INTERNATIONAL MONETARY FUND

Challenges Facing SSNs in Emerging and Developing Economies

An Illustration Using the World Bank's ASPIRE Database

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WP/24/96

2024
MAY

WORKING PAPER

 WP/24/96

IMF Working Paper
Fiscal Affairs Department

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Authorized for distribution by Rodrigo Cerda
May 2024

ABSTRACT: We show how the standard social welfare framework can be used to assess the performance of social safety nets (SSNs) in terms of targeting efficiency and budget effort. We apply this framework to the World Bank's ASPIRE database and find that the variation in poverty alleviation achieved by SSNs in emerging markets and developing economies (EMDEs) is driven mainly by variation in budget effort. Increasing transfer spending is therefore key to strengthening SSNs in EMDEs. However, the inability of many EMDEs to finely target transfers to poor households means the required spending increases are prohibitive over the short term, especially in low-income countries. This emphasizes the importance of enhancing targeting efficiency and we discuss how the use of proxy-means testing can contribute to this emphasizing the importance of careful design to manage the horizontal inequity inherent in such an approach to targeting.

RECOMMENDED CITATION: Brollo, Fernanda, David Coady, Samir Jahan, and Riki Matsumoto. 2024. "Challenges Facing SSNs in Emerging and Developing Economies: An Illustration Using the World Bank's ASPIRE Database." IMF Working Paper No. 24/96, International Monetary Fund, Washington, DC.

JEL Classification Numbers:	D3, D6, H0
Keywords:	Poverty alleviation; social safety nets; transfer targeting; budget effort; proxy-means testing

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WORKING PAPERS

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An Illustration Using the World Bank's ASPIRE Database

Prepared by Fernanda Brollo, David Coady, Samir Jahan, and Riki Matsumoto[1]

[1] We are grateful to staff at the World Bank's ASPIRE group for discussing the database and sharing additional data.

Contents

I. Executive Summary

The Covid-19 pandemic exposed the significant weaknesses of social safety net (SSN) systems in emerging and developing economies (EMDEs).[1] While many countries scaled-up SSN coverage in response to the pandemic, this expansion appears to have been subsequently scaled back to pre-pandemic levels leaving large gaps in coverage of poor households (Gentilini, 2023). This will undoubtedly refocus the attention of policymakers on how to address these coverage gaps. To this end, the setting of country-specific policy priorities needs to be informed by a comprehensive evaluation of the effectiveness of their overall SSN system at reducing poverty in terms of its spending efficiency and spending adequacy.

This paper shows how the standard social welfare-based framework can provide a useful starting point for assessing the effectiveness of SSN systems in achieving their underlying poverty alleviation objectives.[2] It illustrates the application of this framework through conducting a comparative analysis of the challenges facing SSNs in EMDEs by harnessing the rich information available in the World Bank's cross-country *ASPIRE* database.[3] The analysis identifies several related policy challenges. First, the effectiveness of SSNs in EMDEs in achieving their poverty alleviation objectives varies substantially across countries, with these cross-country differences driven in large part by differences in spending levels relative to the size of the poverty problem (i.e., adequacy) rather than by spending (or targeting) efficiency. Strengthening the effectiveness of SSNs will therefore require increasing social assistance spending in many countries, especially low-income countries. Second, a key challenge facing many EMDEs is their weak capacity to channel (or target) a high share of SSN spending to lower-income households, which limits their ability to address low coverage of the poor without substantial leakage of benefits to higher-income households. This introduces a challenging trade-off between achieving high coverage of the poor while containing the associated fiscal cost.[4] Third, in the short term, the combination of tight fiscal constraints, competing claims on public spending, and weak capacity for increasing tax revenues, means that strengthening SSNs will require not only creating fiscal space to increase spending but also enhancing country capacities to effectively target SSN spending to low-income households. Fourth, more widespread use of proxy-means targeting methods can help to strengthen targeting efficiency in the short term, although it needs to be carefully designed to reduce the associated horizontal equities related to different treatment of equally poor households.

The paper is organized as follows. Section II sets out a basic social welfare framework for evaluating SSNs and defines key concepts and performance measures, particularly in relation to spending efficiency and adequacy. Section III summarizes the salient information available in the World Bank's *ASPIRE* database. Section IV illustrates how the framework can be applied to these data to inform a comparative evaluation of the relative effectiveness of SSNs across countries and to identify key policy challenges that need to be addressed. Section V examines the trade-off that exists between expanding coverage of poor households and transfer

[1] These gaps have been well documented in the literature. See, for example, ILO (2021) and World Bank (2018).

[2] The paper focuses on the evaluation of SSNs from the narrow perspective of spending adequacy and targeting efficiency to alleviate current income poverty. Other objectives could include reducing the risk of vulnerable households falling into poverty and the "promotion" role of SSN through, for example, enhancing the human and physical capital of beneficiary households to enhance their capacity to pull themselves out of poverty and avoid future poverty. A comprehensive discussion would therefore need to consider these other objectives as well as associated design and implementation challenges. For a wider discussion of these issues, see Grosh and others (2008).

[3] ASPIRE is an acronym for Atlas of Social Protection Indicators of Resilience and Equity.

[4] Note that undercoverage of poor households means that the tax financing of SSN transfers can exacerbate poverty for those excluded "poor" households and for excluded near-poor households.

efficiency in EMDEs with limited targeting capacity, while Section VI discusses the implications for spending adequacy. Section VII then discusses how EMDEs can strengthen their targeting efficiency over the short term to better manage the trade-off between addressing coverage gaps and containing fiscal cost. Section VIII concludes.

II. Conceptual Framework

The primary objective of SSN spending is to alleviate current income poverty, which in turn requires the redistribution of income from higher-income ("rich") to lower-income ("poor") households. The overall poverty impact of SSN transfers will depend on the size of the transfer budget (*budget effort*) and the ability to target these transfers to "poor" households (*transfer efficiency*). We first focus on how one evaluates the impact of SSN spending within a broader social welfare framework and then interpret the poverty impact of this spending as a special case. This poverty alleviation framework is then applied to *ASPIRE* data in the subsequent section to illustrate a practical application of this approach.

A. Poverty and Social Welfare

Consider an economy with two groups: households and the government. Abstracting from behavioral responses, define y_0 as household "original" income (i.e., income before transfers) and y_1 as household "final" income after income transfers.[5] This implies:

$$y1 = y0 + m \tag{1}$$

where *m* denotes transfer levels. Consider social welfare as described by a standard Bergson-Samuelson function of household welfare:

$$W(\dots, V^h(p, y^h), \dots) \tag{2}$$

where $V^h(.)$ is the indirect utility function of household *h* and ***p*** is a vector of commodity and factor prices facing the household (henceforth assumed fixed). The social welfare impact of a given transfer program with $dy^h = dm^h$ is (Coady and Skoufias, 2004):

$$dW = \sum_h \frac{\partial W}{\partial V^h} \frac{\partial V^h}{\partial m^h} dm^h = \sum \beta^h \mathrm{d}m^h \tag{3}$$

where β^h is the social valuation of extra income to household *h*, the social "welfare weight". Let the total transfer budget (i.e., budget *effort*) equal $B = \sum_h \mathrm{dm}^h$ so that (3) can be rewritten as:

$$dW = \frac{\sum_h \beta^h dm^h}{\sum_h dm^h} B = B \sum_h \beta^h \theta^h = \lambda B \tag{4}$$

[5] In this paper we abstract from the important issue of behavioral responses, which can introduce additional sources of inefficiency, e.g., those related to households reducing their labor supply in the presence of work disincentives. Such responses could potentially be very important in deciding on the optimal level of targeting since they generate an efficiency-equity trade-off (Piketty and Saez, 2013; Bargain, 2017). In the absence of such responses, "original" income (i.e., income before the imposition of taxes and transfers) will equal "market" income (i.e., income after taxes and transfers). In the text, we refer to original income.

where θ^h is the share of the total budget received by household *h* and λ is the *distributional characteristic* capturing the social welfare impact of a unit transfer delivered through the program (Diamond, 1975), which can be interpreted as an indicator of transfer *efficiency*. The greater the proportion of the budget ending up in the hands of lower-income households (i.e., those with relatively high β^h), the higher the distributional characteristic and thus transfer efficiency. Clearly λ can differ across transfer programs when welfare weights differ across households and the distribution of transfers differs across programs. Note also that the distributional characteristic is scale neutral in that it does not change in response to a proportional scaling up or down of transfer levels.

