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Targeting Grenada's Most Deprived Population: A Multidimensional Living Conditions Assessment

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Abstract
Public policies concerned with the reduction of poverty increasingly rely on identifying the most deprived households with the use of statistical targeting techniques. Targeting methods aim to measure deprivation as accurately as possible and use this measurement to identify those who need help the most. This paper proposes an improved method for the construction of a household multidimensional index of deprivation for targeting purposes and applies it in the Grenadian context. The proposed *Grenadian living conditions index* prioritizes quality of life and living conditions, rather than merely income or expenditure and provides a framework for the measurement of the joint depth of multidimensional deprivation. Furthermore, the proposed instrument allows for comparisons across households and over time and can be applied for different purposes and policies. Empirical results shed light on the advantages of using our proposed method for poverty reduction, compared to Principal Component Analysis and Fuzzy Set techniques.

Keywords: targeting, multidimensional poverty, proxy means test, Grenada.

JEL classification: I32, D63 and O20

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1 Introduction

Direct social support policies such as conditional cash transfers employ statistical targeting methods in order to maximize the reduction of poverty, despite having limited information on the household living conditions and within the constraints of a certain governmental budget. Targeting methods that focus on household assessment determine eligibility for public assistance by providing a theoretical and statistical framework for the measurement of deprivation, on the basis of which households are classified as deprived or not.

We discuss the main technical questions that policy makers face when targeting deprived households for public assistance and propose an improved targeting method, which we apply in the Grenadian context. Using household data from the 2008 Grenadian Living Conditions Survey, we provide evidence of the added benefits associated with the proposed instrument by comparing its performance and efficacy over other widely used multidimensional targeting methods. Throughout the developing world, different countries have opted for different targeting methods. Uruguay's SICU (Sistema de identificación y categorización de usuarios), Chile's FPS (Ficha de Protección Social), Mexico's CUIS (Cuestionario Único de Información Socioeconómica), and Jamaica's PATH (Programme of Advancement through Health and Education) apply Proxy Means Test methodologies to target income or expenditure poor households. Differently, Costa Rica, Ecuador and Peru apply a Principal Component Analysis; while Colombia uses a Fuzzy Set approach.

Although methods and their applications vary largely, household-assessment targeting tools can be broadly classified under two categories; the income or expenditure focused measures, and the multidimensional quality of life measures. While income-based measures, such as the Proxy Means Test, focus on resources and expenditure of households, multidimensional quality of life measures focus on measuring living conditions, such as adult illiteracy or access to water (Azevedo and Robles, 2013; Coady, Grosh and Hoddinott, 2004). Both approaches are associated with certain limitations from a public policy perspective.

On the one hand, income-focused measures fail to adequately account for the way resources are translated into a household's living conditions and, as pointed out by Baker and Grosh (1994), do not capture welfare dimensions such as health, literacy or access to public services. Although households that lack access to those services can be categorized as worse off than households with access, targeting solely based on income criteria would place both types of households in the same position of the income distribution, thus failing to capture their differential level of welfare.

On the other hand, existing multidimensional living conditions instruments are subject to statistical pitfalls associated with quantifying quality of life variables and tend to lack the cardinal properties of income in measuring the distance of a household from other households and the overall deprivation threshold. This is often the case with widely used techniques such as Principal Component Analysis and Fuzzy Sets.

Our proposed *Grenadian living conditions index* (GLCI) builds upon the methodologies of Axiomatic Multidimensional Indices developed by Alkire and Foster (2011), Seth (2011) and Diaz (2014). It measures living conditions by estimating a multidimensional index at the household level. Eligibility for public assistance is obtained by the application of deprivation thresholds in each individual's considered dimensions and in each household joint distribution of deprivations. Rather than selecting variables on the basis of their predictability of expenditure and using them to forecast the household's level of resources, our *living conditions assessment* focuses on the kind of life Grenadian's households value and attempts to optimize that measurement while still using expenditure poverty as a calibrating criterion.

As a result, our proposed Grenadian Living Conditions Index is a targeting instrument that seeks to prioritize the households that while being multidimensionally deprived are also most likely to be expenditure poor. We build a multidimensional living conditions index, which employs calibrating procedures based on expenditure poverty information to maximize precision in the identification of program eligibility. The proposed index is meant to be easy to apply for targeting purposes.

Our method identifies presence or absence of deprivation, as well as measures the depth of deprivation of the household. In this sense, our method is a multidimensional targeting instrument that mimics the cardinality of income or expenditure measures, while focusing on household quality of life. In comparison to other multidimensional indices technics used for targeting purposes, as Principal Component Analysis or Fuzzy Sets, this method makes fewer assumptions about the statistical properties of the variables and does not omit information on households' living conditions in an effort to reduce variables to fewer underlying components.

Moreover, the proposed tool can be disaggregated at different geographical levels, as well as dimensions. This decomposability feature provides the policy maker with an important instrument for the design and evaluation of public policies across the country and across different social programs. Additionally, our index provides a living conditions tracking tool, which does not allow for compensation between deprivations and non-deprivations, both at the household and society levels.

The remainder of the paper is structured as follows: the next section introduces Granada's context and the database. The third section explains the conceptual framework and the estimation of the proposed GLCI. Section four compares our proposed approach against the results obtained by techniques such as PCA and Fuzzy sets and an expenditure poverty criterion. The last section is dedicated to policy discussion.

2 Background and Data

2.1 The Grenadian Context

Grenada is an island country located in the south-eastern Caribbean Sea. Along with the two dependent islands Carriacou and Petit Martinique, Grenada is divided into 7 parishes, with St. George's as the capital. Grenada's population was estimated at 104,487 residents in 2010. In 2008, up to thirty seven per cent of Grenada's population was below the poverty line and lived with less than EC$16 a day, which corresponds to 6 USD nowadays. With the purpose of reducing indigence, hunger, and child mortality, Grenada's government launched a program that aimed to assist the most deprived households with conditional cash transfers. The instrument discussed in this paper was developed under this project to identify eligible households as well as to form the basis towards a comprehensive and systematic targeting system to be used for future public assistance programs.

2.2 Data

The application of the targeting instrument and empirical comparisons with other targeting methods are based on household data collected in the 2008 Grenadian Living Conditions Survey (LCS). This survey collects information on Grenadian households' buying habits through a detailed recording of their expenditures, income and other characteristics. It is designed to measure the cost of provision for public health and education services, as well as assess the impact of socioeconomic policies on the living conditions of households. One of the advantages of the LCS for the purposes of this analysis is the wide range of questions on living conditions, in addition to information on income and expenditure, which facilitate the comparison of different methods.

The survey sample is selected from a sample frame derived from the 2001 census and estimated growth to the present. Information collected covers the period from November 2007 to May

2008, ensuring that major seasonal factors are taken into account. The difference between the number of questionnaires obtained and the number of questionnaires expected is a combination of refusals and no contacts with the selected households. In the end, 802 interviews were completed (85.2% from expected).

3 Identifying Grenadian Most Deprived Households

Although there seems to be general consensus on the importance of undertaking poverty measurement, there is less agreement about the way this should be done. When targeting is required and poverty measures are developed for this purpose, the answers to three main technical questions drive most differences across the various targeting methods. The first question relates to which underlying concept of wellbeing each tool sees as most appropriate to rank households from worse off to better off. The focus could be on resources and ability to pay, basic needs, capabilities, functionings, happiness and so on. The second question relates to who is identified as the most deprived, or worst off, under each concept of wellbeing; and the third question is concerned with how to depict society aggregates (Sen, 1976 and 1979; Ravallion, 1992). As a result, the pertinent technical issue relates to the way each method chooses to operationalize those concepts and steps and apply them in the respective policy context. In other words, how does the chosen concept and method affect the ranking of the households in question. We address these issues in the following discussion.

3.1 Which Concept of Wellbeing Is Underlying the Household Ranking?

Sen (1993) argues that income alone is insufficient as a measurement criterion in wealth comparisons. A series of personal characteristics such as age, disabilities, pregnancy, and others, in addition to contextual factors related to the surrounding environment, security, access to health services and education translate income into a certain living standard. Therefore, a more appropriate targeting instrument ought to have the ability to directly assess the living standards of a household, rather than merely its income, by accounting for a variety of indicators of living conditions, across different dimensions.

Targeting instruments that focus on income poverty and use the proxy means test method (PMT), consider the different determinants of a household's income (resources) with the intention of arriving to the best statistical prediction of income poverty. In the past, they have been employed in many countries, such as Argentina (SISFAM), Brazil, Chile, Mexico, Armenia, among others. Under this method, the household score and weights of each indicator are derived from statistical analysis, most commonly Ordinary Least Squares (OLS) regression, and priority is given to variables that best predict household income (Azevedo and Robles, 2013; Coady, Grosh and Hoddinott, 2004). Although this approach can provide a somewhat straightforward manner for the measurement of income poverty, some of its main disadvantages are related to its unidimensionality and exclusive focus on monetary resources (Azevedo and Robles, 2013). Since the PMT approach is concerned with what influences income levels, it does not account for the way these resources are translated into a person's quality of life, or not even to the kind of life that each households attain.

