands.[13] This poverty line has been used in many studies but has its origin in the work of Özler (2007), who derived a poverty line based on the cost of basic needs of R322 in 2000 prices.[14]

4.4 An overview of poverty dynamics in South Africa between 2010 and 2012

Before setting out the theoretical framework used in the rest of the chapter, I provide a brief overview of the trends in income and poverty over the period 2010 to 2012.

The NIDS panel was constructed to observe income and expenditure dynamics of a representative sample of households in South Africa. Table 4.3 shows the development of household mean income and the different income sources for the period 2010 to 2012. There was a positive trend in *per capita* household income from 2010 to 2012. This upward trend was experienced by both the black and white sub-samples, although at very different levels of income.

While the mean household income increased from 2010 and to 2012, the trend using household expenditure is not as clear. For the full sample, there is a small downward trend in mean expenditure, however for median expenditure this trend is clearly upwards. For white individuals in the sample, expenditure seemed to have decreased during the period, however for the black sample it clearly increased. Furthermore, the mean expenditure level is much lower than mean household income.

[12] In this study, I make use of income data with full imputations.

[13] All income and expenditure values have been inflated to August 2012 prices.

[14] Özler (2007) derived this as the lower bound poverty line and also derived an upper bound poverty line, which I do not consider here.

I find indications of a downward trend in poverty in South Africa over the period, as set out in Table 4.4. Using the poverty line of R636 monthly per capita household income, I find that in 2010 approximately 48% of the individuals in the sample lived in poor households. The percentage decreased to about 39% in 2012. Table 4.4 also shows that black individuals remain more vulnerable than white individuals. While only a few white individuals are in poverty over the period, approximately 54% of black individuals are estimated to be in poverty using income as measure in 2010. This figure decreases to 45% in 2012. Comparing the poverty levels for a poverty line of R636 using income and expenditure, the poverty levels are much higher using household expenditure. Following previous studies that have used NIDS (Finn and Leibbrandt, 2013a), I concentrate on using the per capita household income measure in this chapter.

The longitudinal aspect of NIDS enables me to follow the same individuals over time and to study the poverty dynamics of those individuals. However, this also increases the chance of measurement error in the reported values for income and expenditure. This would typically increase the likelihood of individuals misclassified as moving into or out of poverty from one period to the next, confounding the poverty estimates. In order to take this into account, I only count an individual as moving into or out of poverty if their reported *per capita* household income changed by more than 10% of the original 2008 value, in line with what was suggested by May and Woolard (2007).

Table 4.5 shows the poverty dynamics over the period 2010 to 2012, taking this robustness check into account. Individuals who were in poor households when they were first observed in 2010, and then again in poor households in 2012 when they were observed in the last wave of the data, constituted approximately 29% of the sample. I label these individuals as being chronically poor. Conversely, individuals who were observed in a non-poor household in both 2010 and 2012 constitute approximately 44% of the sample. The remaining sample of individuals either moved into or out of poverty (or is misclassified as a result of measurement error that has not been dealt with). Those individuals who were able to "get ahead", i.e. who were observed in a poor household in 2010 but not in 2012, make up approximately 18% and those who fell behind (non-poor in 2008; poor in 2012) 10%.

Although these poverty transitions are very informative to provide some indication of how individuals fared during the period 2010 to 2012, they do not provide a more detailed insight into what exactly happened within households, or where households are on the asset accumulation path. The rest of the chapter is aimed at answering these questions by first looking at a theoretical model to further break down poverty dynamics and then estimating these dynamics empirically.

4.5 Theoretical framework

In the broader framework of income dynamics, the fact that households and individuals are earning an income below the poverty line could be ascribed to one of two things. First, it could be that the household does not have access to the assets required to generate an income which is above the income poverty line. Secondly, it could be that the household experienced an income shock which caused it to earn below the poverty line. The framework which I will be using here therefore decomposes income into two components: a permanent or structural component which is earned as returns to the assets in the household, and a second stochastic or random component which comprises all income shocks in the period. Barrett, Marenya, Mcpeak, Minten, Murithi, Oluoch-Kosura, Place, Randrianarisoa, Rasambainarivo and Wangila (2006) also acknowledge that because the only measure of income that we have is self-reported income from survey data, one should also take into account that income is most likely measured with error, in other words it is only possible to observe $Y_{i,t} = Y^*_{i,t} + \eta_{i,t}$.

Making the assumption for now that it is possible to observe actual asset-holdings, $\mathbf{a}^*_{i,t}$, I use asset-holdings as an input into a production process for which the outcome is reported income. It is therefore useful to think of reported income as consisting of three components, as follows:

$$Y_{i,t} = \mathbf{r}'_{i,t}\mathbf{a}^*_{i,t} + \varepsilon_{i,t} + \eta_{i,t} \tag{4.1}$$

where $\mathbf{a}^*_{it}$ is a vector of all (accurately measured) relevant assets, including physical assets, human capital and all transfers from government grants.[15] Measurement error is captured by $\eta_{i,t}$ and the stochastic error component is captured by $\varepsilon_{i,t}$. In this sense Y_{it} is seen as the output from a production process, with inputs $\mathbf{a}^*_{i,t}$ and returns to each asset are captured in the vector of parameters $\mathbf{r}_{i,t}$.

In order to separate the asset-based structural part of income from the stochastic shocks and measurement error, Barrett, Marenya, Mcpeak, Minten, Murithi, Oluoch-Kosura, Place, Randrianarisoa, Rasambainarivo and Wangila (2006) estimate Equation 4.1 in order to obtain an estimate of the structural income for each household by regressing a measure of reported income on various household assets and predict the expected income, using the coefficients as the predicted returns to the assets. In other words:

$$E[Y_{i,t}|\mathbf{a}^*_{i,t}] = E[\mathbf{r}'_{i,t}\mathbf{a}^*_{i,t} + \varepsilon_{i,t} + \eta_{i,t}|\mathbf{a}^*_{i,t}] = \mathbf{r}'_{i,t}\mathbf{a}^*_{i,t} + E[\varepsilon_{i,t}|\mathbf{a}^*_{i,t}] + E[\eta_{i,t}|\mathbf{a}^*_{i,t}]$$

[15] Baulch and Hoddinott (2007) would add an additional dimension, namely social capital. However, I will follow the approach of Adato, Carter and May (2006) and not add this dimension.

Barrett, Marenya, Mcpeak, Minten, Murithi, Oluoch-Kosura, Place, Randrianarisoa, Rasambainarivo and Wangila (2006) assume $E[\varepsilon_{i,t}|\mathbf{a}^*_{i,t}] = E[\eta_{i,t}|\mathbf{a}^*_{i,t}] = 0$. The first term is assumed to be equal to zero by virtue of its definition ($\varepsilon_{i,t}$ representing stochastic shocks). The second term would only be equal to zero if assets $\mathbf{a}^*_{i,t}$ were reported without error, or if there was measurement error, it was uncorrelated with $\eta_{i,t}$.[16] Much of the motivation for the use of assets comes from the fact that assets are measured with more accuracy than income and consumption.

I relax the assumptions made by Barrett, Marenya, Mcpeak, Minten, Murithi, Oluoch-Kosura, Place, Randrianarisoa, Rasambainarivo and Wangila (2006) in two ways. First, I allow for assets to be measured with error, and I assume it is classical measurement error in the sense that it is conditionally homoskedastic, serially uncorrelated and enters linearly, i.e. $\mathbf{a}_{i,t} = \mathbf{a}^*_{i,t} + \mu_{i,t}$. Second, I further allow the measurement error in the assets, $\mu_{i,t}$, to be correlated with the measurement error in the income, $\eta_{i,t}$.[17] Allowing for the relaxation of these assumptions, Equation 4.1 would become

$$\begin{aligned} Y_{i,t} &= \mathbf{r}'_{i,t}(\mathbf{a}_{i,t} - \mu_{i,t}) + \varepsilon_{i,t} + \eta_{i,t} \\ &= \mathbf{r}'_{i,t}\mathbf{a}_{i,t} - \mathbf{r}'_{i,t}\mu_{i,t} + \varepsilon_{i,t} + \eta_{i,t} \end{aligned} \tag{4.2}$$

Taking expectations, Equation 4.1 becomes:

$$E[Y_{i,t}|\mathbf{a}_{i,t}] = \mathbf{r}'_{i,t}\mathbf{a}_{i,t} - \mathbf{r}_{i,t}E[\mu_{i,t}|\mathbf{a}_{i,t}] + E[\eta_{i,t}|\mathbf{a}_{i,t}] \tag{4.3}$$

since $E[\varepsilon_{i,t}|\mathbf{a}_{i,t}] = 0$. In estimating structural income, $E[Y_{i,t}|\mathbf{a}_{i,t}]$ where $\mathbf{a}_{i,t}$ is measured with error, one introduces bias by virtue of the fact that $E[\mu_{i,t}|\mathbf{a}_{i,t}] \neq 0$ and $E[\eta_{i,t}|\mathbf{a}_{i,t}] \neq 0$ since $E[\mu_{i,t}|\eta_{i,t}] \neq 0$. If I am willing to assume serially uncorrelated measurement errors, then a suitable instrument to use would be the lagged asset values $\mathbf{a}_{i,t-1}$ or $\mathbf{a}_{i,t-2}$ in the case of three periods. Using this instrumental variable would provide unbiased estimates of the stochastic component of income as long as I assume $E[\mu_{i,t}|\mathbf{a}_{i,t-1}] = E[\eta_{i,t}|\mathbf{a}_{i,t-1}] = 0$.