The poverty framework can be interpreted as a special case of this more general social welfare framework. For instance, if we set the welfare weights for poor households (e.g., those in the bottom two income deciles) equal to unity and zero otherwise, then λ will become the share of transfers accruing to the poorest two deciles of the population, a measure of spending efficiency. If all transfers accrue to these poor households (i.e., no leakage to the non-poor) then the perfect (or first-best) transfer program will attain the maximum level of spending efficiency with λ=1. Following (4), we can write the poverty impact of SSN spending as:

$$PI = \lambda . B \tag{5}$$

where PI is the poverty impact, λ can be interpreted as a measure of targeting efficiency (i.e., the poverty impact per unit of transfer spending), and B is budget effort. This measure of targeting efficiency can be compared to different benchmarks, such as to the maximum targeting efficiency that could be achieved with a given transfer budget or to the targeting efficiency levels observed in other countries with similar transfer spending levels.

B. Targeting Efficiency

To better understand the concept of targeting efficiency, consider the *perfect* (first-best) transfer outcome.[6] In the presence of a budget constraint, effectively targeting transfers to "poor" households will result in greater poverty reduction. For instance, suppose we have a total transfer budget that is just sufficient to eliminate poverty and also possess perfect information on actual household income before any transfers. Income before transfers is labelled "original" income and income after transfers labelled "final income" (Figure 1). Maximum and minimum household original incomes are respectively labelled Y_{max} and Y_{min} and *Z* is the poverty line. The line dY_{min} shows that, before the transfer program is in place, household final incomes are equal to their original incomes.

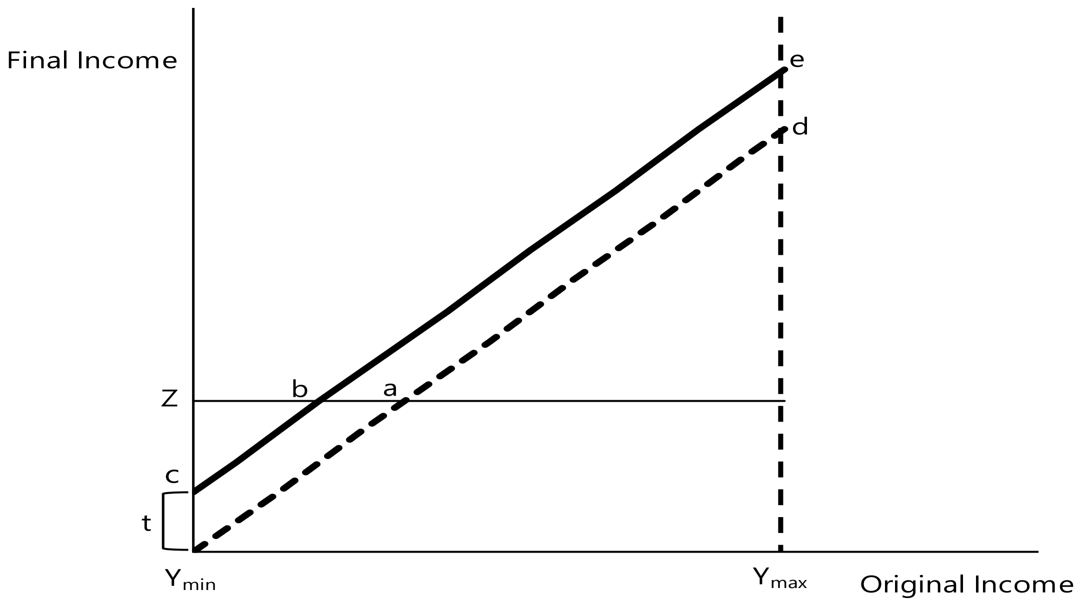
The *perfect* targeting scheme is one that gives transfers to all poor households only (i.e., those with income less than *Z*), with transfer levels equal to their individual "poverty gaps" (i.e., the distance between their original income and the poverty line *Z*).[7] This transfer program brings all poor households up to the poverty line and all

[6] See Besley and Kanbur (1993), Atkinson (1995a,b), van de Walle (1998), and Coady and others (2004a; 2004b).

[7] Therefore, *perfect targeting* involves: (i) *perfect beneficiary targeting* where only the poor receive transfers and all the poor receive transfers; and (ii) *perfect benefit targeting* where all of the transfer budget goes to the poor and the poor receive exactly the gap between their original incomes and the poverty line. We use the term "perfect" to distinguish this scheme from the conventional economic notion of an "optimal" scheme that minimizes the efficiency cost associated with the presence of work disincentives, such as those often associated with means-tested transfers.

non-poor households have equal final and original incomes. The *minimum* transfer budget required to eliminate poverty is thus represented by the area ZaY_{min}. With reference to (5) above, for this transfer scheme, targeting efficiency equals unity (λ=1) since the poverty impact (PI) equals the transfer budget.[8]

Figure 1. Benefits of Perfect Means-tested Targeting



Source: Reproduced from Besley and Kanbur (1993).

Now consider the case of a (non-targeted) transfer program with the same budget that gives a uniform transfer t (= c- Y_{min}) to all "poor" and "non-poor" households. Because of the "leakage" of transfers to non-poor households, the presence of a budget constraint means the transfers to poor households are no longer sufficient to eliminate all poverty. There are two forms of "inefficiency" associated with this uniform transfer: (i) non-poor households receive a positive transfer, and (ii) some poor households (those in the line interval *ba*) receive transfers greater than their poverty gaps. As a result, with a fixed budget, the poorest households also receive lower transfers compared to those received under perfect targeting so that they remain poor. Therefore, poverty is not fully eliminated as it would be under the perfect transfer scheme, with the remaining poverty given by the area Z*cb*. The total transfer "leakage" (reflecting the two sources of inefficiency identified above) is given by the area *bade*, which for a fixed transfer budget must also equal the area *Zcb,* i.e., the level of poverty remaining after the uniform transfer program. Therefore, imperfect targeting (or the presence of "targeting errors" or "targeting inefficiency") results in a lower poverty impact for a given budget.[9] In terms of (5) above, the reduction in the poverty gap (PI) will be less than the transfer budget (*B*) so that spending efficiency is less than unity (λ<1). We expand further on this below.

[8] Note that when transfer budget is less than the poverty gap (and therefore insufficient to eliminate poverty), efficient targeting involves targeting the poorest households first and bringing the incomes of the poorest households up to a common level below the poverty line.

[9] Targeting errors are often categorized as "errors of exclusion" (i.e., some poor do not receive transfers) and "errors of inclusion" (i.e., some non-poor receive transfers). See Coady, Grosh, and Hoddinott (2004a,b) for discussion.

III. World Bank's ASPIRE Database[10]

This section illustrates a practical application of the above framework to a comparative evaluation of the relative effectiveness of SSN systems across EMDEs. We make use of the World Bank's Atlas of Social Protection Indicators of Resilience and Equity (ASPIRE) database. This database covers advanced, emerging, and developing countries, drawing on and harmonizing information from country household surveys. It contains various indicators of the impact and performance of SSN systems and program components, which were estimated through microsimulation techniques applied to the survey data.[11] In our analysis, we utilize the following variables from ASPIRE:

- Poverty Impact defined as the percentage change in the poverty gap index (ΔPGI).[12] This is calculated as the percent decrease in poverty gap resulting from social assistance transfers, i.e., the difference between pre-transfer poverty gap and post-transfer poverty gap divided by pre-transfer poverty gap. As shown below. This can be rewritten as $\Delta PGI = BCR.BR$, which is equivalent to PI = λ.B in equation 5

- Benefit-Cost Ratio (BCR). This is calculated as the ratio of poverty impact to the total social assistance transfer budget and is therefore a measure of transfer efficiency, i.e., of λ in (5).

- Coverage (COV). This is defined as the percentage of "poor" households that receive a social assistance transfer (COV-P). The dataset also contains information on the percentage of all households that receive a social assistance transfer (COV-T).

The above variables are available for two different poverty lines, i.e., for an extreme poverty line and a poverty line set at the 20th percentile so that 20 percent of the population are always deemed to be poor in the absence of transfers. Throughout the rest of the paper, we focus on the poverty gap measure of poverty which is defined as:

$$PGI = \frac{1}{N}\sum_{h=1}^{H}\left(\frac{y^h - z}{z}\right) \quad for\ all\ \ y^h < z$$

where *PGI* is the poverty gap index, y^h is the income of individual *h [equivalized income of household h]*, *z* is the poverty line (set at either the extreme or 20 percent poverty level), *N* is the total population size, and the poverty gaps for individuals above the poverty line are set equal to zero (i.e. $y^h - z = 0$ for all $y^h > z$). This can be rewritten as:

[10] We thank the World Bank's ASPIRE team for clarification discussions and for also making additional data available. For more details on the data construction see https://www.worldbank.org/en/data/datatopics/aspire/documentation.