Additionally, individual welfare does not only depend on the goods and services one is able to buy with their income. Some goods and services that can affect the household's quality of life are provided by the state and do not count towards household expenditures. Some examples include access to education, healthcare, dwelling services (electricity, water, sanitation) or food. Although these benefits are part of household welfare, income-based measures such as the PMT have the tendency to underestimate them. In practical terms, the score obtained from the statistical estimation is likely to assign high degree of income poverty in cases where living conditions do not exhibit the greatest deprivation level, and vice versa.

We argue that a more conceptually and methodologically consistent targeting tool to identify eligible/deprived population, as well as to measure their degree of deprivation, ought to take living conditions into account. Our proposed method looks to incorporate indicators capable to describe the kind of life each household attains, rather than merely the level of resources that have. Our instrument, moreover, includes a series of dimensions and indicators such as health, education, childhood conditions, employment, and access to basic services or housing conditions, among others. Together these dimensions and indicators construct a multidimensional index that attempts to capture the set of deprivations and vulnerabilities that in the Grenadian context can be considered in the common view as detrimental to a good life. The selection of dimensions and indicators follows normative, empirical and targeting operative criteria that are subsequently described.

3.2 Selecting Dimensions

The final selection of dimensions and indicators for the *Grenadian Living Conditions Index* takes into account a series of desirable characteristics: the availability of information across the selected databases for the application of the tool, as well as their ability to reflect Grenada's current living conditions and the distribution of deprivations across its population. We constrain our indicators to the ones available across the 2008 LCS, the 2001 Census, the 2011 Census and the administrative records of the program. This ensures that further evaluations of the behaviour of the GLCI and its ability to depict the living conditions of the Grenadian population can be performed.

Additionally, the selection of indicators considers their susceptibility to misreporting, being more desirable indicators less subject to misreporting; the incentive cost that could be embedded in using them, and the governmental priorities given to deprived population groups. Finally, to reduce the costs associated with the frequency of updating the instrument, attention is given to the time span that each indicator covers. In total, the GLCI includes 22 indicators under seven dimensions of well-being and reflects the outcome of a number of trade-offs and constraints.

The initial universe of indicators from where the set of 22 indicators was excerpted was created upon a literature review of quality of life studies for the Grenadian context. From this universe the aforementioned desirability characteristics were checked and only the indicators that fulfilled those criteria were selected. Additional validation and consultations were performed with experts on social policy in the south-eastern Caribbean Sea island countries, Grenadian stakeholders of the targeting process and field work. We argue that the set of selected indicators characterize the common view of a good life in the Grenadian context.

Our primary obstacle to capture living conditions for the Grenadian context was related to the limited availability of information in the design survey, in this case, the Living Conditions Survey (LCS). The relatively small number of appropriate indicators has deterred us from taking into account a wide range of indicators that have been identified as associated with deprivation or included in other similar multidimensional indices. Furthermore, the small sample size of the LCS (2,688 individuals) significantly limits our ability to build statistically robust disaggregated indicators. Additionally, in some cases the questionnaire design of the survey is not compatible with internationally standardized and comparable definitions of measures, which are crucial to the overall indicator such as the classification of disability and economic activity. A full list of dimensions and indicators is included in Table 1 below.

The first dimension refers to vulnerability related to the demographic composition of the household and health. This dimension is assessed using a number of indicators. Starting with type of household head, we include indicators on the age composition of each household and the balance between working age and non-working age individuals; giving special attention to elderly population and toddlers at home. We also include health related indicators that provide information on vulnerability due to either disability or chronic illness.

Given the importance that childhood has in the future development of a country and its intrinsic vulnerability, a dimension that focuses on child conditions is introduced within the GLCI. This dimension gives priority to households who have faced child mortality in recent years, or households with child labour.

The third dimension refers to the educational environment of the household and includes the indicators for illiteracy, low level of education, and access to the Internet. The fourth dimension captures accessibility to educative services and gives priority to households with children between 3 and 18 years old and accounts for real access to educative services. With regards to labour conditions, indicators include household long-term unemployment rate, informal labour and sub-employment rate.

The sixth dimension is concerned with the household's access to endowment resources such as pensions or public assistance, sharing of facilities with other households, and the number of bedrooms available per person.

Table 1: Selected Indicators by Dimension

Household living conditions Dimension	Deprivation or Vulnerability Indicator
Demographic and health vulnerability	Household demographic composition Elderly at home Children at home Disabled population at home Chronically ill at home
Childhood conditions	Child mortality Child labour
Household educational environment	Illiteracy Low educational attainment Non- internet access
Educative services access	Education non-enrolment Educative lag Restricted access to school: Time to go to school Absence of text books
Labour conditions	Long term unemployment Non-formal employment Sub-employment
Resources at home	Non-assisted Housing facilities shared Critical overcrowding
Dwelling conditions and access to dwelling services	Deprived dwelling conditions (walls, toilet and water) Absence of power supply (lighting and adequate cooking fuel)

Finally, dwelling conditions and access to dwelling services involves a number of important categorical indicators that provide information on the household's infrastructure and access to basic facilities. For the categorical indicators, as an exploratory exercise, we determine the best combination of them using Principal Component Analysis with a polychoric correlation matrix as proposed by Kolenikov and Angeles (2009). The analysis showed that two underlying components capture up to 87.56% of the variability of five dwelling related indicators. The first component considers conditions, such as material of walls, presence of toilet and access to water, whereas the second is associated with the availability of energy such as lighting and adequate cooking fuel. We therefore, use such aggregation to describe deprivation in this dimension.

3.3 Aggregating Indicators and Households

A poverty measurement may be univariate (i.e., it considers only one indicator with a single threshold to identify who are the poor and non-poor) or multivariate (it considers a set of indicators, and at least an aggregated threshold to identify who are the multidimensionally deprived and the multidimensionally non-deprived). Within the multidimensional literature, the axiomatic counting approach, aggregates well-being dimensions by counting the number of deprivations suffered by the household in each dimension.

In the counting poverty measurement literature, there are three alternative procedures to identify poor population: i) the union procedure, ii) the intersection procedure, and iii) the dual cut off point. The union approach identifies as poor those who are deprived in any dimension, whereas the intersection approach identifies as poor only those who are deprived under all dimensions. The union approach was widely applied in Latin American countries during the 1980's by the Unsatisfied Basic Needs Index. While it can produce misleading results by identifying as poor some who are deprived by decision rather than by necessity, this procedure outperforms the intersection approach, since the latter is too strict and can identify as poor only the very lowest section of the distribution. The third identification procedure is the 'dual cut off' method, proposed by Alkire and Foster (2011), which lies between the union and the intersection approach. In fact, both the union and the intersection approach are special cases for the dual cut off point method. This method firstly places thresholds in each single indicator, in order to identify the population suffering deprivation in the respective indicators. Secondly, it classifies as poor those who are below a second threshold, defined as the weighted sum of total deprivations, which have been predefined as sufficient to identify a person as poor.

The Axiomatic Multidimensional Indices (AMI) have not yet been fully formalized in the targeting literature, although, an instrument proposed by Azevedo and Robles (2013) also draws on the multidimensional methodology of Alkire and Foster (2011). The targeting instrument proposed in this paper builds upon the AMI and identifies poor households by using the Alkire and Foster (2011) definition of individual deprivation status in each dimension and identification of the poor procedure; alongside the Diaz (2014) household demographic equalised multidimensional approach and the Seth (2011) proposed aggregation structure for welfare indexes. As a result, deprivation is defined at the individual level and an adding up process is done at the household level to obtain a *household multidimensional deprivation degree.* This household multidimensional deprivation degree constitutes the score to rank households from most deprived to least deprived. An identification threshold is then defined in order to identify the most deprived household. It is worth noting that the household is the unit where the identification of the most deprived occurs and it is the analysis unit as well.

We follow describing below the implemented methodology. In the first step, the individual-level deprivation is specified as follows:

$$g_{ij}^{\alpha}(y_{ij}, z_j) = \begin{cases} \left(\frac{z_j - y_{ij}}{z_j}\right)^{\alpha} & \text{if} y_{ij} < z_j \\ 0 & \text{otherwise} \end{cases}, \quad (1)$$

where y_{ij} refers to the achievement level for the i-individual at the j-dimension, and z_j is the threshold considered as the minimum required for each dimension j. Any individual with an achievement level that lies below z_j is considered as deprived in dimension j. In turn, any individual with an achievement at the level of z_j or above is considered as non-deprived in the respective dimension. For example, if y_{ij} is operationalized as the number of years of education that an i-person older than 18 years old has achieved, and we define $z_j = 9$ as the number of minimum desirable years of education for persons older than 18, then any time a person is identified as having achieved fewer than 9 years of education, we can say that the i-person is deprived in *j*, but if the person has achieved at least 9 years of education, then person is considered as non-deprived in *j*.

