Multidimensional Perspectives on Poverty

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List of Abbreviations

2SLS Two-stage Least Squares

AF Alkire-Foster

CA Capability Approach

CSG Child Support Grant

CSPI Correlation Sensitive Poverty Index

DHS Demographic and Health Survey

FA Factor Analysis

GDI Gender-related Development Index

GEM Gender Empowerment Measure

GDP Gross Domestic Product

HDI Human Development Index

HPI Human Poverty Index

IV Instrumental Variable

LATE Local Average Treatment Effect

MCA Multiple Correspondence Analysis

MDG Millenium Development Goal

MIMIC multiple indicator and multiple choice models

MMP Money Metric Poverty

MPI Multidimensional Poverty Index

MRS Marginal Rate of Substitution

NIDS National Income Dynamics Survey

NMPLS Non-metric Partial Least Squares

OAP old age pensions

OLS Ordinary Least Squares

OPHI Oxford Poverty and Human Development Initiative

OWB Objective Wellbeing

PCA Principal Component Analysis

PLS	Partial Least Squares
PQLI	Physical Quality of Life Index
RDD	Regression Discontinuity Design
SALDRU	South African Labour and Development Research Unit
SEM	structural equation models
SWB	Subjective Wellbeing
UNDP	United Nations Development Programme
UK	United Kingdom
US	United States
USD	United States Dollar

1 Introduction

Robert F. Kennedy, in 1968, aptly described how wellbeing can be dissimilar to income and other such monetary measures:

> "The Gross National Product of the United States is the largest in the world, but that GNP, if we should judge our nations by that, counts air pollution and cigarette advertising and ambulances to clear the highways of carnage. It counts special locks for our doors and jails that break them. It counts the destruction of our redwoods and the loss of our natural wonder and chaotic sprawl. It counts napalm and the cost of a nuclear warhead and armoured cars that fight riots in our streets. Yet the gross national product does not allow for the health of our children, the quality of their education or the joy of their play. It does not include the beauty of our poetry or the strength of our marriages, the intelligence of our public debate or the integrity of our public officials, it measure neither our wit nor our courage, neither our wisdom, nor our learning, neither our compassion nor our devotion to our country. It measures everything, in short, except that which makes life worthwhile."[1]

Since the late 70s, there has been a great focus on the measurement of poverty and wellbeing, especially in view of the large inequality that emerged between developed and developing countries, as well as within countries. Reducing poverty has therefore been a chief concern for development policy, where, despite evidence of the high positive correlation between income and wellbeing, there are several instance of non-overlap between the two. As Kennedy fittingly describes it, people often value achievements and choices that do not appear, or are not easy to measure in an obvious way, in the income or growth figures. Therefore, there is both, a conceptual and ideological distinction between deprivation of choices, and that which primarily results from the inadequacy of income (Kakwani, 2006). This mismatch between income and wellbeing for individuals was first theorized by Sen, with the Capability Approach (CA) (Sen, 1999, 1985).

The Human Development Index (HDI), which was the brainchild of Mahbub ul Haq and Amartya Sen (United Nations, 1990), was the first step towards a measure that focussed on examining economic and social progress in a different way. Soon after the recognition that one required a move away from income or other monetary measures, to more broadly defined indicators of development and wellbeing, the Millennium Development Goals were adopted. These became the standard indicators along which improvements in basic deprivations that people throughout the world suffer from were measured. Both, the HDI and the MDGs, and other such broad based deprivation and poverty measures caught impetus in the wake of the Capability Approach.

The basic premise of the Capability Approach is that one defines an enhancement

[1] Retrieved from Alkire and Deneulin (2009)

or development of wellbeing, by the enlargement of peoples' choices. This may be by way of greater access to health and education services, increased security, cultural and political freedoms, improvement in leisure, better governance, strengthening of familial ties, etc. Therefore, these are all choices that could be modified in line with an individuals' expectations, when they picture progress and development. What Sen and other capabilities researchers argue is that these choices might not go hand in hand with increases in income, at the individual level, or GDP, at the macro level. That is to say, what may be defined as a functioning in one country might not be an option in another, or might hold a different meaning in a third one. This difference is especially relevant in the context of a developing country, as opposed to a developed country. For instance, to be considered healthy, a person's real freedoms and opportunities to achieve this functioning, or their capabilities, might be vastly different. While access to a good medical facility might be what limits this functioning in a poor village in India, in Germany, the issue might often be the quality of the health services. Another example is being able to express oneself freely, which in China may be limited by the freedom of press, whereas in Afghanistan, it is defined by how the restrictions to movement and education for women hinders their choices in life. These choices are often closely linked with human rights as well, and therefore, there is also a scope for differences to emerge not only across regions and countries, but across sub-populations. Practically, this can be observed within the differences in the Gender-related Development Index (GDI), which accounts for differences in these functionings across each gender within a country. Or this may also be reflected in the opportunities and freedoms available to a particular ethnic group, which was the situation for Black South Africans during Apartheid. Often one observes that these aforementioned functionings are not enhances by a larger income or wealth status. Therefore, these differences in capabilities across countries is exactly what defined the underlying differences in wellbeing across countries, ethnicities, regions and individuals.

One of the latest attempts at measuring human wellbeing under the purview of the CA is the Multidimensional Poverty Index (MPI), which was developed by the Oxford Poverty and Human Development Initiative (OPHI) and the United Nations Development Programme (UNDP) in 2010 (Alkire and Santos, 2010). It is an index that measures acute multidimensional 'poverty' at the household level, based on the Alkire-Foster (AF) dual cut-off methodology of measuring deprivations in wellbeing. Similar to the HDI in terms of its setup, consisting of three equally weighted dimensions, namely health, education and standard of living, it follows the guidelines set within the MDGs for defining deprivation in the ten indicators within its dimensions. The threshold for determining whether a household can be considered deprived in living conditions, such as adequate flooring, access to sanitation and drinking water, or the deprivation in health defined by child mortality and malnourishment, and the focus on child enrolment are all similar to the goals set within the MDGs. The MPI was the first of its kind to compute multidimensional poverty for data representing around 78% of the world's population, using three types of datasets (Demographic and Health Survey, Multiple Indicators Cluster Survey and World Health Survey). It was able to provide a more holistic measure of the extent of deprivation that households living in poverty can experience, in comparison to the \$1 a day poverty line proposed as a uni-dimensional measure of poverty.

Another strand of literature that has developed in conjunction with the income literature is one that focusses on happiness, satisfaction and subjective wellbeing as a measure of human welfare. Easterlin (1974) was the first to empirically test the relationship between happiness and income. The idea of using subjective wellbeing also comprises a latent or abstract notion of wellbeing which is hard to capture with a uni-dimensional measure like income. Therefore, the findings in the literature where individuals, despite limited income, are equally happy as individuals who are much more well-off (hedonic adaptation), or two relatively similar countries in terms of income have different levels of satisfaction (cultural influences) indicate different perceptions and ideas of wellbeing.

Recently there have been great strides in the measurement of both of these abstract' notions of wellbeing. The studies that examine happiness as a measure of wellbeing are largely empirical (Diener, 1984; Diener and Suh, 2000; Frey and Stutzer, 2007; Kahneman et al., 1999; Kahneman and Krueger, 2006), while the literature that discusses the CA has theoretical as well as practical applications (Alkire and Foster, 2011a,b; Nussbaum, 2001; United Nations, 1990).

Both of these concepts of wellbeing have been examined in view of their relation to income, and a clear distinction between income and both these measures has been established. However, given the relative novelty and complexity of both these approaches, they have seldom been brought together in scientific work so far. With the recent advances in data collection and survey techniques, a burgeoning list of indicators provide a suitable approximation of the broad concept of wellbeing and satisfaction. Moreover, a bevy of new techniques has also made it possible to undertake research on complicated and connected research questions and thereby assemble these two approaches under a single roof. The third essay in this thesis in an attempt to combine both these approaches and thereby address this gap within the literature.

Not surprisingly, these alternative measures of wellbeing have recently been often employed as either the main outcome, or as a secondary determinant of human development and societal progress. Development policy has also slowly been moving towards these measures as a more accurate description of wellbeing, or regarding them as a meaningful complement to money metric measures. In view of the many national and international schemes or programmes that would prefer overall wellbeing improvements as an outcome, there is surprisingly little work that can help one quantify and assess the impact of a particular programme on overall wellbeing and not just a particular dimension. The second essay in this thesis lays a critical eye on this issue, for the case of South Africa.

Due to the rising popularity of these measures, there is an increasing need for scrutinizing its fundamental capability to do exactly what it claims to do. An increasing number of scholars have delved into the issues that a composite measure like the MPI can suffer from, thereby reducing its ability to measure multidimensional wellbeing. A particular aspect of that is the weighting of each dimension and indicator to define poverty across region, and this thesis, within the first essay, bridges the gap between statistical methods and the optimal weighting schemes that can be used specifically to measure multidimensional wellbeing across countries.

This aim of this work is to contribute to the expanding literature on poverty and wellbeing, largely focussing on the CA, specifically the MPI. The main idea, arguments and implications of each of the essays are condensed below.

Essay 1: Capability Approach and it's regional comparability

The Capabilities Approach gained immense popularity through its operationalisation in the HDI, where the notion of wellbeing beyond income aggregates was considered. However, even with the widespread use and acceptance of the HDI, there were concerns about macro-level aggregates not being able to capture the idea of wellbeing for individuals themselves. This brought about a string of studies that emphasized the need of and the preference towards measurement of individual wellbeing, within the scope of the Capabilities Approach. In 2010, Sabina Alkire and Marie Emma Santos introduced the MPI measure acute multidimensional poverty at the household level (Alkire and Santos, 2010).

While several critiques surfaced with respect to this measure in terms of its dual cut-off methodology, the choice of indicators and dimensions, or its inability to reflect within-dimensions inequality, this essay focuses on another weakness in the conceptualization of the MPI, namely, the weighting of its three dimensions. The current equal weighting of all dimensions has been under scrutiny since its inception. The sensitivity of country rankings to different choices of weights and indicators has been a source of concern amongst the capabilities economists. Meanwhile, several developing countries have modified and developed their own measures to capture poverty as a multidimensional concept, reflecting their own national definitions of relevant deprivations (Alkire and Foster, 2011a). Indeed, it is reasonable to question that all countries have uniform standardized weights for the indicators when the basic socioeconomic conditions underlying them are very different. How far the weighting changes across regions is an empirical question, which Essay 1 aims to contribute towards.

Ravallion (2011b) and Decancq and Lugo (2013) examine indices of wellbeing and poverty critically, in terms of the weights that are derived for each dimension, and raise the issue of implicit trade-offs between dimensions in such indices. In the particular case of the MPI, it assumes that improvements in one dimension make up for the failings in another (like in other equal weighted indices) and concludes that the implicit trade-offs between (and maybe even more importantly, within) dimensions matter for what a poverty or wellbeing index claims to measure. This important consideration prompted the research into the appropriate weighting scheme for multidimensional indices of poverty (used interchangeably with wellbeing in this Essay) and is the main motivation for this essay. Essay 1 presents an analysis of the effect of an alternative weighting scheme on the Multidimensional Poverty Index (MPI), using a data driven - as opposed to a normative-approach for determining weights.

Using the Demographic and Health Survey data, I quantitatively evaluate the weights assigned to each of the indicators in 28 countries. These countries are selected to identify the different regions, which are Africa, Asia, Latin America and East EU-West Asia, and to have the most comparable information for building the MPI. There are several methods that have been discussed in the literature with respect to the creation of a multidimensional measure of wellbeing (Booysen et al., 2008), and Multiple Correspondence Analysis (MCA) is relatively popular in deriving weights for indices on the basis of multi-collinear, binary data- where we believe these latent ideas to identify multidimensional wellbeing in this particular case. Therefore, this methods will be employed within the analysis to determine the regional trends in the weighting of the MPI indicators.

The results show that equal weighting of the three dimensions cannot be justified statistically, and that the derived weights differ systematically across regions. The standard of living indicators are found to have the highest variation in all samples, comprising nearly 85 percent or more of the overall weight in several countries. Furthermore, in terms of regional trends, it can be seen that South Asian countries tend to have a larger weight in terms of the nutrition indicators, while drinking water seems to be particularly important for the Latin American and African regions. In comparison, assets and electricity receive much higher and lower weights, respectively, in the EU-West Asia region. This implies that each of these regions has a larger variation amongst that particular indicator/dimension, and by applying equal weights one might impose incorrect trade-offs between dimension, for that region. Given the large difference in the weights, and the possible regional trends observed, one can conclude that statistical weights are able to represent a statistically sound alternative to the current equal weighting scheme implemented within the MPI.

Essay 2: Capabilities as an outcome of a social intervention scheme

In the second essay, I try to causally establish the importance of the CA in terms of development policy. While the role of macroeconomic and microeconomic policies in influencing money-metric measures of poverty has been largely explored, these measures may over or understate the effectiveness of a particular intervention on mitigating overall deprivation. Therefore, they should ideally be complemented by other non-money metric measures of poverty (Sen, 1985).

The advantage of using the MPI lies not only in the inclusion of more indicators of actual wellbeing than only income or expenditure, but also the fact that it takes into account the intensity of the poverty for the number 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. That is, it is able to account for inequality within dimensions as well. The CSPI is the first additive poverty index that can be decomposed into all of the three I's of poverty: incidence, intensity, and inequality, where this third additional property has been found to make it easier to understand and tackle the associations within the dimensions of multidimensional indices of poverty. Rippin applies this method specifically for the MPI in her recent papers.

This essay makes use of both these indices as measures of multidimensional poverty and inequality, and examines the changes observed due to a public welfare programme in South Africa. For the 2014/15 fiscal year, South Africa allocated an estimated US $12 billion for social grants (Bhorat and Cassim, 2014). Moreover, nearly 76% of these grants were shown to have been received by the poorest 40% of the population, as evidence of the efficacy of this national scheme (Gutura and Tanga, 2014). With an extensive coverage and budget, it is one of the most progressive social security schemes among low and even middle income countries, and has been shown to help mitigate income poverty and inequality. Moreover, it has been shown to have a positive effect on household socioeconomic outcomes such as health and education, employment and other demographic outcomes. However, so far, there is no study that has accounted for the impact of this social security scheme on simultaneous deprivations within a particular wellbeing measure. This can partially be explained by the issue of data quality and comparability, which for a complex and comprehensive measure such as multidimensional poverty, is harder to obtain than for a unidimensional money metric measure. I use the NIDS panel data, over a period of four years, for South Africa, and estimate the impact that social assistance grants have on both the MPI and CSPI.

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, and are also found to be multidimensionally poor, is the simultaneity of both of these occurrences. Therefore, to attend to this issue of endogeneity, Essay 2 uses two well documented methods. For examining the case of child grants, I apply an instrument that has been introduced by Eyal and Woolard (2013), which is the potential difference in the duration of grant receipts. In the case of old age grants, I implement a fuzzy RDD approach to determine their effect on overall wellbeing. The results show that increases in the cash grant income lead to lower multidimensional poverty levels in households. A more important result is how cash grants seem to have also reduced the CSPI, which suggests that inequality among poor South African households is reduced by these grants. In the context of South Africa, which has high level of inequality, as measured by income, this is an important finding. Additionally, breaking this effect down to its core dimensions, health is found to be the major channel through which these grants work towards reduced multidimensional poverty and inequality.

Essay 3: Subjective wellbeing and the Capability Approach

Concurrent to the widespread use of traditional income or consumption based measures for determining human development, there has been growing interest in the economics of happiness since the late 70s. This field of study has analysed the various drivers of subjective wellbeing (SWB), along the lines of numerous theories- including telic, pleasure and pain, activity, top-down, bottom-up, associanistic and judgment. Likewise, there is a broad strand in literature that has defined and commented upon indices that merge numerous 'functionings', based on the capabilities approach, following a myriad of ideological judgments and objectives to determine objective wellbeing (OWB) (Alkire and Foster, 2011a,b; Alkire et al., 2011; Nussbaum, 2003; Ravallion, 2011b). Both these approaches are similar in their belief that income is often a poor determinant of wellbeing, which is a latent notion often better proxied with other broader definitions, subjective or objective.

Nonetheless, both there concepts are also not without issues, especially when one undertakes the exercise of comparing them. Subjective wellbeing (SWB) measures ignore a person's opportunities and understate the individuals' degree of deprivation on account of hedonic adaptation. One of the clearest examples of this hedonic adaptation is the paradox of "happy peasants and miserable millionaires", where individuals can adapt to misfortune and are therefore unmotivated to improve their situation. Moreover, given that these are subjective assessments that have a psychological basis, they might include a high degree of measurement bias. The CA by contrast would correct for both the hedonic adaptation and thereby the subjective nature of the measure by assigning a low functionings achievement to the poor peasant, and a high one to the millionaire, depending on their true capabilities.

On the other hand, the CA suffers from the lack of any guidance on how to choose and weight particular functionings that constitute overall welfare, as has already been mentioned in Essay 1. There have been attempts to define a particular list (Alkire, 2002; Nussbaum, 2003; Sen, 1985), and also methods that have attempted to reconcile functionings into a single index in a so called 'paternalistic setting of weights' (Alkire and Foster, 2011a; Robeyns, 2005). There is a large body of literature that discusses the problems that are imminent with the weights derived for multidimensional indices of wellbeing (Brandolini, 2007; Decancq and Lugo, 2013; Ravallion, 2011b, 2012). What would threaten the reliability of any such index is if there are individuals who have a high level of functionings (which could be because it is based on a particular set of weights or a given set of indicators) but nevertheless claim to be miserable (Binder, 2013). That is to say, if the discrepancy between subjective and objective assessments becomes too large, this approach would fail as a measure of assessing wellbeing. While this is more a general weakness of an OWB measure, in Essay 3, Stephan Klasen and I analyse this property specifically for the weights assignment in an OWB index. It is likely due to the complexities involved in both these aforementioned concepts that the link between non-income measures of well-being, following Sen's capability approach, and the happiness approach, has not been explored to a large degree. So far there is no work that empirically examines all three measures of deprivation together-Objective wellbeing (OWB), Subjective Wellbeing (SWB) and Money Metric Poverty (MMP). This is consequently the main contribution of Essay 3 to the literature on wellbeing deprivation and income poverty, where we generate a new index of wellbeing, which integrate both these measures to determine what individuals consider important for their objective wellbeing.

As a starting point, we explore the determinants of each of the measures of wellbeing-objective and subjective- as well as income poverty for the case of South Africa, using the National Income and Dynamics Survey (NIDS) data. Due to the richness of this panel dataset, we are able to gather information on all but one indicator of the MPI, which we use to operationalise the capability approach, as well as life satisfaction, used as a measure of SWB. We find that there are differences in the relevance of the covariates that determine OWB, SWB and monetary poverty. Therefore there are differences in the grouping of households based on the type of deprivation we are examining. Particularly, satisfaction is found to be largely driven by indicators which reflect the physical and mental condition of an individual, as postulated in the CA.

Thereafter, we derive a new index, based on alternative weights for the dimensions of the MPI that are particularly relevant for SWB and MMP. This is done with the Partial Least Squares (PLS) technique, using satisfaction and income as the response variables. The motivation for using PLS is its ability to determine the relevance of each indicator of the MPI in connection to the given response variable. It thereby allows one to impose an underlying model to fit these weights, unlike in the case of Principal Component Analysis (PCA) and Multiple Component Analysis (MCA) that function without any underlying assumptions as to how these weights are correlated to satisfaction and income. Therefore, our nine MP indicators are now weighted according to their correlation to satisfaction as well as income. As a robustness check, we also use PCA and MCA to derive these weights. This exercise is carried out for the case of South Africa, where we find that PLS and MCA both derive similar weights for the MPI indicators, while PCA slightly diverges, and that the most important indicators in the index are assets and sanitation.

Finally, we examine the nature and degree of hedonic adaptation that is found within our dataset and how the new indices of wellbeing react to this property of SWB. We find that, on average, households adjust to lower incomes and broader deprivations over time. Essentially, in the case of South African households, increasing objective deprivation does not lead to lower levels of satisfaction, relative to the household income. Moreover, we find that these indices that are derives using satisfaction are more sensitive to this property of SWB. Therefore, despite being based on an objective basis of measurement of wellbeing, they also manage to incorporate some of the adaptiveness that accompanies subjective wellbeing.

2 Regional Perspectives on the Multidimensional Poverty Index[1]

This paper analyses the consequences of an alternative weighting scheme for the Multidimensional Poverty Index (MPI), using a data driven approach, as opposed to the currently employed equal weighting scheme. This weighting scheme has been under strong scrutiny since the MPI's inception, given the sensitivity of country rankings to different weight and indicator choices. Therefore, this study employs a different weighting of the indicators and investigates its impact on the scores and relative ranking of 28 countries. The analysis is conducted using the Demographic and Health Survey data, to quantitatively evaluate the weights assigned to each of the indicators, employing Multiple Correspondence Analysis (MCA) techniques. Results show that equal weighting of the three dimensions cannot be statistically justified and that the statistical weights differ systematically across regions. Using the statistical techniques also does not change the household poverty rankings extensively, which indicates that while creating more statistically robust weights, one is able to maintain the poverty definitions to a large extent. Moreover, given the significant correlation between all indicators employed within the MPI- in trying to capture a more multidimensional view of poverty and well-being- there might not actually be so much multidimensionality within the three dimensions of the MPI.

JEL classification: I32, C43.
Keywords: Multidimensional poverty, weights, Principal Component Analysis(PCA), Multiple Correspondence Analysis (MCA)

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2.1 Introduction

In 2010, Sabina Alkire and Marie Emma Santos first published a Human Development Research Paper which aimed at identifying a new index to measure acute multidimensional poverty across 104 developing nations (Alkire and Santos, 2010). It was based on the Alkire-Foster (AF) dual cut-off methodology of measuring multidimensional poverty, which then has been widely used in national and global initiatives to measure multidimensional poverty (Alkire and Foster, 2011a,b).

The proposed Multidimensional Poverty Index (MPI) was not the first attempt to capture the multidimensional nature of wellbeing and deprivations. While some of the early composite indicators that focused on human resource development were already introduced in the 1960's, a greater focus upon more non-monetary/composite indicators of development came later (Santos and Santos, 2014). The Human Development Index (HDI) was a step towards the creation of a composite index, encompassing more than a single dimension of well-being, although it has been criticized on account of its choice in indicators (Ravallion, 1997). Additional examples include the Inequality adjusted HDI (IHDI), Gender Empowerment Measure (GEM), the Gender related Development Index (GDI) and the Human Poverty Index (which was supplanted by the MPI), to name a few. In the meanwhile, several developing countries have developed their own measures to capture poverty and other deprivations as a multidimensional concept (Alkire and Foster, 2011b). Nevertheless, the MPI was the first of its kind to compute multidimensional poverty for around 78% of the world's population using three types of datasets (Demographic and Health Survey, Multiple Indicators Cluster Survey and World Health Survey). It was able to provide a more holistic measure of the extent of deprivation that households living in poverty can experience, in comparison to the $1 a day poverty line, proposed as a uni-dimensional measure of poverty. Although there are several non-income measures of poverty that are of prominence, this is the first that uses micro-level data with a household as the unit of measurement. Dotter and Klasen (2014, p. 6) point out the utmost achievement of the MPI when they say that the main contribution of the MPI, vis-a-vis the existing work, is its breadth of country-coverage and its international comparability.

There are several strands of literature and analyses that discuss the weaknesses that are encountered when one creates a single measure to account for the multidimensional nature of poverty. This literature does not necessarily focus only on the weakness of this most recent attempt to understand the basic needs and capabilities that was suggested by Sen, called the Capabilities Approach (Sen, 1985). Rather, there has been a copious appraisal and a multitude of studies that deal with the challenges of using a dual cut-off method (as within the AF method) and the weighting scheme within the chosen dimensions (Ravallion, 2012, 2011b), the disregard towards the aspect of inequality within the dimensions and populations (Chakravarty and D'Ambrosio, 2006; Jayaraj and Subramanian, 2010; Rippin, 2015, 2012; Silber, 2011), or the need to adjust the dimensions in line with average well-being, to reflect the weakly relative nature of wellbeing and income (Dotter and Klasen, 2014; Ravallion and Chen, 2011).

The aim of this particular study is to calculate the MPI scores of countries, but not as an end in itself. This paper seeks to address a significant concern regarding the formulation of the MPI: Can the use of equal weighting assigned to the three dimensions be statistically justified? Should child mortality take a weight of 1/6 and the asset indicator be assigned a weight of 1/18? This is a specific concern, especially in view of this measure's attempt to quantify multidimensional poverty while maintaining global comparability. Indeed, can all countries have uniform standardized weights for the indicators when the basic socioeconomic conditions underlying them are very different? If not, how much does the weighting change between regions? Clark and McGillivray (2007), for example, suggested that amongst all the other critiques concerning composite indices, it is better to allow the components and weights to vary across regions and countries, taking into account local and regional preferences. An example of this rather infrequently used consensual approach to measuring poverty was the Breadline Britain survey, carried out in the United Kingdom in 1983 and 1990. This method sought to measure poverty in the UK by investigating what the local public perceives as the minimum necessary to be considered non-poor or alternatively, well off, and then identifying those who could not afford these necessities (Gordon and Pantazis, 1997). Based on the overall responses, the proportion of households who fell below this socially-determined or 'consensual' poverty line was then measured. The findings of the survey concluded that the important list of necessities for a British household would comprise of items such as presents for friends/family once a year, a holiday away from home and a washing machine. Not only were these items not featured in the absolute standards that were drafted some fifty years ago for the national poverty line, but they were also hard to imagine as relevant within the context of a middle- or low-income country. While this might be an extreme example of how preferences differ across countries, it is not far-fetched to imagine that different countries perceive different commodities as requisite for wellbeing.

Ravallion (2011a) and Decancq and Lugo (2013) examine indices of wellbeing and poverty critically, in terms of the weights that are derived for each dimension. They discuss the importance of implicit trade-offs between dimensions in such indices (wherein the MPI assumes that improvements in one dimension make up for the failings in another, like other equal weighted indices) and conclude that the implicit trade-offs between dimensions (and more so within dimensions) are important in terms of measuring what a poverty or wellbeing index claims to measure. This is a key theoretical consideration that prompts the research into the appropriate weighting scheme for multidimensional indices. Since the indicators of poverty cannot be considered similar across countries, given the differences in deprivation and needs across regions and changes over time, it also implies varying trade-offs for each dimension within the index itself. Therefore, the motivation of this work is to examine these indicators and dimension weights with the help of a data driven approach, where no paternalistic judgment is set upon definitions of poverty.

There are several methods that have been examined in the literature with respect to the creation of a multidimensional measure of wellbeing, and they will be discussed in further detail here. The main idea for this research builds upon the paper by NguefackTsague et al. (2011), wherein they perform a similar exercise for the Human Development Index and find that statistically, all three dimensions receive the same weight and therefore corroborate the story behind the equal weighing of the HDI. In an attempt to answer the question of the appropriate weighting scheme in the context of the MPI, a detailed analysis of 28 countries, across four different regions, is undertaken. These countries are in South Asia, Africa, Northern Africa-Western Asia-Europe (Eu-West Asia) and Latin America, which is how the Demographic and Health Survey (DHS) has categorized these regions as well. Although Multiple Correspondence Analysis (MCA) is primarily utilized within this analysis to statistically evaluate the weights assigned to each of the indicators, Principal Component Analysis (PCA) is often used as an additional check in some sections.

The results suggest that there are indeed differences in the definition of poverty, based on the distribution of the data. Not only is there no singular weighting scheme that can be used for describing poverty across two regions, this is not even found to be similar for two countries within the same region. This implies that the comparisons intended with the equal nested weights of the MPI are implying inaccurate trade-offs between poverty definitions across countries and regions.

This paper is organized as follows: the following sections provides a brief description of the Multidimensional Poverty Index (MPI), and then discuss the literature surrounding the shortcomings with the current weighting scheme. Section 4.4 explains the methodology and the conducted analyses, section 4.3 describes the data, while section 2.6 details the results from the analysis. The next section tries to test the methods and the results more rigorously. Finally, I discuss the various conclusions that can be drawn from these results and how it can be applied in understanding the nature of multidimensional poverty across countries.

2.2 The Multidimensional Poverty Index (MPI)

The MPI is not the first of its kind to define the multidimensional nature of poverty. There have been closely related multidimensional poverty measures proposed in the literature before Alkire and Foster (2011a,b) suggested their own measure, such as the Physical Quality of Life Index (PQLI) (Morris, 1979), the HDI, or the HPI (United Nations, 1990) to name a few. These are also based on the (weighted) aggregation of deprivations across dimensions, some using ordinal data and some based on original macro data from each country. However, the focus of this paper will not be to examine the differences within these measures, but rather to examine the relevance of the weights of the MPI in a global context, which is among the first multidimensional index applied to many countries using micro-level data and building up an aggregate index from these micro data.

The MPI uses 10 indicators, broadly categorized into 3 dimensions, namely health, education and standard of living. The weights are nominally assigned to each dimension, to constitute an index with equally weighted dimensions, i.e. one third each, and the indicators within these dimensions also assume equal weights amongst themselves (equal nested weights). Table 2.1 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 the particular basic functioning or not. Most of the standard of living indicators follow the Millennium Development Goals (MDG) guidelines, and their cut-offs are set on that basis. Each household receives an *apriori* weight when it fails to pass the cut-off and is therefore considered to be deprived in terms of that particular indicator. In the end, the weights for each of the deprivations are summed up to generate the weighted deprivations matrix for each household. Based on the dual cut-off method, a household has to be deprived in at least the equivalent of 33 percent, or equivalently, have a weighted deprivation score larger than .33, in order to be considered multidimensionally poor. All households that have a score of 0.33 or less are not considered multidimensionally poor as per the MPI.

Table 2.1: The Multidimensional Poverty Index

Indicator	Weight	Deprived
Health	1/3	
Child Mortality	1/6	If any child has died in the family
Nutrition	1/6	If any adult or child in the family is malnourished (BMI<18.5 for adults & z-score<2SD for children)
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/ 8-16
Standard of Living	1/3	
Electricity	1/18	If there is no electricity
Drinking	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

The MPI for a country is calculated as the product of the Headcount (H), which is the percentage of households whose weighted deprivations lie above the 33% cut-off and are therefore considered multidimensionally poor, and the intensity of Deprivation (A), which reflects the weighted sum of deprivation for only the multidimensionally poor households within each country, thereby the average intensity of poverty for these poor households. By construction, those households that are not poor are not included within the intensity and therefore the intensity is always above 33% at least.

Although the AF dual cut-off method does not specify dimensions, indicators, weights or cut-off points, 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, 2010). There has also been a considerable amount of discussion, as well as a stream of literature that discusses the merits of this dual cut-off approach adopted within the AF method, functioning as an intermediary between the intersection and union approaches to multidimensional poverty (Dotter and Klasen, 2014; Ravallion, 2012; Rippin, 2015, 2012).

