Oxford Poverty & Human Development Initiative (OPHI)

Oxford Department of International Development

Queen Elizabeth House (QEH), University of Oxford

OPHI
Research in Progress series 2007

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DRAFT

COUNTING AND MULTIDIMENSIONAL POVERTY[1]

Sabina Alkire and James Foster

Multidimensional poverty has risen to prominence among researchers and policymakers. The compelling writings of Amartya Sen, participatory exercises in many countries, and the Millennium Development Goals (MDGs) all draw attention to multiple deprivations and their interconnections. A key direction for research has been the development of a coherent framework for measuring multidimensional poverty that builds on the techniques developed in unidimensional (monetary) space and can be applied to data on other dimensions.

Why do we need multidimensional measures?

Human progress—whether considered as well-being, fulfillment, the expansion of freedoms, or meeting the MDGs—encompasses multiple aspects of life, such as being educated, employed, and well-nourished. Income and consumption indicators reflect material resources that are vital for the achievement of many capabilities. The use of monetary indicators alone often reflects an assumption that these indicators are good proxies for multidimensional poverty: that people who are consumption poor are nearly the same as those who suffer malnutrition, are ill-educated, or disempowered. But monetary poverty often provides insufficient policy guidance regarding deprivations in other dimensions. As Table 1 illustrates, counting as poor *only* those who are income deprived can result in omitting a significant proportion of poor people in some areas and in over-reporting poverty in others. Ruggeri-Laderchi, Saith and Stewart (2003) observe that in India, 43 percent of children and more than half of adults who were capability poor (using education or health as the indicator) were not in monetary poverty; similarly, more than half of the nutrition-poor children were not in monetary poverty. Monetary poverty appears to significantly misidentify deprivations in other dimensions. Multidimensional poverty measures are required to provide a more accurate representation of the multiple deprivations different people suffer.

The Problem of Complex Poverty Measures

Although more individual and household survey data exists today than at any time previously, the question remains how to condense social and economic indicators into lean measures that can be easily interpreted, and that can inform policy. The problem of overly complex poverty measures has haunted past initiatives. A satisfactory multidimensional poverty measure should satisfy some basic criteria. For example, it must:

- be understandable and easy to describe

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[1] This chapter summarizes S. Alkire and J. Foster, *Counting and Multidimensional Poverty Measures,* OPHI Working Paper Series (7). www.ophi.org.uk, 2007.

- conform to "common sense" notions of poverty
- be able to target the poor, track changes, and guide policy.
- be technically solid
- be operationally viable
- be easily replicable.

The multidimensional poverty methodology presented in this chapter addresses these criteria. It is related to the *user-friendly* 'counting' approaches, but provides a more flexible way to identify who is poor. It satisfies a number of desirable *properties*, including decomposability. It is very *adaptable* to different contexts and purposes, in that different dimensions and indicators can be selected depending on the purpose at hand. For example, different dimensions of poverty might be relevant in different countries. The methodology could also be used within one sector, to represent quality of education, or dimensions of health, for example. In addition, different *weights* can be applied to dimensions or indicators. Furthermore, *ordinal, categorical, and cardinal* data can all be used. The signal advantages of this measure for policy are that it is *highly intuitive*, *easy to calculate*, and *can be decomposed* by geographic area, ethnicity, or other variables. The measure can then be broken down into its individual dimensions to *identify which deprivations are driving multidimensional poverty* in different regions or groups. This last factor makes it a powerful tool for guiding policies to address deprivations in different groups efficiently. It is also an effective tool for targeting.

The Dual Cut-off Method of Identification

Poverty measurement can be broken down conceptually into two distinct steps: the *identification* step defines the cut-off(s) for distinguishing the poor from the non-poor. The *aggregation* step brings together the data on the poor into an overall indicator of poverty.

Choosing an approach by which to identify the poor is more complex when poverty measures draw on multiple variables. At present, there are three main methods of identification: unidimensional, union, and intersection:

1. In the *unidimensional* approach, the multiple indicators of well-being are combined into a single aggregate variable, and a poverty cut-off is set on this aggregate variable. A person is identified as poor when his/her achievements fall below this cut-off level. The unidimensional method of identification takes into account dimensional deprivations, but only insofar as they affect the aggregate indicator. There is minimal scope for valuing deprivations in many dimensions independently of one another, something that is viewed as an essential characteristic of a multidimensional approach.

