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Impact of Cash Grants on Multidimensional Poverty in South Africa

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Abstract

South Africa is estimated to allocate approximately US $12 billion for the 2014/15 fiscal year for social grants (Bhorat and Cassim, 2014). With an extensive coverage and budget, it is one of the most progressive social security schemes among low and even middle income countries. It helps mitigate income poverty and inequality, and has been shown to have a positive effect on household socioeconomic outcomes such as health and education, employment and other demographic outcomes. However, no study has thus far examined the impact of these grants on the overall or associative deprivation across households. This paper uses the National Income Dynamics Survey (NIDS) to derive the Multidimensional Poverty Index (MPI) and Correlation Sensitive Poverty Index (CSPI) for South Africa, and then estimate the impact that social assistance grants have on both of these composite indices of poverty measurement. The results show that increases in the income from a cash grant, leads to lower multidimensional poverty level in households. Another meaningful result is that cash grants seem to have reduced the multidimensional inequality as well. Using an instrument and a fuzzy Regression Discontinuity Design (RDD) to account for the issue of endogeneity in child and old age grants respectively, health and standard of living are found to be the major channels through which these grants work in reducing multidimensional poverty and inequality.

Keywords: Social Assistance Grants, Multidimensional Poverty Index (MPI), Correlation Sensitive Poverty Index (CSPI), National Income Dynamics Survey (NIDS)

JEL codes: H55, I38

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INTRODUCTION

The literature has investigated the role of macroeconomic and microeconomic policies in influencing money-metric measures of poverty. Nonetheless, although money-metric measures of poverty are important and useful in providing an indication of broad poverty dynamics over time, these measures are limited in the sense that they are often considered too simplistic, and therefore fail to encompass the notion of wellbeing. Thus, they are ideally complemented by other non-money metric measures of poverty (Sen, 1985). There are several studies that have discussed the merits of multidimensional measures of poverty over unidimensional, or more precisely, income based measures (e.g. Alkire and Foster, 2011a; Klasen, 2000; Nussbaum, 2003; Sen, 1999). The distinction between income poverty and overall wellbeing as defined by objective or subjective definitions of wellbeing, and is very important in helping to understand and reduce poverty. The shift in focus away from income and towards the real freedoms that people have, based on their capability to undertake such activities, for instance reading, being politically active or being healthy and literate, was first clearly outlined by Sen in the Capability Approach (CA) and extended by several other philosophers and economists (Nussbaum, 2008; Nussbaum et al., 1993; Sen, 1999, 1985).

Alkire (2002) and Ravallion (2012) provide a long list of indicators that can be used to represent development or poverty, as proposed by the World Bank, and several other works that were based on empirical, economic or philosophical foundations. In practical terms, there have been many applications of the CA, starting with the Human Development Index (HDI) (United Nations, 1990) to more recent applications such as the Human Poverty Index (HPI) and the Gender Development Index (GDI). Another contribution of the literature has been the shift in perspective from national and more macro aggregates (e.g. GDP and HDI) towards indicators that use households and individuals to measure poverty and deprivation. More recently, the Millennium Development Goals (MDGs) are defined as a set of dashboard goals that are measured at the level of individuals, while keeping country averages as targets. The popularity of these broad based development and human progress measures is growing. One of the more prevalent ways applied to supplement the usual money-metric measures of poverty, is to make use of a multidimensional wellbeing index, which is generally comprised of a broader range of wellbeing indicators (or dimensions) so as to provide a more complete indication of whether an individual or a household can be considered deprived.

The most popular, recent work on multidimensional poverty measurement, the dual cut off based index of multidimensional poverty, has been proposed and implemented by Alkire and Foster (2011). In their paper, they provide directions on how to integrate various dimensions of deprivation into a single composite index and thereby measure the wellbeing of an individual. The Multidimensional Poverty

Index (MPI), an application of the Alkire and Foster method, was developed by the Oxford Poverty and Human Development Initiative (OPHI) and the UNDP as an index of acute multidimensional poverty. It depicts deprivations through 10 basic indicators for households across 104 countries, making it one of the few measures that have such a global comparison of multidimensional poverty(Alkire and Santos, 2014). Making use of a multidimensional approach allows for the consideration of several dimensions of deprivation, which also allows wellbeing to be measured in the space of capabilities (Alkire and Foster, 2011a). The advantage of using the Multidimensional Poverty Index (MPI) is not only given by the fact that it includes a wider measure of actual wellbeing than only income or expenditure, but also because it takes into account the intensity of the poverty apart from the headcount of deprived individuals (incidence of poverty).

Rippin (2015, 2012, 2010) introduced the Correlation Sensitive Poverty Indices (CSPIs), another multidimensional measure that accounts for the associative nature of simultaneous deprivations across the population and how this affects the headcount of multidimensional poverty. The CSPI is the first additive poverty index that can be decomposed into all “three I’s” of poverty: incidence, intensity and inequality, where this third additional property of inequality has been found to make it easier to understand and consider the associations within the multidimensional indices of poverty. Rippin applies this method specifically for the MPI in her recent papers (Rippin, 2015). In my case, the MPI and the CSPI are the two indices of interest, especially given the background of high inequality in South Africa, which would be used in this paper. Not only are there a sparse number of studies that have incorporated the nature of simultaneous deprivations within a particular wellbeing index, there is very little application of the same in the studies. Part of the reason for this is the issue of data quality and comparability, which, for a complex and comprehensive measure such as multidimensional poverty, is harder to come by, than a unidimensional money metric measure. Moreover, those studies that do exist, at best estimate the level of multidimensional poverty in South Africa by using repeated cross sectional data when examining a time trend[2]. It is this therefore that motivates this particular work.

To begin with, this paper uses panel data, over a period of four/five years, for South African households, to track their MPI and CSPI over time. While these form part of the sample, the main cause of interest is the impact of cash grants on the MPI and CSPI. South Africa has one of the most progressive social security schemes among low- and middle-income countries. Given the large amount of spending, and the evidence that it is well targeted, this is an interesting and relevant question (Gutura and Tanga, 2014). There have been several academic studies and policy reports that look at the impact of these social

[2] There are some studies that do look at a panel, but the time period is shorter than the one in this paper. Moreover they have not been published so far and are only working papers or presentations so far.

grants on household socioeconomic outcomes including health and education, income poverty, employment and other demographic outcomes in the short and long term (Barrientos et al., 2006, 2004; Heinrich et al., 2012; Lund et al., 2008; Woolard and Leibbrandt, 2013). Nonetheless, after an extensive search through the literature, no work looking at multidimensional poverty or inequality, and its relation to the cash grants in South Africa has been found. Additionally, given the very low application of the CSPI measure, this paper serves to fill this important gap in the literature.

There are several complexities that are meant to be addressed with the measurement of multidimensional poverty and inequality, but a big issue among households that receive grants who are considered multidimensionally poor, is the simultaneity of both of these aspects. Therefore, to attend to this issue, this paper uses two well documented methods to correct for this issue of endogeneity. For the case of child grants I apply an instrument that has been introduced by Eyal and Woolard (2013), while in the case of old age grants a fuzzy RDD approach, as described by Angrist and Pischke (2009), is implemented.

In the following section, the literature on the impact of cash grants on poverty and inequality in the case of South Africa is examined, with a focus on multidimensional poverty and inequality. In the section thereafter, the methodology and the data used are explained in detail. This section will also discuss some key characteristics of the data and try to replicate the figures for multidimensional poverty that have been found in the literature on South Africa. Section 4 presents the results from the empirical analysis while the final section will discuss the implications of the results. The conclusion will also suggest the next steps for further research on this topic.

LITERATURE

Multidimensional Poverty in South Africa

There are several papers that examine the nature of income poverty in South Africa (Finn and Leibbrandt, 2013; Leibbrandt and Levinsohn, 2011; Leibbrandt et al., 2010). Since apartheid, South Africa has made advances in growth, and average per capita real incomes have been rising across the distribution, albeit unequally. A large section of the population, generally blacks and coloureds have been lagging behind and therefore inequality is very large. Moreover, they are also the section of society that is especially plagued by the high unemployment situation in South Africa. Within this background, the role of policies, such as social assistance in the form of cash transfers, have been largely helpful in reducing the differences in access to education and other social services over the period. This is line with the idea of Sen (1985) that argues that while income can be an indirect indicators of some capabilities, it is not necessarily a able to perform a transformation into the relevant functionings. The literature that shows the positive impact of these cash endowments in accessing such functionings leads one to believe that there is an impact of these grants on multidimensional deprivation.

One of the earliest works on Multidimensional poverty in general, but looking specifically at the case of South Africa, is from Klasen (2000), who develops a multidimensional index of poverty based on 12 different components of wellbeing. He uses two different techniques (equal weighting as well as PCA derived weights) and arrives at similar results for deprivation with both methods. He finds that although instances of low expenditure and multidimensional poverty are strongly correlated, there are deviations at lower levels of expenditure. This is to say, the worst off South Africans share a greater burden of wellbeing deprivation in comparison to the measure of poverty. This disparity is also observable across other categories including race, gender of the household head, the location of the household and the size of the household.

This work was extended by Bookwalter and Dalenberg (2004), who add a measure of subjective wellbeing to the index, including other household wellbeing indicators. They also find differences amongst groups based on their expenditure, where for the lowest quartile, services such as sanitation, water, energy, education and health are of lower relevance than transport and housing facilities. There are studies that specifically examine child and adolescent wellbeing, and how the welfare of this section of the population has fared in South Africa (Dawes et al., 2007; Noble et al., 2006).

The first study on the Multidimensional Poverty Index (MPI) in South Africa was by Alkire and Santos (2014)[3], who made use of the World Health Survey of 2003. According to their estimates, the MPI score for South Africa in 2003 was approximately 0.014[4], which is much lower than any of the measures using a money-metric approach (Fintel and Zoch, 2015). The most recent figures for multidimensional poverty in South Africa from the Oxford Poverty and Human Development Initiative (OPHI) (2015), using the NIDS dataset, indicate that nearly 11% of the individuals are multidimensional deprived with an average intensity of nearly 40%, bringing the MPI score to 0.044. However, this study only considers the multidimensional poverty levels for a single year.

Finn et al. (2013) compare multidimensional poverty between 1993 and 2010, using two different datasets- the Project for Statistics on Living Standards for Development (PSLSD) dataset for the first

[3] This is an earlier work which has been published in this year.

[4] The headcount figure in this case is 5.2%. However this MPI estimate excludes two indicators that are part of the MPI and are generated using a much smaller sample size of 10633 individuals (where only 57.4% of the overall data was actually used for the MPI estimate) than in the NIDS dataset. The figures for MPI headcount thereafter are derived using 9 indicators from the NIDS dataset with has nearly 90000 observations (most of which is not missing). Therefore this rise in the headcount might make it seem that multidimensional poverty has risen, but there is evidence to show that it has actually decline in the overall period(Finn et al., 2013).

period, and the second wave of the NIDS dataset. Their results show that the headcount for multidimensional poverty has fallen from 37% to 8%, bringing multidimensional poverty figures down to nearly a quarter of the initial levels. Using two different cross sections allows them to only examine the macroeconomic effects that bring about this change in the multidimensional poverty without incorporating any household level indicators. They are unable to examine the specific changes within the household that lead to the improvements in wellbeing[5].

Woolard et al. (2013) use the first two waves of the NIDS data and also find that multidimensional poverty figures fall from 10.7% in 2008 to 9% in 2010. They also suggest that there are non-overlaps between the income and multidimensionally poor individuals, where there are nearly 15% of total households who are multidimensionally non-poor and income poor, and vice versa, in the first and second waves, although the composition changed to a certain extent within both waves. While this is the only study found that examines the dynamic nature of multidimensional and income poverty, there are only two waves used. Furthermore, this work focuses solely on the changes in multidimensional poverty and its relation to the income poor.

Finn and Leibbrandt (2013) examine the channels through which most progress within the MPI has been made and suggest that the highest levels of wellbeing enhancement came from improvements in electricity and water, although in general there has been an overall improvement in reducing the severity of poverty for all indicators. They also looked at the demographic differences in poverty and find that among the different racial groups, the African (Blacks) population has the largest levels of multidimensional poverty, although they were also the group with the largest levels of improvement in wellbeing over time.

Correlation Sensitive Poverty Index (CSPI)

At the end of apartheid, South Africa had one of the highest levels of income inequality in the world and performed poorly in most social indicators, in comparison to countries with similar income levels (Klasen, 1993). More recent work finds that, even for other money-metric measure such as real per capita household expenditures, there has been a decline for those at the bottom end of the expenditure distribution. Even 10 years after the end of apartheid, this disparity existed, resulting in the increase of extreme poverty for the lowest expenditure quantile, especially within the Black population (Özler and Hoogeveen, 2005). The squared poverty gap has also increased for most of those households that fall

[5] At the time their study was published, there were only two waves of the dataset, while by the time of this work there were already three waves in the dataset. This allows a dynamic study of multidimensional poverty in the South African case. It is not clear why they did not consider the first wave of the NIDS dataset. They also chose to forego using the 2003/2004 Demographic and Health Survey Data and 2008/2009 Living Conditions Survey (LCS) for reasons stated within the paper already.

below the poverty lines in the same time period (Özler, 2007). Branson et al. (2012) use income decompositions to show that the labour market is the biggest driver of overall household inequality in South Africa. The large racial gaps in secondary and higher education, and consequently the changing returns to higher education, seem to have impacted the inequality in earnings. Although there is a clear improvement in schooling for Blacks over time, improvement in completion of secondary school has been far less dramatic. The increasing educational attainment offsets the changing returns to education, and thereby has no impact on inequality.

While there has been some pre-existing work on unidimensional measures of inequality in South Africa, so far there is no study that looks at the levels and dynamic changes within the multidimensional inequality in South Africa. Taking a simple average or headcount, as done within most measures of multidimensional poverty measurement (including the MPI), tends to ignore the problem of associativity, the so called *inter-personal inequality*. Although Alkire and Foster (2011) describe a method to calculate inequality adjusted measures of multidimensional poverty, since the MPI itself has no cardinal variables, but only binary variables, this exercise is not possible here. The CSPI is a multidimensional measure that accounts for this and is the first additive poverty index that is able to decompose itself into all "three I's" of poverty: incidence, which is essentially the headcount of deprivation, the intensity of overall deprivation amongst poor households, and lastly the inequality of poverty among deprived households, which is the aspect that the MPI is unable to capture. Therefore this is an inequality sensitive index, where it requires poverty to increase (in the case of the dimensions being substitutes[6]) or decrease (here the dimensions being complements[7]) if an association increasing switch between two individuals comes at the cost of the more deprived individual. That is to say that it follows the principle of pareto efficiency. The last property of the CSPI has the benefit of understanding whether a reduction in multidimensional deprivation has come at the cost of a particular section of the society, which was already more to begin with i.e. if the transfer of deprivations has been regressive. This can be useful in targeting particular policies for a specific part of the population. The reduction in the overall poverty headcount can be achieved in the simplest way by changing the status of those at the upper limit of the poverty line. However, with the CSPI, one is also able to understand where the synergies between dimensions would be highest. Therefore, to only raise those just under the poverty line to being above it would result in a reduction in the poverty headcount alone. On the other hand, the intensity and inequality on the other hand, would be further aggravated given that only those who are the most severely deprived would then

[6] This is the union approach, which is based on the assumption that all the attributes are perfect complements and thus an individual deprived in a single dimension would be considered poor.