[11] A more comprehensive analysis would require country-specific evaluations of administrative capacity as this varies widely across income levels and institutional contexts and has a material impact on the efficacy of the social safety net. In particular, fragile states tend to have very weak implementation capacity due to factors such as governance and institutional quality.

[12] While the use of the poverty gap measure captures well the efficiency of beneficiary targeting, it does not capture the efficiency related to differentiating benefits according to the size of the poverty gap (see footnote 7). This would require the use of a measure such as the severity of poverty which attaches a higher weight to transfers to the poorest of the poor.

$$PGI = \frac{1}{Nz}\sum_{h=1}^{H}(y^h - z) = \frac{1}{Nz}\sum_{h=1}^{H}(PG^h) \quad for\ all\ y^h < z$$

where PG^h is the individual poverty gap of a poor individual, which equals the poverty line minus individual income. Since *Nz* is constant and independent of the size of transfers, we can then calculate the percentage decrease in the *PGI* due to social assistance transfers as:

$$\Delta PGI = \frac{PG_{pre} - PG_{post}}{PG_{pre}}$$

where *PG* is the *total poverty gap* calculated as the sum of individual poverty gaps across poor individuals, with subscripts denoting before (*pre*) and after (*post*) transfers. Since the benefit-cost ratio (*BCR*) in *ASPIRE* is calculated as the numerator (ΔPG) divided by the total transfer budget (*B*) this can be further rewritten as:

$$\Delta PGI = BCR.\frac{B}{PG_{pre}} = BCR.BR \tag{6}$$

so that the poverty impact of transfers (ΔPGI) equals the product of the level of transfer efficiency (*BCR*) and the ratio of the total transfer budget to the total pre-transfer poverty gap (*BR*), i.e., the ratio of the transfer budget to the size of the poverty problem.

Both ΔPGI and *BCR* are available from the *ASPIRE* database for the extreme and 20 percent poverty gaps. With these two parameters, we can back out the *BR* from (6) as (ΔPGI/*BCR*). This facilitates a consistent and complete analysis of the performance of each country's SSN in terms of poverty impact (*PI*), transfer efficiency (*BCR*), and transfer budget ratio (*BR*). Differences in poverty impact (*PI*) across countries can then be separated into differences due to variation in *BCR* and *BR*. When focusing later on the *adequacy* of the total transfer budget we will want to compare the existing transfer budget to that required to eliminate poverty. To do this we use additional information kindly provided by the World Bank's *ASPIRE* team on the size of the existing transfer budget (*B*) and GDP, both in purchasing power parity (PPP) at 2011 prices. Using this, we can calculate the total pre-transfer poverty gap (PG_{pre}) as (*B/BCR*). We will then compare the actual budget (*B*) as a percent of GDP to both the (minimum) budget required under perfect targeting (i.e., the pre-transfer total poverty gap) and under imperfect targeting (i.e., factoring in the inevitable existence of budget leakage to the non-poor). This is discussed further below.

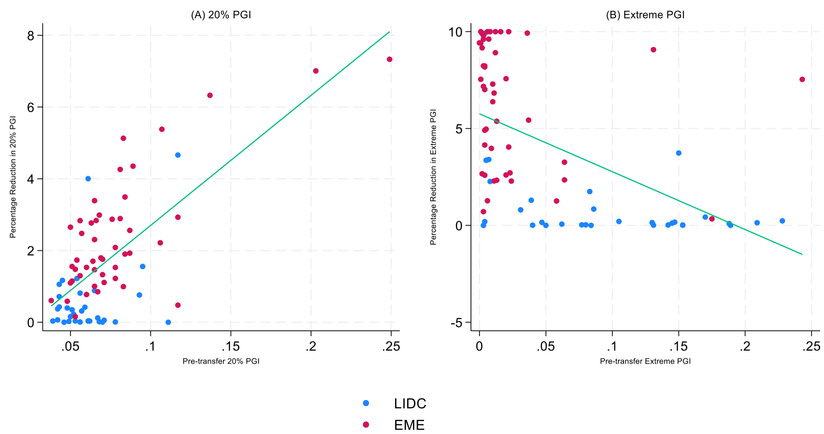
IV. Poverty, Transfer Efficiency, and Budget Effort

We start by discussing the variation in the poverty impact of transfers (PI) and its relationship to initial pre-transfer poverty levels. We then analyze the relationship between PI and its two determinants, namely, transfer efficiency and budget effort. Annex II Figures 1-6 at the end of the paper show the regional distributions of the variables discussed below. Reflecting data availability, we focus on both the extreme poverty gap (i.e., poverty using a common poverty line of $1.9 in 2011 PPP terms) and the 20% poverty gap (i.e., poverty using the 20th percentile income level for each country). In the figures below we add a linear trend line primarily to show the overall (or average) relationship between variables and to provide a starting point for a deeper discussion of the observed relationship, especially where the linear trend is clearly not capturing well the relationship between the variables.

A. Poverty Levels and Impact

While the *ASPIRE* database contains information on the poverty impact of social assistance transfers (i.e., the percentage reduction in *PGI*), it does not have information on pre-transfer and post-transfer poverty indices. However, a more complete database on poverty impacts was available from the World Bank's *ASPIRE* team on request. We therefore use this latter database in Figure 2 to show the relationship between the poverty impact of transfers and pre-transfer poverty levels.[13]

Figure 2. Poverty Impacts and Pre-transfer Poverty Gaps



Source. Authors' calculations based on World Bank ASPIRE database and additional data provided by ASPIRE team.
Note. The sample is made up of 79 countries from CCA(7), EMDE(12), LAC(15), EDA(16), MENA(5), and SSA(24).

Focusing first on the impact of transfers on the 20% Poverty Gap (Panel A), we observe a strong positive correlation between initial pre-transfer poverty levels and the impact of transfers. Therefore, countries with the highest initial poverty levels achieve the highest poverty reductions from transfers. From a visual inspection of Panel A, it should also be clear that this positive relationship would be higher if we excluded outlier countries with high pre-transfer poverty levels, such as Georgia and South Africa. Pre-transfer poverty rates are lowest in the Emerging and Developing Asia (EDA) and Middle East and North Africa (MENA) regions (both with a *PGI*s of 0.059) and highest in the Latin America & Caribbean region (LAC; with a *PGI* of 0.085). The Caucasus and Central Asia (CCA), Emerging and Developing Europe (EMDE), and Sub-Saharan Africa (SSA) regions all have intermediate PGIs at approximately 0.073. The countries with the lowest poverty impacts are in SSA, MENA, and EDA (Appendix Figure 1).

[13] A comparison of the information on the percentage reduction in poverty in both databases shows these are very similar although not identical. The poverty headcount and poverty gap impacts may be underestimated since household surveys do not necessarily include all social protection programs in a country or may not attach a monetary value for some of those included. Pre-transfer income is calculated using ADePT SP v1 simulation and includes 50 percent of social insurance and labor market transfers.

Turning to the impact of transfers on extreme poverty (Panel B), where the extreme poverty line is set at $1.9 per day in all countries, we see a very different relationship. While the average relationship between initial extreme poverty and the extreme poverty impact of transfers is negative, it is not very tight. There are many countries with relatively low extreme poverty impact but with a large variation in initial poverty levels, most of which are in SSA. At the same time, there are many countries with much lower initial extreme poverty but with a very large variation in impact. Among these countries, those with the highest impacts tend to be in the CCA and EMDE regions, followed by countries in LAC with mid-range impacts. Again, Georgia and South Africa are clear outliers with relatively high levels of extreme poverty and poverty impact.