A particular concern that is often raised with the formulation of the MPI, and one that is the main focus of this paper, is the robustness of the current weighing scheme in the AF methodology. Following Atkinson et al. (2002), Alkire and Santos also opted to go for an equal weighting within their dimensions, and equal nested weights within the dimension for each of the indicators. Moreover, they also follow up on the HDI convention and the ensuing literature that discusses the merits and demerits of equal weighting across and between dimensions. Their reasoning for choosing equal weights is related to the issues of transparency, as well as comparability, over space and time. This issue of comparability, however, has already been contended, in the case of the HDI by Srinivasan (1994), who argues that while one achieves international comparability via equal weighting, it comes at the cost of relative comparability across individuals, countries, and socio-economic groups. It therefore questions the conceptual nature of the weights and the biases involved therein. Therefore, the same question arises in the case of the MPI: what do these equal weights imply conceptually and statistically for poverty measurement across countries and over time?

2.3 Choice of Weights

Weights for any composite index of wellbeing can be based on the trade-offs they imply between the dimensions of wellbeing, and these trade-offs can be expressed on the basis of the Marginal Rate of Substitution (MRS) between the dimensions (Ravallion, 2011b). The marginal rate of substitution between two dimensions (indicators) is defined as the amount an individual is willing to give up from one dimension (indicator) for an extra unit of the other dimension (indicator), while maintaining the same level of wellbeing. This MRS is composed of three different components: the ratio of dimension-specific weights, the ratio of the derivative of the transformation function of each dimension, and the ratio of the transformed achievements raised to the power of a value β, which effectively describes the elasticity of substitutability between dimensions (Decancq and Lugo, 2013; Annoni and Weziak-Bialowolska, 2014).

In one of the components, the derivative of the transformation of dimensions, which implies how particular achievements are transformed or rescaled into comparable values, are divided to achieve a ratio.[2] The steeper the transformation of one achievement, the greater the amount of the other achievement is required to compensate a unit loss in the former, while maintaining the same level of poverty. In principle, the ratio of the derivates of the transformation implies that the scarcer the achievements are, the more valuable they become. Therefore, the amount of another dimension (indicator) needed in order to compensate for access to drinking water is higher in a desert or arid nation, in comparison to a tropical, water-abundant one. Nonetheless when the MPI allots equal weight to the drinking water for each country, this implies that these difference across regions are not considered. Similarly, for the case of India, where there are high levels of malnourishment (FAO, 2015; Klasen, 2008), the cost of improving this aspect of wellbeing is much steeper in comparison to Ivory Coast, which has much lower levels of wasting, but has a similar poverty head count. While this particular component is not really affecting the dichotomous counting approach as of each indicator within the MPI, this does affect the overall dimension weight, where health and education weights differ from 0 to 0.167 to 0.33, and more importantly the standard of living dimension, where the weights increase at 0.56 intervals from 0 to 0.33. Therefore, there are several levels or categories of poverty within each dimension.

A second component of the MRS entails the ratio of the dimension specific weights between two dimensions. If dimension A is assigned a larger weight than dimension B, then a person would be willing to give up more than one unit of dimension B in order to compensate for one unit of dimension A. In terms of the MPI, this can be loosely trans-

[2]This transformation is important in the case of indices, such as the MPI, where the included achievements can be measured using different scales, for example, income with money, health with years, nutrition with BMI, etc.

lated to the within dimension comparisons, or alternatively the comparisons between the standard of living indicators versus the education and health indicators, wherein the latter have higher weights. Equal weights imply that in all countries the trade-offs between child mortality and years of schooling are equal. Alternatively, child mortality and sanitation would be traded off at a rate of 1/3. Regional differences in poverty make it much more important to adequately measure this trade-off between dimensions, especially when one accounts for the policy manoeuvres to tackle poverty and improve wellbeing.

The third component of wellbeing relates to the elasticity of substitution between the dimensions. Given that the MPI is a weighted linear aggregation of binary indicators, and therefore imparts perfect substitutability between the dimensions (as well within the indicators), one assumes a constant trade-off between all achievements. Effectively, the MRS is now assumed to be exactly the same as ratio of the weights between the dimensions, i.e. the elasticity is assumed to be equal to 1.[3] Thereby, we assume that each of these dimensions is equally important, although there is a large difference between the dimensions, and especially the indicators within. This implies that a unit increase in any of the health indicators would compensate for a unit decrease in three standard of living indicators. Inherently, these are value judgments, which cause concern in the realm of differential development levels across countries and over time.

Decancq and Lugo (2013) provide an overview of some of the recent studies that have proposed multidimensional indices of wellbeing and poverty. They present a brief discussion on choices while generating weights in creating composite indices. In empirical applications of indices of wellbeing, three different methodologies, which are also employed within the literature, are presented: normative weights, empirically derived or data driven weights and lastly, hybrid weights. For the purpose of this paper only the data driven weights are discussed.[4]

In this approach for weighting dimensions within indices, it is more the distribution of the achievements in the society that are considered important, and there are no value judgements made about how the trade-offs between the dimension should be. One of the three methods that Decancq and Lugo (2013) discuss within data driven weights are statistical weights, which can be further split along two approaches: a descriptive versus an explanatory model. The descriptive approach applies multivariate statistical methods to

[3] This elasticity can lie between 0 and 1, where in the case of increasing deprivation with higher values, increasing this from 0 to 1 implies that more importance would be allotted to the lower end of the distribution.

[4] For a detailed comparison of these other two methods- normative weights and hybrid weights, refer to Decancq and Lugo (2013). Within the category of data driven weights there are three kinds of weighting approaches analysed: frequency based weights, most favourable weights and statistical weights. Frequency based weights are determined as a function of the distribution of the achievements in a particular dimension, i.e. the more frequently there appears to be deprivation in a particular dimension, the more weight this dimension receives. Brandolini (2007), however, empirically shows the weaknesses of the frequency weights in terms of their instability (while applied on Italian data) and moreover the relativity of this measure in terms of describing wellbeing. Most favourable weights, in the same line, are also rather subjective, wherein an individual gets to select the most favourable weighting scheme for themselves. They therefore maximize individual wellbeing, making it hard for comparison purposes. Moreover, it is also problematic in determining the trade-offs between dimensions, as to how a particular individual determines their own wellbeing. This method has also been used to assess macroeconomic performance (Melyn and Moesen, 1991) and more recently also in the construction of composite indices of wellbeing (Despotis, 2005, 2004; Mahlberg and Obersteiner, 2001).

assimilate and summarize information from the data. A statistical technique that is commonly used in this approach is Principal Component Analysis (Klasen, 2000; Noorbakhsh, 1998; Filmer and Pritchett, 2001), which is found to correct for the oft occurring problem of double-counting. This generally occurs when indicators of wellbeing that are usually included within an index, to proxy for deprivation, bear a high degree of correlation to each other, effectively capturing the same latent dimension. The larger the correlation, the greater the overlap of information. These statistical techniques are then useful in reducing the dimensionality of the data, while retaining a large share of the information, i.e. to ascertain the internal statistical consistency of the indicators included to derive a particular latent concept (Annoni and Weziak-Bialowolska, 2014).

The explanatory approach assumes that some of the observed indicators are dependent on a set of unobserved latent variables. This relation manifests itself in the observed indicators, and therefore these single indicators can thereby be used to measure this underlying concept (Krishnakumar and Nagar, 2008). These relations between the observed variable and the unobserved latent concepts can be easily assigned by factor analysis, while more complicated methods, such as structural equation models (SEM), multiple indicator and multiple choice models (MIMIC), Rasch models etc. are also used. On the other hand, Principal Component Analysis and Multiple Correspondence Analysis (MCA) are methods used for purely descriptive weights, i.e. to derive the latent concept behind the variables without assumptions regarding the underlying explanatory model and thereby aggregating several dimensions into a single method of poverty measurement. For the purposes of this analysis MCA is used, and will be explained in further detail later.

The reasoning by Alkire and Santos (2010) for following an equal weighting scheme was based off of a paper by Atkinson et al. (2002) and the merits of using equal weights was not addressed to a large degree. They themselves ascribed these equal weights to have been determined on the basis of normative judgments, or expert opinions based on 'reasoned consensus', which determine health, education and standard of living to have equally intrinsic value. However, as these capabilities are in themselves valued differently across regions, to consider them equally important is a rather strong normative judgment. Therefore, to consider equal weighting a sound aggregation method for an index measuring poverty across regions, often disregards the importance of a capability (indicator) in relation to other capabilities (indicators) as well as how much importance should be accorded to the improvement in one capability with respect to the other in each region.[5]

This paper, aims to examine the literature and contribute to it by providing a more global picture of how the weights within the MPI can differ and how the picture of poverty

[5]Their main reference to resolving the issue of equal weights is the paper by (Chowdhury and Squire, 2006), which provides a more detailed examination of weighting within composite indices, where they specifically examine the HDI. What this paper does is to compare two approaches: equal weighting and consensual approach (where they derive weights based on a regressions analysis of the responses from surveys in the sample countries). While they find that the consensual weights are not very different from the equal weights in their analysis, this cannot be entirely applied to the MPI as well for several reasons. While the HDI uses only three dimensions, the MPI has 10 indicators within, which were also given equal nested weights. The weighting that therefore applies in this case may be different than in the case of only three indicators. Moreover, there were no other methods used apart from regression analysis, wherein they clearly mention that there is sampling bias, especially self-selection. Moreover, given that the respondents were aware of the survey motive itself there was a chance that their responses were primed towards a particular response as well.

changes when one uses more regional definitions of poverty. Moreover, this paper will also attempt to discern the regional differences in weights with the help of a conditional correlation.

2.4 Empirical Methodology

Following the literature on asset index creation, there have been several proposed methods to calculate the appropriate weights for the variables included (Annoni and Weziak-Bialowolska, 2014; Booysen et al., 2008; Chowdhury and Squire, 2006; Decancq and Lugo, 2013; Ravallion, 2011b; Santos and Santos, 2014). When it comes to normally distributed, non-collinear data, one of the examples of establishing the weight of a certain variable could be a linear regression. But often the problems one runs into is that most of the variables that could be used are highly collinear, which is a problem that the OLS method is susceptible to. Therefore, it is necessary to ensure that the proposed method of constructing indices is able to remove this problem entirely, while being able to deal with the large amount of information contained within the data. Data reduction techniques that are most often used in the construction of asset indices, and also incorporate this collinearity issue, include factor analysis (FA), principal component analysis (PCA) and Multiple Correspondence Analysis (MCA). Contingent on the data and its properties, one can decide which one of these multivariate statistical techniques suits the analysis best, and consequently use it in the creation of an asset index.

In terms of the procedures to formulate an index to capture the latent or unobservable underlying concept in any setting, Principal Component Analysis (PCA) is widely used in empirical applications as an aggregating technique (Annoni and Weziak-Bialowolska, 2014; Krishnakumar and Nagar, 2008). It is a method that was first applied in 1933 by Hotelling in the statistical literature, but was then widely used in several disciplines of science, including psychology, biology and anthropology. Recently it has also been extensively applied in finance and economics. In terms of the welfare literature, the earliest application of PCA has been on the three dimensions of the PQLI (Ram, 1982). More recent applications are in Klasen (2000), Nagar and Basu (2002), Filmer and Pritchett (2001), Noorbakhsh (2003), McGillivray (2005) and Annoni and Weziak-Bialowolska (2014).

Despite the suitability of this technique in reducing the dimensionality of large datasets, as well as its ability to perform an orthogonal transformation on seemingly correlated variables, there are also some drawbacks to Principal Component Analysis. There is no underlying explanatory model in this method and often the derived results remain a black box, which are hard to explain. Techniques such as Structural Equation Modelling (SEM) and Multiple Indicators and Multiple Causes Modelling (MIMIC) are more feasible, in that they generate a particular model based on these variables. However, if we believe that the indicators that have been included within the analysis are best able to capture a particular latent concept, then PCA is able to determine scores on these given indicators.

Another important drawback of PCA is its unsuitability for binary data, where methods such as the Non-linear Principal component analysis (Coromaldi and Zoli, 2011), Polychoric PCA Moser and Felton (2007), or the Multiple Correspondence Analysis (MCA) are better suited (Booysen et al., 2008). PCA was a technique developed largely for continuous data, measured in the same units for all variables, while MCA on the other hand imposes fewer restrictions within the data structure and is therefore is considered a better technique for binary and categorical data (Asselin, 2009; Booysen et al., 2008). Since all the variables in the case of the MPI are binary, MCA is found to be the preferred methodology in determining statistical weights in this analysis.

2.4.1 Multiple Correspondence Analysis

Multiple Correspondence Analysis, or MCA, applies the same techniques as Correspondence Analysis (CA), and reduces the dimensionality of the large dataset by creating orthogonal components containing each indicator, wherein the latter have a given weight. It was first developed by Bencrézi in 1973 and presented and explored to a larger extent by Greenacre in 1984 and 2006 (Greenacre, 2007, 1984; Greenacre and Blasius, 2006). The technique resembles PCA, in that it maximizes the separation between column and row scores. However, MCA applies a singular value decomposition instead of an eigenvector decomposition, as in PCA. It disregards the distributional or linearity assumptions, upon which correlation coefficients rely that are nonetheless present in the PCA method. This is a desirable quality in the method, especially given that the deprivation matrix in this paper contains values for households which are only binary. Since binary data are not numerical, the association between categorical and count variables cannot be measured in terms of covariance and correlation, which makes PCA unsuitable to be applied to this type of data (Merola, 2015). As (Booysen et al., 2008) mention, PCA assumes that the distances between the categorical values are the same, which the MCA does not, and imposes a chi-square metric (instead of the Euclidean metric). Moreover, MCA is a multivariate method that can be effectively used to analyse any mixture of binary, categorical, discrete or continuous variables (Traissac and Martin-Prevel, 2012).

It is used to represent and model datasets as 'clouds' of points in a multidimensional space, whereby the relative positions of the points and their distribution along the components are important for the interpretation. The closer the categories are in distribution, the smaller the distance between them in space will be. As in PCA, this is also a descriptive technique, where we do not assume any underlying model that connects these latent variables. While it is similar in terms of the principal behind PCA, MCA is able to overcome the shortcomings that the former suffers from.

For the specific case of poverty index computation, there are two advantages that are cited by Asselin (2009) and Ezzrari and Verme (2013), who apply this technique in a multidimensional poverty analysis for Morocco and Vietnam respectively. First, MCA gives larger weight to categories within the indicator that have a fewer number of observations within a particular dimension. This property, called marginalization preference, overweights the smaller categories within each indicator, while in the case of a binary indicator the marginal category will receive a higher weight. The second computational advantage is reciprocal bi-additivity. In essence, this means that the composite indicator scores derived using MCA are the simple average of the weighted sum of each modality (binary in our case) within each indicator (Asselin, 2009). In other words, MCA can be applied on either the row profile (each observation) or the column profile (each category within the indicator) of the indicatrix-matrix. Njong and Ningaye (2008) use both PCA and MCA, among other techniques, to study multidimensional poverty in Cameroon and find that PCA estimates unambiguously show lower levels of poverty than those that are obtained from MCA. Therefore, it is a method that is more sensitive to capture deprivation in terms of wellbeing. Given the singular vector decomposition in MCA, one arrives at two different weights for each indicators, while the eigenvector decomposition in PCA gives us only one weights per indicator. This is highly crucial in terms of interpretation of these weights for each indicator.

Due to the greater suitability, as well as the general statistical preference of the MCA in creating indices using categorical and binary data, greater confidence is placed upon the results from this method than those of PCA. However, given the similarity in the techniques and thereby the results, as well as the high correlation between the two indices that has also often been found in literature, the former is also used as part of the analyses within the paper.

2.5 Data

The Demographic and Health Survey (DHS) is used for all the 28 countries.[6] The adequacy of this particular dataset can be justified for two reasons. First, standard guidelines for the questionnaire and surveying have been followed, which ensures greater homogeneity and comparability than any other nation based household survey. Second, all relevant and necessary information pertaining to health, education and standard of living is contained in the survey. Although there were many more countries in the analysis initially, several countries could not be considered, since data was only available for 9 or even 8 out of the 10 indicators. Furthermore, in some cases the data for the other indicators was found to be mostly missing or it consisted entirely of missing values. This is also a reason why some of the regions in the analyses have a large number of countries while some have much fewer. Even the OPHI, while computing their global MPI, use different datasets for several countries, especially for Latin America. However, the African region does not have a more standard and comparable survey other than the DHS. Hence, relying only on this survey, there are many more African countries than South Asian, Latin American or from the Eu-West Asian region.

Given the aforementioned reasons, only 28 countries were eventually considered. Thereafter, four regional divisions were made, based on the very same classification made by the DHS as well. From the 28 countries, some were categorized as African countries, namely Benin, Cameroon, Congo DMR, Congo Republic, Ethiopia, Ghana, Kenya, Liberia, Malawi, Mali, Mozambique, Namibia, Niger, Nigeria, Swaziland and Zambia. There were four countries in South Asia (India, Bangladesh, Nepal and Cambodia), four from the Latin American and Caribbean region (Bolivia, Dominican Republic, Haiti and Peru) and lastly

[6] The reasons for the choices of countries in this case are to ensure that there is maximum comparability within the countries. The OPHI used the Demographic and Health Survey (DHS) data for several countries and the World Health Survey (WHS) data and the Multiple Indicator Cluster Survey (MICS) for particular countries. Besides these three main survey data, for some countries in Latin America, they also use individual surveys which have all the information that is contained to form the MPI. Therefore, although the OPHI used different sources for the data collection, the countries that are selected for this study are only those which have the Demographic and Health Survey data available.

Armenia, Azerbaijan and Moldova were part of the North Africa-West Asia-European region (Eu-West Asia).

However, using only the DHS survey has its own shortcomings as well. Ideally, use of the same year data for all countries would have enabled temporarily consistent weights. This is not possible in the case of the DHS since the surveys were conducted in different years in each country. Nevertheless, to mediate this issue as much as possible, surveys between the years 2003 and 2007 are taken for all countries, which yields a mean year of 2005 in the sample. Nonetheless, this should not cause too much concern, since in most cases the same phase of the DHS was captured. Moreover, there should also not be a large jump in progress for the time period, given that the largest difference between two countries was around 3 years.[7]

2.6 Results and discussion

2.6.1 Multiple Correspondence Analysis

In this section, the results related to the MCA techniques. These are displayed in Table 2.2. As a robustness check, Table 2.3 performs the same analysis using PCA. These are followed by additional robustness checks for the MCA technique, to examine how the weights differ with changing samples and if these regional differences are significantly different.

In this study, given that the first component was able to capture, on average, nearly 94% of the overall variation in the data, it is the only one that is utilized for the analysis hereafter. Despite MCA being a better suited technique for categorical and binary data, there are still two countries that have around 23-25% of their variance unexplained (Moldova and Azerbaijan). Nonetheless, since this is approximately only 7% of our total sample of countries, they do not compromise the results in the paper.[8] As mentioned, the use of MCA always leads to a weight ascribed to each of the categories within every indicator, which gives us 20 weights, one each for the 0 and the 1 category of the 10 indicators. Since this different categorization is not so clear in terms of the overall contribution of each indicator, the weights that are shown in the table are produces after summing the values of the contribution of each of the two binary categories. Table A2.6 in the appendix lists the weights derived by each category of the binary indicators individually as well. These weights depict the weight that is laid upon deprived individuals versus non-deprived ones. This varies largely amongst countries, where some have much larger contribution from the deprived individuals (most of the EU-west Asia region, Morocco, Bolivia, Nepal and Camodia), while several have the variation stemming mostly within the 0 binary category, i.e. the non-deprived (Congo DMR, Malawi and Niger).

[7] TableA2.1 in the appendix shows the years and phases of the DHS survey for each country in the sample.

[8] Since the variation explained is still very high, at around 75%, these results are still relevant and cannot be deemed incorrect or misleading in the first place.

Table 2.2: The weights assigned to countries based on MCA

	Years of Schooling	Child Enrolment	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Assets	Variation Explained
Original	16.67	16.67	16.67	16.67	5.56	5.56	5.56	5.56	5.56	5.56	-
Cameroon	9.40	3.80	1.20	0.40	27.10	8.00	0.20	22.90	13.00	14.00	93.77
Congo DMR	3.80	1.60	0.60	0.10	29.70	5.60	6.50	24.50	12.00	15.50	97.16
Congo Republic	3.40	0.70	0.50	0.40	24.80	6.90	10.80	16.70	13.70	22.20	96.48
Ethiopia	8.60	3.10	1.10	0.50	20.00	4.80	11.30	20.20	13.20	17.20	98.94
Ghana	9.10	4.00	1.40	1.90	24.20	16.60	3.60	7.70	22.10	9.40	89.83
Kenya	4.50	1.80	1.30	2.00	23.00	9.80	12.10	20.10	17.40	8.20	95.63
Liberia	11.00	0.20	0.00	0.10	10.00	19.60	5.30	25.20	0.30	28.40	93.94
Malawi	3.60	0.50	0.30	0.20	26.70	23.80	3.70	17.30	19.50	4.50	92.44
Mali	14.70	2.80	1.20	0.60	29.50	5.10	8.80	25.90	1.30	10.00	89.36
Morocco	8.30	4.90	1.50	0.50	18.20	14.30	11.90	15.20	8.10	17.00	98.70
Mozambique	13.60	1.90	0.50	0.60	24.90	11.40	10.90	19.00	9.00	8.10	94.40
Namibia	3.50	1.00	0.50	0.60	22.90	16.00	4.40	17.20	21.90	11.90	97.82
Niger	9.40	2.80	1.10	0.20	22.60	9.80	9.90	22.10	4.80	17.20	95.71
Nigeria	9.60	6.80	3.70	2.10	21.30	6.10	8.50	17.10	18.80	6.10	93.58
Swaziland	2.80	1.70	0.50	0.30	26.60	11.30	12.20	7.90	21.30	15.40	95.53
Zambia	3.40	1.00	0.10	0.20	27.00	9.70	9.80	18.10	21.80	8.90	96.94
Zimbabwe	1.10	1.10	0.40	0.30	27.70	5.50	9.10	14.30	26.70	13.90	97.56
Africa	**7.05**	**2.34**	**0.94**	**0.65**	**23.89**	**10.84**	**8.18**	**18.32**	**14.41**	**13.41**	**95.16**
Armenia	5.20	1.10	0.30	0.10	1.40	6.30	1.80	1.30	7.50	75.20	89.61
Azerbaijan	3.70	1.70	3.00	1.30	7.30	7.70	11.10	4.30	20.00	39.80	75.73
Moldova	4.40	1.60	0.10	0.00	5.00	3.00	1.30	10.00	17.00	57.50	76.82
Eu-West Asia	**4.43**	**1.47**	**1.13**	**0.47**	**4.57**	**5.67**	**4.73**	**5.20**	**14.83**	**57.50**	**80.72**
Bangladesh	8.60	0.50	1.10	3.50	20.20	9.30	0.50	26.90	15.90	13.50	93.68
Cambodia	10.70	3.20	1.30	0.30	29.30	24.80	4.80	0.10	14.50	11.00	92.51
India	7.90	3.00	2.00	2.70	14.70	12.40	2.20	19.70	19.70	15.80	97.80
Nepal	7.90	2.60	1.60	2.40	18.20	8.90	1.80	21.30	16.90	18.60	94.31
Asia	**8.78**	**2.33**	**1.50**	**2.23**	**20.60**	**13.85**	**2.33**	**17.00**	**16.75**	**14.73**	**94.58**
Bolivia	6.40	1.80	0.80	0.20	23.20	3.40	10.40	18.20	21.40	14.20	96.07
Dominican Republic	11.40	1.00	0.20	0.30	13.70	6.00	6.50	12.20	24.00	24.70	97.80
Haiti	14.40	3.50	1.10	0.10	23.30	6.00	4.20	19.10	4.40	23.90	97.15
Peru	5.30	0.50	0.40	0.00	18.00	11.90	8.10	16.50	19.60	19.50	98.21
Latin America	**9.38**	**1.70**	**0.63**	**0.15**	**19.55**	**6.83**	**7.30**	**16.50**	**17.35**	**20.58**	**97.31**
MCA Average	**7.35**	**2.15**	**0.99**	**0.78**	**20.73**	**10.14**	**6.85**	**16.46**	**15.21**	**19.34**	**93.84**

When looking at the weights from Table 2.2, some patterns can be ascertained for countries that lie within each region. At the outset, it is clear that the analysis shows no data driven justification for equal weighting of the dimensions. The weight of the education dimension is around 10% on average, while health gets a relatively low weight of around 2%. In the education dimension, years of schooling seem to take precedence over child enrolment, with nearly 4 times the weight of the latter on average. In some cases, this was much larger (Liberia, Bangladesh and Dominican Republic), while in some it was less than double (Morocco). Child mortality is found to weigh higher on average in comparison to the nutrition indicator, although this is not such a big difference as in the case of the education indicators. However, the standard of living indicators account for more than 85% of the total weight on average and nearly 95% (or even more) in the case of certain countries such as Congo Republic, Democratic Republic of Congo, Namibia, Armenia, Azerbaijan and Peru, to name a few. Within the standard of living indicators, on average, electricity receives the largest weights in the Index (21%). Behind that, the highest weights are assigned to assets (19%), closely followed by flooring (16.5%).

With regards to regional trends, countries in Asia tend to have a much higher weight than normal for the nutrition indicators, except for the case of Cambodia (which falls more in the case of South East Asia and is not geographically/culturally as close to the other three countries). This is not surprising, given that these are countries, especially India, where there are a massive number of people, especially children, who suffer from malnourishment(FAO, 2015; Klasen, 2008). The African countries tend to have higher weights, in comparison to the other countries, for all of the standard of living indicators, most importantly for electricity, except in the case of assets. This is in stark contrast to the EU-West Asian region, where the weight allotted to the assets indicator is very large, and often more than one third of the overall weight itself. Since these largely different weights are quite unexpected, the next section derives weights using PCA, as a check on the MCA weights.

2.6.2 Principal Component Analysis

Table 2.3 depicts the weights that were derived using PCA, but only the first principal component for all the countries. The cronbach's alpha for all the variables in the case of the following countries ranges between 0.65 and 0.8, except for certain countries such as Armenia and Azerbaijan, where it is as low as 0.25 and 0.29 even. All countries with an α-value less than 0.65 have been italicized (9 out of total 28 countries). This can be construed to imply that the variables are not suitable to construct a single latent variable that defines multidimensional poverty and perhaps more than one component is required for constructing an index on wellbeing. Alternatively, it can be concurred that PCA is not a suitable technique for these countries. The results of these countries should perhaps be considered in the context of this deficit of internal consistency.

Table 2.3: The weights assigned to countries based on PCA

	Years of Schooling	Child Enrolment	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Assets	Cronbach's Alpha	Variation explained
Original	16.67	16.67	16.67	16.67	5.56	5.56	5.56	5.56	5.56	5.56		
Cameroon	11.08	4.19	1.77	0.57	22.85	9.67	0.22	20.92	14.52	14.19	0.69	29.32
Congo DMR	*5.09*	*2.33*	*0.77*	*0.25*	*23.79*	*7.34*	*8.44*	*21.69*	*13.70*	*16.61*	*0.64*	*28.75*
Congo Republic	4.41	0.90	0.61	0.44	21.34	8.58	12.27	16.86	14.58	20.01	0.67	27.85
Ethiopia	9.80	3.85	1.51	0.62	18.14	5.90	12.20	18.21	13.62	16.14	0.80	41.47
Ghana	*10.89*	*5.00*	*2.01*	*2.51*	*21.05*	*15.24*	*4.80*	*9.31*	*18.70*	*10.49*	*0.59*	*24.04*
Kenya	5.37	2.17	1.74	2.72	19.10	10.90	13.10	18.60	16.65	9.65	0.75	32.86
Liberia	*12.88*	*0.30*	*0.09*	*0.18*	*11.64*	*18.61*	*7.47*	*23.17*	*0.45*	*25.20*	*0.50*	*23.07*
Malawi	*5.16*	*0.81*	*0.52*	*0.46*	*24.18*	*20.83*	*5.49*	*17.77*	*18.25*	*6.53*	*0.50*	*25.53*
Mali	*15.92*	*3.67*	*1.25*	*0.91*	*24.32*	*6.97*	*11.08*	*22.65*	*2.04*	*11.19*	*0.58*	*23.90*
Morocco	9.06	5.69	1.80	0.54	16.70	14.16	12.36	14.81	9.14	15.71	0.76	33.44
Mozambique	14.74	2.63	0.78	0.92	19.49	12.72	12.52	16.95	9.77	9.49	0.66	28.59
Namibia	3.96	1.43	0.70	0.97	20.40	16.46	5.81	17.26	19.98	13.04	0.77	35.53
Niger	10.66	3.57	1.16	0.34	19.76	11.24	11.14	19.49	6.09	16.55	0.72	34.41
Nigeria	10.69	7.14	4.07	2.52	18.24	7.26	9.60	16.25	17.41	6.81	0.73	30.92
Swaziland	3.49	2.48	0.70	0.47	22.29	12.98	13.68	9.78	19.03	15.10	0.69	28.57
Zambia	4.71	1.52	0.18	0.29	21.69	11.74	11.83	18.05	19.17	10.82	0.73	34.68
Zimbabwe	1.69	1.70	0.62	0.58	22.82	7.53	11.69	15.04	22.31	16.03	0.76	34.05
Africa	8.21	2.90	1.19	0.90	20.46	11.65	9.63	17.46	13.85	13.74	0.68	30.41
Armenia	*9.57*	*4*	*1.27*	*0.05*	*4.24*	*15.5*	*6.92*	*6.38*	*17.31*	*34.75*	*0.25*	*13.77*
Azerbaijan	*4.45*	*2.92*	*4.95*	*2.39*	*7.33*	*10.59*	*13.48*	*7.28*	*17.16*	*29.45*	*0.29*	*14.08*
Moldova	*11,59*	*1.17*	*0.02*	*0.2*	*8.76*	*8.18*	*3.5*	*16.5*	*23.28*	*26.77*	*0.49*	*20.41*
Eu-West Asia	*7.01*	*2.70*	*2.08*	*0.88*	*6.78*	*11.42*	*7.97*	*10.05*	*19.25*	*30.32*	*0.34*	*16.09*
Bangladesh	10.38	0.87	1.73	5.1	20.07	11.45	0.85	20.43	14.45	14.65	0.66	27.38
Cambodia	*11.05*	*4.85*	*2.3*	*0.58*	*23.46*	*22.52*	*6.97*	*0.07*	*15.5*	*12.68*	*0.61*	*25.72*
India	8.84	3.86	2.52	3.26	14.78	13.05	2.78	17.95	17.86	15.09	0.75	32.15
Nepal	8.74	2.85	1.87	2.41	16.88	9.46	6.12	18.68	15.86	17.14	0.71	30.24
Asia	9.75	3.11	2.11	2.84	18.80	14.12	4.18	14.28	15.92	14.89	0.68	28.87
Bolivia	7.33	2.09	0.97	0.24	20.65	4.62	11.99	17.79	19.61	14.71	0.73	32.21
Dominican Republic	12.78	1.48	0.33	0.5	14.62	7.79	8.06	11.79	21.23	21.45	0.65	26.31
Haiti	15.24	4.57	1.61	0.21	20.54	7.54	5.49	18.39	5.56	20.86	0.69	28.35
Peru	6.40	0.78	0.6	0.05	17.46	13.04	9.77	16.05	18.24	17.61	0.77	33.93
Latin America	10.44	2.23	0.88	0.25	18.32	8.25	8.83	16.01	16.16	18.66	0.71	30.20
PCA Average	8.68	2.82	1.37	1.08	18.45	11.50	8.56	16.00	15.05	16.38	0.65	28.63
MCA Average	7.35	2.15	0.99	0.78	20.73	10.14	6.85	16.46	15.21	19.34		93.80

Since the indicators are binary variables and PCA is a method rather designed for continuous, normally distributed data, and additionally, very low variation is explained within the first component of the PCA. Nonetheless, I find that the results are generally similar to what was calculated using MCA, especially in terms of which dimension is assigned the largest weight. When looking at specific regions, Armenia, Azerbaijan and Moldova have a much higher weight than the average, for the assets indicator (although much lower in value in comparison to the MCA weights, reducing the overall assets average to 18% from 19%). Again, nutrition gets a very high weight for the Asian countries, with Bangladesh receiving the highest weight in this indicator, similar to the MCA analysis. Electricity receives the highest average weights again, although this average might be drives by the relatively higher weights in the case of African countries. The fact that these two methods provided relatively similar results is not entirely surprising. There are several studies that point out the similarities between the two methods and show a high correlation between a PCA generated index versus a MCA generated one (Howe et al., 2008; Booysen et al., 2008). But so far, both methods suggest that if one considers multidimensional poverty to be a latent concept that can be captured by the given indicators, there seems to be merit in the idea of putting more weight on the standard of living dimension. At the very least, it is important to consider the possibility that the equal weights applied within the MPI are not reflecting the structural relationships of the information derived from the household survey for each country.