Now, following from Equation (1), α refers to the poverty aversion parameter used by Alkire and Foster (2011) and first introduced in Foster et al. (1984). Notice that when $\alpha = 0$, g_{ij}^{α} is always a dichotomy indicator that takes values of either one or zero. Thus, each individual is classified as deprived or non-deprived in each of the considered dimensions through g_{ij}^{0}. Following our previous example of education, in the case the i-person have less than 9 years of education, g_{ij}^0 takes the value of 1, if the person has achieved 9 or more years of education then g_{ij}^0=0. Another good example can be illustrated for the employment dimension. In this case, y_{ij} could be operationalized as a dichotomous indicator that takes the value of 1 when the i-person is employed, and zero if the person is not employed. In this example, the minimum value expected for this particular j-dimension is 1 $(z_j = 1)$. Therefore, whenever the person is employed, g_{ij}^0 takes the value of zero, and when the person is not employed, it takes the value of 1 ($g_{ij}^0 = 1$). Given that most of the selected indicators are available as descriptors of presence or absence of a particular living condition, we set this α parameter of poverty aversion always at zero.

In the second step, once the individual-level deprivation indicator for each dimension is obtained, we use the multidimensional methodology of deprivation counts at the household level, proposed by Diaz (2014) and construct an $s_{hj}^{\beta,\theta}$ household-level dimensional deprivation degree, for each household h and each dimension j, as follows:

$$s_{hj}^{\beta,\theta} = \begin{cases} \left(\frac{\sum_{i\in h} g_{ij}^0}{(q_{hj})^{\theta}}\right)^{\beta} & if\, q_{hj} > 0 \; and \; \sum_{i\in h} g_{ij}^0 > 0 \\ 0 & Otherwise \end{cases} \quad (2)$$

where q_{hj} denotes the size of the population of reference for each household at the j dimension; $\theta \in [0,1]$ represents the parameter of household relative inequality; and β the parameter of household poverty aversion. We follow describing the interpretation of these three elements of the methodology.

The βparameter's value of household poverty aversion places greater relative importance to the most deprived dimensions. However, to avoid overweighting some dimensions over others, we set this parameter to 1*,* to measure the deprivation degree of the household; and to *0,* to indicate whether or not the household is deprived in such dimension.

The q_{hj} population of reference at the household level is defined as the number of household members who could potentially suffer deprivation in the respective dimension, in order to distinguish between members whose current status excludes them from that dimension. For example, children do not count towards the unemployed persons in the household. Similarly, males do not count towards the potentially pregnant or lactating persons in the household.

Table 2 below describes the numerator and denominator for each of the $s_{hj}^{\theta,\beta}$ Grenadian selected indicators. For instance, the illiteracy indicator is measured as the number of illiterate persons between 15 and 59 years old at home in relation to the total 15-59 years old population at home. Low educational attainment is defined as the number of person's aged 19-59 years old that are literate but have not completed primary (form 5 according to the Grenadian education system); this is calculated in relation to the total population aged 19-59 years old at home.

According with this definition of the $s_{hj}^{\beta,\theta}$ indicators, a household is deprived in each j-dimension whenever at least one of the persons of the population of reference of the indicator is considered to be in deprivation condition. This produces an indicator of absence of deprivation; which following our notation is represented by $s_{hj}^{\beta,\theta}$ when β is set to be zero $\left(s_{hj}^{0,\theta}\right)$.

Using the 2008 LCS, while the greater proportion of households are deprived in the access to internet indicator, the lowest proportion of household in deprivation is observed for the disability indicator; 87% of the Grenadian household report not having internet access and 3% of the households report having at least one disabled household member.

In the third step, following Seth (2011) proposed methodology, which aggregates first individual achievements and then population multidimensional index to obtain a social welfare index. We use the same procedure but we aggregate deprivations rather than achievements to produce a multidimensional measure of deprivations. We, therefore, express the household multidimensional deprivation degree as the weighted mean deprivation degree across dimensions, as follows:

$$\Omega_{h}^{\beta,\theta,\rho} = \left[\sum_{j=1}^{V} w_j \left(s_{hj}^{\beta,\theta}\right)^{\rho}\right]^{1/\rho} \quad \textbf{(3)}$$

where w_j corresponds to a value between zero and one that assigns the relative importance of each dimension such that $\sum_{j=1}^{V} w_j = 1$. The methodology to select these indicators' weights is described below in Section 3.4.

Notice from Equation (3) that we are aggregating deprivations at the household level with a generalized mean of ρ order, where $\rho \neq 0$ and $\rho \in R$. Whenever $\rho = 1$ we obtain a weighted arithmetic mean and when $\rho = -1$ we obtain a weighted harmonic mean. Then, ρ describes the shape of the household multidimensional deprivation function.

Table 2. Indicators Specification by Dimension

Household living conditions dimension (1)	Deprivation or Vulnerability Indicator		
	Indicator label (2)	Deprivation or vulnerability count (Indicator's Numerator) (3)	Population of reference (Indicator's Denominator) (4)
Demographic and health vulnerability	Household demographic composition: mono-parental or bi-parental	Category of household composition: Single headed with children, split union with children, bi-parental with children, other.	All household members*
	Elderly at home	No of 60+ at home	19 years old or above population
	Children at home	No of under 5 years old children and pregnant or lactating women (19-49 years old) at home	19-59 years old population
	Disability	No of non-elderly disabled at home	All household members
	Chronic illness	No of non-elderly, non-disabled, chronically ill at home	All household members
Childhood conditions	Child mortality	No of children born alive from household women aged 14-49 years old that later died.	Women between (14-49)
	Child labour	No of children (15-18) in work	15-18 years old that have been working during the last 12 months
Household educational environment	Illiteracy	No of persons, between 15 and 59 years old, that know how to read and write at home	15-59 years old population
	Low educational attainment	No of 19-59 year-olds with less than form 5 education completed but literate	19-59 years old literate population
	Non- internet access	No of persons aged 11 year-old or older without available internet	11 years old or older population
Accessibility to educative services	Education non-enrolment	No of school-aged children (3-18 years old) not enrolled in education.	3-18 years old population
	Educative lag	No of school-aged children (3-18 years old) with more than two years of extra-age for the current education level.	3-18 years old enrolled within the educational system
	Restricted access to school: Time to go to school	No of enrolled children taking 55+ min to go to school	3-18 years old enrolled within the educational system
	Absence of text books	No of children missing books due to affordability	3-18 years old enrolled within the educational system
Labour conditions	Long term unemployment	No of unemployed for 12+ months	Unemployed population (19+ years old)
	Non-formal employment	No of employed members with non-formal job	Employees at home (19+ years old)
	Sub-employment	No of formal employees, 19+ years old, that work less than 20 hours/week	Formal employees at home (19+ years old)
Resources at home	Non-assisted	No of persons 11 years and older who do not receive public assistance (pensions, social security from the National Insurance System –NIS or Public assistance in general) at home.	11 years old or older population*
	Housing facilities shared	No of shared house facilities	All household members*
	Critical overcrowding	Persons per room	All household members*
Dwelling conditions and access to dwelling services	Deprived dwelling conditions (walls, toilet and water)	No of deprived dwelling conditions (walls toilet water)	All household members*
	Absence of power supply (lighting and adequate cooking fuel)	Number of non-accessed power supply sources (lighting and proper cooking fuel supply+)	All household members*

* Populations of reference defined as 1 for every household member. + Proper cooking fuel supply refers to gas/lpg/cooking gas or electricity.

As a result, our methodology provides several different possible household scores to determine household eligibility and that vary according to the selected combination of the θ, β and ρ parameters. For the Grenadian case, we consider as relevant two different scores that differ among each other according to the value given to the parameter β. This while keeping always constant θ and ρ. First, when $\beta = 0$, similar to the Alkire and Foster (2011) method, $\Omega_h^{\beta,\theta,\rho}$ depicts the weighted sum of deprivations in each dimension. On the other hand, the degree of household multidimensional deprivation is captured by $\Omega_h^{\beta,\theta,\rho}$ when $\beta = 1$. Thus, we set $\beta = \{0,1\}$. In contrast, the θ degree of relative inequality and the ρ order of the generalized mean are selected, as further explained in the following section.

As a result, the Grenadian living conditions index (GLCI), is defined as an advantage synthetic measure on the basis of subtracting from 1000 the value obtained from $\Omega_h^{1,\theta,\rho}$. The GLCI score vary from zero to 1000, where values close to zero indicate worse off households and values close to 1000 better off households.

We follow describing in the next subsection the methodology used to define the indicators weighting system; after that we proceed to describe the criteria taken into account to set the value of the θ degree of relative inequality and the ρ order of the generalized mean.

3.4 The Indicators' Weighting System

Two types of errors cause inefficiencies in the targeting process: inclusion and exclusion errors. Inclusion errors are present when non- expenditure poor population is identified as eligible for assistance, or when poor population receives transfers greater than their poverty gap[1]. In turn, exclusion errors are present when poor population is not classified as eligible, or when poor population receives transfers lower than their gap. Then, inclusion error can be defined as the share of the population that is taken as potential beneficiaries according to a selected threshold of eligibility, although they should not be considered as eligible according to another criterion (for example, expenditure poor). In contrast, exclusion error is defined as the share of the population that is not considered as potential beneficiaries according to the selected threshold of eligibility, although they are considered as eligible according to another criterion.