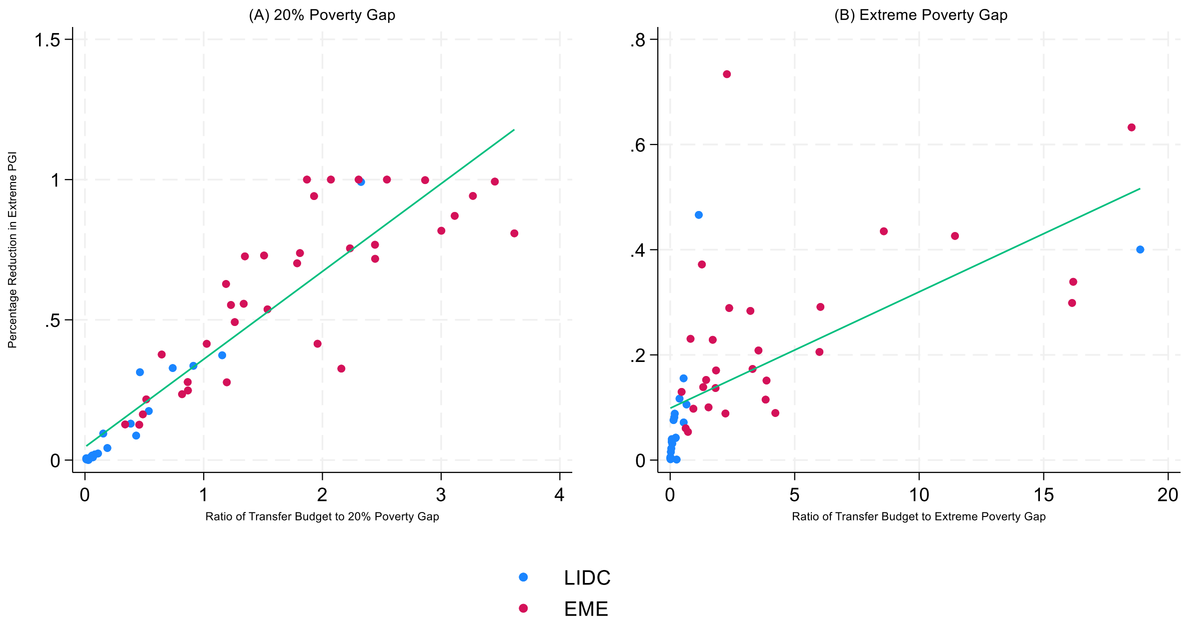
B. Transfer Efficiency and Budget Effort

In Section II we showed that the poverty impact of transfers is a product of transfer efficiency (BCR) and the transfer budget ratio (BR). Figures 3 and 4 present the relationship between these three variables; for this analysis the country sample falls to 59 countries. The relationship between the poverty impact of transfers (PI) and the budget ratio is shown in Figure 2. Focusing on the 20% poverty line, we observe a very strong positive relationship between budget ratio and poverty impact (Panel A). It is notable that among the countries with relatively high poverty impact are several EMDE countries that completely eliminate poverty. The other countries with relatively large budget ratios and poverty impact exceeding 80 percent are mainly CCA countries. Countries in LAC tend to have mid-range budget ratios and poverty impact, while countries in SSA mostly have both low budget ratios and low poverty impact (Appendix Figure 3). While we find a similar positive relationship for extreme poverty (Figure 3, Panel B), this is much weaker, mainly due to a few countries where large budget ratios do not deliver commensurately large poverty impacts because of low efficiency (see below), which in turn reflects low extreme poverty rates.[14]

Figure 4 presents the relationship between transfer efficiency (BCR) and transfer budget ratio (BR) for both 20% poverty (Panel A) and extreme poverty (Panel B). While the relationship is positive for both the 20% and extreme poverty lines, i.e., countries with high budget ratios also tend on average to have high transfer efficiency, it is a very weak relationship in both cases with substantial variation around the average. For instance, if we ignore the 8 countries in Panel A with the lowest transfer efficiency (below 0.2; mostly SSA countries), then countries would be spread across the four quadrants designating high-low transfer efficiency and high-low budget effort. Similarly, in Panel B, countries can be separated into those with low budget ratios and those with low transfer efficiency. Those with low budget ratios have very high variation in transfer efficiency, while those with low transfer efficiency have very large variation in budget ratios. Therefore, for the first country group of mainly SSA countries with transfer budgets below their total extreme poverty gaps, almost all the variation in impact is explained by variation in transfer efficiency. For the second group, almost all the variation in impact is explained by variation in budget effort with many of these countries (mostly in EMDE and LAC regions) having transfer budgets well in excess of their total extreme poverty gaps.

[14] Note that since countries with very low extreme poverty rates likely focus on a broader definition of poverty (e.g., using national poverty lines above $1.9 per day), efficiency is probably more usefully measured with reference to these higher poverty lines.

Figure 3. Poverty Impact and Budget Effort for Extreme and 20% Poverty Gaps

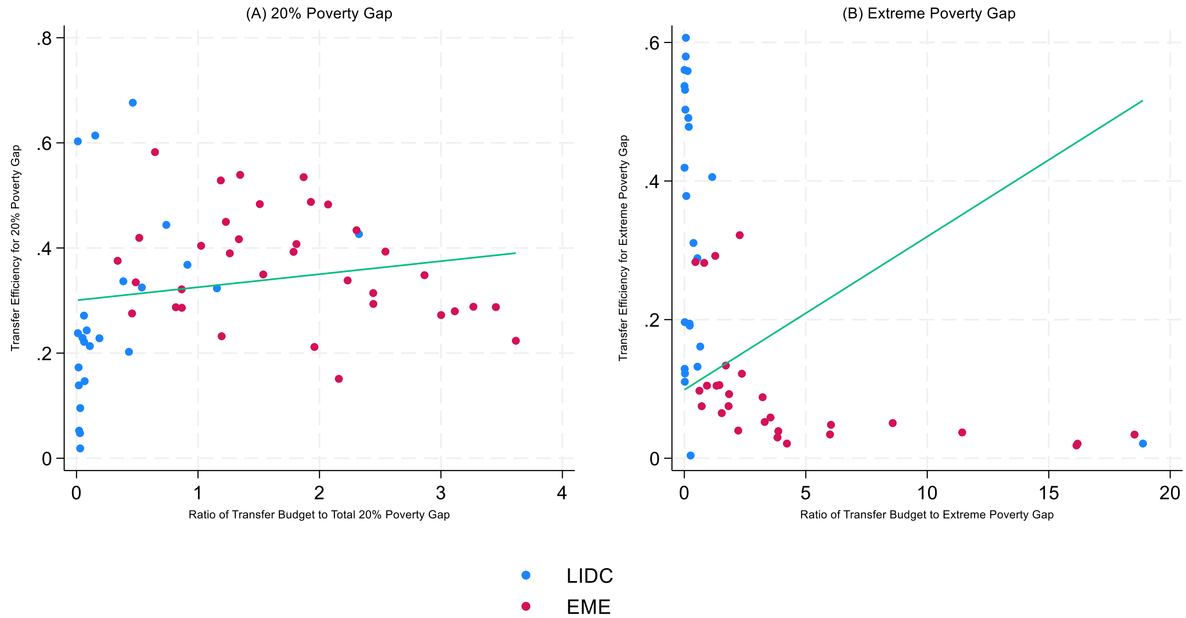


Source. Authors based on World Bank ASPIRE database.
Note. The sample is made up of 59 countries from CCA(4), EDE(8), LAC(13), EDA(13), MENA(2), and SSA(19). For presentational purposes, Panel B drops 7 countries with BR>30 (Belarus, Kazakhstan, Russia, Ukraine, Chile, Uruguay, Malaysia).

We also use ANOVA decomposition to get a sense of the relative importance of variation in budget ratios and in transfer efficiency across countries in determining variation in their poverty impacts from transfers. In the case of the 20% poverty line, the R-squared from separate regressions of poverty impact on transfer efficiency and budget ratio show that while variation in budget ratios explains 84 percent of the total variation in impact, variation in efficiency explains only 19 percent. ANOVA analysis shows that variation in budget ratios explains just over 90 percent of the total explained variation. In the case of the extreme poverty line, ANOVA decomposition shows that each explains approximately half of the total explained variation in poverty impact. However, from Figure 4 (Panel B) we see that most SSA countries have similar small budget ratios with substantial variation in transfer efficiency, while most other countries have similar low transfer efficiency levels but large variation in budget ratios.

In summary, the above discussion makes clear that the main factor explaining the variation in the poverty impact of SSNs in EMDEs is variation in budgets. This finding holds across all EMDEs in the context of the 20% poverty line, and for low-income countries in the context of the extreme poverty line. Section VI below therefore focuses on how much (and how much more) countries need to spend to eliminate poverty. However, it also emphasizes that the answer to this question depends not only on the size of the poverty gap but also the level of transfer efficiency. Therefore, since eliminating poverty also requires full coverage of poor households, we first discuss the relationship between transfer efficiency and coverage.

Figure 4. Transfer Efficiency and Budget Effort for Extreme and 20% Poverty Gap



Source. Authors based on World Bank ASPIRE database.
Note. The sample is made up of 59 countries from CCA(4), EDE(8), LAC(13), EDA(13), MENA(2), and SSA(19). For presentational purposes, Panel B drops 7 countries with BR>30 (Belarus, Kazakhstan, Russia, Ukraine, Chile, Uruguay, Malaysia).