Although these are mostly visual comparisons, and they do not give a concrete value to the differences in weights, there do seem to be differences across certain countries and certain regions that can be perceived here. The next part of the analysis concentrates on the nature of these weights, and how clearly can regional patterns be identified using both techniques. Given that MCA is the preferred method of analysing weights derived from categorical and binary variables, the robustness checks would focus on these weights. The results for the PCA weights are also displayed in the appendix.

2.7 Robustness Checks

2.7.1 Are there significant differences across regions?

Although the previous tables seem to suggest that a regional trend exists, in terms of the weight assigned by PCA and MCA techniques, are there really any perceivable regional differences? A correlation, run on the scores of each of the countries and conditioned on the region for each country, is implemented in the next step. This is to understand how well these regional differences can explain the weighting differences across our results. Given the few observations available, a conditional correlation was the appropriate technique to analyse any significant differences.

Table 2.4 displays the results of the conditional correlation for each country and the regional dummies, with the MPI values for each indicator derived by the MCA. As the results show, belonging to a certain region has a significant impact on the weight of a particular indicator. For example, compared to the Asian region (omitted category), nutrition received lower weights in all of the other regions. Electricity, on the other hand, received lower weights in EU-West Asia, while assets receive higher weights in comparison to all other regions. Compared to Asia, both EU-West Asia and Latin America receive lower weights in sanitation, although this is significant only at the 10% level. On the other hand, both Africa and Latin America seem to receive higher weights in terms of access to drinking water when compared to Asia.[9]

Overall, compared to all other regions, the EU-West Asia region is comparatively the most different, where in addition to the aforementioned indicators, also flooring receives a significantly different weight in comparison to the other countries. However, since the lowest number of countries are in the East Europe- West Asia region, and MCA showed a lower amount of variation explained in the case of two of these three counties, therefore the results from this region should be treated within caution.

The results of the conditional correlation support the argument that uniform weights are not representative of poverty across all countries. What can be seen is that across this sample of countries, there are differences in the level of variation that exists in poverty, and in a multidimensional context this becomes a much harder exercise. This exercise was also conducted for the MCA weights with the HDI score as an additional condition within the correlation, to account for some sort of development goals or tendencies that might be affecting these weights. The results for the same are available in Table A2.7 in the appendix. Despite the addition of the HDI score, nutrition in Asia still receives larger weights in comparison to the African and EU-West Asian region, while electricity and assets still deviate for the EU-West Asian region. In the case of drinking water, Latin America is no longer significant, though Africa still is, even at 1% now.

Table 2.4: Conditional correlation on MCA Weights

	Years of Schooling	Child Enrolment	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Assets
Africa	-1.728	0.0103	-0.565	-1.578***	3.294	-3.009	5.851***	1.318	-2.344	-1.319
	(2.047)	(0.876)	(0.479)	(0.421)	(2.698)	(3.022)	(1.957)	(3.433)	(4.086)	(4.120)
Latin America	0.600	-0.625	-0.875	-2.075***	-1.050	-7.025*	4.975*	-0.500	0.600	5.850
	(2.605)	(1.114)	(0.610)	(0.536)	(3.433)	(3.845)	(2.490)	(4.368)	(5.200)	(5.242)
Eu-West Asia	-4.342	-0.858	-0.367	-1.758***	-16.03***	-8.183*	2.408	-11.80**	-1.917	42.77***
	(2.813)	(1.203)	(0.658)	(0.579)	(3.708)	(4.153)	(2.689)	(4.718)	(5.616)	(5.662)
Constant	8.775***	2.325***	1.500***	2.225***	20.60***	13.85***	2.325	17***	16.75***	14.73***
	(1.842)	(0.788)	(0.431)	(0.379)	(2.427)	(2.719)	(1.761)	(3.088)	(3.677)	(3.707)
Observations	28	28	28	28	28	28	28	28	28	28
R-squared	0.137	0.047	0.086	0.433	0.629	0.191	0.298	0.325	0.029	0.793

2.7.2 High correlation between the standard of living indicators and double counting

The high value given to the standard of living indicators and the lower weights for the other two dimensions using MCA indicates the typical problem of double counting that has been mentioned by Klasen (2000) and Noorbakhsh (1998). In most empirical applications, one finds a high correlation between the selected indicators or variables in capturing the latent dimensions (Decancq and Lugo, 2013) and this has also found to be the case in this data. A

[9]There was no particular reason to use Asia as the omitted category. To show that the results do not change with changes in the omitted category, the results where the omitted category has been changed are presented in Tables A2.8-A2.10.

correlation between each indicator in the MPI for four countries (each country representing each region) is presented in Tables A2.2-A2.5 in the appendix. As shown, each indicator is highly correlated with the other (except in the case of Azerbaijan), whereby the standard of living indicators have the highest degree of correlation amongst themselves. This may be a likely explanation for the high weights received by the standard of living indicators, versus those for health and education, given the large overlap of information within these highly correlated indicators.

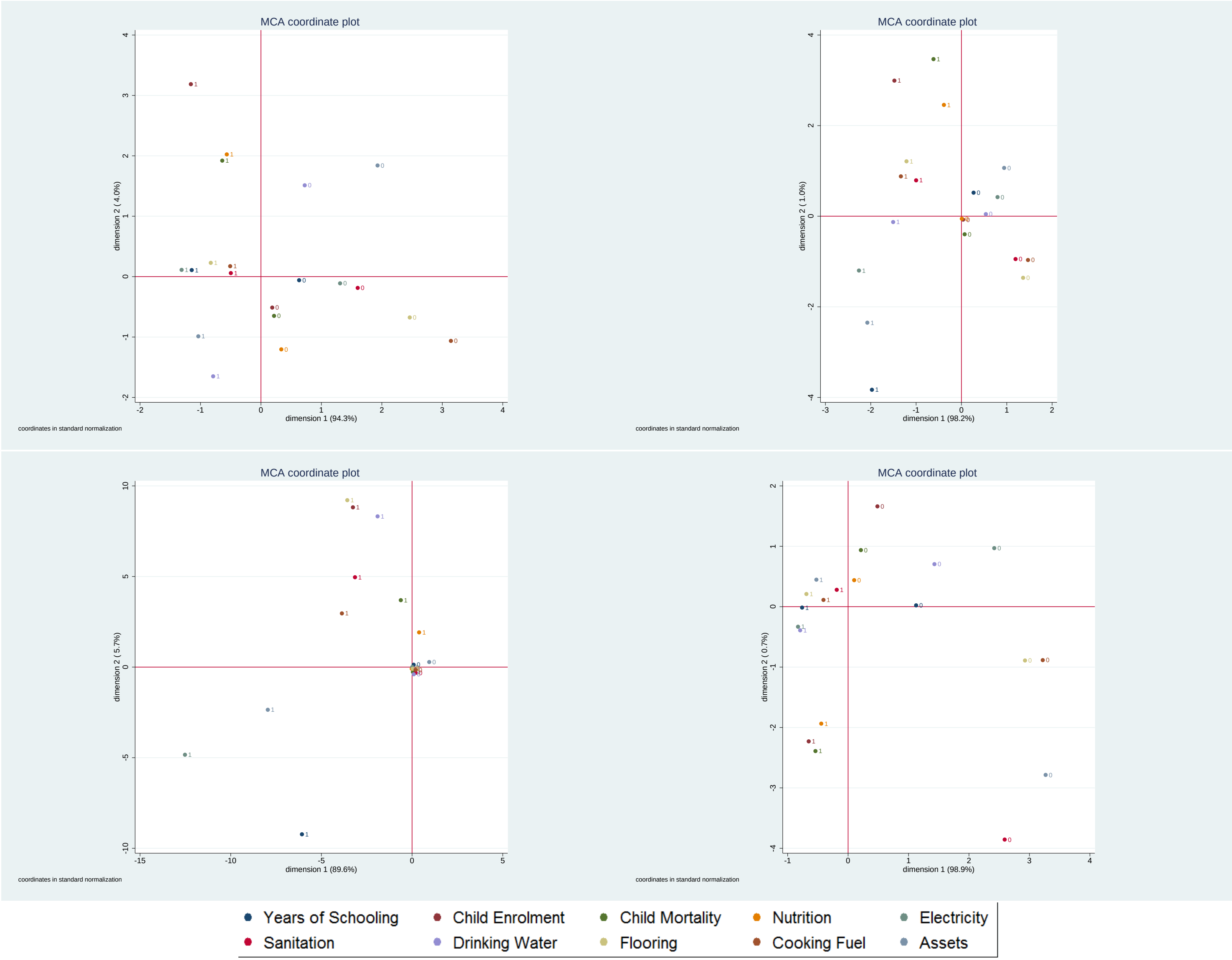
To prevent the high correlation and thereby the problem of double counting from detracting from the analysis, a further step is undertaken. In the case of the standard of living indicators, three of the six indicators which have the highest correlation are removed from the analysis. The results for the reduced indices are shown in Table 2.5. On average, education now receives 34% of the total weight, which makes this equivalent to the weight that education receives in the normal MPI formulation. Health, on the other hand, still receives low weights, around 5.5% of the total. Summing up these two, even after reducing the number of standard of living indicators to three from the original six, the overall weights for this dimension is around 60% of the overall weight. This is a reduction of nearly 25%, but it is still nearly two thirds of the overall weight. Even using only half of the original six standard of living indicators, there is a disproportionately large weight that is allocated to this dimension, while health nonetheless receives only a fraction of the total weight.

Another explanation for this large difference in weights amongst the three dimensions can be ascertained from the coordinate plots of the first and second dimensions of the MCA. The plots for one country from each region are shown in Figure 2.1 below. The choice of country is based on the highest total variation that is explained by the first dimension. These plots are a tool to visually analyse the information that is found within the data along given dimensions, and to determine the inclination of the binary categories towards each of the two dimensions on the plot. Normally, each category within each indicator will be represented within the diagram, which in this case would be the deprived and non-deprived individuals. Along the axis (but not necessarily only), these points can form clouds that distinguish the various types of latent ideas that can be derived from the analysis. Therefore, within this figure, we can examine the data points across two axis (the first and second dimensions, where the largest variation is along the former) and how they behave in terms of the types of poverty that exist within the data. There appears to be a clear distinction between the deprived and the non-deprived individuals along the second axis (represented by 0 and 1 for each indicator) for nearly all countries, except for A. The principal axis makes a greater distinction between the substantive categories. Points with similarities are placed closer on the map, where the distance between points would give a measure of their similarity. Thus households in the data are found to be similar on the basis of either being deprived in terms of the standard of living indicators or health and education indicators(specifically child enrolment, child mortality and nutrition).

Table 2.5: Weights assigned to indicators based on fewer standard of living indicators

	Years of Schooling	**Child Enrolment**	**Child Mortality**	**Nutrition**	**Electricity**	**Sanitation**	**Drinking Water**	**Flooring**	**Cooking Fuel**	**Assets**	**Variation explained**
Original	16.67	16.67	16.67	16.67	5.56	5.56	5.56	5.56	5.56	5.56	-
Cameroon	22.2	29.4	7.3	3.2		17.2			20.8		22.2
Congo DMR	4.3	6.4	6.1	1.4		19.9	23.4		38.4		4.3
Congo Republic	5	2	2.7	1.2		26	30.6		32.4		5
Ethiopia	20.5	8.4	4.2	1.4		9.4	28.8		27.3		20.5
Ghana	24.4	26.6	5.1	7.2			4.3	24.7		7.8	24.4
Kenya	14.3	28.9	2.6	4.7		13.9	15.2			20.4	14.3
Liberia	73.5	0.2	0.5	0.3	7		18.3		0.3		73.5
Malawi	20.8	3.4	0.7	0.8			11.3	45.1		17.8	20.8
Mali	66.5	5.2	2.2	1.4		8	0		2.4	14.2	66.5
Morocco	15.4	11.5	4	0.9		29.8	23.3		15		15.4
Mozambique	35.2	4.5	1.1	1		23.3	0		13.2	21.9	35.2
Namibia	12.2	3.6	1.3	1.5		32.7	8.5			40.1	12.2
Niger	17.4	8.9	4.2	1		34.1	18.4		16.2		17.4
Nigeria	20.7	24.6	12.9	7.8		10.5	12.7			10.9	20.7
Swaziland	14.9	5.3	1.6	1.1		20.2	27.3	29.6			14.9
Zambia	18.3	3.5	0	0.5		21.5	22.6			33.5	18.3
Zimbabwe	3.2	3.4	1.7	1.5		15.9	18.9	55.5			3.2
Africa	22.9	10.3	3.4	2.2	7	20.2	17.6	38.7	18.4	20.8	22.9
Armenia	0.6	1.5	0	0.1	1.4	0	0.8	95.6			0.6
Azerbaijan	90.8	0.2	5.2	1.4	2.2	0.1	0				90.8
Moldova	11.6	0.5	0	0.3	3.4	67.1	16.8				11.6
Eu- West Asia	34.3	0.7	1.7	0.6	2.3	33.6	8.8	47.8			34.3
Bangladesh	25.2	1.4	3.4	7.9		21.8			9.9	30.5	25.2
Cambodia	31.1	11.6	5.9	1.2		0	7.6		9.3	33.4	31.1
India	21	9.3	6.2	7.4	31	21.8	3.3				21
Nepal	17.7	10.8	6.1	8.6		20.3	4.8		32		17.7
Asia	23.8	8.3	5.4	6.3	31	21.3	5.2		17.1	32	23.8
Bolivia	24.3	0.9	0.8	0.2		12.6	18.8			42.4	24.3
Dominican Republic	62	1.9	0.3	0.6		10.7	9.8	14.6			62
Haiti	34.9	21.1	5.1	0.7		20.5	8		9.7		34.9
Peru	9.1	1.2	1.2	0.1	35.8	17		35.4			9.1
Latin America	32.6	6.3	1.9	0.4	35.8	15.2	12.2	25	9.7	42.4	32.6
MCA Average	25.6	8.4	3.3	2.3	13.5	20.6	14.5	37.6	17.5	24.8	

Figure 2.1: MCA coordinate plot for Nepal, Peru, Ethiopia and Armenia (clockwise starting top left) with the first two dimensions



The contrast between the standard of living indicators versus the health and education indicators is noticeable, given that the former are generally aligned on the other side the principal axis, or at the very least, are far from the points representing the health indicators. Interestingly, years of schooling is often close further away compared to these two points and also received a much higher weight compared to these two. These two results suggest that the current MPI is formulated with a larger number of indicators than necessary or required, where the standard of living indicators have a large overlap of information, but also most of the health and education indicators are rather similar in their information content. With the help of these statistical indices, one is able to reduce the issue of double counting and information overlap, by reducing the dimensionality of the data. This sheds a critical light on the issue of equal normative weighting and its applicability in measuring poverty.

2.7.3 Correlation between normative MPI and data driven MPI

While the weights using MCA have completely changed from the MPI equal weighting formula, this might result in a change in the picture of poverty that is presented as well. One of biggest question raised with the case of MCA or other such statistical methods is the inability to decipher what lies behind the weights. But if one were to consider equal weights to therefore be a better measure of poverty, a simple rank correlation can determine if these new weights wreak havoc in terms of policy.

Table 2.6: Household ranking with MCA weights and the normative MPI score

Country	Households Rank Correlation for MCA	Country MPI based on normative weights
Armenia	0.9501	0.002
Azerbaijan	0.8345	0.009
Bangladesh	0.7349	0.237
Bolivia	0.6737	0.097
Cambodia	0.713	0.211
Cameroon	0.7824	0.260
Congo DMR	0.8049	0.399
Congo Republic	0.9081	0.192
Dominican Republic	0.7936	0.026
Ethiopia	0.8576	0.537
Ghana	0.843	0.144
Haiti	0.8262	0.242
India	0.8048	0.282
Kenya	0.8076	0.226
Liberia	0.8156	0.459
Malawi	0.8415	0.332
Mali	0.8278	0.533
Moldova	0.8697	0.005
Mozambique	0.8715	0.390
Namibia	0.8774	0.200
Nepal	0.8443	0.197
Niger	0.8757	0.584
Nigeria	0.8714	0.239
Peru	0.8804	0.043
Swaziland	0.8735	0.113
Zambia	0.888	0.318
Zimbabwe	0.9336	0.181
Average	0.8345	-

To check how the ranks within households change with the MPI calculated using MCA, in comparison to the normatively weighted indices, the MPI weighted scores for each household in the country are calculated. Therefore, there are two different MPI scores for each household, one calculated using the normative weights, and the other using MCA. The results of the correlation for each country can be found in Table A4.2.

Using the MCA weights, there is no drastic change in the rankings of the households in comparison to those generated using the MPI weighted score. On average, the household rank correlation between the normative weights and MCA, is around 83%. The highest poverty score rank correlation is for Armenia, while the lowest is for Cambodian households. Nonetheless, these are very strong correlations, despite the differences in the rankings across countries. This implies that using MCA, one is able to provide a statistically more robust poverty weighting scheme, while not completely reversing the ranking amongst households, and thereby lead to errors in the identification of multidimensionally poor households.

2.7.4 Weights with only multidimensionally poor households

A reason why these MCA weights might be so different, may be on account of not so poor households, that drive the weights for health or education down. To examine whether the high standard of living dimension's weight is largely due to the changes in the poor households, or those at the fringe of being considered multidimensionally poor, only those households which have a normatively weighted MPI deprivation score of more than 0.33 are taken as a subset. The entire MCA analysis is then carried out for these set of households for all countries in the sample. This leads to a difference in the number, as well as in the identification of those households, which are multidimensionally poor. The results can be seen in the Table 2.7, and are now somewhat different in comparison to the whole sample.

The largest change is in the case of years of schooling which has increased from an average of 7% of the overall weight to more than 25%. However, this difference is largely driven by particular countries, mostly from the region of Latin America (and from Swaziland, Namibia and Morocco from Africa, and Moldova from EU-West Asia). Year of schooling now is the indicator with the highest weight. The health dimension also receives a larger weight now, increasing by nearly 10% from the initial 2%. This implies that within the poorest sample, there is less overlap of information across dimensions, leading to higher weights in both the education and health dimensions. The standard of living dimension still receives the highest weight of a little over 60%, which is about 25% lower than that in the full sample. Flooring, however, has become the most important indicator instead of household assets. Otherwise, all of the other indicators follow a pattern similar to one that had been calculated using the entire sample, where electricity and assets again receive the next highest weights. Likewise, years of schooling and child mortality receive a higher weight in their respective dimension, although the difference between the two indicators in the education dimension is much starker.[10]

[10]The results for the PCA analysis are also found to be in line with those from the MCA analysis, with larger changes in the weights assigned to the health indicators, as can be seen in Table A2.12 of the appendix.

Table 2.7: MPI constructed only with Poor households (with weighted average score more than 0.33) using MCA

	Years of Schooling	**Child Enrolment**	**Child Mortality**	**Nutrition**	**Electricity**	**Sanitation**	**Drinking Water**	**Flooring**	**Cooking Fuel**	**Assets**	**Variation Explained**
Original	16.67	16.67	16.67	16.67	5.56	5.56	5.56	5.56	5.56	5.56	
Cameroon	6.2	0.5	12	1.3	29.4	6.5	0.3	27.8	4.1	11.9	72.86
Congo DMR	1.2	0	91.8	0	1.3	0.3	0.4	2.3	0.5	2.3	92.66
Congo Republic	4.5	0.2	4.2	2.5	33	2.2	0.9	29.2	4.1	19.1	79.31
Ethiopia	3.6	0.2	0.3	0.3	34.4	3.4	9.5	21.3	11.9	14.9	94.56
Ghana	22.6	0	6.4	1.7	45.6	3.8	0.2	13.4	2.3	4.1	66.49
Kenya	1.6	0.3	3.2	0.4	20	10	14.4	31.4	9.5	9.2	81.58
Liberia	14.3	3.1	3.4	0.9	7.5	8.1	7.2	27.2	28.3	0	85.9
Malawi	6.8	0.4	7.5	1.6	20.8	11.5	4.4	15.8	20.7	10.5	65.27
Mali	17.1	0.9	8.3	2.8	22.8	2	6.6	23.5	0.2	15.9	80.67
Morocco	95.3	0.5	1.2	0.7	0.5	0.5	0.2	0.3	0.1	0.8	81.99
Mozambique	13.9	0	4.4	0.7	10.7	14.6	8.2	40.8	2.5	4.2	81.68
Namibia	85.5	0.1	2	3.8	1.3	2.2	0	0.4	1.9	2.7	67.58
Niger	11.7	4.4	1.7	0.4	17.3	2.2	25.3	26.2	0.1	10.7	78.21
Nigeria	11.7	20.2	10	6.3	13	0.3	0	34.7	0.9	2.6	66.97
Swaziland	59.6	1.4	10.8	1.8	3.6	1.6	1.2	7.8	0.6	11.5	58.75
Zambia	3.3	0.1	4.7	2	31.9	3.9	6.6	14.8	24.7	7.9	83.47
Zimbabwe	0.2	0.1	2.9	3.3	23.9	6.2	6.7	16.2	32.4	8.1	81.41
Africa	21.1	1.9	10.3	1.8	18.6	4.7	5.4	19.6	8.5	8.0	77.6
Armenia	24.1	0	5.9	18.9	3.8	12.6	0.6	10.8	10.2	13.2	64.1
Azerbaijan	0.1	0	0.4	0.2	0.0	1.1	0.9	0.3	3.5	93.4	95.8
Moldova	54.0	3.7	13.6	9.7	0.0	3.6	0.5	0.5	3.7	10.7	84.3
Eu-West Asia	26.1	1.2	6.6	9.6	1.3	5.8	0.7	3.9	5.8	39.1	81.4
Bangladesh	26	0.1	3.9	5.6	13.7	6.9	0.7	14.7	14.7	13.6	73.36
Cambodia	4.1	0.1	2.8	6.2	18.4	3.1	19.1	6.6	5.3	34.2	72.86
India	16.6	1.9	2.3	0.3	15.7	4.2	0.4	30.8	19.2	8.3	79.14
Nepal	6.2	0.5	12	1.3	29.4	6.5	0.3	27.8	4.1	11.9	75.81
Asia	13.2	0.7	5.3	3.4	19.3	5.2	5.1	20	10.8	17	75.3
Bolivia	38.2	8.3	7.6	0.7	10.8	3.4	3.5	6.6	10.3	10.7	78.69
Dominican Republic	96.7	0.8	1.2	0.3	0.2	0	0	0	0.4	0.5	89
Haiti	17.1	0.1	4.6	3.9	17.8	2.6	5.8	27.2	1.3	19.5	85.33
Peru	66.9	1.8	15.4	1.8	2.9	0.2	0.2	0.5	1.1	9.3	60.3
Latin America	54.7	2.8	7.2	1.7	7.9	1.6	2.4	8.6	3.3	10.0	78.3
MCA Poor Average	**25.3**	**1.8**	**8.7**	**2.8**	**15.3**	**4.4**	**4.4**	**16.4**	**7.8**	**12.9**	**77.8**
MCA Average	**7.3**	**2.2**	**1.0**	**0.8**	**20.7**	**10.1**	**6.8**	**16.5**	**15.2**	**19.3**	**93.8**

This change in the indicators is not very drastic, and even expected, given that weights derived with the help of a statistical technique are sensitive to changes in the sample. The variation explained using only poor households is also much lower than that of the whole sample, likely on account of there being larger inequalities and differences between the indicators that might not be easily captured along the first dimension. This is an indication of the need to differentiate between the degrees of deprivation that we categorize households in and therefore introduce weights that incorporate these sensitivities within them. With equal weighting we are unable to capture the multidimensionality that often occurs across different regions, countries and even within a single survey sample. Thereby, we lose a lot of information that is helpful when tackling the question of multidimensional poverty.

2.8 Conclusion

The regional differences in multidimensional poverty are not only conceptually challenged, but also statistically, within this paper. Using MCA (corroborated with PCA), popular techniques in the literature for the construction of wealth indices, the weights for each dimension, and within these, each indicator, are derived for 28 countries, constituting 4 different geographical regions, of the world. This exercise has revealed that equal standardized weights across regions may be ideal for comparison purposes, but it entails certain value judgements upon the importance of the included indicators and the trade-off between them. Therefore, while we achieve international comparability, these normative judgements affect the relative compatibility of poverty across nations and over time.

Naturally, the choice of weights is dependent on the ideology that is followed when determining the weights in the first place: whether they are to be equal (normative), data driven, or hybrid. These are all judgements that the AF method has been rigorously scrutinized over. In this particular study, using data driven weights, it is found that, on average, close to 85% of the weight is allocated to the standard of living indicators. Health and Education on the other hand receive low weights, of only around 2% and 15% respectively.Even within dimensions there are differences in where some indicators receive a higher weight, that also contradicts the equal nested weighting applied by the OPHI.

These results imply that the standard of living indicators are those where the largest variation in the data is found and therefore a larger proportion of weights are assigned there. However, the high value given to these standard of living indicators reflects the problem of double counting and how much overlap there is in the information provided by the given indicators and dimensions. Both MCA and PCA are highly advantageous when trying to reduce the commonalities that exist within the data that are used in developing the indices of wellbeing, as has even been noted by the authors of the HDI. Therefore, one can use a fewer number of indicators to derive an index with nearly the same amount of information. Nonetheless, for the current analysis, all the given indicators are retained, preserving the entire dimensionality of the data. This implies that those indicators with higher correlation would receive higher weights, which in the case of the MPI are the standard of living indicators. As an additional check, those indicators, which are highly correlated to each other are removed, and the results still do not change dramatically. While education now seems to receive much higher weights (nearly equivalent in all regions to approximately 33%), weights for nutrition do not shoot up similarly, peaking at 11% for the Asian region. However, standard of living indicators receive higher weights than the 33% allocated by equal weighting, around 60% of the overall weight on average.

The low weight allotted to these consensually important indicators like health and education does not mean that they are redundant in terms of determining welfare for an individual, but rather that the choice of these dimensions is one that contains overlapping information in terms of household deprivation. This might be one of the biggest problems with the MPI, that also ultimately compromises the simplicity of this index. Using statistical methods, this paper shows that even when reducing the number of indicators one is able to preserve the definition of multidimensional poverty, which focusing on the most relevant fronts.

The coordinate plot analysis suggests that there are two particular types of deprivations that one can extract from the entire data. One dimension of deprivation is sufficiently covered by either the health or education dimensions, as both are essentially plotted close together. The other aspect is covered under the umbrella of the standard of living indicators, which are found to be dissimilar to the education/health indicators. This is not such a perplexing result, given that deprivation in these three types of dimensions emerge under two possibilities, especially at the much more basic level we define the health and education indicator cut-offs as compared to the standard or living ones. In the case of the latter, there is a large role that is also played by the state and its ability to deliver adequate facilities, such as drinking water, cooking fuel, sanitation or electricity in remote areas, which is the second possibility.In case the state is unable to deliver these, then the income of the household affects the variability in these deprivations. Naturally, this also extends to schooling and medical facilities, but these are generally the primary concerns when thinking of development goals and moreover the cut-off for these are set at levels which are easier to address than those of the standard of living indicators. Therefore, income would play a smaller role in this case, than the government facilities. Nonetheless, these are judgements to be made in terms of the nature of the indicator and its underlying importance for each country and household. This distinction can thus be perceived within the analysis here.

This paper provides further argument against the use of these equal weights and shows that the definition of poverty changes over regions. The case for differences across dimensions of poverty can be made in terms of trends that can be ascribed to be unique to a region, as the analyses shows. The indicators included as part of the MPI were largely advertised to have provided a indexed solution to the 2015 MDGs. One can also observe the differences in the weights from these statistical techniques as reported by the UN in their target report for the 2015 MDGs. For example, South Asian countries have a larger share of weight in terms of the nutrition indicator, and this is also the region with the largest burden of undernourished individuals. Drinking water also seems to be an important indicator for African countries, and they were the only region that were unable to achieve this MDG target as well. On the other hand, assets and electricity receive much higher and lower weights, respectively, for the EU-West Asian region.

Given that the MPI is and will continue to become one of the more well-known methods to calculate multidimensional poverty, the current weighting scheme, which attempts to make the index more comparable across nations, seems to be under-utilizing its potential with respect to detecting poverty in terms of its regional characteristics. The question of a trade-off between a data driven and statistically sounder method, and comparability across nations is one which is not clearly answered in the literature. However, the study suggests that there are regional differences in weights and that one needs to keep this in mind when assigning weights that define poverty in different countries, regions or even households. Admittedly, the sample is too small to be able to make generalizations over the given regions and to draw concrete policy conclusions on the basis of it. More countries from Asia, EU-West Asian and Latin America would have been ideal to be included in the analysis before conclusively accepting or rejecting the theory behind these equal weights. However, in view of the data constraints that this particular study had, there are not too many more countries that could have been included from these particular regions. The next steps could be to include later waves, where a larger sample seems to be made available due to the difference in outreach of the Demographic and Health Surveys. This would be an interesting dynamic analysis, one which would also be relevant for policy conclusions and applications. The analysis in this paper shows that using equal weights to measure multidimensional poverty might only be a possible practice in the case of a static comparison for one time period. However, this is not ideal, and to some extent is even an atheoretical approach to the issue of measuring a generally confounding and highly abstract concept as multidimensional poverty. Moreover, one can also entirely question the premise of the particular indicators to be employed when measuring multidimensional poverty.

The question then remains, what possible improvements or changes could be made and are necessary for a better measurement, which would enable a sturdier comparison of poverty across different regions and nations in practice. It seems to be the case that using statistical weights might be a complementary way to examine the data and derive the best weights, without making any assumptions about the trade-offs between the indicators. Since the MCA approach derived these weights based on the variation available in the data, to a large extent one can comment on their suitability in placing larger weights on those indicators that have a greater variation and inequality amongst the sample population. The biggest drawback of this method is the loss in transparency, and spatial and temporal comparability. But despite this, one could circumvent this problem to examine the issue of poverty keeping comparability in mind. In terms of dynamic comparison for each country, this technique would still provide answers, taking these particular weights as the benchmark level of poverty. Thereafter, any changes would be caused by the variation among deprivation in the sample, which could steer us towards a dimension that has evolved or changed within a country. Alternatively, MCA is also useful regardless of the number of indicators and types of indicators that would thereby be included. An even larger set of indicators could be part of this measure without involving another overhaul of the ideology behind the determination of the weights. Therefore, data driven methods like MCA might overcome the traditional issues with normative weighting, and maintain the integrity of the poverty analysis simultaneously. These are therefore extremely helpful methods to determine poverty, which when used in complement with the normative weights, can be especially useful in guiding policy towards the key problems in multidimensional poverty.

