Selection Criteria and Targeting the Poor for Poverty Reduction: The Case of Social Safety Nets in Sri Lanka

Abstract

Reducing poverty and improving the living standard of the poor and vulnerable populations in Sri Lanka have been among the critical agendas of governments. Hence, the incumbent government too has designed and accelerated poverty-targeting programs to reduce poverty. The relevant government agencies play a significant role in determining low-income families, supporting and assisting them in multiple ways in achieving sustainable development. Thus, the government provides families with cash transfers, microfinance and various community-based and livelihood development activities. The main safety - net program currently targeting the poor in Sri Lanka is the “Samurdhi” programme. Although consecutive governments have spent vast amounts of money for several decades on social safety net programs, impoverished people have unfortunately been excluded and remain poor. The high vulnerability is due to mistargeting, less transparency and accountability, political influences in the implementation of programs, and weakness of beneficiary selection methods. Thus, it is essential to redesign the selection criteria for social safety-net programmes to target the poor effectively. This article explores measures to identify the target and potential beneficiaries, assessing the deprivations at the household level in multidimensional aspects named “Multidimensional Deprivation Score Test (MDST)”. This programme captures the experiences of the poor in several dimensions simultaneously. It computes the weighted deprivation score by weighting each deprivation derived by a data-driven approach to capture the poorest and most vulnerable people more accurately. Empirical evidence via the Household Income and Expenditure Survey data in 2019 conducted by the Department of Census and Statistics, National Statistical Office in Sri Lanka, ensures the effectiveness of the criteria. The output indicates that shifting to the MDS test to select beneficiaries could improve the targeting and significantly increase the impact of social protection programs on poverty.

Keywords: Poverty, Social safety net, Selection Criteria

Introduction

Sri Lanka, since independence, has under successive governments initiated much effort to ensure sustainable and viable economic development. Consequently, Sri Lanka had achieved various financial successes before the Covid-19 pandemic and subsequent economic crises. Earlier, Sri Lanka's economy peaked at 8.7 per cent in 2011. The country's per capita income reached US$ 4,293 in 2017 (DCS, 2023). With the expansion of economic activities, the unemployment rate declined to 4.0 per cent in 2012 from 4.2 in 2011. 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). It was 9.2 per cent at the end of 2012.

Moreover, the poverty headcount index decreased dramatically from 46.8 per cent to 14.3 per cent from 2002 to 2019. However, following the Covid and economic crisis from March 2022, Sri Lanka's economic outlook is uncertain due to unsustainable debt and a severe balance of payment crisis. Hence, the economy contracted by -11.7 per cent year to year in the third quarter of the year 2022 (DCS, 2023) and CCPI year-to-year Inflation reached two digits from December 2021 and an unprecedented 69.8 per cent in September 2022 due to mainly to high food inflation of 94.9 per cent. Subsequently, it decreased to 54.2 per cent in January 2023 (DCS, 2023).

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 (MDG, 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 (welfare programs target the poor), social security as an old age pension scheme and labor market programs as unemployment benefit schemes. 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 Lankan economy has faced a massive economic recession. Many people and households hit by the crisis face the hardship of their livelihood. 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.

Reducing poverty and improving the living standard of the poor population in Sri Lanka has been a critical agenda of successive governments. 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 fairly well-established. 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 Sri Lanka is the "Samurdhi" programme launched under the Department of Divinaguma. Besides, schemes cover disability, old age, CKDU, health care and school food programs, maternal programs and other social softy net programs targeting the poor and social security schemes; old age pension, and lump-sum payment at the retirement of government and non-government workers.

Research Problem

Post-independence, successive governments implemented several social protection programs such as Janasaviya, Samurdhi and the school-meal programs, investing yet more resources; However, the outcome has not been commensurate with such investments, and none achieved its desired target (Samaraweera, 2010). One of the main issues is the gap in coverage by the existing schemes. According to the Household Income and Expenditure Survey (HIES) -2019 conducted by the 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 receive 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 little impact on poverty (DCS, 2021a). Sri Lanka's social protection system has fundamentally managed risk. 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, called using a Proxy Means Test (PMT). However, the targeting accuracy was not as expected (Narayan & Yoshida, 2005). Kidd & 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. Therefore, this study carried a new selection criterion to build clear social protection strategies for effectively targeting the poor in Sri Lanka with the following objectives.