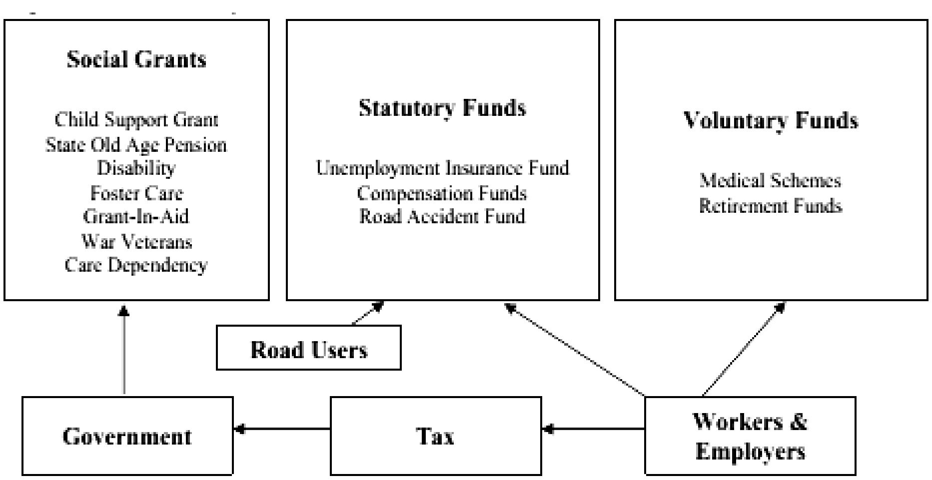
[7] This is the intersection method, where all attributes are considered substitutes and only if the individual is deprived in all of the dimensions are they considered poor.

exist below the poverty line. Since this is essential in determining the appropriate policy instruments, a measure such as the MPI, which only accounts for the absolute number of poor, will fail to give an accurate description of the dynamics behind the change in poverty figures.

One of the foremost methods adopted by the government, to address the problem of poverty and inequality since the fall of apartheid, is the social security system. The cash grants for children and old age pensions are targeted schemes for those in the lowest quantiles of the income distribution, but there are no numbers that can describe the inequities in a multidimensional measure. These are harder to address and require a fully rounded policy based on the exact dynamics of this inequality. Therefore, it is imperative to examine the performance of multidimensional deprivation with the CSPI. The South African NIDS Panel serves as an ideal dataset that can be exploited for all the aforementioned objectives.

Social security in South Africa

Figure 1: Social security in South Africa



Source: (Woolard and Leibbrandt, 2013)

South Africa allocated R155.3 billion for the 2015/16 fiscal year for social grants: the child support grants, old age pensions, disability grants, foster grants, etc. There are around 16.4 million beneficiaries for these grants (more than 10 million for child grants alone). Apart from these grants, there are a range of other complementary programmes for the poor, such as the contributory unemployment insurance and pensions, public works programmes for the working poor and the ‘social wage’ package, which comprises access to several basic means to wellbeing including education and health (Hagen-Zanker et al., 2011). Figure 1 depicts the full extent of the social security system in South Africa.

In terms of the allotted sum in the budget as well as the extent and reach of these grants go, South Africa has one of the most extensive social security schemes within low and middle income countries around the world. Fiscal incidence estimates indicate that 76% of government spending on social grants is received by the poorest 40 percent of the population which indicates that this is a well targeted cash grant system (Gutura and Tanga, 2014). The impact of these grants has been proven in several studies, which find that they have led to declining poverty and inequality over time (Bhorat and Westhuizen, 2012; Leibbrandt and Levinsohn, 2011; Woolard and Leibbrandt, 2013). Therefore, they form an integral part of any programme that targets poverty and inequality in South Africa.

Woolard and Leibbrandt (2013) examine the impact of cash grants on household income poverty and other long run effects and find that there is a positive impact of these grants on all of the measures they have examined, especially over the longer term. These effects relate to lower levels of income poverty, improved child health outcomes, better enrolment and schooling etc. Positive effects of the grants on enrolment are found by Eyal and Woolard (2013). Leibbrandt et al. (2013) also examine the impact of cash grants on labour supply, concentrating on female labour force participation. They find ambiguous results, wherein, depending on the income level, the decision to work was affected by the receipt of grants. In some cases, with the grant income supplementing other household income, women decided to stay at home rather than earn additional income by working. On the other hand, Woolard and Leibbrandt (2013) on the other hand find that there exists an overall positive relation between grant income and labour supply. The same result is found in the case of health and education as well, which are two of the three equally weighted dimensions of the MPI.

Other studies evaluate the influence of cash grants and in particular, the child cash grants on indicators of poverty, especially measures of child health and wellbeing. While there is evidence of the Child Support Grant (CSG) addressing the issue of poverty, it fails to reach household who are the poorest, or alternatively misinformation about the grants meant people did not apply for these grants, thereby raising concerns about the barriers to access (Goldblatt, 2005). Agüero et al. (2006) examine the impact of the unconditional CSG on child nutrition and find improvements in child nutrition via the extra grant income, especially when given at earlier stages of the child's life. Therefore there is evidence of an overall improvement in child development outcomes as a consequence of CSGs. For the literature on multidimensional measures of poverty itself, Fintel and Zoch (2015) derive three different types of multidimensional poverty indices[8] and extend the definition of child poverty to one that is more applicable for South African households, using the three waves of the NIDS dataset from 2008 to 2012. This includes other freedoms such as the household's access to the labour market, employment in the household as well as the household's life satisfaction and hopefulness for the future. They find that

[8] They base their indices on the MPI used by Alkire and Santos (2014) and Finn et al. (2013)

although MPI poverty has declined over time, a large proportion of those children who have been identified as being MPI poor remain deprived in many of the dimensions, including access to basic amenities, quality schooling, and life satisfaction.

There is also extensive work done on the old age grants in South Africa (Ardington and Lund, 1995; Bertrand et al., 2003; Case and Deaton, 1998; Duflo, 2000; Pelham, 2007; Posel et al., 2006; Ranchhod, 2006). So far the studies show these old age grants have led to a decline in poverty, similarities in household expenditures compared to non-pension incomes (Case and Deaton, 1998), intra-household allocation towards the nutritional improvements of female grandchildren from grandmothers (Duflo, 2003), allocation of resources towards raising an orphaned grandchild (Ardington et al., 2009) and a reduction in the labour supply amongst adults in pension eligible households, especially amongst prime age men (Bertrand et al., 2003). This goes to show that there is evidence of intra-household allocation in old age pension receiving households. Alternatively, several studies also show that there was no impact on labour supply, although thereafter there are fewer transfers from children to elderly parents (Jensen, 2004). There is also evidence that co-residence patterns also change, where prime-age women depart and children under five and young child bearing women disproportionately increase (Edmonds et al., 2005). Consequently, there exists sufficient evidence on the use of these relatively generous grants for smoothing over consumption in cases where adult household income is likelier to be used.

Most of these studies support the success story of each of these well targeted cash grants in South Africa. There is a plethora of literature on the positive impact of cash grants on indicators of wellbeing around the world. Barrientos et al. (2006, 2004) summarize this literature to a great extent and discuss the improvements in child poverty figures resulting from several in-kind and cash transfer programmes that exist around the world, conditional and otherwise. But the impact of conditional or unconditional Cash Transfers on multidimensional poverty and inequality is an element still lacking in the literature. While all of the components of well-being that are used in this paper have been examined individually, there has been no exercise which includes the entire spectrum of variables, and the association between them, as measured by the MPI and CSPI.

Another key issue related to cash grants, is that they are generally targeted at the lowest income percentiles. As per the process of selecting the eligible households, the means testing approach implies that only households with the lowest incomes are selected for these grants[9]. Naturally, this is to target

[9] Means test for **old age grant**: Annual income must be less than 64,680 Rand for a single person or 129,360 Rand for a couple, and assets must be no more than 930,600 Rand for a single person or 1,861,200 Rand for a couple. Means test for **child support grant**: Annual income must be less than 39,600 Rand for a single person; 79,200 Rand for a couple. The exchange between the US dollar and the Rand is equivalent to approximately 12.7 Rand/US dollar currently (OECD.Stat,). The means test figures have

those households which need these grant the most, i.e. the poorest. The poorer these households are the more likely they are to fall under the income restriction for receiving these grants. In fact, as can be seen in Table 17 in the Appendix, there is a negative correlation (significant at the 1% level) between grant income and per capita household income. Likewise, there is a positive and significant correlation with the MPI weighted score as well as the CSPI score. Even when we run a correlation test between grant income and other socioeconomics indicators of wellbeing, there is a significant and negative relation between the two[10], implying that the household with lower levels of income and a lower standard of wellbeing and living are the most likely to receive these grants. By inference, when analysing the role of increasing grants on poverty and deprivation, one expects to find a high correlation between the two, and that of a positive nature. This is based solely on the direction of causality between the grant receipt and the improvements in wellbeing and income indicators. Therefore, the relationship being established here is suffering from simultaneity bias and when adding controls, one cannot be sure of what the end result might be. Using information available on the child grant income, as well as the old age pension, I am able to specifically examine the effects of both of these grants on the MPI as well as each of its dimensions, also taking into account the simultaneity that might exist between receiving grants and the poverty levels of households.

The aim of this study is to answer the question: how well can one capture the effect of these cash grants on multidimensional poverty and inequality in South Africa? I argue that the panel structure of this data as well as the use of lags would address this issue to some extent. Moreover, by using the IV or RDD methods, the question of endogeneity is answered in a more robust manner. Other biases that might occur on the basis of omitted variables are also addressed with these methods. Thereafter, I attempt to examine the impact of these cash grants on each component of multidimensional poverty and in particular, the channels they may be might be working through. This would involve a breakdown of the Multidimensional Poverty Index into each of its dimensions: health, education and standard of living. These methods and their application in the current study will be further elaborated on in the section on Methodology.

DATA

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been taken from the South African government web page. More information on the same and other grants can be found here: http://www.gov.za/services/services-residents/social-benefits.

[10] Results are available upon request with the author.

The MPI uses 10 indicators, broadly categorized into 3 dimensions namely, health, education and standard of living. The weights are equally assigned to each dimension i.e. 1/3 each; and the indicators within these dimensions also assume equal weights amongst themselves. Figure 2 provides a basic overview of the MPI as explained above. It also describes the threshold set within each indicator to determine whether a household is to be considered deprived in a particular basic functioning or not (Alkire and Santos, 2014).

Most of the standard of living indicators follow the MDG guidelines, and their cut-offs are set on that basis. Each household receives the *apriori* weight when it fails to pass the cut-off and is therefore considered to be 'poor' in terms of that particular indicator. In the end, the weights for each household are summed up to generate the weighted deprivations matrix for each household. A household has to be deprived in at least the equivalent of 33 percent, or equivalently, have a weighted deprivation score equal to or larger than .33, to be considered multidimensionally poor. This is the so called dual cut-off that Alkire and Foster apply in their method, to overcome the problem of using either the intersection or the union approach (Alkire and Foster, 2011). Therefore, at the first cut-off it is determined whether the household is deprived in that indicator or not, and at the second cut-off, if their weighted score lies above 0.33, they are considered multidimensionally poor.

Figure 2: The Multidimensional Poverty Index

Indicator	Weight	Deprived
Health	**1/3**	
Child Mortality	1/6	If any child has died in the household
Nutrition	1/6	If any adult (BMI<18.5) or child (Z-score< -2SD) in the household is malnourished
Education	**1/3**	
Years of Schooling	1/6	If no household member has completed 5 years of schooling
Child Enrolment	1/6	If any school-aged child is out of school in years 6-14 / 7-15[11]/ 8-16
Standard of Living	**1/3**	
Electricity	1/18	If there is no electricity
Drinking Water	1/18	If MDG standards are not satisfied
Sanitation	1/18	If MDG standards are not satisfied including shared toilet
Flooring	1/18	If flooring is made of earth, sand or dung
Cooking Fuel	1/18	If wood, charcoal or dung is used
Assets	1/18	If household does not own more than one of radio, television, telephone or motorbike; and does not own a car/truck

Based on the dual cut-off method, the MPI for a country is calculated as the product of Headcount (H), which is the percentage of multidimensionally poor households whose weighted deprivations lie

[11] In the case of South Africa we are looking for kids in the age group of 7 to 15.

above the 33% cut-off, and the Intensity of Deprivation (A), which reflects the average deprivation within these multidimensionally poor households. If more than 30% of the population is found to be multidimensionally deprived, then the country is also labelled as multidimensionally poor, according to their poverty definition. Although the original Alkire Foster method (Alkire and Foster, 2011) does not specify dimensions, indicators, weights or cut-offs, its current global formula does set the aforementioned 10 indicators within the 3 dimensions and assigns equal weight within each dimension, and to each dimension as well (Alkire and Santos, 2014). The dual cut-off method was a proposal that fell halfway between the intersection and union method[12] of determining poverty at the households' level, and then eventually to determine deprivation at the regional (country) level.

For the NIDS data, the MPI was calculated at the household level using the household information that was available. Of the aforementioned 10 variables in the original MPI, only flooring was excluded due to data limitations. Therefore, the MPI value that has been calculated is derived using only 9 variables. These were also the exact same variables used to generate the Correlation Sensitive Poverty Index (Rippin, 2012, 2010). The method to derive the CSPI figure for each individual/household in the dataset was essentially to raise the MPI weighted deprivation score to the power of 2, thereby allowing higher scores to be penalized at a non-linear rate. Therefore, small changes at the lower end of the spectrum will be given higher weight than those in the middle.

The first part of the analysis attempts to replicate the figures of MPI, as has been found in the literature, as well as calculate the CSPI for each household. While the MPI I calculate will be compared to those in existing literature, to ensure that they correspond, the true contribution of this paper is the calculation of the CSPI for this particular sample. The second portion of the analysis deals with the relation between cash grants and multidimensional poverty and inequality in South Africa, over the four years of the survey. The weighted scores and squared weighted scores of the MPI and CSPI respectively would then be used in the second half of the analysis, which is presented in the results section.

The data used for the empirical analysis is the National Income and Dynamics Survey (NIDS) from South Africa. This is a nationally representative panel data with 3 waves: 2008, 2010 and 2012[13]. The South African Labour and Development Research Unit (SALDRU) is the research team responsible for this very rich dataset, which contains information on approximately 8,000 households, yielding in

[12] The intersection method claims that being deprived even in a single indicator makes the household poor, while the union method is the exact opposite and states that only if the household is deprived in all of the given indicators is it to be considered multidimensionally deprived. By using a particular cut off that is based on the weighted sum of deprivations, one is able to set a criterion that does not fall under either extreme. As has often found to be the case, the level of poverty is extremely high when using the intersection method while it is inordinately low when using the union method.

[13] The fourth wave is set to be released soon.

total more than 90,000 observations over three years on a large number of variables, including most of those contained in the Multidimensional Poverty index indicators (except flooring). It also contains information on several socioeconomic and demographic indicators, cash grants, income and expenditure variables, how households perceive their state of wellbeing / hopefulness and several other wellbeing and shock variables at the individual level[14].

One major drawback of the dataset for this analysis is that it does not follow households, but rather individuals over time. Consequently, one only has the identifier for each household and the household link variables for each individual for every wave, which allows one to determine in what household each individual was in each wave. But since there is no common identifier for each household across the waves, there is no possibility to track a household over time[15]. This poses a challenge for the empirical analysis, given that the MPI and CSPI are household level indicators and that there is no single correct way to track a household over time. Therefore, a strategy is implemented, to manually identify and categorize households to form a household level panel for the three waves of the NIDS dataset that were available at the time of the analysis.[16] Without carrying out this exercise to generate a single household identifier, household identifiers are only available for each wave i.e. they are wave-specific, making it impossible to track households over time. With this method, nearly 18000 households are identified over the three waves, which amount to over 9000 actual households followed over time. On average, each household was repeated around 2.3 times in the panel.