Within this framework, it is now possible to test for the existence of poverty traps by making use only of structural income, after removing both measurement error (arising from recorded income or asset data) as well as any stochastic shocks in income.

There are various ways in which one may wish to test for a poverty trap. For the purpose of this chapter, I wish to test for the existence of a multiple equilibrium poverty trap which results from locally

[16]Or if $\eta_{i,t}$ is uncorrelated with the levels of assets owned by households, which I will assume here to not be the case. This might not be such as a strong assumption, since the definition of assets in this chapter includes not only physical assets, but household characteristics as well, some of which we have no reason to believe that they would systematically be correlated with the measurement error on income.

[17]Both of these adjustments address the criticisms raised by Antman and McKenzie (2007) against the use of assets when testing for poverty traps.

increasing marginal returns to assets, as set out by Carter and Barrett (2006), which essentially involves testing for any non-linearities in the persistence of income. I therefore assume a non-linear relationship between income in the initial and subsequent periods, which may be tested using a parametric approach (in this regard, Antman and McKenzie (2007) make use of a third order polynomial of lagged income to model the relationship between income and lagged income) or nonparametric approach as in Carter and Barrett (2006), Barrett, Marenya, Mcpeak, Minten, Murithi, Oluoch-Kosura, Place, Randrianarisoa, Rasambainarivo and Wangila (2006) and Adato, Carter and May (2006).

I make use of the predicted asset values (or the asset-weighted livelihood index, as referred to by Adato, Carter and May (2006)), as predicted from Equation 4.3. These predicted values are a proxy of the structural component of income and they are referred to as $\hat{Y}_{i,t}$. In its most general form, where the relationship between predicted assets (as proxy of the structural part of income) of period t is modelled as a nonparametric function of the structural income of the previous period, $\hat{Y}_{i,t-1}$, the relevant equation is:

$$\begin{aligned} \hat{Y}_{it} &= \phi(\widehat{Y}_{i,t-1}) + \omega_{it} \\ & \omega_{it} \sim_{iid} N(0, \sigma^2_{\omega}) \end{aligned} \tag{4.4}$$

where ϕ is a function of unspecified form.

As an example, assume that ϕ is a third-order polynomial. Testing for a poverty trap under this assumption would involve estimating the following:

$$\hat{Y}_{it} = \alpha + \beta_1 \widehat{Y}_{i,t-1} + \beta_2 (\widehat{Y}_{i,t-1})^2 + \beta_3 (\widehat{Y}_{i,t-1})^3 + \omega_{it} \tag{4.5}$$

And then finally solving Equation 4.5 where structural income in the first period is equal to structural income in the second period, i.e. where $\hat{Y}_{it} = \widehat{Y}_{i,t-1}$. Graphically, this occurs where the dynamic structural income line crosses the 45-degree line. If this occurs more that once, it is possible that there are multiple equilibrium points, in line with the findings by Adato, Carter and May (2006) for South Africa between 1993 to 1998.

In essence the methodological approach of the chapter uses the framework of the asset-based approach to the measurement of poverty traps, but is also cognisant of the potential for measurement error in the reported asset values, as discussed by Antman and McKenzie (2007). It therefore expands the traditional asset-based approach to poverty measurement, but at the same time also incorporates the traditional literature on measurement error in reported income by introducing a more flexible (non-parametric) way of estimating the income dynamics, in line with the asset-based approach.

4.6 Results

The starting point for examining income dynamics and testing for the existence of multiple dynamic equilibrium points is to estimate the structural component of income. For this I follow the approach in Adato, Carter and May (2006) and Giesbert and Schindler (2012) and estimate Equation 4.1. Instead of making use of income as is, I transform the income variable by dividing it by the poverty line of R636 in order to measure the income dynamics in what has been referred to in the literature as Poverty Line Units (PLU). Given the inequality of South Africa's income distribution, I further log the PLU, in line with the suggestion by May and Woolard (2007). A household who would was earning exactly on the poverty line, will after this transformation be at PLU=0.

Given the broad definition of assets discussed earlier, I include variables which will capture both human and physical capital, as well as earnings-potential from government transfers.[18] More specifically, I include measures of household employment,[19] education[20] and whether the household is headed by a female as indicators of human capital. I also include a measure of the mean self-reported health levels of the household.[21] As proxies for physical capital, I include a living index which is compiled with the use of multiple component analysis. The index includes various indicators of the household's physical well-being, namely the type of dwelling (formal house, flat, informal dwelling, etc.), material used for roof and walls, the source of the household's drinking water, sanitation facilities, the main material used for lighting, heating and cooking and whether the household owns a fridge, washing machine, electric or gas stove. In addition, I also include a variable capturing whether the household owns the dwelling in which they live. Last, as indicators of transfer income received from the government, I include variables capturing the household size,[22] and what proportion of the household comprises pension-aged individuals or children aged younger than 18 years.[23]

In order to allow assets to enter as unconstrained as possible, I estimate the equation by including a third-order polynomial for all of the assets which are not measured as binary variables. Last, I estimate the regression for each of the years separately, in order to allow for variations in the coefficients across the three waves.

The results are set out in Table 4.6. The signs of the coefficients are as expected, with some small differences between the results for the two waves. For completeness' sake, I also include the pooled

[18] It should be noted that I exclude all non-resident household members from my analysis.

[19] Household employment is calculated as the rate of all working-aged adults aged 16 to 64 (both inclusive) who indicated that they were employed (this definition of "working aged adults" has been commonly used in the literature).

[20] Mean education in the household is calculated as the number of years completed education for every household member aged 18 years or older.

[21] The self-reported health variable in NIDS is coded as 1 indicating excellent health and 5 indicating poor health.

[22] In the regression analysis, I divide the household size by 10 in order to avoid very small coefficients.

[23] The last two variables would be correlated with whether the household would be eligible for a Child Support Grant or an Old Age Pension from government.

panel results. In order to provide a sense of the distribution of the predicted structural component of income, I report the kernel density functions of actual income as well as asset-weighted (structural) income in Figure 4.2. Some sense of the magnitude of poverty looking only at this structural component of income is provided in Figure 4.3, which plots the cumulative density of individuals in households which have been classified as poor using asset poverty as a concept. The cumulative density curves illustrate how poverty has decreased over time, in line with what is observed when using income.

Next, I use the predictions from Table 4.6 to estimate Equation 4.4, for which I use a local polynomial regression with kernel weighted local polynomial smoothers. A third degree polynomial and kernel bandwidth of 0.2 are used. Although this technique has the advantage of providing a large amount of flexibility in the functional form, it has other disadvantages in that it does not allow for the inclusion of any other covariates which should be included (such as time-invariant fixed effects, for example). However, Naschold (2013) shows how parametric and nonparametric estimation techniques provide similar conclusions, especially where the asset accumulation process over time is close to being linear, which appears to be the case in the current analysis.

In order to contrast the structural income dynamics with the reported income dynamics, I also include the nonparametrically estimated income dynamics using only the reported income data. The results are set out in Figure 4.4. The results are vastly different from the results by Adato, Carter and May (2006), who found evidence for a multiple equilibrium poverty trap. Instead, the results seem to indicate that the asset dynamics only crossed the 45-degree line once, from above, and thereafter becomes statistically indistinguishable from the 45-degree line.

It would appear that there is little evidence of multiple equilibrium poverty traps and a Micawber threshold as described by Adato, Carter and May (2006). Instead, the evidence seems to point towards a threshold above the poverty line, beyond which there does not seem to be much mobility (upward or downward), but rather income dynamics which seem to suggest large-scale persistence.[24]

This result should be interpreted within the framework of the broader macroeconomic environment prevalent during the two periods - first during 1993 to 1998, when the study by Adato, Carter and May (2006) was conducted, and then during the period of the current study, namely 2010 to 2012. The period immediately subsequent to the end of the apartheid regime was characterised by the implementation of the Growth, Employment and Redistribution (GEAR) macroeconomic programme, initiated in 1996, which was largely in line with the goals envisaged by the Washington Consensus. As Adato, Carter and May (2006) point out, the underlying philosophy of this programme was that time would be an ally in alleviating poverty and that, by allowing market forces to run their course, poverty wuld be

[24]Similar results have been reported by Giesbert and Schindler (2012) for rural Mozambique from 2002 to 2005. The interpretation of the results are not clear from the literature. While Barrett, Carter and Little (2006) argue that this type of poverty trap is quite prevalent and should not be seen as evidence of the absence of a poverty trap, Antman and McKenzie (2007) interpret similar results for Mexico as evidence that no poverty trap exist.

alleviated in the long run. The findings by Adato, Carter and May (2006), which indicate the existence of a Micawber threshold as well as multiple asset accumulation equilibrium points and the existence of a poverty trap, should be seen in light of this macroeconomic environment, where poverty was rising, and direct intervention by government in the form of social support to alleviate poverty, was minimal.