V. Household Coverage and Transfer Efficiency

A key challenge facing many EMDEs is how to effectively channel resources to poor households while containing the associated fiscal cost. Most EMDEs do not have the capacity to effectively implement well-targeted means-tested transfer schemes. This can reflect a range of factors such as low administrative capacity, a large "informal" sector constituting small-scale and self-employment activities, individuals with multiple and volatile sources of income (including in-kind income), and poor or non-existent bookkeeping. These characteristics make verification of income very difficult, especially for low-income individuals. There may also be a reluctance to do means testing for social or political reasons (e.g., beneficiary stigma or the desire to ensure middle-class support for redistribution), or the costs of individuals acquiring sufficient capacity to comply may be deemed undesirable or prohibitive.[15]

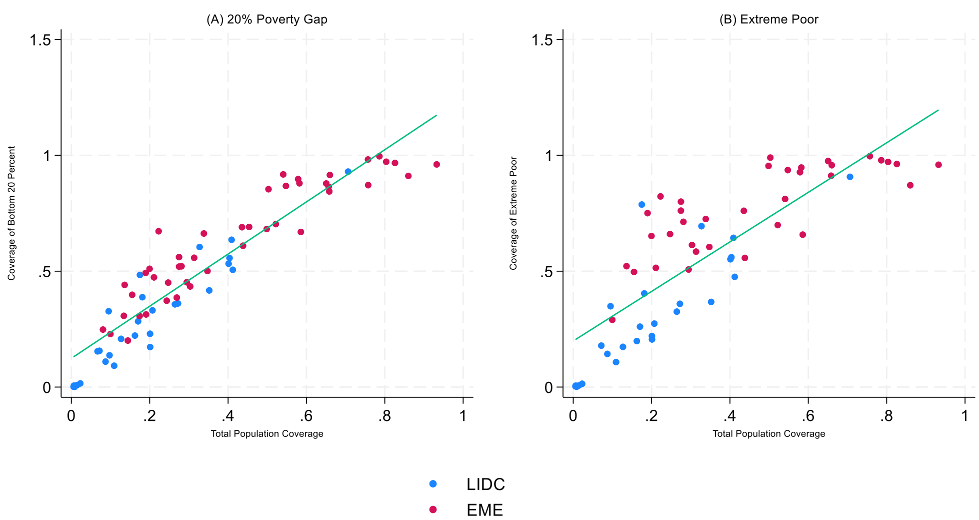
In such circumstances, countries often revert to less sophisticated approaches to targeting transfers, including the use of categorical criteria that are deemed to be closely related to poverty, such as being disabled, having young children or elderly parents in the household, or living in very poor areas. However, the use of such categorical targeting presents its own challenges that limit its targeting effectiveness. While narrow categorical

[15] Increasingly, digitalization could be a ready solution to many administrative and informational problems and may be able to be implemented without prohibitive cost (see, for example Chapter 2 of the IMF's April 2018 Fiscal Monitor). However, digitalization may still be out of reach in some countries and so the discussion of other approaches to targeting below still hold.

targeting—such as basing eligibility for transfers on being disabled, orphaned, or an elderly widow—can be effective at channeling most of the transfer budget to low-income households, it significantly limits coverage of poor households resulting in very large coverage gaps. On the other hand, while broad categorical targeting (such as say child benefits or social pensions) can expand coverage, it typically comes with substantial leakage to higher-income households. For instance, while many children may live in poor households, not all children are poor (resulting in leakage to the non-poor) and not all poor households have children (resulting in undercoverage of the poor). One could, for example, start by focusing on very young children to limit leakage (i.e., improve transfer efficiency) but his would result in high undercoverage of poor households. Expanding eligibility across age groups will help to increase coverage of poor households but at the cost of increasing leakage to the non-poor.

This targeting constraint means that we expect to see substantial leakage of transfers to non-poor households in countries that attempt to achieve high coverage of poor households using categorical targeting methods. This is confirmed by the data presented in Figure 5, which shows the relationship between total population social assistance coverage (COV-T) and coverage of poor households (COV-P). For both poverty lines, we see a strong positive relationship between total coverage and coverage of the poor. In both cases, no country achieves high coverage of poor households without having high total coverage. This relationship in turn suggests that increasing coverage of the poor inevitably comes with higher leakage and thus *ceteris paribus* lower targeting efficiency. All of the countries with coverage of the poor above 80 percent have total population coverage above 50 percent. In the context of the poorest 20 percent, those achieving near to full coverage of the poor have total coverage above 70 percent.

Figure 5. Population Coverage for Extreme and 20% Poor



Source. Authors based on World Bank ASPIRE database.
Note. The sample is made up of 84 countries from CCA(7), EDE(14, LAC(15), EDA(16), MENA(7), and SSA(25).

One also expects that leakage to the non-poor decreases as the share of the population in poverty (i.e., the poverty headcount) increases—clearly when everyone is deemed poor then leakage will always be zero. Table 1 presents regression results capturing the relationship between coverage of the poor and total coverage as well as, in the case of extreme poverty, the poverty headcount. For both poverty lines, and consistent with Figure 5, coverage of the poor increases with total coverage but at a decreasing rate, and all coefficients are significant at the 1 percent level. For extreme poverty, as expected, we also find a negative relationship between coverage of the poor and the share of the population that are classified as poor.

Table 1. Relationship Between Coverage of Poor, Total Coverage, and Poverty Headcount

	20% Poverty		Extreme Poverty			
Total coverage	1.125***	1.906***	1.069***	2.219***	0.957***	1.879***
Total coverage squared		-0.928***		-1.356***		-1.072***
Poverty Headcount					-0.634***	-0.567***
Constant	0.124***	0.189***	0.199***	0.040***	0.341***	0.200***
R-squared	0.872	0.906	0.688	0.758	0.807	0.85
No. of Observations	70	70	61	61	60	60

Source: Authors calculations based on *ASPIRE* data.
Note: The regressions for the poorest 20 percent do not control for the initial pre-transfer poverty headcount rate since this should be 20 percent constant across countries. However, it seems that *ASPIRE* bases the poverty headcount on post-transfer income. "***" denotes significant at the 1 percent level.

For simulation purposes, we can use the regression results to determine the total population coverage required to reach a certain level of coverage of the poor. We can write the regression specification as (ignoring the error term):

$$C_P = a + b_1 . C_T + b_2 . H$$

where C_P is the coverage of the poor, C_T is total coverage, H is the poverty headcount, and the *b*s are the associated regression coefficients. Solving out for total coverage gives:

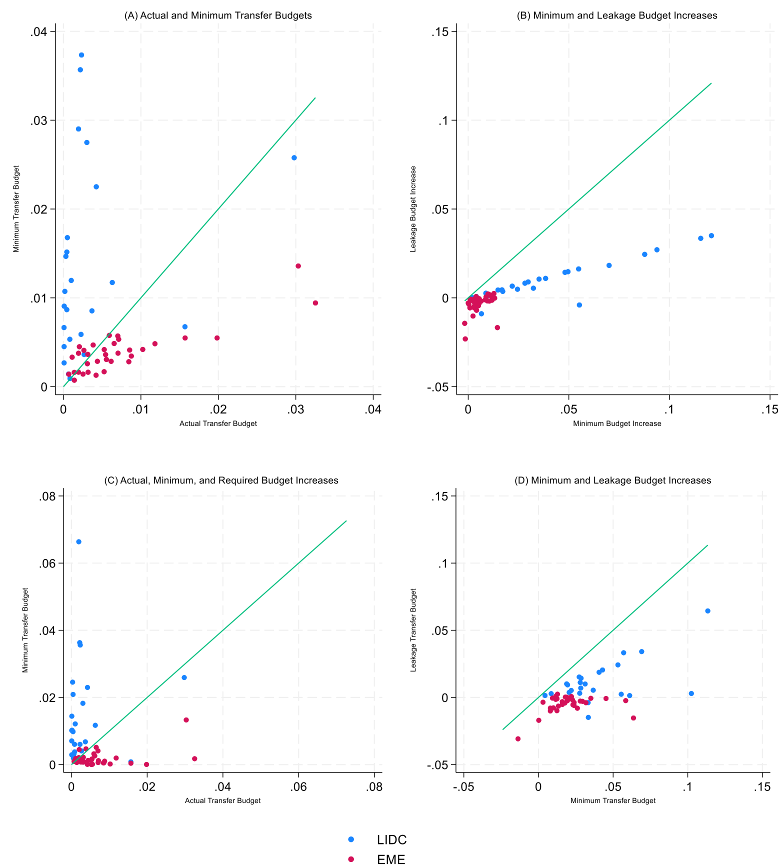
$$C_T = \left(\frac{C_P - a}{b_1}\right) - \frac{b_2}{b_1} H$$

We can then use this equation and the results in Table 1 to find the required total coverage to reach a target coverage of the poor. If we ignore the role of *H*, i.e., calculate required coverage based on the first and third columns of Table 1, then in the context of the poorest 20 percent we would require a total coverage of (60, 69, 78) percent to reach a target coverage of the poor of (80, 90, 100) percent. The corresponding required total coverage for extreme poverty would be (56, 66, 75) percent. However, in the context of extreme poverty, the required total coverage would also decrease with the extreme poverty headcount rate. We will use such calculations below to calculate the required budget to eliminate poverty in the presence of leakage.