Inclusion and exclusion errors could vary from 0% to 100%. In the case of living conditions measure, as the GLCI, which greater score value denotes better living conditions, the inclusion error is 0% when the selected threshold is the minimum possible value that the score could take,

[1] Poverty gap refers to the difference from the expenditure household aggregate and the poverty threshold.

this is because a very low chosen threshold would produce that none of the households are considered as potential beneficiaries, therefore, the inclusion error by definition is 0%. On the contrary, the inclusion error takes the 100% value when the selected threshold is at its maximum. Conversely, exclusion error is 100% when the selected threshold is the minimum possible value that the score could take, and 0% when the selected threshold is the maximum value of the score.

However, in order to obtain exclusion and inclusion errors, we need an alternative criterion of eligibility to compare against ours. For this purpose, we classify households as potential beneficiaries if they are identified as poor based on the national expenditure measure of poverty and have at least one person whose characteristics are given priority in the design of the program eligibility rules (disabled, pregnant, etc.). By using these additional criteria to minimize inclusion and exclusion errors, we ensure that the decision to classify households as eligible rests at the intersection between multidimensional deprivation, expenditure poverty, and population eligibility.

Given the set of selected indicators, the proposed method to calibrate the weight that each indicator receives consists on the optimum solution that simultaneously maximizes the number of expenditure poor households classified as eligible while minimizing the non-expenditure poor households classified as non-eligible.

The method that we follow in this regard is the one proposed by Sanchez-Cespedes (2014); this method estimates the weights that minimize the mismatch across criteria, expenditure poverty and multidimensional deprivation in addition to employing a combination of normative restrictions. For the Grenadian context, the optimal weighting system identified assigns weight proportional to each indicator. However, the joint distribution of the indicators produces negative weights in some cases, therefore we implement a minimum weight level of 1.5% out of 100% possible as a normative criterion. Since we consider as relevant two different scores, named the weighted sum of deprivations and the GLCI, a different set of weights was calculated for each.

3.5 Parameters Selection

In the construction of the index, the step of aggregation of individual deprivations into the household level is essential in identifying the degree of deprivation for the household. This can be approached either as the share of deprivations over the household population, or alternatively as the count of deprivations in the household (Diaz, 2014). In the share-based approach, deprivation is expressed as the number of persons that do not reach the z_j level of achievement, as a proportion of the population of reference at the household level (relative inequality). In the count-based approach, deprivation is expressed directly as the number of persons in the household that do not reach the achievement (absolute inequality).

There are disadvantages embedded in either choice. In the case of unemployment, for instance, the share-based approach defines household unemployment as the share of economically active persons in the household who are unemployed. Under this scenario, each person in society does not have the same value, since a household with ten active persons and five of them unemployed would produce the same deprivation share of 0.5, as a household with two persons, of which only one is unemployed. Contrarily, the count-based approach argues that each person's intrinsic value does not change, regardless of the size of the household they belong to. Under the count-based approach, deprivation would be defined as five in the 10-person household, and one in the two-person household. However, the count-based aggregation is likely to prioritize large sized households over households with fewer persons, which would always be identified as less deprived.

To bypass this problem, we use an intermediate approach that follows the intuition proposed by Bossert and Pfingsten (1990) and Chakravarty and Tyagarupananda (2009) for a general class of subgroup of decomposable inequality indices. We adopt the proposed functional form of dimensional deprivation degree proposed by Diaz (2014), which includes a combination of both approaches. Under this method, the θ parameter discussed in the previous section is of central importance. A value of one for the parameter produces the share-based approach, whereas a value of zero produces the count-based approach. Values between these two integers result in an intermediate approach. Consequently we argue that the choice of θ is best when guided by both empirical and normative considerations of the context in question.

At this point, it is plausible to suggest that building the index at the individual, rather than household-level could eliminate the problem altogether. However, such decision would introduce various other problems as the diverse criteria to compare individuals vary by demographic group. The purpose of this instrument is the measurement of deprivation for use in targeting policies, therefore, households are a more relevant and appropriate frame of reference.

On the other hand, the value of ρ was therefore defined, first by taking into account the desired properties of the index according to Seth's (2011) proven theorems; and secondly, by an optimization procedure that seeks to minimize inclusion and exclusion errors using expenditure poverty figures.

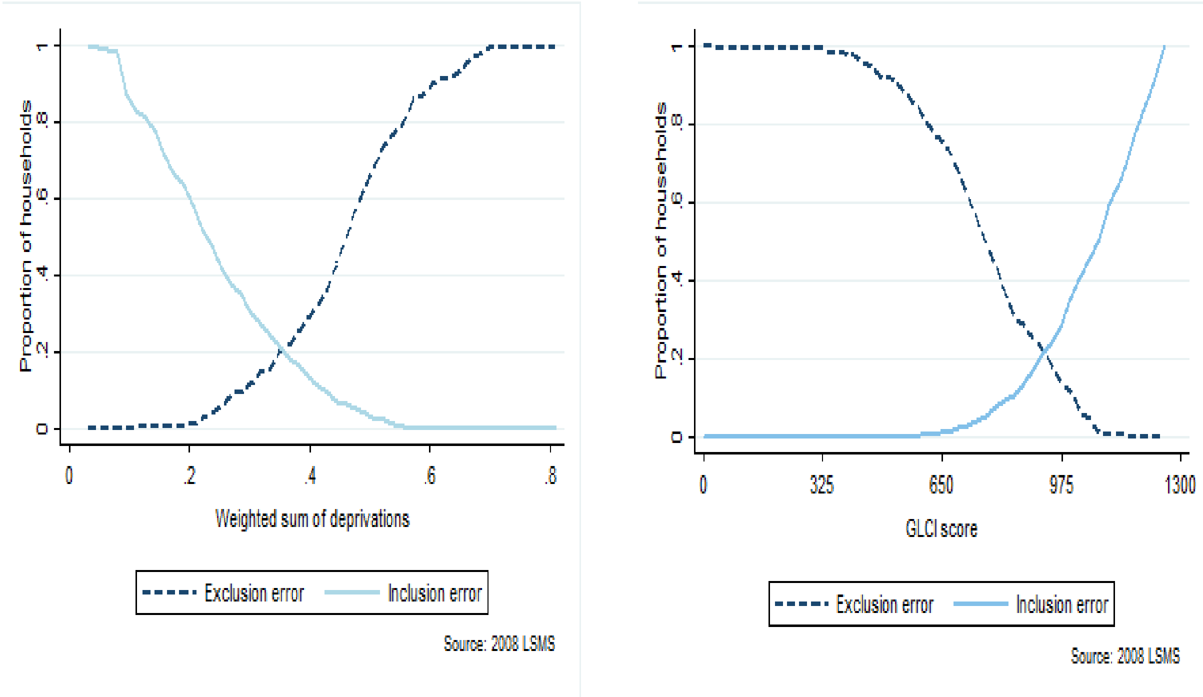
As a result, a finite set of possible combinations of β and θ parameters was defined and the produced score and the minimum inclusion and exclusion errors were recursively calculated across all the defined possible combinations of parameters. The parameter of relative inequality got set at 0.4 $(\theta = 0.4)$ and the ρ order of generalized mean that aggregates at the household level at 0.8 $(\rho = 0.8)$.

3.6 Setting the Eligibility Thresholds

Both, inclusion error and exclusion error vary along the possible selected threshold of eligibility. While inclusion error increases as the possible thresholds increase, exclusion error decreases when the thresholds increase. Due to this divergent relationship, there is no scenario where both errors can take 0% as a value. The objective is to minimize both, inclusion and exclusion error, at the same time. In presence of a suboptimum targeting scheme, we seek to calibrate the threshold in a way that minimizes both exclusion and inclusion errors. The intersection point of the two error curves is, by definition, where both errors can be minimized.

Using our selected combination of parameters and while defining each possible score cut-off as the eligibility threshold, we simulate the proportion of households that would get classified as excluded or included against an expenditure poverty measure. Figure 1 below plots the result of this exercise, the dark dashed line indicates the proportion of households that is expenditure poor while classified as non-eligible using each particular threshold. The light solid line indicates the proportion of households that are not expenditure poor while classified as eligible when using each threshold of eligibility. The intersection of the two curves in Figure 1.a corresponds to the K-threshold of eligibility across the weighted sum of deprivations. The intersection of the two curves in Figure 1.b shows the T-threshold for the GLCI where both errors are minimized. We, consequently, define as the most deprived households any household that simultaneously exhibit a weighted sum of deprivations greater than a K-threshold and a GLCI score lower than an T-threshold. The use of these two thresholds assures that the households identified as the most deprived are not only the ones that exhibit a greater number of deprivations but also higher household multidimensional deprivation degree.