2.9 Appendix

Table A2.1: The countries in the sample, which DHS was taken and observations within

Country	**Year**	**Phase**	**Observations**
Cameroon	2004	DHS-IV	49478
Congo DMR	2007	DHS-V	47602
Congo Republic	2005	DHS-V	29868
Ethiopia	2005	DHS-V	66388
Ghana	2003	DHS-IV	26307
Kenya	2003	DHS-IV	36687
Liberia	2007	DHS-V	34344
Malawi	2004	DHS-IV	59714
Mali	2006	DHS-V	73045
Morocco	2003-04	DHS-IV	62891
Mozambique	2003	DHS-IV	62262
Namibia	2006-07	DHS-V	40794
Niger	2006	DHS-V	47420
Nigeria	2003	DHS-IV	35269
Swaziland	2007	DHS-V	21523
Zambia	2007	DHS-V	34909
Zimbabwe	2005-06	DHS-V	41749
Armenia	2005	DHS-V	24888
Azerbaijan	2006	DHS-V	30114
Moldova	2005	DHS-V	31297
India	2005	DHS-V	516251
Nepal	2006	DHS-V	42271
Bangladesh	2004	DHS-IV	52902
Cambodia	2005	DHS-V	72342
Bolivia	2003	DHS-IV	80546
Dominican Republic	2007	DHS-V	120904
Haiti	2005-06	DHS-V	46678
Peru	2004-06	DHS-V	182891

Table A2.2: Correlations between each indicator for India at 5% significance level

	Years of Schooling	**Child Enrolment**	**Child Mortality**	**Nutrition**	**Electricity**	**Sanitation**	**Drinking Water**	**Flooring**	**Cooking Fuel**	**Assets**
Years of Schooling	1									
Child Enrolment	0.1629*	1								
Child Mortality	0.0545*	0.1502*	1							
Nutrition	0.0337*	0.1293*	0.1577*	1						
Electricity	0.3187*	0.1794*	0.1425*	0.1570*	1					
Sanitation	0.2570*	0.1362*	0.1252*	0.1628*	0.3126*	1				
Drinking Water	0.0854*	0.0679*	0.0426*	0.0549*	0.1437*	0.1292*	1			
Flooring	0.2863*	0.1715*	0.1484*	0.1839*	0.5009*	0.4016*	0.1985*	1		
Cooking Fuel	0.2828*	0.1786*	0.1681*	0.2170*	0.4074*	0.4328*	0.2107*	0.5349*	1	
Assets	0.3621*	0.1513*	0.0990*	.1191*	0.3939*	0.4062*	0.1532*	0.3916*	0.4331*	1

Table A2.3: Correlations between each indicator for Nigeria at 5% significance level

	Years of Schooling	**Child Enrolment**	**Child Mortality**	**Nutrition**	**Electricity**	**Sanitation**	**Drinking Water**	**Flooring**	**Cooking Fuel**	**Assets**
Years of Schooling	1									
Child Enrolment	0.2593*	1								
Child Mortality	0.1021*	0.2954*	1							
Nutrition	0.0987*	0.2168*	0.2117*	1						
Electricity	0.3243*	0.2216*	0.1474*	0.0894*	1					
Sanitation	0.1618*	0.0915*	0.0861*	0.0639*	0.2676*	1				
Drinking Water	0.1848*	0.1471*	0.1077*	0.0788*	0.3416*	0.2284*	1			
Flooring	0.3584*	0.2544*	0.1674*	0.1458*	0.5290*	0.2057*	0.2666*	1		
Cooking Fuel	0.2979*	0.2361*	0.2111*	0.1533*	0.5106*	0.3288*	0.3727*	0.4000*	1	
Assets	0.2677*	0.0547*	0.0025	-0.0119	0.3060*	0.2054*	0.1676*	0.2688*	0.2364*	1

Table A2.4: Correlations between each indicator for Peru at 5% significance level

	Years of Schooling	**Child Enrolment**	**Child Mortality**	**Nutrition**	**Electricity**	**Sanitation**	**Drinking Water**	**Flooring**	**Cooking Fuel**	**Assets**
Years of Schooling	1									
Child Enrolment	0.008	1								
Child Mortality	-0.0499*	0.0713*	1							
Nutrition	-0.0213*	0.0289*	0.0400*	1						
Electricity	0.2721*	0.1090*	0.0778*	0.0286*	1					
Sanitation	0.2012*	0.0708*	0.0748*	0.0134*	0.3855*	1				
Drinking Water	0.1572*	0.0759*	0.0524*	0.0196*	0.4394*	0.3328*	1			
Flooring	0.2455*	0.0856*	0.1078*	0.0256*	0.4470*	0.4502*	0.2829*	1		
Cooking Fuel	0.2776*	0.0941*	0.1140*	0.0259*	0.4975*	0.4564*	0.3271*	0.5882*	1	
Asset Ownership	0.3736*	0.0821*	0.0550*	0.0198*	0.5877*	0.3824*	0.3334*	0.4548*	0.5324*	1

Table A2.5: Correlations between each indicator for Azerbaijan at 5% significance level

	Years of Schooling	**Child Enrolment**	**Child Mortality**	**Nutrition**	**Electricity**	**Sanitation**	**Drinking Water**	**Flooring**	**Cooking Fuel**	**Assets**
Years of Schooling	1									
Child Enrolment	0.0015	1								
Child Mortality	-0.0475*	0.0365*	1							
Nutrition	-0.0235	0.0295*	0.0363*	1						
Electricity	0.0398*	-0.0123	-0.0041	0.0064	1					
Sanitation	0.0237*	0.0485*	0.0489*	0.0252*	-0.0039	1				
Drinking Water	0.0109	0.0271*	0.0784*	0.0480*	0.007	0.0717*	1			
Flooring	0.0071	0.0079	0.0272*	0.0052	0.0025	0.0644*	0.0678*	1		
Cooking Fuel	0.0343*	0.0064	0.0316*	0.0259*	0.1347*	0.0046	0.0163	0.0941*	1	
Asset Ownership	0.1131*	0.0545*	0.0459*	0.0280*	0.0854*	0.1108*	0.1248*	0.0274*	0.1479*	1

Table A2.6: MCA weights derived for both 0 and 1 binary categories

	Years of Schooling		Child Enrolment		Child Mortality		Nutrition		Electricity		Sanitation		Drinking Water		Flooring		Cooking Fuel		Assets		Proportion explained
Original	16.7		16.7		16.7		16.7		5.6		5.6		5.6		5.6		5.6		5.6		
Category	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	
Cameroon	2.5	6.9	0.5	3.3	0.3	0.9	0	0.4	14.8	12.3	6.3	1.7	0.1	0.1	11.5	11.4	10.6	2.4	8.5	5.5	93.4
Congo DMR	0.4	3.7	0.1	0.7	0.1	0.4	0.1	0.3	15.1	7.4	5.7	0.5	2.9	6	7.3	12.5	11.9	2.5	13.3	9.1	97.1
Congo Republic	0.8	2.8	0.4	1.2	0.2	0.4	0	0.1	22.9	4.6	4.6	0.1	8.3	5	18	5.6	9.8	0.5	10	4.7	96.1
Ethiopia	5.1	3.5	1.4	1.8	0.3	0.8	0.1	0.4	14.9	5.1	4.5	0.3	7.2	4	16.3	3.9	11.7	1.5	14.8	2.4	98.7
Ghana	3.1	7	1.1	3.5	0.4	1.2	0.4	1.8	16.7	12	5.8	0.7	3.2	6	1.5	7.9	17.3	1.6	5	3.8	88.9
Kenya	1	4.5	0.2	1.8	0.3	1.2	0.4	1.9	18	4.3	0.5	0.3	5.9	6.5	13.3	9.1	16.9	4.7	5.4	3.9	92.1
Liberia	4	7	0.1	0.1	0	0	0	0.1	9.7	0.3	17.8	1.8	2	3.5	14.9	10.2	0.3	0	21.1	7.1	94.1
Malawi	2.5	4.4	0.1	0.7	0.1	0.3	0.1	0.3	36.4	2.2	0.9	1	2.5	2.6	19	4.2	15	0.2	4.8	2.8	90.7
Mali	10.9	5.2	1.3	1.8	0.4	0.6	0.2	0.4	25.6	5.1	0.4	0.3	2.6	3.8	21.8	6.7	1.4	0	5.2	6.3	88.2
Morocoo	2.6	5.7	0.7	4.2	0.3	1.2	0.1	0.3	4.5	13.7	3.8	10.5	3	9.4	3	12.1	0.8	7.2	4.2	12.7	
Mozambique	7.7	5.5	0.4	1.3	0.2	0.3	0.1	0.5	17.6	2.2	5.2	4.4	3.9	1.2	15.1	6.4	16.3	3.6	5.4	2.7	96.8
Namibia	0.5	3	0.1	0.9	0.1	0.4	0.1	0.5	13.6	9.2	10.6	5.2	0.8	3.8	8.1	9.4	14	7.8	4.6	7.1	97.9
Niger	6.2	3.2	1.4	1.4	0.5	0.6	0	0.2	18.9	3.7	9.1	0.7	5.7	4.3	17.8	4.3	4.7	0.1	13.3	3.8	95.7
Nigeria	2.7	6.9	1.3	5.5	1.2	2.5	0.5	1.6	10.2	11.1	5.6	0.5	5.3	3.2	5.6	11.5	13.6	5.2	2.6	3.5	93.6
Swaziland	0.4	2.4	0.2	1.5	0.1	0.4	0	0.3	16.4	10	8.2	3.1	4	8.2	0.9	7.4	11.9	9.4	5.4	9.9	95.5
Zambia	0.6	2.8	0.2	0.8	0	0.1	0	0.2	22.1	4.9	7.8	1.9	5.9	3.9	11.4	6.7	18.8	3	4.6	4.3	96.9
Zimbabwe	0.1	1	0.1	1	0.1	0.3	0	0.3	18	9.7	3.3	2.2	3	6.1	4.9	9.6	18.3	8.3	8.5	5.3	
Africa	3.0	4.4	0.6	1.9	0.3	0.7	0.1	0.6	17.4	6.9	5.9	2.1	3.9	4.6	11.2	8.2	11.4	3.4	8.0	5.6	94.4
Armenia	0.1	5.1	0.0	1.1	0.0	0.3	0.0	0.1	0.0	1.4	0.4	5.9	0.1	1.7	0.0	1.3	0.4	7.1	8.0	67.2	85.1
Azerbaijan	0.1	3.3	0.0	1.3	0.2	1.4	0.0	0.6	0.0	5.0	1.0	3.8	0.4	2.1	0.5	14.0	1.4	9.5	6.1	49.2	81.9
Moldova	3.6	52.2	0.0	0.2	0.0	0.0	0.0	0.1	0.0	2.4	0.8	2.2	0.1	0.9	0.3	6.4	1.5	11.0	1.9	16.5	76.8
EU-West Asia	1.3	20.2	0.0	0.9	0.1	0.6	0.0	0.3	0.0	2.9	0.7	4.0	0.2	1.6	0.3	7.2	1.1	9.2	5.3	44.3	81.3
Bangladesh	2.7	6.0	0.1	0.4	0.3	0.8	1.5	2.0	11.3	8.9	3.6	5.8	0.0	0.2	21.8	5.3	14.2	1.6	6.4	7.2	
Cambodia	3.4	7.3	0.8	2.4	0.3	1.0	0.0	0.3	23.3	6.0	19.7	5.1	2.4	2.4	0.0	0.1	13.6	0.9	4.2	6.8	
India	1.4	6.6	0.4	2.5	0.4	1.7	0.9	1.9	3.2	11.8	7.7	5.0	0.4	2.0	7.2	12.0	11.5	8.0	7.0	8.6	97.8
Nepal	2.8	5.1	0.4	2.2	0.4	1.2	0.9	1.5	9.1	9.1	6.8	2.1	0.3	1.5	15.9	5.4	14.5	2.4	12.1	6.5	95.9
Asia	2.6	6.3	0.4	1.9	0.4	1.2	0.8	1.4	11.7	9.0	9.5	4.5	0.8	1.5	11.2	5.7	13.5	3.2	7.4	7.3	96.8
Bolivia	1.0	5.0	0.5	1.7	0.2	0.6	0.0	0.2	6.4	16.8	2.8	0.4	2.0	8.2	6.1	12.9	8.2	13.7	3.7	9.6	95.9
Dominican Republic	2.1	9.9	0.0	1.0	0.0	0.2	0.0	0.3	1.1	14.1	1.2	5.3	0.2	1.2	0.6	11.5	4.5	20.6	5.2	21.0	
Haiti	5.5	8.4	0.6	3.1	0.2	0.9	0.0	0.1	17.0	6.6	5.0	0.9	2.5	3.0	7.5	10.6	4.2	0.2	16.2	7.4	
Peru	0.7	5.0	0.0	0.5	0.0	0.4	0.0	0.0	4.5	12.8	9.8	6.3	0.9	3.2	7.2	8.9	10.8	8.7	6.4	14.0	98.3
Latin America	2.3	7.1	0.3	1.6	0.1	0.5	0.0	0.2	7.3	12.6	4.7	3.2	1.4	3.9	5.4	11.0	6.9	10.8	7.9	13.0	97.1
MCA Average	2.7	6.8	0.4	1.7	0.2	0.7	0.2	0.6	13.3	7.6	5.7	2.8	2.7	3.7	9.2	8.1	9.9	5.1	7.6	11.0	93.1

Table A2.7: Conditional correlation with HDI on MCA Weights

	Years of Schooling	**Child Enrolment**	**Child Mortality**	**Nutrition**	**Electricity**	**Sanitation**	**Drinking Water**	**Flooring**	**Cooking Fuel**	**Assets**
HDI	-18.39**	0.168	0.890	2.633	-8.520	6.848	4.359	-27.39*	46.87***	-7.390
	(8.031)	(3.806)	(2.074)	(1.748)	(11.59)	(13.06)	(8.459)	(13.79)	(14.84)	(17.84)
Africa	-3.194	0.0237	-0.494	-1.368***	2.615	-2.463	6.199***	-0.867	1.394	-1.909
	(1.993)	(0.944)	(0.515)	(0.434)	(2.877)	(3.240)	(2.099)	(3.421)	(3.681)	(4.428)
Latin America	2.490	-0.642	-0.966	-2.346***	-0.174	-7.729*	4.527	2.315	-4.217	6.610
	(2.539)	(1.203)	(0.656)	(0.553)	(3.665)	(4.129)	(2.674)	(4.359)	(4.690)	(5.641)
Eu-West Asia	-1.323	-0.886	-0.513	-2.191***	-14.63***	-9.308*	1.693	-7.304	-9.611*	43.99***
	(2.909)	(1.379)	(0.751)	(0.633)	(4.200)	(4.731)	(3.064)	(4.995)	(5.375)	(6.464)
Constant	18.12***	2.239	1.048	0.886	24.93***	10.37	0.109	30.92***	-7.080	18.48*
	(4.422)	(2.096)	(1.142)	(0.963)	(6.384)	(7.191)	(4.658)	(7.592)	(8.169)	(9.826)
Observations	28	28	28	28	28	28	28	28	28	28
R-squared	0.297	0.047	0.094	0.484	0.638	0.200	0.306	0.424	0.323	0.795

Table A2.8: Conditional correlation on MCA weights with Africa as omitted category

	Years of Schooling	**Child Enrolment**	**Child Mortality**	**Nutrition**	**Electricity**	**Sanitation**	**Drinking Water**	**Flooring**	**Cooking Fuel**	**Assets**
Asia	1.728	-0.0103	0.565	1.578***	-3.294	3.009	-5.851***	-1.318	2.344	1.319
	(5.178)	(0.882)	(0.482)	(0.420)	(2.703)	(3.022)	(1.964)	(3.387)	(4.077)	(5.485)
Latin America	2.328	-0.635	-0.310	-0.497	-4.344	-4.016	-0.876	-1.818	2.944	7.169
	(5.178)	(0.882)	(0.482)	(0.420)	(2.703)	(3.022)	(1.964)	(3.387)	(4.077)	(5.485)
Eu-West Asia	14.52**	-1.335	0.165	-0.147	-20.19***	-5.175	-3.543	-14.22***	-1.073	31.06***
	(5.835)	(0.994)	(0.543)	(0.473)	(3.046)	(3.405)	(2.213)	(3.816)	(4.594)	(6.181)
Constant	7.047***	2.335***	0.935***	0.647***	23.89***	10.84***	8.176***	18.32***	14.41***	13.41***
	(2.260)	(0.385)	(0.210)	(0.183)	(1.180)	(1.319)	(0.857)	(1.478)	(1.779)	(2.394)
Observations	28	28	28	28	28	28	28	28	28	28
R-squared	0.205	0.082	0.084	0.433	0.648	0.191	0.298	0.367	0.036	0.520

Table A2.9: Conditional correlation on MCA weights with Latin America as omitted category

	Years of Schooling	**Child Enrolment**	**Child Mortality**	**Nutrition**	**Electricity**	**Sanitation**	**Drinking Water**	**Flooring**	**Cooking Fuel**	**Assets**
Africa	-2.328	0.635	0.310	0.497	4.344	4.016	0.876	1.818	-2.944	-7.169
	(5.178)	(0.882)	(0.482)	(0.420)	(2.703)	(3.022)	(1.964)	(3.387)	(4.077)	(5.485)
Asia	-0.600	0.625	0.875	2.075***	1.050	7.025*	-4.975*	0.500	-0.600	-5.850
	(6.588)	(1.123)	(0.613)	(0.535)	(3.440)	(3.845)	(2.499)	(4.309)	(5.188)	(6.979)
Eu-West Asia	12.19*	-0.700	0.475	0.350	-15.85***	-1.158	-2.667	-12.40**	-4.017	23.89***
	(7.116)	(1.213)	(0.662)	(0.577)	(3.715)	(4.153)	(2.699)	(4.654)	(5.603)	(7.539)
Constant	9.375*	1.700**	0.625	0.150	19.55***	6.825**	7.300***	16.50***	17.35***	20.58***
	(4.659)	(0.794)	(0.434)	(0.378)	(2.432)	(2.719)	(1.767)	(3.047)	(3.668)	(4.935)
Observations	28	28	28	28	28	28	28	28	28	28
R-squared	0.205	0.082	0.084	0.433	0.648	0.191	0.298	0.367	0.036	0.520

Table A2.10: Conditional correlation on MCA weights with East Europe-West Asia as omitted category

	Years of Schooling	**Child Enrolment**	**Child Mortality**	**Nutrition**	**Electricity**	**Sanitation**	**Drinking Water**	**Flooring**	**Cooking Fuel**	**Assets**
Africa	-14.52**	1.335	-0.165	0.147	20.19***	5.175	3.543	14.22***	1.073	-31.06***
	(5.835)	(0.994)	(0.543)	(0.473)	(3.046)	(3.405)	(2.213)	(3.816)	(4.594)	(6.181)
Asia	-12.79*	1.325	0.400	1.725***	16.90***	8.183*	-2.308	12.90**	3.417	-29.74***
	(7.116)	(1.213)	(0.662)	(0.577)	(3.715)	(4.153)	(2.699)	(4.654)	(5.603)	(7.539)
Latin America	-12.19*	0.700	-0.475	-0.350	15.85***	1.158	2.667	12.40**	4.017	-23.89***
	(7.116)	(1.213)	(0.662)	(0.577)	(3.715)	(4.153)	(2.699)	(4.654)	(5.603)	(7.539)
Constant	21.57***	1	1.100**	0.500	3.700	5.667*	4.633**	4.100	13.33***	44.47***
	(5.379)	(0.917)	(0.501)	(0.437)	(2.808)	(3.139)	(2.040)	(3.518)	(4.236)	(5.699)
Observations	28	28	28	28	28	28	28	28	28	28
R-squared	0.205	0.082	0.084	0.433	0.648	0.191	0.298	0.367	0.036	0.520

Table A2.11: Conditional correlation on PCA Weights

	Years of Schooling	**Child Enrolment**	**Child Mortality**	**Nutrition**	**Electricity**	**Sanitation**	**Drinking Water**	**Flooring**	**Cooking Fuel**	**Assets**
Africa	-1.96	-0.375	-1.017	-2.090***	0.583	-3.421	4.571**	2.396	-2.845	-1.656
	-2.414	-1.046	-0.618	-0.535	-2.854	-2.777	-2.19	-3.272	-3.669	-2.791
Latin America	0.685	-0.878	-1.228	-2.588***	-0.48	-5.873	4.648	1.723	0.242	3.767
	-3.071	-1.331	-0.786	-0.681	-3.631	-3.534	-2.786	-4.164	-4.668	-3.552
Eu-West Asia	-1.216	-0.411	-0.025	-1.957**	-12.02***	-2.697	3.787	-4.229	3.332	15.43***
	-3.317	-1.437	-0.849	-0.735	-3.922	-3.817	-3.009	-4.498	-5.042	-3.836
Constant	9.752***	3.107***	2.105***	2.837***	18.80***	14.12***	4.180**	14.28***	15.92***	14.89***
	-2.172	-0.941	-0.556	-0.481	-2.568	-2.499	-1.97	-2.944	-3.301	-2.511
Observations	28	28	28	28	28	28	28	28	28	28
R-squared	0.062	0.018	0.166	0.431	0.394	0.106	0.159	0.126	0.104	0.563

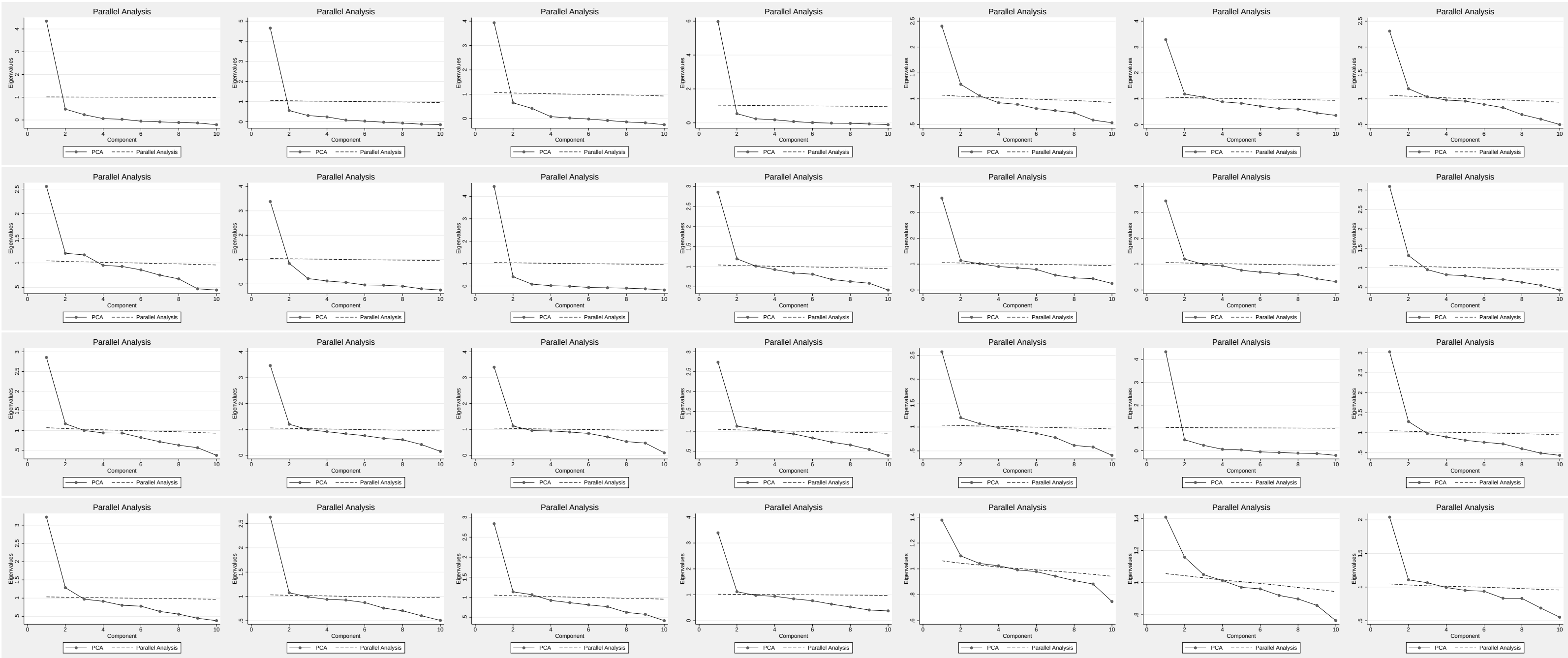
Table A2.12: MPI constructed only with Poor HH (with weighted average score more than 0.33) using PCA

	Years of Schooling	Child Enrolment	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Assets
Original	16.67	16.67	16.67	16.67	5.56	5.56	5.56	5.56	5.56	5.56
Cameroon	8	0.75	14.98	2.05	23.92	8.5	0.34	23.78	5.31	12.39
Congo DMR	6.03	0.4	6.19	4.16	26.02	3.69	1.63	25.21	6.01	20.66
Congo Republic	6.85	1.46	7.78	5.9	16.02	5.47	6.15	22.8	8.67	18.9
Ethiopia	5.18	0.29	0.6	0.51	25.21	4.95	11.76	20.97	14.06	16.48
Ghana	24.32	0.82	12.3	5.33	17.36	7.51	0.79	14.94	5.85	10.77
Kenya	1.55	0.43	4.34	0.56	18.71	12.03	15.78	25	11.22	10.37
Liberia	16.42	4.75	4.97	1.48	5.58	9.7	9.53	23.37	24.19	24.11
Malawi	8.66	0.48	9.31	2.84	16.65	10.43	6.89	18.19	13.81	12.75
Mali	18	1.35	7.68	4.13	19.22	2.67	8.85	20.11	0.33	17.67
Morocco	6.19	1.21	7.98	5.76	17.4	15.53	8.92	12.77	6.45	17.79
Mozambique	16.3	0.11	7.18	1.51	14.44	16.35	10.16	22.89	4.18	6.87
Namibia	4.03	0.31	6.28	5.15	17.55	17.18	6.7	12.77	18.69	11.34
Niger	13.65	4.96	0.97	0.45	18.11	3.15	22.72	23.03	0.15	12.79
Nigeria	15.9	19.7	10.52	8.33	13.7	0.51	0.1	26.28	1.47	3.5
Swaziland	15.9	19.7	10.52	8.33	13.7	0.51	0.1	26.28	1.47	3.5
Zambia	5.87	0.19	7.69	3.3	20.34	6.05	9.92	17.82	17.52	11.3
Zimbabwe	0.76	0.35	5.11	5.59	20.3	9.07	9.99	16.11	20.78	11.94
Armenia	16.24	0.12	7.55	17.17	4.81	12.37	0.86	12.26	12.57	16.03
Azerbaijan	4.19	0	6.25	3.53	0	6.69	8.65	4.46	20.8	45.44
Moldova	21.85	5.83	19.32	15.53	0.26	8.16	1.37	1.83	8.66	17.21
Bangladesh	9.04	2.91	3.8	0.44	19.94	6.93	0.74	24.66	19.71	11.84
Cambodia	24.08	0.43	9.18	5.59	16.56	14.09	1.34	0.16	9.16	19.43
India	12.22	0.23	5.47	6.01	15.9	9.97	1.29	16.11	16.65	16.16
Nepal	7.11	0.18	4.75	8.28	18.8	5.22	13.45	8.88	7.32	26
Bolivia	12.45	9.31	9.96	0.89	15.04	5.62	6.64	10.86	14.68	14.54
Dominican Republic	11.11	8.85	15.51	2.48	12.48	3.66	1.56	4.76	19.29	20.3
Haiti	13	0.16	6.38	5.6	19.04	3.98	7.86	21.04	2.09	20.85
Peru	5.21	2.31	19.38	4.13	20.9	3.63	11.28	2.55	6.49	24.13
Average	11.07	3.13	8.28	4.82	16	7.63	6.62	16.42	10.63	16.25
PCA entire sample	**8.53**	**2.71**	**1.31**	**0.99**	**17.8**	**10.92**	**8.03**	**15.53**	**14.58**	**16.08**

Table A2.13: Conditional correlation with HDI on PCA Weights

	Years of Schooling	Child Enrolment	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Assets Assets
HDI	-21.92**	-0.199	0.958	1.397	-8.964	6.568	-0.656	-29.68**	34.66**	-10.15
	-9.445	-4.546	-2.679	-2.308	-12.26	-12	-9.519	-12.81	-14.22	-11.95
Africa	-3.708	-0.391	-0.941	-1.978***	-0.132	-2.897	4.518*	0.0291	-0.0807	-2.466
	-2.343	-1.128	-0.665	-0.573	-3.043	-2.977	-2.362	-3.179	-3.528	-2.965
Latin America	2.938	-0.857	-1.326	-2.731***	0.441	-6.548*	4.715	4.773	-3.319	4.811
	-2.986	-1.437	-0.847	-0.73	-3.877	-3.793	-3.009	-4.05	-4.495	-3.778
Eu-Asia	2.383	-0.378	-0.182	-2.187**	-10.55**	-3.775	3.894	0.644	-2.357	17.10***
	-3.421	-1.647	-0.971	-0.836	-4.443	-4.346	-3.448	-4.641	-5.151	-4.329
Constant	20.90***	3.209	1.618	2.127	23.36***	10.78	4.513	29.37***	-1.703	20.05***
	-5.201	-2.503	-1.475	-1.271	-6.753	-6.606	-5.241	-7.054	-7.829	-6.579
Observations	28	28	28	28	28	28	28	28	28	28
R-squared	0.24	0.018	0.17	0.44	0.408	0.118	0.16	0.291	0.288	0.576

Figure A2.1: Parallel analysis showing how many components to consider in PCA



Notes: The countries starting from the right in the first row: Cameroon, Congo DMR, Congo Republic, Ethiopia, Ghana, Kenya and Liberia. In the second row, they are Malawi, Mali, Morocco, Mozambique, Namibia, Niger and Nigeria. The third row countries are Swaziland, Zambia, Zimbabwe, Bangladesh, Cambodia, India and Nepa. The last row countries are Bolivia, Dominican Republic, Haiti, Peru, Armenia, Azerbaijan and Moldova.

3 The Impact of Social Security Schemes on Multidimensional Poverty and Inequality in South Africa[1]

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. **JEL classification:** I38, H55.