VI. Transfer Spending Adequacy

The analysis in Section IV found that variation in budget ratios explained most of the variation in poverty impact across countries when we focused on the 20 percent poverty line, and for most low-income countries for extreme poverty. Increasing transfer budgets is therefore a priority for countries wishing to eliminate poverty. We can get a sense of the budget required to achieve poverty elimination in each country by first looking at the size of the total poverty gap, which represents the *minimum* budget required under perfect targeting.[16] Figure 6a (Panel A) shows that this budget gap is large (e.g., greater than 1 percent of GDP) in many countries, especially in SSA. Outside of SSA, this gap is lower or even negative, especially in EDE, CCA, and LAC countries. However, this comparison is a significant underestimate of the budget actually required given that expanding coverage of the poor in most EMDEs, which is needed to fully eliminate poverty, inevitably requires leakage of transfers to the non-poor and therefore a budget higher than the minimum budget.

Figure 6. Actual, Minimum, and Required Budget Increases



Source. Authors based on World Bank ASPIRE database.
Note. The 45-degree diagonal lines represent combinations where the minimum budget equals the actual budget. Countries situated above (below) this line have actual budgets below minimum budgets. For presentational purposes we drop Belarus, which as an actual transfer budget of 7.3 percent of GDP.

Here we focus on the results for the 20% poverty line (Figure 6a), which are qualitatively very similar to those for the extreme poverty line (Figure 6b). Based on the analysis in the previous section, which showed that higher coverage of the poor requires higher leakage to the rich, if we take a conservative target of 90 percent coverage of the poor then we need to cover 70 percent of the population rather than 20 percent under the *minimum* budget. Assuming a uniform transfer set at the average individual poverty gap, this means that the

[16] It's important to highlight that our concept of spending adequacy encompasses both coverage of the poor and the levels of benefits they receive. A more thorough examination of the trade-offs between these two aspects necessitates detailed household survey data.

required budget in the presence of leakage is 3.5 (i.e., 70/20) times larger than the minimum budget. Figure 6a (Panel B) shows that the required budget increase to achieve this exceeds 3 percent of GDP in many countries, especially in SSA. Such an increase is clearly not feasible in most of these EMDEs, many of whom have total tax ratios below 15 percent of GDP and many competing claims on the budget in support of broader development goals (Clements and others, 2015; Gaspar and others, 2016; Coady, 2018). Given their low tax capacity, most of these countries would even struggle to increase government revenues by 1 percentage point of GDP in the short term.

VII. Enhancing Targeting Efficiency

In the short term, revenue raising constraints imply that many countries will need to enhance their capacity to better target SSN transfers to lower-income households both by minimizing leakage to higher-income households and delivering higher benefit levels to those with lower incomes. Given administrative and structural constraints, most EMDEs are unlikely to be able to quickly develop the more sophisticated means-tested program designs observed in higher-income countries.[17] However, adoption of some form of *proxy-means testing* can, if carefully designed, may provide a more promising approach to enhancing targeting efficiency in the short term.[18]

Basing eligibility for transfers on proxy-means tests (PMTs) has become more prevalent, and indeed more contentious, in recent years. A PMT is essentially a more sophisticated form of categorical targeting, and attaches a continuous score to households based on various household characteristics found to be strongly correlated with household welfare—the "weights" attached to these variables are often based on the coefficients from a regression analysis of income or consumption on these characteristics.[19] It has been argued that, by design, this approach is prone to significant leakage of benefits to non-poor households and undercoverage of the target poor population, especially when targeted at the poorest population (Brown, Ravallion, and van de Walle, 2016). The horizontal inequity resulting from undercoverage, the random nature of exclusion, and the associated lack of transparency in defining eligibility, all have the potential to generate significant community unrest as excluded poor households observe the unfair inclusion of similarly poor households and even better-off households. This points to the central challenge of minimizing the trade-off

[17] It is commonly argued that the capacity of a country to target transfers (e.g., through use of means-tested programs) increases over the long term with the level of its development, reflecting both changes in the structure of the economy (e.g., in the relative size of the formal sector) and increases in human capital. Indeed, a simple regression analysis based on *ASPIRE* data finds that a 10 percent increase in GDP per capita is associated with a 4.6 percent increase in targeting efficiency. One also expects sustained inclusive economic growth to make a significant contribution to decreasing the size of the poverty problem both through its direct impact on household incomes and on higher revenues that can be used to finance higher social assistance transfers and other inclusive social spending. A recent analysis by Ravallion (2022) estimates an average elasticity of the poverty rate to growth in mean income of -2.2, i.e., on average, there is a 2.2 percent decrease in poverty for every 1 percent growth in per capita real income. Therefore, on average, a growth in mean income of 25 percent over say 5 years would decrease poverty by just over 55 percent.

[18] In this section we focus primarily on the technical dimensions of PMTs. Implementing such systems requires a range of supporting investments, including in strengthening information systems, implementation capacity, institutional arrangements, and fiscal capacity (Grosh et al. 2022). Numerous countries have successfully strengthened their SSN systems to facilitate the adoption of PMTs, including Argentina, Brazil (*Bolsa Familia*), Chile (*Ingreso Familiar de Emergencia*), Colombia (*Ingreso Solidario*), Peru, Mexico (*Progresa/Opportunidades*), Moldova (*Ajutor Social*), and Pakistan (*Ehsaas Emergency Cash*). See Annex I for a discussion of the needed complementary investments required for enhancing targeting efficiency.

[19] The use of categorical targeting based on relatively exogenous characteristics not easily manipulated by households may also reduce the inefficiency associated with graduated transfers reflecting work disincentives.

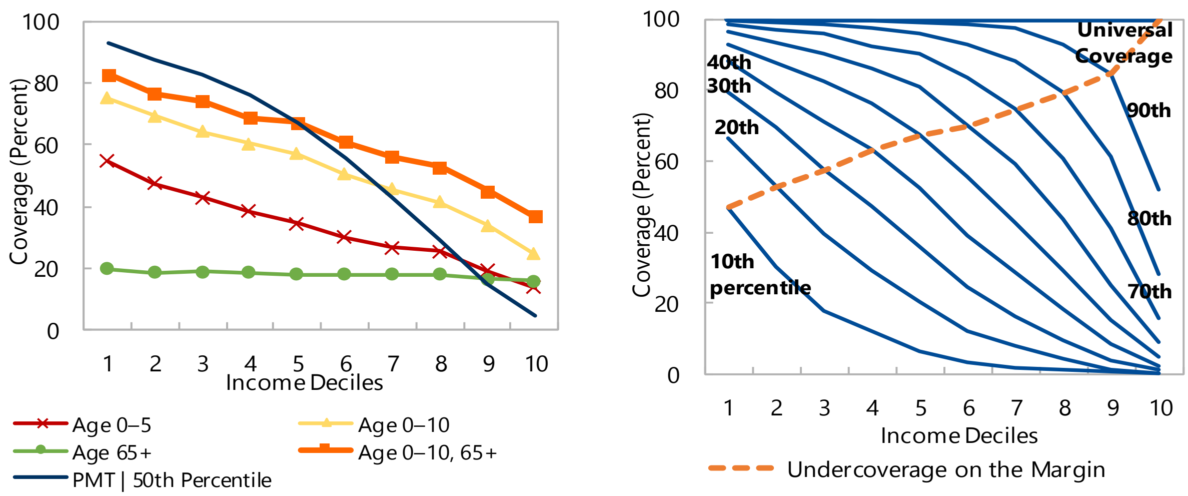
between enhancing targeting efficiency (or vertical equity) and exacerbating undercoverage and leakage (or horizontal equity).[20]

To get a sense of the potential benefits and challenges associated with the use of PMTs, we draw on the results of a simulation analysis undertaken by Coady and Le (2020) based on household survey data for India. Figure 7 presents the salient results. The left-hand side panel compares coverage under different, relatively simple categorically targeted schemes based on age (i.e., universal child benefits and social pensions) to that under a PMT. The slopes of the coverage lines capture targeting efficiency with a steeper slope indicating higher efficiency. Uniform transfer levels for children up to 5 years are relatively progressive, with coverage starting at 50 percent for the bottom two (poorest) quintiles and falling to around 15 percent for the top (richest) quintile. Expanding eligibility to children up to 10 years would increase *total* household coverage from 33 percent to 50 percent, with coverage increasing similarly across all income groups. Further expanding eligibility to include the elderly would similarly increase coverage across all income groups, with total coverage increasing to 62 percent and coverage of the bottom two deciles to approximately 80 percent.

