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ORIGINAL RESEARCH

Weighting the Dimensions of the Multidimensional Poverty Index: Findings from Sri Lanka

N. P. Ravindra Deyshappriya[1] · Simon Feeny[2]

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Abstract

The Oxford Poverty and Human Development Initiative's Multidimensional Poverty Index has become a widely adopted measure of wellbeing. However, it is criticised for applying equal weights to its three dimensions: health; education; and living standards. There is no a priori reason to expect that all three dimensions equally contribute to wellbeing. This article reports on a Discrete Choice Experiment that involved a sample of 670 Sri Lankans who selected their preferences for the weights. The findings suggest that health is the most important dimension and should receive a weight of 0.38. In comparison, education has a weight of 0.33 and living standards a weight of 0.29. Cluster analysis reveals that location, age, education level and number of dependents are important in explaining differences in weight preferences. Finally, the paper demonstrates that poverty rankings of districts and provinces differ across the different approaches to weighting the index dimensions.

Keywords Multidimensional Poverty Index · Sri Lanka · Discrete Choice Experiment · Cluster Analysis

JEL Classification I32 · O12 · C25

1 Introduction

There is no universal definition of poverty. It is broadly accepted as the deprivation of wellbeing which encapsulates monetary and non-monetary attributes (Bourguignon & Chakravarty, 1999). The monetary approach defines poverty as a shortfall of income or consumption below an arbitrarily defined threshold. However, while increased consumption can increase welfare it does not guarantee improvements in wellbeing (Chakravarty et al., (2006). Sen (1985) argues that measures of poverty should capture monetary and non-monetary components that reflect peoples' capabilities. Non-monetary attributes of

✉ N. P. Ravindra Deyshappriya
ravindra@uwu.ac.lk

Simon Feeny
simon.feeny@rmit.edu.au

[1] Uva Wellassa University of Sri Lanka, RMIT University, Melbourne, Australia

[2] RMIT University, Melbourne, Australia

poverty cannot be purchased when markets do not exist (for example public good provision) or when markets are imperfect (such as the market for credit). Moreover, high levels of (or increases in) consumption of the non-poor might reflect high health expenditures due to chronic illness and therefore will not reflect improvements in wellbeing. This highlights the importance of assessing poverty using non-monetary deprivations (Kabubo-Mariara et al., 2011).

As a response, the Oxford Poverty and Human Development Initiative (OPHI) devised the Multidimensional Poverty Index (MPI). The index has become a highly respected and widely used measure of poverty. It draws from a broad literature that explores multifaceted elements of poverty extending beyond a lack of income. The index is based on three dimensions of wellbeing—health, education and living standards—that are, in turn, based on ten wellbeing deprivations.[1] Despite its broad acceptance by the international development community, the MPI (as well as many other multidimensional indices of wellbeing) are criticised *inter alia* because of the arbitrary equal weighting of their dimensions. Duclos et al. (2006), Demombynes and Verner (2010) and Ravallion (2011) argue that assigning weights to the dimensions of an index is just as important as the actual choice of dimensions. This article addresses this issue by conducting a Discrete Choice Experiment (DCE) in Sri Lanka to ascertain the preferences for the weights attached to the three dimensions of OPHI's MPI.

There is a strong case for using Sri Lanka as a case study. How to measure poverty is a contentious issue in the case of Sri Lanka. Different ways of measuring poverty lead to very different conclusions regarding its prevalence. Table 10 in the "Appendix" provides the incidence of poverty (according to different measures) for Sri Lanka as well as other South Asian countries. It shows that while Sri Lanka had reduced extreme income poverty (defined as living below US$1.90 per day measured in Purchasing Power Parity terms) to below one per cent in 2016, almost 42 per cent of the population were living below a higher threshold of US$5.50 per day.

Romeshun and Mayadunne (2011) argue that applying these income-based poverty lines to Sri Lanka has a number of limitations. For example, the poverty lines are based on a monetary measure and so they do not actually determine whether basic needs are actually met. The subjective determination of the poverty thresholds and their inability to measure deprivation across multiple dimensions are also highly questionable. Romeshun and Mayadunne (2011) argue that poverty is under-estimated in Sri Lanka if consideration is given to other dimensions of wellbeing. This is confirmed by the official data provided in the final column of Table A1, which reveals that there are more than three times the proportion of people living in multidimensional poverty in 2020 than extreme poverty in 2016. This is surprising given that Sri Lanka is also well known for achieving high social indicators relative to other countries at similar levels of income (Sen, 1988; Athukorala et al., 2017). While it is widely agreed that poverty should be measured using a multidimensional index in Sri Lanka, the lack of a consensus with respect to the weighting of the index dimensions provides further motivation for this study.

[1] Some studies and government Ministries have adapted the OPHI MPI to be more relevant to national contexts. Examples include Mexico (Coneval, 2010), Chile (Ministerio de Desarrollo Social, 2015), Colombia (Angulo et al., 2013), Madagascar (Feubi Pamen & Kuepie, 2017), Kenya (Kabubo-Mariara et al., 2011) and the United States (Dhongde & Haveman, 2015). However, these studies still apply equal weights to the index dimensions.