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

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3.1 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 (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, 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(2011a; 2011b). In their papers, 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, 2010). 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 Is 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 is 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 for 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 three waves of a South African household panel data, over a period of four/five years, to track the changes in their MPI and CSPI over time. While these are the outcomes within this study, the main variable of interest for us is the impact of cash transfers on these two indicators of overall wellbeing and deprivation. 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), 2014). There have been several academic studies and policy reports that look at the impact of these social 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, 2010). 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. Therefore, even though the aforementioned literature has looked at each dimension of the MPI individually, there has been no work that examines their impact on the joint distribution of the three dimensions of health, education and standard of living. This is an important undertaking, given that there are many synergies that exist between all these forms of deprivation, which reinforce each another and thereby could lead to a much more aggravated picture of overall wellbeing than one imagines. Additionally, given the very low application of the CSPI measure, this paper also intends to

[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.

fill the gap in the literature and examine these broad based deprivations within households and the correlation between the dimensions and the consequent levels of inequality that differs between households.

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. Using these methods, it is found that both types of grants reduce multidimensional poverty and inequality within households. Since the old age grants are also larger in size, their impact is also found to be larger.

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.

3.2 Literature

3.2.1 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. Sen (1985) laid the argument for the Capabilities Approach based on the argument that that while income can be an indirect indicators of some capabilities, it is not necessarily 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 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. (2010) 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,

[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).

[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.

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.

3.2.2 Inequality in South Africa and the 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 below the poverty lines in the same time period (Özler, 2007). Branson et al. (2013) 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 head-count, 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, 2011a 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 Is 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 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.

3.2.3 Social Security in South Africa

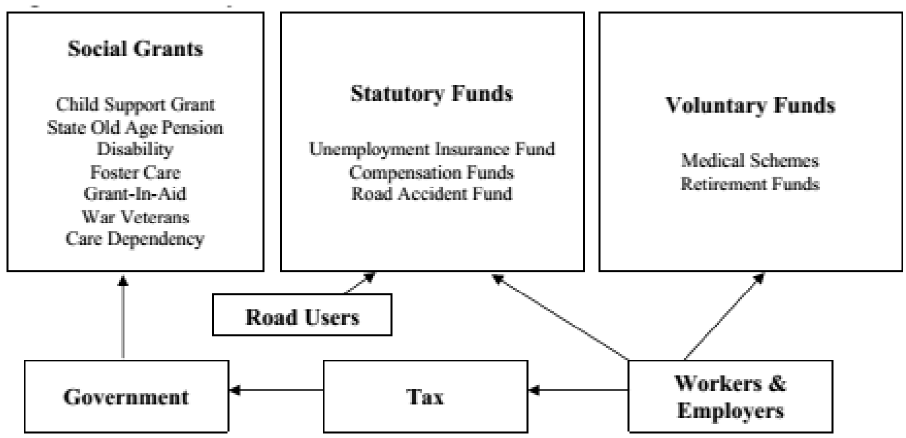
South Africa allocated R155.3 billion for the 2015/16 fiscal year for social grants: the child support grants, old age pensions, disability grants, foster grants, etc. There are around 16.4 million beneficiaries for these grants (more than 10 million for child grants alone). Apart from these grants, 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 3.1 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

[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.

Figure 3.1: Social security in South Africa



Source: Woolard and Leibbrandt (2010)

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, 2010). Therefore, they form an integral part of any programme that targets poverty and inequality in South Africa.

Woolard and Leibbrandt (2010) 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 (2010) 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). Agero 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 childs 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 households access to the labour market, employment in the household as well as the households life satisfaction and hopefulness for the future. They find that 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, 2003; 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., 2010) and a reduction in the labour supply amongst adults in pension eligible households, especially amongst prime age men (Bertrand et al., 2003). This empirical literature indicates that there is evidence of intra-household allocation and pooling of resources 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). Co-residence patterns also found to have changed, where prime-age women depart and children under five and young child bearing women disproportionately increase in grant receiving households (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 those households which need these grant the

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

[9] Means test for the **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 the **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 (from OECDStat, extracted in March,

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 A4.2 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 socioeconomic 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.

3.3 Data

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. Table 3.1[11] 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, 2010).

Most of the standard of living indicators follow the MDG guidelines, and their cut-offs

2015). The means test figures have 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.

[11]In the case of South Africa, for the Child Enrolment we are looking at children in the age group of 7 to 15.

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, 2011a). Therefore, at the first cut-off it is determined whether the households 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.

Table 3.1: The Multidimensional Poverty Index

Indicator	Weight	Deprived
Health	1/3	
Child Mortality	1/6	If any child has died in the family
Nutrition	1/6	If any adult or child in the family is malnourished (BMI¡18.5 for adults)
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/ 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 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, 2011a) 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, 2010). 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

[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.

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 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 directly.[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 exer-

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

[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

cise 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, around 16500 households are identified across the three waves, which amount to over 7300 actual households followed over time. On average, each household was repeated around 2.2 times in the panel. Table 4.2 provides the summary statistics for some of the important socioeconomic and demographic variables of this dataset.

Table 3.2: Summary Statistics for the households over three waves

Variable	Observations	Mean	Minimum	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	1.209.712	.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 can be seen from the summarized descriptives of the households in the pooled data. 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

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.

[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.

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.

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, 2008). 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 3.3: 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

As can be seen in Table 3.3, the grant receiving households are poorer not only in

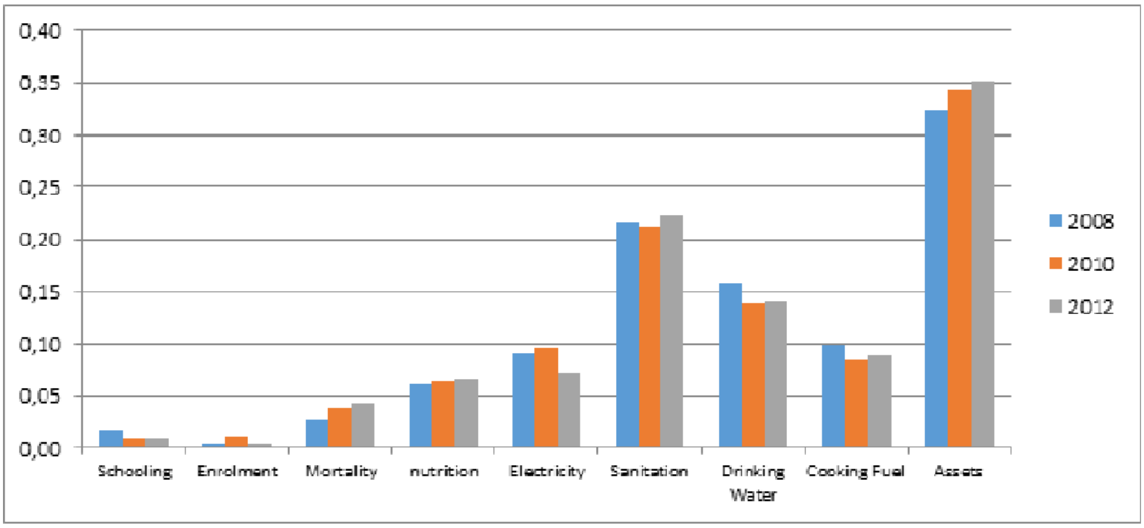
[18] This is a small amount equivalent to approximately 25$ (based on the OECD exchange rates for South Africa from 2000-2015: https://data.oecd.org/conversion/exchange-rates.htm#indicator-chart). The WDI database puts South Africas per capita income at 6483$ at current prices for the year 2014-15.

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

[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/).

terms of income, but also in multidimensional deprivation. For example, the per capita income for grant households is 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.

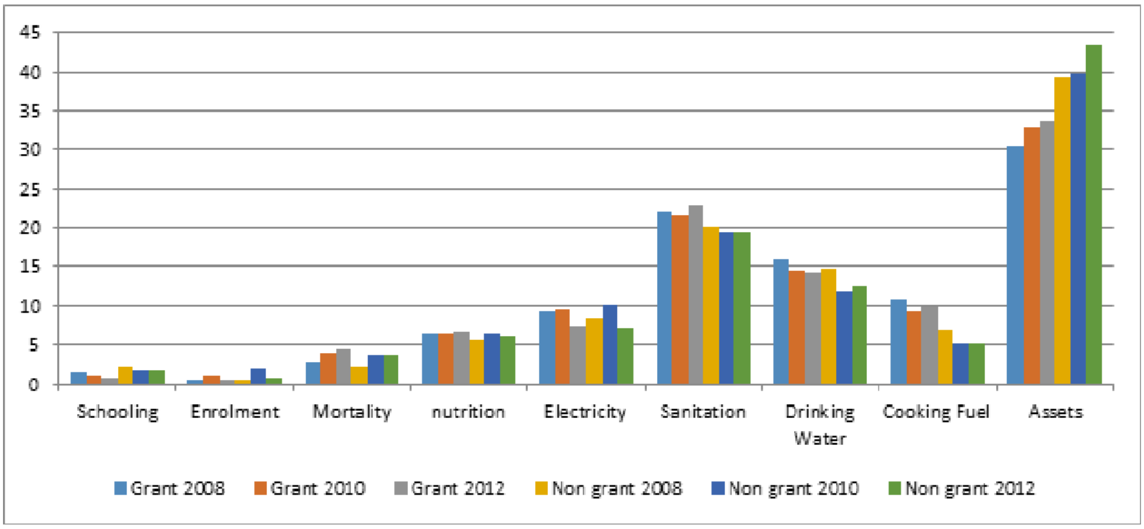
Figure 3.2: Contribution of each indicator for the households



Source: Own data

Figure 3.2 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.

Figure 3.3: Contribution of each Indicator divided by grant and non-grant households



Source: Own data

The particular impact of each indicator on the overall poverty headcount, separated by grant households and non-grant households is examined in Figure 3.3.[21] It shows us which indicator of the MPI plays a large role in wellbeing deprivation between the two groups.[22]

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.

3.4 Empirical 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

[21] Tables A3.8 and A3.9 in the appendix provide the numbers for the deprived in each indicator for grant and non grant households respectively.

[22] The contribution for each indicator without any division is in Figure A3.1 in the appendix.

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:

$$Y_{it} = \beta_X X_{it} + \beta_\theta \theta_{it} + \alpha_i + \epsilon_t + \mu_{it} \tag{3.1}$$

Here X_{it} are household demographics, province dummies, locality, employment status and other socio-economic controls[24], at the household level, θ_{it} 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 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 3.4.

[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.

Table 3.4: Potential Duration of Child Support Grant receipt by year of birth

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	7
1999	9	12	14	7
2000	8	11	13	7
2001	7	10	12	7
2002	6	9	11	8
2003	5	8	10	9
2004	4	7	9	10
2005	3	6	8	11
2006	2	5	7	12
2007	1	4	6	13
2008	0	3	5	14
2009	.	2	4	15
2010	.	1	3	16
2011	.	.	2	17
2012	.	.	1	18

* indicates those who have interrupted receipt, for example those born in 1994 will miss out on the receipt in 2001, 2002, 2003 and 2008. Here Eyal and Woolard (2013) assume 1999 as the first full year of exposure, given that the grant was first rolled out in October, 1998 and initial take up was very low.

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 3.5, where for example, the proportion of 14 years olds receiving CSG increased from 11% in 2008 to 60% in 2012.

This instrument of potential eligibility of the grant, Z is then introduced into a 2SLS

Table 3.5: 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

setup where the first stage is given as:

$$\theta_{it} = \beta_x X_{it} + \beta_z Z_{it} + \alpha_i + \epsilon_t + \mu_{it} \tag{3.2}$$

The other variables in equation 4.4 are specified exactly the same as in equation 4.4. The instrument is assumed to generate predicted values for the otherwise endogenous variable θ_{it}, given as $\hat{\theta}$, which would then be introduced into equation 3 to produce consistent estimates for all the parameters, particularly, β_θ.

$$Y_{it} = \beta_x X_{it} + \beta_\theta \hat{\theta}_{it} + \alpha_i + \epsilon_t + \mu_{it} \tag{3.3}$$

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. The potential duration that a child may receive this grant is arguably not correlated with the other determinants of the dependent variables, given that these changes in the age of eligibility were exogenously determined by the government. Let us suppose one source of bias could be the macro trends in reducing poverty, which might then influence any changes in the social grant system. Using a fixed effects estimation, given our panel structure, will control for these macro trends. Personal characteristics that might be linked to poverty, and to receiving a grant, would also be controlled for within the fixed effects. Moreover these should not influence government decisions. 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, because of their relation to a particular cohort of children, these can be allayed in view of the following reasons. The dependent variables and also the instrument itself are both collapsed and measured at the household level. Therefore the cohort effect or other similar trends between the enrolment of a child and the receipt of the grant is contained by this averaging of the number of children as well as the other members of the household. Moreover, within the overall MPI score, the enrolment indicator only has 1/6th of the overall weight, which would also therefore eb averaged within the score. Lastly, between the years of 2008 and 2012 there is in general universal enrolment between the ages of 7 and 15, which means there is very little variation within the enrolment indicator in the first place.[26] 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 womens 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). Another concern that often comes along in this method is the anticipation of the treatment that might alter the final outcomes. In the case of these old age grants, the anticipation would mean that people might therefore already start making expenditure which would improve their wellbeing. This change in their behaviour is likely to bias the results upwards for the control group and hence suppress the actual size of the effect. Therefore, it is believed that this is not of concern in this particular study.

[26] Table A3.10 in the appendix shows the variability within enrolment for all relevant age cohorts in the three years of the waves.

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.

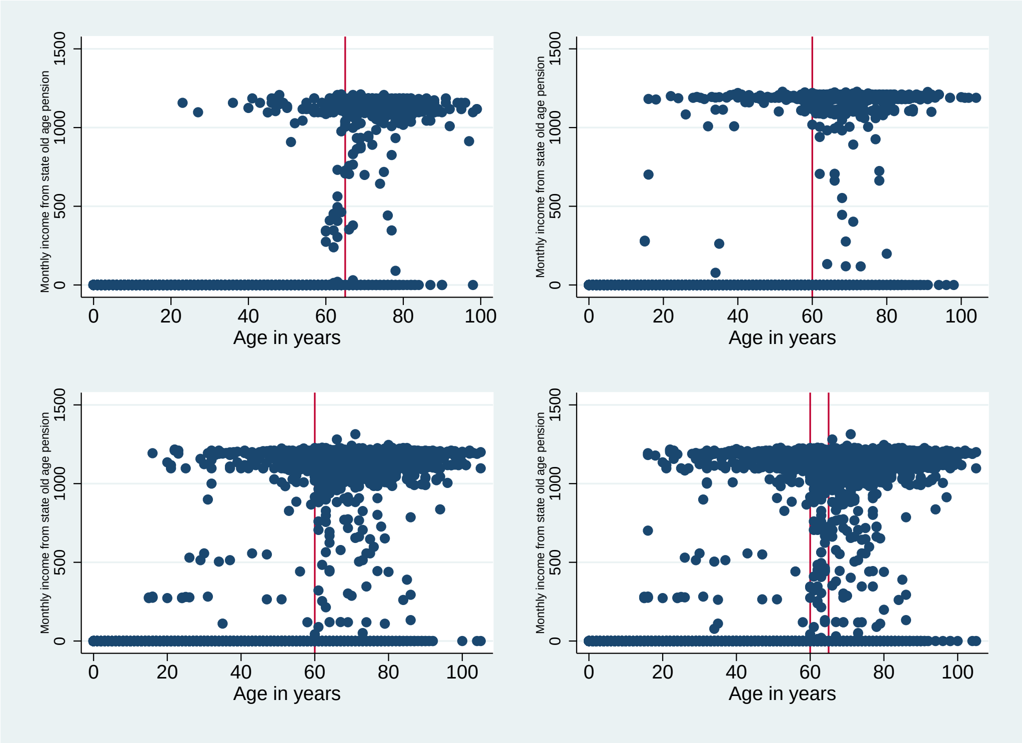
Figure 3.4 shows how the OAP are distributed according to the age of the household. The top two graphs are those for men in 2008, and in 2010 and 2012 respectively (to account for the change in the ages for eligibility in 2010 these are two separate graphs) while the bottom two are for women and the 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.[27] 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 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.[28] I therefore implement a fuzzy RDD for the case of OAP 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.

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 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

[27] 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.

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

Figure 3.4: The pension scheme amongst the South African population



Source: Own calculations

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 3.6. 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 3.6, 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

Table 3.6: Baseline differences between social pension households and non-social pension households

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

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 A3.11. 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.[29]

[29]The baseline differences between treatment and control households, 5 years from the cut-off are shown in Table A3.11 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

3.5 Results and discussion

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 3.7 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.

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 3.7: OLS, 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

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 Tables 3.8 and 3.9 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

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 is available upon request from the author.

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 3.8: 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

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 Tables 3.8and 3.9, 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 Tables 3.8 and 3.9, 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 specifi-

Table 3.9: Fixed effects regression with CSPI and cash grants

	1	2	3	4
Dependent 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

cation of Tables 3.8 and 3.9. 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. 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.

3.5.1 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 3.10, 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 3.10: 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

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 3.11 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.[30]

Table 3.11: 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
	(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

3.5.2 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 3.12 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 [31]. This would imply that most of our variation stems from the between component of the

[30] 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.

[31] As shown in the appendix Tables A3.12 and A3.13, where the overall between and within variation is shown, I lose most of the variation in the variable if I use fixed effects.

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.[32]

Table 3.12: IV approach- effect of child grant on MPI

Variables	OLS MPI	FE MPI	First stage Grant value	2SLS MPI	IV:FE 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

Table 3.13: IV approach- effect of child grant on CSPI

Variables	OLS CSPI	FE CSPI	First stage Grant value	2SLS CSPI	IV:FE 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

Table 3.13 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 Tables A3.14 and A3.15 in the appendix. As can be seen, the 2SLS specifications are still significant (where the significance even increases

[32]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.

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 3.14. Since we are removed the possibility of having additional years of grants , 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 3.14: 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		

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 3.15 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

Table 3.15: RDD approach- Effect of old age pension on CSPI

Variables	OLS CSPI	FE CSPI	First stage Pension dummy	RDD: 2SLS CSPI
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		

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 Tables A3.18 to A3.21 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 Tables 3.16 and 3.17. 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.

From Table 3.16 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

Table 3.16: Effect of child grants on each dimension of MPI

Variables	First stage	2SLS Health	FE Health	2SLS Education	FE Education	2SLS Standard of living	FE 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

Table 3.17: Effect of old age pension on each dimension of the MPI

Variables	First stage	2SLS Health	2SLS Education	2SLS 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

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.

3.6 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.

3.7 Appendix

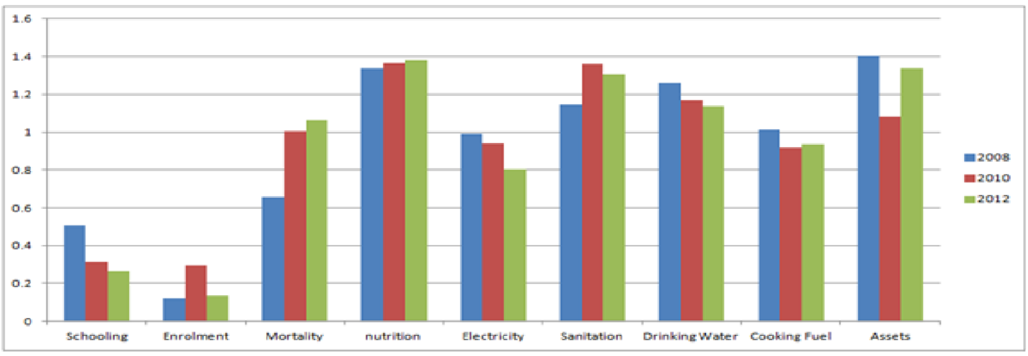
Table A3.1: Correlation between grant income and other multidimensional and income poverty (significant at 1%)

Correlation	**Household grant income**	**Percapita household income**	**MPI score**	**CSPI score**
Household grant income	10.000			
Per capita household income	-0.1145*	10.000		
MPI score	0.2425*	-0.2704*	10.000	
CSPI score	0.1595*	-0.1281*	0.8102*	10.000

Table A3.2: 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

Figure A3.1: Weighted contribution of each indicator on total MPI



Source: Own data

Table A3.3: 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

Table A3.4: 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

Table A3.5: Fixed effects regression for MPI and cash grants (constant households)

	1	2	3	4
VARIABLES	MPI	MPI	MPI	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

Table A3.6: Fixed effects regression for CSPI and cash grants (constant households)

	1	2	3	4
Variables	CSPI	CSPI	CSPI	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

Table A3.7: Random effects Model for grants impact on MPI and CSPI

	1	2	3	4	5	6
VARIABLES	MPI	MPI	MPI	CSPI	CSPI	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	9,37	2,873	1,383	1,965
R-squared	6,94	4,826	5,806	1,318	846	1,253
Number of hhid	2.62e-05***			2.68e-05***		

Table A3.8: Deprived households in each year for grant households

Indicator	**2008**	**2010**	**2012**
Schooling	1,6	1	0,8
Enrolment	0,5	1	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	0,8

Table A3.9: 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
Electricity	8,3	10,2	7,1
Sanitation	20	19,4	19,4
Drinking Water	14,8	11,8	12,5
Cooking Fuel	6,9	5	5,3
Assets	39,3	39,9	43,4
Total	2,2	1,6	1,7

Table A3.10: Child enrolment between the ages of 7 to 15 in the sample

	Wave 1		Wave 2		Wave 3	
Age	Percentage	Observations	Percentage	Observations	Percentage	Observations
7	99.65	576	100	11	100	6
8	99.18	609	99.82	555	99.87	747
9	99.67	605	99.52	619	100	722
10	99.67	601	99.53	641	100	660
11	99.84	640	99.37	633	99.47	752
12	99.53	643	99.69	644	99.6	750
13	99.07	644	99.25	665	99.58	707
14	97.98	642	98	651	99.2	748
15	95.79	546	85.82	684	95.01	742
Total	98.96	5,506	97.49	5,103	99.07	5,834

Table A3.11: Difference in Baseline characteristics for restricted sample of 5 years

	Observations (receiving)	Mean	Observations (not-receiving)	Mean	Difference
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 A3.12: Within, Between and Overall variation in the MPI score and CSPI score

Variable	**MPI score**			**CSPI score**		
	overall	between	within	overall	between	within
Mean	0.1901457			0.0334991		
Std. Dev.	0.1392994	0.130785	0.056264	0.0753977	0.066603	0.0388491
Min	0	0	-0.1209654	0	0	-0.2065009
Max	0.8333333	0.7666667	0.5234791	0.6944444	0.5877777	0.3712768
Observations	N = 15029	n = 7133	T-bar = 2.10697	N = 15029	n = 7133	T-bar = 2.10697

Table A3.13: Within, Between and Overall variation in dimensions of MPI

Variable	**Health**			**Education**			**Standard of liv**		
	overall	between	within	overall	between	within	overall	between	within
Mean	0.0186196			0.0068867			0.1618471		
Std. Dev.	0.0583095	0.0478154	0.0350773	0.0334501	0.0300711	0.0181727	0.3403723	0.2984819	0.1691676
Min	0	0	-0.2036027	0	0	-0.15978	0	0	-0.504819
Max	0.3333333	0.3333333	0.2408418	0.3333333	0.25	0.1735534	1	1	0.828513
Observations	N = 15029	n = 7133	T-bar = 2.10697	N = 15029	n = 7133	T-bar = 2.10697	N = 15029	n = 7133	T-bar = 2.10

Table A3.14: 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	9370	9370	14338	9370	9370
R-squared	0.345	0.025	0.177	0.119	
Number of hhid		5,806			5,806

Table A3.15: 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	9,37	9,37	14,338	9,37	9,37
R-squared	0.142	0.022	0.177	-0.012	
Number of hhid		5,806			5,806

Table A3.16: 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		

Table A3.17: RDD approach: Effect of old age pension on CSPI with five years around the cut-off

VARIABLES	OLS MPI	FE MPI	First stage Pension dummy	RDD : 2SLS 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		

Table A3.18: RDD approach: Effect of old age pension on MPI with smaller sample, 2 years around cut-off

VARIABLES	OLS MPI	FE MPI	First stage Pension dummy	RDD : 2SLS 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		

Table A3.19: 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		

Table A3.20: 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		

Table A3.21: 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		

4 The link between Subjective Wellbeing and Objective Wellbeing in South Africa[1]

There now exists a large scientific literature that empirically establishes the economic link between the social and economic environment around an individual and their sense of satisfaction. Nonetheless the link between non-income dimensions of well-being, following Sen's capability approach, and the happiness approach has been less explored. Moreover, there is no work that empirically examines all three measures of deprivation: Objective wellbeing (OWB), Subjective Wellbeing (SWB) and money metric poverty (MMP). This paper uses the Multidimensional Poverty Index (MPI) as our starting point for operationalising the capability approach. Thereafter, new weights for the MPI that correlate to satisfaction (SWB) and income (MMP) are devised, using Partial Least Squares (PLS). The new weights allocated to the indicators are different from those that are assigned within the equal weighing scheme by Alkire and Foster, and assets and sanitation receive much higher weights, while the education and health dimensions receive much lower weights. Furthermore, the new indices also suggest evidence of hedonic adaptation within households. That is to say, despite a greater level of broad based deprivation, these households are not found to be more unsatisfied, compared to other households with similar income ranks. The indices that are correlated with satisfaction are found to be the most susceptible to this adaptation.

JEL classification: I31, I32, C43.
Keywords: Satisfaction, Subjective wellbeing, Multidimensional poverty, Capability Approach, South Africa, NIDS, hedonic adaptation

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"You will never be happy if you continue to search for what happiness consists of"—
Albert Camus, Nobel Prize in literature, 1957

4.1 Introduction

...but Camus was a writer/philosopher and we are economists! It is therefore not surprising that interest in the science of happiness or subjective well-being has been burgeoning, in general, and in the field of economics more recently. Since the 1980's, the 'happiness literature' has covered solid ground in explaining the relation between subjective wellbeing (SWB) and socioeconomic and demographic variables.

Despite the widespread use of traditional income or consumption based measures for analysing human development, these have received a lot of criticism about their inability to capture all elements that represent human and societal progress. The growing literature that explores broader wellbeing, as opposed to increments in income and material goods, tries to overcome this weakness- prominently with the subjective wellbeing (SWB) and the capability approaches (CA). In the formulation of both of these approaches, there are elements of intangible notions of individual wellbeing, where the literature so far is highly debated on how to best extract quantitative information from these, as such, abstract concepts. While there has been a large discussion on the problems in the interpersonal comparison of utility as a measure of satisfaction, there have been huge strides forward in the measurement of such a measure of SWB. There is a significant literature that has established a way to quantify happiness within individuals (Diener and Ryan, 2009; Diener and Suh, 2000; Kahneman et al., 1999; Kahneman and Krueger, 2006; Stutzer and Frey, 2012), and empirically establishes the econometric, and in general economic, link between the social and economic environment around an individual and their sense of satisfaction (a comprehensive review can be found in Diener and Ryan (2009), Dolan et al. (2008)). Likewise, there is a broad literature that has defined and commented upon various indices that merge numerous value functionings as in the CA, following a variety of ideological judgements and objectives (Alkire and Foster, 2011a; Nussbaum, 2003; Ravallion, 2011a). There have also been various applications of these multidimensional indices in literature as well as in practice (Alkire and Deneulin, 2009; Klasen, 2000; Morris, 1979; United Nations, 1990).

Nonetheless, several problems arise comparing these two measures of wellbeing. "While measures of subjective wellbeing are attractive because they directly ask individuals for their own assessment on their situation, the capability approach offers a much broader informational space to assess the situation of a person, including a focus not only on outcomes but also on agency and a person's substantive opportunities"(Binder, 2013). Therefore, while Subjective wellbeing (SWB) measures incorporate the individuals own assessment of wellbeing, they ignore a person's opportunities and understate or overstate the individuals' degree of deprivation on account of hedonic adaptation. One of the clearest examples of this hedonic adaptation is the paradox of "happy peasants and miserable millionaires", where monetarily deprived individuals adapt to misfortune and are therefore unmotivated to improve their situation. Alternatively, richer individuals adapt to their wealth and comfort, and perceive themselves to be unhappy with their current status in life. Given that subjective assessments have a psychological basis, they might include a lot of measurement bias, depending on the circumstances at the time of the response. On the other hand, within the CA, an objectively low functionings achievement would correct for hedonic adaptation and the volatile subjectivity in an individuals' judgement of their wellbeing at given points in time.

In terms of the weaknesses in the CA, there is a lack of any guidance on how to choose and weight particular functionings that constitute overall welfare. There have been attempts at listing a set of relevant functionings (Alkire, 2002; Nussbaum, 2003; Sen, 1985) and also methods that have attempted to reconcile them in a so called 'paternalistic setting of weights' within an index (Alkire and Foster, 2011b; Robeyns, 2005). However there is the imminent problem of 'choice' in the weights derived for any multidimensional index of wellbeing (Brandolini, 2007; Decancq and Lugo, 2013; Ravallion, 2011b). What could specifically affect the reliability of a composite index, based on a particular set of functionings and compiled along a particular weighting scheme, is if there emerge individuals who have a high level of functionings but nevertheless claims to be miserable (Binder, 2013). That is to say, if the discrepancy between subjective and objective assessments becomes too large, this approach would fail as a measure of assessing individual wellbeing.

This paper tries to bridge the gap in the literature that examines objective and subjective wellbeing for individual welfare, in line with these shortcomings in both methods. As a starting point, we explore certain drivers of each of the measures of wellbeing- objective and subjective- and additionally income poverty. We find evidence of differences in the particular drivers of each kind of 'poverty', where what seems to affect satisfaction (SWB) in relation to income and OWB are variables that depict the mental and physical conditions prevalent at the time of the survey. This is an expected result for SWB, but it is also found to not affect the other measures to such an extent, thereby distinguishing the 'subjective' nature of the former in comparison to the latter.

Thereafter, we develop indices where the generated weights for the dimensions of the MPI are particularly relevant for SWB and money metric poverty (MMP). This is done using the Partial Least squares (PLS) method, where first, satisfaction, and second, income, perform the role of the response variable. This helps us to better understand the linkages between the dimensions of the MPI in explaining the concept of objective wellbeing, and how closely these are related to income and satisfaction, other commonly used predictors of wellbeing. Principal Component Analysis and Multiple Component Analysis (MCA) are other robustness techniques used to derive weights, but these methods work without any underlying assumptions as to how the latent idea derived might be correlated to satisfaction and income. This exercise is carried out for the case of South Africa, where it is found that PLS and MCA both derive similar weights for the MPI, and there appears to be an overlap of information between MPI and satisfaction and MPI and income. In the case of both these response variables, it is found that the most important indicators in the index are assets accumulated by the household, followed by the sanitation facilities and drinking water access.

This helps us to better understand the linkages between the dimensions of the MPI in explaining the concept of objective and subjective wellbeing measured by income and satisfaction respectively. Additionally, we use Principal Component Analysis (PCA) and Multiple Correspondence Analysis (MCA) to derive weights. PCA and MCA are typical data driven methods to derive weights in economics (Booysen et al., 2008; Filmer and Pritchett, 2001) and can be served as references. We will use data from South Africa for our empirical exercise.

The next section then examines the nature of hedonic adaptation that is found within our dataset and how these different indices react to this broad based adaptation. Using three cross sections as well as a fixed effects specification, we are able to examine the nature of this adaptation, and find that households adapt to lower incomes as well as broad based deprivations on average. This implies that households with similar levels of income are able to adapt to a change in their circumstances over time, and this is concluded within a single cross section of households as well.

