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Selection criteria and targeting the poor for poverty reduction: the case of social safety nets in Sri Lanka

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Abstract

Reducing poverty and improving the living standards of the poor and vulnerable populations in Sri Lanka have been one of the country's key goals. The government has designed poverty-targeting programs with relevant government agencies working to support low-income families. The programs include cash transfers, microfinancing and various community-based and livelihood development activities, including the "Aswasuma" program, which is the primary safety net initiative. Although safety net programs have been receiving significant financial support for decades, many people still remain excluded as a result of mistargeting, lack of transparency and poor beneficiary selection methods. To address these challenges, the selection criteria have to be redesigned to effectively target poverty. This article explores the Multidimensional Deprivation Score Test (MDST), which assesses the multiple dimensions of household deprivation by weighting each deprivation through a data-driven approach. This methodology aims to identify the poorest and most vulnerable people more accurately. Using the data collected during the 2019 Household Income and Expenditure Survey, conducted by the Department of Census and Statistics, the MDST has improved targeting accuracy and thus the impact of social protection programs. It is therefore crucial to increase the efficiency of data collection and to compile the weighted deprivation score. Moreover, incorporating a community-level evaluation and regular monitoring is essential for maximizing the accuracy and effectiveness of targeting poverty.

Key words: poverty, social safety net, selection criteria.

1. Introduction

Under successive governments, Sri Lanka has initiated much effort to ensure sustainable and viable economic development since independence. Consequently, Sri Lanka had witnessed mixed results prior to the COVID-19 pandemic and the subsequent economic crisis. Sri Lanka's economy recorded an 8.7 per cent GDP growth

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rate in 2011 and the country's per capita income reached US$ 4,293 in 2017 though witnessed some setbacks in subsequent years (DCS,2023a). With the expansion of economic activities, the unemployment rate hovered around 5 per cent during the last decade. In addition, despite several global and domestic challenges, inflation had been retained at a single digit for four consecutive years as measured by year to year at Colombo Consumer Price Index (CCPI) (DCS, 2023b). Moreover, the poverty headcount index decreased dramatically from 46.8 per cent to 14.3 per cent from 2002 to 2019 (DCS, 2021a).

In the aftermath of the COVID-19 and economic crisis in 2022, Sri Lanka's economic outlook turned uncertain due to unsustainable public debt and a severe balance of payment crisis. Hence, the economy contracted by 11.7 percent year-on-year in the third quarter of 2022 (DCS, 2023a) and CCPI year-to-year. Inflation reached two digits from December 2021 and an unprecedented 69.8 per cent in September 2022 due to high food inflation of 94.9 per cent. Subsequently, it decreased to 54.2 per cent in January 2023 (DCS, 2023b).

Due to economic imbalance described above, many people in the country face severe economic hardships exacerbating vulnerability and increasing number of people live in poverty. Understanding the past economic experiences in the country it is crucial to shape the policies to overcome the existing challenges and adapt to economic dynamics effectively. Reducing poverty and improving the living standard of the poor population in Sri Lanka has been a critical agenda of the government. Hence the incumbent government has also designed and accelerated poverty-targeting programs to reduce poverty to increase the living standard of poor people. Successive governments have implemented Social Protection policies and programs since the 1940s, such as universal free education and health and food subsidy programs (Ganga & Sahan, 2015). Currently, there are many fragmented social protection schemes in the country. Ministry of Social Empowerment and Welfare (MoSEW) plays a significant role in identifying low-income families and supporting them in numerous ways to lift their living standards and achieve sustainable development by providing them cash transfers, microfinance, and various community-based and livelihood development activities. The primary safety net program currently targeting the poor in terms of Sri Lanka is the "Samurdhi/Aswasuma" program launched under the Department of Samurdhi Development/Welfare Benefit Bord (WBB). The schemes mainly cover disability, old age, and Chronic Kidney Disease of Unknown Etiology (CKDU). Besides, there are schemes covering health care, school food programs, maternal programs and other social safety net programs targeting the poor and social security schemes, old age pensions, and lump-sum payments at the retirement of government and non-government workers.

The social protection floor system is one of the main policy instruments in developing countries to target the poor to reduce chronic poverty and protect vulnerable people. One of the main targets of global and local development agendas is reduced poverty (Goal one of MDG and SDG). The development of the human capital of the poor through social safety net programs is a long-lasting solution to poverty. Social protection covers social assistance, social security, social care, and labor market inclusion and productive employment. Developing countries have recently increased social protection coverage by expanding their social protection systems. Due to the COVID-19 impact and the economic crisis, the Sri Lanka economy has faced a sizable economic recession. Many people and households hit by the crisis face the hardships of their livelihoods. This situation further increases the focus on social protection programs to protect impoverished and vulnerable individuals and families coping with generated fiscal shock and economic crises.

During the post-independence, successive governments in Sri Lanka implemented several social protection programs such as Janasaviya, Samurdhi and the food subsidy programs, investing yet more resources. However, the outcome has not been commensurate with such investments, and none achieved its desired target (Samaraweera, 2010). The previous social protection programs have reported high inclusive and exclusive errors. Specifically, these programs have not effectively targeted their intended beneficiaries resulting in both inclusion of individuals who are not eligible with criteria (inclusive errors) and exclusion of individuals who are eligible (exclusion errors). These discrepancies challenge the effectiveness and quality of the social protection programs. Hence, it is very crucial to address these issues to improving the accuracy and impact of social protection programs. Therefore, this research investigates these errors and proposes to enhance the accuracy of social protection programs.