Table 1 MPI dimensions, indicators and deprivations. *Source*: Adapted from Alkire and Santos (2010)

Dimension (and weight)	Indicator (and weight)	Deprivation/cut-off
Education (1/3)	Year of Schooling (1/6)	No household member has completed five years of schooling
	School Attendance (1/6)	At least one school-aged child is not attending school from grade one to year eight
Health (1/3)	Child Mortality (1/6)	A child has died within the household
	Nutrition (1/6)	Any adult or child for whom their nutritional information is available is malnourished
Standard of living (1/3)	Electricity (1/18)	The household has no electricity
	Sanitation (1/18)	The household does not have adequate sanitation (per Millennium Development Goals [MDGs] guidelines) or it is a shared house
	Water (1/18)	The household does not have clean drinking water (per MDGs guidelines) or it is more than a 30-min walk away
	Floor (1/18)	The household's floor is dirt, sand or dung
	Cooking Fuel (1/18)	The household cooks on wood, dung or charcoal
	Assets (1/18)	The household does not own more than one radio, television, telephone, bike, motorbike or refrigerator and does not own a car or truck

In Sri Lanka, disaggregating measures of poverty by sector and region is also very important. For example, the estate sector comprises workers in the tea estates who receive free housing from the owners of the estates. Despite the income poverty for the population in this sector falling from 28% in 2006 to approximately 10% in 2012–2013, only 5.6% of the poor estate workers owned a house in 2012–2013 compared to 90.4% of the poor rural workers on average. Moreover, in 2012–2013, only 2.3% of adults living in the estate sector had completed secondary school, in comparison to 8.8% of adults living in the rural sector (The World Bank, 2019).

The discussion above provides the basis of research for Sri Lanka by (i) examining the nature of poverty using a MPI (rather than examining income poverty), (ii) adopting a technique to elicit the population's preferences for the weights attached to the dimensions of this index and (iii) examining whether the weights attached to the index differ across sectors, regions and demographic characteristics. Alkire and Santos (2010), Sanjeewanie et al. (2012), Kumara (2013), and Nanayakkara (2017) have previously examined multidimensional poverty in the context of Sri Lanka.[2] Nanayakkara (2017) and Alkire and Santos (2010) applied equal weights, while Kumara (2013) applied weights based on Principal Component Analysis (PCA) results; these weights are highly data driven and do not necessarily reflect individuals' perception of the importance of each dimension.

This article contributes to the existing literature in three important ways. To the authors' knowledge it is the first to conduct a DCE on a sample of Sri Lanka's population to determine their preferences for the weights attached to the MPI dimensions. Secondly, cluster analysis is undertaken to examine how the sector, region and socio-economic characteristics of Sri Lanka's population explain the variation in preferences. Thirdly, Sri Lanka's MPI is recalculated using these DCE weights to examine how conclusions regarding the incidence of poverty change in comparison to an equally weighted MPI.

The remainder of this article is structured as follows. The method for calculating the MPI as devised by Alkire and Foster (2009, 2011) is discussed in Sect. 2. The design of the experiment conducted to elicit the preferences for the three MPI dimension weights is discussed in Sect. 3 and the results from the DCE and cluster analysis are provided in Sect. 4. The sensitivity of poverty ranking to different MPI weights is examined in Sect. 5 and conclusions and policy implications are provided in Sect. 6.

2 The Multidimensional Poverty Index

Developing multidimensional poverty indices has a history extending back more than two decades. Anand and Sen (1997) devised the Human Poverty Index (HPI), which partially incorporated Sen's capability approach. The index comprises three dimensions: (i) longevity—measured by the probability at birth of not surviving to age 40; (ii) knowledge—measured by the adult literacy rate; and (iii) a decent standard of living—measured by the percentage of malnourished children under five years, the percentage of people without access to safe drinking water and the percentage of the population without access to health services. The three dimensions are equally weighted in constructing the HPI. The HPI

[2] Sanjeewanie et al. (2012) examined multidimensional poverty in the Badulla district of Sri Lanka, focusing on the 'missing' dimensions of the MPI. This study is qualitative in nature and only focuses on the poorest households in the Badulla district.

index is a continuous variable. It does not specify a specific threshold below which countries or households are classified as poor.

At OPHI, Alkire and Foster (2009, 2011) devised a more comprehensive index of poverty which is based on three dimensions: health; education; and living standards and ten indicators of deprivation. While the weights attached to the ten indicators vary, each of the three dimensions used to calculate the MPI are weighted equally (one-third) (see Table 1). The choice of deprivations was based on the data that are commonly collected through regular surveys conducted by international organisations and government departments, which ensures that the index can be constructed and compared across many developing countries. The most recent MPI statistics have been calculated for 101 countries and thus cover most of the world's population (approximately 5.7 billion people) (United Nations Development Programme & Oxford Poverty and Human Development Initiative, 2019).

The MPI is the product of two numbers, calculated by multiplying the Multidimensional Headcount Index (MHI) (which captures the incidence rate of poverty) by the Intensity of Deprivation (ID) (which captures the severity of poverty calculated as the average proportion of indicators in which the poor are deprived).