Figure 1. Optimized Thresholds of Eligibility against Expenditure Poverty



(a) K-threshold of eligibility across the weighted sum of deprivation

(b) T-threshold of eligibility across GLCI

This definition can also be employed to obtain country-level figures of multidimensional deprivation. This by defining a P multidimensional deprivation headcount, $P = \frac{1}{N}\sum_h Q_h p_h$, where Q_h is the size of the h household and p_h is a dummy descriptor that takes the values of one when the household is identified as multidimensionally deprived, or zero otherwise. According to this procedure, the proportion of multidimensionally deprived households in Grenada in 2008 is 26%, a proportion that corresponds to about 43% of the total population. This headcount ratio can be monitored throughout forthcoming living conditions surveys or census.

Our proposed targeting tool assures that very low deprivation in one dimension does not cancel out high deprivation in another. Equally, when the index is aggregated at the national level, very good living conditions among the multidimensionally non-deprived will not lead to an underestimation of deprivation of the multidimensionally deprived. Furthermore, this method has the ability to produce a set of measures that can be used for different public policy purposes and remain comparable across programs. The GLCI allows for households to be ranked, which by default produces a distribution of deprivations with those with a greater degree of deprivation appearing at the bottom of the distribution, thus mimicking the cardinality of income or expenditure. Finally, the combination of the selected parameters can produce linkages between the chosen dimensions to assess deprivation, property named by Seth (2011) as association sensitive inequality. Therefore, the measured deprivation degree will depend on the relative position of a household in terms of multidimensional deprivation and the correlation between its dimensional results.

4 Who are Identified as the Most Deprived When Using Different Techniques?

Within the strand of household targeting mechanisms based on an objective score built upon certain household characteristics and that ranks households from worse off to better off, two main approaches are found in policy practice, the income or expenditure-focused measures, and the multidimensional quality of life measures. On one hand, for income or expenditure-focused measures, the widely applied method is the Proxy Means Test (PMT). A PMT approach seeks to approximate as best as possible the income or expenditure level of the household based on observable and measurable household characteristics, as for instance the tool proposed by Bisogno and Chong (2001) for foreign aid targeting in Bosnia and Herzegovina or the food subsidies targeting instrument proposed by Akhter and Howarth for Egypt. On the other hand, in terms of multidimensional living conditions methods, the calculated instruments differ largely depending on how they choose to operationalize quality of life indicators, how they aggregate indicators of different units of measurement, and how they determine deprivation thresholds. In this section, we compare our proposed *living condition assessment* with regards to a strictly expenditure measure and two other widely used methods for constructing multidimensional targeting instruments: Principal Component Analysis (PCA) and Fuzzy Sets (FS). We first highlight the advantages of our methodology by discussing the main differences across methods. We then move on to empirically compare the results we obtain when applying the different methods using Grenadian data.

In terms of expenditure based measures, any Proxy Means Test approach gives priority to indicators that are more likely to predict best the income or expenditure deprivation (Azevedo and Robles, 2013; Coady, Grosh and Hoddinott, 2004), still households comparisons based solely on monetary resource deprivation do not account for many other dimensions of quality of life; dimensions that do not necessarily successfully predict income, but that are related to the ability of the households to lead a valuable life in their societal context. As a result, income-focused measures fail to adequately capture the multidimensional feature of living conditions.

In fact, PMT approaches do not capture welfare dimensions as health, literacy or access to public services, even though households that lack those services can be categorized as worse off than households that account with them. Whenever both type of households are placed in the same position of the income distribution, targeting solely based on income criteria would fail to capture their differential level of welfare (Baker and Grosh, 1994). As long time pointed out by Sen (1993), income alone is insufficient as a measurement criterion for wealth comparisons.

Consequently, if the purpose of the targeting tool is to identify the most deprived households, the deprivation criteria embedded in a PMT approach is still not sufficient for that matter. Therefore, when trying to depict households' deprivation and to rank them according to it, multiple aspects should be taken into account in order to capture as comprehensively as possible the actual living standard that a household achieves. This is in fact the approach of a living conditions assessment through multidimensional methods.

Similarly to the proxy means test method, multidimensional methods estimate a living conditions index at an individual or household level. However, rather than selecting the indicators that predict income, these methods selects indicators that ought to depict as best as possible the kind of life each individual/household has. Ultimately, these methods, similarly to the *proxy means tes*t, resolve eligibility by the application of a determined threshold.

In terms of multidimensional living conditions targeting instruments constructed using Principal Component Analysis or Factor Analysis, as the ones used in countries such as Costa Rica, Ecuador and Peru, PCA and Factor Analysis provide a statistical method for reducing many dimensions/indicators that are highly correlated, both numerically and qualitatively, into fewer underlying uncorrelated components, retaining most of the variation present in the data (Jolliffe, 2002). When these statistical methods are employed for measuring living conditions and targeting deprived population, however, they are prone to certain inaccuracies. These methods follow most linearity and normality assumptions of OLS regression and look at inter-correlations among living conditions indicators to compute a linear prediction of the household's 'quality of life'. Under these methods, the first underlying component or factor computed acts as the deprivation index of each household. This method of aggregation by reduction of dimensions, however, discards any variance that is not retained in the first component. In targeting instruments this is likely to discard extreme values at the bottom end of the distribution if they do not correlate highly with other deprivations and lead to an under or over-estimation of some households' degree of deprivation. In fact, the main critique in applying PCA in a targeting scenario is that this method gives lower weight to dimensions that are poorly correlated. This is crucial, since some important dimensions of well-being tend to not exhibit high correlation

(Somarriba and Pena, 2009). In addition, it is very likely that correlations do not represent the real effects of an indicator on well-being (Nardo et al., 2008).

On the other hand, targeting tools based on Fuzzy Set theory, such as the one recently implemented by Colombia (SISBEN III)[2], consider the quality of life dimensions as a set of conditions in which each value of a living conditions indicator has a degree of membership to the set of the eligible population, namely the most deprived. This degree of membership is represented by a membership function. Indices using the fuzzy set methodology vary across each other by the configuration of this membership function. For instance, Colombia's SISBEN III uses the membership function proposed by Cheli and Lemmi (1995). Cheli and Lemmi's (1995) membership function assigns to each of the categories of the indicators that compose the multidimensional index a value that vary between zero and one and that represents the risk to be deprived in such indicator. The zero value represents in this case, the lowest deprivation degree and one the highest deprivation degree. The value assigned to each indicator's intermediate category is defined as a function of the sampling distribution using a specific membership function. Once the indicators are specified using this structure, they are aggregated using a system of weights that also could vary across indicators. The weights proposed by Cheli and Lemmi (1995) assign higher value to an indicator's category when the frequency of deprivation is lower in the population. This weighting system is used under the premise that a household is likely to feel more deprived if it belongs to a minority group (Deutsch and Silber 2005: 150). This method applied for targeting purposes, however, can directly interfere with the shape of the distribution by assigning more weight to deprivation indicators that identify the most unlikely and extreme membership cases, considering them as the most deprived.

As a result, we argue that both Fuzzy Sets and PCA methodologies limit the analysis to a set of indicators which are estimated as having relative importance over others due to their statistical properties. These statistical properties and the produced weights for each indicator and dimension, however, are to an extent outside the discretion of the policy maker and do not necessarily correspond to what is perceived as desirable and socially valuable. Therefore, they are likely to overlook deprivations that are normatively important if they are not statistically predictive.

On the contrary, our proposed methodology allows analysts and policy makers to define the criteria of living conditions that are deemed the most appropriate for a given context, on the basis of a careful selection of indicators, following both statistical criteria and normative

[2] SISBEN is the Spanish acronym of Identification System of Social Programs.

evaluations. As part of the Axiomatic Multidimensional Indices (AMI) and an extension of the Alkire and Foster (2011) counting approach, we identify eligible households as the ones whose weighted sum of dimensional deprivation degrees and weighted sum of deprivations are both greater that a determined threshold. This method has the advantage of making fewer assumptions about the statistical properties of the indicators, as well as not omitting any information about households' living conditions in an effort to reduce indicators to fewer components.

Under the methods of PCA and FS, when one indicator registers a high relative weight over other indicators in the overall score, it can result in a household being classified eligible for social assistance, with deprivation only in that one indicator. So, households with deprivations across several dimensions may not be identified as eligible, if those deprivation indicators do not get a high relative weight in the overall score. Furthermore, indicators are likely to be assigned low relative weights if they don't correlate highly with other deprivations and therefore do not fit within the estimated underlying components/factors.

Importantly, when identifying the multidimensionally deprived population, our approach is the first multidimensional targeting method that identifies the degree of deprivation of a household, rather than just classifies it as deprived or not. Consequently, our instrument can rank households by its deprivation degree, from most deprived to least deprived, and calculate the distance of each household from other households and from the overall threshold. In this sense, it provides an index that mimics the cardinality of income measures, while focusing on the quality of life that households value. Finally, following the benefits of the Axiomatic Multidimensional Indices, our method sums deprivations, therefore it does not allow for high living standards in one dimension to compensate for low living standards in another. This leads to a measure that is less sensitive to undesirable distortions produced by the behaviour of the upper tail of the data distribution and thus produces a more robust ranking across households at the society level as well.

