MULTIDIMENSIONAL POVERTY MEASURES:
NEW POTENTIAL

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When poverty measures reflect the experiences of poor people, then this empowers those working to reduce poverty to do so more effectively and efficiently. The literature on Multidimensional Poverty Measures has surged forward in the last decade. This paper describes the broad directions of change, then presents a new and very simple measurement methodology for multidimensional poverty. It illustrates its application for poverty measurement, for targeting of social protection programmes, for monitoring and evaluation, and for poverty analysis. It also identifies how participatory input from communities can be directly reflected in the poverty measure.
1.1.1 Why Multidimensional Poverty

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

Effective multidimensional poverty measures have immediate practical applications. They can be used:

- to replace, or supplement, or combine with the official measures of income poverty that are reported each year, and so to provide an annual summary measure of all relevant goals at a time. This would redefine who is poor and directly affect government services to reduce poverty.

- to monitor the level and composition of poverty, and the reduction of poverty, over time. The measure not only provides a change in aggregate, but can also be broken down by dimension to identify the dimensions in which deprivations have been reduced the most. This would lead to better understanding of what policies work and what practical applications need to be modified.

- to evaluate the impact of programmes. A multidimensional measure can provide a summary of trend information for the selected dimensions across different project areas – and again the summary measure can be decomposed easily. This would lead to better evaluation data of programme results.

- to target the poorest more effectively. The new multidimensional measures are very well designed for targeting social protection schemes to families that suffer multiple deprivations.\(^1\) This is accomplished by identifying the families that are multiply deprived. Given that data are often of poor quality, these methods can be more accurate than existing methods, and in addition the decomposition of the measure provides useful information for policy.

- to identify poverty traps and chronic poverty. That is, to identify persons, households, or groups that have specific patterns of deprivation, or specific kinds of vulnerability, whether for targeting or other purposes. This is interrelated to an approach developed specifically for chronic poverty (Foster 2008). Similar measurement techniques are used in a positive sense to identify ‘early adopters’ or incidents of ‘positive deviance’. Multidimensional measures can pinpoint those who experience multiple deprivations for many periods.

- to compare the composition of poverty in different districts or for different ethnic groups, regions, and kinds of household, or for men and women if the data permit. It may be that one particular group is particularly deprived – for example an indigenous group, or women. This can be identified by decomposing the poverty measure and comparing groups.

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\(^1\) Alkire and Seth 2009, Azevedo and Robles 2008.
The same general approach to measurement can be fruitfully applied in other contexts. Applications to date of OPHI’s multidimensional measurement methods have used individual or household level data and constructed multidimensional poverty measures. More recently the methodology is being applied to different units of analysis and with respect to different focal areas:  

- **Quality of Education** – comparing schools’ outcomes
- **Governance** – comparing nations’ performance
- **Child Poverty** – to strengthen existing measures
- **Fair Trade** – to monitor cooperatives’ performance
- **Targeting** – to direct social protection interventions most effectively
- **Gender** – to better represent the differential burdens of poor women.
- **Gross National Happiness** – Bhutan’s 2009 GNH Index employs the methodology described below to measure well-being.

Taken as a whole effective poverty measures identify more accurately who the poor are; better data brings in view hidden but instrumentally potent variables. This shift in definition will increase the efficiency of funds spent on poverty alleviation because the policies will be better targeted, and the constituent elements of poverty will be understood directly.

**Income or Multidimensional Measures?**

Human progress—whether it is understood as well-being, fulfillment, the expansion of freedoms, or the achievement of 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 people’s exercise of many capabilities. The use of monetary indicators alone, however, 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 are disempowered. But monetary poverty often provides insufficient policy guidance regarding deprivations in other dimensions. As Table 1 illustrates, it is an empirical question as to whether counting as poor only those who are deprived in consumption will result in omitting a significant proportion of poor people in some areas and in overreporting poverty in others – or not. 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 thus appears to significantly misidentify deprivations in other dimensions. In such situations, multidimensional poverty measures are required to provide a more accurate representation of the multiple deprivations different people suffer.