2. The *union* approach regards someone who is deprived in a single dimension as multidimensionally poor. It is very commonly used, but as the number of dimensions increases it may be overly inclusive and may lead to exaggerated estimates of poverty. For example, using Indian NFHS data with 11 dimensions, 91 percent of the population would be identified as poor.

3. The *intersection* method requires someone to be deprived in all dimensions in order to be identified as poor. This is often considered to be too restrictive, and generally produces untenably low estimates of poverty. In the Indian example mentioned above, no one was deprived in all 11 dimensions by the intersection method.

The problems with existing approaches have been widely acknowledged, and the need for an acceptable alternative is clear. Our method of identification uses two forms of cut-offs and a counting methodology. The *first cut-off* is the traditional dimension-specific poverty line or cut-off. This is set for each dimension, and identifies whether a person is deprived with respect to that dimension. The *second cut-off* delineates how widely deprived a person must be in order to be considered poor. If the dimensions are equally weighted, the second cut-off is simply the number of dimensions in which a person must be deprived to be considered poor. This equally-weighted approach is known as the *counting* approach, and is widely used in policy work. For example, Mack and Lansley (1985) identified people as poor if they were poor in 3 or more of 26 deprivations, and the UNICEF *Child Poverty Report 2003* identified any child who was poor with respect to two or more deprivations as being in extreme poverty.

We then *aggregate* using a natural extension of the Foster Greer Thorbecke (FGT) poverty measures in multidimensional space.

12 Steps to a Multidimensional Poverty Measure

Our methodology can be intuitively introduced in 12 steps. The first six steps are common to many multidimensional poverty measures; the remainder are more specific to our methodology.

Step 1: Choose Unit of Analysis. This is most commonly an individual or household, but could also be a community, school, clinic, firm, district, or other unit.

Step 2: Choose Dimensions. The choice of dimensions is important, but is less haphazard than people assume. In practice, most researchers implicitly draw upon five selection methods, either alone or in combination:

- Ongoing deliberative *participatory exercises* that elicit the values and perspectives of stakeholders. A variation of this is to use survey data on people's perceived necessities.

- A list that has achieved a degree of legitimacy due to *public consensus*, such as the declaration of universal human rights, the Millennium Development Goals, or similar lists at national and local levels.

- *Implicit or explicit assumptions* about what people do value or should value. At times these are the informed guesses of the researcher; in other situations they are drawn from convention, social or psychological theory, or philosophy.

- *Convenience or a convention that is taken to be authoritative*, or because these are the only data available that have the required characteristics.

- *Empirical evidence regarding people's values* or data on consumer preferences and behaviors, or studies of what values are most conducive to mental health or social benefit.

Clearly these processes overlap and are often used in tandem empirically; for example; nearly all exercises will need to consider data availability or data issues, and often participation or at least consensus is required to give the dimensions public legitimacy.

Step 3: Choose Indicators. Indicators are chosen for each domain on the principles of *accuracy* (using as many indicators as necessary so that analysis can properly guide policy) and *parsimony* (using as few indicators as possible to ensure ease of analysis for policy purposes and transparency). Statistical properties are often relevant – for example, when possible and reasonable, choosing indicators that are not highly correlated.

Step 4: Set Poverty Lines. A poverty cut-off is set for each dimension. This step establishes the first cut-off in the methodology. Every person can then be identified as deprived or non-deprived with respect to each dimension. For example, if the dimension is schooling ("How many years of schooling have you completed?") then '6 years or more' might identify non-deprivation while '1-5 years' might identify deprivation in the domain. Poverty thresholds can be tested for robustness, or multiple sets of thresholds can be used to clarify explicitly different categories of the poor (such as poor and extreme poor).