The paper is structured as follows: the next section reviews the literature on the approaches to subjective wellbeing (SWB) and objective wellbeing, and work that looks at both of these measures. Specifically, studies looking at both these measures of welfare in the South African case are examined. In the section thereafter, the data used will be discussed and selected descriptives relating to the sample population will provide a preliminary examination of the three types of deprivation we are looking at: OWB, SWB and income poverty. Section 4.4 will then look at the methodology that is being used in each section of the analysis, followed by a section which will provide the results. Section 4.6 will conclude.

4.2 Literature

4.2.1 Theories of wellbeing

There has been abundant evidence to demonstrate that happiness cannot necessarily be reduced to economic wellbeing. One of the very first work on this is the seminal paper by Easterlin (1974), where he examines the positive association between happiness and economic growth within nineteen developed and developing countries between 1946 and 1970. He does not find similar evidence for national comparisons however, citing the importance of an individual's relative status in determining increases in overall happiness, rather than average incomes. Many others continued this work, notably Diener (1984), who replaced the more global concept of happiness, making the essential distinction between the affects and cognition parts of satisfaction. A plethora of theories sprouted up in the wake of the happiness literature, including telic, pleasure and pain, activity, top-down, bottom-up, associanistic and judgement theories (Diener, 1984). There are numerous overviews on the results of the satisfaction with life literature which are listed for readers who prefer a more specific examination of the satisfaction literature (Dolan et al., 2008; Frey and Stutzer, 2002; Layard and Layard, 2005; Schokkaert, 2007).

There are three different relationships that have been discussed in the happiness literature- individuals with high income and low incomes at a given point in time, increases in income over time, and rich countries versus poor countries. While richer people in general report higher wellbeing, an increase in material welfare has not been shown to lead to a proportional increase in life satisfaction over time or on average. There appears to be a concave relation between income and happiness, where marginal utility decreases when absolute income increases. However, relative income has been found to significantly influence wellbeing. Individuals are found to compare themselves to others with respect to income, consumption, status or utility. Over time it has also been shown that in high percapita income countries, while incomes have sharply risen, average happiness has mostly stayed constant or even declined over the same period. The results seem to point to the fact that there is more to SWB than just the income level. Again, comparisons seem to play a role here, where an overall increase in income might not mean an overall increase in happiness. Inter country comparisons, however, mostly based on the world values survey data, show that people living in richer countries are in general happier than those living in poor countries (Easterlin, 1974). This might be a combination of factors, such as a stable political structure, better average health due to improved medical facilities, and secure human rights in rich countries compared to poor ones, which complement the rise in happiness along with rising incomes.

More recent work has shown that relative changes in income (within countries) are more relevant for poorer individuals than for richer ones, meaning that there is no satiation point, where increasing income leads to no additional happiness. According to these studies, there exists a robust positive relationship between wellbeing and income across countries and over time (Deaton, 2008; Stevenson and Wolfers, 2013, 2008). This is because there exists a log linear association between income and life satisfaction, where the marginal utility of income declines somewhat faster in proportion to the rise in income (Layard and Layard, 2005). Theoretical work on this has also shown that within the endogenous growth model as well, the relationship between income and satisfaction does not decline at higher levels of consumption (Strulik, 2015). Therefore the relation between income and satisfaction has been well explored.

A glaring critique related to any measure of SWB is how does one go about interpreting the answer to the responses in surveys that relate to global life satisfaction or happiness? Satisfaction is neither a direct, verifiable experience, nor is it a known personal fact such as age or marital status. It is more so a retrospective judgement determined largely by the respondent's mood and memory within the present context (Kahneman and Krueger, 2006). Moreover, it is often based on a ordinal scale which might also not necessarily be interpersonally comparable Frey and Stutzer (2002). This scale is also bounded (be it 1 to 10 or 0 to 4) while income is not and therefore one runs into the problem of biases in measurement. Lastly, 'utility' or satisfaction itself has long been considered multidimensional in the psychology literature (Fluerbaey et al., 2009).

There were two big arguments against the normative theory on happiness and satisfaction, as put forward by Sen (1985), and summarized under the title of the Capability Approach (CA). Previously, the standard hypothesis was that people made commodity choices so as to maximize utility (which could be captured by happiness derived from that particular choice). Sen argued that this dual concept of 'commodity' and 'utility' should be replaced with three: 'commodities', 'functionings' and 'valuations'. Functionings are what a person manages to do: their achievement. If a visit to the doctor, or some medicine, is a commodity, then basic health can be considered as the relevant functioning that the individual can achieve. Depending on the commodities available, there can be a long list of functionings, that could include everything from longevity, to literacy, to be able to visit people one would like to see, to vacationing and travelling (Usher, 1987). Therefore commodities are means of obtaining certain functionings. If the former cannot be purchased with money or are underprovided in a market system, this would affect the capability set (functionings which are only achievable given the commodities themselves) of individuals. Sen then substitutes between 'values' and 'utility', where the latter can be identified with happiness. Even if one might be happier with option A, they might still choose option B because it has higher value to the user. Valuing a life is a reflective activity in a way that 'being happy' or 'desiring' need not be (Sen, 1985, p. 29). This was the important problem that he labelled as valuation neglect. Therefore, any approach to wellbeing should take into account the valuation that individuals subjectively make themselves (Schokkaert, 2007).

The other problem that Sen addresses is the issue of physical-condition neglect, that is to say, utility is grounded in the mental attitude of the personal and may disregard their real physical circumstances. As Sen put it: A person who is ill-fed, undernourished, unsheltered and ill can still be high up on the scale of happiness or desire-fulfilment if he or she has learned to have 'realistic' desires and to take pleasure in small mercies (Sen, 1985, p .21). Or alternatively, as in the case of expensive tastes, where an increase in aspirations may leave one 'worse-off'. Or alternatively, as in the case of expensive tastes, where an increase in aspirations may leave one 'worse-off'.[2] Individual satisfaction has been shown to be significantly affected by the physical conditions surrounding them, where the role of unemployment and the general unemployment in the economy, inflation, the state of health, and the degree of personal, economic and political freedom is fairly important. Not only being unemployed but also a general state of high unemployment is shown to negatively affect reported satisfaction among individuals. Increasing inflation is also found to reduce satisfaction.

A step towards the more objective, non-welfarist approach would be to follows Sen's capability approach towards defining wellbeing via the demarcation of a set of functionings. In 2010, the UNDP, in collaboration with OPHI, developed the Multidimensional Poverty Index (MPI) based on the Alkire-Foster methodology (Alkire et al., 2011; Alkire and Foster, 2011a,b) which derives its conceptual basis from Sen's seminal work on wellbeing and capabilities (Alkire and Santos, 2010).[3] This index was assumed to be a proxy for determining the individual level of wellbeing along 10 different functionings, assigned under three particular dimensions: health, education and standard of living. Within these three broader dimensions, there are 10 indicators that are aggregated using a dual cut-off approach into a single value that quantifies wellbeing. These indicators were selected so as to reflect one's physical condition in life. In this paper, we choose to focus on this particular vector of 'functionings' that describes the life of the individual along a list of relevant dimensions that have already been defined in the Multidimensional Poverty Index

[2] This quote was picked up from (Fluerbaey et al., 2009).

[3] This is only the latest application of the CA. The first of these wellbeing indices was the Human Development Index (HDI) in 1990, or the Human Poverty Index (which was supplanted by the MPI), the GDI or IDGI, etc.

(MPI). These different dimensions would then be aggregated using a method which seeks to respect individuals' well-informed ordinal preferences, reflecting their own valuation of welfare. A more detailed description of the method would follow in the next section on data. Recently, a lot of scientific work on objective wellbeing has followed this measure to define functionings achievements for households.

While the normative views in welfarism, its problems, and the related literature have been described above, there are also problems within the non-welfarist approach/CA. We restrict ourselves to the main issues that arise in the construction of a multidimensional deprivation index which is relevant for our paper: how to measure a multidimensional concept and secondly, what aggregation technique can be used to synthesize this individual's wellbeing into an index. The first critique on the choice of functionings has been described to some extent in the literature[4], and is not highly relevant for our analysis. Therefore, we confine ourselves to the second issue raised here in the following subsection, which will also motivate our work in this paper.

4.2.2 Weights in Index creation

The literature on index creation with respect to wellbeing is highly critical and detailed about the various choices that are available and in use (Booysen et al., 2008; Chowdhury and Squire, 2006; Decancq and Lugo, 2013; Ravallion, 2011a,b,a). Ravallion (2011b) critically examines indices of wellbeing and poverty in terms of the weights that are derived for each dimension. When assigning particular weights, one assumes certain trade-offs between dimensions in such indices (wherein the MPI assumes that improvements in one dimension make up for the failings in another, as in other equal weighted indices). He emphasises that the explicit trade-offs between dimensions (and more so within dimensions) are crucial in terms of measuring what a poverty/wellbeing index claims to measure. Decancq and Lugo (2013) make a highly informative classification of setting weights while creating indices: whether they are equal, data driven or hybrid.

In terms of data driven weights, there have been several proposed methods to calculate appropriate weights for the variables included. Given the high degree of collinearity that is expected within satisfaction and other variables that form part of domains that influence satisfaction (such as health, education, and standard of living as in the case of the MPI) techniques that deal with the problem of collinearity are required. Within the literature there has been a large focus on data reduction techniques such as Principal Component Analysis (PCA) and Multiple Correspondence Analysis (MCA), which orthogonally transform the data to create uncorrelated variables for an index. Both these techniques extract the largest variance in the data, to thereby derive weights that adequately represent the importance of the original indicators, while capturing the latent concept behind these indicators (Booysen et al., 2008; Filmer and Pritchett, 2001). While PCA is used more in the case of continuous data, for binary or count data MCA is found to be a more suitable technique (Greenacre, 2007, 1984). Nonetheless, both these techniques have certain shortcomings which are important for the analysis that is intended within

[4] Alkire (2002) summarizes a large list of indicators along political, philosophical and economic ideologies. Sen, himself, provides a list of social indicators, taken from the World Development Reports, which might be improved upon if one develops data towards the improvement of the CA (Sen, 1985).

this paper. The problem with both these methods is that one cannot explicitly define the underlying explanatory model, and the results are often derived from factor loadings which can be hard to interpret. Therefore, when we derive weights using MCA and PCA, we are unable to confirm whether the latent concept captured behind the variance in these methods does indeed relate to wellbeing. What would be even more interesting, is to see if these same indicators can be an adequate representation of subjective wellbeing. This is the main question that is examined in this work: how can we combine the OWB concept to also reflect an individuals' evaluation of wellbeing (SWB) and thereby derive a set of statistically sound weights for the MPI. Moreover, it is also interesting to examine how different this would be in comparison to an income aggregate, which is the second set of weights that are derived for this index.

To the knowledge of the authors of this paper, while there is ample work (empirical and also theoretical) on subjective and objective wellbeing separately, there is a large gap for studies that takes both these measures of deprivation and compares them empirically, especially in contrast to income poverty. As a bridging measure, capability researchers often include a measure of 'happiness' as a valuable functioning in their approach as in Binder and Coad (2011). Thus far, most studies have dealt with examining the differences and synergies between the two different measures of wellbeing: satisfaction and the capability approach). Comim (2005) details the key differences between the two methods, apart from the problem of valuation neglect/ adaptation that has already been mentioned. While the CA emphasizes wellbeing as a dimension of moral thought and political philosophy, SWB stresses the roles of psychological and neurological aspects of human behaviour. Moreover, apart from the ideological differences, the determinants of the two notions of wellbeing also differ. The capability approach puts emphasis on 'autonomy', 'freedom' and 'agency' as the most important features of wellbeing, while the SWB literature analyses a wide range of factors that influence people's own perceptions of their wellbeing, with no exclusive attention to any particular aspect. This has also been shown by Veenhoven (2010), who investigates the various causal mechanisms for each of these approaches. He concludes that while objective capabilities are a requisite for happiness, the less obvious subjective happiness is also necessary to foster particular capabilities (particularly health).

Other studies carry out a conceptual investigation of all three measures without delving deeper into a more applicative approach. Gasper (2005) conceptually describes the discrepancies that exist between the ranking of income, subjective wellbeing and objective wellbeing. Thereafter he conceptually analyses 8 different responses that can help operationalise these three measures based on different ideological and conceptual grounds. Teschl and Comim (2005) also illustrate the important role culture plays in these discrepancies between SWB across regions and in differences in adaptation. They emphasize the synergies between CA and SWB and discuss the role of temporal dimension where the role of instant utilities might differ from that of remembered utilities when combining both approaches.

Binder (2013) was the only work we found that develops a theoretical subjective wellbeing framework that incorporates insights from the capability approach as well. He notes several problems in his method, which we encounter directly or indirectly in our work as well. First, is the issue of which value functionings are to be included into the set of individual's wellbeing evaluation (Angelini et al., 2013). For that we choose to stick to the Multidimensional Poverty Index, which follows the three traditional dimensions of wellbeing: health, education and standard of living.[5] Second is the question of the dynamic orientation of these valuations, which might change over time. Moreover, when determining our weights for the MPI, we have to be certain that the weights are relevant for both the subjective wellbeing indicator as well as income. In this particular case, Partial Least Squares (PLS) is highly useful. The PLS approach starts with the goal of helping the researcher obtain determinate values of the latent variables for predictive purposes. While in the case of PCA and MCA we use the model for explaining the covariation of all the indicators, here the focus switches to minimizing the variance of the dependent variable. Thus parameter estimates are obtained based on the ability to minimize the residual variances of dependent variables (both latent and observed). A simple introduction to the method can be found within Chin (1998), Geladi and Kowalski (1986) and Haenlein and Kaplan (2004). Nonetheless, we would use all three methods- PCA MCA and PLS- to check for the differences in the weights derived from each method. Using our methodology, we would be able to account for differences in valuation according to the changes in the data variation itself. This is also able to circumvent another issue, which is the trade-offs between the different dimensions. Since these would imply value judgements, we are able to overcome this by simply estimating a measure that relies on the statistical derivation of these weights.

Most studies in developing countries that examine the concept of SWB employ single or repeated cross-sectional regressions. The same can be said to some extent about the MPI, although this is changing now that countries have their own specific MPI and are generating data to facilitate dynamic comparisons. Our work will improve upon existing literature by examining the same in a panel framework for the case of South Africa. In general, there is a lack of quality happiness/SWB data in the case of developing or transition countries and with access to three waves of the National Income and Dynamic Survey (NIDS) data, we are able to exploit the changes in satisfaction, multidimensional and income poverty for these households. This is not necessarily the case for South Africa which has a large literature that does look at SWB and OWB, which will be discussed in the following subsection.

4.2.3 Empirical evidence on wellbeing in South Africa

The literature on SWB has progressed along various channels, and using various datasets, for South Africa. Møller and Saris (2001) investigate the direction of relation between domain satisfaction and SWB. While previous studies established the direction of causality to run from overall SWB to affect satisfaction in a particular domain, be it income, housing, health or social contact, this paper examines the extent to which SWB affects a particular set of domain in South Africa. Evidence in the literature finds that in low income countries, the effect of income satisfaction aligns with a bottom up approach of Domain Satisfaction affecting overall SWB. In richer countries, on the other hand, this effect might be reversed

[5] While the MPI has also received a fair share of criticism in its choice of indicators, these are not impractical or even inadequate choices when determining the physical condition around an individual. For the indices generated in this paper, we also choose to follow these functionings, which are clearly motivated in literature and are relevant to an individual's valuation of their own welfare. These are also a preferable choice given that the overall vagueness in defining a good as a resource or as a conversion factor is not so large within these indicators. For example, being in good health could be seen as a functioning but it might also be a conversion factor to achieve being well nourished.

of even non-existent. This is line with Inglehart's post materialist theory which speculates that in Western developed counties income plays a smaller role in comparison to non-material issues, while in poorer countries, these factors are not as salient given that basic needs and security are not satisfactory themselves. The authors investigate the disparities along different racial groups in South Africa and its impact on overall SWB. The Asians in the sample seem to correspond more to the former group while the coloured seem to identify more with the less developed countries group. The results for the Blacks and the Whites on the other hand also show that by increasing overall wellbeing, satisfaction in income domains will also be positively affected.

Bookwalter and Dalenberg (2004) extend the analysis from Klasen (2000), which bases its work on the capability approach, to include a measure of subjective wellbeing into an index of wellbeing. They find that improvements in housing are relevant for wellbeing of the lowest quartile in their study. Moreover, better transport facilities would also be reflected in better satisfaction of the lower income group. The study additionally concludes that there exist differences amongst groups based upon their expenditure, mostly in the factors that generate the largest marginal impact on the satisfaction. While the two factors mentioned above seem to be of greatest importance in the case of the lowest quartile, sanitation, water, energy, education and health are relatively more important for the rich. This disparity between richer and poorer sections of the population has been found in a large set of papers, especially when combined with lower attainment of education (Davids and Gaibie, 2011; Higgs, 2006; Howell and Howell, 2008). Therefore, as in the studies discussed before, there is evidence of increasing satisfaction at higher levels of income for South Africa as well.

There is also work that examines the role of relative (perceptions of) income and wellbeing, that is the question of adaptation raised by Sen. Kingdon and Knight (2007) find that it matters whether the relative income of others who are in the local residential cluster is higher than that of more distance households. The authors proposed that higher income of a household within a small community is found to increase SWB, possibly as a result of altruism and fellow feeling. Furthermore, this impact has been found to be larger in a racially fractured society such as South Africa. On a more broader level, Howell and Howell (2008) find the same effect for high education and high income countries, from a sample of 54 economically developed countries. This is a result not uncommon in the literature in general (Cummins et al., 2003; Ferrer-i Carbonell, 2005; Luttmer, 2005). Bookwalter and Dalenberg (2010), find the same effect, whereby they make a distinction between races and find that in non-white households, the increase in income of a particular cluster of close by households leads to a greater increase in wellbeing than for white households. Posel (2014) looks at the case of South Africa, using the first two waves of the same dataset to investigate the relationship between life satisfaction and perceived economic rank in a multivariate model. She finds that African (Black) adults are less satisfied in life than white adults. They also were found to perceive their relative economic standing as having deteriorated, displaying lower hopes for their future upward mobility along the economic variables, in comparison to the white adult population.

Neff (2006) is the first paper that introduces ethnicity as a concept of analysis in SWB in the developing country context. Using a combination of race classifications and languages, he finds that to a certain extent there are cultural differences in the levels of SWB. There is other work that examines the impact of pensions on life satisfaction

(Lloyd-Sherlock et al., 2012), differences in the perceptions of wellbeing between younger adults and parents (Tibesigwa et al., 2015), exposure to crime and its negative impact on satisfaction values (Powdthavee, 2005), unemployment and dissatisfaction (Powdthavee, 2006) and informal housing and satisfaction (Richards et al., 2006).

The first published work on the multidimensional poverty index (MPI) for South Africa is in Alkire and Santos (2014).[6] They make use of the 2003World Health Survey data to estimate multidimensional poverty for South Africa. Recent MPI headcount figures for the year 2012 in South Africa lie around 8-9% of the population, depending on which estimates are examined (Fintel and Zoch, 2015). Using the study by (Woolard and Leibbrandt, 2010) the estimate lie a little higher, at around 9% in 2010, falling from nearly 11% in 2008. All of the studies estimate the level of multidimensional poverty in South Africa, using two waves of cross sectional data at best. This paper also suggests that there are non-overlaps between the income and multidimensionally poor individuals, where there are nearly 15% 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. The most recent figures for multidimensional poverty in South Africa from (Initiative, 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.

Finn et al. (2013) look at multidimensional poverty from 1993 and 2010, using two different datasets- the PSLSD dataset for the first period, while using one wave of the NIDS dataset for the second cross section in 2010. The results show that the headcount of multidimensional poverty has fallen from 37% to 8%, implying that nearly 30% of the total South African population that was multidimensionally poor is not so anymore, bringing multidimensional wellbeing figures down to nearly a quarter of the initial levels. Finn and Leibbrandt (2013) also examine the channels through which most progress in multidimensional wellbeing has been made and suggest that the highest levels of enhancement came from improvements in electricity and water, although in general there has been an overall improvement in severity of poverty over all indicators. They also looked at the demographic differences in poverty, for instance, and find that among the races, the African population is the one that has the largest levels of multidimensional poverty, although they were also the group with the largest levels of improvement in wellbeing.

In the South African context, there is some work that has measured wellbeing using the capability approach with statistically derived weights. Klasen (2000) develops a deprivation index using twelve aggregated measures, combining information on 14 indicators that measure health, income, sense of safety, sanitation, housing, perceptions of wellbeing, and education among other things, using PCA and equal weighting. He finds that expenditure and multidimensional poverty are always correlated but that there are also large disparities between the two measures. Moreover, these deviations are higher at lower levels of expenditure, i.e. the not so well off South Africans share the greater burden of deprivation in the measures of poverty the most. This disparity is also observable across other categories such as race, headship of the household, the location of the household (which influences the access to several services) and so on.

[6]This is an earlier work from 2003 which has been published in the year 2014.

4.3 Data

We use the three waves (2008, 2010 and 2012) of the National Income Dynamics Survey from South Africa, containing a little above 90000 observations. This is a rich, household level, nationally representative panel dataset, containing information on several variables related to socioeconomic wellbeing, demographic indicators and other indicators or variables that indicate wellbeing. It also has information on 9 of the 10 indicators of wellbeing that are used to form the MPI. The indicators used and the weights assigned are presented in Table 4.1 below. These weights are then aggregated on the basis of a deprivation matrix,[7] and the overall weighted score of households is representative of the degree of deprivation of this household. The larger the weighted score, the worse off are the households. Our other variable of interest is satisfaction and represents the longer run utility level of individuals, in comparison to happiness which is more representative of 'instantaneous utility'. It is an ordered variable with response from 1 to 10, defined as the current level of satisfaction with life and was asked from each of the respondents in the household.[8] The third variable to define poverty is income, which in our case if the log of per capita household income. As is common in the wellbeing and poverty literature, the log adult equivalised income is also generated.[9]

Table 4.1: The Multidimensional Poverty Index

Indicator	**Weight**	**Deprived**
Health	1/3	
Child Mortality	1/6	If any child has died in the family
Nutrition	1/6	If any adult or child in the family is malnourished (BMI<18.5 for adults & z-score<2SD for children)
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/ 8-16
Standard of Living	1/3	
Electricity	1/18	If there is no electricity
Drinking	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

Figure A4.1 in the appendix shows the distribution of all the aforementioned variables. Log income, log equivalised income and satisfaction all tend toward being normal,

[7]The deprivation matrix is nothing but an information set that provides data on whether a household is deprived in a particular indicator. Given that we are using 9 indicators to reflect multidimensional poverty, this deprivation matrix would include a row/column of 9 binary values: 1 in case the household is deprived in that indicator and 0 otherwise. When multiplying this deprivation (row) matrix by the weight (column) matrix, the 1 values are the only indicators that receive weight and are added to the overall aggregated score.

[8]Each individual could choose how satisfied they are with their life as a reply to this question: Using a scale of 1 to 10 where 1 means Very dissatisfied and 10 means Very satisfied, how do you feel about your life as a whole right now?

[9]The equivalence scales are based on the International Expert's scare, which divides the household income by the square root of the households size (Binder and Ward, 2011; D'Ambrosio and Frick, 2007; Headey et al., 2004).

apart from the slight peak in density at the highest category. The deprivation count on the other hand is skewed towards the left, meaning that there are many more multidimensionally well-off individuals in the data than expected. The following can also be seen in the summary statistics in 4.2 below.

Table 4.2: Summary statistics for the pooled data at individual level

Variable	Observations	Mean	Min	Max
Wellbeing indicators				
Satisfaction	41574	4.996	1	10
MPI weighted score	74994	0.203	0	0.833
Household characteristics				
Household size	81346	6.386	1	41
Female headed households	81346	0.610	0	1
Children	81346	2.569	0	20
Age	81226	25.658	0	105
Elders	81346	0.403	0	4
Adults	81346	3.414	0	20
Demographic characteristics				
Married	69851	0.187	0	1
Indian	81346	0.011	0	1
Coloured	81346	0.139	0	1
Black	81346	0.823	0	1
White	81346	0.027	0	1
Employed	21602	0.625	0	1
Rural	81346	0.092	0	1
Urban	81124	0.435	0	1
Tribal	81346	0.471	0	1
Socio-economic Characteristics				
Per capita income	78489	962.621	0.011	164598.4
Per capita grant income	81346	187.852	0	7706422
Receiving grants	81346	0.763	0	1
Shocks	41574	.243	0	1
Per capita Expenditure on:				
Food items	80350	222.254	333.945	12033.3
Non-food items	80350	466.921	.1	79854.52

All three waves of the NIDS data are pooled together for the descriptives below. It appears that only half of the total of the nearly 90000 individuals in households answered the question related to life satisfaction. The average score of the individuals who answered was nearly 5, which is the middle category. The other measure of wellbeing we have here is the MPI weighted score derived from the deprivation of nine indicators[10] which have been weighted according to the method described above and the overall score (which can

[10]There is no question related to flooring and therefore this is the indicator that has been left out.

lie between 0 and 1) has an average of 0.2, which falls below 0.3, the value above which one is considered multidimensionally poor. The average household has a little more than 6 members, where on average nearly 20% of the individuals are married (this is not so intuitive since there might be many spouses who are not part of the same households due to migration or other such reasons). There are nearly 2.5 children per household and less than 0.5 elders per household. The remaining household members, adults, i.e. the population that lies between the ages of the 15 and 60, form the remaining 3.5 individuals in the household.

The largest share of the dataset was comprised of African (Black) individuals, at nearly 82%, followed by the coloureds (14%) and the whites (2.7%). The smallest community represented here are the Indians (1.1%). Nearly 40% of the population was found to be unemployed, which is the representative of the current state of high youth unemployment in South Africa (Klasen and Woolard (2008). The average per capita income of the household is around 963 Rand[11] in 2012 prices, where nearly 20% of the average income is derived from some form of grant that a household receives (whereby nearly 76% of the households received grants). Also, approximately 24% of the respondents stated that they suffered from some kind of shock in the past year (related to death not within friends or non-resident members, loss of job, illness etc.).

We now look at other trends between income, satisfaction, and multidimensional poverty, to study to what extent the evidence found in the literature otherwise is also reflected in our data. We first plot the share of satisfied people along each of the income deciles, as shown in Table 4.3. The various columns represent the income deciles along which the household has been demarcated and the rows represent the levels of satisfactions as reported by the respondents. The cells marked in green are those that have more than 10% of the population within that particular income decile belonging to the given satisfaction level. Those marked in red are those where more than 15% of the population in the decile has reported that particular satisfaction level. The boxes marked in green and red show that at the lowest income deciles, a majority of the population reported lower levels of satisfaction in life (scores lower than 6). Alternatively, in the highest income deciles, the majority are those with satisfaction values of 5 or above. However, the larger share of individuals is under the middle value of 6 and mostly they are under 5 as shown in the last average shares column. The values in bold are those satisfaction values which were reported by more than 10% of the survey population. Looking at this table we confirm the findings from the literature that higher levels of income correspond to higher levels of satisfaction in our data as well.

While Table 4.3 indicates the distribution of satisfaction levels within different income deciles, Table 4.4 examines the mismatch between multidimensional and unidimensional measures of wellbeing, and subjective wellbeing for the South African population.[12] Income poverty has been determined as per the South African poverty line set at 363 Rand per person (2008 prices) and those who are below this level are described as income poor. Likewise, the measure of multidimensional poverty is to have a weighted

[11] This is around 179$ international, in purchasing power parity terms as given by the WDI (5.388) for 2014. This is much lower than the GDP per capita (PPP for current international $) of 12450 in the same dataset. We are therefore looking at very income poor households

[12] This is shown only for the case of the last wave in our sample, although all the cross sections are shown in Table A4.3 in the appendix.

Table 4.3: Trends of satisfaction with income deciles (pooled data)

Current life satisfaction	Income deciles 1	2	3	4	5	6	7	8	9	10	Average
1	15.07	12.1	8.87	8.94	7.34	6.9	6.61	5.58	3.96	2.26	8.27
2	12.38	11.52	9.4	8.94	8.85	7.34	7.77	4.81	3.58	1.95	8.22
3	16.1	14.66	15.21	14.23	14.38	12.11	11.82	8.91	6.86	4.21	**12.6**
4	16	18.03	16.01	17.38	15.11	16.23	13.96	12.12	9.18	7.09	**14.81**
5	15.07	17.22	17.93	18.76	19.47	19.62	19.81	19.71	18.97	14.35	**18.28**
6	9.07	9.21	11.37	11.1	12.52	12.5	11.98	13.15	14.13	13.06	**11.62**
7	5.77	7.21	7.45	7.31	7.48	9.11	9.38	12.43	14.31	16.87	9.04
8	3.6	4.01	4.94	5.2	5.77	6.63	7.31	10.01	13.4	21.79	7.17
9	1.88	1.29	2.37	2.78	2.96	3.1	3.35	4.41	5.36	7.79	3.17
10	5.06	4.75	6.45	5.38	6.1	6.47	8.01	8.88	10.26	10.63	6.82
Total	100	100	100	100	100	100	100	100	100	100	100

score which is higher than 0.33. Last, although the subjective wellbeing is a categorical variables lying on a scale from 1 to 10, it was divided into three levels: Poor, Medium and non-poor. All values from 1 to 4 were assigned a value of Poor, those from 5 to 7 were Medium while those from 8 to 10 were considered as highly satisfied and non-poor. The numbers marked in italics alone are those that depict the mismatch between subjective and objective wellbeing, while the numbers marked in both, bold and italics, are the differences between those who are income poor versus those who are subjectively not well off.

Table 4.4: Mismatch between SWB, OWB and satisfaction in the sample (2012, percentages)

		Subjective wellbeing Poor	Medium	Non-poor	Total
MPI	Non-poor	***18***	17	45	80
	Poor	5	4	***11***	20
Income	Non-poor	***10***	12	27	48
	Poor	13	9	***29***	52
	Total	23	21	56	

As the Table 4.4 shows, there are differences when identifying deprivation along a single versus a more broad definition of wellbeing. The mismatch is relatively large for the case of income poverty and satisfaction level, where even up to 39% of the population has been mismatched as non-poor in one of the dimensions. A larger share of these mismatches is that of individuals who are income poor but consider themselves satisfied. These are the happy peasants that we are looking in our dataset. The largest share of miserable millionaires in our dataset is 10%. In the case of MPI and satisfaction, the mismatch is lower, but still as high as 29% of the population. Therefore, subjective valuations are found to also be different from objective valuations of wellbeing in this dataset. The next section would therefore examine the different covariates that can perhaps explain these differences amongst all three measures of deprivation.

4.4 Empirical Methodology

There are three sections in the analysis: the first part examines the differences in the drivers of these three measures of deprivation according to demographic categories, the second is where we generate weights for an OWB measure that are particularly relevant for SWB and income measures, and third where we test how well these indices adapt to expectations, as has been the main criticism of the subjective wellbeing approach as opposed to the CA.