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2 Papers applying multidimensional methodologies to targeting, child poverty, quality of education, governance, fair trade, and gender are available on OPHI’s website, www.ophi.org.uk.
Table 1—Lack of overlap between monetary poverty and other measures of poverty

<table>
<thead>
<tr>
<th>Consumption non-poor</th>
<th>Other non-poor</th>
<th>Other poor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumption poor</td>
<td>NP-NP</td>
<td>Error omission (I)</td>
</tr>
<tr>
<td></td>
<td>Error inclusion (II)</td>
<td>Poor-Poor</td>
</tr>
</tbody>
</table>

Recent Advances in Multidimensional measures:

Interest in multidimensional approaches to poverty and well-being has risen sharply, as the following examples suggest:

- Of the 38 existing international composite measures of multidimensional poverty and well-being, 28 have been developed since 2000. This is in line with Bandura’s (2006) finding that over 50% of composite indicators surveyed had been developed within the past five years.
- Interest in institutionalising broader measures of poverty and well-being spans developed and developing countries, as evidenced by these examples:
  - the Government of Mexico by law is moving to a multidimensional measure of poverty
  - India’s planning commission is exploring the development of an index of multiple deprivation
  - South Africa and Great Britain each implement indices of multiple deprivation,
  - the Sarkozy Commission on the Measurement of Economic Performance and Social Progress (CMEPSP) recommended the development of Quality of Life measures
  - the United Nations Development Programme 2010 report Re-thinking Human Development may address multidimensional measurement
  - The attention that the OECD’s project on Measuring the Progress of Societies achieved testifies to the broad appeal of wider-than-economic representations of human progress.

- The academic literature shows a proliferation of unprecedented empirical techniques and applications that seek to measure and analyse multidimensional poverty and inequality, as well as applications of these techniques.

The impetus to developing such a multidimensional framework has a range of diverse sources, which gives it a distinctive strength and stability. Amartya Sen, Robert Fogel, and other leading social scientists have provided a normative account of the need for multidimensional approaches. At the same time, empirical research has clarified the reach and limitations of income-based measures. In practical terms, relevant microdata sources have expanded greatly, and better computer infrastructure enables better multidimensional analyses. In terms of policy, the MDGs have drawn attention to interconnected aspects of human suffering and achievement.

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4 http://www.stiglitz-sen-fitoussi.fr/en/index.htm This sub-group is chaired by Alan Kreuger and reports to the co-chairs of the Commission, Joe Stiglitz and Amartya Sen.
5 http://www.oecd.org/pages/0,3417,en_40033426_40033828_1_1_1_1_1_1_00.html
Most composite measures such as the Human Poverty Index (HPI) use data aggregated first across people, and subsequently across domains. Building on a long history of ‘counting’ measures used by NGOs and in policy (Atkinson 2003), the measure described here reflects the breadth of deprivation. The advantage of the new multidimensional poverty measures is that:

- they are **flexible** and can be adapted to different contexts, with different units of analysis (household, school, individual, country)
- the **choice of dimensions** can be done locally, to promote ownership and reflect local contexts, or fixed at some level, to enable comparisons across contexts, countries, and time.
- the **choice of indicator**, and the aggregation of indicators within dimensions, is flexible
- the measures can be constructed with **binary, ordinal, categorical, qualitative, or cardinal data**
- the **weights** for indicators and dimensions can be varied
- the **poverty cutoffs** can be varied.
- **robustness tests** can be applied to test how sensitive the results are to small changes
- **The identification of ‘who is poor’ is transparent** and can be communicated easily at a popular level. As the number of dimensions goes up, like a magnifying glass, the measure focuses more acutely on the poorest of the poor.

**Introduction to a new methodology:**

Although more individual and household survey data exist 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;
- conform to “common sense” notions of poverty’
- be able to target the poor, track changes, and guide policy;
- be technically solid;
- be operationally viable; and
- be easily replicable.

Alkire and Foster (2007) developed a measure that aims to address 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, is 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.
**Who is poor? The Counting approach (adapted)**

Poverty measurement can be broken down conceptually into two distinct steps: (1) the identification step defines who is poor (2) 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 cutoff is set on this aggregate variable. A person is identified as poor when his or her achievements fall below this cutoff 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 any single dimension as multidimensionally poor. It is 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 National Family Health Survey (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. Often considered to be too restrictive, this method generally produces untenably low estimates of poverty. According to the intersection method, in the Indian example mentioned, no one was deprived in all 11 dimensions.