The conversion of individual data to households led to a dataset with nearly 16500 households over the three waves. Table 1 provides the summary statistics for some of the important socioeconomic and demographic variables of this dataset.

[14] This includes individual/household level shocks including deaths, loss of income in some form etc.

[15] This was a deliberate strategy on the part of the survey researchers, who wanted individuals to have complete freedom to shift household and then try and follow them even across different households. Therefore marriage, or divorce or migration may have divided households into two or more parts in the consequent wave. Indeed, there are several cases where a household divides in the second wave and then comes together in the third wave. Alternatively there are also cases where two households combine within the second and third wave to become one household. And there exist many more cases where a household divides into completely different households which do not intersect over any of the following waves.

[16] The method to determine a household is as follows: whole households that do not change across time are given the household identifier from the first year. In the cases where households divided, the household where the majority of members went is followed and given the first wave identifier, even if that household did not include the household head of the first wave. In the case that the household divided itself equally, then the household with the household head from the first wave is considered the original household in the consecutive wave, while the other household gets the new household identifier. When the household head dies and then the household divides itself equally, then the household where the oldest member of the original household went is considered the original household. In case the age is not clear or missing, if any of the original members are not the household head in the new households, then that household is considered as a new household.

Table 1: Summary Statistics for the households over three waves

Variable	Observations	Mean	Min	Maximum
MPI weighted score	15029	0.190	0	.833
CSPI score	15029	0.033	0	.694
Household size	16440	4.948	1	41
Married	16438	0.210	0	1
Female head	16440	0.611	0	1
Age	16433	28.555	5	101
Children	16440	1.880	0	20
Elders	16440	0.396	0	4
Adults	16440	2.672	0	20
Per capita Income	15702	1209.712	.0114	164598.4
Per capita Income without grants	15702	983.954	0	164506.3
Per capita Grant Income	16440	215.624	0	7.706
Per capita Old Age Pensions	16440	124.323	0	1227.77
Per capita Child Grants	16440	57.180	0	2.829
Grant recipient	16440	0.711	0	1
Rural	16440	0.094	0	1
Urban	16383	0.477	0	1
Tribal authority areas	16440	0.426	0	1
Employment Status	12036	0.647	0	1
Education level	16640	1.156	0	3
Indian	16440	0.012	0	1
Coloured	16440	0.146	0	1
Black	16440	0.797	0	1
White	16440	0.044	0	1

Some interesting trends in the pooled data can be seen from Table 1. For instance, around 61% of the households are female headed, which is an implausibly high figure but relates to the way household headship information was gathered[17]. Household per capita income is about 6 times higher than grant income, which would suggest that grant income is actually a large fraction of income for the survey households which are receiving any form of grant (the grant size is around 320 Rand for children[18] and 1350 Rand for the old age pension[19]). According to the means testing method for ascertaining eligibility for receiving grants, a recipient is eligible to receive a child grant if their income is not more than 10 times the grant value (McEwen et al., 2009) and therefore some of the poorest households are being captured.

[17] Since it was believed that household headship is not a well-defined concept, in the field work, the first person listed (often the respondent) in the household roster is called the 'household head'. Therefore there are an exceptionally large number of female headed households, which might not necessarily be the case in actuality. Nonetheless this is a variable that needs to then be omitted from the analysis, despite the evidence that female headed households generally have higher levels of poverty.

[18] This is a small amount equivalent to approximately 25$ (based on the OECD exchange rates for South Africa from 2000-2015: https://data.oecd.org/conversion/exchange-rates.htm#indicator-chart). The WDI database puts South Africa's per capita income at 6483$ at current prices for the year 2014-15.

[19] Approximately 106$ at the exchange rate of 13 Rand per US$.

The dataset also indicates large levels of unemployment, at least for the sample considered, since 35% are categorized as unemployed. This is not surprising given the high rate of unemployment in South Africa, which has been consistently rising since the 90s, especially among more vulnerable groups, including young individuals (Banerjee et al., 2008; Kingdon and Knight, 2004; Klasen and Woolard, 2009). Since the given sample is very young (on average 31 years old), this would mean a large number of people are likely to be unemployed. Although this analysis is at the household level, even having done this analysis at the individual level yielded an employment rate of only 64%. Limiting the sample to individuals aged 18 to 65 still leaves us with a 68% unemployment rate. The South African Black population actually has the highest unemployment rate among the various demographic groups, which represent nearly 80% of the current sample, whereas the lowest unemployment rate is among the whites, which represent only 4.5% of the total sample. Per household, there are on average nearly 2 children, few elders (0.3), and the remaining part of the household of 5 members if made up of adults (2.7). Nearly half the sample resides in urban areas (48%), while tribal areas (43%) and rural areas (9%) form the remainder sample. On average, household members have a low level of education attainment[20]. In other words, the sample has only been able to achieve a level of education slightly above the basic standard that has been recognized by the South African government, and only a small fraction is able to achieve an education at a secondary or higher level.

In order to delve deeper into the topic of multidimensional poverty, we also examine how the MPI figures look when separating the sample along the lines of beneficiaries and non-beneficiaries of the social security system.

Table 2: Multidimensional poverty statistics separated by grant receipt

Variable	**Non-Grant households**			**Grant households**		
Year	2008	2010	2012	2008	2010	2012
Per capita household income	3924.98	5278.02	4866.74	818.31	875.10	974.45
CSPI	.014	.013	.008	.039	.034	.028
MPI	.012	.013	.010	.035	.050	.048
Headcount	0.08	0.08	0.04	0.22	0.197	0.16
Intensity	0.4115	0.4027	0.4036	0.4084	0.4070	0.4107

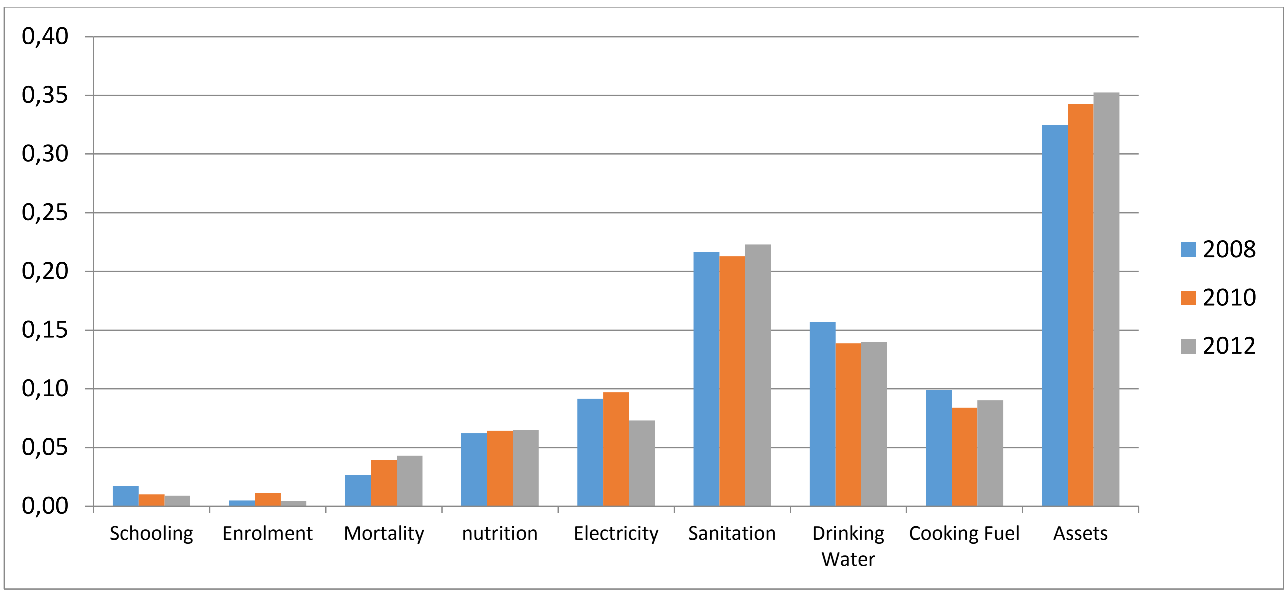
Source: Own calculations

As can be seen in Table 2, the grant receiving households are poorer not only in terms of income, but also in multidimensional deprivation. For example, the per capita income for grant households is

[20] The variable is generated such that individuals with no education would be coded as 0, individuals with upto 8 years of schooling would be coded as 1, individuals with 9 or more years of schooling would be coded as 2 and all those who have finished schooling and gone for higher education in the form of university would be coded as 3. These grouping have been done on the basis of the information available from the Ministry of Basic Education (http://www.education.gov.za/) and the Ministry of Higher Education and Training (http://www.dhet.gov.za/).

between 4.5 to 6 times lower than those in non-grant households. Also, the MPI headcount is more than double and sometimes nearly triple in all three years for grant receiving households. This supports the idea that grant households are those that are much poorer, and thus also likelier to be recipients of social support. The overall MPI score for households which are receiving grants is also higher than for those that are not receiving grants. The multidimensional inequality, on the other hand, has a clear declining trend in both samples. In the same time period, the absolute decline in multidimensional inequality is much higher for grant households than for non-grant households (0.011 and .006 respectively). In relative terms, this decline has been much higher for the non-grant households (28% and 42% respectively). This would suggest that the strides in reducing multidimensional inequality have been much larger for non-grant households.

Figure 3: Contribution of each indicator for the households

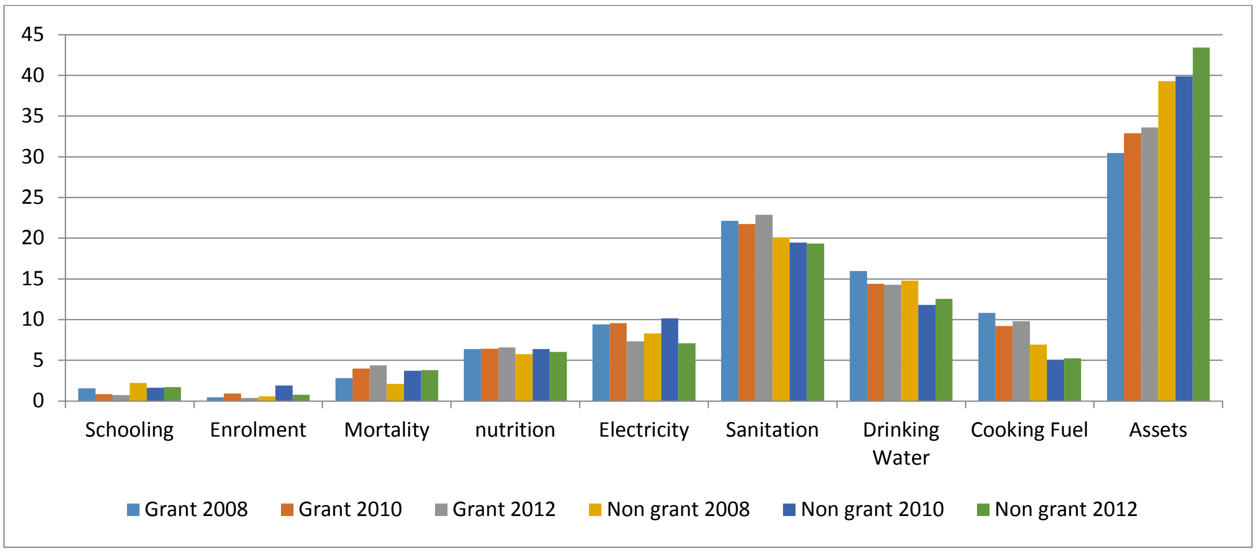


Source: Own calculations

Figure 3 depicts the contribution of each indicator to the overall level of multidimensional poverty, where the largest role is that of the standard of living indicators. Within this dimension, the indicators of assets and sanitation (above 30% and 20% for all three years respectively) are the largest concerns. Another interesting consequence of the universal secondary school enrolment observed in the numbers for South Africa is the very low rate of deprivation in the case of schooling and especially enrolment. Therefore, the share of education deprived individuals in overall deprivation is very low. Health on the other hand has a larger contribution (nutrition maximum at around 7%), although also not as large as any single one of the standard of living indicators (electricity and cooking fuel are lowest at around 9%). This would indicate towards two possible failings in the case of the South African households. First, there is large room for improvement on both the delivery and access to public services, especially in regards to sanitation and drinking water facilities. Secondly, the differences in income are also largely translated into differences in the standard of living indicators. Income does not play a very large role in terms of the education dimension though, since South Africa has nearly universal secondary schooling enrolment, regardless of where on the income distribution a household stands.

The particular impact of each indicator on the overall poverty headcount, separated by grant households and non-grant households was also examined in Figure 4[21]. It shows us which indicator of the MPI plays a large role in wellbeing deprivation between the two groups[22].

Figure 4: Contribution of each Indicator divided by grant and non-grant households



Source: Own calculations

As shown, within both groups, there are not so many differences in terms of the contribution, except for the share of assets, where the relative contribution is very high for the non-grant households. This is not surprising, because otherwise the relative contribution for each other indicator is lower for the grant households. In the case of the education dimension there is a slight difference amongst the two types of households, and no more than 3% of the population is deprived in any of the indicators. On the other hand, in the health dimension there is again no large difference between grant and non-grant households, although a larger share of households are deprived in comparison to education. The largest contribution in the deprivation index is the standard of living dimension, where sanitation and assets have the largest share in both grant and non-grant households.

[21] Table 26 and Table 27 in the appendix provide the numbers for the deprived in each indicator.
[22] The contribution for each indicator without any division is in Figure 6 in the appendix.

METHODOLOGY

This paper carries out an empirical analysis on the impact of cash grants on multidimensional poverty using data in a panel structure, which covers a dimension of three periods (corresponding to four/five years). Given the structure of the data, it is possible to apply a fixed effects model, considering the individuals as the panel variable. With the procedure described above in the data, fixing the households as the panel variable is also made possible. There are several reasons why this adjustment of the data was carried out. Since the MPI is a household level variable, conducting a panel analysis at the individual level can lead to several empirical and methodological problems and biases. For example, the individuals that are household members would have common factors which would influence the standard errors if the analysis was at the individual level, which is not necessarily addressed through clustering. Other forms of omitted information, which are biased at the household level, are also likely to ail the analysis. This technique is therefore considered the most robust form of this dataset to examine the MPI and CSPI over time, although I consider several other specifications to ensure an informative and comprehensive analysis. Moreover, to streamline the analysis, all those households which do not have any of the eligible members for the grant are removed. Therefore any household which did not have elderly above the age of 60 and children under age 18 were removed from the analysis.[23]

The following fixed effects specification with the weighted deprivation score as the dependent variable is applied:

$$Y_{it} = \beta_{xi}X_{it} + \beta_{\theta i}\theta_{it} + \alpha_i + \varepsilon_t + \mu_{it} \tag{1}$$

Here X_{it} are household demographics, province dummies, locality, employment status and other socio-economic controls[24], at the household level, θ is the variable of interest, that is the value of cash grants[25], α_i are the household fixed effects, ε_t are the year/ wave fixed effects and μ_{it} is the random component of the error term.

Given the possibility of endogeneity through simultaneity, as discussed in the previous section, an IV strategy is proposed. To control for endogeneity in terms of the overall grant value, no plausible

[23] The analysis was also carried out with these households included and the results are the same. The only difference is that the coefficients are slightly smaller in size, but the direction or the significance was not reduced.

