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Estimating measures of multidimensional poverty in Stata

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Abstract. This paper describes the multidimensional poverty measures developed by Alkire and Foster (2011) and shows how they can be computed in Stata with the command `mpi`.

Keywords: st0001, mpi, multidimensional poverty, Alkire Foster method

1 Introduction

Poverty can depend on a plurality of simultaneous disadvantages other than the shortage of financial resources. For instance, a person who is not identified as poor in terms of income or expenditure can still experience other types of deprivations, such as malnutrition, little schooling or lack of clean water and electricity.

Alkire and Foster (2011) have proposed a methodology that considers a plurality of not-perfectly-overlapping deprivation indicators, summarising the information into a consistent parametric class of multidimensional poverty indices. These indices can be used for a variety of policy-relevant issues, such as creating measures of well-being, monitoring and evaluating anti-poverty programs and improving the targeting of in-kind and cash benefits.[1] The Alkire Foster (AF) measures build on the Foster-Greer-Thorbecke (FGT) indices introduced in James Foster (1984) and, in the same way, they can be perfectly decomposed by population sub-groups (e.g. ethnicity, geographic area, etc.) and deprivation domains (e.g. education, income, health, etc.), a feature that makes them suitable for policy evaluations. Similar to the FGT measures, the AF measures depend on a parameter α that ensures they satisfy a broad range of multidimensional poverty-measurement axioms, such as replication invariance, symmetry, poverty focus and weak monotonicity.[2]

In this contribution, we review the AF method and show how to apply it in Stata with the command `mpi`. An important feature of `mpi` is its flexibility: depending on the type of data, `mpi` estimates the whole range of AF multidimensional poverty measures for arbitrary values of α and computes their decomposition by deprivation indicators and population sub-groups. The command allows for an indefinite number of indicators,

1. For a review of applications the reader can refer to the Oxford Poverty and Human Development Initiative, the UNDP-HDRO Human Development Reports, Alkire (2013) and OECD (2015).
2. For $\alpha \geq 0$ the AF indices satisfy: decomposability, replication invariance, symmetry, poverty and deprivation focus, weak and dimensional monotonicity, nontriviality, normalisation, and weak rearrangement. For $\alpha > 0$ they also satisfy monotonicity, and for $\alpha \geq 1$ the axiom of weak transfer. See Alkire and Foster (2011) for definitions and proofs.

 st0001

with the possibility to use a flexible weighting structure for each of them. The survey design is also fully taken into account when computing the indices and the corresponding standard errors.

The remainder of this paper proceeds as follows. Section 2 overviews the Alkire and Foster method; section 3 overviews the `mpi` command; section 4 concludes with an empirical application based on the original data used in Alkire and Foster (2011).

2 The Alkire Foster method

In this section, we overview the main concepts used in the AF framework to derive the related class of poverty measures. The AF method can be divided into two sequential parts: the *identification* of poor individuals and the *measure* of poverty based on such identification.

2.1 Identifying the poor

Let us consider a sample of N individuals and $D \geq 2$ deprivation indicators. Indicators related to the same area of deprivation can be grouped into *deprivation domains*. For instance, the domain *health* can be identified in the data with two indicators, e.g. the number of visits to the doctor and the distance to the closest medical center. Let Y be a NxD matrix whose entry y_{ij} denotes the level of indicator j for individual i. The 1xD vector $z = (z_1, ..., z_D)$ contains the deprivation cutoffs of the D indicators and is used to determine if a person is deprived in each of the D dimensions. In this section, for simplicity we assume that for a indicator j and individual i the deprivation occurs when y_{ij} falls strictly below the respective cutoff, i.e. $y_{ij} < z_j$.

Indicators can enter the analysis with different weights depending on their policy relevance. Weights are collected in a 1xD vector $w = (w_1, ..., w_D)$, with $0 < w_j < 1$ and $\sum_{j=1}^{D} w_j = 1$. For instance, if each indicator is viewed as having equal importance all weights will be equal to $1/D$.

Let g^0 be the NxD matrix whose entry is w_{ij} if $y_{ij} < z_j$ and 0 otherwise. This is called the *deprivation matrix* in the Alkire and Foster (2011) framework because for each individual of the population it contains the policy relevance of each deprivation when such deprivation occurs. The row sum of g^0 is the number of *weighted* deprivations faced by individual i: $c_i = \sum_{j=1}^{D} g_{ij}^0$.