Objectives

To develop a selection criterion for targeting the poor in a multidimensional approach
To evaluate the inclusion and exclusion errors according to the existing and the new method

This paper is structured as follows; Section 2 presents the literature to review different methods used as beneficiary selection criteria for targeting the poor used to identify inclusive and exclusive errors. Section 3 describe the methodology use to assess the selection criteria and new method used to compute Multidimensional Deprivation Score for identify the new target group. Section 4 presents results and output. Finally, section 6 concludes the paper with discussion.

2. Literature review

Effective targeting increases the impact of poverty and lift-up the standard of living of the poor. Different countries have different selection criteria for identifying the poor people for targeting (Kidd & Wylde, 2011) (Alatas, Banerjee, Hanna, Olken, & Tobias, 2012), (Alkire & Seth, Selecting a targeting method to identify BPL households in India, 2013) (Brown, Ravallion, & Van de Walle, 2018) (Sabates-Wheeler, Hurrell, & Devereux, 2015) (Diamond, et al., 2016). The social safety net programs have promotion and protection effects (Devereux, et al., 2017). SiMorestin, F., Grant, P., & Ridde, V. (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) (Sen, 1992) (Sen, 1997). People are poor in income, and many other aspects, such as health, education, shelter, inadequate sanitation facilities, social exclusion, access to essential services and lack of assets (Alkire, et al., 2015). SiMorestin, F., Grant, P., & Ridde, V. (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. 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 SiMorestin, F., Grant, P., & Ridde, V. (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 an inclusive and exclusive error of the selection criteria.

The Proxy Mean Test (PMT) is a widely use method to select the poor for targeting. This method is based on a score produced from set 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 could be considered.

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 -2001. In this exercise, seven models were developed, and different cut-offs based on per capita consumption were applied for the selection. 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 25per cent cut-off, and at the 40 per cent cut off, coverage ranges from 20per cent to 31per cent, and leakage varies from 31 per cent to 35 per cent based on the selected models 7, 10 and 11.

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

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 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 & 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.

3. Methodology

The targeting accuracy of the selection method can be evaluated through the Type I and Type II errors, which indicate the share of under coverage2 and leakage3 , respectively. Type I error show 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.

Illustration of Type I and Type II errors

	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 who 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].

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

[3] 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.

Beneficiary selection method for main safety net program in Sri Lanka

This para will review the existing main social safety net programme in Sri Lanka, "Samurdhi. 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 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 (20 per cent above the bottom 20per cent),18.7 per cent are in the third quintile, 9.7 per cent are in the fourth quin, and quintile 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, the Department of Census and Statistics introduced a new criterion for identifying beneficiary’s potential beneficiaries more efficiently through a new criterion for effective target beneficiaries and assessing the deprivations at the family level in multidimensional aspects called “Multidimensional Deprivation Score Test (MDST)”. 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 multiple aspects, reflecting the deprivation at the family level. This approach considers the dimensions; Education, Health, Economic Level, Assets and Housing characteristics and Family Demography and develops an index in computing a deprivation score for each family directly using the survey data. This method applies 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 lower frequency of families to be ‘definitely poor’, and higher significance to families with increased frequency of ‘definitely poor’ in a dimension. This weight can be introduced as an attempt to achieve Sustainable Development Goals (SDGs) in the concept of no one behind all its form everywhere.

For example, they were considering an indicator of having safe drinking water. In an area called A, most families need access to a secure 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 family’s deprivation score is constructed based on a weighted average of the deprivations, and each family is identified as deprived or non-deprived based on a deprivation cut-off. If a family is denied, that family 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 family level. This score is between 0 to 100, 0 indicates completely not deprived, and 100 means completely deprived.

Calculation of the deprivation score for a family is done in three steps;

a. Calculation of indicator deprivation
b. Computation of weight for indicators
c. Calculation of weighted deprivation score for individual

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

Calculation of indicator deprivation

If i^{th} individual owns indicator j, then his/her indicator deprivation can be calculated using the following equation;

$x_j(i)$ is the individual value on indicator j

Then

$$\mu_j(i) = 1\ ;\ if\ \ individual\ diprived\ in\ indicator\ j$$
$$\mu_j(i) = 0\ ;\ if\ \ individual\ \ does\ not\ diprive\ in\ indicator\ j$$

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 families for each indicator in the area of interest (ex., district). The steps for calculating indicator weight are given below;

- Count the sum of the number of deprived families in every indicator in the area of interest
- Get the natural log value of the inverse of the sum of the number of deprived families 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

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 dimension in which many families turn out to be 'definitely poor', and higher weight to families with a high frequency of 'definitely poor' in a dimension. The mathematical formula is given below;

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

Where; $f_j$denotes the frequency of people completely deprived on the j^{th} indicator and ω_j is the weight for the j^{th} indicator. Lower weights mean the criterion many people are less deprived of; lower weights indicate lower importance. Higher weights mean a high frequency of 'deprived people' in a criterion that people highly belong to deprivation of that criterion. Higher weights indicate more significant importance.