On the other hand, since the late 1990's, the focus has shifted to more direct interventions in the lives of the poor. The most recent vision of the South Africa government, contained in the National Development Plan, clearly sets out the prioritisation of government of the alleviation of poverty. The decrease in poverty within an environment of pro-poor policy interventions, could partly explain why no evidence was found for a poverty trap, in contrast with the earlier findings.

4.6.1 Considering measurement error in reported assets

Despite the growing literature on the use of assets in order to estimate the existence of multiple thresholds for asset and income dynamics and subsequent conclusions about the existence of poverty traps in countries such as Kenya and Madagascar (Barrett, Marenya, Mcpeak, Minten, Murithi, Oluoch-Kosura, Place, Randrianarisoa, Rasambainarivo and Wangila, 2006) and South Africa between 1993 and 1998 (Adato, Carter and May, 2006), others remain sceptical about whether the techniques and data used in these analyses are sufficient to make conclusions about the existence of a micro-level poverty trap, especially since many other studies have found no evidence of multiple thresholds.[25]

Naschold (2013) examines whether the divergent views on the existence of multiple dynamic equilibrium poverty traps are as a result of the variation in techniques employed in the various studies. Considering parametric, nonparametric as well as semi-parametric techniques, Naschold (2013) find little difference in the results for panel data from Ethiopia as well as Pakistan. Naschold (2013) concludes that although the estimation technique does not seem to make a difference when using these two datasets, it might be as a result of the fact that asset dynamics in both these countries appeared to be relatively smooth and linear and notes that the estimation technique might have more of an impact in instances where the asset accumulation process is more non-linear.

Kraay and McKenzie (2014) argue that the general scarcity of long household panels as well as the lack of convincing methods to control for measurement errors in income and asset data mean that the evidence in favour of poverty traps have thus far been unconvincing. Kraay and McKenzie (2014) cite these two reasons, along with the positive growth experienced by most developing economies over the last 50 years as the main reasons why poverty traps are most likely not a very frequent phenomenon.

[25] For example Giesbert and Schindler (2012) in Mozambique, Antman and McKenzie (2007) in Mexico and Jalan and Ravallion (2002) in China.

I attempt to address at least one of these criticisms by taking into consideration the potential of measurement error in the reported assets. The use of an asset-based approach is aimed at minimising the fears around measurement error. This is based on the assumption that assets are less likely to be measured with error than income or expenditure. As discussed by Giesbert and Schindler (2012), this assumption is based on the fact that assets are less susceptible to fluctuations than income and expenditure. In addition, questions regarding asset ownership are less likely to be consistently misinterpreted (and therefore lead to consistently over- or under- reported data), which would lead to autocorrelation in the measurement errors over time.

In order to test whether this assumption is correct, this chapter takes this criticism into account by making use of the lag of asset values as an instrument to control for any possible measurement error in the assets.

The results from this approach are reported in Table 4.7, where I re-estimate Equation 4.1, however this time I include the lagged values of assets as instruments for the assets which are most likely reported with error (which include all assets in the equation apart from the assets which are reported as binary variables).

In order to take into account the fact that these asset values enter the equation non-linearly, I make use of various control functions,[26] one for each of the potentially endogenous asset values. I report the coefficients and standard errors of the included residual in the second stage next to each of the relevant variables. The statistical significance of the coefficients of these predicted residuals provide evidence of measurement error (and endogeneity) in the reported assets. Figure 4.5 reports these results. Introducing the instrumental variables approach increases the persistence of structural income subsequent to the threshold of approximately 0.6 PLU (taking into account the confidence interval). However, it does not substantially change any of the main results.

4.6.2 Parametric estimation of structural income dynamics

Apart from the existence of a poverty trap, I am also interested to estimate the thresholds at which the structural income dynamics line crosses the 45-degree line as this will provide some indication of the point to which income converges. In order to estimate this threshold, I make use of a non-linear parametric approach which will allow me to solve for Equation 4.5 and find the point at which the dynamic structural income line crosses the 45-degree line.

Although the evidence in the previous section did not point towards the existence of a poverty trap, there might also be evidence of a poverty trap existing in a sub-sample of the population. There are

[26] As described in Imbens and Wooldridge (2007).

many reasons to expect the existence of a poverty trap for certain groups in the country and not for others, including social exclusion[27] (Barrett and Carter, 2013) as well as geographic location (Jalan and Ravallion, 2002). Given the low level of income and expenditure for the black population in South Africa, this sub-sample would be the most likely individuals to be subject to a poverty trap, should one exist. I therefore start by estimating Equation 4.5, first for the entire sample and then for the sub-sample of black individuals.

The results from the OLS estimation of Equation 4.5 are set out in Table 4.8. The regression output reported in Table 4.8 comes from parametric regressions where the predicted structural income values are used. I run two sets of regressions - first without controlling for potential measurement error in the assets and then again using the same approach as discussed in the previous section where I instrument for the presence of measurement error, making use of the lagged asset values as instruments.[28]

I also report the results from these regressions graphically in Figures 4.6 and 4.7. The general pattern of structural income dynamics observed in the previous section, is repeated. In other words, it appears as if, for the full sample as well as the black sub-sample, there is a general pattern of upward mobility up to a low-level threshold, after which there is persistence in structural income and no further upward mobility takes place.

In order to obtain an estimate of the location of this threshold for each of the sub-samples, I report the solution to Equation 4.5 in Table 4.8. There are clear differences in the location of the threshold, as expected. For the full sample, the threshold is situated at approximately 1.1 logged PLU (without taking into account measurement error in reported assets) and approximately 2.1 logged PLU (after taking measurement error in reported assets into account). For the black population, this is much lower at approximately approximately 0.9 logged PLU (without taking into account measurement error in reported assets), and approximately 1.4 (after taking measurement error in reported assets into account).

The location of this threshold provides information on the structural income dynamics. When translating it into monetary terms, the threshold for the full sample is estimated to be located at approximately R1 970 (which is equal to 1.132 logged PLU) without taking measurement error n reported assets into account and R5 450 (which translates into 2.148 logged PLU) after taking into account measurement error in reported assets. Similarly, the threshold for the black sample is estimated to be at approximately R1 421 (which translates into 0.805 logged PLU) and R2 560 (which translates into 1.393 logged PLU). The threshold is therefore slightly lower for the black sample than the full sample. It is clear that upward mobility is restricted for these samples, in line with expectations.

[27] Social exclusion has been highlighted as a real issue from interviews with poor households in KwaZulu-Natal (Adato, Lund and Mhlongo, 2007).

[28] It should also be noted that I re-estimate the regressions in Table 4.6 and 4.7 for the black sample so as to use the return to assets applicable to the black sample only when predicting the structural income.

4.7 Conclusion

In this chapter I examine income dynamics and test for the existence of a poverty trap in South Africa using the NIDS panel data from 2010 to 2012. Making use of the framework developed by Carter and Barrett (2006), I make use of asset ownership in the household in order to obtain an estimate of structural income which is not subject to stochastic shocks over time. In addition, I allow for measurement error in the reported asset values, for which I control with lagged asset values.

By introducing the possibility of measurement error in reported assets, I expand the traditional literature on the measurement of poverty traps using assets in order to obtain a sense of the structural component of income over time. In addition, by allowing for a non-parametric estimation of the relationship between structural income over time, I also add to the current literature on income dynamics.