With cardinal indicators, the matrix of deprivations g^0 can be complemented with the *matrix of normalised deprivation gaps*, g^1, whose entries are given by $g_{ij}^1 = g_{ij}^0 \frac{z_j - y_{ij}}{z_j}$. In other words, g_{ij}^1 represents a measure of the extent to which individual i is deprived in dimension j whenever $y_{ij} < z_j$. More generally, for any α, let us define the matrix g^α by raising each entry of g^1 to the power of α: $g_{ij}^\alpha = (g_{ij}^0 \frac{z_j - y_{ij}}{z_j})^\alpha$. Hence, similarly to the FGT class of poverty measures, the higher the value of α the higher the entries of g^α with the biggest gaps, i.e. the focus on the poorest among the poor in the calculation of the overall index.

Let us define $0 < k < 1$ as the *poverty cutoff*. This value is key in the AF method as it represents the minimum extent of *weighted* deprivations a person must suffer to be considered poor. For example, if there are 10 indicators of equal importance and $k = 0.4$ a person is considered poor if she experiences 5 or more deprivations simultaneously. The use of indicator *and* poverty cutoffs is what justifies the term *dual-cutoff* approach when referring to the AF method.

Let us define the *identification function* $\rho_k(y_i, z)$, which takes values 1 when individual i with vector of deprivations y_i is classified as poor given the selected poverty cutoff k and indicator cutoffs z. The identification function $\rho_k(y_i, z)$ modifies the entries of matrix g^α as $g^\alpha_{ij}\rho_k(y_i, z)$, so that if person i is not identified as poor then the row-vector g^α_i is replaced with zeros. Alkire and Foster define to the resulting matrix as $g^\alpha(k)$ and call it the *censored* deprivation matrix.

2.2 Measuring multidimensional poverty

The simplest index of multidimensional poverty in the AF framework is the *multidimensional headcount ratio*, which measures the *incidence* of poverty in the population:

$$H = \frac{\sum_{i=1}^{N} \rho_k(y_i, z)}{N} = \frac{q}{N}$$

The numerator is the number of poor individuals identified with the identification function defined above and N is the population size. Despite its simplicity and widespread use in the policy debate, H does not have the desirable property of increasing when a poor person becomes deprived in a new dimension.[3] An index that increases with the number of deprivations experienced by the poor individuals can be derived from the censored deprivation matrix, $g^0(k)$. Let $|g^0(k)|$ be the *sum* of all entries of matrix $g^0(k)$: $|g^0(k)| = \sum_{j=1}^{D}\sum_{i=1}^{N} g^0_{ij}(k)$. Alkire and Foster define the index A as the ratio between the weighted number of deprivations faced by the poor individuals, $|g^0(k)|$, and the number of poor individuals (q):[4] $A = \frac{|g^0(k)|}{q}$.

A poverty measure that simultaneously takes into account the incidence (H) and the breadth (A) of simultaneous deprivations can be derived from the product of H and A:

$$M_0 = H \cdot A = \frac{|g^0(k)|}{N}$$

Alkire and Foster define M_0 as the *adjusted multidimensional headcount ratio*, also

3. This is the measurement axiom of *dimensional* monotonicity in the Alkire and Foster framework.
4. The denominator of index A in the original Alkire and Foster contribution is qD. In the context of the present paper, the use of indicator weights that sum up to 1 implies that the extent of all possible deprivations for the generic individual i is also standardised to 1.

known as the Multidimensional Poverty Index (MPI).

The MPI can be computed with binary, ordinal or real-valued data. However, when ordinal or real-valued indicators are available, the measure M_0 can be complemented with other indices that also take into account the *depth* of each deprivation. Let $|g^1(k)|$ be the sum of the poverty gaps of poor individuals. The *average poverty gap* across the extent of all possible deprivations faced by the poor is $G = \frac{|g^1(k)|}{|g^0(k)|}$. A poverty measure that considers jointly the incidence of poverty (H), the average range of deprivations (A) and the average depth across deprived dimensions (G) can be computed as:

$$M_1 = M_0 \cdot G = \frac{|g^1(k)|}{N}$$

More importantly, M_1 respects the traditional monotonicity axiom, i.e. it increases as a poor person becomes *more* deprived in a given dimension.