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 cutoffs and a counting methodology. The first cutoff is the traditional dimension-specific poverty line or cutoff. This cutoff is set for each dimension and identifies whether a person is deprived with respect to that dimension – assets, nutrition, education, water, housing, empowerment etc. The second cutoff delineates how widely deprived a person must be in order to be considered poor. If the dimensions are equally weighted, the second cutoff is simply the number of dimensions in which a person must be deprived to be considered poor.\(^7\) This equally weighted approach, known as the counting approach, is widely used in policy work. It is clear and easy to understand. For example, Mack and Lansley (1985) identified people as poor if they were poor in 3 or more of 26 deprivations, and the United Nations Children’s Fund (UNICEF) *Child Poverty Report 2003* identified any child who was poor with respect to two or more deprivations as being in extreme poverty.

\(^7\) If the dimensions are not equally weighted, the cutoff is set across the weighted sum of dimensional deprivations.
How poor are we? Aggregation into a national measure:

Now we have identified who is poor – it is, for example, everyone who is deprived in 4 out of 10 dimensions, or whose weighted sum of deprivations is more than 50%. How do we construct an overall measure of poverty? As you shall see, this is also very easy. The intuition is as follows. If data are ordinal, you multiply together \( H \times A \).

- The headcount, or percentage of people who are poor (H)
- The average [weighted] number (A) of dimensions in which poor people are deprived

That is the measure! It is very simple to compute as well as interpret, as we shall see.

If data are cardinal, and you also want to look at the depth of deprivation within each dimension, you multiply the above by a third term, namely the average normalized poverty gap (the poverty cutoff minus the actual achievement, divided by the poverty cutoff). As in the Foster Greer Thorbecke class of income poverty measures, each value can also be squared, to emphasise the condition of the poorest of the poor.

So to summarize, we propose a class of measures \( M_\alpha \) comprising three measures:

- \( M_0 \): the measure described below, suitable for ordinal and binary and qualitative data, that represents the headcount and the breadth of poverty
- \( M_1 \): \( M_0 \) times the average normalized gap, to represent the headcount, breadth, and depth of poverty (appropriate where data are cardinal)
- \( M_2 \): \( M_0 \) times the average squared normalized gap, to represent the headcount, breadth, and inequality among the poor (focuses on the poorest poor, where data are cardinal).

In practice: 12 Steps to a Multidimensional Poverty Measure for ordinal data

The above methodology can be taught in 12 steps. The first 6 steps are common to many multidimensional poverty measures; the remainder are more specific to our methodology.

**Step 1: Choose Unit of Analysis.** The unit of analysis 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 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 method is to use survey data on people’s perceived necessities.
- A list that has achieved a degree of legitimacy through public consensus, such as the universal declaration of human rights, the MDGs, 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 used 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 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, and using exploratory factor analysis.

Step 4: Set Poverty Lines. A deprivation cutoff is set for each dimension. This step establishes the first cutoff in the methodology. Every person can then be identified as deprived or nondeprived 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 nondeprivation 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 “body mass index,” people are identified as being deprived or nondeprived 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, his or her value in that dimension is higher than the cutoff), and D indicates that the person is deprived (his or her value is lower than the cutoff).

<table>
<thead>
<tr>
<th>Person</th>
<th>Health</th>
<th>Living standard</th>
<th>Quality of education</th>
<th>Empowerment</th>
<th>Total count</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Access to good health clinic</td>
<td>Body mass index</td>
<td>Housing quality</td>
<td>Employment</td>
<td>Composite indicator</td>
</tr>
<tr>
<td>Person 1</td>
<td>ND</td>
<td>D</td>
<td>ND</td>
<td>D</td>
<td>D</td>
</tr>
<tr>
<td>Person 2</td>
<td>ND</td>
<td>ND</td>
<td>D</td>
<td>ND</td>
<td>D</td>
</tr>
<tr>
<td>Person 3</td>
<td>D</td>
<td>D</td>
<td>D</td>
<td>ND</td>
<td>ND</td>
</tr>
<tr>
<td>Person 4</td>
<td>D</td>
<td>D</td>
<td>D</td>
<td>D</td>
<td>D</td>
</tr>
</tbody>
</table>

Step 6: Count the Number of Deprivations for Each Person. This step is demonstrated in the last column of Table 2. (Equal weights among indicators are assumed for simplicity. General weights can be applied, however, in which case the weighted sum is calculated.)