Now, for an empirical perspective, we follow discussing the advantages of our method over PCA, Fuzzy Sets and an expenditure measure. In particular, we describe the main results obtained when applying our proposed GLCI to the 2008 LCS and compare these results to those obtained implementing the three other ranking criteria used for constructing targeting instruments.

An important issue that arises during these comparisons is what criteria should be used to comparatively assess the performance and efficacy of the different tools. Since PCA and Fuzzy sets results only allow for rankings but do not provide information in terms of the depth or degree of deprivation, comparisons required to be done exclusively in terms of the classification performance of each method. As a result, our comparisons follow two criteria, i) the household classification produced by each method, and ii). the number of deprived dimensions underlying each ranking. We follow, therefore, describing the results of these evaluations.

4.1 Comparing the Household Classification across Methods

For the comparison of our GLCI against PCA we built the PCA score using the same set of 22 deprivation indicators selected by the GLCI, but we expressed each of them as the proportion of the deprived population at home. We retain the first component and use such as the score to rank households from most deprived to least deprived. On the other hand, for the score using a Fuzzy Sets technique, we follow the Cheli and Lemmi (1995) membership function and weighting system, as in use for the case of the Colombian targeting tool, SISBEN II. In this case, similar to the PCA score, we use the set of 22 indicators expressed as the proportion of deprived population at home, and proceed to apply over them the Cheli and Lemmi (1995) membership function and weighting system. Finally, in terms of the expenditure measure we use the expenditure aggregate provided by the 2008 LCS which corresponds to the total household adult equivalent percapita expenditure[3].

As a result, every household in the dataset is assigned four scores: the first corresponds to our GLCI, the second and third to its PCA and FS version. The fourth corresponds, then, to the household adult equivalent per-capita expenditure. Based on those four different population ranks, we select, according to each methodology, the 43% most deprived population as eligible for social programs

To highlight differences and similarities across the different tools, we group together households that are classified as eligible for assistance across methods. Also, we group together those households that have been identified as not in need for assistance across methods. While the proportion of households classified as eligible by the four methods together reaches 14.2%, the proportion of households classified as non-eligible by all four methods is 52.0%. Thus, 66.2% of

[3] According to the technical report of the Country Poverty Assessment (CPA) presented by Caribbean Development Bank (2009), the expenditure aggregation follows the United Nations Classification of Individual Consumption According to Purpose. This includes food and non-food expenditure during the last two weeks, the last three months and the last year according to each item. The per capita estimates are reported by the CPA using an equivalence scale that assigns to each person in the household a number equal to or less than one, where the total number of equivalent adults is always less than or equal the number of persons in the household (Caribbean Development Bank, 2009: 19).

the households result in being consistently classified across the four methods and 33.8% of the households differ in classification across methods.

Since the three multidimensional methods ought to describe living conditions rather than expenditure levels, it is expected that the greater proportion of population classified as eligible only by one method correspond to households classified as expenditure poor. The proportion of households classified as eligible by only one method correspond to 15.4% of the total. Out of this group of non-consistently classified households, 41.0% correspond to exclusively expenditure deprived population. Within the households classified as eligible by only one method, 39.2% of them correspond to exclusively to FS eligible households. This is despite the fact that the Fuzzy Sets score is built upon the same 22 living conditions indicators identified as key for the Grenadian context. In contrast, within this same set of households, only 10.3% and 9.4% are GLCI and PCA eligible. The greater proportion of FS eligible households not consistently classified as eligible by the other methods indicates that FS is prioritizing rather than the most deprived households (according to their joint distribution of deprivations), the more dissimilar households. This FS characteristic was previously discussed when describing the generality of the method and is evident in this particular analysis.

We now compare the three living conditions indices, namely our GLCI, its PCA and the FS version, against the expenditure poverty classification depicted by the official poverty line (Caribbean Development Bank, 2009). Table 3 below includes the classification comparison results of the three indices against expenditure poverty. Our GLCI and the expenditure poverty criterion classify consistently 78.1% of the population, from which 30.2 percentage points correspond to population classified as eligible by the GLCI and expenditure poor by the official poverty estimates, and 47.9 points to population simultaneously not eligible under the GLCI and non-expenditure poor. Similarly, 77.5% of the population is consistently classified by the PCA version and expenditure poverty as eligible (29.9%) and not eligible (47.5%). The FS version differs from the GLCI by 7.1 percentage points- consistently classifying 71.0% of the population. If we define exclusion errors against expenditure poverty as the proportion of population that is expenditure poor and not classified as eligible according to the designed living conditions index, our GLCI produces 9.5% of exclusion error, its PCA and Fuzzy Sets versions, 9.8% and 13.1%, respectively. Similarly, inclusion errors are statistically significantly lower in the GLCI than the ones obtained by the PCA or FS version; being 12.4%, 12.8% and 15.9%, respectively. This slightly lower exclusion and inclusion errors of our GLCI in comparison to PCA and Fuzzy sets result from the use of expenditure poverty as calibration criterion for the GLCI's weighting system.

Table 3. Eligibility Results of the GLCI, PCA and Fuzzy Sets against Expenditure Poverty

	GLCI		PCA		Fuzzy Sets	
Eligibility category	Proportion of population	Std. Err.	Proportion of population	Std. Err.	Proportion of population	Std. Err.
Expenditure poor and eligible under the living conditions criterion	30.2	0.145	29.9	0.145	26.6	0.140
Eligible under the living conditions criterion only	12.4	0.104	12.8	0.106	15.9	0.116
Expenditure poor only	9.5	0.093	9.8	0.094	13.1	0.107
Not eligible under both criteria	47.9	0.158	47.5	0.158	44.4	0.157

Source: LSMS. Note: Estimates using the weighting system provided by the LSMS.

Now, between our method and PCA, there is agreement about eligibility and ineligibility for about 87% of the households. Less than 9% of households under PCA fall under the scenario where our method does not identify them as deprived but the PCA does prioritize them. When the reverse is the case, approximately 4% of households are excluded by PCA, although our index identifies them as deprived/eligible. Thus, with regards to the classification made by our GLCI and PCA, they differ in 12.5% of the households. Between our method and Fuzzy Sets, there is classification agreement for about 82% of the households. Under Fuzzy Sets, 13.0% of households are classified as eligible but not using the GLCI criterion; and approximately 5% of households are excluded by Fuzzy Sets, although our index identifies them as deprived/eligible. Thus, Fuzzy Sets and our method disagree on classifying 18.1% of households.

4.2 Comparing the Number of Deprived Dimensions Underlying Each Ranking

We next examine, within the group of households that are classified differently by one or another method, their number of deprived dimensions. Figure 2 below plots the proportion of households according to their number of deprived dimensions and eligibility status, when comparing the GLCI and the expenditure poverty criterion. The horizontal axis in the Figure shows the number of possible deprived dimensions that a household could face, while the vertical axis shows the expanded share of households that face such number of deprived dimensions, for each category of eligibility. The GLCI is able to consistently capture households that exhibit a greater number of deprivations, while expenditure poverty solely evaluates deprivations of tradable goods and fails to capture other valuable living standard dimensions. For instance, 27.5% of the households that experience deprivation in 12 or more (out of the 22 selected) indicators, are not classified as program eligible under an expenditure poverty criteria; also, 8.8% of the households that exhibit deprivation in less than seven indicators are classified as eligible by the expenditure poverty criterion. The empirical mismatch between a living standard measure and the poverty criterion is consistent with their conceptual difference. We, therefore, argue that the households in more need are the ones that are deprived in several dimensions at the same time.

On the other hand with regards to PCA and Fuzzy sets, we can show that the PCA and Fuzzy Sets methods are more likely to assign eligibility in a manner that appears normatively arbitrary. This, when analysing the number of deprived dimensions of those households where the living conditions methods are in disagreement over classification. In particular, Figure 3 compares the GLCI with PCA and Figure 4 the GLCI with Fuzzy Sets.

The figures reveal important discrepancies between methods for households in the middle and top of the deprivation distribution, namely those having four or more indicators on deprivation. In Figure 3, households with only four deprived indicators have been identified as eligible under PCA, when households with eleven and twelve deprived dimensions have been classified as non-eligible. In total, 14.2% of the households with 10 or more indicators in deprivation are identified as PCA eligible. Similarly, Fuzzy Sets has prioritised households with only four and five deprived dimensions, while excluding 14.1% of the households 10 or more deprived dimensions. These inclusion and exclusion errors are likely related to PCA and Fuzzy Sets assigning relative weights to particular indicators. This likely led to an overestimation of the deprivation of some households that exhibit specific deprivations while underestimating the deprivation of households with many more deprivations. The GLCI method is less likely to over or under-estimate the living conditions of households by assigning more weight to certain indicators due to their statistical properties. Therefore, our method produces fewer discrepancies between the households statistically identified as the most deprived and the households that are evidently suffering from a large number of deprivations across many dimensions.