In devising the MPI, Alkire and Foster (2011) adopted a method that utilises the counting approach proposed by Atkinson (2003), which first identifies the poor by counting a person's deprivations with respect to the individual indicators. After aggregating these weighted deprivations into a single index, they apply a cut-off to determine whether a person is classified as multidimensionally poor. It is noted that specifying the threshold at one third is arbitrary and contentious. A 'union' approach proposes that a household must be deprived in one or more indicators to be considered multidimensional poor, while an 'intersection' approach suggests that a household must be deprived in all dimensions to be considered multidimensional poor. Therefore, Alkire and Foster (2011) adopted an intermediate approach by specifying the poverty threshold as being deprived in at least one-third of the weighted indicators.

Alkire and Santos (2010) formally elaborated on the calculation of MHI and ID in constructing the MPI:

$$MHI = \frac{q}{n} \tag{1}$$

where q is the number of people who are deemed multidimensional poor and n is the total population. ID provides the proportion of weighted indicators (d) in which poor people are, on average, deprived. It can be calculated as follows:

$$ID = \frac{\sum_1^d c}{qd} \tag{2}$$

where c is the total number of weighted deprivations experienced by the poor and d is the number of indicators (ten in the case of the OPHI MPI). The weighted deprivations are summed and divided by the total number of indicators only for the poor households. The MPI score is then calculated in a third stage:

$$MPI = MHI * ID \tag{3}$$

Additionally, the incidence of vulnerability to multidimensional poverty is calculated as the proportion of households that are deprived in 20–33% of the indicators. The incidence of severe poverty is calculated as the proportion of households that are deprived in more than 50% of the indicators.

As discussed, Alkire and Foster (2009, 2011) and Alkire and Santos (2010) apply arbitrary equal weights (one-third) to the three dimensions of the MPI, which is a major criticism of the index. For example, Ravallion (2011) argues, 'It is hard to believe that weights could be the same for all countries, and (indeed) all people within a country … the values attached to non-market goods will clearly vary with the setting, including country or individual attributes. For example, the weight attached to access to a school will depend on whether the household has children' (p. 12).

Importantly, the MPI is based on a flexible methodology and there is scope to allocate different weights to the different dimensions and their indicators. Indeed, the MPI creators encourage adapting it to national contexts and using alternative weights to reflect national priorities. However, it is difficult to achieve this task in a scientific manner. Decancq and Lugo (2013) provide a review of the different approaches to assigning weights.[3] One approach is to adopt data-driven weights generated by PCA, which provides a way of transforming the MPI indicators into new (uncorrelated) components that are ordered according to their correlation with the MPI. Under this approach, each principal component provides a weight for the group of indicators; however, it is entirely data driven and fails to capture individuals' true weighting preference for each dimension.

Ravallion (2011) argued that while determining non-arbitrary weights is challenging, 'Public opinion can be an important clue. A mashup index might be thought of as the first step in a public debate about what the weights should be. Stimulating such a debate would be a valuable contribution, but there is little sign as yet that this has led to new weights' (pp. 15–16). In response, this paper elicits the preferences for OPHI's MPI dimension weights from a sample of Sri Lanka's population using a DCE.

3 Data and Methodology

3.1 Data

The DCE was conducted in three Sri Lankan districts: Colombo; Monaragala; and Nuwara Eliya. These districts, while not nationally representative, were selected because they distinctly represent the urban, rural and estate sectors of Sri Lanka respectively.[4] The Colombo district is located on Sri Lanka's west coast and hosts the nation's capital city. It has the highest population and population density. Monaragala is a rural, landlocked district located in the country's south-east. It is one of Sri Lanka's largest districts and forms a part of Uva Province. Nuwara Eliya district is located in central Sri Lanka and represents the estate sector with a large number of tea plantations. Over 50% of this district's population are of Indian Tamil origin.

[3] Other related studies include Tkach & Gigliarano (2020) who devise weights that account for the dependence between MPI dimensions. Ravallion (2012) examines the implications of the trade-offs between the dimensions of the HDI. Alkire & Santos (2014) and Santos & Villatoro (2018) examine how sensitive MPI rankings are to weights while Nájera Catalán (2019) examines the relationship between reliability and weighting for multidimensional poverty measures.

[4] As a robustness exercise, the weights from the DCE were adjusted to reflect the relative importance of the three sectors (estate, rural and urban) in Sri Lanka's total population. In practice, this made little difference with the respective weights calculated to be 0.40, 0.33 and 0.27 for health, education and living standards respectively (compared to our reported weights of 0.38, 0.33 and 0.29 in Sect. 4).

Table 2 MPI dimensions and mean weights (part-worth utilities). *Source*: Calculated by authors based on DCE survey data

Attribute	Weight
Health	
Low	0.00
Medium	0.21
High	0.38
Education	
Low	0.00
Medium	0.18
High	0.33
Living Standards	
Low	0.00
Medium	0.17
High	0.29

The DCE utilised Sri Lanka's electoral register and randomly selected households in each district. The experiment used 1000minds and Qualtrics (web-based DCE and survey software) to collect each participant's socio-economic data. Enumerators were recruited from Sri Lanka's Uva Wellassa University and were trained on the research approach and how to use mobile phones and tablets to administer the DCE and survey. A total of 700 participants completed the DCE and survey; however, 30 participants failed to provide all the requisite information. The data for 670 participants were therefore used in the analysis for this article.