Following James Foster (1984), ideal poverty measures should also respect the *transfer* principle, i.e. they should increase *at a faster rate* when the depth of deprivation gets worse for those individuals who are already highly deprived. An index with such property can be easily derived within the AF framework by simply substituting $|g^1(k)|$ with $|g^2(k)|$ in the computation of the G index. This leads to a measure of *average severity of deprivations*: $S = \frac{|g^2(k)|}{|g^0(k)|}$.

A multidimensional poverty measure that jointly considers all the aspects defined above can be derived from the product of M_0 and S:

$$M_2 = M_0 \cdot S = \frac{|g^2(k)|}{N}$$

More generally, the AF class of multidimensional poverty measures is given by:

$$M_\alpha = M_0 \cdot S_\alpha = \frac{|g^\alpha(k)|}{N},\ \alpha \geq 0$$

A key property of the AF measures M_α is the perfect decomposability by population sub-groups and indicators. *Perfect* decomposability into population sub-groups means that the overall measure can be obtained as the weighted average of sub-group poverty levels with weights given by the sub-group population shares.

$$M_\alpha = \sum_{g=1}^{G} \frac{N_g}{N} M_{\alpha,g}$$

Where $M_{\alpha,g}$ is the index for sub-group g and N_g the corresponding population size. The percentage contribution of group g is therefore: $C_{\alpha,\,g} = \frac{N_g}{N} \frac{M_{\alpha,g}}{M_\alpha}$.

The AF class of poverty measures can be further decomposed by indicators of deprivation. Let $|g_j^\alpha(k)|$ be the sum of the $j-$column entires of $g^\alpha(k)$. Then, $M_\alpha = \sum_{j=1}^{D} |g_j^\alpha(k)|/N$. The percentage contribution of each indicator to the overall measure is therefore $CI_{\alpha,\,j} = \frac{|g_j^\alpha(k)|}{N \cdot M_\alpha}$. The contribution of a group of indicators follows simply as the sum of the contributions of the individual indicators.

3 The `mpi` command

The command **`mpi`** estimates the AF poverty measures described in section 2.2 and provides the exact decomposition by deprivation indicators. It computes standard errors taking into account the survey design and allows for a flexible weighting structure of the indicators. It also provides the decomposition by population sub-groups and shows the contribution of each deprivation indicator in each sub-group. When real-valued indicators are available, `mpi` computes the whole parametric class of AF poverty measures for arbitrary values of α and provides the decomposition by population sub-groups and indicators for each M_α.

An important characteristic of `mpi` is the possibility to group indicators into policy domains. This does not affect the statistical derivation of the AF measures but facilitates the interpretation of the results. Let us consider 2 deprivation domains, say, *monetary poverty* and *health*. The domain *monetary poverty* could be identified by 1 indicator, e.g. household income, whereas the domain *health* by 2 indicators, e.g. the number of visits to the doctor and the distance to the closest medical centre. In this example, there are therefore 3 deprivation indicators for 2 policy domains and `mpi` provides information at the indicator and domain level.

3.1 Syntax

The generic syntax for `mpi` is:

`mpi d1(`*varlist*`)` [`d2(`*varlist*`) ... w1(`*numlist*`) w2(`*numlist*`) ... t1(`*threshold*`)` `t2(`*threshold*`) ...`] [*if*] [*in*] [*weight*] `, cutoff(#)` [`by(`*varname*`) alpha(`*numlist*`) svy level(#) categories(#) nosummary nodecomposition`]

3.2 Required options

`d1(`*varlist*`), d2(`*varlist*`), ...` denote deprivation domains, e.g. health, monetary poverty, education, etc. Users can specify an indefinite number of domains and, for each domain, an indefinite number of indicators. At least 1 indicator is required. Indicators can be binary, ordinal or real-valued variables. When the indicator is binary, the variable can take only values one (deprived) and zero (not deprived). When the indicators are ordinal or real-valued, the user must specify the related poverty thresholds using the corresponding `mpi` option. If no thresholds are specified, `mpi` assumes that all indicators are binary and will give an error is that is not the case. Observations with missing values are excluded from the estimation sample.