Step 5: Apply Poverty Lines. This step replaces the person's achievement with their status with respect to each cutoff—for example, in the dimension of health where the indicators are "access to health clinic" and "self-reported morbidity," people are identified as being deprived or non-deprived for each indicator. The process is repeated for all indicators for all other dimensions. Table 2 provides an example for a group of four people. ND indicates that the person is not deprived (in other words, their value in that dimension is higher than the cut-off), and D indicates that the person is deprived (their value is lower than the cut-off).

Step 6: Count the number of deprivations for each person as demonstrated in the last column of Table 2. (Equal weights among indicators are assumed for simplicity. However, general weights can be applied in which case the weighted sum is calculated.)

Step 7: Set the second cut-off, which we call k. Assuming equal weights for simplicity, set a second identification cut-off, k, which gives the number of dimensions in which a person must be deprived in order to be considered multidimensionally poor. In practice, it may be useful to calculate the measure for several values of k. Robustness checks can be performed across all values of k. In the example in Table 2, k is set to 4 and the shaded people are identified as poor.

Step 8: Apply cut-off (k) to obtain the set of poor persons and censor all non-poor data. The focus is now on the profile of the poor and the dimensions in which they are deprived. All information on the non-poor is replaced with zeros. This is shown in Table 3.

Step 9: Calculate the Headcount, H. Divide the number of poor people by the total number of people. In our example, when k = 4, the headcount is merely the proportion of people who are poor in at least 4 of d dimensions. For example, as seen in Tables 2 and 3, two of the four people were identified as poor, so H = 2 /4 = 50 percent. The multidimensional headcount is a useful measure,

but it does not increase if poor people become more deprived, nor can it be *broken down* by dimension to analyse how poverty differs among groups. For that reason we need a different set of measures.

Step 10: Calculate the Average Poverty Gap, A. A is the average number of deprivations a poor person suffers. It is calculated by adding up the proportion of total deprivations each person suffers (for example in Table 3, Person 1 suffers 4 out of 6 deprivations and Person 4 suffers 6 out of 6) and dividing by the total number of poor persons. $A = (4/6 + 6/6)/2 = 5/6$.

Step 11: Calculate the Adjusted Headcount, M_0. If the data are binary or ordinal, multidimensional poverty is measured by the Adjusted Headcount, M_0, which is calculated as H times A. Headcount poverty is multiplied by the 'average' number of dimensions in which all poor people are deprived to reflect the *breadth* of deprivations. In our example, $HA = 2/4 * 5/6 = 5/12$.

Step 12: Decompose by group, and break down by dimension. The adjusted headcount M_0 can be decomposed by population subgroup (such as region, rural/urban, or ethnicity). After constructing M_0 for each subgroup of the sample, we can break M_0 apart to study the contribution of each dimension to overall poverty. To break down by dimension, let A_j be the contribution of dimension j to the average poverty gap A. A_j could be interpreted as the *average deprivation share* across the poor in dimension j. The dimension-adjusted contribution of dimension j to overall poverty, which we call M_{0j}, is then obtained by multiplying H by A_j for each dimension.

Basic Properties of the Multidimensional Measure M_0.

The adjusted headcount M_0 is useful for a variety of reasons worth mentioning:

- It can be calculated for different groups in the population, such as people from a certain region, ethnic group, or gender, for example.

- The poverty level increases if one or more people become deprived in an additional dimension, so it is sensitive to the multiplicity of deprivations.

- It adjusts for the size of the group it is being calculated for, allowing for meaningful international comparison across different sized countries.

- It can be broken down into dimensions to reveal to policymakers what dimensions contribute the most to multidimensional poverty in any given region or population group.

Related Multidimensional Measures: Calculate the Adjusted Poverty Gap (M_1), and Squared Poverty Gap (M_2). If at least some data are cardinal, replace the '1' for each deprived person by their normalized poverty gap (the poverty line minus their achievement divided by the poverty line), and calculate the *average normalized poverty gap G*, which is the sum of the values of the poverty gaps, divided by the number of deprivations (in the case of ordinal data, the poverty gap will always be 1). The Adjusted Poverty Gap M_1 is given by HAG, or the M_0 measure above multiplied by the average poverty gap. The Squared Poverty Gap M_2 is calculated by squaring each poverty gap individually, and replacing G with the average *squared normalized poverty gap S*, so the measure is HAS. The Squared measure reflects inequality among the poor.