[24] Apart from the ones that are not mentioned about, these are those that have already been mentioned within the summary statistics. Although some of these do not vary so much over time, there is still some variation that is found in variables such as province dummies, or locality. This implies that there is still some movement over the waves for the households itself.

[25] In some specification this is lagged or alternatively included as a dummy. In alternative specifications we also use just the value of the child grants or the old age grants. This is actually the case in the main specification where we control for endogeneity using IV and RDD methods.

instrument that passed the exclusion restriction was found. However, a review of the literature revealed a study that used an innovative and exogenous policy shock to generate an instrument that can also be used to control for the endogeneity in the relation between child grants and multidimensional poverty. As described in Eyal and Woolard (2013), it is the difference in the potential years of exposure to the grants that can be exploited to examine the impact of child grants on multidimensional poverty and inequality.

Ever since the grant was introduced in 1998, there have been several amendments to the age of eligibility of the recipients. Between the years of 1998 and 2012, which is the last wave in our case, the government decided to change the maximum age of eligibility amongst children from 7 years to now 18 years, as can be seen in Table 3.

Table 3: Potential Duration of Child Support Grant receipt by year of birth

National Income Dynamics Survey
Potential Years of Exposure to the Child Support Grant

Year of Birth	Wave 1 2008	Wave 2 2010	Wave 3 2012	Age Limit
1992	0	0	0	-
1993	3*	3*	3*	-
1994	6*	6*	6*	-
1995	6*	11*	13*	-
1996	9	12	14	-
1997	9	12	14	-
1998	9	12	14	-
1999	9	12	14	7
2000	8	11	13	7
2001	7	10	12	7
2002	6	9	11	7
2003	5	8	10	9
2004	4	7	9	11
2005	3	6	8	14
2006	2	5	7	14
2007	1	4	6	14
2008	0	3	5	14
2009	-	2	4	15
2010	-	1	3	16
2011	-	-	2	17
2012	-	-	1	18

Source: (Eyal and Woolard, 2013)

This exogenous change in the age of eligibility introduces variation in the potential duration of grant receipt between children. With these changes, an individual born in 2001 would have had 10 potential uninterrupted years of receiving a grant in 2010. On the other hand, a child born 5 years before, in 1995, would miss out on receiving a grant in 2002. Those born in the year 1994 miss out on years 2001, 2002, 2003 and 2008. Because of this, it can be assumed that there are differences in the potential years of exposure to the child grant for each individual. Those born in 1996 receive 14 years of uninterrupted child support, while those born in 1993 could have received their child support for a maximum of 3 years, interrupted over the entire durations. Even for the years 2008 to 2012, the age of eligibility was increased from recipients under the age of 14 in 2008, to under 16 in 2010, and finally under 18 in 2012. This implies that there was suddenly a much larger proportion of older children who then had access to grants, especially in the increase from 11 to 14 in 2004. This can be seen in Table 4, where for example, the proportion of 14 years olds receiving CSG increased from 11% in 2008 to 60% in 2012.

Table 4: CSG Receipt by Age Category in all years of the NIDS data

	Wave 1	**Wave 2**	**Wave 3**
Age	2008	2010/2011	2012
Upper age limit	14	16/17	18
0	0.30	0.35	0.43
1	0.53	0.62	0.66
2	0.56	0.64	0.60
3	0.59	0.71	0.73
4	0.62	0.63	0.70
5	0.66	0.69	0.73
6	0.65	0.67	0.70
7	0.64	0.65	0.71
8	0.61	0.71	0.72
9	0.65	0.62	0.74
10	0.56	0.62	0.65
11	0.60	0.61	0.66
12	0.51	0.62	0.67
13	0.48	0.54	0.66
14	0.11	0.55	0.60
15	0.01	0.33	0.44
16	0.00	0.15	0.45
17	0.00	0.03	0.34
18	0.00	0.00	0.00

Source:(Eyal and Woolard, 2013). The lines in each column depict the age of eligibility for each year.

This instrument of potential eligibility of the grant (Z) is then introduced into a 2SLS setup where the first stage is given as:

$$\theta_{it} = \beta_{xi}X_{it} + \beta_{zi}Z_{it} + \alpha_i + \varepsilon_t + \mu_{it} \quad (2)$$

The other variables in equation 1 are specified exactly the same as in equation 2. The instrument is assumed to generate predicted values for the otherwise endogenous variable θ, given as $\hat{\theta}$, which would then be introduced into equation 3 to produce consistent estimates for all the parameters, particularly, $\beta_{\theta i}$.

$$Y_{it} = \beta_{xi}X_{it} + \beta_{\theta i}\hat{\theta}_{it} + \alpha_i + \varepsilon_t + \mu_{it} \quad (3)$$

To ensure that the instrument is a good predictor of the endogenous variable, the coefficient β_{zi} should be significant in the first stage of the regression. The other important condition for a valid IV is the exclusion restriction, which is to say that the exogenous instrument is uncorrelated with any other determinants of the dependent variables, which in our case if the multidimensional poverty and inequality scores. It can be convincingly argued that this instrument satisfies the exclusion restriction and is therefore a valid instrument in the IV setup. Supposing one source of bias could be the macro trends in reducing poverty, which might be related to changes in the social grant system. Using a fixed effects estimation, given our panel structure, will control for these. Personal characteristics that might be linked to poverty, and to receiving a grant, would also be controlled for within the fixed effects. While the possibility of an inherent correlation between the instrument and some of the indicators that are measured in the case of the education dimension may be a cause for concern, these can be allayed in view of the following. First, the dependent variables and eventually the instrument are collapsed and measured at the household level, and therefore the cohort effect or other similar trends between the two is contained. Second, the cash grants in the sample are included for individuals of ages 14 until 18, depending on the wave of cross sectional data. On the other hand, the enrolment variable is only captured for children who are between the ages of 7 to 15. Therefore, there is very little, if any, overlap that might cause some form of correlation at this level. It is highly implausible to believe that these changes in the age of eligibility are not exogenous to the level of multidimensional poverty and inequality. In this way, the effect of one part of the grants are explained using this instrumental strategy.

Information is also available in the case of old age pensions, which enables me to check their effect on multidimensional poverty and inequality. However, there are no such changes in the age of eligibility, except in the case of the men, whose age of eligibility was changed from 65 to 60 in 2010, to become comparable to the women's age of eligibility. This might not be enough exogenous variation to exploit, and therefore another technique that is used in the literature will be implemented here: Regression Discontinuity Design (RDD).

The idea behind using the RDD is that for a particular treatment (in this case the old age pensions receipt), where one has universal allocation, the assignment to the treatment is subject to a particular threshold. In this particular case, this threshold can be considered the age of eligibility, which is 60 for men and women. It is assumed that there is very little difference between the individuals who fall shortly on either side of the threshold, that is to say an individual who is aged 59 years and one who is 60 years old. Therefore this threshold is the "random" assignment of individuals into a treatment or not. It is believed that the only aspect that differs between both of these individuals on either side of the cut-off is that one receives the treatment while the other does not. So any difference in the final outcome, which in our case is multidimensional poverty and inequality, would be on account of the treatment effect itself. The most important condition is that this change in the treatment assignment should be arbitrary and therefore introduce some form on 'discontinuity' in the sample population (Angrist and Pischke, 2009).

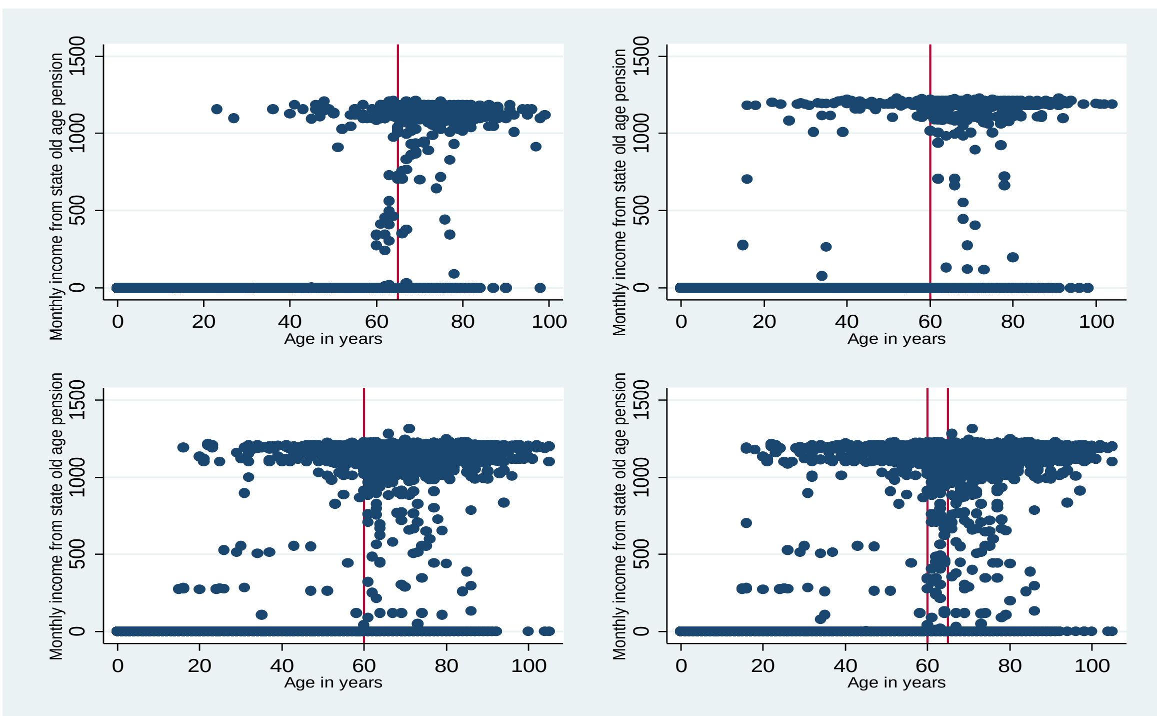
There are two types of RD designs that are popular in the research: sharp and fuzzy. The first refers to the case where the probability of treatment jumps directly from 0 to 1 when the individuals are beyond the threshold. In our case this would be when a woman turns from 59 to 60, she would be eligible for the grant and would definitely receive it. Fuzzy discontinuity, on the other hand, is when the probability of treatment increases, but not sharply from 0 to 1. Therefore, there might be instances of non-compliance, where even though the individual lies beyond the age cut-off, he or she does not, or chooses not to, receive these grants. In the South African case, it is not found that immediately after crossing the threshold, the household starts receiving the grants. This might lie on a variety of factors, for example bureaucratic issues, incomplete information, etc. that may prevent households from applying for the pensions.

Figure 5 shows how the old age pensions are distributed according to the age of the household. The top two graphs are those for men in 2008, and in 2010 and 2012 respectively (to account for the change in the ages for eligibility in 2010 these are two separate graphs) while the bottom two are for women and the population as a whole. The households which are not receiving grants are represented by the line of blue dots at the bottom on the graph, and the households that are clustered at the values just above 1000 are those that are receiving grants. There is definitely a discontinuity that is visible in the figures, at the cut-off given by the red line.[26] However, the absence of a sharp jump along the line for the age of eligibility, reflects a fuzzy implementation. This implies that at the cut-off for the running variable (that is age), there is no sharp change in the treatment; only the probability for the individual to receive treatment increases at this cut-off. Above the age of eligibility, there is a larger mass of observations (on

[26] Besides the visual representation, I also run a simple regression, showing that individuals crossing the age of eligibility are significantly more likely to receive grants. Results are available from the author upon request.

the right hand side of this line) which receive these grants. Therefore, the probability of receiving a grant rises after the age of eligibility increases. However, there are still points that indicate that even below the age of eligibility, there are individuals who are receiving these old age grants. This is rather surprising since it would imply that certain individuals in the sample are receiving less than the prescribed amount by the government. It cannot be interpreted in changes in the pension value over the years, since these points can also be observed in the first graph which is only for men in 2008. However, what is most relevant for my analysis is the mass around the zero which still exists beyond the age of eligibility, showing that many people who could are not entering the scheme, indicating incompliance[27]. I therefore implement a fuzzy RDD for the case of old age grants to address the issue of endogeneity. The interval that is used for the cut-off is 2 years around the age of eligibility i.e. ages 58 to 62, although I also use 5 years around the eligibility age as an additional check, which corresponds to individuals who are aged 55 to 65 in the sample.

Figure 5: The pension scheme amongst the South African population



The second condition that is important for the RDD to be implemented is to make sure that there is no discontinuity amongst other households' characteristics that might affect the outcome variables. For the same, I need to distinguish households who are receiving grants in the second period and compare

[27] This could be on account of two things: they are not eligible on the basis of the means test for the old age pension or there might be non-compliance on behalf of eligible elderly individuals.

them with non-grant receiving households at the baseline. Therefore, all households who are receiving grants in the first wave are removed from the entire analysis. Moreover, in the simplest form of the analysis, we remove households from the third wave. The remaining households in 2010 are then compared at the baseline, which is 2008. To incorporate more observations in the analysis, given concerns over the power and therefore the significance of the results, I try to include households in the third wave. Those households who are receiving grants in the second wave are removed from the analysis in the third wave, so that households already receiving grants in the previous period are not included within the analysis. This leads to a near doubling of the sample size. The test of the sample characteristics for both households with 2 years around the cut-off are shown in Table 5. Here, households which are eligible to receive grants in the second period, and those who are not, are compared along their socioeconomic and demographic characteristics in period one, i.e. at baseline. The objective of this exercise is to ensure that the households compared in period two are not very different along certain characteristics before their eligibility for the treatment, which might be driving the end results.

As shown in Table 5, there are some differences within the two samples at the baseline. The non-grant households are larger, with more children and fewer married people. This can be expected, given that the average difference for the forcing variables, age, is nearly 13 years. Since the household not receiving grants in the next period would technically be slightly younger (hence not eligible), this could explain some of the difference in the mean age. The remaining difference can be explained by the larger number of children and young non-married adults in the non-grant households. Other significant differences in the two samples lie between the race of the household and the locality where the household is situated. Also more grant receiving households are from the tribal authority areas and significantly less in urban areas. But this is also expected since the majority of the population that lives in these homelands are the Black-African population, which is the section of population that mostly benefits from these old age grants. The most concerning difference in my case is the difference in education attainment, but this may also be not such an issue. There can be two effects that emerge from this difference between the treatment and control groups. The control group might therefore earn more, and also have a lower multidimensional deprivation score, but this would actually depress the results in the opposite direction rather than biasing them upwards. The other argument could be that the difference in education might affect information and the group that might be more informed would therefore be better capable of applying and receiving the grant. However, since these are the households which are eventually not receiving the grants, this is not something that should not affect our results either. Nonetheless all these different characteristics will all be controlled for within the RDD analysis. The baseline difference in household characteristics for 5 years around the age of eligibility is provided in the appendix in Table 26. There are no significant difference in characteristics between the two samples in our study and therefore we choose to stick to the cut-off of ±2 years, since that gives us more observations and likely to be more internally valid.[28]

Table 5: Baseline differences between social pension households and non-social pension households

	Observations (receiving)	Mean (receiving)	Observations (not-receiving)	Mean (not-receiving)	Difference
Number of household residents	**1256**	**5.916**	**652**	**5.100**	**0.817*****
Number of children in household	**1256**	**2.238**	**652**	**1.603**	**0.635*****
Married	**1256**	**0.207**	**652**	**0.337**	**-0.131*****
HH has female head	1256	0.568	652	0.578	-0.011
Female	1256	0.571	652	0.550	0.021
Age in years	**1256**	**26.323**	**652**	**39.657**	**-13.334*****
Indian	1256	0.011	652	0.015	-0.005
Coloured	1256	0.146	652	0.154	-0.008
African	**1256**	**0.832**	**652**	**0.664**	**0.168*****
White	**1256**	**0.011**	**652**	**0.167**	**-0.155*****
Province 1. Western Cape	1256	0.107	652	0.201	-0.094***
Province 2. Eastern Cape	1256	0.137	652	0.100	0.037*
Province 3. Northern Cape	1256	0.066	652	0.089	-0.023
Province 4. Free State	1256	0.051	652	0.054	-0.003
Province 5. KwaZulu-Natal	1256	0.326	652	0.262	0.064**
Province 6. North West	1256	0.082	652	0.075	0.007
Province 7. Gauteng	1256	0.068	652	0.077	-0.008
Province 8. Mpumalanga	1256	0.041	652	0.052	-0.012
Province 9. Limpopo	1256	0.122	652	0.090	0.031*
Rural	1256	0.076	652	0.103	-0.027
Urban	**1252**	**0.427**	**649**	**0.516**	**-0.089*****
Tribal	**1256**	**0.495**	**652**	**0.379**	**0.116*****
Is the respondent employed	977	0.637	443	0.656	-0.020
Non grant income recalculated	**1184**	**0.004**	**622**	**0.012**	**-0.008*****
Observations			1908		

RESULTS

The specification for the baseline model, as explained in the methodology, was initially tested by pooling the data and running an OLS model with year/wave dummies. The results for the OLS model on the MPI as well as the CSPI score for the entire sample described above, are given in Table 6 below. The first and third specifications use the actual value of the grant and of income, while the second and third specifications use the log values of both.