For the first section, we use OLS and a fixed effects estimation to determine which set of determinants play an important role in affecting each of the measures we are discussing. These measures are therefore the dependent variable and might be the values on satisfaction as SWB, the MPI weighted score as OWB, or log per capita income as MMP (Y_i).

$$Y_i = \beta X_i + \epsilon_t + \mu_i$$

In the previous OLS specification, X_{it} are covariates[13] that fall under one of these two broad groupings: demographic controls, or the moral, physical and psychological state of the household, ϵ_t denote the wave fixed effects and μ_i is the random error term. The standard errors are clustered at the households' level. We use a within transformation in the case of the fixed effects, where we remove the time invariant characteristics of the household, α_i:

$$Y_{it} - Y_{it-1} = \beta_i(X_{it} - X_{it-1}) + (\alpha_i - \alpha_i) + \mu_{it}$$

For all three measures, the tables are divided into four specifications, where the first two columns are the whole sample (OLS and Fixed Effects), the third column limits the observations to those for which all values are measure values are available, and the fourth specification removes all entries for individuals who are below 18. The satisfaction question within the survey was only asked of individuals who were 15 and above. Therefore, the sample is limited in the sense that there are no satisfaction observations for children which are 14 and below. Moreover, since the motivation for satisfaction between adults and children are not necessarily similar, these observations are left out.

The second part of the section thereafter deals with the weights in MPI that are correlated to income and SWB. The issue of paternalistic choices in weight determinance within aggregated indices are of particular concern when reconciling the welfarist and non-welfarist approaches of human development. Using a method that is common to the field of Chemistry and Psychology, the Partial Least Squares (PLS), this paper creates an index that assigns weights using a particular set of functionings, but including the correlation of the functionings with a particular outcome variable. In our case, we use

[13]These will be described in the results section to a larger extent. Some of these variables (especially those related to the demographic) have already been summarized in Table 4.2 above.

satisfaction and income as the outcome variables. Thereby we want to create weights for the dimensions of the MPI that are particularly closely related to income or satisfaction. This helps us better understand the linkages between the MPI and its dimensions on the one hand, and income and satisfaction on the other. Hence we look at a broad based definition of individual wellbeing, to take into account the issue of valuation neglect and physical conditionality. Simultaneously, we account for the preferences that individuals state within the aggregation technique.

PLS is a technique introduced by Wold (1973), which seeks to maximize the variance explained by the matrices of the dependent variable and the independent variables (Haenlein and Kaplan, 2004). It is a method that comprises of three parts: the structural part reflecting the relation between the latent variables (the regression constants) which in itself are derived from the measurement part, and quantifies this relation between the latent variable and their set of indicators (the loadings). The loading however are derived from the third component, which are the weights estimates, the estimates of case values for the latent variables (Chin, 1998). Therefore, in the three parts that this technique comprises of, the weights relations are technically the first and most important step in the whole analysis, since they form the basis for the technique and further analysis. The derivation of these consists of an iterative process that almost always converges to a stable set of weight estimates. In recent literature, PLS is used to determine the weights in the reduced indices given the choice of indicators. Within PLS, an outcome variable is required to capture the highest covariance between the X matrix (indicator matrix) and this response variable (some variable which functions as a proxy for well-being) matrices. Therefore, the variables in the X matrix that show high covariance with respect to satisfaction or income will be emphasized within the composite index (Yoon, 2015).

In this paper, PLS is used to identify the latent relation observed in the X matrix, comprising of the indicators in the Multidimensional Poverty Index (MPI), and its structural relationship with the outcome variable, Y i.e. satisfaction or income. However instead of utilizing all three steps of this method, only the first step, where the weights estimates for each of the indicators is generated will be utilized. The point of using PLS here, instead of just relying on PCA and MCA, is that it can suggest possible relationships between indicators and propositions for testing later (Chin, 1998). PCA and related methods find the weights which maximize the variance of the vector of independent variables. PLS weights on the other hand, maximizes the covariance between variance of the covariates and a certain response variable (Yoon, 2015). This is the main contribution of this paper.

The last section deals with the differences between the three measures and what role hedonic adaptation plays in the case of SWB versus OWB and income. For the same we generate a gap measure that looks at the differences in the ranks of households. This gap measure is based on the ranks of satisfaction for each household subtracted by the ranks of income for each household and is given by the following formula:

$$Gap = rank^{satisfaction} - rank^{income}$$

To interpret this rank gap would be easier with an example. Suppose we take two households, A and B. Household A is satisfied but poor (so the happy peasants in our hypothesis) and Household B is a normal household, which has a middle rank in income as well as satisfaction: Household A would then have a high rank for satisfaction and a low rank for income, which when plugged into the formula means that the gap value would be high and positive. On the other hand, Household B would be ranked similar in terms of both income and satisfaction and therefore the gap value would be close to zero. This gap value would also apply to those households which are poor and dissatisfied in life, as well as those who are rich and also content in life. Alternatively, the lowest gap value (negative) would be for those households which have a high income and therefore a higher rank, while also being displeased in life (the miserable millionaires in our hypothesis). Therefore, an increase in the gap value would signal a relative improvement in the satisfaction level.

Before beginning our analysis though, we had to transform the dataset, which so far measured all variables at the individual level.[14] Since both the MPI and household income are more of a household concept, we decided to convert our unit of analysis from the individual to the household. For this reason, the entire dataset was collapsed to a single household figure, which is the mean of the values for each individual of the household. The collapse of the dataset to household values would imply that the mean value of any observation available for that household would be assigned to each member. Therefore, several variables which are actually constant over time like gender or married would be varying now that the values would depend on the overall household composition. Given that the per capita income and MPI are the same for each member of the household, the transformation serves no other purpose than to assign that value to the household itself. On the other hand, the satisfaction observations are available for each member of the households above the age of 15. Therefore, satisfaction is the only variables that has been run at the individual level and not collapsed at the household level.

Subsequently, to examine the degree of hedonic adaptation of these gap measures, we regress certain demographic and socio-economic variables (X) and the three different MPIs that have been generated (θ), based on equal weights, the PLS weights from satisfaction

[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 directly. 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. The method to determine a particular 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. Using this, I was able to determine the household identifier.

and those from Income (Y).

$$Y = \beta_1 X + \beta_2 \theta + \mu$$

The coefficient on these new indices will show the extent to which these indices are able to depict how well people adapt to poor circumstances in relation to income. These are compared to the normal weighted MPI to examine if these new measure are able to provide a more adaptive view of wellbeing. The covariates introduced in this regression correspond to those that are used in the first part of the analysis, to examine how other demographic and state of being ('physical' condition) variables are affected with these new measures. This specification will be run for all three waves separately and is therefore a cross sectional analysis and the results are presented in the following section.

4.5 Results

We begin our analysis by examining how income, satisfaction and the equal weighted Multidimensional Poverty Index (AF methodology MPI or equal weighted MPI from now on) behave in the South African context. Thereafter the paper discusses the new indices of wellbeing. It finally concludes the analysis with the gap rank measure to determine the various changes in the three measures of poverty across households.

4.5.1 Drivers of SWB, OWB and MMP

Given the large literature, some of which has been already discussed, that examines the impact of demographic and socioeconomic factors, and physical and psychological state of an individual on the level of satisfaction, Table 4.5 examines this relationship for the case of South Africa. Table 4.6 is where the same set of regressors have been regressed on the MPI weighted score and Table 4.7 runs the same specification but in the case of income this time. There are two different sets of variables which were introduced into the regression, based on the literature so far and as well as data availability. The first set of indicators is related to the demographic characteristics of the individuals, and the second are meant to capture the individuals' physical, and psychological state at the point of the interview. Since these are three difference measures, the OLS coefficients as well as the normalized beta coefficients have been reported to facilitate comparison. In the Fixed effects regressions, the variables have all been standardized to again make the units of measurement comparable.

Table 4.5: Satisfaction and its covariates

Variables	**OLS**	**FE**	**Equal observation**	**Adults only**
Household size	0.0524**	-0.155	-0.110	-0.0634
	(0.0765)	(0.122)	(0.127)	(0.134)
Number of Adults	-0.0458**	0.0836	0.0647	0.0336
	(-0.0405)	(0.0752)	(0.0778)	(0.0822)
Number of children	-0.0640***	0.135*	0.117	0.0716
	(-0.0512)	(0.0755)	(0.0781)	(0.0824)
Married	0.210***	-0.0108	0.00414	-0.0127
	(0.0374)	(0.0184)	(0.0190)	(0.0185)
Female	-0.0528*	-	-	-
	(-0.0106)			
Age	0.00289***	3.329***	3.105***	2.896***
	(0.0219)	(0.645)	(0.674)	(0.689)
Rural	-0.0659	0.00179	0.00279	-0.0110
	(-0.00786)	(0.0479)	(0.0526)	(0.0512)
Urban	-0.0522	0.110*	0.111	0.126*
	(-0.0107)	(0.0658)	(0.0699)	(0.0698)
Indian	0.441***	-	-	-
	(0.0177)			
Coloured	-0.663***	-	-	-
	(-0.0927)			
Black	-1.874***	-	-	-
	(-0.286)			
Employment status	0.218***	0.0273**	0.0210	0.0337**
	(0.0400)	(0.0136)	(0.0143)	(0.0137)
Shocks	0.272***	0.0595***	0.0528***	0.0573***
	(0.0755)	(0.00925)	(0.00953)	(0.0101)
Hopeful	0.231***	0.102***	0.109***	0.0966***
	(0.115)	(0.00955)	(0.0100)	(0.0104)
Religious	0.725***	0.0400***	0.0423***	0.0414***
	(0.0848)	(0.00742)	(0.00788)	(0.00809)
Health Status	-0.265***	-0.0959***	-0.0986***	-0.0958***
	(-0.120)	(0.0111)	(0.0116)	(0.0117)
Crime	-0.122***	-0.0775***	-0.0725***	-0.0826***
	(-0.0643)	(0.0109)	(0.0115)	(0.0116)
Year	0.140***	-0.193***	-0.174***	-0.158**
	(0.0576)	(0.0586)	(0.0614)	(0.0625)
Constant	-275.5***	-1.756***	-1.627***	-1.961***
		(0.321)	(0.332)	(0.444)
Observations	29,385	29,385	27,746	25,659
R-squared	0.158	0.043	0.045	0.041
Number of pid		20,106	19,477	17,592

Notes: i) Normalized beta coefficients in parentheses for the OLS, ii) *** p<0.01, ** p<0.05, * p<0.1, iii) Omitted variables are number of elderly people, Province9, Tribal and White, iv) for fixed effects regressions (2, 3 and 4) there are no values for 2008 and therefore the omitted year variable is 2010 with the values of year 2012 in comparison v) Specification 3 refers to the case where one those observations where each of the poverty indicators was not missing were kept.

Table 4.6: MPI and its covariates

Variables	**OLS**	**FE**	**Equal observation**	**Adults only**
Household size	-0.00340	0.175	0.175	0.233*
	(-0.0692)	(0.122)	(0.122)	(0.131)
Number of Adults	0.00414*	-0.0673	-0.0673	-0.0951
	(0.0530)	(0.0774)	(0.0774)	(0.0834)
Number of children	0.0143***	-0.0273	-0.0273	-0.0200
	(0.172)	(0.0792)	(0.0792)	(0.0868)
Married	-0.0398***	0.0164	0.0164	0.0134
	(-0.0885)	(0.0143)	(0.0143)	(0.0168)
Female	-0.00231	-0.0122	-0.0122	-0.0207
	(-0.00381)	(0.0245)	(0.0245)	(0.0271)
Age	0.000862***	0.0988**	0.0988**	0.137***
	(0.0834)	(0.0390)	(0.0390)	(0.0448)
Rural	-0.0133***	-0.117*	-0.117*	-0.117*
	(-0.0285)	(0.0598)	(0.0598)	(0.0685)
Urban	-0.112***	-0.142	-0.142	-0.0379
	(-0.410)	(0.110)	(0.110)	(0.123)
Indian	-0.00219	0.585**	0.585**	0.691**
	(-0.00159)	(0.237)	(0.237)	(0.270)
Coloured	0.0731***	0.419	0.419	0.313
	(0.184)	(0.815)	(0.815)	-1.097
Black	0.0961***	0.629	0.629	0.239
	(0.269)	(0.854)	(0.854)	-1.179
Employment status	-0.0344***	-0.0114	-0.0114	-0.00209
	(-0.0829)	(0.0132)	(0.0132)	(0.0159)
Shocks	-0.000869	-0.0157*	-0.0157*	-0.0204*
	(-0.00413)	(0.00898)	(0.00898)	(0.0103)
Hopeful	-0.00217**	-0.00383	-0.00383	-0.00838
	(-0.0170)	(0.00841)	(0.00841)	(0.00934)
Religious	-0.0688***	-0.0206**	-0.0206**	-0.0217**
	(-0.0675)	(0.0100)	(0.0100)	(0.0107)
Health Status	0.00666***	0.00174	0.00174	0.00632
	(0.0370)	(0.0119)	(0.0119)	(0.0135)
Crime	0.000361	0.0291***	0.0291***	0.0299***
	(0.00342)	(0.0105)	(0.0105)	(0.0115)
Year	-0.00351***	-0.0882***	-0.0882***	-0.0960***
	(-0.0257)	(0.0139)	(0.0139)	(0.0155)
Constant	7.231***	0.0148	0.0148	-0.00469
		(0.0333)	(0.0333)	(0.0367)
Observations	9,944	9,944	9,944	8,352
R-squared	0.362	0.031	0.031	0.040
Number of hhid		6,394	6,394	5,514

Notes: i) Normalized beta coefficients in parentheses for the OLS, ii) *** p<0.01, ** p<0.05, * p<0.1, iii) Omitted variables are number of elderly people, Province9, Tribal and White, iv) for fixed effects regressions (2, 3 and 4) there are no values for 2008 and therefore the omitted year variable is 2010 with the values of year 2012 in comparison v) Specification 3 refers to the case where one those observations where each of the poverty indicators was not missing were kept.

Table 4.7: Income and its covariates

Variables	**OLS**	**FE**	**Equal observation**	**Adults only**
Household size	0.0726***	0.109	0.129	0.173*
	(0.197)	(0.0972)	(0.103)	(0.103)
Number of Adults	-0.0823***	-0.0876	-0.0977	-0.129**
	(-0.142)	(0.0622)	(0.0652)	(0.0660)
Number of children	-0.166***	-0.145**	-0.155**	-0.189***
	(-0.263)	(0.0644)	(0.0677)	(0.0688)
Married	0.364***	0.0142	0.0153	0.0166
	(0.109)	(0.0144)	(0.0151)	(0.0165)
Female	0.0181	-0.00928	-0.0217	-0.00162
	(0.00403)	(0.0205)	(0.0223)	(0.0239)
Age	0.0188***	0.273***	0.282***	0.261***
	(0.247)	(0.0272)	(0.0297)	(0.0282)
Rural	-0.0854***	0.0109	0.0115	-0.00663
	(-0.0247)	(0.0375)	(0.0433)	(0.0514)
Urban	0.271***	0.0666	0.0781	-0.0808
	(0.133)	(0.0733)	(0.0832)	(0.0937)
Indian	-0.451***	0.194	0.183	-0.0366
	(-0.0445)	(0.124)	(0.124)	(0.190)
Coloured	-1.089***	0.218	0.316	0.703
	(-0.369)	(0.326)	(0.331)	(0.443)
Black	-1.222***	-0.151	-0.142	0.624
	(-0.461)	(0.349)	(0.357)	(0.497)
Employment status	1.231***	0.311***	0.306***	0.322***
	(0.400)	(0.0138)	(0.0145)	(0.0157)
Shocks	0.0164	-0.00439	-0.00645	0.00645
	(0.0104)	(0.00772)	(0.00814)	(0.00866)
Hopeful	0.0104	0.0110	0.0155*	0.00167
	(0.0110)	(0.00821)	(0.00868)	(0.00902)
Religious	0.333***	0.00455	0.00106	0.00545
	(0.0440)	(0.00895)	(0.00931)	(0.00953)
Health Status	-0.0520***	0.00747	0.0108	0.00105
	(-0.0391)	(0.0108)	(0.0112)	(0.0120)
Crime	-0.0195***	0.00876	0.00516	0.0161
	(-0.0248)	(0.00933)	(0.00985)	(0.0103)
Year	0.0567***	0.123***	0.116***	0.118***
	(0.0557)	(0.0126)	(0.0135)	(0.0137)
Constant	-107.4***	-0.0389**	-0.0344*	-0.0474***
		(0.0174)	(0.0193)	(0.0169)
Observations	10,586	10,586	9,944	8,892
R-squared	0.497	0.220	0.219	0.217
Number of hhid		6,569	6,394	5,685

Notes: i) Normalized beta coefficients in parentheses for the OLS, ii) *** p<0.01, ** p<0.05, * p<0.1, iii) Omitted variables are number of elderly people, Province9, Tribal and White, iv) for fixed effects regressions (2, 3 and 4) there are no values for 2008 and therefore the omitted year variable is 2010 with the values of year 2012 in comparison v) Specification 3 refers to the case where one those observations where each of the poverty indicators was not missing were kept.

With a brief glance upon all three tables, one can see that accounting for time invariant characteristics (or in this case the reduction in the variation in these) removes much of the significance for these households. For the demographic features, fewer variables affect the satisfaction level and the multidimensional poverty score in comparison to income. A larger number of adults or children in comparison to elderly people, in a household lead to lower levels of satisfaction, higher deprivation scores and more income poverty in the OLS specification. On the other hand, for the fixed effects both satisfaction and multidimensional poverty reverse signs, indicating an improvement with the addition of adults (although insignificant). In the case of children, for income, the coefficient is negative and significant in all specifications, which is plausible since children only contribute by decreasing percapita income, while having no effect on the overall household income. In the other two cases, an increasing number of children leads to a wellbeing improvement. Being married only has a significant and enhancing effect on all dependent variables in the case of OLS regression and in nearly none of the fixed effects regressions. Again, the sign reverses and decreases wellbeing in the case of satisfaction and MPI. This is contrary to what is generally found in the literature. Increasing age has a positive effect on satisfaction and income in all specifications, but leads to an increase in multidimensional deprivation. That is to say, ceteris paribus, as individuals get older, they are more deprived and richer in life (the same conclusion cannot be made for satisfactions since the effect is insignificant).

Living in the tribal authority areas (previous homelands for specific ethnic groups, where there was restricted movement between groups but free movement within during Apartheid) aggravated objective wellbeing deprivation in comparison to residing in a rural area. It was found to be insignificant in the case of all the fixed effects specification for satisfaction and income. On the basis of the sign of the coefficient though, in the case of income, living in an urban or rural area positively affects household income in comparison to living in the tribal authority areas. Surprisingly, the OLS specification for satisfaction seems to show that there is a greater level of dissatisfaction with living in rural areas in comparison to living in these tribal areas. According to ethnic groupings, an Indian household is found to be the most satisfied, followed by the whites, then the coloured and the Blacks seem to be the most dissatisfied, in nearly all specification.

On the other hand, in terms of multidimensional poverty, there appears to be no significant difference between the Indians and the White, while the Coloured and Black households are found to be the most deprived. In the case of income on the other hand, the whites are the richest, followed by the Indians, the coloured, and the blacks are found to be the poorest. According to all these measures, the blacks seem to be the worst off ethnic group in South African, while the Indians fare relatively well in most measures, specifically multidimensional poverty. Finally, contrary to the evidence in much of the empirical literature, being a female negatively affects SWB (Dolan et al., 2008) but also income, although seems to reduce multidimensional poverty.

The second set of indicators include a physical measure, given by health status, and the mental state of mind, measured by shocks that the person might have experienced in the last 24 months, how hopeful the person is currently, the amount of crime they witnessed in the neighbourhood and whether they have been employed. The final variable of the physical condition variables is derived from the literature that concludes that religious people are in general more satisfied in life than non-religious ones (Ferriss, 2002; Rehdanz and Maddison, 2005). Again, a brief overview of these set of variables determines that these 'current status' variables are most relevant for subjective wellbeing and only slightly for the other two. As per the literature, having a form of religious belief positively affects satisfaction and multidimensional wellbeing, but has no effect on income. The level of crime observed in the neighbourhood is also found to not only reduce satisfaction but also depress multidimensional wellbeing. The effect on income on the other hand is not significant. Being employed on the other hand has no effect on any of the wellbeing indicators, which it affects income positively, which is an obvious result. The variable for shocks in personal, social or professional aspects of life is wellbeing enhancing, while it is insignificant in the case of income. Having a more hopeful outlook in life seems to increase satisfaction but leave multidimensional wellbeing and income unaffected. A deteriorating health status negatively affects only satisfaction and is not significant for multidimensional wellbeing or income.

Overall, there are some trends that can be observed from this analysis about differences in the drivers of each of these poverty/deprivation measures. In general, those indicators that were representative for the demographic determinants were slightly more relevant for OWB and Income, and not so much in the case of SWB. On the other hand, the second set of indicators looking at the physical, psychological and moral state of households are the ones that are highly relevant for SWB, while they are only somewhat relevant for income and mostly insignificant in the case of multidimensional wellbeing. The divergences that are found between the three methods in the literature are also visible in the analysis here. The third set of indicators that are related to the income and money metric measures of poverty are found to be most relevant for the income and not so much for objective and subjective wellbeing. Although these are endogenous, even across the three different measures these are found to have lesser effects. These different determinants are especially relevant in the case of policy measures where one can see how difference across groups affect different measures of deprivation and wellbeing.

4.5.2 PLS weights for multidimensional wellbeing and income

The previous section has shown that the determinants differ for the three welfare concepts used. We now intend to exploit the structural relationship between these concepts to create weights that best describe the underlying latent concept of wellbeing captured by the MPI, which are particularly related to income and satisfaction as outcome variables. As discuss above, PLS is a method that is ideally suited to this task.

In the formulation of these weights, the question then arises as to whether the weights would differ substantially if income or satisfaction was used as the dependent variable. We can perform a crude exercise to that effect and determine how these three perform in explaining each other. In Tables A4.5 to A4.6 in the appendix we regress each measure onto the other singly, and then jointly, to determine the increase in variation explained by a particular measure. What is clear after this analysis is that income and MPI, which is an OBW and incorporates standard of living indicators, which are representative of the income status of the households, are much more similar to each other, than satisfaction. While they are all found to significantly influence the other, with the appropriate sign of the coefficients, the variation explained by satisfaction on the other two is quite low, and vice versa. Although this has been informative in the overlaps of information between these three variables, we can test how this overlap varies when we account for the high collinearity that exists between all three of these measures, and that cannot be address with a simple OLS. Using PLS, we can remove the correlation between all the indicators of the MPI and then derive weights that reflect their overlap of information with the other two measures. Therefore, two different set of weights are derived for the MPI: one from the satisfaction and the other for income variable.

Table A4.2 in the appendix shows the correlation between satisfaction and adult equivalized Income with each of the nine indicators of the MPI, and each of them are highly correlated to the indicators that are meant to measure wellbeing under a broader framework. Interestingly the correlation for the standard of living indicators is found to be higher for the case of adult equivalized income, while those for child mortality and years of schooling are higher for the case of satisfaction. Depending on the perspective to which factors are more important for a particular capability set and consequently the value functionings, we choose to use both of these indicators as the Y variable in our PLS analysis.

Table 4.8 shows the results for the various methods that are used to determine the weights for the relation between satisfaction and the 9 indicators of wellbeing as mentioned within the MPI, for the years 2008, 2010 and 2012 respectively. In the case of both PCA and MCA, only the first component was utilized. Both of these are traditionally exploratory methods, and therefore representative of an index that can be derived from the latent concept explained by these 9 indicators. They do not indicate how well they are able to express satisfaction or income deprivation, as the latent concept might be indicative of where the highest variation in the data is for the first component. Therefore PLS is a much better method to impose the constraint on these nine indicators to reflect a concept that is closely aligned with satisfaction (columns 1 in Table 4.8) and income (column 2 in Table 4.8).

The results show that the weights from both the income and satisfaction variables are rather similar. The weights marked in bold are those that represent the largest shares in the weights, or at least larger than 15%. But there are some interesting differences. Despite the regressions showing the low variability explained by satisfaction for the income measure, when removing the high correlation between these three, there are actually many similarities between the two. This is contingent on the MPI being the indicators that represent OBW and there being a covariance overlap between the outcome variable. While in a normal OLS regression run before there appears to be a large difference in the variability explained by income and SWB, this is not so substantial when using PLS.

The PLS weights differ substantially from the technocratic MPI weights (column 3 in Table 4.8), and are more similar to the PCA and MCA weights (columns 4 and 5 respectively). Specifically, the weights from MCA are highly correlated to the one derived using PLS (with a correlation coefficient of .99). This represents the higher suitability of the MCA in terms of generating a latent concept of wellbeing using these 9 indicators, while there more differences between PLS and PCA weights. When PCA is used to derive weights, in all three years, electricity, sanitation, drinking water, and cooking fuel have larger weights than when satisfaction is used; the reverse is the case for assets. Overall we find the health and education components are allocated much lower weights (1.8% and 9.6% respectively) than the standard of living indicators. This would indicate that amongst these nine indicators, assets and sanitation are considered more important for the satisfaction and income outcomes. Moreover, there are also very few differences that are observed across the years, meaning these valuations change very little across the period that we have considered.

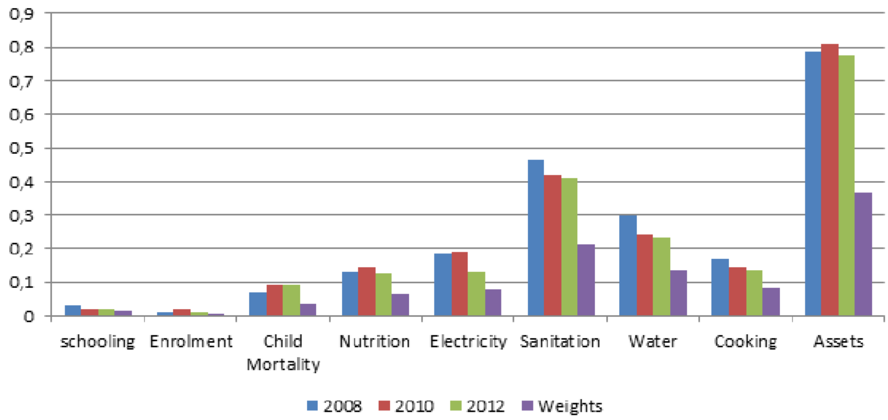
Table 4.8: Weights for MPI indicators using different methods, by year

Indicator	**PLS Satisfaction**	**PLS Income**	**MPI**	**PCA**	**MCA**
		2008			
Years of schooling	0.013	0.014	0.167	0.016	0.014
Enrolment	0.005	0.005	0.167	0.002	0.007
Child Mortality	0.027	0.028	0.167	0.003	0.027
Nutrition	0.069	0.066	0.167	0.003	0.064
Electricity	0.083	0.087	0.067	**0.193**	0.092
Sanitation	**0.212**	**0.215**	0.067	**0.250**	**0.217**
Drinking water	0.148	**0.153**	0.067	**0.241**	**0.159**
Cooking Fuel	0.097	0.098	0.067	**0.208**	0.102
Assets	**0.345**	**0.334**	0.067	0.083	**0.319**
		2010			
Years of schooling	0.008	0.008	0.167	0.009	0.007
Enrolment	0.013	0.013	0.167	0.001	0.014
Child Mortality	0.039	0.041	0.167	0.008	0.041
Nutrition	0.072	0.068	0.167	0.000	0.065
Electricity	0.088	0.095	0.067	**0.188**	0.096
Sanitation	**0.212**	**0.213**	0.067	**0.258**	**0.215**
Drinking water	0.134	0.135	0.067	**0.254**	0.140
Cooking Fuel	0.077	0.084	0.067	**0.215**	0.085
Assets	**0.357**	**0.344**	0.067	0.067	0.338
		2012			
Years of schooling	0.008	0.008	0.167	0.008	0.007
Enrolment	0.004	0.005	0.167	0.001	0.004
Child Mortality	0.046	0.046	0.167	0.006	0.043
Nutrition	0.070	0.069	0.167	0.001	0.065
Electricity	0.066	0.068	0.067	0.177	0.072
Sanitation	**0.220**	**0.222**	0.067	**0.255**	**0.227**
Drinking water	0.135	0.136	0.067	**0.251**	0.141
Cooking Fuel	0.090	0.090	0.067	**0.230**	0.094
Assets	**0.361**	**0.355**	0.067	0.071	**0.347**

Figure 4.1 depicts the contribution of each of the indicators weighted with PLS using satisfaction, assuming that a household is considered poor if they have a weighted score of more than 0.33. Since assets itself accounts for more than 36% of the total weight, this is also observed in the graph where assets have the largest contribution to overall subjective poverty (depicted by the purple bar). Sanitation gets the second highest weights and has the second highest contribution to overall deprivation as well. As can be

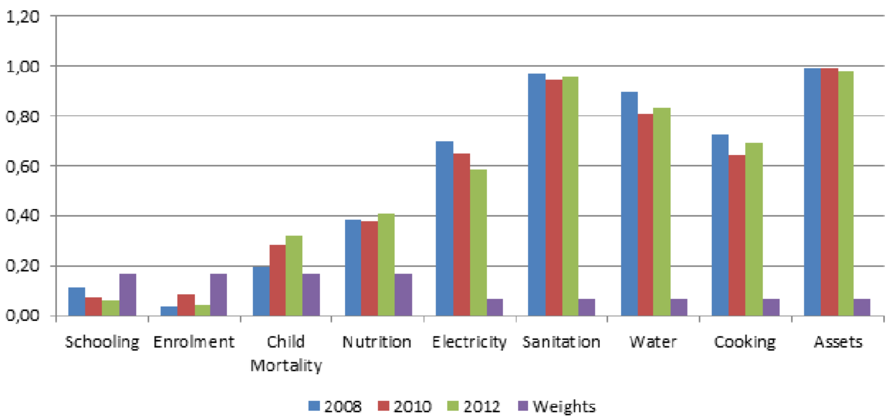
seen, the contribution of each indicator is similar to the weight it has derived using the PLS. When comparing them to the normal MPI weights in Figure 4.2, we see that assets had still contributed the largest to the poverty score of the household. Now though, other standard of living indicators contribute much lower, in comparison to before. Therefore, the new weighting also affects the contribution of each indicator to the overall poverty score. To summarize, PLS provides rather different weights for MPI indicators when outcome variables such as income and satisfaction are being used, while they differ only slightly between the two outcome variables.

Figure 4.1: Contribution of each indicator when assigned weights as per the PLS method



Source: Own calculation

Figure 4.2: Contribution of each indicator when assigned equal weights



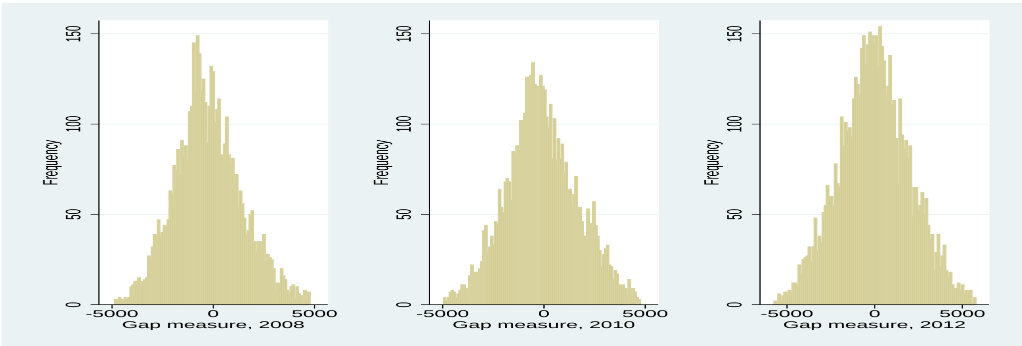
Source: Own calculation

In the following subsection, we attempt to quantify this gap and therefore examine how each of these indicators react in turn to the different types of multidimensional indices that have been generated using the AF methodology as well as the PLS weights from Satisfaction and Income.