According to the Household Income and Expenditure Survey (HIES) 2019 conducted by the Department of Census and Statistics (DCS), out of 13 main social protection programs, currently, 33.8 per cent of poor people are not covered (Under-coverage), and 70.6 per cent of non-poor people has received transfers (leakage). Hence, the impact of social protection spending to reduce poverty has not achieved the desired results. This is due to weak targeting in which the welfare benefit has not always benefitted the needy. Thus, social protection programs have limited impact on poverty (DCS, 2021a). An early study has been carried out by the World Bank for Sri Lanka using the data from the Sri Lanka Integrated Survey (SLIS), conducted by the World Bank in collaboration with local institutions in 1999–2000, using a Proxy Means Test (PMT). However, the targeting accuracy was not as expected (Narayan & Yoshida, 2005). Kidd and Wylde (2011) studied the regression accuracy of PMT for Bangladesh, Indonesia, Rwanda, and Sri Lanka and found that high in-built inclusion and exclusion errors were high. This study has developed a criterion that enhances effectiveness of targeting which is essential in minimizing the exclusion and inclusion errors in poverty reduction programs.

This paper is structured as follows. Section 2 presents the literature review presenting different methods used as beneficiary selection criteria for targeting the poor. Section 3 describes the methodologies employed to assess the selection criteria and new method used to compute Multidimensional Deprivation Score for identifying the new target group. Section 4 presents results and output. Finally, Section 5 concludes the paper with discussion and some recommendations.

2. Literature review

Effective targeting increases the impact of poverty reduction and raises the standard of living of the poor. Different countries have different selection criteria for identifying the poor people for targeting (Kidd &Wylde, 2011; Alatas et al., 2012; Alkire & Seth, 2013; Brown, Ravallion, & Van de Walle, 2018; Sabates-Wheeler, Hurrell, & Devereux, 2015; Diamond, et al., 2016; Bird & Hanedar, 2023). The social safety net programs have promotion and protection effects (Devereux, et al., 2017). Morestin, Grant & Ridde (2009) did a systematic review of literature on selection criteria presenting 68 experiences used by developing countries, of which 27 were in sun-Sahara Africa. This study has identified 30 incidents of the identification of the poor based on administrative, community-based, and mixed processes.

Poverty is a multidimensional phenomenon. Amartya Sen's capability concept significantly contributed to the development of multifaceted poverty measures of understanding poverty after his seminal work (Sen, 1983,1995,1997). People are poor in terms of income, and many other aspects, such as health, education, shelter, inadequate sanitation facilities, social exclusion, access to essential services and lack of assets (Sabina ,2023; Sabina, et al., 2015). Morestin, Grant & Ridde (2009) found 260 selection criteria based on 68 surveyed and categorized those into 11 dimensions. The eleven dimensions are: 1) Possession of goods and means of production; 2) Household compositions; 3) Income; 4) Condition of dwelling; 5) Occupational status; 6) Food security; 7) State of health; 8) Education; 9) Access to essential services and to credit; 10) Expenses; and 11) Physical appearance and clothing. Further, this study identified that in administrative processes, in 48 per cent of experiences, the program manager was responsible for determining the poor. In the community process, 36 per cent of studied community members have identified the poor. In the mixed method, in 20 per cent of surveys, the first selection was made by the program manager decided the final beneficiaries. Based on the study review Morestin, F., Grant & Ridde (2009) conclude that there are no perfect criteria for selecting beneficiaries and that developing countries should pay more attention to implementing an effective process for choosing beneficiaries. The effectiveness is based on inclusive and exclusive error of the selection criteria.

The Proxy Mean Test (PMT) is a widely used method to select the poor for targeting. This method is based on a score produced from a set of coefficients of variables reflecting the household living condition chosen for the best regression model (WB, 1999). This method commonly targets the poor for social safety net programs when income or consumption expenditure data are unavailable. The early contribution of the PMT method for selection criteria was made by Grosh (1994) for Latin America. He concluded that this method produces the best targeting outcomes reducing inclusion and exclusion errors. Proxy Mean Test (PMT) model is based on a statistical method used to estimate income or expenditure based on observable characteristics correlated with income or consumption expenditure. This method is based on national household surveys. The term "Proxy Mean Test" describes estimating income or consumption when precise measures are unavailable or difficult to obtain. Brown, Ravallion and Van de Walle (2018) state that "Proxy-means testing is a popular method of poverty targeting with imperfect information". The methodology estimates household income or expenditure by associating indicators or proxies. They include demographic characteristics (such as the age of household members and size of household), human capital characteristics (such as education of household head and enrolment of children in school), physical housing characteristics (such as type of roof or floor), durable goods (such as refrigerators, televisions, or cars) and productive assets (such as land or animals), etc. It uses the weights for the variable derived through statistical analysis of household survey data like Household Income and Expenditure Survey. Using the agreed weights, a score is calculated for each household. Households that score below the cut-off point are eligible for social protection programs.