[28] The baseline differences between treatment and control households, 5 years from the cut-off are shown in Table 26 in the appendix. The two bandwidths are also run for households in the first two waves, where the third wave is completely dropped. This however leads to a fewer number of observations and therefore I decided to use it simply as a robustness check. The baseline differences for both the 2 year and 5 years for this smaller sample are available upon request from the author.

As discussed, the positive impact of the cash grants on the MPI and CSPI, in the models expressed in levels, is suggestive of endogeneity: indeed, one unit increase in the grants leads to a 0.00003 unit increase in the MPI weighted score. If interpreted directly, without taking into account the potential endogeneity, this would imply that the receipt of the grant is actually causing deprivation (as measured by the MPI) to increase. There are several biases that might affect these results in a pooled OLS structure, and to therefore control for at least the unobserved time invariant heterogeneity, we decide to use the fixed effects model. The second and fourth specifications are the log values for both the MPI and CSPI, but they are not found to be significant.

Table 6: OLS specification for effect of cash grants on MPI and CSPI

	(1)	**(2)**	**(3)**	**(4)**
VARIABLES	MPI	MPI	CSPI	CSPI
Grant	3.00e-05***		9.69e-06***	
	(4.41e-06)		(2.80e-06)	
Income	-4.11e-06***		-5.42e-07**	
	(3.93e-07)		(2.49e-07)	
Log grant		0.000933		0.000547
		(0.00212)		(0.00136)
Log income		-0.0125***		-0.00507***
		(0.000884)		(0.000568)
Constant	0.116***	0.157***	-0.0116	0.00230
	(0.0111)	(0.0198)	(0.00706)	(0.0127)
Observations	14,338	7,978	14,338	7,978
R-squared	0.382	0.320	0.158	0.147

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned shown in the summary statistics in Table 1 are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

After the pooled OLS, the same specification was implemented using a fixed effects setting, therefore controlling for the time invariant characteristics of the households. The results for the MPI and the CSPI are presented in Table 7 & Table 8 respectively. As can be seen from the results however, even after controlling for potential sources of omitted variables which are related to time-invariant characteristics, I find that an increase in the grant income leads to an increase in multidimensional poverty and inequality respectively. For example, as seen in column 1 of each Table, a unit increase in the grant income leads to a 0.000085 unit increase in multidimensional poverty and a 0.000076 unit increase in the CSPI. These are very small numbers, but they are significant at the 5% level. The small size of the coefficient might be affected by the fact that both the MPI weighted score and the CSPI weighted score lie between 0 and 1 (where the CSPI has even smaller values due to it being the square value of the MPI score). When examining the log grant income values, the effect is non-significant, although still positive for both multidimensional poverty and inequality (column 2 of both Tables).

Table 7: Fixed Effects regression with MPI and cash grants

	(1)	**(2)**	**(3)**	**(4)**
VARIABLES	MPI	MPI	MPI	MPI
Grant	8.52e-06*		1.54e-05**	1.54e-05***
	(4.48e-06)		(7.44e-06)	(5.49e-06)
Income	0.0211		0.0255	0.0851
	(0.0880)		(0.0880)	(0.0849)
Log grant		0.00231		
		(0.00322)		
Log income		-0.00233**		
		(0.00112)		
Square grant			-2.34e-09**	
			(1.17e-09)	
Grant#income				-0.000670**
				(0.000286)
Constant	0.101***	0.201***	0.101***	0.101***
	(0.0288)	(0.0576)	(0.0288)	(0.0288)
Observations	14,338	7,978	14,338	14,338
R-squared	0.033	0.028	0.033	0.034
Number of hhid	6,958	4,849	6,958	6,958

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned shown in the summary statistics in Table 1 are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 8. Fixed effects regression with CSPI and cash grants

	(1)	(2)	(3)	(4)
VARIABLES	CSPI	CSPI	CSPI	CSPI
Grant	7.58e-06**		1.33e-05**	1.06e-05***
	(3.29e-06)		(5.27e-06)	(3.92e-06)
Income	0.0450		0.0486	0.0729**
	(0.0308)		(0.0311)	(0.0309)
Log grant		-0.000280		
		(0.00214)		
Log income		-0.000878		
		(0.000794)		
Square grant			-1.96e-09**	
			(8.18e-10)	
Grant#income				-0.000292**
				(0.000131)
Constant	-0.0460*	0.0340	-0.0460*	-0.0459*
	(0.0277)	(0.0352)	(0.0277)	(0.0278)
Observations	14,338	7,978	14,338	14,338
R-squared	0.019	0.018	0.019	0.019
Number of hhid	6,958	4,849	6,958	6,958

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned shown in the summary statistics in Table 1 are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

This also raises concerns regarding the channels through which the grant might be affecting the degree of deprivation of poor households. It could be the size of the grants that are determining their effect on the households' well-being. In this regard, a square grant term has been included within the third specification of Table 7 and Table 8, to examine if there are perhaps non-linear effects of these grants, i.e. with increasing size of income the effect of the grant would also be larger. As can be seen from columns 3 and 4 of Table 7 & Table 8, there seems to be a negative effect of cash grants on multidimensional poverty and inequality at higher values of the grant income. Upon calculation, it appears that the turning point of this positive effect of grants on the MPI score to one that reduces the MPI score is at around 3393 Rand per person. This is more than 15 times the size of the average per capita grant income of the households. Either a larger grant, or alternatively the same grant over a longer time period might turn out to have a larger impact on multidimensional poverty and inequality as well.

Another scenario could be that the grant incomes are only helpful as additional supplements to income. In our dataset we find several households that are able to sustain themselves only on the basis of grant incomes. It therefore becomes necessary to ascertain whether this might be an important channel through which grants might impact multidimensional poverty and inequality. To that end, I implemented an interaction term between grant income and other household income and included it in the fourth specification of Table 7 and Table 8. It can be seen that there is indeed a negative effect of grant income on multidimensional poverty and inequality, at higher levels of income. This effect is significant at the 5% level.

The results and inference based on the last two columns of the previous tables suggest that it is not the case that receiving grants leads to increasing multidimensional poverty or inequality, but rather it is the size of the grant, as well as its effect in combination with household income, that leads to a better standards of well-being for South African households. The fact that there is a positive effect when controlling for the time invariant variables in a fixed effects regression would mean that there are some variables or correlations that are not being introduced in these specifications. Moreover, the issue of simultaneity is also one that has been raised within this paper before. Therefore, one of the big questions that we are dealing with here is the issue of endogeneity. Endogeneity is therefore one of the bigger concerned that need to be addressed. Given that those who get grants are also those who are likely to be poor and there exists a positive relation between these two (that is the poorer one is the more grants one would also receive), we need to control for this simultaneity issue in the current setup.

There are, however, several checks that are conducted to eliminate different sources of bias; alternatively, we examine different sub-samples to determine whether this positive impact of grants on the MPI score survives for specific sub-groups of the underlying population. These are investigated, and the results are briefly described below, though the tables can be found in the appendix, and will be noted in the following sub-sections. In summary, all of them still suffer from the issue of simultaneity and therefore predict a decrease in wellbeing with the receipt of a grant. In some cases though, there is a change in the direction of the effect (though insignificant), or alternatively, a loss in significance. Therefore I report results in the main section for analysis that correspond to methods that are undertaken to correct for different potential sources of endogeneity.

Types of grant

I check for the type of grant that a household receives and how it influences the wellbeing therein. It could be that a particular grant divides households along particular characteristics and this might therefore affect the overall outcome. For instance, households receiving child grants are likely to be those which might suffer from larger deprivation in education and health indicators on account of the children that live there. Or alternatively, given the larger size of the old age pensions, households receiving them may be those that are significantly better off and therefore show a strong effect. Information on grant amount was only available for old age grants and child grants, and results for both of them are provided in Table 18 and Table 19 in the appendix. The effect of child grants on the MPI is still found to be positive, though insignificant, while the effect on CSPI is positive and significant at the 10% level. For old age grants the results are positive and significant for both CSPI and MPI as well.

Effect on each dimension of poverty

In the case of the MPI, it could be that there is a particular dimension driving these converse results. Each dimension is set to identify a different set of deprivations that a household undergoes, and these might be affected differently by a grant. For instance, as discussed before, the child grant is found to significantly affect child education and health outcomes. On the other hand, old age pensions have been used towards child-raising and income pooling in general. Therefore these effects could affect the first two dimensions as well. Since there is nearly universal enrolment in South Africa, I expect there to be no, or very small, effects of these grants on the education dimension, since these have very little variability in the first place. Therefore, to identify the source of the effect, one could check for the particular impact of cash grants on each dimension of poverty, and where the effects are the largest. Moreover, it is also interesting to determine which one, out of all three dimensions, require the most attention in terms of the policy response. The results for which are presented in Table 20 in the appendix, and show that education might be the dimension that is largely driving this positive coefficient, since it is the only one found to be positive (only at 10% level). Therefore it might be that the issue of endogeneity is largest in the case of the education dimension.

Constant households

Another restriction was placed on the NIDS dataset to examine the robustness of the results. In the case of this dataset and the tested hypothesis, there is some concern on the changes in the level of the MPI and CSPI figures, and how they are being brought about. For example, it could be the inclusion of a completely new household into the old household that makes it susceptible to higher levels of multidimensional poverty. Alternatively, households breaking up might also be the case as to why a household is thereafter multidimensionally better off. Another concern is of a more anecdotal nature, which was revealed upon speaking with the SALDRU researchers, where in some cases, mothers apply for child grants in a particular household and then choose to move to another household where better and larger opportunities for work and employment are available. These children are then raised by the grandparents or other guardians and the mother may choose to transfer the money to them. In light of these cases, it was decided to observe the trends in MPI and CSPI over households which are constant over the three waves and therefore do not introduce any unobservable biases within the analysis. The results for this sample are presented in Table 21 and Table 22 in the appendix. Now the effect for the MPI is not significant, although it is still positive, while for CSPI it is still highly significant (1% even) and positive.

All of these checks have at best been able to remove the significance from the coefficient of grant income, or alternatively to convert the sign to negative but still insignificant. Therefore, I now move on to methods that can be used to control for the issue of endogeneity that is apparent in the current setup.

Endogeneity

As discussed before, a highly probable factor of concern that affects the results is the simultaneity that might exist in our test hypothesis. Only those households which are really poor would apply and receive the grant, and consequently those who receive social assistance are those who are worse off in the first case, which influences the empirical analysis. It might be one of the reasons why the entire sample of households shows a positive relation between grants and MPI and CSPI scores. To mitigate this issue, there are several crude alternatives that will be discussed, before we move on to the IV estimation and the RDD. The quantity of the grant is replaced with a dummy depicting whether the house receives a grant in one of the specifications. This would rectify the bias to some extent, since the households receiving multiple grants (much higher in value) would now be treated the same as households receiving only a single grant. This would control for the exactly issue of reverse causality that we discussed above. The results for the same can be found in Table 9, where the first two columns are the whole sample and the second two are those that represent only the constant households. It is shown that when using grant dummies, instead of the grant values, the results in the case of multidimensional poverty disappear (although still positive), while the results for the CSPI are significant and positive (Columns 2 and 4 of the Table) at the 10% for the whole sample, and at 5% for the constant sample. Therefore, removing a large part of the variability in the grant receipt, the significance is reduced or completely removed.

Table 9: Dummy for receiving grants (including for constant households)

	(1)	(2)	(3)	(4)
VARIABLES	MPI	CSPI	MPI	CSPI
Grant	0.00518	0.00414*	0.00456	0.00868**
	(0.00327)	(0.00213)	(0.00604)	(0.00401)
Income	1.36e-07	2.34e-07	-4.40e-08	3.65e-07*
	(5.46e-07)	(1.46e-07)	(4.58e-07)	(1.91e-07)
Grant#income	-1.15e-06	-1.74e-07	-6.31e-07	-1.32e-07
	(8.51e-07)	(3.57e-07)	(6.53e-07)	(2.92e-07)
Constant	0.0633**	-0.0621**	0.193***	-0.000199
	(0.0309)	(0.0285)	(0.0565)	(0.0353)
Observations	14,081	14,081	2,873	2,873
Number of hhid	6,940	6,940	1,318	1,318
R-squared	0.029	0.019	0.026	0.025

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned shown in the summary statistics in Table 1 are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Another crude method to correct for simultaneity is to This introduces the possibility of considering dynamic effects, which are likely to suffer less from endogeneity: the grant in a certain period t might be correlated with the degree of deprivation in periods t and (t-1), but it is less obvious that it would be correlated with the degree of poverty in (t+1), also because one of the goals of the grants is to reduce specific deprivations. Furthermore, with the dynamic component, we are able to assess whether the households use the grants instantaneously or whether a certain period of time is required for its application in the consumption of the household. Within Table 10 are the results for the lagged grant income (wherein those of the constant household are mentioned in specifications 3 and 4) and no significant impact of grant income on multidimensional poverty or inequality is found, in the two year period. Furthermore, the coefficient showing the lagged impact of these grants on the MPI is negative.[29]

Table 10: Lag of grant income (also constant households)

	(1)	(2)	(3)	(4)
VARIABLES	MPI	CSPI	MPI	CSPI
Lag of Grant	-1.49e-06	1.95e-06	-1.29e-06	-3.18e-06

[29] It was also intended to run the regression with a two period lag, however, due to an insufficient amount of observations this were not possible.