Step 7: Set the Second Cutoff. Assuming equal weights for simplicity, set a second identification cutoff, \( k \), 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 Cutoff \( k \) to Obtain the Set of Poor Persons and Censor All Nonpoor Data. The focus is now on the profile of the poor and the dimensions in which they are deprived. All information on the nonpoor is replaced with zeros. This step is shown in Table 3.

Table 3—Example, part II

<table>
<thead>
<tr>
<th>Person (poor)</th>
<th>Health</th>
<th>Living standard</th>
<th>Quality of education</th>
<th>Empowerment</th>
<th>Total count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Person 1</td>
<td>ND</td>
<td>D</td>
<td>ND</td>
<td>D</td>
<td>4</td>
</tr>
<tr>
<td>Person 2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Person 3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Person 4 (poor)</td>
<td>D</td>
<td>D</td>
<td>D</td>
<td>D</td>
<td>6</td>
</tr>
</tbody>
</table>

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 analyze 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.
- 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 for which it is being calculated, 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 or 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 or she self reports “fair” or “poor” health.
3. **Health insurance**: a person is deprived if he or she lacks health insurance.
4. **Schooling**: a person is deprived if he or 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.

Table 4—Profile of U.S. poverty by ethnic/racial group

<table>
<thead>
<tr>
<th>Group</th>
<th>Population (2)</th>
<th>% contribution (3)</th>
<th>Income poverty headcount (4)</th>
<th>% contribution (5)</th>
<th>H (6)</th>
<th>% contribution (7)</th>
<th>M0 (8)</th>
<th>% contribution (9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hispanic</td>
<td>9,100</td>
<td>19.8</td>
<td>0.23</td>
<td>37.5</td>
<td>0.39</td>
<td>46.6</td>
<td>0.23</td>
<td>47.8</td>
</tr>
<tr>
<td>White</td>
<td>29,184</td>
<td>63.6</td>
<td>0.07</td>
<td>39.1</td>
<td>0.09</td>
<td>34.4</td>
<td>0.05</td>
<td>33.3</td>
</tr>
<tr>
<td>Black</td>
<td>5,742</td>
<td>12.5</td>
<td>0.19</td>
<td>20.0</td>
<td>0.21</td>
<td>16.0</td>
<td>0.12</td>
<td>16.1</td>
</tr>
<tr>
<td>Others</td>
<td>1,858</td>
<td>4.1</td>
<td>0.10</td>
<td>3.5</td>
<td>0.12</td>
<td>3.0</td>
<td>0.07</td>
<td>2.8</td>
</tr>
<tr>
<td>Total</td>
<td>45,884</td>
<td>100.0</td>
<td>0.12</td>
<td>100.0</td>
<td>0.16</td>
<td>100.0</td>
<td>0.09</td>
<td>100.0</td>
</tr>
</tbody>
</table>


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, whereas 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 M0 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 earlier to identify the dimension-specific changes driving the variations in M0. The final column of Table 5 reproduces the group poverty levels found in Column 8 of Table 4, and 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 M0 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 percentage contribution of the income dimension to the Hispanic level of M0 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 result explains why, in comparison with traditional income-based poverty, the percentage of overall multidimensional poverty originating in the Hispanic population rises, whereas the contribution for African Americans is lower. The example shows how the measure M0 can be readily broken down by population subgroup and dimension to help explain its aggregate level.
Table 5—Contribution of each dimension to overall $M_0$