Narayan and Yoshida (2005) applied the PMT method for Sri Lanka using household data from the Sri Lanka Integrated Survey (SLIS) conducted by the World Bank in collaboration with local institutions in 1999–2000[3]. In this exercise, seven main models were developed, and different cut-offs based on per capita consumption were applied for the selection. Further, considering several modifications, four additional models, Model 8, Model 9, Model 10, and Model 1, were developed based on Model 7. The model shows that the inclusion and exclusion errors were high. For example, the under-coverage rate varies from 50 per cent to 55 per cent. The leakage rate varies from 39 per cent to 40 per cent based on a 25 per cent cut-off, and at the 40 per cent cut-off, coverage ranges from 20 per cent to 31 per cent, and leakage varies from 31 per cent to 35 per cent based on the selected models 7, 10 and 11.

Proxy Means Test has become a popular method with many advocates and detractors. The Australian Agency for International Development (AusAID) supports evidence-based debates to investigate the PMT's strengths and weaknesses further. This study assesses the regression accuracy of the PMT model in Bangladesh, Indonesia, Rwanda, and Sri Lanka, which was done in this exercise earlier and found that inclusion and exclusion vary between 44 per cent and 55 per cent with the coverage of 20 per cent of the population and 57 to 71 per cent when 10 per cent were covered (Kidd & Wylde, 2011). In addition to non-sampling errors of the dependent survey's accuracy of PMT partially depend on the interaction with error arising from the regression with the

[3] The survey data was excluded for the analysis for Northern and Eastern provinces due to conflict and concern with the quality of the data.

correlation of proxies and consumption expenditures. According to the finding of the new PMT test done by the WB based on the currently conducted survey and the assessment made by Kidd and Wylde (2011). The Australian Agency for International Development based on the PMT test done by WB for Sri Lanka in 2003 evident that PMT regression-based method is inaccurate for targeting and the majority of eligible poor households may be permanently excluded from the social grant scheme from the results from PMT scoring. Further, capturing the dynamic changes of a focus unit family/household or individual is impossible. However, it can be updated after doing a large-scale household survey frequently maintaining the integrity of the specifications.

3. Methodology

Table 1 presents the targeting accuracy of the selection method. It can be evaluated through the Type I and Type II errors, which indicate the share of under-coverage[4] and leakage[5], respectively. Type I error shows the number of individuals incorrectly excluded (exclusion error). Type II error (inclusion error) indicates the individuals incorrectly identified as eligible by the selection criteria as a share of the total population. When increased the under-coverage reduces the impact of the program and does not affect the cost of the welfare budget; however, leakage does not affect the program's impact but unnecessarily increases the cost of the welfare budget.

Table 1: Illustration of Type I and Type II errors

Type	Target group	Non-target group	Total
Eligible: predicted	Targeting Success (S1)	Type II Error (e2)	m_1
Ineligible predicted	Type I Error (e1)	Targeting Success (S2)	m_2
-	n1	n2	n

Those in the bottom quintile of per capita expenditure or poor constitute the “target group”, while those predicted and grouped by eligibility threshold constitute the “eligible” group. The individual correctly classified as eligible by the formula that belongs to the target group (bottom per capita expenditure quintile or poor) is “Targeting Success”. A person who is incorrectly excluded by the procedure is a case of Type I error. Conversely, a person incorrectly identified as eligible constitutes a Type II error; under-coverage is calculated by dividing the number of cases of Type I error by the total number of individuals who should get benefits [e1/n1]. Leakage is calculated by dividing the number in the Type II error category by the number of persons classified as eligible by the formula [e2/m1].

[4] Under-coverage is the percent of poor individuals that do not receive the social transfer.

[5] Leakage is the percent of individuals that receive social transfer and are not poor.

Effectiveness is the capacity to identify the actual beneficiaries or the "real" poor. Conversely, two types of errors are possible: excluding poor individuals and including persons who are not poor as beneficiaries. Therefore, it is more desirable to reduce both under-coverage and leakage for effective targeting. The efficiency of the selection criteria can be evaluated through the magnitude of Type I and Type II error. Arguably in a climate of "no method is perfect", it is essential to minimize these two errors as much as possible.

Existing beneficiary selection procedure in Sri Lanka

This will review the present main social safety net program in Sri Lanka, "Samurdhi[6]. The beneficiaries of the Samurdhi program are currently selected based on self-reported income level. However, that method generates high inclusion and exclusion errors. The 2019 Household Income and Expenditure Survey data shows that Samurdhi covered only 42 per cent (direct and indirect beneficiaries) of the total poor population, which under-coverage is 58 per cent, and leakage is 62 per cent. Among the leakage, 29 per cent are in the second quintile[7], 18.7 per cent are in the third quintile, 9.7 per cent are in the fourth quintile, and 4.5 are in the richest fifth quintile (top 20 per cent). In other words, of the non-poor population, 15.7 per cent are receiving Samurdhi benefits. To mitigate this issue, this study introduced a new criterion for identifying beneficiary's potential beneficiaries more efficiently through a criterion for effective target beneficiaries and assessing the deprivations at the family level in multidimensional aspects called "Multidimensional Deprivation Score Test (MDST)".[8] The following section presents the method of MDST.

