Chapter 3

Counting and Multidimensional Poverty

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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 among 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 of poverty.

Why Do We Need 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 3.1 illustrates, it is an empirical question whether counting as poor only those who are deprived in terms of consumption can result in omitting a significant

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This chapter summarizes S. Alkire and J. Foster, Counting and multidimensional poverty measures, OPHI Working Paper Series 7, 2007, <www.ophi.org.uk>.

Table 3.1 Lack of overlap between monetary poverty and other measures of poverty

	Other nonpoor	Other poor
Consumption nonpoor	Nonpoor-Nonpoor	Error omission (I)
Consumption poor	Error inclusion (II)	Poor-Poor

Source: Devised by the authors.

proportion of poor people in some areas and in over-reporting poverty in others. Ruggeri-Laderchi, Saith, and Stewart (2003) observed 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.

The Problem of Complex Poverty Measures

Although more individual and household survey data are available 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 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.

The multidimensional poverty methodology presented in this chapter meets these criteria. It is related to the user-friendly "counting" approaches but provides a more flexible way to identify who is poor. It has 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 in 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 efficiently address deprivations in different groups. It is also an effective tool for targeting.

The Dual-Cutoff Method of Identification

Poverty measurement can be broken down conceptually into two distinct steps: (1) the identification step defines the cutoffs for distinguishing the poor from the nonpoor, and (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 independent 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 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 data with 11 dimensions, 91 percent of the population would be identified as poor.

3. The *intersection* method requires that someone be deprived in all dimensions in order to be identified as poor. Often considered 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. 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. This equally weighted approach, known as the counting approach, is widely used in policy work. For example, Mack and Lansley (1985) identified people as poor if they were deprived in 3 or more of 26 dimensions, and the United Nations Children's Fund's *Child Poverty Report 2003* identified any child who was deprived in two or more dimensions as in extreme poverty. Once we have identified the cutoffs in terms of who is poor and who is not, we aggregate our data using a natural extension of the Foster Greer Thorbecke poverty measures in multidimensional space.

12 Steps to a Multidimensional Poverty Measure

Our methodology can be intuitively introduced 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 on five means of selection, 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 assumptions 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,* data on consumer preferences and behaviors, or studies of what values are most conducive to people's 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 dimension 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, it is best to choose indicators that are not highly correlated.

Step 4: Set Poverty Lines. A poverty 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?"), "6 years or more" might identify nondeprivation, while "1–5 years" might identify deprivation in the dimension. 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 extremely poor).

Step 5: Apply Poverty Lines. This step replaces the person's achievement with his or her status with respect to each cutoff; for example, in the dimension of health, when the indicators are "access to health clinic" and "self-reported morbidity 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 3.2 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).

Step 6: Count the Number of Deprivations for Each Person. This step is demonstrated in the last column of Table 3.2. (Equal weights among indicators are

Table 3.2 Example of application of poverty lines, part 1

	Health		Living standard		Quality of education	Empowerment	
Person	Access to a good health clinic	Body mass index	Housing quality	Employment	Composite indicator	Autonomy	Total count
Person 1	ND	D	ND	D	D	D	4
Person 2	ND	ND	D	ND	D	ND	2
Person 3	D	D	D	ND	ND	ND	3
Person 4	D	D	D	D	D	D	6

Source: Devised by the authors.
Notes: ND, not deprived; D, deprived. Shading indicates people who are poor (defined as deprived in at least four dimensions).

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 3.2, k is set to 4 and the persons whose data are shaded 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 3.3.

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 3.2 and 3.3, 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 3.3, 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. $A = (4/6 + 6/6)/2 = 5/6$.

Table 3.3 Example of application of poverty lines, part 2

Person	Health: Access to a good health clinic	Health: Body mass index	Living standard: Housing quality	Living standard: Employment	Quality of education: Composite indicator	Empowerment: Autonomy	Total count
Person 1	ND	D	ND	D	D	D	4
Person 2	0	0	0	0	0	0	0
Person 3	0	0	0	0	0	0	0
Person 4	D	D	D	D	D	D	6

Source: Devised by the authors.
Notes: ND, not deprived; D, deprived. 0 denotes the censored observations of the nonpoor. Shading indicates people who are poor (defined as deprived in at least four dimensions).

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, $HA = 2/4 \times 5/6 = 5/12$.

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 the group 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 his or her normalized poverty gap (the poverty line minus the person's 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 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 older ($n = 45{,}884$). Four indicators were used:

1. *Income:* a person is deprived if he or she lives in a household that falls 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 3.4 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 $k = 2$

Table 3.4 Profile of U.S. poverty by ethnic/racial group

Group (1)	Population (2)	Percent contribution (3)	Income poverty headcount (4)	Percent contribution (5)	M (6)	Percent contribution (7)	M_0 (8)	Percent contribution (9)
Hispanic	9,100	19.8	0.23	37.5	0.39	46.6	0.23	47.8
White	29,184	63.6	0.07	39.1	0.09	34.4	0.05	33.3
Black	5,742	12.5	0.19	20.0	0.21	16.0	0.12	16.1
Other	1,858	4.1	0.10	3.5	0.12	3.0	0.07	2.8
Total	45,884	100.0	0.12	100.0	0.16	100.0	0.09	100.0

Source: S. Alkire and J. E. Foster, Counting and multidimensional poverty measurement, Oxford Poverty and Human Development Initiative Working Paper 7, University of Oxford, Oxford.