Table 11 in the "Appendix" summarises the demographic characteristics of the sample. It indicates that 52.25% of the sample were male and over 70% were aged between 18 and 44. 39.01% of respondents possess educational qualifications at a secondary level and 25.86% possess qualifications at a tertiary level. 40 respondents (5.98%) had not received any formal schooling. Regarding the employment status of the respondents, 79.1% were employed (29.1% in the private sector, 23.13% were self-employed, 13% in the government sector and 3% in the semi-government sector). 57.39% of respondents reported a monthly household income of between Rs.10,000–40,000 while 9.57% of respondents' reported an income of below Rs.10,000 and 4.63% of respondents an income of more than Rs.100,000 per month.

3.2 The Discrete Choice Experiment

A DCE is a common approach for eliciting individual preferences. In this study, it revealed how participants value different dimensions of poverty. The participants were presented with hypothetical alternatives and were asked to state their preference. The alternatives contained different levels of attributes (i.e., low, medium and high), with the attributes corresponding to the three MPI dimensions (health, education and living standards). A DCE can be conducted using choice sets or pairwise rankings. In a choice set scenario, two alternatives are presented to the participant and each includes information on all attributes and a specified level. Pairwise ranking is similar, differing only with two attributes (with levels) presented to a participant each time. This analysis used the latter method because it has the advantage of providing specific weights for each individual participant, which allows cluster analysis to be undertaken.

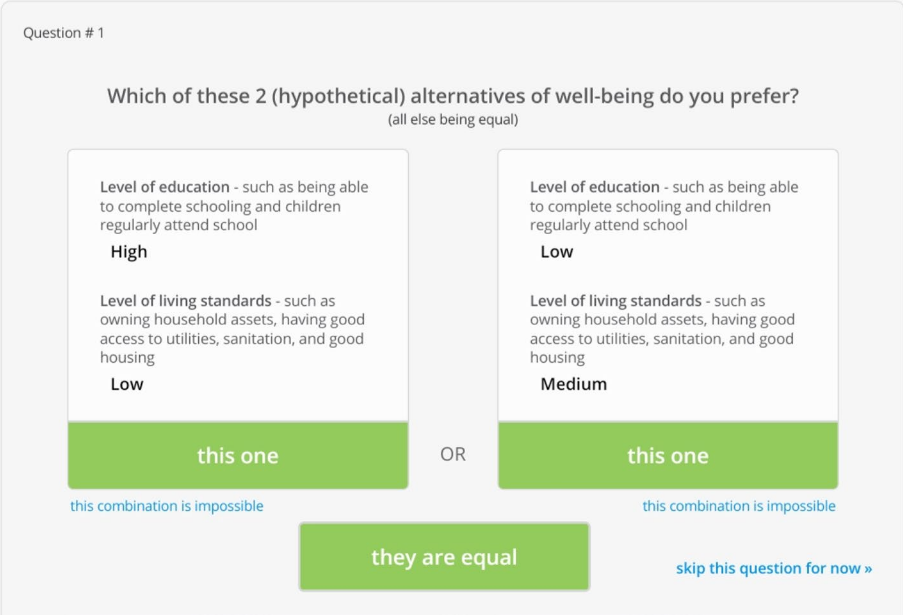

Fig. 1 An example of a DCE pairwise ranking question

The DCE was undertaken using 1000minds which implements the 'Potentially All Pairwise RanKings of all possible Alternatives' (PAPRIKA) method (Hansen & Ombler, 2008).[5] This method determines the weights, or 'part-worth utilities' that participants attach to the dimensions (attributes) of the MPI and their levels. Participants answered a series of questions and chose between pairs of hypothetical wellbeing outcomes that were defined two attributes each time. The pair of outcomes represented a trade-off, while the third attribute remained the same (see Fig. 1 for an example). The experiment utilised plain English and simple language that participants could understand. A participant's answers determined the type and amount of questions asked.[6] Using each participant's answers to the pairwise ranking questions, mathematical methods based on linear programming were used to calculate each participant's part-worth utilities, representing the weights for the MPI dimensions.[7]

3.3 Cluster Analysis

By obtaining individual level weights for the MPI dimensions, a cluster analysis was conducted on the participants. A cluster analysis uses statistical techniques to identify groups

[5] For more information, see www.1000minds.com.

[6] Each time a participant pairwise ranks two hypothetical wellbeing outcomes, the PAPRIKA method applies the property of transitivity to identify all other pairs of hypothetical wellbeing outcomes that can be pairwise ranked. If alternative *X* is ranked ahead of *Y* and *Y* is ranked ahead of *Z*, then, by transitivity, *X* must be ranked ahead of *Z*. This method ensures that all hypothetical wellbeing outcomes (defined by two attributes each time) are pairwise ranked, either explicitly or implicitly (by transitivity); however, a participant is only required to make a relatively low number of choices.