Multidimensional Deprivation Score Test (MDST)

Multidimensional Deprivation Score Test (MDST) assesses the living standard of the poor in terms of multiple aspects, reflecting the deprivation at the family level. However, this research used the data from Household Income and expenditure survey conducted by DCS in 2019 and has collected information at the household level. Hence, this analysis considered the dimensions: Education, Health, Economic Level, Assets and Housing characteristics and Family Demography by household level.[9] Under these dimensions 22 indicators were considered (Appendix). These dimensions and indicators were selected normatively. This method proposed a data-driven weight function in which the frequency of the 'definitely poor' phenomenon weights each dimension. This weight function is built to assign lower weight to the extent in which

[6] In Household Income and Expenditure Survey in 2019 capture the Samurdhi.

[7] Based on per capita consumption expenditure.

[8] This method was introduced by DCS to the WBB (see gazette in No. 2302/23 - Thursday, October 20, 2022).

[9] This approach recommended to apply to the survey data collected from vulnerable and poor people to develop an index in computing a deprivation score for each family. Usually, social protection benefits are given to the poor and vulnerable families or individuals rather than households.

lower frequency of families is 'definitely poor', and higher significance to families with higher frequency of 'definitely poor' in a dimension. This weight can be introduced as an attempt to achieve Sustainable Development Goals (SDGs) with current information in the concept of no one behind all its form everywhere.

For example, an indicator of having safe drinking water, in an area called A, most households need access to a safe source of drinking water. Thus, definitely, the poor frequency for that indicator would be very high. Therefore, assigning a very high weight to that indicator is reasonable. In area B, the frequency of access to safe drinking water could be higher. Then a low weight was given to that indicator for that area. Each household's deprivation score is constructed based on a weighted average of the deprivations, and each household is identified as deprived or non-deprived based on a deprivation cut-off. If a household's weighted deprivation score is above the cut-off that household should be considered eligible for the social protection program.

Computation of Multidimensional Deprivation Score

MDST develops an index called the Multidimensional Deprivation Score (MDS) at the unit of the analysis. In this research, the unit of analysis is a household. This score is between 0 to 100, 0 indicates completely not deprived, and 100 means completely deprived.

Calculation of the deprivation score for a household is done in three steps:

a. Set of indicator deprivation
b. Computation of weight for indicators
c. Calculation of weighted deprivation score for each household

Every indicator is assigned a deprivation cut-off, and if a household is deprived in the relevant indicator, then it is considered completely deprived and assigned 1 for that indicator and otherwise 0. Accordingly, every indicator is assigned one and zero.

Indicator deprivation

Deprivation cut-off for each and every indicator was assigned as given in Appendix. If the deprivation cut-off is denoted as z_j then the household is considered deprived if the i^{th} family/household achievement of indicator x_j is below the cut-off $(x_j < z_j)$.

If i^{th} household owns indicator j, then its indicator deprivation can be calculated using the following equation:

$x_j(i)$ is the household value on indicator *j*.

Then

$\mu_j(i) = 1$; if household deprived in indicator *j*,

$\mu_j(i) = 0$; if household is not deprived in indicator *j*.

The formula for the weight function

This method uses the frequency-based data-driven weight function to weight the indicators considering the number of completely deprived household for each indicator in the area of interest (e.g. district or any administrative or geographical level). The steps for calculating the indicator weight are given below:

- Count the sum of the number of deprived households in every indicator in the area of interest.
- Get the natural log value of the inverse of the sum of the number of deprived households in every indicator in the area of interest.
- Get the total sum of natural log values obtained for every indicator for the area of interest.
- Finally, get the ratio of the natural log values to the total sum of natural log values (normalize the weight).

Getting this natural log of the inverse of deprived frequency is smoothing out the weight and reducing the over-dispersion of values. This weight function is built to assign lower weight to the indicator in which many households turn out to be ‘definitely poor’, and higher weight to households with a high frequency of ‘definitely poor’ in an indicator. The mathematical formula is given below:

$$\omega_j = \frac{ln\frac{1}{f_j}}{\sum_{j=1}^{k} ln\frac{1}{f_j}} \times 100\ ;\ j = 1,2, \dots \dots k \tag{1}$$

where f_j denotes the frequency of households completely deprived in the jth indicator and ω_j is the weight for the j^{th} indicator. Lower weights mean the criterion many households are less deprived of; lower weights indicate lower importance. Higher weights mean a high frequency of deprived households’ in a indicator that households highly belong to deprivation of that indicator. Higher weights indicate greater importance.

Calculation of weighted deprivation score for individual

$$\mu_{wi} = \sum_{j=1}^{k} \omega_j \times \mu_j \tag{2}$$

Where μ_{wi} is the weighted deprivation score for ith households. The weighted deprivation score gets values between 0 and 100, in which zero (0) is not deprived, and one (100) is completely deprived.

4. Results

The data used for this study is the Household Income and Expenditure Survey (HIES) conducted in 2019 by the Department of Census and Statistics. The sample of this survey was drawn scientifically to represent the entire country's population. It was conducted throughout the year to capture the seasonal variation of the living standard of the household population in Sri Lanka. Two-stage stratified sampling method was used to draw the survey sample, and the sample size was 25,000 housing units in Sri Lanka. This survey collects information on household income and consumption expenditure and details on living standards and selected main social welfare programs. The Official Poverty Line (OPL) of Sri Lanka is computed based on consumption expenditure collected from this survey (DCS, 2021a).