Calculation of weighted deprivation score for individual

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

Where $\mu_{wi}$is the weighted deprivation score for ith individual. The weighted deprivation score gets values between 0 and 1, in which zero (0) is less deprived, and one (1) is highly deprived.

4. Results

The data used for this study was 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 stages 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.

Table 1: 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 2: 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

HIES in 2019 revealed that of the total population in Sri Lanka, 14.3per cent (3,042,300 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 percent of people has been lifted out of poverty due to the thirteen social protection programs including Samurdhi programe considered in this survey. Table 1 shows the coverage of the Samurdhi program by per capita expenditure decile, and Table

2 shows the distribution of Samurdhi beneficiaries by real per capita expenditure decile. That is the proportion of Samurdhi beneficiaries in each decile group. The total coverage of Samurdhi is 20.6 per cent of the total population. Both Tables 1 & 2 evidence that there is an inefficient targeting of the Samurdhi programme shows that the beneficiaries are also in the richest top 2 deciles. It's evident that among all beneficiaries, 4.4 per cent are in the top 20 per cent.

The Table 4 present the estimated number of people who are correctly and incorrectly classified as 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

	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)
	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[4] = [e1/n1] = 62.5per cent

Leakage[5] = [e2/m1] = 63.6per cent

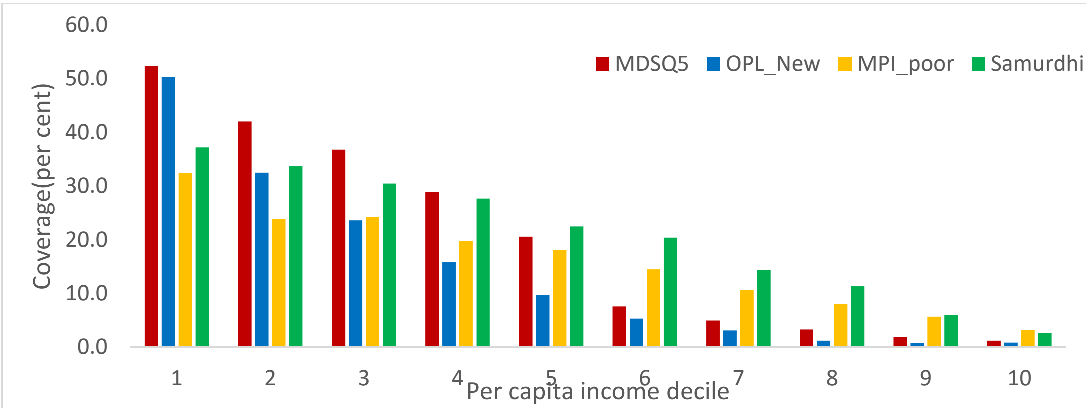
Comparing the coverage and distribution of beneficiaries by different approaches

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 predicted population 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 Alkire and foster method. Finally, Samurdhi represents the actual 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.

[4] Under coverage is the percent of poor individuals that do not receive transfer- (exclusion error)

[5] Leakage is the percent of individuals that receive transfer and are not poor - (Inclusion error)

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



There are vast discrepancies in coverage of actual Samurdhi beneficiaries and predicted and targeted individuals across districts (Figure 2). According to the official multidimensional poverty index Colombo district (3.5 per cent) has the lowest incidence of poverty. In comparison, Nuwara Eliyaa (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 (2.3per cent), while the highest was from Mullaitivu (44.5 per cent) (DCS, 2021a). When examining the Nuwara Eliya district, more than halves 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 OPL, three-tenth and more than one-tenth are poor in MDST and MPI, and Samurdhi coverage is almost 50 per cent. While the Mannar district, the coverage of Samurdhi is much higher than the share of predicted and targeted beneficiaries. These findings evidence that the existing beneficiary selection method for the leading social net program in Sri Lanka should have to revisit for effective targeting.