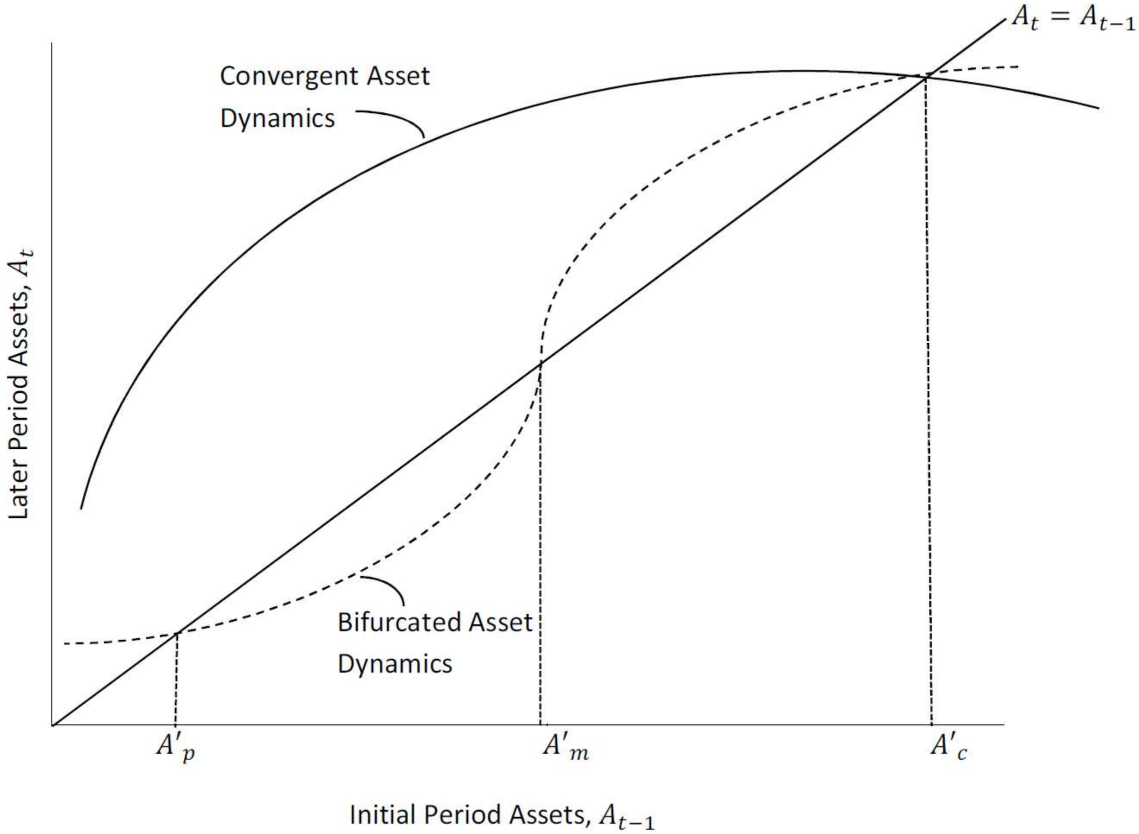
The evidence does not confirm the existence of a poverty trap of the type found by Adato, Carter and May (2006), in which multiple equilibrium points existed as a result of locally increasing marginal returns to productive assets. Rather, using the NIDS data, I find a single equilibrium in the dynamics of assets (or structural income) in terms of which there appears to be upward mobility up to a certain threshold, beyond which structural income remains very persistent.

This finding seems to be consistent with what has previously been found by Finn and Leibbrandt (2013b). These authors find that while income mobility is high for individuals at the bottom of the income distribution, income mobility at the top of the income distribution is relatively low. Calculating the specific threshold at which the structural income dynamics crosses the 45-degree line provides further insights into the level beyond which structural income dynamics becomes persistent. It would appear that for the black sample this threshold is lower than for the full sample, indicating lower levels of mobility for black South Africans compared to individuals who are from other race groups.

The prioritisation by government of the alleviation of poverty through direct interventions (rather than relying on macroeconomic growth to push the poor out of poverty over time, as was the case during the 1990's) might explain the absence of a poverty trap. In addition, the existence of this threshold confirms what one would expected, given the macro movements in income during this period. Whilst there was an increase in income, as indicated in Table 4.3, and whilst the South African economy was in a growth phase during the years 2010 to 2012, inequality remained high and persistent. The existence of a low-level threshold, beyond which structural income mobility is restricted, is consistent with these conditions.

Appendix to Chapter 4

Figure 4.1: Theoretical bifurcated asset dynamics



Source: Adato, Carter and May (2006, p. 232) and Giesbert and Schindler (2012, p. 1595)

Table 4.1: Attrition in NIDS 2008, 2010 and 2012 (number of individuals who completed the interview in parentheses)

	2008	2010	2012	Total
Only 2008	3 214 (2 970)	0	0	3 214 (2 970)
Only 2010	0	2 582 (2 490)	0	2 582 (2 490)
Only 2012	0	0	6 330 (6 161)	6 330 (6 161)
2008 & 2012	2 394 (2 089)	2 394 (2 089)	0	4 788 (4 178)
2010 & 2012	0	4 152 (3 953)	4 152 (3 953)	8 304 (7 906)
2008 & 2012	2 365 (2 138)	0	2 365 (2 138)	4 730 (4 276)
2008, 2010 & 2012	20 253 (18 818)	20 253 (18 818)	20 253 (18 818)	60 759 (56 454)
Total	28 226 (26 015)	29 381 (27 350)	33 100 (31 070)	90 707 (84 435)

Source: NIDS data (2008, 2010, 2012).

Notes: Un-weighted data.

Table 4.2: Differences between attriters and non-attriters

	Mean (standard error)		
	Attriters	Non-attriters	t-statistic
Per capita monthly hh income (2012 Rands)	1 508.65 (20.69)	1 271.97 (16.74)	8.490
Per capita monthly hh expenditure (2012 Rands)	1 154.80 (15.89)	955.84 (9.35)	9.016
Mean household education in years	8.187 (0.020)	7.858 (0.013)	13.994
Number of pension-aged individuals in hh	0.346 (0.004)	0.367 (0.003)	-4.751
Mean age of household	26.222 (0.065)	26.969 (0.045)	-9.467
Household size	6.002 (0.023)	5.909 (0.014)	3.588
Mean employment rate in hh	0.355 (0.002)	0.336 (0.002)	7.408
Proportion black	0.808 (0.002)	0.834 (0.002)	-9.447
Sample size	27 981	56 454	

Source: NIDS data (2008, 2010, 2012).

Notes: Attriters include all individuals who were not observed in the data in all three waves.

Table 4.3: Trends in mean and median income and expenditure, 2010 and 2012

In Rand 2012 prices	Income			Expenditure		
	Mean	Standard deviation	Median	Mean	Standard deviation	Median
2010						
Full sample	1 827.51	3 852.15	674.72	1 472.80	3 725.54	469.39
Black sample	1 173.33	2 184.37	578.13	867.93	1 919.76	387.41
White sample	8 910.71	9 011.46	7 631.01	8 036.91	9 557.323	5 783.37
2012						
Full sample	2 123.15	4 300.05	810.62	1 430.30	2 791.56	518.08
Black sample	1 427.28	2 627.45	703.24	937.37	1 744.07	435.69
White sample	9 925.15	9 874.96	7 348.33	6 596.96	5 472.67	5 155.94

Source: NIDS data (2010 and 2012).

Note: Calculated for balanced sample remaining in panel for all three waves. Panel weights used.

Table 4.4: Poverty Headcount Rate per race (%)

	2010	2012
Income-based		
Full sample	47.38	38.77
Black	53.98	45.20
White	0.98	2.95
Expenditure-based		
Full sample	60.70	55.00
Black	68.49	63.10
White	0.57	2.06

Source: NIDS data (2010 and 2012).

*Note*s: Unbalanced sample.

Table 4.5: Poverty dynamics between 2010 and 2012

		2012	
		Poor	Non-poor
2010	Poor	28.81% chronically poor	17.59% got ahead
2010	Non-poor	9.82% fell behind	43.78% never poor

Source: NIDS data (2010 and 2012).

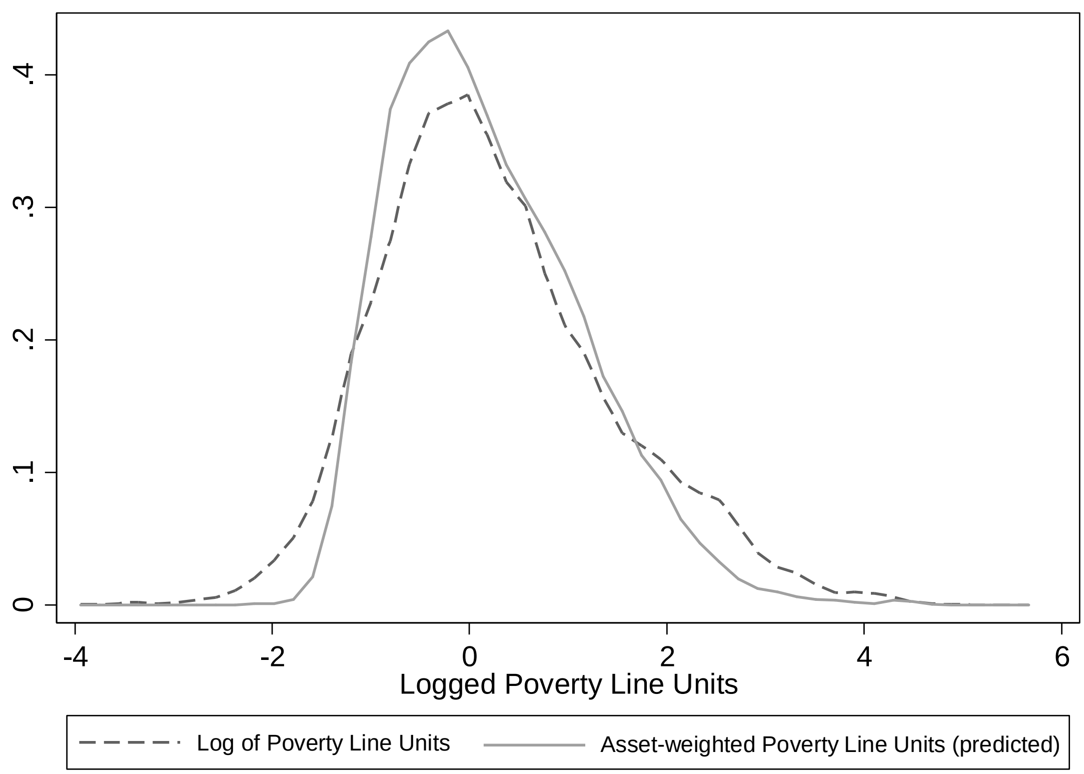
Notes: Using balanced sample. As additional control, only individuals for whom a change of more than 10% of 2008 reported income were counted as moving up or down. Poverty line of R636 in 2012 Rands.