The HIES, which was conducted in 2019, revealed that of the total population in Sri Lanka, 14.3 per cent (3.04 million individuals) live in poverty based on Official Poverty Line while from the total households, 11.9 per cent (681,800 households) live in poverty (DCS, 2021a). The Survey found that approximately out of every six (16 per cent) people are multidimensionally poor (DCS, 2021b). Further, it shows that 6.2 per cent of people has been lifted out of monetary poverty due to the thirteen social protection programs including the Samurdhi program considered in this survey. Table 1 shows the coverage of the population by the Samurdhi program by per capita expenditure decile, and Table 2 shows the distribution of direct and indirect Samurdhi beneficiaries by real per capita expenditure decile. That is the proportion of direct and indirect Samurdhi beneficiaries in each decile group. The total coverage of Samurdhi is 20.6 per cent of the total population. Both Tables 2 & 3 indicated the inefficient targeting of the Samurdhi program shows that the beneficiaries are also in the richest top two deciles. It is evident that among all beneficiaries, 4.6 per cent are in the top 20 per cent.

Table 2: Coverage of the Samurdhi program by real per capita expenditure decile

Per capita expenditure decile	Coverage of Samurdhi (Per cent)
Sri Lanka	20.6
1	40.5
2	34.6
3	32.7
4	28.0
5	21.1
6	18.2
7	12.1
8	9.6
9	7.0
10	2.4

Table 3: Distribution of beneficiaries by real per capita expenditure decile

Per capita expenditure decile	Proportion of beneficiaries (%)
Sri Lanka	100.0
1	19.6
2	16.8
3	15.8
4	13.6
5	10.2
6	8.8
7	5.8
8	4.7
9	3.4
10	1.2

The Table 4 presents the estimated number of people who are correctly and incorrectly classified as direct and indirect Samurdhi beneficiaries within the poorest 20 percent of the population based on real per capita expenditure quintile. The finding reveals that the exclusion error (under-coverage) is 62.5 and inclusion error (leakage) is 63.6 percent.

Table 4: Distribution of eligible and ineligible Samurdhi beneficiaries by target and non-target group

Specification	Target group (Q1)	Non-target group	Total
Eligible:	1,595,043 (S1)	2,786,943 (e2)	4,381,986 (m1)
Ineligible	2,654,626 (e1)	14,211,736 (S2)	16,866,362 (m2)
Total	4,249,669 (n1)	16,998,679 (n2)	21,248,348

The Target group is the individual who is in the bottom real per capita expenditure quintile (Q1)

Direct and indirect Samurdhi beneficiaries

Under-coverage[10] = [e1/n1] = 62.5 per cent

Leakage[11] = [e2/m1] = 63.6 per cent

[10] Under-coverage is the percent of poor individuals that do not receive transfer.

[11] Leakage is the percent of individuals that receive transfer and are not poor.

Comparing the coverage and distribution of beneficiaries by different approaches

Figure 1. presents the coverage of three types of targeting approaches for poor individuals and actual Samurdhi beneficiaries by per capita income deciles to examine their effectiveness for better targeting. MDSQ5 represents the individuals in the poorest 20 per cent based on Multidimensional Deprivation Score Test. OPL_new means the individuals who live in poverty based on the official monetary poverty line. MPI_poor means the individuals who are multidimensionally poor on official multidimensional poverty index based on the Alkire and Foster method. Finally, Samurdhi represents the actual direct and indirect beneficiaries currently receiving benefits, while looking at the output reveals that among the poorest 40 per cent (bottom four deciles), the highest number of poor individuals are covered by the individuals identified by the MDST method.

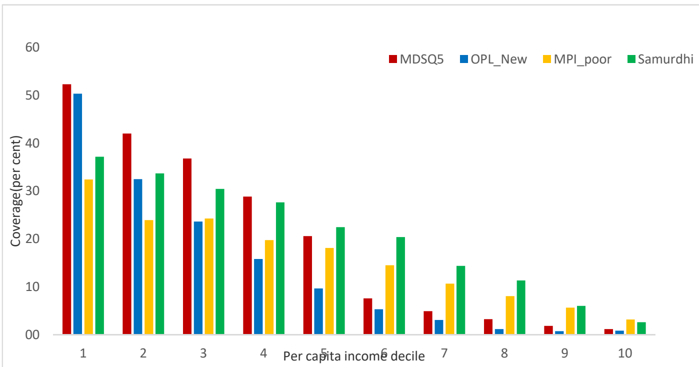

Figure 1. Distribution of predicted, targeted and Samurdhi beneficiaries by per capita income decile

There are vast discrepancies in coverage of actual direct and indirect Samurdhi beneficiaries and targeted individuals across districts (Figure 2). According to the official multidimensional poverty index the Colombo district (3.5 per cent) has the lowest incidence of poverty. In comparison, Nuwara Eliya (44.2 per cent) shows the highest poverty (DCS, 2021b). However, based on official monetary poverty based on consumption expenditure, the lowest poverty incidence was reported from Colombo (2.3 per cent), while the highest was from Mullaitivu (44.5 per cent) (DCS, 2021a). When examining the Nuwara Eliya district, more than half of the individuals are poor on MDS, more than two-fifths are poor on MPI, and more than one-fourth are poor on OPL, but coverage of Samurdhi is 10 per cent. The situation is different in Mullaitivu; two-fifths are poor in terms of OPL, three-tenth and more than one-tenth are poor in terms of MDST and MPI, and the Samurdhi coverage is almost 50 per cent, while in the Mannar district, the coverage of the Samurdhi is much higher than the share of the targeted beneficiaries. These findings demonstrate that the existing beneficiary selection method for the leading social net program in Sri Lanka should be revised for effective targeting.