`cutoff(#)` is required and specifies a number between 0 and 1, above which the individual is considered poor. Following the approach outlined in section 2, for each individual `mpi` computes the *weighted* sum of the indicators and the individual is considered poor only if the resulting score is higher then the selected poverty cutoff. Weights are specified in the corresponding `mpi` option (see below); if no weights are specified, `mpi` assumes equal weights at the domain level and within each domain. Hence, when the number of indicators is equal to the number of domains and the indicators have equal weights the poverty cutoff will simply indicate the percentage of simultaneous deprivations above which a person is considered poor.

Let us consider an example. The command line below uses three indicators and a poverty cutoff of 0.66. Since no thresholds are specified, `mpi` assumes that the indicators are all binary variables. Since no weights are specified, `mpi` assumes equal weights between and withing domains. In the example below, a person is therefore considered poor if she faces at least 2 deprivations, as the weighted sum of 2 deprivations would be just above the poverty cutoff.[5]

```
mpi d1(ind1 ind2 ind3), cutoff(0.66)
```

Let us consider now the case of 3 indicators and 2 deprivation domains, the first containing 2 indicators (`ind1` and `ind2`) and the second 1 indicator (`ind3`). Since weights are not specified, `mpi` assumes equal weights between and withing domains. In the example below, each domain has therefore a weight of 0.5 and the first 2 indicators each have a weight of 0.25. Given a poverty cutoff of 0.74, an individual deprived in `ind1` and `ind3` would therefore be considered poor because the weighted sum of their deprivations would be just above the poverty cutoff.

```
mpi d1(ind1 ind2) d2(ind3), cutoff(0.74)
```

`t1(numlist), t2(numlist), ...` denote the deprivation thresholds for the indicators of each domain. This option is required only when using ordinal or real-valued indicators. Depending on the indicator, the deprivation can occur for values *below* or *above* the threshold. The user can therefore specify *the direction* of the deprivation by typing the sign $<$ or $>$ in front of the threshold value. If no signs are specified, `mpi` assumes that the deprivation occurs when the indicator is *below* the threshold.[6]

The command line below shows an example of different deprivation thresholds: for `ind1` and `ind3`, deprivation occurs for values strictly below 4 and 5 respectively, whereas for `ind2` the deprivation occurs when the indicator is strictly above 3.

```
mpi d1(ind1 ind2) d2(ind3) t1(<4 >3) t2(5), cutoff(0.74)
```

5. Note that the commands: `mpi d1(ind1 ind2 ind3), cutoff(0.66)` and `mpi d1(ind1) d2(ind2) d3(ind3), cutoff(0.66)` are equivalent.
6. Individuals are considered deprived for values *strictly* above or below the thresholds. No empty spaces between the signs $<$ or $>$ and the threshold value are allowed. `mpi` considers the absolute value of the poverty gaps; this affects the computation of the sole $M1$ index in the special case of a negative threshold.

3.3 Other options

`w1(numlist), w2(numlist), ...` denote the weights of the indicators. Weights are numbers between zero and one and they must sum up to 1; when this is not the case, `mpi` gives an error. It is required to use as many weights as the number of indicators and the list of weights must follow the same structure of the corresponding list of indicators. The default option is equal weighs between and within domains. The two command lines below are therefore equivalent:

```
mpi d1(ind1 ind2) d2(ind3), cutoff(0.74)
```

```
mpi d1(ind1 ind2) d2(ind3) w1(0.25 0.25) w2(0.5), cutoff(0.74)
```

`by(`*varname*`)` computes the decomposition of the AF measures by categories of *varname*. The variable must be numeric. Missing values are excluded from the estimation sample.

`svy` allows taking into account complex survey designs. The data have to be `svyset` before using `mpi`. When the only information about the survey design relates to the sampling weights the user can supply `svyset` with such information and use the `svy` option of `mpi`. Equivalently, the user can specify the sampling weights in the command line using the standard syntax.[7]

`alpha(`*numlist*`)` triggers the computation of additional, non-standard indices M_α in the case of ordinal and real-valued indicators. The M_1 and M_2 indices are always computed.

`level(`#`)` changes the confidence levels for the estimation of the confidence intervals.