4.5.3 Hedonic adaptation using the new index

To test how well the new indices are able to depict the property of adaptation amongst individuals, we generated a gap measure that has already been described, using the rank of the households. Figures A4.2, to A4.4 in the appendix show the distribution of ranks in the sample households for satisfaction, weighted multidimensional deprivation and income, respectively. It can be seen that the ranks of households according to income are a lot more divers in comparison to satisfaction and more so in the case of Multidimensional poverty. In fact, there are only a maximum of 185 different average ranks of satisfaction and 20 different average ranks of multidimensional deprivation scores amongst all three years that were derived after collapsing the dataset at the household level. The satisfaction values for each household member was an average of the household members over each year, which introduced more than the given 10 values, while for the case of the MPI weighted score, since the values for each member of the household was the same, the average value was not different. This naturally meant that there was much less variation in the deprivation score at the household level as well. However, when examining the gap measure for the case of satisfaction and income in Figure 4.3, there is a rather normal distribution for the differences in the ranking. The summarized gap measures in Table A4.4 in the appendix also seem to support this.

Figure 4.3: Distribution of satisfaction-income gap for households, by year



Source: Own data

Tables 4.9, 4.10 and 4.11 are the cross-sectional regressions where the demographic and status of being characteristics of the household, and the new indices generated in the previous section are regressed on the gap generated using the method above, for the year 2008, 2010 and 2012 respectively. The variable of interest in our case is the MPI, which is positive and significant in all the years. The column one in each Table are where all the covariates are regressed on the gap measure, without the multidimensional wellbeing indices. The first column was added just to facilitate comparison of the other covariates and measure the improvement in the adjusted R-square to determine the improvement in the variation explained. The column two in each Table corresponds to the MPI score which was derived from the Alkire-Foster methodology, which assigns all three dimensions equal weights, and each indicator within gets equal weights as well. This corresponds to Column 3 in Table 4.8. The third columns uses the MPI score that is derived for each household using the weights derived using PLS with satisfaction as the response variable (column 1 in Table 4.8). The fourth column in each table displays the relation between the covariates and the MPI that is derived using PLS and income as the response variable (column 2 in Table 4.8), and the gap measure.

At first glance, we can see that the inclusion of these indices into the regression does increase the overall fit of the model. In nearly all cases the best fit is obtained in the set of indices that represent satisfaction correlation PLS weights. The coefficient on the MPI score seems to suggest that a drop in multidimensional wellbeing (increase in the MPI score) leads to an increase in the rank gap. To elaborate on the interpretation of this coefficient, the multidimensionally poorer households are more satisfied given their income status in this dataset. That is to say that their rank difference between income and satisfaction goes up when multidimensional wellbeing declines. This is likely represented as a fall in income rank but no proportional decline in the satisfaction ranks. This may suggest evidence of hedonic adaptation in terms of subjective wellbeing in the case of South Africa. People are adapting to deprivation, as given by the MPI. This is found for all three years, where the size of the effect seems to be increasing over time. When we look at the difference between the three MPI indices, we find another interesting result. The effect is usually highest for the satisfaction weighted MPI, and the lowest for the equally weighted MPI. This shows that the MPI index developed using satisfaction has the largest effect on the rank gaps in general, i.e. it appears to be the most sensitive to the adaptation of households. Therefore, it suggests that weighting indices on a structure correlated with satisfaction incorporates this subjective aspect into the index itself. These new indices objectively defined wellbeing, but also incorporate the subjective nature of wellbeing in their construction.

A larger household seems to decrease satisfaction, given a particular income level, which is not an expected result. However, as can be seen in the covariates regression, a larger household tend to improve satisfaction levels and income levels both, this decrease in the gap likely stems from improvements in income ranking. Also, being employed affects the household satisfaction income gap negatively, whereby the effect most likely largely stems from the decline in the satisfaction ranks being smaller in comparison to the decline in income rankings. Compared to having a larger number of elderly in the household, an increasing number of adults and children seem to increase this satisfaction-income gap as well. Compared to their income status, a larger number of married individuals in the household as well as older individuals seem to have lower satisfaction levels, given income levels. The latter probably also explains the reason why this gap rank is also lower for elderly in comparison to children and adults. Coming from urban areas seems to reduce the satisfaction-income gap as well, in comparison to living in a tribal authority area, in nearly all the specifications. Although this results is unlike what is found in the literature, we believe this largely stems from the increase in income rankings rather than the decrease in satisfaction rankings. In terms of racial differences, apart from 2008, being Black is shown to have a negative impact on this gap in comparison to being white. In the case of Coloured and Indians this is the reverse, and the coefficient is positive in all the cases. This would suggest that the blacks are not as adaptive given their income, in comparison to the White, Indians or Coloured. Shocks seem to have an ambiguous result. On the other hand, other physical condition variables such as being hopeful in life, having a religious belief and a high health status seem to improve satisfaction ranks.

Table 4.9: Effect of weighted multidimensional poverty on the gap, 2008

	Dependent variable: Gap measure			
Variables	None	Equal weighted	PLS Satisfaction	PLS Income
MPI score		749.5***	912.2***	908.0***
		(213.0)	(132.5)	(132.8)
Household size	-311.0***	-328.5***	-335.6***	-335.2***
	(47.69)	(50.13)	(49.86)	(49.86)
Number of adults	188.8***	216.3***	229.0***	228.7***
	(48.05)	(50.38)	(50.21)	(50.21)
Number of children	387.2***	397.8***	406.7***	406.2***
	(56.48)	(59.60)	(59.13)	(59.14)
Married	-188.3*	-94.59	-37.03	-38.90
	(107.3)	(116.5)	(116.2)	(116.2)
Female head	83.65	105.4*	93.08	93.88*
	(54.21)	(56.81)	(56.69)	(56.69)
Age	-14.24***	-14.97***	-13.93***	-13.95***
	-2.665	-2.970	-2.953	-2.953
Rural	-77.60	-61.43	-2.750	-1.379
	(89.35)	(94.13)	(93.89)	(93.92)
Urban	-404.5***	-302.4***	-129.3*	-126.6
	(67.44)	(74.96)	(78.39)	(78.69)
Indian	360.6**	407.1**	429.5***	431.7***
	(154.2)	(161.8)	(163.1)	(163.1)
Coloured	729.2***	724.0***	604.9***	611.2***
	(96.31)	(104.6)	(106.3)	(106.1)
Black	409.8***	325.0***	136.2	141.7
	(91.04)	(100.6)	(106.0)	(105.7)
Employment status	-1,121***	-1,091***	-1,056***	-1,057***
	(69.57)	(73.57)	(73.73)	(73.71)
Shocks	-65.65*	-53.13	-51.88	-52.19
	(37.36)	(38.79)	(38.73)	(38.74)
Hopeful	Nov 75	7.651	13.81	13.66
	(23.78)	(25.21)	(25.14)	(25.14)
Religious	-420.0**	-306.7*	-266.0	-266.2
	(174.9)	(182.1)	(182.2)	(182.2)
Health Status	-118.4***	-136.0***	-143.7***	-143.4***
	(31.54)	(33.26)	(33.28)	(33.27)
Constant	1,152***	980.4***	643.1**	644.5**
	(249.7)	(265.4)	(272.2)	(272.3)
Observations	4,86	4,452	4,452	4,452
Number of hhid	0.143	0.143	0.150	0.149

Notes: i) Robust standard errors in parentheses, ii) *** p<0.01, ** p<0.05, * p<0.1, iii) Omitted variables are number of elderly people, Province9, Tribal and White.

Table 4.10: Effect of weighted multidimensional poverty on the gap, 2010

		Dependent variable: Gap measure		
Variables	None	Equal weighted	PLS Satisfaction	PLS Income
MPI score		1,037***	1,013***	995.5***
		(211.1)	(138.4)	(138.8)
Household size	-266.1***	-280.2***	-299.1***	-298.4***
	(46.65)	(47.70)	(47.55)	(47.57)
Number of adults	170.1***	181.1***	206.9***	206.2***
	(47.04)	(48.31)	(48.14)	(48.16)
Number of children	271.8***	275.0***	298.5***	297.8***
	(54.93)	(56.35)	(56.07)	(56.09)
Married	-606.4***	-530.0***	-455.5***	-460.7***
	(111.5)	(115.8)	(116.1)	(116.1)
Female head	7.261	26.34	17.97	18.55
	(52.99)	(54.95)	(54.75)	(54.76)
Age	-14.71***	-15.98***	-14.35***	-14.37***
	-2.698	-2.827	-2.828	-2.828
Rural	146.7*	185.5**	248.0***	247.2***
	(86.46)	(90.06)	(90.96)	(91.01)
Urban	-413.9***	-308.2***	-164.8**	-166.2**
	(65.66)	(70.92)	(75.42)	(75.70)
Indian	102.4	29.18	58.41	62.93
	(224.2)	(239.7)	(236.7)	(236.8)
Coloured	407.6***	223.3	89.04	100.0
	(147.3)	(154.1)	(154.8)	(154.6)
Black	-89.94	-273.6**	-440.2***	-428.5***
	(129.7)	(138.2)	(141.4)	(141.1)
Employment status	-1,731***	-1,734***	-1,687***	-1,690***
	(83.07)	(85.60)	(85.84)	(85.84)
Shocks	14.88	13.92	13.92	13.94
	(37.58)	(39.24)	(38.94)	(38.95)
Hopeful	241.2***	240.8***	239.3***	239.4***
	(22.33)	(23.01)	(22.86)	(22.87)
Religious	498.8***	674.6***	717.0***	716.9***
	(157.7)	(168.7)	(169.6)	(169.7)
Health Status	-375.2***	-382.3***	-388.4***	-387.9***
	(33.57)	(35.29)	(35.23)	(35.23)
Constant	983.8***	797.4***	439.0	447.1
	(253.1)	(267.8)	(273.5)	(273.7)
Observations	4,831	4,469	4,469	4,469

Notes: i) Robust standard errors in parentheses, ii) *** p<0.01, ** p<0.05, * p<0.1, iii) Omitted variables are number of elderly people, Province9, Tribal and White.

Table 4.11: Effect of weighted multidimensional poverty on the gap, 2012

	Dependent variable: Gap measure			
Variables	None	Equal weighted	PLS Satisfaction	PLS Income
MPI score		1,212***	1,245***	1,242***
		(223.3)	(134.8)	(135.1)
Household size	-337.5***	-326.3***	-341.1***	-340.9***
	(52.65)	(54.23)	(54.01)	(54.01)
Number of adults	189.2***	172.1***	196.2***	195.9***
	(52.42)	(54.16)	(53.93)	(53.94)
Number of children	434.9***	407.9***	426.8***	426.5***
	(61.95)	(63.99)	(63.56)	(63.56)
Married	-379.4***	-300.9***	-211.8***	-213.4***
	(77.20)	(80.08)	(80.91)	(80.90)
Female head	32.81	26.71	21.66	21.87
	(55.93)	(57.45)	(57.20)	(57.21)
Age	-12.63***	-13.86***	-11.98***	-11.98***
	-2.884	-3.008	-2.987	-2.988
Rural	-97.60	-65.34	30.81	31.94
	(89.27)	(92.33)	(93.30)	(93.34)
Urban	-788.2***	-649.6***	-453.9***	-451.9***
	(67.17)	(73.22)	(77.69)	(77.84)
Indian	357.0	366.6	343.4	347.0
	(230.6)	(240.6)	(244.0)	(244.0)
Coloured	604.6***	516.6***	341.3***	346.4***
	(127.2)	(130.7)	(130.9)	(130.9)
Black	-86.78	-187.7	-411.5***	-406.8***
	(126.5)	(130.1)	(132.6)	(132.5)
Employment status	-1,812***	-1,843***	-1,785***	-1,786***
	(82.01)	(84.52)	(84.93)	(84.92)
Shocks	268.6***	275.1***	274.7***	274.6***
	(36.14)	(36.61)	(36.19)	(36.19)
Hopeful	66.02***	54.38**	53.93**	53.91**
	(23.80)	(24.33)	(24.25)	(24.25)
Religious	813.2***	872.1***	930.4***	930.4***
	(197.2)	(201.9)	(202.0)	(202.0)
Health Status	-273.3***	-278.8***	-283.4***	-283.3***
	(34.94)	(36.03)	(35.84)	(35.84)
Constant	1,088***	937.1***	476.7	477.6
	(295.3)	(305.9)	(311.9)	(312.0)
Observations	5,968	5,655	5,655	5,655
Adjusted R- squared	0.177	0.184	0.192	0.191

Notes: i) Robust standard errors in parentheses, ii) *** p<0.01, ** p<0.05, * p<0.1, iii) Omitted variables are number of elderly people, Province9, Tribal and White.

Table 4.12: Effect of multidimensional poverty on gap measure, fe

	Dependent variable: Gap measure			
Variables	None	Equal weighted	PLS Satisfaction	PLS Income
MPI score		-261.0	528.0*	489.4*
		(381.2)	(271.8)	(272.9)
Household size	-398.2***	-401.1***	-406.3***	-405.8***
	(118.3)	(126.9)	(126.0)	(126.1)
Number of adults	280.2**	289.7**	294.9**	294.4**
	(119.9)	(127.9)	(127.2)	(127.2)
Number of children	430.6***	443.9***	447.3***	446.9***
	(131.0)	(139.9)	(139.0)	(139.0)
Married	-439.8***	-285.6*	-291.6*	-291.2*
	(157.5)	(164.4)	(164.4)	(164.4)
Female head	-120.1	-165.1**	-166.5**	-166.4**
	(74.25)	(78.46)	(78.37)	(78.38)
Age	-21.65***	-22.76***	-22.96***	-22.98***
	(7.059)	(7.808)	(7.757)	(7.760)
Rural	-373.3	-281.0	-215.8	-218.8
	(379.4)	(449.8)	(459.0)	(458.8)
Urban	-49.92	27.67	98.82	94.94
	(381.6)	(438.4)	(444.2)	(443.9)
Indian	1,920	2,100	1,423	1,463
	(3,503)	(3,898)	(3,878)	(3,879)
Coloured	-3,561	-4,506	-4,838	-4,813
	(3,317)	(3,585)	(3,425)	(3,436)
Black	-2,193	-2,415	-2,804	-2,770
	(3,130)	(3,276)	(3,108)	(3,121)
Employment status	-1,675***	-1,668***	-1,667***	-1,667***
	(122.5)	(130.9)	(130.5)	(130.6)
Shocks	202.9***	182.8***	185.8***	185.7***
	(39.94)	(41.72)	(41.65)	(41.66)
Hopeful	164.4***	162.4***	163.5***	163.4***
	(25.48)	(26.95)	(26.94)	(26.94)
Religious	765.9***	780.5***	806.3***	805.2***
	(206.5)	(224.0)	(223.7)	(223.8)
Health Status	-372.8***	-387.1***	-386.0***	-386.2***
	(42.91)	(46.02)	(46.05)	(46.05)
Crime	-106.8***	-99.63***	-103.0***	-102.9***
	(23.14)	(24.39)	(24.42)	(24.42)
Constant	4,256	4,870	4,867	4,866
	(3,135)	(3,347)	(3,197)	(3,209)
Observations	10,584	9,943	9,943	9,943
Adj R squared	0.113	0.113	0.113	0.113
Number of hhid	6,567	6,393	6,393	6,393

Notes: i) Robust standard errors in parentheses, ii) *** p<0.01, ** p<0.05, * p<0.1, iii) Omitted variables are number of elderly people, Province9, Tribal and White.

The Table 4.12 shows the same relations as in the previous Tables, but in a fixed effects setting. As can be seen, most of the variability is lost removing the within component only, and in the case of the normal MPI, it appears that the people are also not seemingly adapting over time, or at least there is not significant difference that can be seen. The coefficient for the new indices regressed on the gap rank however still have a negative sign, albeit significant only at the 1% level. This suggest that we still observe a adaptation over time amongst household with relation to these new indices. The other covariates also behave in similar manner as in the cross sectional regressions.

These regressions depict some interesting results when comparing them to literature from before. Nonetheless, these are largely explained by the relative changes between these ranks. For the case of the measure of wellbeing, we do see that there appears to be some form of adaptation towards a broad definition of deprivation amongst individuals in the dataset. Given that the indices using satisfaction as the outcome variables are able to best reflect this adaptation, it would suggest that although these are indices that have objective valuations behind their formation, they are still able to capture the interpersonal subjectivity of the households to their situation in life.

4.6 Conclusion

Due to the influence of utilitarianism, economists are enamoured with the idea of subjective utility being the appropriate metric for the evaluation of the distribution of social advantages (Fluerbaey et al., 2009). However, Fluerbaey provides three important failings when using data from satisfaction surveys given ordering preferences. First, this type of data is unable to account for the physical condition of the individual (characteristics that are specific to everyone but differ across individuals such as childhood histories and bodily, mental and personal characteristics) that influence adaptation when providing information about the link between these preferences. In comparison the actual state of wellbeing might be different but these specific characteristics that differ across individuals also affect their evaluation of their utility. The second limitation is that we measure average preferences along subgroups defined by certain characteristics, which ignore any personal level variation. Therefore, when we determine ethnicity or age based difference, we are unable to incorporate variation that exists for each particular individual in that analysis. Third, the amount of noise one captures in the satisfaction variable can be affected by the mental and emotional state on that day, and therefore one needs to ensure that the conditions the respondent faces are adequately similar for an appropriate analysis. Therefore, inter-personal comparison of wellbeing has a few failings that it is unable to account for. Nonetheless, the mass of data and large scientific evidence on happiness and satisfaction so far help us conclude that there is enough regularity within human psychology to extract valuable information in terms of an individual's wellbeing. Therefore, they are important tools which are intensively used in welfare economics.

A full-fledged utilitarian will only concern themselves with a subjective assessment of wellbeing, such as satisfaction. Non-welfarists will choose to go beyond this measure and inquire as to reasons behind the differences in life satisfaction despite similarities in other indicators of affluence (Schokkaert, 2007). This is the reasoning behind this new set of indices that have been introduced within this paper. We prefer to assign a broad set of functionings to represent wellbeing, but assimilate them within an index to represent the ordinal preferences that have been pivotal to the welfarist approach. Using the Multidimensional Poverty Index as the basis for determining the objective welfare of a household, we use the PLS method to derive the best weights for these dimensions based on the satisfaction responses within the data. Our indices show that there are differences in the weights that are assigned when incorporating the information that is contained within the satisfaction variable. The indices largely diverge from the traditional equal weighting scheme that is preferred amongst the present practical applications of multidimensional indices of deprivation, most popularly, the AF MPI, or the HDI, HPI etc. Instead we find that there are large variations in the weights among the indicators selected, with Assets and Sanitation receiving the highest weights for the South African sample. These results is quite surprising, given that the health dimension receives a much lower weight instead. Given that our research was done at the cross-sectional level, in the future we intend to extend the analysis for testing the dynamic effect of this index.

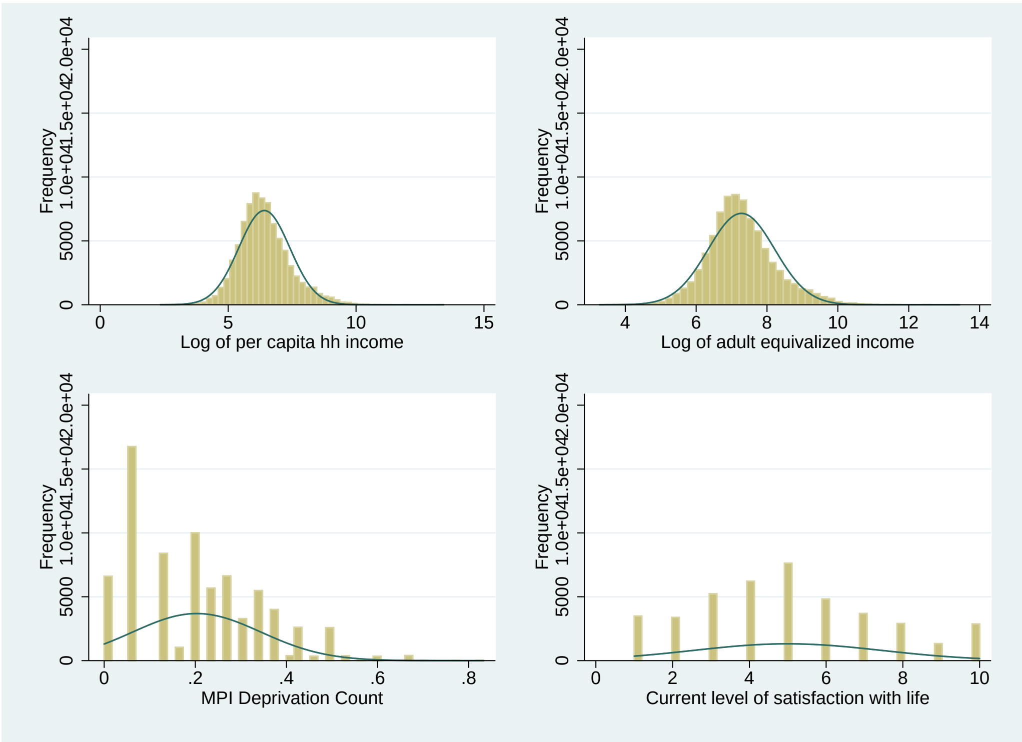
The critical issue with this method is that with the introduction of new data, the weight might be entirely different, thereby rendering any comparison over time or across regions pointless. However, the issue of temporal comparability is allayed if one takes the weights of a particular year as the yardstick for future comparison. One can also tackle issues of spatial comparability when comparing all other regions to a particular region which might be considered most representative. Nonetheless, since the point of this analysis is not to extend comparisons of poverty, but rather to extract the wellbeing variation amongst the population, along certain indicators of wellbeing, we do not consider this a major shortcoming in the method. The weights derived using PCA and PLS are not as contrasting as equal weighting, but still differ. Therefore, the rescaling that is performed by the MCA and PLS to account for little variation in the data does seem to affect the end result. What is interesting, is that the weights derived using satisfaction as an outcome variable is very similar to those where income is the outcome variable. Moreover, the correlation between MCA and these PLS indices are also very high. This can be due to several reasons. Satisfaction is an ordinal variable and therefore using dummy coding PLS might not be the most appropriate method. Alternatively, one can check with NMPLS, or run data simulations to test the prediction of these different models. Moreover, the ordinal structure is also constrained when imposing a linear regression and therefore an appropriate link function may improve the performance of this technique as well. These are all possible route for future research.

4.7 Appendix

Table A4.1: Summary of each variable of interest by year

Variable	Observations	Mean	Std.	Min	Max
		2008			
Satisfaction	11188	5.47	2.49	1	10
Log per capita income	24855	6.41	1.04	2.35	11.31
MPI weighted score	22899	0.20	0.15	0	0.833333
		2010			
Satisfaction	14597	4.63	2.45	1	10
Log per capita income	26678	6.32	1.01	3.13	13.43
MPI weighted score	23830	0.21	0.14	0	0.7
		2012			
Satisfaction	15789	5.00	2.40	1	10
Log per capita income	29791	6.51	0.94	2.63	11.34
MPI weighted score	28265	0.20	0.14	0	0.766667

Figure A4.1: Distribution of all the variables of interest for SWB, OWB and MMP



Source: Own data

Table A4.2: Correlation between Satisfaction and MPI indicators

	Satisfaction	**Adult Equivalized Income**
Years of schooling	-0.0266*	-0.0627*
Enrolment	-0.0302*	-0.0248*
Child Mortality	-0.0650*	-0.0561*
Nutrition	-0.0269*	-0.0779*
Electricity	-0.1534*	-0.2150*
Sanitation	-0.2078*	-0.3765*
Drinking water	-0.1602*	-0.3150*
Cooking Fuel	-0.1299*	-0.2480*
Assets	-0.1903*	-0.4519*

* p<0.01

Table A4.3: Mismatch between poor and non-poor between SWB and OWB/Income (in percentages)

			Subjective wellbeing			Total
			Poor	Medium	Non-poor	
2008	MPI	Non-poor	*11*	16	50	76
		Poor	6	4	*15*	24
	Income	Non-poor	***5***	10	27	43
		Poor	11	9	***37***	57
2010	MPI	Non-poor	*20*	17	40	77
		Poor	8	4	*11*	23
	Income	Non-poor	***10***	10	22	43
		Poor	20	1	***36***	57
2012	MPI	Non-poor	*18*	17	45	80
		Poor	5	4	*11*	20
	Income	Non-poor	***10***	12	27	48
		Poor	13	9	***29***	52

Table A4.4: Summary statistics of the gap measure, by year

Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Gap rank 2008	4876	-240.02	1663.456	-4868	4764.5
Gap rank 2010	4923	-102.91	1759.293	-4960	4744
Gap rank 2012	5974	-7.6	2013.792	-5734	5769.5

Table A4.5: Variation explained by income and SWB with MPI score as dependant variable

VARIABLES	(1)	(2)	(3)	(4)
Income	-0.0602***		-0.0540***	-0.0303***
	(0.000983)		(0.00105)	(0.00122)
Satisfaction		-0.0162***	-0.00901***	-0.00377***
		(0.000499)	(0.000490)	(0.000453)
Constant	0.631***	0.271***	0.630***	6.042***
	(0.00749)	(0.00281)	(0.00742)	-1.089
Observations	15,023	14,676	14,671	14,576
Controls	No	No	No	Yes
Adjusted R-squared	0.178	0.068	0.198	0.417

Notes: i) Robust standard errors in parentheses, ii) *** p<0.01, ** p<0.05, * p<0.1.

Table A4.6: Variation explained by income and OWB for Satisfaction as dependant variable

VARIABLES	(1)	(2)	(3)	(4)
Income	0.708***		0.544***	0.350***
	(0.0172)		(0.0197)	(0.0237)
MPI score		-4.173***	-2.557***	-1.301***
		(0.127)	(0.138)	(0.155)
Constant	-0.139	5.837***	1.548***	253.5***
	(0.128)	(0.0305)	(0.160)	(20.15)
Observations	15,773	14,676	14,671	14,576
Controls	No	No	No	Yes
Adjusted R-squared	0.097	0.068	0.114	0.217

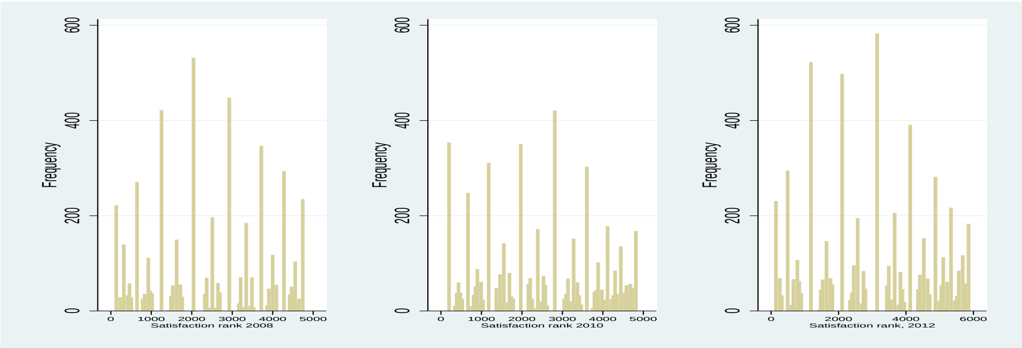
Notes: i) Robust standard errors in parentheses, ii) *** p<0.01, ** p<0.05, * p<0.1.

Table A4.7: Variation explained by SWB and OWB for income as dependant variable

VARIABLES	(1)	(2)	(3)	(4)
Satisfaction	0.137***		0.0918***	0.0442***
	(0.00358)		(0.00340)	(0.00298)
MPI score		-2.960***	-2.586***	-1.320***
		(0.0519)	(0.0546)	(0.0524)
Constant	6.642***	7.879***	7.353***	-68.16***
	(0.0181)	(0.0122)	(0.0231)	-7.084
Observations	15,773	15,023	14,671	14,576
Controls	No	No	No	Yes
Adjusted R-squared	0.097	0.178	0.220	0.484

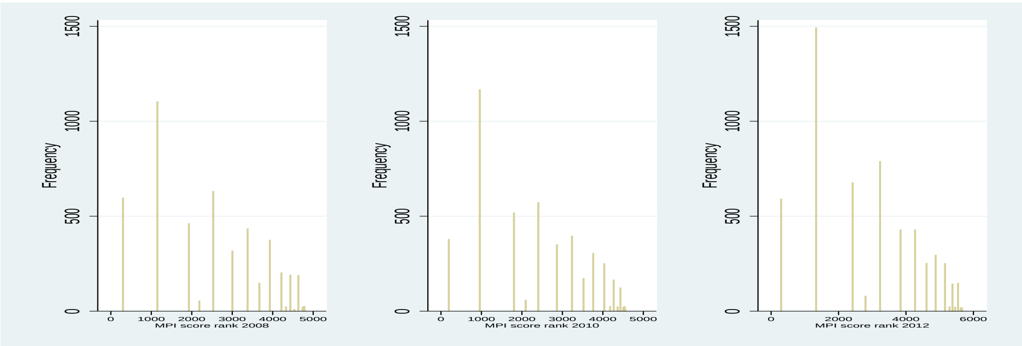
Notes: i) Robust standard errors in parentheses, ii) *** p<0.01, ** p<0.05, * p<0.1.

Figure A4.2: Distribution of ranks of satisfaction in all years



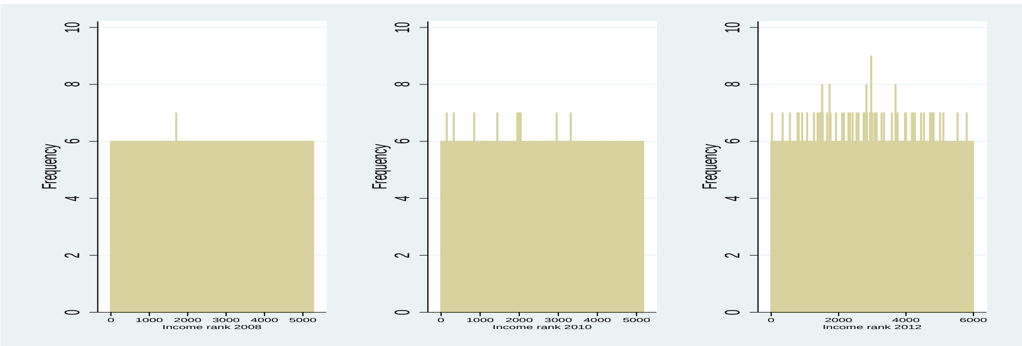
Source: Own data

Figure A4.3: Distribution of ranks of MPI score in all years



Source: Own data

Figure A4.4: Distribution of ranks of income in all years



Source: Own data

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1. The opportunity for the existing doctoral project was not made commercially available to me. Especially, I have not engaged any organisation that seeks thesis advisors against a fee for the preparation of dissertations or performs my obligations with respect to examination components entirely or partly.
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