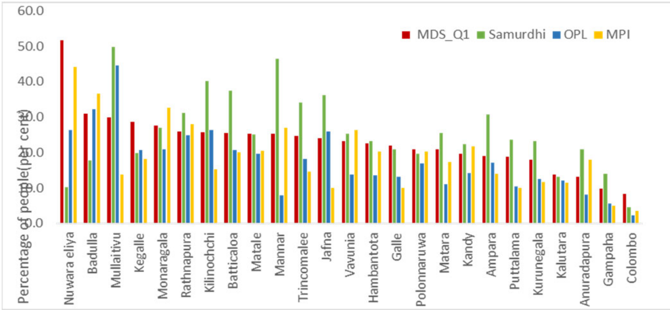

Figure 2: Distribution of predicted, targeted and Samurdhi beneficiaries by district

Figure 3 presents the graphical presentation of the distribution of the Multidimensional Deprivation Score. It appears as the normal distribution and has no skewness.

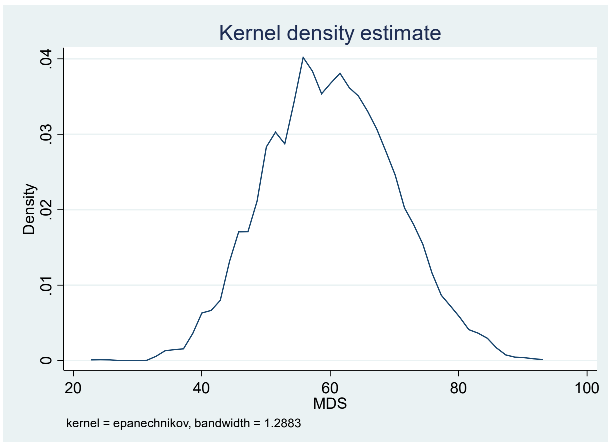

Figure 3: Distribution of Multidimensional Deprivation Score (MDS)

Selection cut-off

It is essential to identify the most appropriate cut-off for selection of beneficiaries for welfare programs. For this purpose, it is necessary to decide the targeting group either in monetary, non-monitory or mixed approach or to decide normatively on policy decisions. For instance, it can be per capita income or consumption expenditure decile or quintile or multidimensional deprivation quintile or decile. The coverage of the target population is very high; then the selection cut-off is more accurate with less under-coverage. Figure 4 plots the percentage of deprived people based on multidimensional deprivation scores by different cut-offs concerning the per capita expenditure quintiles. The graph shows that the MDST cut-off concerning the AA' line covers 100 per cent of the bottom 20 per cent of the poor individual (first per capita expenditure quintile). The exclusion error is very low, and the cut-off on the BB' line shows that the richest top 20 per cent is excluded 100 per cent, and the inclusion error is significantly less. Further, it reveals that when increase the cut-off exclusion error is reduced. Accordingly, the plot provides valuable information to decide the cut-off with minimum inclusion and exclusion errors.

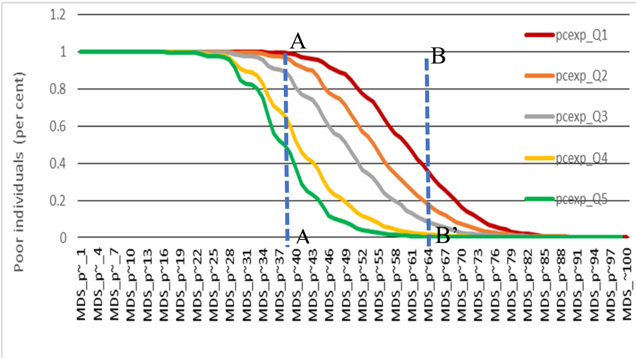

Figure 4: Distribution of multidimensional poor of per capita expenditure quintile by different deprivation cut-off k

Target Performance

Table 5 presents the under-coverage and leakage of currently existing Samurdhi beneficiaries and predicted Samurdhi beneficiaries on MDS test considering different target groups. To assess the existing Samurdhi beneficiaries three target groups were considered[12]. For predicted Samurdhi beneficiaries instead of target group 3 a new target group 4 was considered[13].

Table 5 shows that the existing selection method report high exclusion errors on all three targeting groups. Further, it reveals that the predicted Samurdhi beneficiaries-based om MDST is much more accurate than the currently available method, (under coverage and leakage is less for three types of targeting groups on MDST in compared with the currently available selection method). Nevertheless, these findings strongly suggest that the current selection beneficiary method should be reevaluated. Table 6 shows the exclusion errors with three different MDS selection cut-offs. It reveals that when increase the cut-off exclusion error is reduced due to increase of the coverage.