[7] See Feeny et al. (2019) for a recent application of this type of DCE, conducted on a sample of UK participants to elicit their preferences with respect to the inter-country allocation of UK government aid.

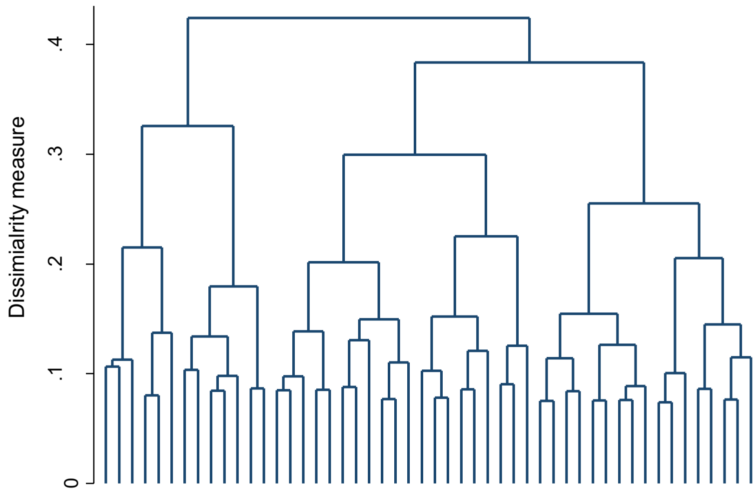

Fig. 2 Dendrogram of the participant sample. *Note*: Dendrogram is based on the weighted-average hierarchical clustering approach and displays only the top 50 branches

of participants who have similar weights—known as clusters—and the results from cluster analysis can be used to examine the link between the probability of belonging to each cluster and the demographic characteristics of individuals. One method used to identify the number of distinct clusters in data is a dendrogram—a graphical representation of hierarchical clustering that groups individuals with others that have similar weights. A dendrogram indicates the agglomerated clusters and the degree of dissimilarity between clusters by the vertical distance between different levels. In addition to hierarchical dendrogram-based clustering, this study also applies the *K*-means partition clustering method, in which *K* is determined by the researcher. The Calinsk and Harabasz pseudo-F index can help identify the optimal number of clusters using different *K*.

4 Results and Discussion

4.1 Mean Weights for MPI Dimensions

Table 2 summarises the mean part-worth utilities (weights) calculated for each level of the attributes (MPI dimensions). The mean weights relevant to each 'high' level are considered the overall part-worth utilities for respective attributes and sum to one.

Table 2 indicates that the most important MPI dimension for the participants is health, which is attributed a weight of 0.38. Education is valued as the second most important dimension with a weight of 0.33, followed by living standards with a weight of 0.29. Therefore, health is 1.15 and 1.31 times more important than education and living standards respectively. This finding is interesting since Sri Lanka has higher achievements in health and education relative to other countries with similar levels of income. Pairwise *t*-tests reveal that the weight values are statistically different from one another, which implies that an equal weighting of MPI dimensions is inappropriate in the case of Sri Lanka.

Table 3 Cluster mean weights (part-worth utilities). *Source*: Calculated by the authors based on DCE survey data

MPI Dimension/Attribute	Health Cluster (n = 260)	Education Cluster (n = 186)	Living Standards Cluster (n = 224)
Health	0.5076	0.2879	0.3069
Education	0.2773	0.4789	0.2651
Living Standards	0.2152	0.2333	0.4280

4.2 Cluster Analysis

As discussed, cluster analysis is undertaken to group participants with similar weights, and to examined the link cluster membership and the demographic characteristics of individuals. Initially, a dendrogram approach was applied to the data and this indicates that there are three distinct clusters (see Fig. 2). This was confirmed using the *K*-means clustering approach and the test results from the Calinsk and Harabasz pseudo-F index. The three clusters from the *K*-means approach are therefore used in the analysis.

Table 3 summarises the mean part-worth utilities of each cluster and clearly demonstrates that each cluster favours one of the three MPI dimensions. The health cluster includes 260 respondents, which accounts for the majority (38.8%) of respondents. In this cluster, the health attribute has the highest mean part-worth utility (0.51), followed by education (0.28) and living standards (0.22). In the education cluster, the education attribute exhibits a mean weight of 0.48 and in the living standards cluster, the living standards attribute indicated a weight of 0.43.

4.3 Multinomial Logit Analysis

A multinomial logit regression analysis was performed on the data for the three clusters to examine the relationship between respondents' socio-economic characteristics and the probability of membership of each cluster. Specifically, the following model was specified and estimated:

$$\begin{aligned} f(y,i) =& \beta_1 Male_i + \beta_2 Location_i + \beta_3 Age_i + \beta_4 Education_i + \beta_5 Married_i \\ &+ \beta_6 Dependents_i + \beta_7 Income_i \end{aligned} \tag{4}$$

where the function $f(y, i)$ predicts the probability that participant i belongs to cluster j. *Male* is a binary dummy variable taking the value of one if the participant is male and zero otherwise. *Location* is a categorical variable which captures the district in which the participant lives, *Age* captures the recipients age, while *Education* is a variable capturing the level of education that a respondent has completed. *Married* is a dummy variable taking the value of one if the respondent is married and *Dependents* measures the number of dependents a recipient has. Finally, *Income* is household income per capita.