	(6.67e-06)	(4.60e-06)	(1.09e-05)	(6.76e-06)
Income	-7.67e-07	8.20e-08	-1.67e-07	-8.82e-08
	(6.15e-07)	(2.79e-07)	(7.28e-07)	(2.52e-07)
Constant	0.226***	0.0143	0.0295	-0.0269
	(0.0313)	(0.0232)	(0.0866)	(0.0481)
Observations	9,370	9,370	1,965	1,965
Number of hhid	5,806	5,806	1,253	1,253
R-squared	0.025	0.022	0.036	0.023

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned shown in the summary statistics in Table 1 are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

IV and RDD

The use of lags and dummies already shows that corrections to accommodate for reverse causality are necessary, and this goes beyond the use of further controls (including fixed effects) for omitted variables. I deepen that argument in the current section by making use of Instrumental Variables and Regressions Discontinuity for child grants and old age pensions respectively.

As discussed in the methodology section, the instrument being used is the potential duration of grants, which varies for children in the sample on account of the random changes to the age of eligibility by the South African government. Table 11 shows the results for the IV approach on the effect of the child grants on multidimensional poverty. While the first two columns are normal OLS and fixed effects specifications, the last two display the 2SLS and IV in fixed effects structures, respectively. As can be seen, when using a 2SLS approach, there is a negative impact of child grants on the multidimensional poverty. The significance of this effect vanishes in a fixed effects setting, but the reason behind this can lie in the little variability in the within variation of the MPI score[30]. This would imply that most of our variation stems from the between component of the analysis, and therefore it is preferable to interpret the results for the 2SLS specification. It is shown that a unit increase in the child grant would lead to a 0.1% increase in the multidimensional wellbeing, significant at the 1% level. The first stage has also been shown in the Table (column 3) and there is a negative and significant relation between the instrument and the grant value. Since this equation is exactly identified, there is no concern for underidentification or overidentification. The Kleibergen-Paap Wald F statistic was 56.622, suggesting that the instrument is not weak.[31]

[30] As can be seen in the appendix Table 27 where the overall between and within variation is shown, I lose most of the variation in the variable if I use fixed effects.

[31] Concerns about the validity of the instrument are diminished once we consider that the Wu-Hausman test-statistic has a value of 31.143, not rejecting the null hypothesis that there is no endogeneity in the variables of interest, i.e. the child grant value.

Table 11: IV approach- effect of child grant on MPI

	OLS	FE	First stage	2SLS	IV:FE
VARIABLES	MPI	MPI	Grant value	MPI	MPI
Grant value	9.99e-05***	1.23e-05		-0.00102***	-0.0177
	(1.27e-05)	(1.60e-05)		(0.000258)	(0.108)
Income without	-1.064***	-0.0283	-405.7***	-1.521***	-1.055
	(0.0608)	(0.0910)	(143.0)	(0.483)	(6.465)
Potential Exposure			3.417***		
			(0.505)		
Constant	0.223***	0.0699**	71.52***	0.319***	0.995
	(0.00616)	(0.0308)	(4.496)	(0.0237)	(5.116)
Observations	14,338	14,338	14,338	14,338	14,338
R-squared	0.368	0.028	0.177	0.025	
Number of hhid		6,958			6,958

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 12: IV approach- effect of child grant on CSPI

	OLS	FE	First stage	2SLS	IV:FE
VARIABLES	CSPI	CSPI	Grant value	CSPI	CSPI
Grant value	2.69e-05***	1.71e-05*		-0.000440***	-0.00589
	(8.01e-06)	(1.03e-05)		(0.000137)	(0.0365)
Income without	-0.160***	0.0212	-405.7***	-0.350***	-0.321
	(0.0382)	(0.0296)	(143.0)	(0.127)	(2.176)
Potential Exposure			3.417***		
			(0.505)		
Constant	0.0209***	-0.0585**	71.52***	0.0609***	0.287
	(0.00388)	(0.0286)	(4.496)	(0.0128)	(1.722)
Observations	14,338	14,338	14,338	14,338	14,338
R-squared	0.155	0.017	0.177	-0.045	
Number of hhid		6,958			6,958

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature

Table 12 shows how the CSPI score responds to the child grants. As in the previous case, the fixed effects specification is negative but not significant (again due to the low variability in the within effects). The 2SLS on the other hand is found to be negative and significant, at the 1% level. This suggests that multidimensional inequality declines by approximately 0.04% with a unit increase in grant income. In order to further strengthen the results, I use the lag of grants in the Table 28 and Table 29 in the appendix. As can be seen, the 2SLS specifications are still significant (where the significance even increases in the case of the CSPI), although now the coefficients are now slightly smaller. This is expected since we are looking at the lagged effect of grants. Therefore within the IV specification, we hope to have overcome the issue of endogeneity in the case of the child grants. I therefore move on to the analysis for the old age grants in the RDD setup.

The results of the fuzzy RDD approach to determine the impact of receiving the old age pension on the overall MPI are presented in Table 13. Since we are removed the possibility of having additional years of grants[32], we only are able to look at the results over a cross section, and to account for any form of year specific biases I also add year dummies to the 2SLS specification. The results for the OLS and FE regressions are shown in columns 1 and 2, where in the case of the OLS we still find a positive effect of old age pensions on multidimensional poverty (although it is insignificant). In comparison, within the FE estimation, the sign is already reversed although still insignificant. For the 2SLS specification, where I use the Local Average Treatment Effect (LATE) to distinguish the effect between compliers and potential recipients around the cut-off, I find negative and significant results for the 2SLS approach, significant at the 1% level. The size coefficient in this case is nearly the same as in the OLS regression. The results show that a household receiving grants is able to lower its multidimensional poverty by 4.53%. In comparison to the child grants, this effect is nearly 100 times larger, but we cannot be entirely sure about the comparison, as using a cut-off of 2 years around the age of eligibility, and estimating the LATE has severely reduced the internal validity of the results.

Table 13: RDD approach- Effect of old age pension on MPI

	OLS	**FE**	**First stage**	**RDD : 2SLS**
VARIABLES	MPI	MPI	Pension dummy	MPI
Pension dummy	0.00465	-0.00201		-0.0453***
	(0.00708)	(0.00793)		(0.0176)
Income without grants	-0.542***	0.166	-2.100**	-0.646**
	(0.167)	(0.171)	(1.055)	(0.262)
Pension eligibility			0.434***	
			(0.0294)	
Constant	0.220***	-0.180	-0.00522	0.201***
	(0.0191)	(0.313)	(0.0682)	(0.0274)
Observations	1,670	1,670	1,670	1,670
R-squared	0.427	0.041	0.387	0.410
Number of hhid		857		

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 14: RDD approach- Effect of old age pension on CSPI

	OLS	**FE**	**First stage**	**RDD : 2SLS**
VARIABLES	CSPI	CSPI	Pension dummy	CSPI

[32] As explained in the methodology, this is because of the removal of households who received grants in the first wave altogether, and those households who receive grants in the second wave, in the third wave.

Pension dummy	-0.00153	0.00422		-0.0248**
	(0.00473)	(0.00540)		(0.0111)
Income without grants	-0.0802	0.0253	-2.100**	-0.129*
	(0.112)	(0.0687)	(1.055)	(0.0690)
Pension eligibility			0.434***	
			(0.0294)	
Constant	0.0304**	-0.390	-0.00522	0.0218
	(0.0128)	(0.349)	(0.0682)	(0.0208)
Observations	1,670	1,670	1,670	1,670
R-squared	0.171	0.044	0.387	0.158
Number of hhid		857		

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

The first stage results show that the instrument is significant with respect to the pension dummy, with a relatively large R-square of 0.38. Again, the Kleibergen-Paap Wald F statistic was very large (217.213) and it therefore suggests that the instrument is valid and not weak. The Wu-Hausman test statistic was also not rejected (10.912), which indicates that there is an issue of endogeneity that was addressed using this instrument. Table 14 displays the results for old age grants on multidimensional inequality. While in the case of multidimensional poverty there is a large influence, for the CSPI, there is a smaller influence (around 2.5% reduction in multidimensional inequality), and the significance is also reduced, although still at 5% level. Interestingly the OLS is found to be negative and significant in this regression, although insignificant, while the FE results are positive. This would imply that the old age grants are successful in reducing multidimensional poverty and inequality within our sample.

The results for the sample with 5 years around the cut-off, and both bandwidths in the case of the sample without values for 2012 are displayed in Table 30 to Table 35 in the appendix. Extending the bandwidths in the larger sample leads to a decline in the significance level (at 5% now), while the coefficient is also half the size. This makes the effect closer in size to the one found from the child grants. Regardless, one could expect a larger coefficient on the grant, on account of the larger size of the grant. In the case of the smaller sample excluding 2012, the significance is nearly gone in the case of the 2 years bandwidth, and is insignificant in the 5 years bandwidth. The coefficients, on the other hand, are still comparable in size. However, this might be due to a fall in the power, given the smaller number of observations available in both the treatment and control groups.

It is also interesting to determine the channels through which we can observe the improvement in the MPI. To do this, I divide the Index into its three dimensions of health, education and standard of living, to examine which dimension has the largest effect here. The results for both, the child grants and the old age pension, can be found in Table 15 and Table 16. The first column in both tables is the first stage of the 2SLS, while the remaining three dimensions as the dependent variables are specified in the next columns. In the case of the child grants, the first column within each dimension shows the results of the 2SLS, while the second depicts the fixed effects IV regressions.

Table 15: Effect of child grants on each dimension of MPI

	First stage	2SLS	FE	2SLS	FE	2SLS	FE
VARIABLES		Health		Education		Standard of living	
Grant value		-0.000598***	-0.00808	0.000105*	0.00229	-0.00144**	-0.0382
		(0.000130)	(0.0497)	(5.70e-05)	(0.0142)	(0.000586)	(0.234)
Income without	-405.7***	-0.319***	-0.471	-0.0533*	0.129	-1.251***	-2.110
	(143.0)	(0.120)	(2.964)	(0.0296)	(0.849)	(0.478)	(13.99)
Potential Exposure	3.417***						
	(0.505)						
Constant	71.52***	0.0622***	0.388	-0.00921*	-0.107	0.299***	1.871
	(4.496)	(0.0119)	(2.346)	(0.00523)	(0.672)	(0.0545)	(11.07)
Observations	14,338	14,338	14,338	14,338	14,338	14,338	14,338
R-squared	0.177	-0.530		0.040		0.098	
Number of hhid			6,958		6,958		6,958

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 16: Effect of old age pension on each dimension of the MPI

	First stage	2SLS	2SLS	2SLS
VARIABLES		Health	Education	Standard of living
Pension dummy		-0.0123	-0.00743*	-0.0815*
		(0.00922)	(0.00420)	(0.0494)
Income without	-2.100**	-0.0691	-0.0284	-0.524*
	(1.055)	(0.0437)	(0.0251)	(0.284)
Pension eligibility	0.434***			
	(0.0294)			
Constant	-0.00522	0.00888	0.00103	0.186***
	(0.0682)	(0.0129)	(0.00881)	(0.0684)
Observations	1,670	1,670	1,670	1,670
R-squared	0.387	0.090	0.046	0.203

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

From Table 15 it can be seen that the effect of the child grant is negative and significant for both the health and standard of living indicators, but surprisingly it is positive and even significant at the 10% level for the education dimension. So while a unit increase in grants would make health deprivation and standard of living deprivation fall by around 0.06% and 0.14% respectively, it would lead to an increase in the educational dimension deprivation by 0.02%. These results imply that child grants work mostly through Health and Standard of living indicators, to diminish deprivation of household. In terms of the old age grants, there is a negative and significant effect of these pensions on all dimensions of the MPI, but significant for the education and standard of living dimensions (only at 10% level). This suggests that receiving an old age pension leads to a 0.74% improvement in the education dimension and a 0.082% increase in the standard of living dimension. On the other hand, the old age pensions work largely via improvements in education and standard of living.

CONCLUSION

This paper analyses an important policy question, since it investigates the effect of social grants on non-traditional measures of poverty. Money-metric measures may over/understate the effectiveness of social grants, and a multidimensional approach provides a finer measure of how effective these cash transfers really are. In the South African context, only a few studies have measured poverty multidimensionally. Moreover, there is no previous study that looks at the link between the South African cash grant system and multidimensional poverty. Furthermore, there is no analysis that examines the link between cash grants and multidimensional inequality. In fact, despite the better availability of data in developed countries, work on multidimensional inequality is still sparse, with a few exceptions. Therefore, this study attempts to link a state intervention in South Africa, i.e. the social security system and examine its impact on multidimensional wellbeing.

The OLS and fixed effects estimations suggested that multidimensional poverty and inequality rise when an individual or a household receives grants or cash transfers. However, a brief look at the literature would suggest that cash grants would lower the deprivation levels across households. When examining several sub-samples, I find similar results, although some become sensitive in the robustness analysis. This indicates that there might be an endogeneity problem, namely, the simultaneity between the situation of being an income poor and likely multidimensionally deprived household and being eligible for these grants. To counteract this problem, the empirical strategy was modified to correct for any form of bias.

Given the information available on receipt of child grants to the household, a suitable instrument was found to examine their effect on multidimensional poverty and inequality. This instrument exploits the exogenous changes in the age of eligibility since the start of these grants, which bring about a random variation in the potential years of receipt of these grants for each child. The results show that despite the small size of these grants, they were able to reduce multidimensional poverty and inequality amongst each household. Previous studies have shown that these child grants have been highly pivotal in enhancing child development outcomes like health and education over the long run. Therefore it is an expected result, as both the health and education dimensions are affected by the deprivation that a child in the households suffers from. Contrary to our hypothesis, we find that while deprivation in health and standard of living indicators has fallen due to these grants, they seem to have affected the education dimension adversely. This is a puzzling result, but given the very little variation that can be found in educational deprivation measure across time and households in South Africa, we believe that perhaps the result is driven by this.

The other set of grants for which there was also information available were the old age grants. Since there was no such exogenous change that could function as in instrument in the case of old age grants, it was decided to use a Regression Discontinuity Design (RDD) to correct for any kind of endogeneity bias. Using a 2 year and 5 years bandwidth around the age cut-off, I was able to examine the effect of these grants for individuals who were slightly below the cut-off age to those who were just above. The results of the RDD were also found to show that when households receive old age pensions, multidimensional poverty and inequality decreased. There might be several reasons for this and the foremost of these might be related to the pooling of pensions into households income that have been widely discussed in the related literature, and would thereby affecting overall household wellbeing. Moreover, there is also significant evidence of income transfers from elderly adults towards grandchild and orphans. This could also explain why when examining each particular dimension, the effects are significant for the education dimension, where the indicators are largely driven by child outcomes. On the other hand, the large size of the grants also enables an improvement in the standard of living for these elderly, and that is also reflected in that particular dimension.

When we look at the case of CSPI, which also includes the inequality component of wellbeing, we find that the grants also lead to lower levels of inequality in the South African case. This is highly insightful given the current high levels of inequality that exist within the local population. Therefore, over the course of its development, South Africa has been able to reduce its multidimensional inequality component as well. This effect is smaller than that for multidimensional poverty, but this might be on account of the more sluggish nature of this aspect of wellbeing, especially in an income-fractionalized nation like South Africa. Between the two grants, there appears to be a larger impact of old age pensions on the inter-personal inequality between the dimensions. This could imply that the size of the grant might also affect the overall multidimensional inequality, and the larger the grant, the greater the impact on inequality. Overall, in a highly unequal society like South Africa, these small grants are not likely to bring such a large difference on such a broad based definition of development. The effect might be stronger for income based/money-metric aggregates of development.

Nonetheless, in the case of both the MPI and the CSPI, it is better to refrain from making any strong statements about long run effects. This data spans over a period of 4 to5 years, and therefore one might miss out on many changes that take effect over a longer time frame. Further research on long terms impact of multidimensional poverty and inequality would be possible only with additional waves of the data. Furthermore, some of the issues that emerged in this analysis could have been tackled with a longer time frame and the possibility for longer lags of the grant income. This is another avenue for future research.