Showing How Multidimensionality Matters

This example of the measurement methodology and its variations is based on U.S. data from the 2004 National Health Interview Survey for adults aged 19 and above (n = 45,884). Four indicators were used:

1. *Income*: a person is deprived if he/she lives in a household falling below the standard income poverty line; income is measured in poverty line increments and is grouped into 15 categories.
2. *Health*: a person is deprived if he/she self reports 'fair' or 'poor' health.
3. *Health insurance*: a person is deprived if he/she lacks health insurance
4. *Schooling*: a person is deprived if he/she lacks a high-school diploma

The population was divided into four groups: Hispanic/Latino (Hispanic), White (Non-Hispanic), Black/African American, and Other. Table 4 presents the traditional income poverty headcount (the share of the population below the income cutoff), and the multidimensional measures H and M_0, where the latter are evaluated using k = 2 and equal weights. Column 3 gives the population share in each group while Column 5 presents the share of all income-poor people found in each group. Comparing these two columns, it is clear that the incidence of income poverty is disproportionately high for the Hispanic and African-American populations.

Moving now to the multidimensional headcount ratio H, Column 7 gives the percentage of all multidimensionally poor people who fall within each group. The percentage of the multidimensionally poor who are Hispanic is much higher than the respective figure in Column 5, while the percentage who are African-American is significantly lower, illustrating how this multidimensional approach to identifying the poor can alter the traditional, income-based poverty profile. Whereas Column 7 gives the distribution of poor people across the groups, Column 9 lists the distribution of *deprivations* experienced by the poor people in each group. The resulting figures for M_0 further reveal the disproportionate Hispanic contribution to poverty that is evident in this dataset.

Why does multidimensional poverty paint such a different picture? Table 5 uses the methodology outlined above to identify the dimension-specific changes driving the variations in M_0. The final column of Table 5 reproduces the group poverty levels found in Column 8 of Table 4, while the rows break these poverty levels down by dimension. The factor contributions to poverty were calculated by aggregating the share of the respective population that is both poor and deprived in one particular dimension and dividing it by the total number of dimensions. The first row gives the decomposition for the Hispanic population, with Column 2 indicating that 20 percent of Hispanics are both multidimensionally poor and deprived in income. Column 6 has the overall M_0 for Hispanics, which is simply the average of *H1* through *H4*. The second row expresses the same data in percentage terms, with Column 2 providing the percent contribution of the income dimension to the Hispanic level of M_0 or, alternatively, the percentage of all deprivations experienced by the Hispanic poor population that are income deprivations. Notice that for Hispanics, the contribution from health insurance and schooling is quite high, whereas the contribution of income is relatively low. In contrast, the contribution of income for African-

Americans is relatively high. This explains why, in comparison to traditional income-based poverty, the percentage of overall multidimensional poverty originating in the Hispanic population rises, while the contribution for African-Americans is lower. The example shows how the measure M_0 can be readily broken down by population subgroup and dimension to help explain its aggregate level.

Additional applications are underway in China, India, Pakistan, Bhutan, Sub-Saharan Africa, and Latin America. These papers demonstrate different qualities of the measure:

- **The measure can identify and target particularly distressed households for public support**. The conditional cash transfer program *Oportunidades* in Mexico and the 'BPL' or Below the Poverty Line' calculations in India all use a particular measure to identify qualified recipients for public support. In India, the M_0 measure (white) in rural areas (with dimensions that match the government's below-the-poverty-line measure) is in some case strikingly different from income poverty estimates (blue), and from the (widely criticised) government measure to identify and target those who live 'below the poverty line' (BPL - purple.