The marginal effects from the multinomial regression analysis are provided in Table 4. Note that the sum of the marginal effects for each table row is equal to zero, as changes in the socio-economic characteristic can both reduce and increase the probability of being attributed to certain clusters.

According to the regression results, there is no statistically significant association between gender and cluster attribution; however, location is influential. Relative to the respondents from

Table 4 Multinomial regression analysis results. *Source*: Calculated by authors based on DCE survey data. The omitted location variable is Colombo

Variables	Health	Education	Living Standards
Male	−0.0235	−0.0084	0.0320
	(−0.61)	(−0.23)	(0.86)
Monaragala	0.1135**	−0.0168	−0.0966*
	(2.15)	(−0.35)	(−1.88)
Nuwara Eliya	0.1466**	−0.0908	−0.0558
	(2.16)	(−1.43)	(−0.86)
Age	0.0221	−0.0282*	0.0061
	(1.29)	(−1.73)	(0.37)
Education	0.0851**	−0.0175	−0.0675**
	(2.81)	(−0.62)	(−2.36)
Married	−0.0253	−0.0312	0.0566
	(−0.45)	(−0.16)	(1.05)
Dependents	0.0388	0.1139**	−0.1527***
	(0.75)	(2.35)	(−3.23)
Income	0.0092	0.00042	−0.0096
	(0.40)	(0.02)	(−0.43)

***Significant at 1% level, **Significant at 5% level, *Significant at 10% level

Table 5 Multidimensional poverty in Sri Lanka

Weights	MHI	ID	Index (MHI*ID)
Equal Weights	0.031	0.397	0.012
DCE Weights	0.027	0.409	0.011

Colombo district, respondents from both the Monaragala and Nuwara Eliya districts are more likely to belong to the health cluster and Monaragala respondents are less likely to belong to the living standards cluster. Older respondents are less likely to belong to the education cluster. A potential explanation is that if they have passed schooling age, education becomes less important to them relative to other dimensions of wellbeing. High educational attainments were associated with a higher probability of belonging to the health cluster and a lower probability of belonging to the living standards cluster. Respondents with dependents were more likely to belong to the education cluster and less likely to be members of the living standards cluster, possibly reflecting their aspirations for their dependents to receive a good education. Marital status and household income are not important factors in determining cluster membership.

5 MPI Sensitivity Analysis

With respect to the incidence and pattern of poverty in Sri Lanka, this section examines how the results differ when DCE weights are applied to the MPI instead of the standard application of equal weights. Household Income and Expenditure Survey (HIES) 2016 data were used to compute the MPI for Sri Lanka and to apply the different weights.

Table 5 provides the incidence rate and intensity of household multidimensional poverty as well as the overall index values for the two MPI measures. For the equally weighted

Table 6 Poverty, vulnerability and severe poverty in Sri Lanka

Weights	MPI Poor (%)	Vulnerable (%)	Severely Poor (%)
Equal Weights	1.95	9.92	0.24
DCE Weighs	1.60	9.81	0.21

Table 7 Poverty, vulnerability and severe poverty by sector in Sri Lanka

Sector	MPI Poor (%)		Vulnerable (%)		Severely Poor (%)	
	Equal	DCE	Equal	DCE	Equal	DCE
Urban	0.93	0.74	5.66	5.71	0.04	0.02
Rural	1.86	1.52	10.52	10.41	0.24	0.22
Estate	7.09	6.04	14.95	14.37	0.98	0.84

MPI, the incidence of poverty is 3.1%. This result is slightly higher than the incidence rate of poverty if the DCE weights are applied to the MPI (2.7%). However, the intensity of multidimensional poverty is higher for this latter index, which results in a very similar overall MPI index value. In other words, while the incidence of multidimensional poverty is slightly lower when applying the DCE weights, the households that are considered poor are, on average, deprived on a greater number of indicators relative to the households considered poor when applying equal weights.

Table 6 provides the incidence rate of poverty, vulnerability and severe poverty using individual level data (accounting for the number of people in each household). If a household is deemed to be living in multidimensional poverty, then every member of the household is classified as poor. As the HIES data are nationally representative, Table 6 demonstrates that, according to the equally weighted index, 418,080 members of the population are multidimensionally poor and, according to the DCE weighted index, 343,040 members of the population are multidimensionally poor. Therefore, more than 75,000 additional people are categorised as poor when the equally weighted MPI is used. However, the incidence rate of vulnerability and severe poverty vary less between the two MPI measures. Less than 0.25% of the population are living in severe poverty. However, according to both MPI measures, the incidence rate of vulnerability is much higher (almost 10% of the population).

Table 7 disaggregates the poverty measures by sector. It demonstrates that multidimensional poverty is highest in the country's estate sector (a 6–7% incidence of poverty), with less than 1% of the urban population and less than 2% of the rural population classified as poor according to these measures. However, the incidence of vulnerability is deemed to be much higher—approximately 5% for the urban population, 10% for the rural population and 15% for the estate sectors.