REFERENCES

Agüero, J.M., Carter, M.R., Woolard, I.D., University of Cape Town, Southern Africa Labour and Development Research Unit, 2006. The impact of unconditional cash transfers on nutrition: the South African child support grant. Southern Africa Labour and Development Research Unit, University of Cape Town, Cape Town.

Alkire, S., 2002. Dimensions of Human Development. World Dev. 30, 181–205. doi:10.1016/S0305-750X(01)00109-7

Alkire, S., Foster, J., 2011. Understandings and misunderstandings of multidimensional poverty measurement. J. Econ. Inequal. 9, 289–314. doi:10.1007/s10888-011-9181-4

Alkire, S., Santos, M.E., 2014. Measuring Acute Poverty in the Developing World: Robustness and Scope of the Multidimensional Poverty Index. World Dev. 59, 251–274. doi:10.1016/j.worlddev.2014.01.026

Angrist, J.D., Pischke, J.-S., 2009. Mostly harmless econometrics: an empiricist's companion. Princeton University Press, Princeton.

Ardington, C., Case, A., Lam, D., Leibbrandt, M., Menendez, A., Olgiati, A., 2009. The Impact of AIDS on Intergenerational Support in South Africa: Evidence From the Cape Area Panel Study. Res. Aging. doi:10.1177/0164027509348143

Ardington, E., Lund, F., 1995. Pensions and development: Social security as complementary to programmes of reconstruction and development. Dev. South. Afr. 12, 557–577. doi:10.1080/03768359508439839

Banerjee, A., Galiani, S., Levinsohn, J., McLaren, Z., Woolard, I., 2008. Why has unemployment risen in the New South Africa?1. Econ. Transit. 16, 715–740. doi:10.1111/j.1468-0351.2008.00340.x

Barrientos, A., DeJong, J., Childhood Poverty Research and Policy Centre, Save the Children Fund (Great Britain), Chronic Poverty Research Centre, 2004. Child poverty and cash transfers. Childhood Poverty Research and Policy Centre, London.

Barrientos, A., Jong, D., Jocelyn, 2006. Reducing Child Poverty with Cash Transfers: A Sure Thing? (SSRN Scholarly Paper No. ID 925060). Social Science Research Network, Rochester, NY.

Bertrand, M., Mullainathan, S., Miller, D., 2003. Public Policy and Extended Families: Evidence from Pensions in South Africa. World Bank Econ. Rev. 17, 27–50. doi:10.1093/wber/lhg014

Bhorat, H., Cassim, A., 2014. South Africa's Welfare Success Story II: Poverty-Reducing Social Grants. Brook. Inst.

Bhorat, H., Westhuizen, C.V.D., 2012. Poverty, Inequality and the Nature of Economic Growth in South Africa (Working Paper No. 12151). University of Cape Town, Development Policy Research Unit.

Bookwalter, J.T., Dalenberg, D., 2004. Subjective Well-Being and Household Factors in South Africa. Soc. Indic. Res. 65, 333–353. doi:10.1023/B:SOCI.0000003546.96008.58

Branson, N., University of Cape Town, Southern Africa Labour and Development Research Unit, 2012. Education and inequality the South African case. Southern Africa Labour and Development Research Unit, University of Cape Town, Cape Town.

Case, A., Deaton, A., 1998. Large Cash Transfers to the Elderly in South Africa. Econ. J. 108, 1330–1361. doi:10.1111/1468-0297.00345

Dawes, A., Bray, R., Van der Merwe, A., Rädda barnen (Society) (Eds.), 2007. Monitoring child well-being: a South African rights-based approach. HSRC Publishers ; Distributed in North America by Independent Publishers Group, Cape Town, South Africa : [Chicago].

Duflo, E., 2003. Grandmothers and Granddaughters: Old-Age Pensions and Intrahousehold Allocation in South Africa. World Bank Econ. Rev. 17, 1–25. doi:10.1093/wber/lhg013

Duflo, E., 2000. Child Health and Household Resources in South Africa: Evidence from the Old Age Pension Program. Am. Econ. Rev. 90, 393–398. doi:10.1257/aer.90.2.393

Edmonds, E.V., Mammen, K., Miller, D.L., 2005. Rearranging the Family?: Income Support and Elderly Living Arrangements in a Low-Income Country. J. Hum. Resour. XL, 186–207. doi:10.3368/jhr.XL.1.186

Eyal, K., Woolard, I., 2013. School Enrolment and the Child Support Grant: Evidence from South Africa (SALDRU Working Paper No. 125). Southern Africa Labour and Development Research Unit, University of Cape Town.

Finn, A., Leibbrandt, M., 2013. The dynamics of poverty in the first three waves of NIDS (SALDRU Working Paper No. 119). Southern Africa Labour and Development Research Unit, University of Cape Town.

Finn, A., Leibbrandt, M.V., Woolard, I., University of Cape Town, Southern Africa Labour and Development Research Unit, 2013. What happened to multidimensional poverty in South Africa between 1993 and 2010? Southern Africa Labour and Development Research Unit, Rondebosch, South Africa.

Fintel, M. von, Zoch, A., 2015. The dynamics of child poverty in South Africa between 2008 and 2012: An analysis using the National Income Dynamics Study (Working Paper No. 05/2015). Stellenbosch University, Department of Economics.

Goldblatt, B., 2005. Gender and social assistance in the first decade of democracy: A case study of South Africa's Child Support Grant. Politikon 32, 239–257. doi:10.1080/02589340500353581

Gutura, P., Tanga, P.T., 2014. The Intended Consequences of the Social Assistance Grants in South Africa. Mediterr. J. Soc. Sci. 5, 659.

Hagen-Zanker, J., Morgan, J., Meth, C., 2011. South Africa's social security system: Expanding coverage of grants and limiting increases in inequality. Overseas Development Institute.

Heinrich, C., Hoddinott, J., Samson, M., Mac Quene, K., van Niekerk, I., Renaud, B., 2012. The South African Child Support Grant Impact Assessment. Evidence from a survey of children, adolescents and their households. UNICEF South Africa, Pretoria.

Jensen, R.T., 2004. Do private transfers "displace" the benefits of public transfers? Evidence from South Africa. J. Public Econ. 88, 89–112. doi:10.1016/S0047-2727(02)00085-3

Kingdon, G.G., Knight, J., 2004. Unemployment in South Africa: The Nature of the Beast. World Dev. 32, 391–408. doi:10.1016/j.worlddev.2003.10.005

Klasen, S., 2000. Measuring Poverty and Deprivation in South Africa. Rev. Income Wealth 46, 33–58. doi:10.1111/j.1475-4991.2000.tb00390.x

Klasen, S., 1993. Gender inequality and development strategies: lessons from the past and policy issues for the future (ILO Working Paper). International Labour Organization.

Klasen, S., Woolard, I., 2009. Surviving Unemployment Without State Support: Unemployment and Household Formation in South Africa. J. Afr. Econ. 18, 1–51. doi:10.1093/jae/ejn007

Leibbrandt, M., Levinsohn, J., 2011. Fifteen years on: Household incomes in South Africa. National Bureau of Economic Research.

Leibbrandt, M., Lilenstein, K., Shenker, C., Woolard, I., 2013. The influence of social transfers on labour supply: A South African and international review (SALDRU Working Paper No. 112). Southern Africa Labour and Development Research Unit, University of Cape Town.

Leibbrandt, M.V., Woolard, I., Finn, A., Argent, J., 2010. Trends in South African income distribution and poverty since the fall of apartheid. OECD Paris.

Lund, F., University of KwaZulu-Natal, School of Development Studies, 2008. Is there a rationale for conditional cash transfers for children in South Africa? University of KwaZulu-Natal, School of Development Studies, Durban.

McEwen, H., Kannemeyer, C., Woolard, I., 2009. Social Assistance Grants: Analysis of the NIDS Wave 1 Dataset.

Monthly Monetary and Financial Statistics (MEI) : Exchange rates (USD monthly averages) [WWW Document], n.d. URL http://stats.oecd.org/index.aspx?queryid=169 (accessed 3.24.16).

Noble, M., Wright, G., Cluver, L., 2006. Developing a child-focused and multidimensional model of child poverty for South Africa. J. Child. Poverty 12, 39–53. doi:10.1080/10796120500502136

Nussbaum, M.C., 2008. Women and human development: the capabilities approach, 13. print. ed, The John Robert Seeley lectures. Cambridge Univ. Press, Cambridge.

Nussbaum, M.C., Sen, A., World Institute for Development Economics Research (Eds.), 1993. The Quality of life, WIDER studies in development economics. Clarendon Press ; Oxford University Press, Oxford [England] : New York.

Oxford Poverty and Human Development Initiative, 2015. South African Country briefing.

Özler, B., 2007. Not Separate, Not Equal: Poverty and Inequality in Post-apartheid South Africa. Econ. Dev. Cult. Change 55, 487–529. doi:10.1086/511191

Özler, B., Hoogeveen, J.G.M. (Hans), 2005. Not Separate, Not Equal: Poverty and Inequality in Post-Apartheid South Africa (SSRN Scholarly Paper No. ID 669147). Social Science Research Network, Rochester, NY.

Pelham, L., 2007. The Politics Behind the Non-Contributory Old Age Social Pensions in Lesotho, Namibia and South Africa (SSRN Scholarly Paper No. ID 1653353). Social Science Research Network, Rochester, NY.

Posel, D., Fairburn, J.A., Lund, F., 2006. Labour migration and households: A reconsideration of the effects of the social pension on labour supply in South Africa. Econ. Model., Ninth Annual Conference on Econometric Modelling for Africa, School of Economics, University of Cape Town, 2004 23, 836–853. doi:10.1016/j.econmod.2005.10.010

Ranchhod, V., 2006. The Effect of the South African Old Age Pension on Labour Supply of the Elderly. South Afr. J. Econ. 74, 725–744. doi:10.1111/j.1813-6982.2006.00098.x

Ravallion, M., 2012. Mashup Indices of Development. World Bank Res. Obs. 27, 1–32. doi:10.1093/wbro/lkr009

Rippin, N., 2015. Multidimensional Poverty in Germany: A Capability Approach. Forum Soc. Econ. 1–26. doi:10.1080/07360932.2014.995199

Rippin, N., 2012. Distributional Justice and Efficiency: Integrating Inequality Within and Between Dimensions in Additive Poverty Indices (No. 128). Courant Research Centre: Poverty, Equity and Growth - Discussion Papers.

Rippin, N., 2010. Poverty Severity in a Multidimensional Framework: The Issue of Inequality between Dimensions (Courant Research Centre: Poverty, Equity and Growth - Discussion Paper No. 47). Courant Research Centre PEG.

Sen, A., 1999. Development as freedom, 1st. ed. ed. Knopf, New York.

Sen, A., 1985. Commodities and capabilities, Professor Dr. P. Hennipman lectures in economics. North-Holland ; Sole distributors for the U.S.A. and Canada, Elsevier Science Pub. Co, Amsterdam ; New York : New York, N.Y., U.S.A.

United Nations (Ed.), 1990. Human development report 1990. Published for the United Nations (New York) Development Programme. Oxford Univ. Pr, New York.

Woolard, I., Leibbrandt, M., 2013. The evolution and impact of unconditional cash transfers in South Africa. Dev. Chall. Postcrisis World 363.

Woolard, I.D., Finn, A., Klasen, S., 2013. MPI versus Income Poverty in South Africa using the South African National Income Dynamics Study.

APPENDIX

Table 17: Correlation between grant income and other multidimensional and income poverty (significant at 1%)

Correlation	Household grant income	Percapita household income	MPI score	CSPI score
Household grant income	1.0000			
Per capita household income	-0.1145*	1.0000		
MPI score	0.2425*	-0.2704*	1.0000	
CSPI score	0.1595*	-0.1281*	0.8102*	1.0000

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

Table 18: Household only received child grants

VARIABLES	(1) MPI	(2) MPI	(3) MPI	(4) CSPI	(5) CSPI	(6) CSPI
Grant	1.33e-05	3.75e-05*	2.00e-05	1.70e-05*	2.42e-05*	1.96e-05*
	(1.60e-05)	(2.03e-05)	(1.66e-05)	(1.03e-05)	(1.40e-05)	(1.13e-05)
Income	-1.48e-07	-1.05e-07	2.69e-09	1.34e-07	1.46e-07	1.92e-07
	(5.51e-07)	(5.49e-07)	(5.42e-07)	1.70e-05*	2.42e-05*	1.96e-05*
Square grant		-5.56e-08***			-1.66e-08	
		(1.72e-08)			(1.02e-08)	
Grant#income			-6.60e-09			-2.55e-09
			(5.43e-09)			(2.36e-09)
Constant	0.0701**	0.0698**	0.0692**	-0.0594**	-0.0595**	-0.0597**
	(0.0300)	(0.0302)	(0.0300)	(0.0283)	(0.0283)	(0.0283)
Observations	14,338	14,338	14,338	14,338	14,338	14,338
R-squared	0.028	0.028	0.028	0.017	0.018	0.018
Number of hhid	6,958	6,958	6,958	6,958	6,958	6,958

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 19: Household only received old age pensions

VARIABLES	(1) MPI	(2) MPI	(3) MPI	(4) CSPI	(5) CSPI	(6) CSPI
Grant	1.87e-05**	-6.76e-06	2.23e-05***	1.27e-05**	2.05e-06	1.39e-05**
	(8.30e-06)	(1.67e-05)	(8.43e-06)	(6.13e-06)	(1.22e-05)	(6.28e-06)
Income	-4.48e-08	-4.92e-08	3.46e-07	2.00e-07	1.98e-07	3.32e-07*
	(5.48e-07)	(5.49e-07)	(5.23e-07)	(1.83e-07)	(1.83e-07)	(1.76e-07)
Square grant		2.77e-08*			1.16e-08	
		(1.55e-08)			(1.20e-08)	
Grant#income			-7.04e-09***			-2.39e-09**
			(2.67e-09)			(1.20e-09)
Constant	0.0752**	0.0768**	0.0742**	-0.0549*	-0.0542*	-0.0552*
	(0.0300)	(0.0305)	(0.0300)	(0.0284)	(0.0287)	(0.0284)
Observations	14,338	14,338	14,338	14,338	14,338	14,338
R-squared	0.028	0.029	0.029	0.018	0.018	0.018

Number of hhid	6,958	6,958	6,958	6,958	6,958	6,958

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 20: Impact of cash grant on particular dimensions of MPI

VARIABLES	(1) Education	(2) Education	(3) Health	(4) Health	(5) Std. of living	(6) Std. of living
Grant	3.72e-06*		3.61e-06		1.81e-05	
	(1.95e-06)		(2.51e-06)		(1.27e-05)	
Income	7.47e-09		2.91e-08		7.65e-07	
	(1.13e-07)		(1.84e-07)		(8.15e-07)	
Log of grants		0.00162*		-0.00134		-0.00560
		(0.000948)		(0.00205)		(0.00935)
Log of Income		-0.000340		-0.000170		-0.00580
		(0.000358)		(0.000726)		(0.00374)
Constant	-0.00914	-0.00986	-0.0512**	0.0383*	-0.00478	0.104
	(0.00793)	(0.0112)	(0.0258)	(0.0224)	(0.0685)	(0.104)
Observations	14,338	7,978	14,338	7,978	14,338	7,978
R-squared	0.023	0.025	0.013	0.012	0.022	0.024
Number of hhid	6,958	4,849	6,958	4,849	6,958	4,849