Table 4.6: Estimation of asset-weighted (structural) income

Dependent variable: log of PLU	2010	2012	2010 and 2012
Mean employment rate in hh°	2.160*** (0.430)	1.923*** (0.294)	1.341*** (0.350)
(Mean employment rate in hh)^2	-0.916 (1.192)	-0.744 (0.946)	0.427 (0.931)
(Mean employment rate in hh)^3	-0.344 (0.791)	-0.216 (0.685)	-0965 (0.596)
Household size/10	-1.764*** (0.293)	-1.365*** (0.230)	-1.408*** (0.153)
(Household size/10)^2	0.960*** (0.222)	0.752*** (0.194)	0.666*** (0.120)
(Household size/10)^3	-0.148*** (0.043)	-0.118*** (0.041)	-0.085*** (0.024)
Proportion of pension-aged in hh	3.581*** (0.006)	2.148*** (0.346)	3.599*** (0.491)
(Proportion of pension-aged in hh)^2	-8.512*** (2.377)	-4.142*** (1.022)	-9.144*** (2.046)
(Proportion of pension-aged in hh)^3	5.553*** (2.006)	2.886*** (0.828)	6.348*** (1.840)
Living index°°	0.364*** (0.039)	0.396*** (0.034)	0.355*** (0.034)
(Living index)^2	0.320*** (0.037)	0.362*** (0.025)	0.323*** (0.041)
(Living index)^3	0.084*** (0.012)	0.090*** (0.008)	0.0879*** (0.013)
Mean years of education in hh°°°	-0.020 (0.040)	0.032 (0.026)	0.017 (0.029)
(Mean years of education in hh)^2	-0.006 (0.006)	-0.014*** (0.004)	-0.0112*** (0.004)
(Mean years of education in hh)^3	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Proportion of children <18 in hh	-1.838*** (0.423)	-1.608*** (0.413)	-1.516*** (0.352)
(Proportion of children <18 in hh)^2	2.540 (1.550)	1.719 (1.269)	1.584 (1.239)
(Proportion of children <18 in hh)^3	-1.468 (1.365)	-0.964 (1.122)	-1.001 (1.099)
Mean health of hh°°°°	0.735** (0.324)	0.583 (0.375)	0.439* (0.194)
(Mean health of hh)^2	-0.327** (0.126)	-0.201 (0.155)	-0.187* (0.100)
(Mean health of hh)^3	0.043*** (0.015)	0.020 (0.019)	0.023* (0.012)
Owns dwelling	0.063* (0.0354)	0.082*** (0.030)	0.066* (0.036)
Female-headed hh	-0.190*** (0.041)	-0.099*** (0.022)	-0.191*** (0.044)
Number of observations	17 550	17 550	35 100
R squared	0.640	0.673	0.639

Source: NIDS data (2010 and 2012). *Notes*: OLS regression coefficients with standard errors (clustered at the district level). All estimations include district council fixed effects. Sample consists of individuals remaining in panel for all 3 waves. Poverty Line Unit (PLU) is equal to the reported per capita household monthly income divided by the poverty line of R636. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level. °Proportion of individuals aged between 16 and 64 (both inclusive) in the household who are employed. °°Living index contains type of dwelling, material used for roof and walls, source of drinking water, sanitation, material used for lighting, heating and cooking and whether household owns a fridge, washing machine, electric or gas stove.°°°Education in the household is calculated only for individuals aged 18 years and older. °°°° Perceived health status is measured on a scale from 1 to 5 with 1 being the best and 5 the worst.

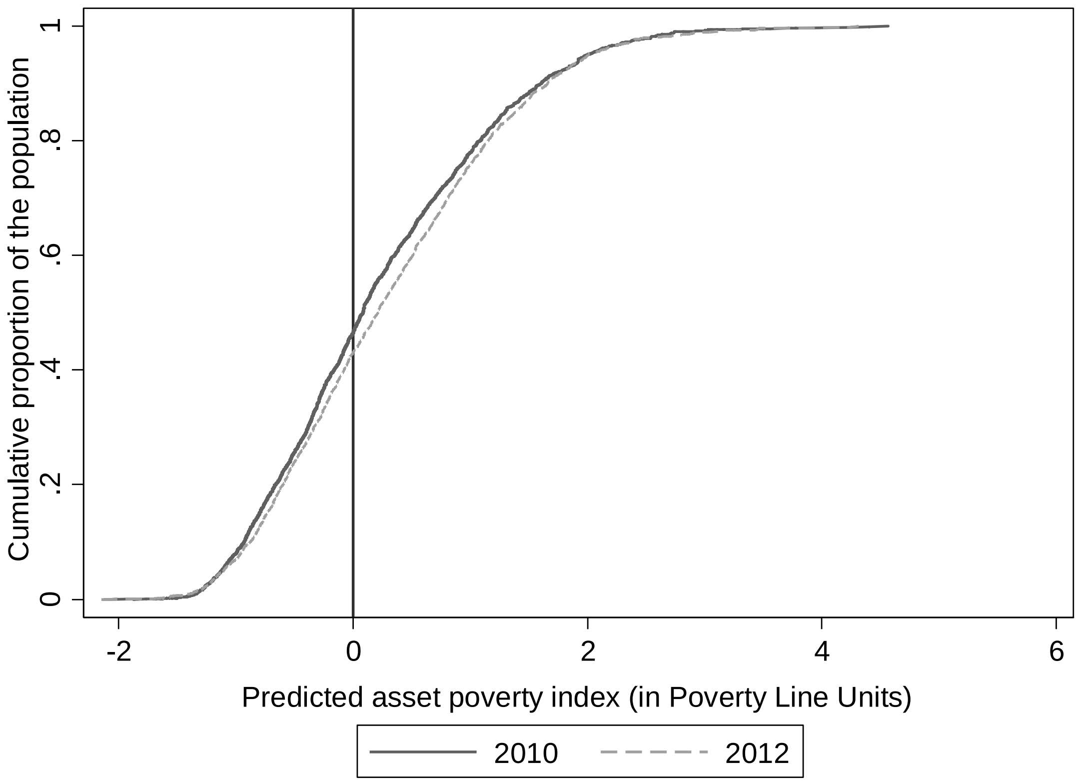
Figure 4.2: Distribution of reported and asset-weighted (structural) income



Source: NIDS data (2008 and 2010).

Notes: Using sample of individuals remaining in panel for all 3 waves. Poverty Line Unit (PLU) is equal to the reported per capita household monthly income divided by the poverty line of R636. This is then logged. If logged PLU=0 the household is exactly on the poverty line. The predicted PLU is obtained from the OLS regression of reported assets on logged PLU.

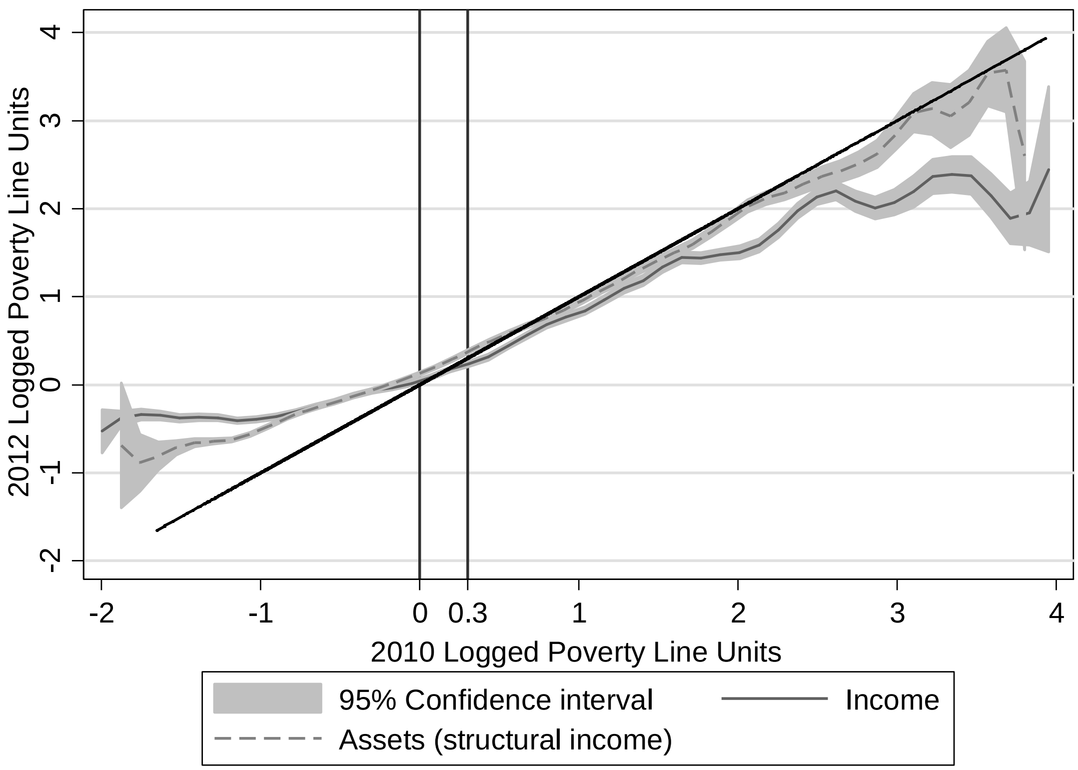
Figure 4.3: Predicted poverty using an asset index



Source: NIDS data (2010 and 2012).