`categories(`#`)` changes how `mpi` detects ordinal indicators by counting the number of different observational values characterizing the variable. The default is 20. When a variable has less than 20 different values `mpi` shows an alert. This is important because mixing ordinal and real-valued variables is possible but not advisable: ordinal variables automatically receive a higher weight than real-valued variables in the calculation of the AF measures based on the normalised poverty gaps.[8]

`nosummary` suppresses the display of the summary table at the beginning of `mpi`'s output.

`nodecomposition` suppresses the computation and the display of the decompositions along the lines of the domains and indicators. This slightly increases the execution speed.

---

7. Since `mpi` is not a standard estimation command, in the sense that it does not imply estimating a covariance matrix, the Stata `svy` prefix in front of the command name, i.e. `svy: mpi ...`, is not allowed.
8. The same happens when mixing binary and real-valued indicators: in this case the binary indicators receive a higher weight in the analysis simply because the poverty gaps are always the highest possible. See Alkire and Foster (2011) for a discussion about mixing variables of different type in the calculation of the AF measures with $\alpha \geq 1$. When this is necessary the indicator weights can be used to counterbalance the implicit higher weight of binary indicators.

3.4 Returned values

Scalars

r(H)	Multidimensional Headcount Ratio
r(M0)	Adjusted Multidimensional Headcount Ratio
r(A)	Multidimensional Poverty Intensity
r(M1)	Adjusted Multidimensional Poverty Gap
r(G)	Average Poverty Gap
r(M2)	Adjusted Foster-Greer-Thorbecke Measure
r(S)	Average Severity
r(N)	Number of used observations

Matrices

r(mpi)	Indices as in 'Scalars'	r(mpi_se)	Std.-Err. thereof
r(ind)	Indicator contribution (%)	r(ind_se)	Std.-Err. thereof
r(dom)	Domain contribution (%)	r(dom_se)	Std.-Err. thereof

by-Matrices

r(by_mpi)	Indices, by subgroups	r(by_mpi_se)	Std.-Err. thereof
r(by_mpi_pc)	Contribution of subgroups	r(by_...._se)	Std.-Err. thereof
r(by_ind)	Indicator contrib, by subgroups	r(by_ind_se)	Std.-Err. thereof
r(by_dom)	Domain contrib, by subgroups	r(by_dom_se)	Std.-Err. thereof

Functions

e(sample)	Marks estimation sample

4 Empirical applications

For the empirical application of mpi we use the 2000 Indonesian Family Life Survey (IFLS). Alkire and Foster (2011) use the same data, which can be freely downloaded with the related Stata codebook.[9]

The analysis applies the same settings of the original Alkire and Foster contribution: we consider all adults above 19 years old and 3 deprivation indicators: household expenditure (exp), the Body Mass Index (BMI) and the years of schooling (educ). Expenditure variables are adjusted by the square root of the household size. The deprivation thresholds are the following: expenditure below 150,000 Rupiah, a BMI lower than 18,5 kg/m^2 and less than 6 years of schooling. The final sample consists of 17,678 individuals, whereas in the original Alkire and Foster contribution the sample is 19,752. The difference is arguably due to the calculation of the years of schooling from the raw data and the related treatment of implausible and missing values. The next table shows the first 5 rows of the dataset.

```
. list hid id sex BMI exp ex_food ex_nofood educ weights in 1/5, table
```

	hid	id	sex	BMI	exp	ex_food	ex_nof~d	educ	weights
1.	1	1	Female	21	482947	462731	20217	3	0.85
2.	1	2	Male	23	482947	462731	20217	7	0.60
3.	2	3	Female	17	133736	131532	2205	0	0.95
4.	2	4	Male	20	133736	131532	2205	3	0.91
5.	3	5	Male	22	165981	154333	11647	4	0.95

9. Strauss et al. (2004), material available at http://www.rand.org/labor/FLS/IFLS/ifls3.html.

The variables `hid` and `id` are the household and the person identifiers, `weights` represents the survey weights, `ex_food` and `ex_nofood` the food and non-food household expenditures. In the first application, we show how to use `mpi` with binary indicators. We therefore construct 3 binary indicators using the deprivation thresholds defined above and then estimate the AF measure with a poverty cutoff equal to 0.66. This means that only persons with *at least* 2 simultaneous deprivations are considered poor.

```
. generate exp_i = (exp < 150000)
. generate educ_i = (educ < 6)
. generate BMI_i = (BMI < 18.5)
. mpi d1(exp_i) d2(educ_i) d3(BMI_i) [pw=weights] , cutoff(0.66)
Summary of mpi indicators
```