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[12] 1). Target group 1 - Target group is poor with respect to OPL- 2019 (Updated 2012/13_NCPI)
2). Target group 2 - First real per capita expenditure quintile Q1
3). Target group 3 - Multidimensional deprivation score 5th quintile-Q5

[13] Target group 4- MPI poor

Table 5: Targeting errors on existing and predicted Samurdhi beneficiaries on different target groups

	Existing Samurdhi beneficiaries		
	Target group1(OPL)	Target group2 (rlpcexpQ1)	Target group3 (MDSQ5)
Under-coverage	60.4	61.9	62.1
Leakage	72.5	63.1	63.4
	Predicted Samurdhi beneficiaries (MDS 5th quintile)		
	Target group1(OPL)	Target group2 (rlpcexpQ1)	Target group4 (MPI poor)
Under-coverage	47.3	50.5	55.1
Leakage	62.2	50.3	63.8

Note: Under-coverage – exclusion errors.
Leakage - inclusion errors.

Key findings of multidimensional poverty on MDS approach

Multidimensional Deprivation Score can be used as a tool to measure poverty through multidimensional lens. To identify the poor individuals, it necessitates to identify the poverty cut-off. With the evidence of Figure 4, the poverty cut-off was set as k=0.5. It says that if an individual is deprived at least 11 indicators out of 22, that person is considered multidimensionally poor. Accordingly, Table 6 presents the key significant finding of MDS poor.

Table 6 reveals the incidence of poverty on MDS multidimensional score test, i.e. that the percentage of poor people is 47 per cent. The average of deprivation experience by multidimensional poor individual is 60%. That is the average proportion of weighted indicators experience by a poor person. MPI means that the poor people experience 28.2 percent of total deprivation if all people were deprived in all indicators.

Table 6: Incidence, Intensity and Multidimensional Poverty Index (MPI) for MDS, 2019

Specification	**Index**	**Value**	**Confidence interval (95%)**	
Poverty cut-off K=50%	MDS_MPI	0.282	0.276	0.288
	Incidence, H (%)	47.0%	46.1%	48.0%
	Intensity, A (%)	60.1%	0.599	0.603

Comparison of poverty measures by different approach

The approaches use to measure poverty depends on different objectives. The main objective of monetary poverty is to identify the individual or household experiencing economic hardship and lack of resources necessary for minimum standard of living to inform policy makers to design targeted interventions allocating necessary resources for reducing poverty effectively. The multidimensional poverty measure aims to identify the individuals who are experiencing deprivation in non-monetary aspect from different factors at the same time to targeting poor by identifying specific indicators cause poor to formulate policies to reduce poverty at whole more effectively. Hence, multidimensional poverty measures are complimentary to the monetary poverty. Poverty headcount depends on the conditions and the techniques used in each method.

Figure 5 shows the poverty headcount given by three main approaches in Sri Lanka. Multidimensional deprivation Test Score mainly focuses on identifying the targeting beneficiaries among poor reducing exclusion and inclusion errors to support them by providing social protection assistance to uplift their living standard. Hence, in the selection process it is important to identify the individuals who rely on assistance from others to meet their daily living needs.

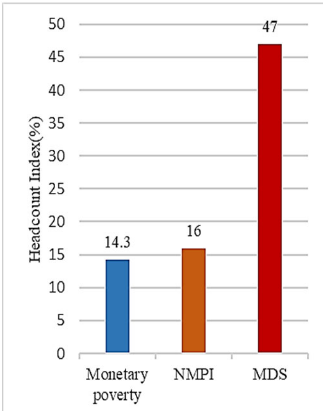

Figure 5: Poverty headcount ratio by different approaches

5. Conclusion and discussion

Developing countries face a massive challenge in implementing effective poverty reduction programs due to less effective criteria for identifying eligible welfare recipients and political interferences. The people are poor not only lack money but also the experience of deprivation in other dimensions such as health, education, shelter, nutrition, and assets at the same time. Therefore, for effective targeting, it is essential to correctly identify the needy through a selection criterion on a multidimensional approach to provide social welfare benefits.

Poverty reduction is the main objective lined with social safety net programs. Subsequently, policymakers are more concerned about exclusion errors than inclusion errors with the allocated budget. To achieve this, a proper method should be applied to cover the needy people broadly. The countries use different methods for selecting beneficiaries. Proxy Mean Test (PMT) is widely used by developing countries. However, many countries have reported a significant exclusion error based on some conceptual and methodological limitations. Hence, the countries are rethinking new selection criteria.

This paper discussed a multidimensional selection criterion for the leading social safety net for Sri Lanka, Multidimensional Deprivation Score Test (MDST). In this paper, this method has been applied to the HIES-2019 data and reveals that the exclusion error is less than the existing selection criteria when compared with different targeted groups. The MDS method computes a multidimensional deprivation score for every household. Thus, according to the selection cut-off, Samurdhi/welfare beneficiaries can be identified. The cut-off is the more critical policy decision and should be determined in terms of the impact of poverty and for an affordability within a budget. In addition, to impact of poverty, the transfer schemes should be varied concerning the severity of poverty. Otherwise, if all the beneficiaries get the same amount of money, the impact on poverty is unlikely to change significantly. In addition, to identify the suitable beneficiaries, MDST help to compute the contribution of deprivation in every dimension, which is taken into consideration by household or family, community, or geographical levels.