<table>
<thead>
<tr>
<th>Group (1)</th>
<th>$H_1$ Income (2)</th>
<th>$H_2$ Health (3)</th>
<th>$H_3$ Health insurance (4)</th>
<th>$H_4$ Schooling (5)</th>
<th>$M_0$ (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hispanic</td>
<td>0.200</td>
<td>0.116</td>
<td>0.274</td>
<td>0.324</td>
<td>0.229</td>
</tr>
<tr>
<td>% contribution</td>
<td>21.8</td>
<td>12.7</td>
<td>30.0</td>
<td>35.5</td>
<td>100</td>
</tr>
<tr>
<td>White</td>
<td>0.045</td>
<td>0.053</td>
<td>0.043</td>
<td>0.057</td>
<td>0.050</td>
</tr>
<tr>
<td>% contribution</td>
<td>22.9</td>
<td>26.9</td>
<td>21.5</td>
<td>28.7</td>
<td>100</td>
</tr>
<tr>
<td>African American</td>
<td>0.142</td>
<td>0.112</td>
<td>0.095</td>
<td>0.138</td>
<td>0.122</td>
</tr>
<tr>
<td>% contribution</td>
<td>29.1</td>
<td>23.0</td>
<td>19.5</td>
<td>28.4</td>
<td>100</td>
</tr>
<tr>
<td>Others</td>
<td>0.065</td>
<td>0.053</td>
<td>0.071</td>
<td>0.078</td>
<td>0.067</td>
</tr>
<tr>
<td>% contribution</td>
<td>24.2</td>
<td>20.0</td>
<td>26.5</td>
<td>29.3</td>
<td>100</td>
</tr>
<tr>
<td>Overall</td>
<td>0.089</td>
<td>0.073</td>
<td>0.096</td>
<td>0.121</td>
<td>0.095</td>
</tr>
<tr>
<td>% contribution</td>
<td>23.4</td>
<td>19.3</td>
<td>25.4</td>
<td>31.9</td>
<td>100</td>
</tr>
</tbody>
</table>


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

A key feature is that the measure can identify and target households for public support more accurately than income poverty. The conditional cash transfer program Oportunidades in Mexico and the Below the Poverty Line (BPL) calculations in India all use a particular measure to identify qualified recipients for public support. In India, the multidimensional headcount measure with Alkire and Foster identification method (the dark bar in Figure 1) in rural areas (with dimensions similar to the government’s below-the-poverty-line measure) is in some cases strikingly different from income poverty estimates (light bar).

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8 OPHI Working papers number 13-18, and
The following box gives some other examples of applications.

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Examples of Multidimensional Poverty Measures

This box presents a battery of examples of how the measures might be used, drawing on recent applications.

To replace, or supplement, or combine with the official measures of income poverty.

Example: The chart below reports the proportion of poor persons in 10 states according to income, social protection participation, and multidimensional poverty. It is evident from the figure that Andhra Pradesh, one of the least poor Indian states in terms of income poverty, does not perform well in terms of multiple deprivations. For a state such as Orissa, however, both the income poverty measure and the multidimensional poverty measure identify roughly the same proportion of poor.

To compare the composition of poverty in different districts or for different ethnic/geographic groups and kinds of household, or for men and women if the data permit.

Example: the inset from Bhutan compares two districts. Gasa fell 11 places when ranked by multidimensional poverty rather than by income poverty; Lhuntse rose 8 places. We can see that most deprivation in Gasa is driven by shortfalls in electricity, drinking water, and overcrowding. In contrast, in Lhuntse the relative contribution of income poverty is high relative to shortfalls in other dimensions.

Table 1. Bhutan: comparison of 2 districts

Table 2. MD poverty across time in China

To monitor the level and composition of poverty, and the reduction of poverty, over time.

Example: the chart shows the decomposition of multidimensional poverty across four periods in China. As you can see, the relative contribution of unemployment is rising, while health and resource deprivations are decreasing.
Conclusion

The two critical priorities for the next decade are, arguably, climate change, and poverty reduction. To reduce poverty, and empower the poor to shape their own lives and livelihoods, requires a number of ingredients. To date, however, our measures of poverty have too often led to misunderstandings of who is poor, of the nature of poverty and of poverty traps. Hence the policies to reduce poverty have not reflected the interconnections among deprivations, nor the extreme poverty of those whose lives are battered by suffering of so many different kinds. We argue that to move from poverty to power does require a shift in poverty measurement.

This paper has introduced a new methodology for multidimensional poverty measurement. The methodology consists of (1) a dual cutoff identification method to identify who is poor, 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 this measure with national poverty measures (such as income or any other measure) in more than 20 countries. A further exploration is underway for international comparisons using DHS data. 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.

Incomplete references:


Econometrica, 52, 761-766.


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