Indicator	Type	Weight	Deprived
Domain 1			
exp_i	Binary	.33	31.477 %
Domain 2			
educ_i	Binary	.33	38.318 %
Domain 3			
BMI_i	Binary	.33	16.006 %

Index	Estimate	Std Err	[95% Conf	Interval]
Main				
M0	0.166	0.003	0.161	0.172
Additional				
H	0.229	0.004	0.222	0.237
A	0.725	0.002	0.720	0.729

Note: Adjusted Multidimensional Headcount M0 = H*A

Indicator	M0
domain 1	
exp_i	0.383
domain 2	
educ_i	0.412
domain 3	
BMI_i	0.204
Total	1.000

Contribution of each indicator (%)

The first part of the `mpi` output is a table with a summary of the deprivation indicators. Indicators are organised in deprivation domains and for each of them `mpi` shows the type (binary, ordinal or real-valued), the policy weight (*equal weights* in this example, the default option) and the share of deprived individuals.

The second table shows the AF poverty measures with the related standard errors.

This table is divided in two parts containing the estimated M_α parameters (upper part) and the related sub-indices (bottom part). Since in this example there are only binary indicators, `mpi` computes only M_0, which is derived as the product of sub-indices H (the incidence of the poor in the population) and A (the average intensity of simultaneous deprivations among the poor).

The third table shows the percentage contribution of each indicator to the overall index. In this example the deprivation in household expenditures accounts for 62.3% of the overall value of M_0.

The next example shows how to allow for a different weighting structure in the relevance of each deprivation indicator and the decomposition of the AF measures by population sub-groups:

```
. mpi d1(exp_i) w1(0.5) d2(educ_i) w2(0.3) d3(BMI_i) w3(0.2) [pw=weights], ///
>     cutoff(0.66) by(sex)
Summary of mpi indicators

Indicator Type     Weight    Deprived

Domain 1
  exp_i   Binary   .5        31.477 %
Domain 2
  educ_i  Binary   .3        38.318 %
Domain 3
  BMI_i   Binary   .2        16.006 %
```

Index	Estimate	Std Err	[95% Conf	Interval]
Main				
M0	0.159	0.003	0.153	0.164
Additional				
H	0.191	0.003	0.185	0.198
A	0.829	0.002	0.826	0.833

```
Note: Adjusted Multidimensional Headcount          M0 = H*A
```

Indicator	M0
domain 1	
exp_i	0.603
domain 2	
educ_i	0.317
domain 3	
BMI_i	0.080
Total	1.000

```
Contribution of each indicator (%)

Decomposition by subgroups
```

MPI by: sex

	Male	Female	Total
H	0.160	0.217	0.191
M0	0.131	0.181	0.159
pop share	0.454	0.546	1.000

Indices by subgroup (absolute)

	Male	Female	Total
H	0.380	0.620	1.000
M0	0.376	0.624	1.000

Contribution of subgroups to indices (%)

	Male	Female	Total
M0			
exp_i	0.610	0.599	0.603
educ_i	0.298	0.328	0.317
BMI_i	0.093	0.073	0.080
Total	1.000	1.000	1.000

Contribution of each indicator (%)

The indicator `exp` enter the analysis with a relevance of 0.5, whereas `educ` amd `BMI` have a weight of 0.3 and 0.2 respectively. The different weighting structure affects both the identification of the poor and the measurement of poverty: H, the share of poor in the population, is now lower whereas A is slightly higher, implying an overall lower value of M_0.

When the user specifies the `by(varname)` option, `mpi` computes the related decomposition by categories of `varname`. In this example, `mpi` provides the decomposition by gender.