The results of the MDS method show that the individuals who are not identified as poor based on official poverty measures are poor in terms of the MDS method, and there are considerable gaps of the incidence of poverty across districts. Further, when compared with current Samurdhi targeting, the performance varies across district and evidence that the current selection method is associated with high exclusion errors.

Sri Lanka is currently selecting the beneficiaries considering the family aspect based on monetary measures. This paper utilizes HIES 2019 data and assesses the selection performance at the household level. Consequently, the outcome performance might not match accurately. The Samurdhi beneficiary family background might be different from the household background.

Poverty-targeting measures are more productive when the analysis is focused on poor people. The MDST method for selection criteria is more productive to apply to get information from existing and potential beneficiaries first and then apply the MDST criteria. The MDST method is a data-driven approach focusing on the target population to make an evidence-based policy decision to reduce poverty based on current information. MDST depends on the dimensions and indicators decided use for the criteria and the selection cut-off. This test provides important policy decisions for the government for effective targeting to reduce poverty.

This analysis has been carried out considering the entire population based on a representative sample used for the Household Income and Expenditure survey conducted in 2019. The proposed MDST for the selection performance can be properly assessed when applied to the targeting group based on the multidimensional poverty approach and considering the selected beneficiaries from the MDS method. To improve the effectiveness of this method it would be more accurate to collect the information from existing and potential beneficiaries and assess the targeting performance through a subjective evaluation at the community level.

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Appendix

The list of Dimensions, Indicators, and definition

Dimension	Indicator	Definition
1. Education	1. Education Level of family members	A household is considered poor based on this indicator when all household members have less than O/L (or poor) education
	2. Number of non-school going children between the age of 5-16 years	A household is considered poor based on this indicator if at least one school aged (5-16) child is not enrolled in school
2. Health	1. Family members suffering from long term chronic diseases	A household is considered poor based on this indicator if at least one family member has suffered from a chronic disease
	2. Family members with disabilities	A household is considered poor based on this indicator if at least one family member is disabled
3. Economic Level	1. Monthly per capita expenditure	A household is considered poor based on this indicator when monthly per capita expenditure is less than Rs. 13,500
	2. Monthly per capita income	A household is considered poor based on this indicator when monthly per capita income is less than Rs. 14,000
	3. Electricity consumption less than 60 units per month	A household is considered poor based on this indicator when electricity consumption is less than 60 units (Rs.472) per month
4. Assets	1. Not having ownership of the occupied house and land to a family member	A household is considered poor based on this indicator if it does not have ownership of the occupied house and land to a family member
	2. Not having ownership of other house or a building to a family member	A household is considered poor based on this indicator if it does not have ownership of other houses and buildings
	3. Not having at least 0.5 acre of cultivable highland to a family	A household is considered poor based on this indicator if it does not have at least 0.5 acre of highland to a family
	4. Not having at least one acre of cultivable paddy land to a family	A household is considered poor based on this indicator if it does not have at least one acre of paddy land to a family
	5. Not having at least one asset related to mobility (Motor bike CC 125>, Three-wheeler, Car, Van, Jeep, Bus, Lorry, Tipper, Hand tractor (2 wheels), Tractor (4 wheels)	A household is considered poor based on this indicator if it does not have at least one asset related to mobility

The list of Dimensions, Indicators, and definition (cont.)

Dimension	Indicator	Definition
	6. Not having at least one asset related to economic activity (Fishing boat, Combined harvest machines, Threshers)	A household is considered poor based on this indicator if it does not have at least one asset related to mobility
	7. Not having at least one asset related to livelihood (5 cattle for milk, 20 goats, 50 chickens, 50 ducks, 10 swine)	A household is considered poor based on this indicator if it does not have at least one asset related to livelihood
5. Housing condition	1. Living in line room/row house/slum/shanty or other.	A household is considered poor based on this indicator when living in line room/row house/slum/shanty or other
	2. Not having a living home with a permanent wall and permanent floor and permanent roof	A household is considered poor based on this indicator if it does not have a living home with a permanent wall, floor, and roof
	3. Total floor area is less than 500 square feet	A household is considered poor based on this indicator if it lives in a house with floor area less than 500 square feet
	4. No access to clean drinking water	A household is considered poor based on this indicator if it does not have access to clean drinking water
	5. No access to adequate sanitation	A household is considered poor based on this indicator if it does not have access to adequate sanitation
	6. Not access to electricity	A household is considered poor based on this indicator if it does not have access to electricity
6. Family Demography	1. Dependency ratio (number of people aged 0-14 and those aged 65 and over/number of people aged 15 – 64) greater than 0.65	A household is considered poor based on this indicator if dependency ratio is greater than 0.65
	2. Single parent family	A household is considered poor based on this indicator when the family is a single parent family. ** In HIES data file households are nuclear families or extended families or one person **Here we can only identify single parents with children age<18, when a single parent is the head of the household only