Table 8 displays the incidence rate of poverty, vulnerability and severe poverty by province in Sri Lanka for both MPI measures. According to both measures, the Central Province has the highest incidence of poverty, while Western Province has the lowest. As measured by both MPIs, the incidence rate of poverty in the Eastern Province is quite low. However, it has the highest incidence rate of vulnerability. Similarly, the Northern Province also has a high incidence of vulnerability relative to its incidence of poverty. In contrast, Uva Province displays very low rates of vulnerability (second only to the Western

Table 8 Poverty, vulnerability and severe poverty by province in Sri Lanka

Province	MPI Poor (%)		Vulnerable (%)		Severely Poor (%)	
	Equal	DCE	Equal	DCE	Equal	DCE
Western Province	0.65	0.57	5.50	5.49	0.06	0.06
Central Province	3.10	2.47	11.46	11.28	0.30	0.23
Southern Province	1.76	1.59	10.78	10.56	0.27	0.25
Northern Province	1.70	1.14	11.88	12.06	0.15	0.15
Eastern Province	2.63	2.12	13.36	13.30	0.28	0.24
North Western Province	2.40	1.92	10.17	10.24	0.28	0.28
North Central Province	1.77	1.41	9.92	9.84	0.26	0.26
Uva Province	2.46	2.24	9.73	8.95	0.47	0.41
Sabaragamuwa Province	2.82	2.38	12.02	11.90	0.44	0.36

Table 9 Contribution of MPI dimensions and indicators to poverty in Sri Lanka

Dimension/Indicator	Contribution to MPI Poverty (Equal Weights)	Contribution to MPI Poverty (DCE Weights)
Health		
Child mortality	0.320	0.401
Nutrition	0.019	0.024
Education		
Years of schooling	0.101	0.084
School attendance	0.219	0.209
Living standards		
Electricity	0.047	0.039
Sanitation	0.045	0.035
Water	0.062	0.051
Floor	0.124	0.105
Cooking Fuel	0.044	0.036
Assets	0.018	0.016
Total	1	1

Province) but exhibits the highest incidence rate of severe poverty according to both MPI measures population and 15% for the estate sectors.

It is also important to consider the differences in rankings across the two MPI measures. For example, under an equally weighted MPI, the Central Province exhibits the third-highest incidence of severe poverty. Yet when using the DCE weighted MPI, it is reduced to the third-lowest incidence rate. This demonstrates that changing the MPI weights creates a different way in assessing poverty in Sri Lanka, which becomes even more apparent when examining poverty at the district level (see Table A3). For example, the Badulla district ranks lower in poverty incidence when the equally weighted MPI is used; however, the opposite is true for Mullaitivu district. Further, the Badulla district ranks higher in the incidence rate of vulnerability using the equally weighted MPI compared to the DCE weighted index. In addition to the previously discussed methods to examine the two MPI measurements, each dimension and indicator's contribution to poverty can also be analysed (see Table 9). As expected, the contribution of child mortality and nutrition indicators are higher for the DCE weighted MPI due to the higher weight attributed to the health dimension. In addition to child mortality, indicators of school attendance and flooring conditions contribute the most to MPI poverty in Sri Lanka.

6 Conclusions and Recommendations

This article determined country-specific weights for the dimensions of a MPI by conducting a DCE on a sample of 670 members of Sri Lanka's population. The DCE results indicated that health is valued as the most important MPI dimension with a mean part-worth utility of 0.38, followed by education (0.33) and living standards (0.29). Therefore, health is judged to be 1.15 and 1.31 times more important than education and living standards respectively. Moreover, pairwise *t*-tests revealed that the weights are statistically different from one another, which implies that an equal weighting of the MPI dimensions is inappropriate for Sri Lanka. Cluster analysis and multinomial logit regressions revealed that factors such as location, age, level of education and having dependents significantly affected respondents' preferences for MPI dimensions.

A sensitivity analysis was also conducted, which examined how the incidence and nature of poverty in Sri Lanka differ when DCE weights are applied to the MPI (instead of equal weights). According to the household level analysis, an equally weighted MPI yields a slightly higher incidence of poverty than the DCE weighted MPI. Consequently, individual data demonstrated that, when using the equally weighted MPI, an additional 75,000 people are categorised as poor. However, the intensity of multidimensional poverty is higher for the DCE weighted MPI and both weighting approaches generated a very similar overall MPI index value.

Sectoral analysis indicated that the estate sector accounts for the highest incidence rate of multidimensional poverty, vulnerability and severe multidimensional poverty, in comparison to both rural and urban sectors—irrespective of the application of the different MPI weights. Further analysis indicated that Central Province has the highest incidence of poverty while the Western Province has the lowest. Regarding vulnerability and severity of multidimensional poverty, Eastern and Uva Provinces account for the highest incidences according to both MPI measures.