Figure 7. Coverage Under Alternative Categorical and Proxy-means Targeting

A. Categorical Targeting

B. Proxy-means Testing ("Onion effect")



Source: Reproduced from Coady and Le (2020; Figure 4) based on Indian 2011 National Sample Survey.
Note: Income (or welfare) deciles are based on household per capita income, with 1 being the poorest and 10 the richest. The PMT regression includes explanatory variables reflecting: Household size, Number of Dependents 0–14, Age of the Household Head, Marital Status of the Household Head, Education of the Household Head, District dummies, Employment category, and Social Group.

The simulation results help bring out the trade-off between expanding coverage under categorical targeting, poverty impact, and fiscal cost. If the level of the uniform transfer is held constant across transfer schemes, then the total transfer budget for the expanded child benefit (0–10yrs) program would be 57 percent higher than the smaller (0–5yrs) program, and 87 percent higher when the elderly are included. But, of course, the poverty impact would also be higher. Alternatively, under a fixed budget, transfer levels would need to fall by 36 percent and 46 percent, respectively, resulting in a lower poverty impact.

[20] Neither does the structural nature of the PMT approach lend itself to addressing poverty arising from income shocks since such shocks may significantly change the relationship between poverty and structural variables included in the PMT score. For a discussion of how SSNs can be used to better address shocks, and the associated administrative challenges, see Brollo et al (2024).

This trade-off can be reduced through PMT, which has the steepest line in Panel A and therefore the highest transfer efficiency. The simulated PMT covers 50 percent of the population with coverage of approximately 90 percent of the bottom two deciles, falling to around 50 percent at the fifth decile, and almost zero coverage of the top decile. This compares very favorably to the empirical relationship observed in Figure 5 where 90 percent coverage of the poorest 20 percent of the population required a total population coverage of 70 percent. This would in turn imply a lower budget requirement at about 70 percent (i.e., 50/70) of that estimated in Figure 5.

The right-hand panel of Figure 7 shows the implications of targeting different levels of population coverage with the PMT. The solid lines show how coverage across deciles varies for a given level of population coverage, with population coverage increasing from the south-west to north-east of the graph. As the program expands upwards from 10 percent of the population to 100 percent, coverage of lower-income groups increases significantly, reaching around 80–90 percent for the bottom quintile at 50 percent total population coverage. Expanding population coverage also results in the "iso-coverage line" changing from being convex to the origin to being concave, with the switch occurring around 50 percent population coverage. The declining steepness of each curve over the lower deciles captures their converging levels of coverage. This also points to a decline in horizontal inequity over these income groups, although this is never fully eliminated. For instance, the broken line shows how coverage in the marginal decile changes as total coverage expands (the "coverage on the margin" line). At 10 percent population coverage, around 50 percent of the first decile is covered by the transfer program, while at 40 percent population coverage around 60 percent of the fourth decile is covered, and at 70 percent population coverage around 75 percent of the seventh decile is covered.

Transfer efficiency and horizontal inequities can be further reduced by differentiating transfer levels across households with different proxy-means scores, e.g., by giving higher transfer levels to households in lower deciles in Figure 7. This would have the effect of increasing the share of transfers accruing to lower-income groups above their share of beneficiaries (i.e., above their coverage share). It would also help to further dilute issues of horizontal inequity as the cost of misclassification of a poor household would be lower (i.e., a lower benefit rather than "all or nothing"), especially since misclassification tends to be greater around the cut-off point (i.e., around the total population coverage level).

Where countries do not have the administrative capacity or information required to design and implement a comprehensive PMT eligibility system, they can often make substantial inroads towards such a system over the short term by prioritizing some components, including by:

- Prioritize unifying beneficiary databases to create a unified registry of social programs to eliminate unwarranted double-dipping, cross-check information, and harmonize eligibility criteria. These databases can be combined with other administrative information that reinforces cross checking such as information from energy utilities and land registries. A good example of this approach can be found in Brazil's *Cadastro Unico*, the Federal unified registry of social programs, which acts as the focal point for undertaking eligibility assessments and calculating entitlements for a range of social assistance payments, including the flagship poverty alleviation program, *Bolsa Familia*. To enroll in the *Cadastro Unico*, a household must undertake an interview with municipal staff. While eligibility for *Bolsa Familia* is solely based on estimated household per capita income, staff collect information on additional household characteristics during the registration interview, including information on family composition, monthly expenses, access to water and electricity, schooling, and labor market status. This information is then used to flag any inconsistencies in the information provided as well as assist with the targeting of other forms of social assistance (Hellmann, 2015). Information is largely self-reported by households, but subjected to various external and internal cross-checks, including use of proxy indicators, to identify inconsistencies or anomalies in the information provided. Since 2016, the *Cadastro Unico* has been connected to an additional ten databases to further verify income and other household characteristic information (Brollo et al. 2024).

- Increasing coverage using simple but progressive demographic-based transfers (such as child benefits for 0-5 years in Figure 7A).

- Complementing more universal demographically targeted programs (such as child benefits and social pensions) that deliver basic benefit levels with other programs that require self-selection, such as geographically targeted public works programs. The differentiation of benefits across better targeted programs can make significant contributions to enhancing targeting efficiency.

- Requiring applicants to self-select into the program by applying online and providing information that can be used to undertake a basic PMT. Care should be taken to ensure the target poor population has the capacity to opt-in at affordable cost and that the information provided can eventually be verified. Households can provide information additional to that needed for the PMT, e.g., self-reported income and assets, that can be used as an initial screening mechanism and cross check (so-called hybrid PMTs). An example of a hybrid PMT can be found in Moldova's *Ajutor Social*. Initial eligibility for social protection is determined by the Social Assistance Automated Information System (SAAIS), which pools administrative data, including the transport, social insurance, and land registries as well as the employment agency database. Applications for transfers are entered into the system by social workers and are automatically cross-checked against these administrative data. Once verified, households are subjected to a two-stage "hybrid means-test" (Grosh and others, 2022). The first stage resembles a standard income means test based on formal income (verified against administrative data) plus estimates of imputed income (typically relating to hard-to-assess agricultural income). Households with income below a threshold are then subject to a proxy means-test which takes account of household characteristics such as disability status, number of children, and energy consumption. The result of this proxy means-test is a "deprivation score", which is compared to a threshold to determine final eligibility.

- Allowing households that were deemed ineligible by a basic PMT to provide additional supporting evidence regarding their poverty (i.e., an appeals system), although clear procedures and criteria to overturn PMT classifications are needed, possibly with the involvement of community organizations (e.g., churches, social groups).

- Gradually expand the PMT program by first targeting the poorest municipalities in the country. This helps to strengthen capacity for effective broader expansion, although it obviously leaves coverage gaps and raises concerns regarding horizontal inequity (e.g., many poor households live in non-poor municipalities). As indicated above, the PMT program can be complemented by a more universal categorical program that is eventually integrated into the PMT. Elements of this approach can be seen in Peru's *Juntos* cash transfer program. Eligibility for *Juntos* transfers is determined by a three-step process (ECLAC, 2024; Perova and Vakis, 2009). First, a household must live in an eligible district, with eligibility determined by Geographic Weighting Index (IPG), a multidimensional poverty index which considers variables such as exposure to violence, fulfillment of basic needs, the poverty gap, child malnutrition, and extreme income poverty. Districts with an IPG score over a certain threshold are deemed eligible for the transfer. Second, once a district is deemed eligible, a comprehensive survey is then undertaken of all resident households and the data collected used in a proxy means-test to determine a shortlist of eligible households. Third, the shortlist of eligible households is subjected to verification by community members and local and state authorities.

- Excluding many high-income households from the program using social security income data typically available only for those working in the formal sector.

- Using the personal income tax system to claw back benefits from high-income individuals.

VIII. Summary and Conclusions

In this paper we show how the standard social welfare framework can be used to assess the performance of SSNs in EMDEs in alleviating poverty and to identify key policy challenges. Within this framework, the poverty impact of a SSN system is decomposed into its transfer targeting efficiency (i.e., how ell transfers are channeled to lower-income households) and its budget effort (i.e., the size of SSN spending relative to the extent of the poverty challenge a country faces).