Three tables relate to the decomposition by population sub-groups. The first table shows the absolute value of the indices in each sub-group and, in the last row, the related population shares. In this example, 54.6% of the population are women. In this sub-group the incidence of poverty is significantly higher (21.7% against 16.0%), as well as the overall level of M_0 (0.181 against 0.131). The last column of the table shows the overall value of the indices in the population, which is given by the weighted sum of the indices in the two sub-groups with weights given by the related population shares: $0.131 * 0.454 + 0.181 * 0.546 = 0.159$

The second table shows the percentage contribution of each sub-group. In this example, 62.4% of the overall value of M_0 is attributable to the group of women. The values in this table are computed by dividing the *weighted* indices of each sub-group by the overall index, with weights given by the related population share.

The third table shows the percentage contribution of each indicator in each subgroup. As can be seen, the significantly different contribution of `educ` is driving the differences between M_0 in the two groups.

The next example shows an application with real-valued indicators and with more than one indicator in the first deprivation domain. Specifically, the indicator of household expenditure is replaced with two indicators: household food expenditures and other non-food expenditures. The overall relevance of this domain is kept at 0.5 and equal weights are assigned to the two indicators, which implies that each indicator of this domain enters with a weight of 0.25 in the `mpi` analysis. The relevance of the other two domains is also the same as before: 0.3 for the years of education and 0.2 for the BMI.

When using ordinal or real-valued indicators, the user has to specify the related deprivation thresholds in the syntax. In what follows, the chosen thresholds for the first domain are 100,000 Rupiah for food and 12,000 Rupiah for non-food expenditure. The thresholds for the other domains are as before: less than 6 years of schooling and a BMI lower than 18,5 kg/m^2. With real-valued indicators, `mpi` computes the whole class of the AF poverty measures: M_0, M_1 and M_2; the user can specify additional values of α by using the related option (`alpha(3)` in the example below).

```
. mpi d1(ex_food ex_nofood)   t1(<100000 <12000)  w1(0.4 0.1)     ///
>     d2(educ)                t2(6)               w2(0.3)         ///
>     d3(BMI)                 t3(18.5)            w3(0.2)         ///
>     [pw=weights], cutoff(0.66) alpha(3)
```

Summary of mpi indicators

Indicator	Type	Weight	Threshold	Poor if	Deprived
Domain 1					
ex_food	Real-valued	.4	100000	below	19.941 %
ex_nofood	Real-valued	.1	12000	below	25.709 %
Domain 2					
educ	Real-valued	.3	6	below	38.318 %
Domain 3					
BMI	Real-valued	.2	18.5	below	16.006 %

Index	Estimate	Std Err	[95% Conf	Interval]
Main				
M0	0.094	0.002	0.089	0.098
M1	0.043	0.001	0.041	0.045
M(2)	0.031	0.001	0.029	0.033
M(3)	0.026	0.001	0.025	0.028
Additional				
H	0.117	0.003	0.111	0.122
A	0.804	0.003	0.799	0.809
G	0.460	0.004	0.451	0.468
S(2)	0.330	0.005	0.321	0.339
S(3)	0.279	0.005	0.270	0.288

```
Note: Adjusted Multidimensional Headcount          M0   = H*A
      Adjusted Poverty Gap                         M1   = H*A*G
```

Adjusted Foster-Greer-Thorbecke (FGT) Measure M(a) = H*A*S(a)

Indicator	M0	M(1)	M(2)	M(3)
domain 1				
ex_food	0.497	0.318	0.194	0.122
ex_nofood	0.080	0.091	0.083	0.072
domain 2				
educ	0.346	0.579	0.721	0.806
domain 3				
BMI	0.076	0.012	0.002	0.000
Total	1.000	1.000	1.000	1.000

Contribution of each indicator (%)

Domain	M0	M(1)	M(2)	M(3)
domain 1	0.578	0.409	0.277	0.194
domain 2	0.346	0.579	0.721	0.806
domain 3	0.076	0.012	0.002	0.000
Total	1.000	1.000	1.000	1.000

Contribution of each domain (%)

The summary table at the top now shows that the indicators are real-valued, together with the related thresholds and the *direction* of each deprivation, which in this example is always for values *below* the threshold (the default).

The second table shows the values of the AF class of poverty measures with the related sub-indices. Since the command line includes the option `alpha(3)`, the table shows also the value of M_3 and the related sub-index S_3 as defined in Section 2.2.

The third table shows the contribution of the indicators to each poverty measure, M_0, M_1, M_2 and M_3, whereas the last table provides the contribution of the deprivation domains.

5 References

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