Note: *H,* headcount.

and equal weights. Column 2 gives the population share in each group, while column 4 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 in 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 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 than the traditional, income-based poverty profile? Table 3.5 uses the methodology outlined earlier to identify the dimension-specific changes driving the variations in M_0. The final column of Table 3.5 reproduces the group poverty levels found in column 8 of Table 3.4, 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 M_0 for Hispanics, which is simply the average of H_1 through H_4. The second row expresses

Table 3.5 Contribution of each dimension to overall adjusted headcount, M_0

Group	H_1 (Income)	H_2 (Health)	H_3 (Health insurance)	H_4 (Schooling)	M_0
Hispanic	0.200	0.116	0.274	0.324	0.229
Percent contribution	21.8	12.7	30.0	35.5	100
White	0.045	0.053	0.043	0.057	0.050
Percent contribution	22.9	26.9	21.5	28.7	100
African American	0.142	0.112	0.095	0.138	0.122
Percent contribution	29.1	23.0	19.5	28.4	100
Other	0.065	0.053	0.071	0.078	0.067
Percent contribution	24.2	20.0	26.5	29.3	100
Overall	0.089	0.073	0.096	0.121	0.095
Percent contribution	23.4	19.3	25.4	31.9	100

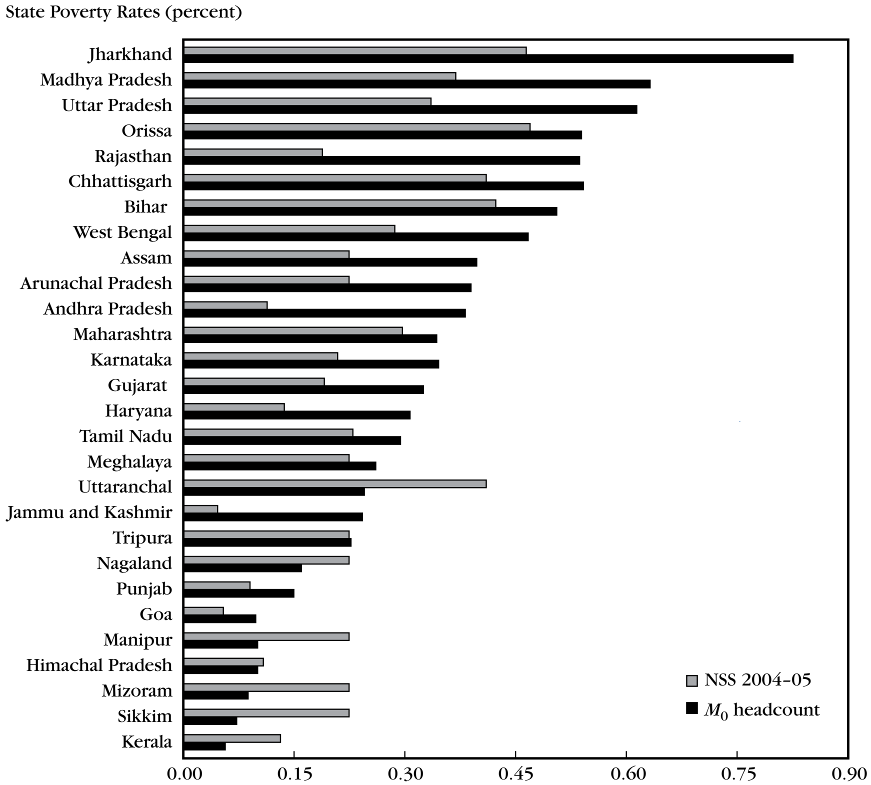
Source: S. Alkire and J. E. Foster, Counting and multidimensional poverty measurement, Oxford Poverty and Human Development Initiative Working Paper 7, University of Oxford, Oxford.
Note: M_0, adjusted headcount; H, headcount.

the same data in percentage terms, with column 2 providing the percentage 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 result explains why, in comparison with traditional income-based poverty, the percentage of overall multidimensional poverty originating in the Hispanic population is rising, whereas 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 under way in Bhutan, China, India, Pakistan, Latin America, and Sub-Saharan Africa. These demonstrate different qualities of the measure:

- *The measure can identify and target particularly for public support more accurately than can measures of income poverty.* The conditional cash transfer (CCT) 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 M_0 taken using the identification method we have recounted elsewhere (the dark bar in Figure 3.1) in rural areas (with dimensions similar to the government's BPL measure) is in some cases strikingly different from income poverty estimates (light bar).