*Note*s: Sample of individuals remaining in panel for all 3 waves. Structural income dynamics estimated with a local polynomial regression using kernel weighted local polynomial smoothers. A third degree polynomial and kernel bandwidth of 0.2 are used. Poverty Line Unit (PLU) is equal to the reported per capita household monthly income divided by the poverty line of R636. This is then logged. If logged PLU=0 the household is exactly on the poverty line. The predicted PLU is obtained from the OLS regression of assets on logged PLU..

Figure 4.4: Nonparametric estimation of asset and income dynamics - 2010 to 2012



Source: NIDS data (2010 and 2012).

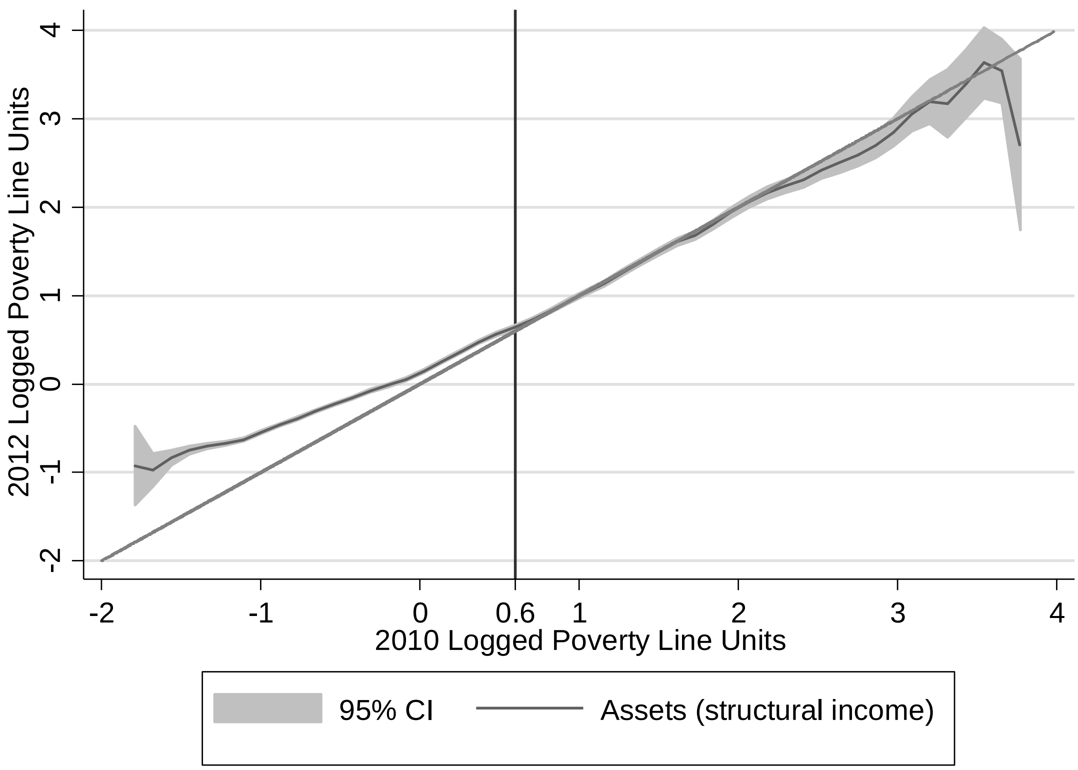
*Note*s: Sample of individuals remaining in panel for all 3 waves. Asset dynamics estimated with a local polynomial regression using kernel weighted local polynomial smoothers. A third degree polynomial and kernel bandwidth of 0.2 are used. Poverty Line Unit (PLU) is equal to the reported per capita household monthly income divided by the poverty line of R636. This is then logged. If logged PLU=0 the household is exactly on the poverty line. The predicted PLU is obtained from the OLS regression of assets on logged PLU..

Table 4.7: Estimation of asset-weighted (structural) income controlling for measurement error

Dependent variable: log of PLU	2010		2012	
	Second Stage OLS	Coefficients (standard errors) of predicted residuals in second stage	Second Stage OLS	Coefficients (standard errors) of predicted residuals in second stage
Mean employment rate in hh°	2.779*** (0.479)	-0.705*** (0.176)	2.406*** (0.383)	-0.595*** (0.207)
(Mean employment rate in hh)^2	-0.976 (1.203)		-0.659 (0.981)	
(Mean employment rate in hh)^3	-0.269 (0.802)		-0.262 (0.710)	
Household size/10	-1.649*** (0.232)	0.010 (0.127)	-1.255*** (0.318)	-0.111 (0.186)
(Household size/10)^2	0.900*** (0.181)		0.732*** (0.210)	
(Household size/10)^3	-0.139*** (0.035)		-0.118*** (0.043)	
Proportion of pension-aged in hh	3.674*** (0.596)	-0.378 (0.277)	2.099*** (0.341)	0.113 (0.143)
(Proportion of pension-aged in hh)^2	-8.507*** (2.191)		-4.165*** (1.057)	
(Proportion of pension-aged in hh)^3	5.793*** (1.875)		2.887*** (0.782)	
Living index°°	0.428*** (0.043)	-0.164*** (0.044)	0.412*** (0.035)	-0.072*** (0.022)
(Living index)^2	0.302*** (0.038)		0.348*** (0.027)	
(Living index)^3	0.081*** (0.012)		0.087*** (0.008)	
Mean years of education in hh°°°	-0.001 (0.044)	-0.027* (0.015)	0.035 (0.026)	-0.026** (0.010)
(Mean years of education in hh)^2	-0.007 (0.006)		-0.013*** (0.004)	
(Mean years of education in hh)^3	0.001*** (0.000)		0.001*** (0.000)	
Proportion of children <18 in hh	-1.833*** (0.447)	-0.012 (0.149)	-1.783*** (0.515)	0.100 (0.221)
(Proportion of children <18 in hh)^2	2.473 (1.560)		2.084 (1.363)	
(Proportion of children <18 in hh)^3	-1.418 (1.384)		-1.258 (1.207)	
Mean health of hh°°°°	0.710** (0.348)	-0.019 (0.109)	0.678* (0.371)	-0.035 (0.073)
(Mean health of hh)^2	-0.305** (0.124)		-0.222 (0.145)	
(Mean health of hh)^3	0.0403*** (0.015)		0.022 (0.018)	
Owns dwelling	-0.003 (0.042)		0.078*** (0.034)	
Female-headed hh	-0.111*** (0.042)		-0.030 (0.039)	
Number of observations	17 550		17 550	
R squared	0.648		0.678	

Source: NIDS data (2008, 2010, 2012). *Notes*: Second stage regression coefficients from control function with standard errors (clustered at the district level) All estimations include district council fixed effects. Sample consists of individuals remaining in panel for all 3 waves. Poverty Line Unit (PLU) is equal to the reported per capita household monthly income divided by the poverty line of R636. °Proportion of individuals aged between 16 and 64 (both inclusive) in the household who are employed. °°Living index as described in notes to Table 4.6.°°°Education in the household is calculated only for individuals aged 18 years and older. °°°° Perceived health status is measured on a scale from 1 to 5 with 1 being the best and 5 the worst. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level.

Figure 4.5: Nonparametric structural income dynamics controlling for measurement error - 2010 to 2012



Source: NIDS data (2008, 2010, 2012).

Notes: Sample of individuals remaining in panel for all 3 waves. Structural income dynamics estimated with a local polynomial regression using kernel weighted local polynomial smoothers. A third degree polynomial and kernel bandwidth of 0.2 are used. Poverty Line Unit (PLU) is equal to the reported per capita household monthly income divided by the poverty line of R636. This is then logged. If logged PLU=0 the household is exactly on the poverty line. The predicted PLU is obtained from the OLS regression of reported assets on logged PLU.