Two policy recommendations arise from this research. The first is for the Sri Lankan government and the international donor community to devote a greater share of their resources towards the poorest households according to the DCE weighted multidimensional poverty measure. This includes those employed in the estate sector and households located in Central and Uva Provinces. Secondly, this article recommends using country-specific weights that reflect the preferences of the country's population when making future assessments of multidimensional poverty. Where ascertaining such weights is not possible, poverty measurements should be subjected to alternative sets of weights to examine any differences with respect to the incidence and depth of poverty, both nationally and regionally.

Appendix

See Tables 10, 11 and 12.

Table 10 Measures of poverty for South Asian countries. *Source*: UNDP (2019); OPHI (2020)

Country name	Year	Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population)	Poverty headcount ratio at $5.50 a day (2011 PPP) (% of population)	Multidimensional poverty (population headcount %)
Bangladesh	2016	14.5	84.3	41.1 (2014)
Bhutan	2017	1.5	38.9	5.8
India	2011	22.5	87.4	27.5 (2016)
Nepal	2010	15	83	28.6 (2014)
Pakistan	2015	4	75.6	38.8
Sri Lanka	2016	0.9	41.7	2.9 (2020)

Table 11 Demographic characteristics of the sample. *Source*: Calculated by authors based on DCE survey data

Variables	Categories	Number	Percentage
Gender	Male	320	52.24
	Female	350	47.76
Age	18–24 Years	97	14.48
	25–34 Years	190	28.36
	35–44 Years	184	27.96
	45–54 Years	102	15.22
	55–64 Years	70	10.45
	65 Years or Above	27	4.03
Education	No Schooling	40	5.98
	Primary	195	29.15
	Secondary	261	39.01
	Tertiary	173	25.86
Employment Status	Employed	44	6.57
	Government Sector	87	12.99
	Private Sector	195	29.10
	Retired	21	3.13
	Self-Employed	155	23.13
	Semi-Government	19	2.84
	Student	45	6.72
	Unemployed	95	14.18
Income (Rs)	< 10,000	64	9.57
	10,000–20,000	129	19.28
	20,000–30,000	129	19.28
	30,000–40,000	126	18.83
	40,000–50,000	80	11.96
	50,000–60,000	67	10.01
	70,000–80,000	29	4.33
	80,000–90,000	7	1.05
	90,000–100,000	7	1.05
	> 100,000	31	4.63

Table 12 Poverty, vulnerability and severe poverty by MPI measure and district

District	MPI poor (%)				Vulnerable (%)				Severely poor (%)			
	Equal	Rank	DCE	Rank	Equal	Rank	DCE	Rank	Equal	Rank	DCE	Rank
Ampara	1.41	17	1.07	18	8.79	20	8.45	20	0.23	13	0.23	13
Anuradhapura	2.16	12	1.53	12	9.65	19	9.65	17	0.28	10	0.28	9
Badulla	1.92	14	1.81	10	10.84	11	9.48	18	0.45	5	0.45	3
Batticaloa	3.05	6	2.62	5	16.93	1	16.62	1	0.23	12	0.23	12
Colombo	0.57	24	0.49	24	3.54	25	3.54	25	0.01	24	0.01	24
Galle	1.79	15	1.51	14	10.41	14	10.41	13	0.21	16	0.21	16
Gampaha	0.53	25	0.47	25	6.31	24	6.27	24	0.03	23	0.03	23
Hambantota	1.06	20	0.99	19	9.77	17	9.47	19	0.17	20	0.17	18
Jaffna	2.47	9	1.55	11	12.00	7	12.88	5	0.11	21	0.11	19
Kalutara	1.01	21	0.85	22	7.73	22	7.76	22	0.18	18	0.18	17
Kandy	3.10	5	2.50	7	11.81	9	11.65	8	0.18	17	0.10	20
Kegalle	2.75	8	2.19	8	10.68	13	10.82	12	0.38	9	0.35	6
Kilinochchi	0.87	22	0.87	21	14.89	3	13.94	4	0.22	14	0.22	14
Kurunegala	2.02	13	1.53	13	9.75	18	9.87	16	0.22	15	0.22	15
Mannar	1.32	18	0.88	20	10.71	12	11.08	10	0	25	0	25
Matale	1.61	16	1.27	16	12.91	6	12.07	7	0.17	19	0.08	21
Matara	2.20	11	2.08	9	11.88	8	11.47	9	0.41	7	0.34	8
Moneragala	3.23	3	2.84	3	8.17	21	8.22	21	0.49	3	0.34	7
Mullaitivu	2.41	10	1.43	15	14.38	4	14.73	3	0.45	4	0.45	2
Nuwara Eliya	4.17	1	3.29	1	9.91	16	10.15	14	0.57	1	0.54	1
Polonnaruwa	1.24	19	1.24	17	10.29	15	10.10	15	0.24	11	0.24	11
Puttalam	3.18	4	2.70	4	11.03	10	11.00	11	0.41	8	0.41	4
Ratnapura	2.88	7	2.55	6	13.22	5	12.86	6	0.49	2	0.36	5
Trincomalee	3.97	2	3.08	2	15.66	2	16.34	2	0.42	6	0.26	10
Vavuniya	0.74	23	0.60	23	7.67	23	7.15	23	0.07	22	0.07	22

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