BPL Vs. NSS Vs. Multidimensional Head Count (Countries are Ranked by M0)
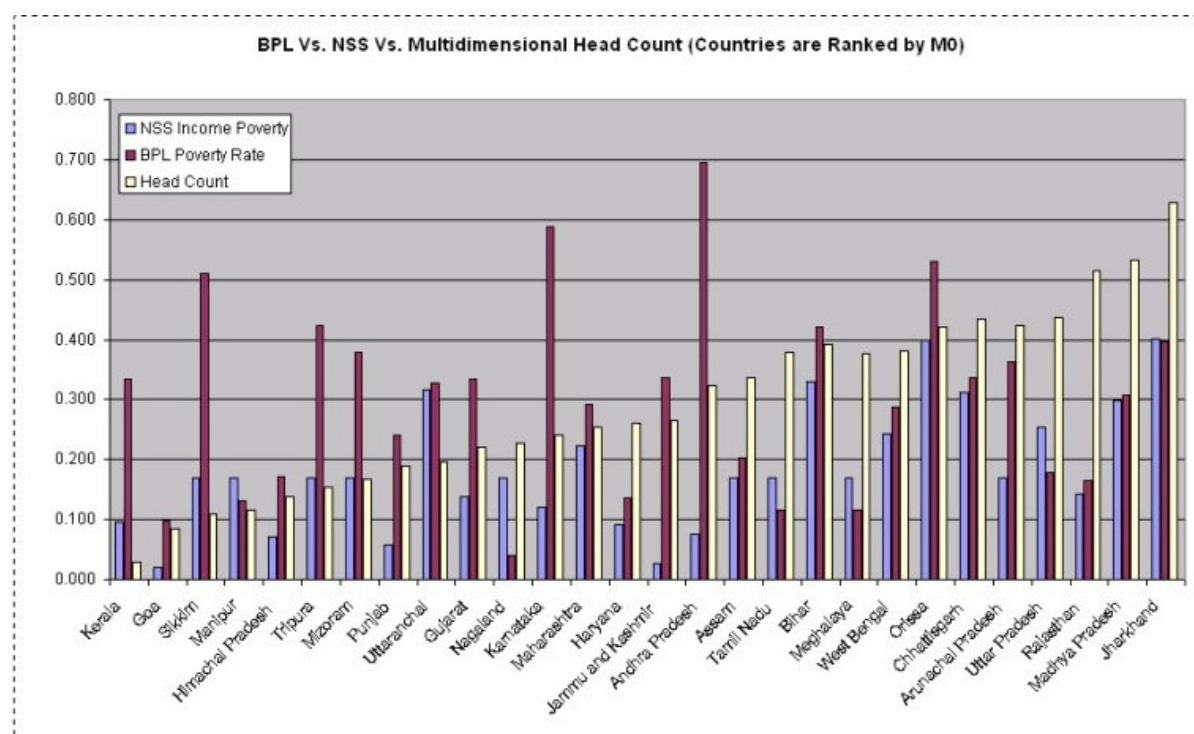
- **The measure can be decomposed to see what is driving poverty in different regions or groups.** In Bhutan, the rank of the districts changed when moving from income to multidimensional poverty. The relatively wealthy state of Gasa fell 11 places when ranked by multidimensional poverty rather than by income, and the state of Lhuntse, which was ranked 17th of 20 by income, rose 9 places when ranked by multidimensional poverty. When the M_0 measure is decomposed by dimension, we find that in Gasa, poverty is driven by a lack of electricity, drinking water, and overcrowding; income is hardly visible as a cause of

poverty. In Lhuntse, income is a much larger contributor to poverty than other dimensions, hence its increase. Although further analysis is required, these results suggest that policy priorities to reduce multidimensional poverty in each state will differ significantly.