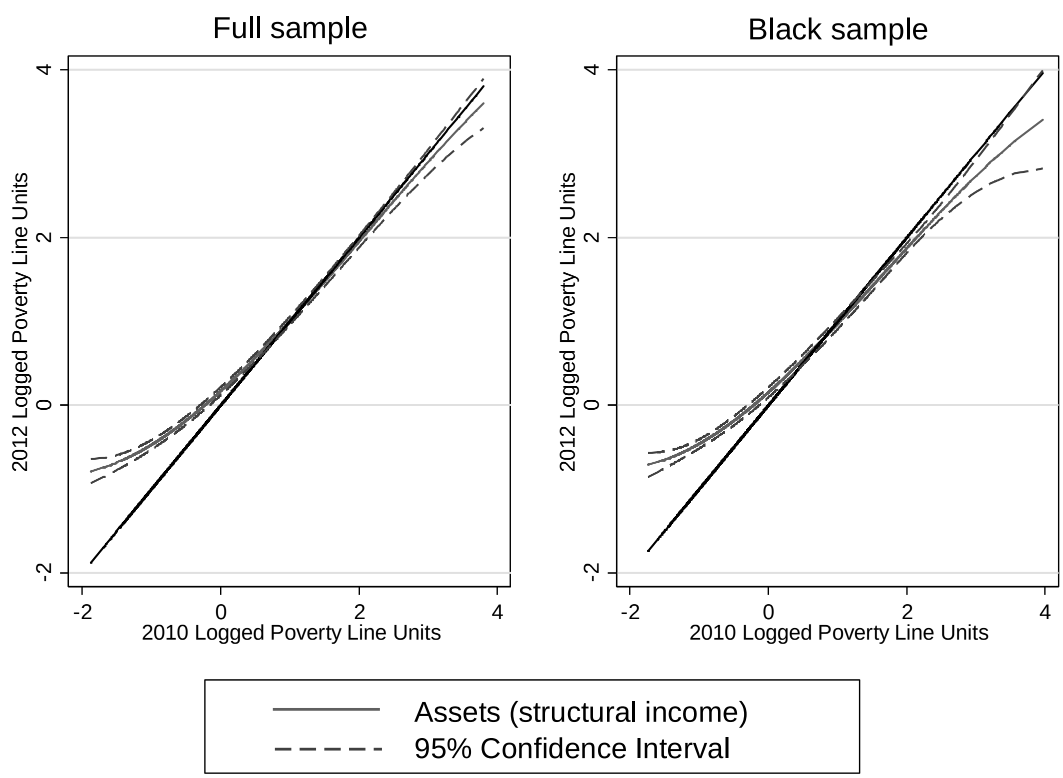
Table 4.8: Parametric estimates of structural income dynamics

Dependent variable: Structural income 2012	Structural income - no measurement error considered		Structural income - measurement error considered	
	All	Black sample	All	Black sample
Constant	0.170***	0.156***	0.169***	0.158***
	(0.025)	(0.031)	(0.023)	(0.029)
Structural income 2010	0.756***	0.737***	0.800***	0.793***
	(0.016)	(0.021)	(0.014)	(0.019)
(Structural income 2010)^2	0.101***	0.102***	0.093***	0.102***
	(0.014)	(0.017)	(0.004)	(0.016)
(Structural income 2010)^3	-0.016***	-0.020**	-0.017***	-0.025***
	(0.005)	(0.008)	(0.004)	(0.007)
Solution to equation	1.132	0.805	2.148	1.393
$\hat{Y}_{it} = \alpha + \beta_1 \widehat{Y}_{i,t-1} + \beta_2 (\widehat{Y}_{i,t-1})^2 + \beta_3 (\widehat{Y}_{i,t-1})^3$	(0.026)	(0.033)	(0.036)	(0.030)
Observations	17 550	14 669	17 550	14 699
R-squared	0.669	0.554	0.727	0.623

Source: NIDS data (2008, 2010, 2012).

Notes: OLS regression coefficients with standard errors (clustered at the district level). Sample consists of individuals remaining in panel for all 3 waves. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level. $^{\circ}$Measurement errors in reported assets were considered by making use of lagged asset values as instruments using control functions.

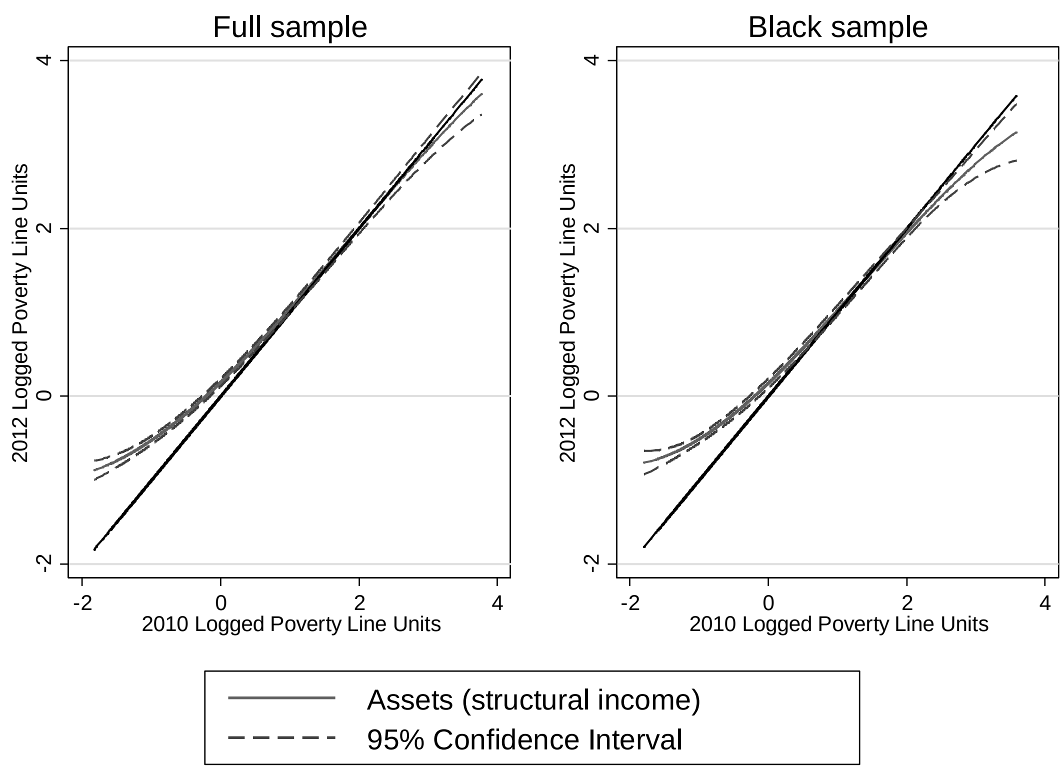
Figure 4.6: Parametric estimates of structural income dynamics for full sample and black sample



Source: NIDS data (2008, 2010, 2012).

Notes: Sample of individuals remaining in panel for all 3 waves. Poverty Line Unit (PLU) is equal to the reported per capita household monthly income divided by the poverty line of R636. This is then logged. If logged PLU=0 the household is exactly on the poverty line. The predicted PLU is obtained from the OLS regression of assets on logged PLU.

Figure 4.7: Parametric estimates of structural income dynamics for full sample and black sample (taking measurement error into account)



Source: NIDS data (2008, 2010, 2012).

Notes: Sample of individuals remaining in panel for all 3 waves. Poverty Line Unit (PLU) is equal to the reported per capita household monthly income divided by the poverty line of R636. This is then logged. If logged PLU=0 the household is exactly on the poverty line. The predicted PLU is obtained from the OLS regression of assets on logged PLU.

Chapter 5

Conclusions

In this dissertation, I have dealt with three topics related to the lack of social mobility and cohesion in post-apartheid South Africa. The three topics are all either mechanisms enforcing the current polarisation and economic inequality or are vital for understanding the existence of the current divisions.

The first topic, discussed in Chapter 2, examined the impact of school quality on the performance of disadvantaged children. This topic is important in the discussion of social mobility, as the lack of access to quality schooling experienced by the poor is arguably one of the most important mechanisms enforcing the cycle of inter-generational poverty.

Second, in Chapter 3, the dissertation touched on the concept of social cohesion. In a country where inter-racial contact is limited and households reside in geographic pockets of affluence or poverty, social cohesion has been listed as one of the focus areas in the government's National Development Plan. The third chapter sought to obtain a sense of the reference groups used in the subjective assessment by South Africans of their well-being.

The last topic I examined in the dissertation was one of income mobility and poverty traps. In Chapter 4, I test for the existence of poverty traps within the framework of identifying structural income, using assets. The concept of poverty traps provides a useful lens through which to view the existence of chronic poverty, where households and individuals remain in poverty over time and through which social and economic divisions are entrenched.

Each one of these three concepts provided interesting conclusions, which are summarised below.

5.1 Chapter 2: School quality and the performance of disadvantages learners

The focus of Chapter 2 was to estimate the impact on the academic performance of black children as a result of attending a historically white school. Because of South Africa's history of racial division and the lasting legacies of the discriminatory apartheid policies which ensured that historically white schools were much more likely to provide a quality education, the sample of black children remains a good proxy for children coming from the poorest households where school choice is most likely limited to low quality schools.