Figure 2. Number of Deprived Dimensions by Eligibility Group – GLCI and Expenditure Poverty

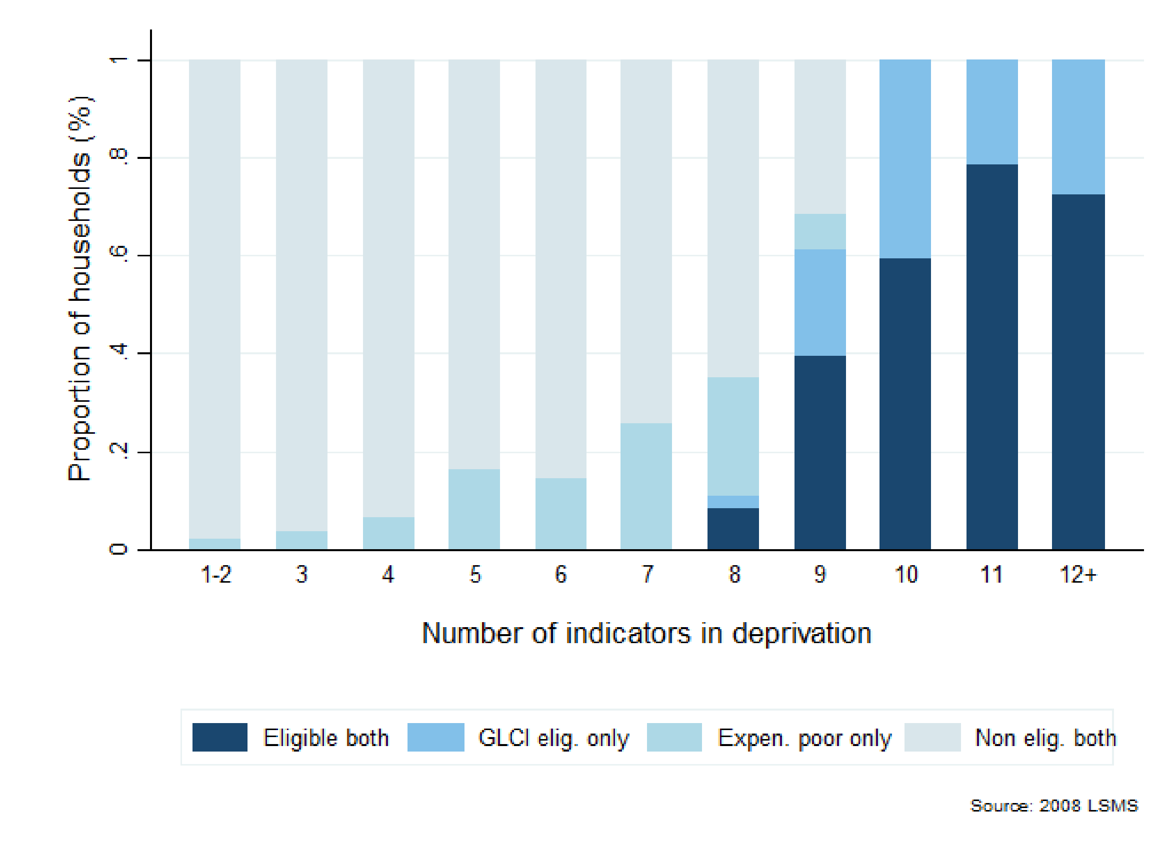


Figure 3. Number of Deprived Dimensions by Eligibility Category – GLCI and PCA

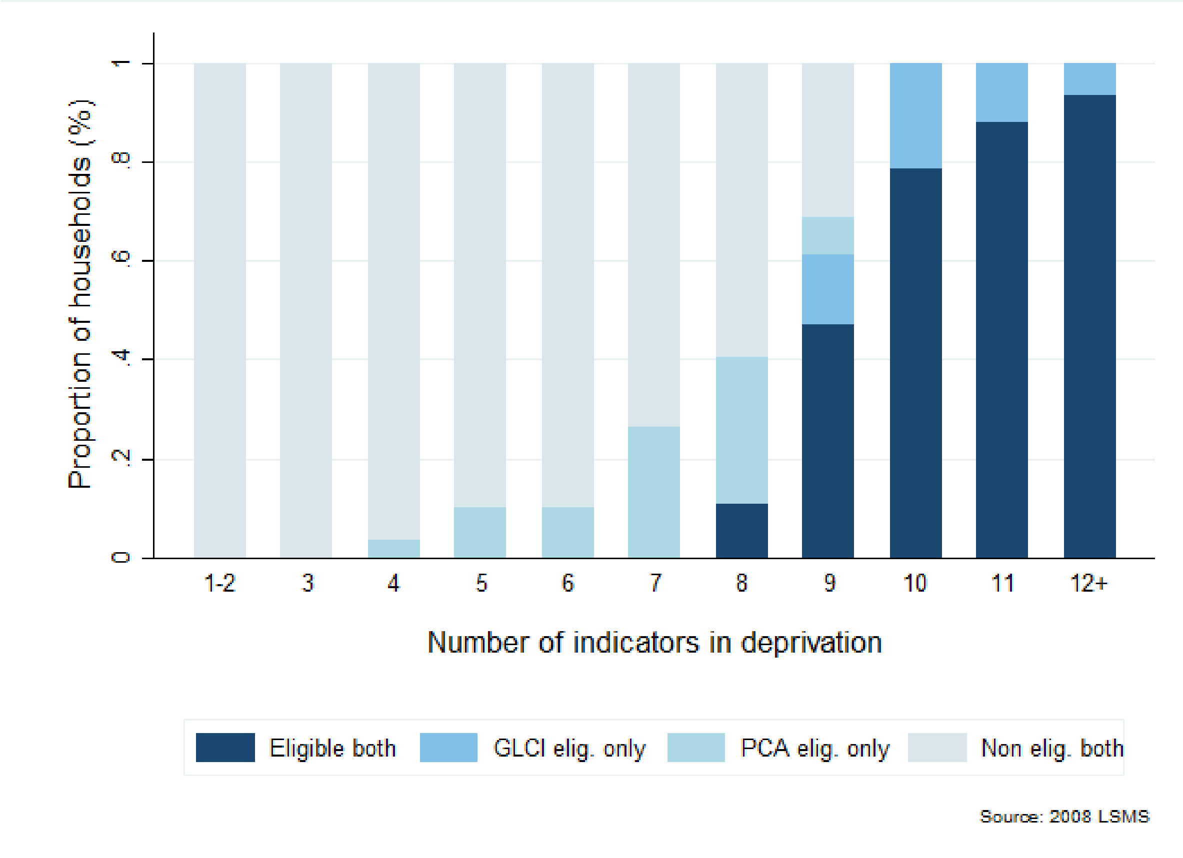
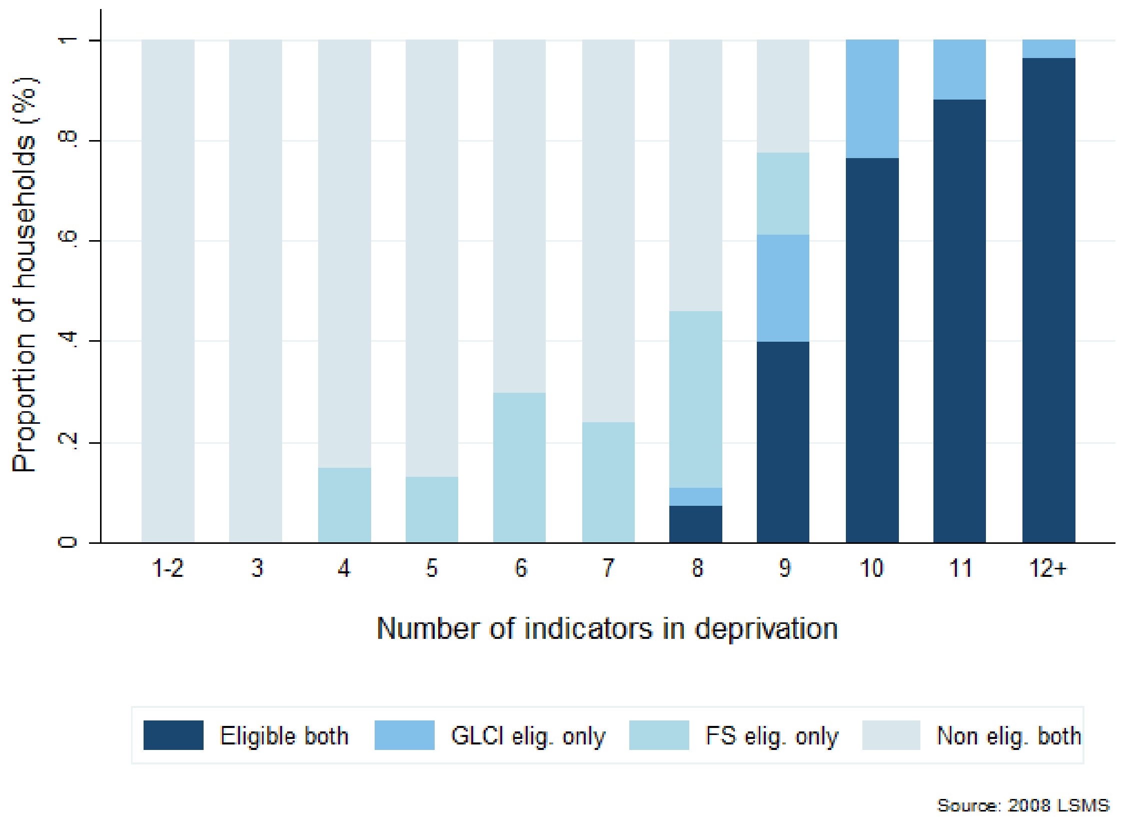


Figure 4. Number of Deprived Dimensions by Eligibility Category – GLCI and Fuzzy Sets



4.3 Counterfactual Policy Scenarios

Similarly to expenditure figures, our method allows comparisons across households in terms of their depth of deprivation. This advantage enables policy makers to design benefits proportional to the size of the deprivation even in absence of household expenditure figures. In order to illustrate this feature of our proposed methodology we compare two counterfactual policy scenarios, named Policy A and Policy B. While Policy A corresponds to a transfer to all GLCI eligible households of 130 $Eastern Caribbean Dollars per equivalent adult per month; Policy B corresponds to a transfer of the same total societal amount but in this case allocated proportional to the size of the GLCI score.