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 21: Fixed effects regression for MPI and cash grants (constant households)

VARIABLES	(1) MPI	(2) MPI	(3) MPI	(4) MPI
Grant	9.19e-06		1.21e-05	1.03e-05
	(7.95e-06)		(1.29e-05)	(8.15e-06)
Income	-1.47e-07		-1.36e-07	-1.15e-09
	(4.90e-07)		(4.92e-07)	(4.72e-07)
Log grant		0.000326		
		(0.00869)		
Log income		-0.00466		
		(0.00310)		
Square grant			-1.49e-09	
			(2.79e-09)	
Grant#income				-1.68e-09
				(1.35e-09)
Constant	0.00658	0.649	0.00689	0.196***
	(0.0657)	(0.429)	(0.0656)	(0.0560)
Observations	2,873	1,383	2,873	2,873
R-squared	0.026	0.034	0.026	0.027
Number of hhid	1,318	846	1,318	1,318

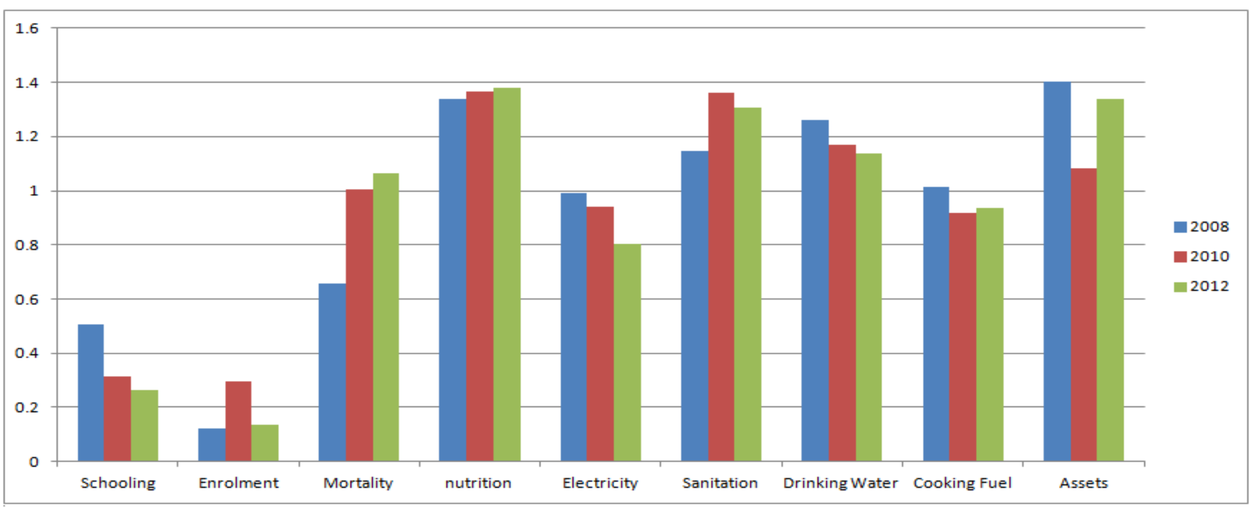
Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 22: Fixed effects regression for CSPI and cash grants (constant households)

VARIABLES	(1) CSPI	(2) CSPI	(3) CSPI	(4) CSPI
Grant	1.59e-05***		2.53e-05***	1.61e-05**
	(6.09e-06)		(9.25e-06)	(6.31e-06)
Income	3.98e-07*		4.35e-07*	4.33e-07**
	(2.20e-07)		(2.23e-07)	(2.17e-07)
Log grant		0.00214		
		(0.00571)		
Log income		-0.00200		
		(0.00266)		
Square grant			-4.81e-09**	
			(2.11e-09)	
Grant#income				-4.03e-10
				(5.25e-10)
Constant	-0.00748	0.122	-0.00648	0.00372
	(0.0364)	(0.277)	(0.0362)	(0.0344)
Observations	2,873	1,383	2,873	2,873
R-squared	0.026	0.036	0.027	0.026
Number of hhid	1,318	846	1,318	1,318

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Figure 6: Weighted Contribution of each Indicator on total MPI



Source: Own calculations

Table 23: Random effects Model

VARIABLES	1 MPI	2 MPI	3 MPI	4 CSPI	5 CSPI	6 CSPI
Grant	2.62e-05***			2.68e-05***		
	(5.94e-06)			(8.22e-06)		

Income	-3.10e-06***		-3.36e-06**	-2.58e-06***		-3.20e-06***
	(1.07e-06)		(1.44e-06)	(5.89e-07)		(8.91e-07)
Log of grant		0.00289			0.000403	
		(0.00210)			(0.00509)	
Log of income		-0.00922***			-0.0159***	
		(0.000889)			(0.00223)	
Lag of grant			2.08e-05***			3.04e-05***
			(5.22e-06)			(8.91e-06)
Constant	0.0880***	0.113***	0.0880***	0.0939***	0.164***	0.107***
	(0.0118)	(0.0216)	(0.0154)	(0.0237)	(0.0471)	(0.0286)
Observations	14,081	7,866	9,370	2,873	1,383	1,965
R-squared	6,940	4,826	5,806	1,318	846	1,253
Number of hhid	2.62e-05***			2.68e-05***		

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 24: Deprived households in each year for grant households

Indicator	2008	2010	2012
Schooling	1.6	1.0	0.8
Enrolment	0.5	1.0	0.4
Mortality	2.9	4.4	4.7
nutrition	6.5	7.1	7.1
Electricity	9.6	10.6	7.9
Sanitation	22.6	16.2	17.2
Drinking Water	16.3	15.9	15.3
Cooking Fuel	8.9	10.2	10.5
Assets	31.1	33.6	36.1
Total	1.6	1.0	0.8

Table 25: Deprived households in each year for non-grant households

Indicator	2008	2010	2012
Schooling	2.2	1.6	1.7
Enrolment	0.6	1.9	0.8
Mortality	2.1	3.7	3.8
nutrition	5.8	6.4	6.0
Electricity	8.3	10.2	7.1
Sanitation	20.0	19.4	19.4
Drinking Water	14.8	11.8	12.5
Cooking Fuel	6.9	5.0	5.3
Assets	39.3	39.9	43.4
Total	2.2	1.6	1.7

Table 26: Difference in Baseline characteristics for restricted sample of 5 years

	Observations	Mean	Observations	Mean	Difference
	(receiving)		(not-receiving)		

Number of household residents	2240	5.753	889	4.859	0.894***
Number of children in household	2240	2.173	889	1.494	0.679***
Married	2240	0.206	889	0.335	-0.129***
HH has female head	2240	0.583	889	0.565	0.018
Female	2240	0.567	889	0.550	0.017
Age in years	2240	26.088	889	40.728	-14.639***
Indian	2240	0.010	889	0.012	-0.002
Coloured	2240	0.141	889	0.150	-0.009
African-Black	2240	0.832	889	0.652	0.179***
White	2240	0.016	889	0.185	-0.169***
Province 1. Western Cape	2240	0.104	889	0.200	-0.097***
Province 2. Eastern Cape	2240	0.150	889	0.106	0.044**
Province 3. Northern Cape	2240	0.062	889	0.083	-0.021*
Province 4. Free State	2240	0.046	889	0.060	-0.013
Province 5. KwaZulu-Natal	2240	0.307	889	0.245	0.062***
Province 6. North West	2240	0.084	889	0.071	0.013
Province 7. Gauteng	2240	0.079	889	0.083	-0.004
Province 8. Mpumalanga	2240	0.055	889	0.052	0.003
Province 9. Limpopo	2240	0.113	889	0.100	0.013
Rural	2240	0.079	889	0.105	-0.025*
Urban	2236	0.445	885	0.524	-0.079***
Tribal	2240	0.474	889	0.369	0.105***
Is the respondent employed	1761	0.641	575	0.656	-0.015
PC non-grant income recal	2122	0.005	847	0.013	-0.009***
Observations			3129		

Table 27: Within, Between and Overall variation in the variables of interest

Variable		**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**
MPI	overall	0.1901457	0.1392994	0	0.8333333	N = 15029
score	between		0.130785	0	0.7666667	n = 7133
	within		0.056264	-0.1209654	0.5234791	T-bar = 2.10697
CSPI	overall	0.0334991	0.0753977	0	0.6944444	N = 15029
score	between		0.066603	0	0.5877777	n = 7133
	within		0.0388491	-0.2065009	0.3712768	T-bar = 2.10697
Health	overall	0.0186196	0.0583095	0	0.3333333	N = 15029
	between		0.0478154	0	0.3333333	n = 7133
	within		0.0350773	-0.2036027	0.2408418	T-bar = 2.10697
Education	overall	0.0068867	0.0334501	0	0.3333333	N = 15029
	between		0.0300711	0	0.25	n = 7133
	within		0.0181727	-0.15978	0.1735534	T-bar = 2.10697
Standard	overall	0.1618471	0.3403723	0	1	N = 15029
of living	between		0.2984819	0	1	n = 7133
	within		0.1691676	-0.5048196	0.8285138	T-bar = 2.10697

Table 28: IV approach: Effect of lagged child grants on MPI

VARIABLES	OLS MPI	FE MPI	First stage Grant value	2SLS MPI	IV:FE MPI
Lag of Grant value	0.000121***	4.61e-05**		-0.000851***	-0.000836
	(1.71e-05)	(2.34e-05)		(0.000214)	(0.000783)
Income without	-0.896***	-0.127	-405.7***	-1.206**	-0.299
	(0.0701)	(0.102)	(143.0)	(0.469)	(0.263)
Potential Exposure			3.417***		
			(0.505)		
Constant	4.402*	0.250***	71.52***	0.290***	0.221***
	(2.354)	(0.0402)	(4.496)	(0.0205)	(0.0655)
Observations	9,370	9,370	14,338	9,370	9,370
R-squared	0.345	0.025	0.177	0.119	
Number of hhid		5,806			5,806

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 29: IV approach: Effect of lagged child grants on CSPI

VARIABLES	OLS CSPI	FE CSPI	First stage Grant value	2SLS CSPI	IV:FE CSPI
Lag of Grant value	3.79e-05***	1.74e-05		-0.000396***	-0.000487
	(1.06e-05)	(1.62e-05)		(0.000118)	(0.000511)
Income without	-0.134***	0.0146	-405.7***	-0.272**	-0.0842
	(0.0433)	(0.0460)	(143.0)	(0.112)	(0.172)
Potential Exposure			3.417***		
			(0.505)		
Constant	0.0153***	0.0714**	71.52***	0.0476***	0.0275
	(0.00460)	(0.0334)	(4.496)	(0.0116)	(0.0427)
Observations	9,370	9,370	14,338	9,370	9,370
R-squared	0.142	0.022	0.177	-0.012	
Number of hhid		5,806			5,806

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 30: RDD approach: Effect of old age pension on MPI with 5 years around the cut-off

VARIABLES	OLS MPI	FE MPI	First stage Pension dummy	RDD : 2SLS MPI
Pension dummy	-0.000136	-0.00210		-0.0295**
	(0.00566)	(0.00671)		(0.0123)
Income without grants	-0.706***	-0.0211	-2.657***	-0.789***
	(0.144)	(0.204)	(0.927)	(0.244)
Pension eligibility			0.500***	
			(0.0233)	
Constant	0.195***	-0.164	0.0273	0.184***
	(0.0145)	(0.215)	(0.0473)	(0.0190)

Observations	2,746	2,746	2,746	2,746
R-squared	0.430	0.026	0.403	0.424
Number of hhid		1,407		

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 31: RDD approach: Effect of old age pension on CSPI with five years around the cut-off

	OLS	FE	First stage	RDD : 2SLS
VARIABLES	MPI	MPI	Pension dummy	MPI
Pension dummy	-0.00272	0.00429		-0.0158**
	(0.00368)	(0.00453)		(0.00757)
Income without grants	-0.131	-0.0744	-2.657***	-0.167***
	(0.0939)	(0.0680)	(0.927)	(0.0614)
Pension eligibility			0.500***	
			(0.0233)	
Constant	0.0200**	-0.237	0.0273	0.0149
	(0.00942)	(0.231)	(0.0473)	(0.0138)
Observations	2,746	2,746	2,746	2,746
R-squared	0.178	0.028	0.403	0.174
Number of hhid		1,407		

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 32: RDD approach: Effect of old age pension on MPI with smaller sample, 2 years around cut-off

	OLS	FE	First stage	RDD : 2SLS
VARIABLES	MPI	MPI	Pension dummy	MPI
Pension dummy	-8.86e-05	-0.0103		-0.0481*
	(0.0104)	(0.0113)		(0.0263)
Income without grants	-0.764***	-0.338	-1.892*	-0.865***
	(0.234)	(0.234)	(1.049)	(0.276)
Pension eligibility			0.377***	
			(0.0369)	
Constant	0.219***	0.0187	0.0387	0.206***
	(0.0255)	(0.425)	(0.0809)	(0.0363)
Observations	866	866	866	866
R-squared	0.459	0.061	0.444	0.445
Number of hhid		542		

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 33: RDD approach: Effect of old age pension on CSPI with smaller sample, 2 years around the cut-off

VARIABLES	OLS MPI	FE MPI	First stage Pension dummy	RDD : 2SLS MPI
Pension dummy	0.00394	0.00765		-0.0265
	(0.00723)	(0.00820)		(0.0171)
Income without grants	-0.116	-0.0716	-1.892*	-0.180*
	(0.163)	(0.123)	(1.049)	(0.0968)
Pension eligibility			0.377***	
			(0.0369)	
Constant	0.0258	-0.384	0.0387	0.0176
	(0.0177)	(0.426)	(0.0809)	(0.0296)
Observations	866	866	866	866
R-squared	0.192	0.070	0.444	0.175
Number of hhid		542		

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 34: RDD approach: Effect of old age pension on MPI with smaller sample, 5 years around the cut-off

VARIABLES	OLS MPI	FE MPI	First stage Pension dummy	RDD : 2SLS MPI
Pension dummy	-0.00188	-0.00420		-0.0219
	(0.00833)	(0.00948)		(0.0184)
Income without grants	-0.874***	-0.516	-2.315**	-0.923***
	(0.211)	(0.400)	(0.979)	(0.250)
Pension eligibility			0.433***	
			(0.0297)	
Constant	0.195***	0.0834	0.0440	0.188***
	(0.0195)	(0.356)	(0.0559)	(0.0252)
Observations	1,502	1,502	1,502	1,502
R-squared	0.436	0.050	0.425	0.434
Number of hhid		955		

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.

Table 35: RDD approach: Effect of old age pension on CSPI with smaller sample, 5 years around the cut-off

VARIABLES	OLS MPI	FE MPI	First stage Pension dummy	RDD : 2SLS MPI
Pension dummy	-0.00158	0.0102		-0.0142
	(0.00556)	(0.00690)		(0.0115)
Income without grants	-0.150	-0.216	-2.315**	-0.181**
	(0.141)	(0.210)	(0.979)	(0.0793)
Pension eligibility			0.433***	

			(0.0297)	
Constant	0.0232*	-0.224	0.0440	0.0192
	(0.0130)	(0.352)	(0.0559)	(0.0202)
Observations	1,502	1,502	1,502	1,502
R-squared	0.186	0.054	0.425	0.183
Number of hhid		955		

Notes: i)*** p<0.01, ** p<0.05, * p<0.1; ii) standard errors in parenthesis iii) all of the variables mentioned within the summary statistics are also part of the regression but they are not shown here since the signs are similar to that found in the literature.