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

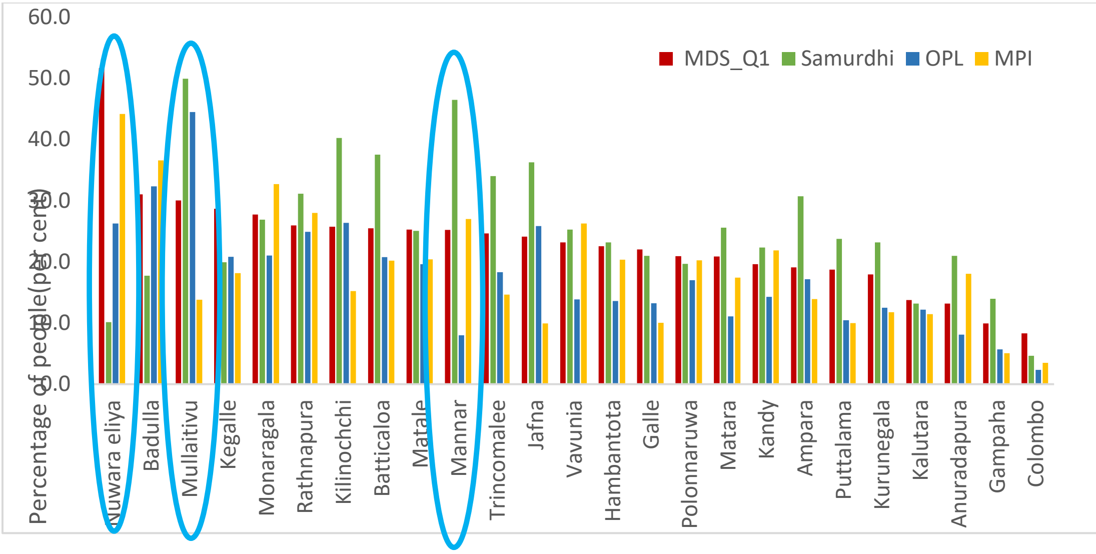
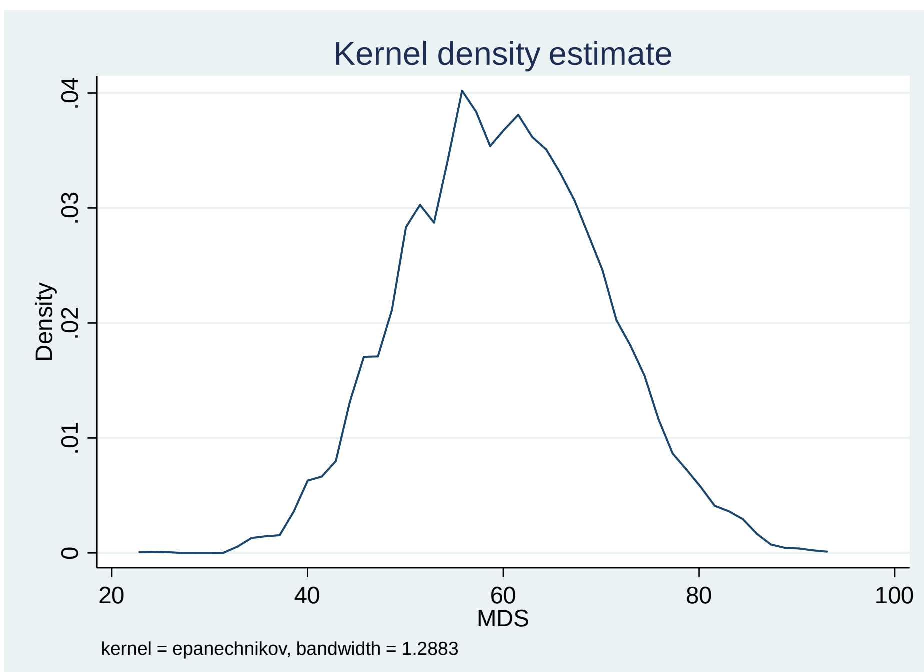


Figure 3 presents the graphical presentation of the distribution of the Multidimensional Deprivation Score. It appears as the normal distribution and has no skewness.