Table 4 shows the mean expenditure poverty headcount ratio evaluated before any of the policies and then under each of the policies. The difference between the two policies suggests that Policy B reduces expenditure poverty by 2.4 percentage points more than Policy A. In relation to the poverty gap, Policy B reduces the poverty gap 7.2 $Eastern Caribbean Dollars more than Policy A and generates a more equitable distribution, reducing the Gini coefficient 0.8 points more than Policy A. This more effective result of policy B over Policy A is due to the ability of the GLCI to not only to rank and determine the eligibility state of households, but also the deprivation degree. This feature is not present neither when using PCA nor Fuzzy sets.

Table 4. Evaluated Effect over Expenditure Poverty across Policy Scenarios

	Poverty headcount ratio (%)	Std. Error	Average poverty gap among the poor population (Monthly $ECD)	Std. Error	Gini coefficient	Std. Error+
Initial state	39.8	0.155	130.3	0.457	36.9	0.995
Policy A	24.8	0.137	88.0	0.496	31.9	0.981
Policy B	22.4	0.132	80.8	0.465	31.0	0.992
Difference (A-B)	2.4	0.095***	7.2	0.350***	0.8	0.011***

Source: LSMS. *** indicates difference statistically significant at 99% of confidence. + Bootstrapped standard errors with 1000 replications.

5 Policy Discussion

As discussed in this paper, several methods are available for targeting purposes and they can vary according to the goals and limitations of public policy. Our proposed method aims to identify the most deprived households using an approach that can be seen as an intersection between the proxy means test and the living conditions assessment. We build a multidimensional living conditions index, but also employ calibrating procedures using information on expenditure poverty to maximize precision in the identification of program eligibility. In terms of public policy, this allows us to minimize the danger of misidentifying the conditions of households and misclassifying their eligibility status. A more accurate and reliable targeting instrument is more likely to increase acceptance and trust towards the decision making process among the public, as well as reduce the number of appeals from households that feel wrongly classified.

Different social programs often have different populations of interest. The approach we are proposing allows policy makers to change the eligibility thresholds according to the focus and desirable criteria of each program, while minimizing both inclusion and exclusion errors for the respective populations of interest. Therefore, by tailoring the population of interest, this method has the ability to act as an umbrella tool and can be applied consistently across different social programs.

Moreover, our method can measure the depth of deprivation of the household, as well as classify it as deprived or not. Consequently, this method allows for the design of social program interventions that take the depth/intensity of deprivation into account.

Given the characteristics of our targeting tool, we assure some important poverty measurement properties are fulfilled. The targeting instrument can be used to depict societal multidimensional deprivation figures disaggregated a) by dimension of deprivation, and b) by geographical area. When dimension of deprivation is of interest, this decomposability feature supplies policy makers with an important tool for the design of policies across the country and across social policy sectors, such as programs focusing on child poverty, maternity, or adult labour market exclusion. On the other hand, the sensitivity of the index solely to deprived dimensions provides an accurate tracking tool that does not allow compensation between non-deprivation and deprivation. Therefore it is informative about any improvement or deterioration in living conditions within the dimensions of interest of each program and less subject to distortions associated with changes on non-deprived dimensions. A household with greater correlation among deprivation indicators is given greater priority.

Certain social policy contexts require the poverty thresholds to vary by lower geographical areas, such as regions, counties or districts. In order to achieve that, some targeting techniques combine census data with household surveys using imputation methods, to approximate the level of expenditure poverty at low geographical units (Elbers et al., 2007). In contrast, rather than using an expenditure proxy, our GLCI can be consistently applied for pre-geographical targeting by estimating the same living conditions assessment index with census data, at various geographical levels. This method is thus a more consistent conceptual approach across different units of analysis, starting from household level, until any chosen society level.

Finally, another important advantage is the improved behaviour of our instrument within the middle section of the deprivation distribution. As shown in the empirical section, the other techniques tend to include households with lower number of deprived dimensions as eligible. Contrarily, our method more accurately identifies the populations of interest and therefore allows policy makers to target those households that will benefit the most from the respective policy program.

References

Ahmed, A. U. and Bouis, H. E. (2002). "Weighing What's Practical: Proxy Means Tests for Targeting Food Subsidies in Egypt." *Food Policy*, 27(5): 519-540.

Alkire, S. and Foster, J. (2011). "Counting and Multidimensional Poverty Measurement." *Journal of Public Economics,* 95(7–8): 476–487.

Azevedo, V. and Robles, M. (2013). "Multidimensional Targeting: Identifying Beneficiaries of Conditional Cash Transfer Programs." *Social Indicators Research*, 112(2): 447–475.

Baker, J. and Grosh, M. (1994). "Poverty Reduction Thought Geographic Targeting: How Well Does It Work?." *World Development*, 22(7): 983-995.

Bisogno, M. and Chong, A. (2001). "Foreign Aid and Poverty in Bosnia and Herzegovina: Targeting Simulations and Policy Implications." *European Economic Review*, 45(4): 1020-1030.

Bossert, W. and Pfingsten, A. (1990). "Intermediate Inequality: Concepts, Indices, and Welfare Implications." *Mathematical Social Sciences*, 19(2): 117–134.

Caribbean Development Bank (2009). *Country Poverty Assessment: Greneda, Corricou and Petit Martinique*. Final report.

Chakravarty, S. R. and Tyagarupananda, S. (2009). "The Subgroup Decomposable Intermediate Indices of Inequality." *Spanish Economic Review*, 11(2): 83–97.

Cheli, B. and Lemmi, A. (1995). "A Totally Fuzzy and Relative Approach to the Multidimensional Analysis of Poverty." *Economic Notes: Economic Review of Banca Monte dei Paschi di Siena*, 24: 115-134.

Coady, D. P., Grosh, M. E., and Hoddinott, J. (2004). *Targeting of Transfers in Developing Countries: Review of Lessons and Experience*: World Bank Publications.

Deutsch, J. and Silber, J. (2005). "Measuring Multidimensional Poverty: An Empirical Comparison of Various Approaches." *Review of Income and Wealth*, 51 (1): 145-174.

Diaz, B.Y (2014). *Household Multidimensional Comparisons: An Approach to Measurement*. Mimeo

Elbers, C., Fujii, T., Lanjouw, P., Ozler, B., and Yin, Wesley (2007). "Poverty Alleviation Thought Geographic Targeting: How Much Does Disaggregation Help?" *Journal of Development Economics*, 83(1): 198-213.

Jolliffe, I. T. (2002). *Principal Component Analysis.* 2nd ed. Springer.

Kolenikov, S. and Angeles, G. (2009). "Socioeconomic Status Measurement with Discrete Proxy Variables: Is Principal Component Analysis a Reliable Answer?" *Review of Income and Wealth*, 55(1): 128-165.

Nardo, M., Saisana M., Saltelli A., Tarandola S., Hoffman A. and Giovannini E., (2008). *Handbook on Constructing Composite Indicators: Methodology and Guide.* OECD Publishing.

Ravallion, M. (1992). "Poverty Comparisons. A Guide to Concepts and Methods." *Living Standard Measurement Study Working Paper* 88.

Sanchez-Cespedes, Lina M. (2014) *Weights for Targeting Indices: Between Income or Consumption Based Weights And Normative Weights.* Mimeo.

Sen, A. (1976). "Poverty: An Ordinal Approach to Measurement." *Econometrica: Journal of the Econometric Society*, 44(2): 219–231.

Sen, A. (1979). "Issues in the Measurement of Poverty." *The Scandinavian Journal of Economics*, 81(2): 285–307.

Sen, A. (1993). "Capability and Well-Being," in M. Nussbaum and A. Sen (eds.), *The quality of life*. Oxford University Press.

Seth, S. (2011). "A Class of Distribution and Association Sensitive Multidimensional Welfare Indices." *Journal of Economic Inequality*, 11(2): 1-30.

Somarriba, N. and Pena, B., (2009). "Synthetic Indicators of Quality of Life in Europe." *Social Indicator Research*, 94(1): 115-133.