Composition of Multidimensional Poverty in Two Districts - Mo with k=2
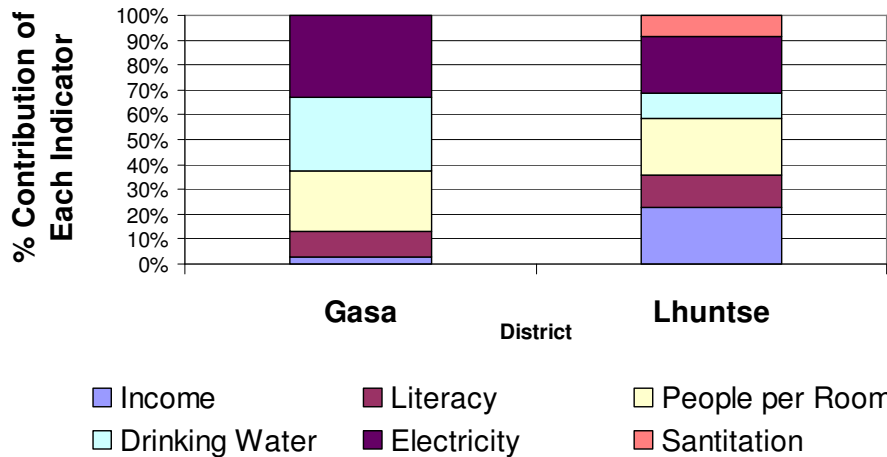
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- **The robustness of multidimensional poverty can be tested using different assumptions.** In Sub-Saharan Africa, five countries were compared using DHS data. For all possible values of *k* (the second cut-off) we find that Burkina is *always* poorer than Guinea, regardless of whether we count as poor persons those who are deprived in only *one* dimension or in *every* dimension (assets, health, education, and empowerment, in this example).

Figure 3: M0 as cutoff _k_ is varied in the five countries
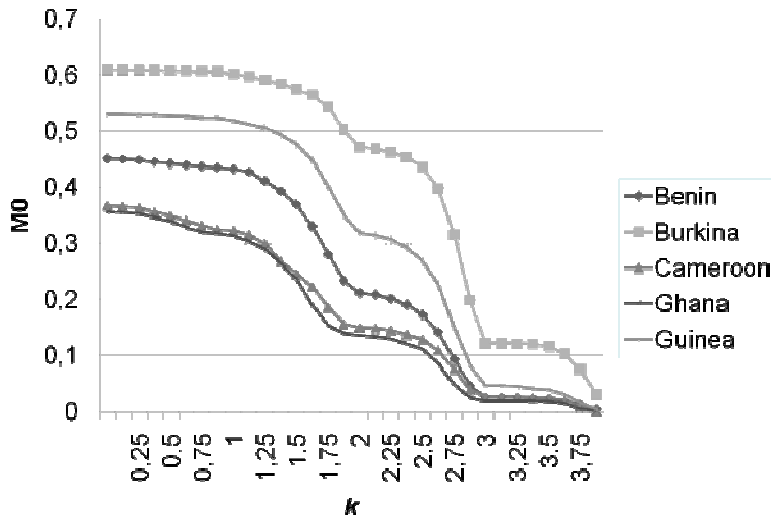
CONCLUSION

This chapter has introduced a new methodology for multidimensional poverty measurement. The methodology consists of 1) a dual cut-off identification method that extends the traditional intersection and union approaches, and 2) a set of poverty measures that satisfy a range of desirable properties including decomposability. This multidimensional methodology is appropriate for reporting multidimensional poverty in the same way as income poverty lines, and tracking changes in poverty in a nation or state over time. The instrument is also particularly suited to targeting the poor. At present, work is ongoing to compare the above developed measure with national poverty measures (such as income or any other measure) in over 20 countries. Further extensions are applying the methodology to address other multidimensional issues such as quality of education, governance, child poverty, fair trade, and targeting of conditional cash transfers.

Suggested readings:

S. Alkire and J. Foster, *Counting and Multidimensional Poverty Measures*. OPHI Working Paper Series (7). www.ophi.org.uk, 2007;

A.B. Atkinson, "Multidimensional deprivation: Contrasting social welfare and counting approaches," *Journal of Economic Inequality* (Vol. 1, No. 1, 2003);

J.E. Foster, J. Greer, and E. Thorbecke, "A Class of Decomposable Poverty Indices," *Econometrica* (Vol. 52, p. 761-766, 1984.

Sabina Alkire (Sabina.alkire@qeh.ox.ac.uk) is the director of Oxford Poverty & Human Development Initiative (OPHI), University of Oxford; **James Foster** (James.E.Foster@vanderbilt.edu) is a professor at the Department of Economics, Vanderbilt University and Research Associate at the Oxford Poverty & Human Development Initiative (OPHI), University of Oxford, UK. This chapter draws on S. Alkire and J. Foster, 2007.