Figure 3.1 Measures of poverty for states in India, 2004–05

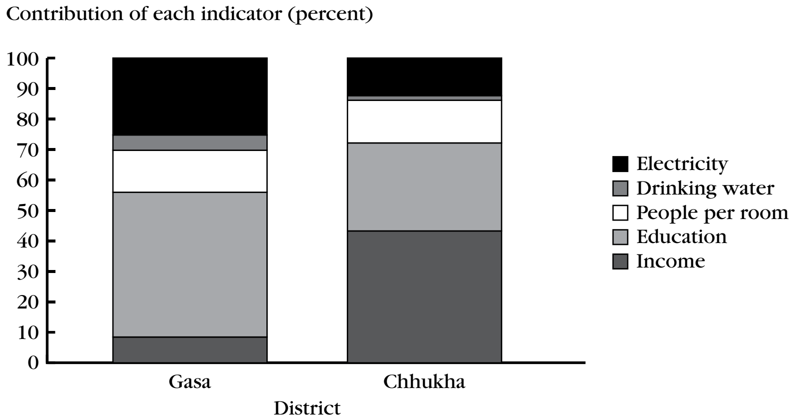


Source: S. Alkire and S. Seth, Multidimensional poverty and BPL measures in India: A comparison of methods, Oxford Poverty and Human Development Initiative Working Paper 15, University of Oxford, Oxford, 2009.

Note: NSS, National Sample Survey; M_0, multidimensional headcount.

- *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 poverty 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 Chhukha, which was ranked 11th of 20 by income, rose 3 places when ranked by multidimensional poverty. Decomposing the M_0 measure by dimension reveals that in Gasa, poverty is driven by a lack of electricity, drinking water, and overcrowding; income is hardly visible as a cause of poverty (Figure 3.2). In Chhukha, income is a much greater contributor to poverty than other dimensions; hence its increase. Although further analysis is required, these results

Figure 3.2 Composition of multidimensional poverty in two districts of Bhutan (M_0 with k = 2), 2007



Source: Based on M. E. Santos and K. Ura, Multidimensional poverty in Bhutan: Estimates and poverty implications, Oxford Poverty and Human Development Initiative Working Paper 14, University of Oxford, Oxford, 2008.

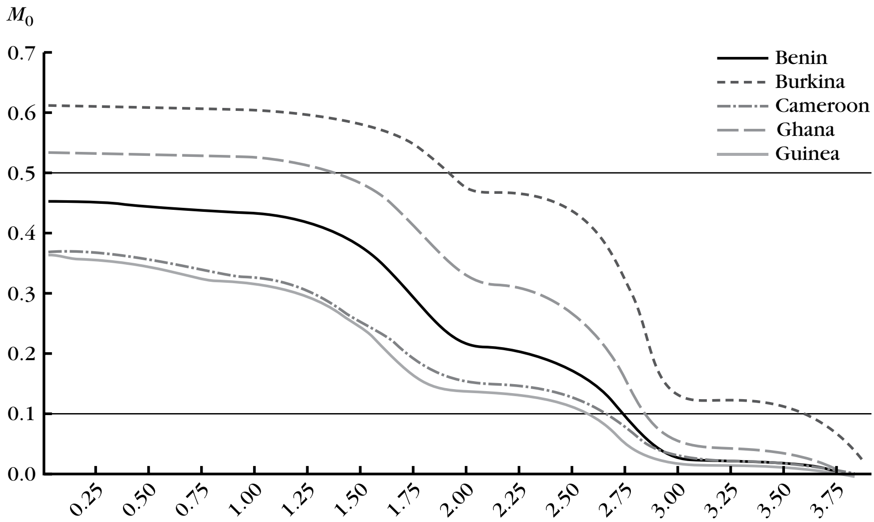
suggest that policy priorities to reduce multidimensional poverty will differ significantly in each state.

- *The robustness of multidimensional poverty can be tested using different assumptions.* In Sub-Saharan Africa, five countries were compared using Demographic and Health Survey data (Figure 3.3). For all possible values of k (the second cutoff), Burkina Faso is always poorer than Nigeria, regardless of whether we count as poor persons those who are deprived in only one dimension or those deprived in every dimension (assets, health, education, and empowerment, in this example).

Conclusion

This chapter has introduced a new methodology for multidimensional poverty measurement. The methodology consists of (1) a dual cutoff identification method that extends the traditional intersection and union approaches and (2) a set of poverty measures that have 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 also for 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

Figure 3.3 Adjusted multidimensional headcount M_0 as poverty cutoff k is varied in five countries



Source: Y. M. Batana, Multidimensional measurement of poverty in sub-Saharan Africa, Oxford Poverty and Human Development Initiative Working Paper 13, University of Oxford, Oxford, 2008.

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 CCTs.

For Further Reading

Alkire, S., and J. Foster. Counting and multidimensional poverty measures. OPHI Working Paper Series 7. Oxford Poverty and Human Development Initiative, Oxford, 2007. <www.ophi.org.uk>.

Atkinson, A. B. Multidimensional deprivation: Contrasting social welfare and counting approaches. *Journal of Economic Inequality* 1, no. 1 (2003): 51–65.

Foster, J. E., J. Greer, and E. Thorbecke. A class of decomposable poverty indices. *Econometrica* 52, no. 3 (1984): 761–66.