For this purpose, I made use of the National School Effectiveness Study data, collected from the same students in grade 3 (2008), grade 4 (2008) and grade 5 (2009). The data includes a host of individual student, household and school controls and also test scores from numeracy and literacy tests written in each year.

In order to control for the selection bias inherent in the choice of school, the analysis in Chapter 2 made use of the richness of the National School Effectiveness Study data and controlled for a wide variety of child- and household-level characteristics. In addition, a value-added approach was implemented. More specifically, the value-added approach employed made use of lagged test scores as a control for the unobserved learner heterogeneity in the form of past endowment and ability which would otherwise have biased the estimates of the effect of attending a former white school.

In Chapter 2, I initially estimated an increase of 0.7 of a standard deviation on English test scores and 0.5 of a standard deviation on mathematics test scores for black children attending a former white school. Interpreting these estimates within the context of previous empirical evidence on the speed of learning in South African schools leads to the conclusion that they represent more than a year's worth of learning. In addition to these initial estimates, Chapter 2 also explored the heterogeneity of the impact of attending a former white school using only the grade 4 data and then only the grade 5 data. Results seemed to indicate that the former white school impact becomes less important over time, as the lagged test score from the previous year (a measure of inherent ability and past inputs) becomes more important.

Finally, Chapter 2 addressed some of the concerns with the estimates that remain. First, the possibility that the estimates were confounded by a language effect which may have arisen from the language policy implemented in primary schools in South Africa, was considered. Second, because of the high attrition rate in the National School Effectiveness Study data, inverse probability weighting was implemented to control for biases arising from selective attrition. Last, the analysis controlled for measurement error in the test scores by including the lagged scores of the other tested subject (under the assumption that the measurement errors in the English and mathematics tests are not correlated). In addition, the issue of remaining unobserved individual child ability was also addressed by using an instrumental variable. The robustness of the estimates from the OLS value-added model was confirmed by these checks.

The results have important implications for education policy in South Africa. Although it is not feasible to improve the school system by moving all children from historically black schools to historically white schools, a measure of the causal impact of attending these former white schools is necessary in the policy debate regarding the improvement of government schools which has been taking place on an on-going basis between policy makers and other interest groups. Estimating the causal effect of attending a former white school provides much-needed information on separating the effect of higher quality schools from the impact of household circumstances.

5.2 Chapter 3: Subjective well-being and reference groups

The main aim of Chapter 3 was to answer two questions. In the first place, what weight did individuals place on their own race versus other race groups in the determination of reference groups when evaluating their relative standing within the framework of their utility function (as captured by their subjective well-being)? In the second place, the question was: was there heterogeneity in the size of the weight as the distance between individuals increased?

The answers to these questions provide information on the current state of social cohesion within South Africa, specifically social cohesion across racial and geographic borders.

In order to answer these questions, the analysis in Chapter 3 commenced with a replication of the studies by Kingdon and Knight (2006, 2007). Using data from 1993, they have, *inter alia*, come to the conclusion that own-race comparisons, as measured by the mean income of others in the residential cluster who are of the same race or by the race-specific income quintile of the household, was an important input into subjective well-being or utility functions. The conclusion from 1993 was therefore that the correct reference group to which comparisons are made in South Africa was one which was racially defined. This conclusion made sense in the context of the racial divisions imposed by the apartheid legislation.

Replicating these studies seemed to suggest that race remained an important contributing factor to the determination of reference groups. However, as indicated in Chapter 3, the approach taken by Kingdon and Knight made specific assumptions regarding the size of the race parameter and the way in which the various parameters entered the utility function. The main contribution of Chapter 3 is that it developed a more flexible way in which to estimate the race and geographic parameters in the utility function.

In the more flexible model developed in Chapter 3, the weights placed on race as well as the geographic distance are allowed to enter the utility function in a non-linear way. Using this unrestricted model, I came to certain conclusions regarding the size of parameters in the utility function. In the first place, although greater weight is still placed on individuals of the same race in the determination of the reference group than on others of a different race, I estimated the weight placed on individuals of the same race to be approximately 0.7 to 0.9, depending on the specification, with the weight placed on individuals of other race groups estimated to be around 0.1 to 0.3. There is therefore some evidence that individuals of other race groups also enter the utility function in the determination of the reference group. However, I was unable to reject the hypothesis that the estimated race parameter is equal to one, as assumed by Kingdon and Knight (2006, 2007).

In addition, the findings in Chapter 3 indicated that while others living in the same residential cluster as the household enter the utility function positively, when considering others in the district and nationally, then the sign of the weight turns negative. The most likely explanation for the positive sign on the cluster parameter appeared to be the altruistic nature of relationships within the smaller geographic region of the cluster.

Chapter 3 also explored the robustness of this result by including geographic fixed effects and making use of various alternative definitions of income. The initial results however remained robust to these checks.

The contribution to the literature from Chapter 3 is three-fold. In the first place, it revisited the previous results regarding the spatial variation of the reference group and found evidence that households in closer proximity enter the individual's utility function positively while more far-off individuals enter the utility function negatively. This is in line with previous findings for South Africa in 1993. Second, the chapter tested the hypothesis that reference groups are delineated along racial lines.

The final contribution of the chapter relates to the methodology implemented. Instead of using linear models to estimate the size of the weight placed on the race and distance of others in the utility function, which are very restrictive, I specified a more flexible non-linear model which allowed the estimation of the weight placed on the relative standing of one's own race group compared with other race groups, while simultaneously estimating the weight placed on the geographic distance of others. This is a methodological innovation which has not been implemented in studies on this topic before. The introduction of this more flexible approach opens up opportunities to test assumptions which have been made regarding the form of the utility function in previous studies and which assumptions have not been tested before.

5.3 Chapter 4: Income dynamics, assets and poverty traps

The last concept considered in this dissertation appears in Chapter 4 and deals with the existence of poverty traps in South Africa.

Chapter 4 commenced by setting out the general income dynamics which have taken place in South Africa over the period 2010 to 2012. The main aim of Chapter 4 was however to test for the existence of poverty traps. In this regard Chapter 4 first discussed the theoretical framework for the estimation of income dynamics. Two sets of literature were used to inform the estimation technique. On the one hand, I considered the literature on income dynamics and impact of measurement error. On the other hand, I considered the literature pioneered by Carter and Barrett (2006) in which poverty traps may be estimated using an asset-based approach. In the framework of Carter and Barrett (2006), income dynamics may be separated into three parts - a structural (long-run) component; a stochastic (short-run or random) component and measurement error. The aim of Chapter 4 was to separate the structural component of income in order to evaluate structural income dynamics over time so that the existence of poverty traps may be established.

According to Carter and Barrett (2006), non-linearities in structural income indicate the existence of poverty traps. The authors postulate the existence of multiple equilibrium points where the line depicting the relationship between structural income in this period *versus* the previous period crosses the 45-degree line. At one such a point, the structural income growth paths bifurcate, which leads some individuals to remain in poverty and allows others to escape poverty by moving to a new higher income.

Making use of the 2010-2012 National Income Dynamics Study data, I test for the existence of a poverty trap in South Africa by using a nonparametric estimation technique to estimate the relationship between structural income in 2012 and 2010. In order to separate the structural component of income, I used data on reported assets in order to obtain a sense of the expected income of each individual, given their asset ownership. The analysis in Chapter 4 found no evidence of the existence of poverty traps. However, there appeared to be upward income mobility up to a certain point, beyond which income appeared to be very persistent, with very little movement from one period to the next. This result is in contrast to the findings of previous studies using data from 1993-1998, however the result makes sense in the context of high income inequality which is persistent in South Africa.

In addressing one of the criticisms raised against the use of the asset-based approach, I also dealt with the possibility of measurement error in the data on asset ownership. The results were robust to the use of an instrumental variables approach in which control functions were used to minimise the impact of measurement error in the reported asset data.

Chapter 4 also tested for the existence of a poverty trap parametrically with the use of a non-linear model. This approach allowed me to solve for the equilibrium points.

The analysis in Chapter 4 contributes to the current literature by drawing from both the literature on income dynamics and measurement error, as well as the literature on poverty traps. It also addresses the criticism raised by Antman and McKenzie (2007) against the use of an asset-based approach to testing for poverty traps. More specifically, it considers the possibility of measurement error not only in reported income data, but also in the data on assets. This expands the traditional literature on poverty traps and confirms the validity of the use of assets in order to estimate the structural component of income.

5.4 Final comments

The dissertation examined the lack of economic mobility in post-apartheid South Africa and also considered the lack of social cohesion which has been entrenched by a history of racial divide and polarisation by focussing on three topics within this broader literature.

For all three the topics discussed in the dissertation, the findings seem to confirm that the apartheid divides remain present in the everyday lives of South Africans. Twenty years after the end of apartheid society remains fragmented and income mobility remains low, although no evidence was found for the existence of a poverty trap. A child born into a poor household in South Africa therefore will most likely not easily move out of poverty. However, one of the paths which does allow for mobility over time is the improvement of school quality, which was shown to have a large and significant impact on the academic performance of poor children, and would most likely provide the necessary input to allow them access to the formal labour market and a way out of poverty.

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