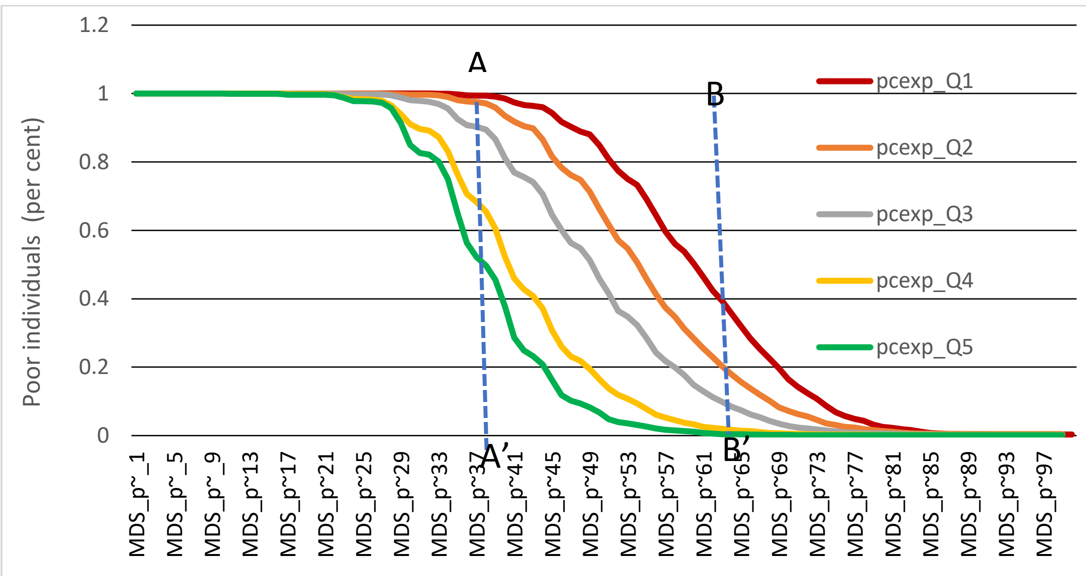
Figure 3: Distribution of Multidimensional Deprivation Score (MDS)



Selection cut-off

It's essential to identify the most appropriate cut-off for selection of beneficiaries for Samurdhi. For this purpose, it, is necessary to decide the targeting group either in monetary, non-monitory or mixed approach. 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 20per cent of the poor individual (First per capita expenditure quintile). The exclusion error is verry 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. Accordingly, the plot provides valuable information to decide the cut-off with minimum inclusion and exclusion errors according to the number of possible beneficiaries in the available government budget allocation.

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



Target Performance

Th Table 5 present 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.[6] For predicted Samurdhi beneficiaries instead of target group 3 a new target group4 were considered[7].

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

	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

Table 5 shows that existing selection method report high exclusion errors on all three targeting groups. Further it reveals that the predicted Samurdhi beneficiaries-based om MDST is more accurate that currently available method, (Under coverage and leakage is less for three type of targeting groups on MDST in compared with currently available selection method. Table 6 shows the exclusion errors with three different MDS selection cut-offs. It reveals that when increase the cut-off exclusion error is reduce due to increase of the coverage.

Table 6: Targeting errors on predicted Samurdhi beneficiaries based on MDST for targeting population living in the poorest per capita expenditure decile

MDS eligibility cut-off	Under coverage (per cent) (Exclusion error)
Poorest 20 per cent	50.5
Poorest 30 per cent	34.4
Poorest 40 per cent	21.8

5. Conclusion and discussion

Developing countries face a massive challenge in implementing effective antipoverty programs due to less effective criteria for identifying eligible welfare recipients. 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 providing social welfare benefits.

[6] 1. Target group1-Target group is poor with respect to OPL (Updated 2012/13_NCPI)
2. Target group2-First real per capita expenditure quintile Q1
3. Target group3 - Multidimensional deprivation score 5th quintile-Q5

[7] . 4. Target group 4- MPI poor

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

This paper discussed a multidimensional selection criterion for the leading social safety net for Sri Lanka, MDST. This method has been applied to the HIES-2019 data and reveal that 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/family. 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 term of the impact of poverty and for a given budget. In addition, to impact of poverty, the transfer schemes should be varied concerning the severity of poverty. Otherwise, if all the beneficiaries get same amount of money, the impact on poverty will not be 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 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 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 and, in this paper, utilizes HIES -2019 data and assess the selection performance at household level. Consequently, the outcome performance might not be accurately match. The Samurdhi beneficiary family background might be different from the housing unit background.

Poverty-targeting measures is more productive when the analysis is focused on poor people. MDST method for selection criteria is more productive to apply to get information from existing and potential beneficiaries. The MDS method is a data-driven approach focusing on the target population to make an evidence-based policy decision to reduce poverty. MDST depends on the dimensions and indicators decided use for the criteria and the selection cut-off and available welfare budget. As these are not independent of each other, those are 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 selection performance can be properly assessed applying 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 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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