When we apply this framework to the World Bank's ASPIRE database, we find that the variation in the poverty alleviation achieved by SSNs in EMDEs is in large part driven by variation in the amount countries spend on their SSNs. This indicates that increasing SSN budgets is key to strengthening SSNs in EMDEs, especially in low-income countries. However, we also argue that a central challenge facing EMDEs is how to expand SSN coverage of poor households while containing leakage of benefits to higher-income households. No country in the sample of EMDEs examined achieves high SSN coverage of poor households without achieving high levels of total population coverage. We show that the implied spending increases for alleviating poverty with this level of leakage are substantially larger than that suggested by the gap between the minimum budget required (i.e., the size of the total poverty gap) and existing budget spending levels, with such gaps being prohibitive in most low-income countries. Therefore, given tight short-term financing constraints, reflecting difficulties in raising tax revenue ratios and competing development claims on the budget, countries will also have to find ways to improve transfer efficiency to enable high coverage of the poor while containing leakage to higher-income households.

We finish by discussing the potential for proxy-means testing to address this policy challenge, emphasizing the importance of careful design to manage the extent of horizontal inequity inherent in such an approach to targeting. Our simulations suggest that such an approach could reduce the required spending by about one third, or even more if transfer levels are differentiated according to proxy means scores. We also identify various coverage expansion strategies that countries with limited targeting and administrative capacity could employ in the short run as they gradually develop the capacity of their SSNs.

Annex I. Prerequisites for Effective Targeting Systems

At the center of high-performing SSN systems that accomplish broad coverage of poor and vulnerable households is the capacity to collect and process a wide range of socio-economic information to enable cost-effective program expansion through efficient targeting. In this respect, collecting information beyond income is crucial given the difficulties in verifying income of poor and vulnerable households with multiple and volatile sources of income. In addition, governments need the capacity to deliver transfers to eligible beneficiaries in a timely, reliable, and cost-effective manner. Enhancing targeting capacity therefore requires investment in the requisite institutional infrastructure, including (Grosh and others, 2008, 2022; Brollo and others, 2024):

- *Strong information systems*. This includes comprehensive and reliable identification systems and the ability to collect and verify existing and new socio-economic information (e.g., data on household characteristics, employment, and income), as well as the capacity to store and manage this information in a timely manner. During the pandemic, countries with comprehensive integrated social registries containing up-to-date information and broad coverage of the poor and the vulnerable population were able to successfully leverage these systems to provide additional support to existing beneficiaries and expand coverage to include additional vulnerable households at reasonable fiscal cost. Some countries that lacked unified social registries but had well-integrated sources of administrative data, including registries of beneficiaries of different social protection programs, civil registries, and tax records, were able to leverage this information to scale-up SSN programs and verify eligibility. On the other hand, countries that lacked social registries and integrated (or "interoperable") sources of administrative data, or where those systems had low coverage of the vulnerable population and out-of-date information, faced difficulties identifying those in need and had to collect new information under tight timeframes, with challenges for eligibility verification.

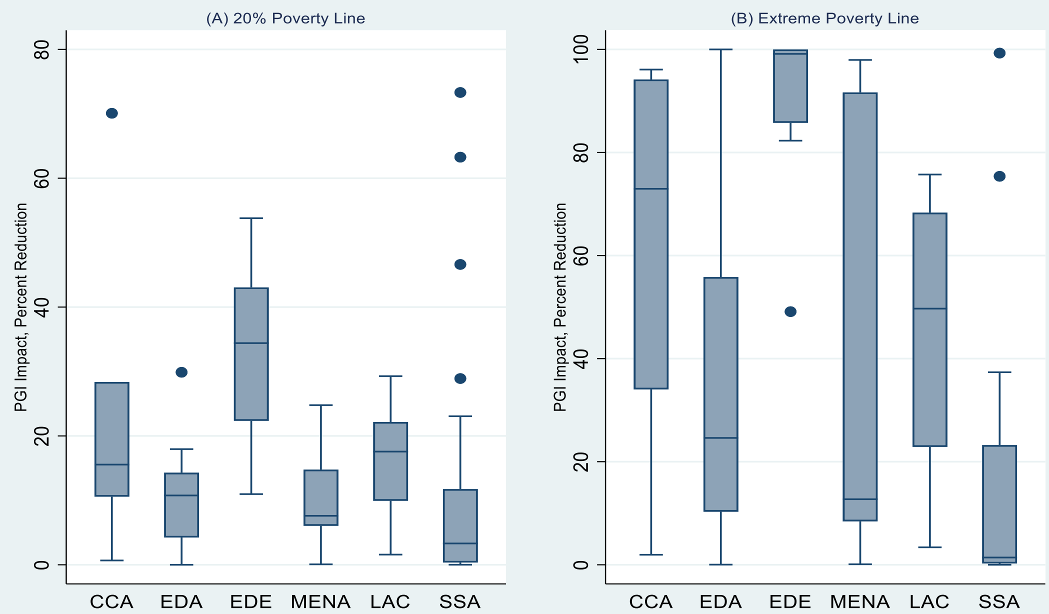
- *Strong implementation capacity*. This includes the capacity to deliver benefits to intended beneficiaries in a reliable, cost-effective, and timely manner. This requires administrative systems for service delivery, integrated across social protection programs, as well as robust systems for informed decision-making and accountability enhancement (e.g., grievance mechanisms and monitoring and evaluation systems), adequately supported by the required human resource capabilities and staffing. Electronic payment systems ("digital transfers") can help to increase the efficiency and transparency of cash-transfer delivery. However, while digital payments can be effective, they require an adequate payment ecosystem, including a strong legal framework for digital payments, interoperable payments infrastructure, broad electronic payments acceptance, strong cash out networks, and financial literacy.

- *Strong institutional arrangements*. This includes the capacity to develop clear and appropriate national social protection policies, implementation strategies, and supporting laws and regulations. Strong government leadership and clear roles and responsibilities of the different government entities involved in social protection are critical. Strong coordination mechanisms can help to enhance the efficiency and effectiveness of the SSNs and their response to shocks by reducing duplication, avoiding unnecessary delays, and improving the response to the needs of affected populations. Where relevant, governments also need to establish clear standards and procedures to guide the integration of non-governmental organizations and humanitarian actors.

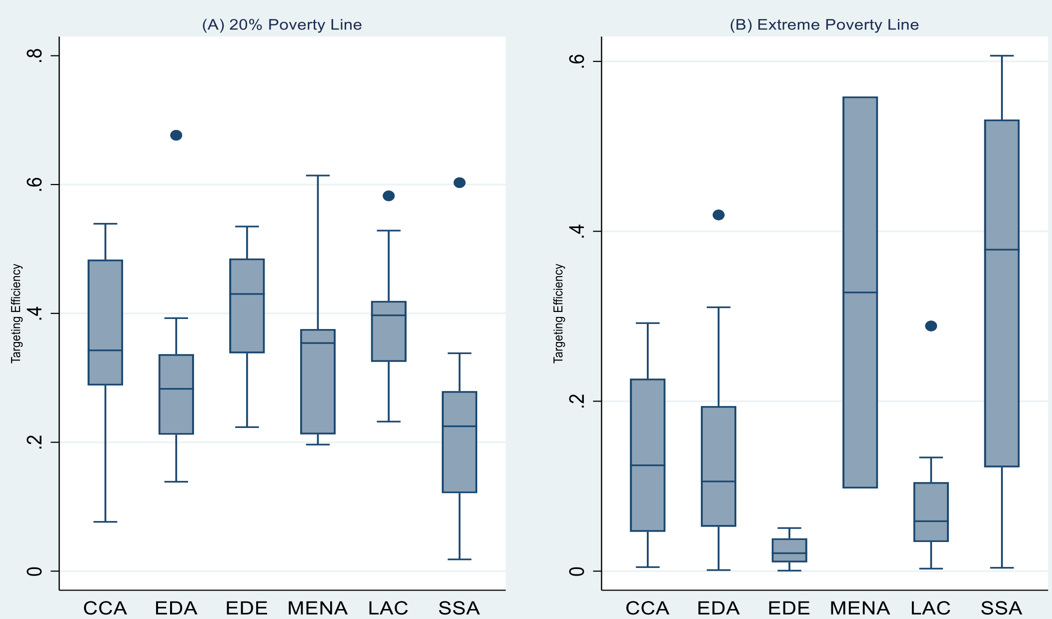
- *Strong fiscal systems*. Strengthening the capacity of SSN systems to address poverty and effectively respond to economic shocks requires creating the needed fiscal space in a sustainable and progressive manner to avoid undermining fiscal and macroeconomic stability. This should be predicated on a credible Medium-term Fiscal Frameworks (MTFFs) that reflects other spending needs and revenue mobilization capacity, including the required fiscal and economic reforms. Strong MTFFs help build fiscal buffers and can also facilitate the withdrawal of discretionary fiscal measures as the economy recovers.

Annex II. Tables: Distribution of Key Variables by Region

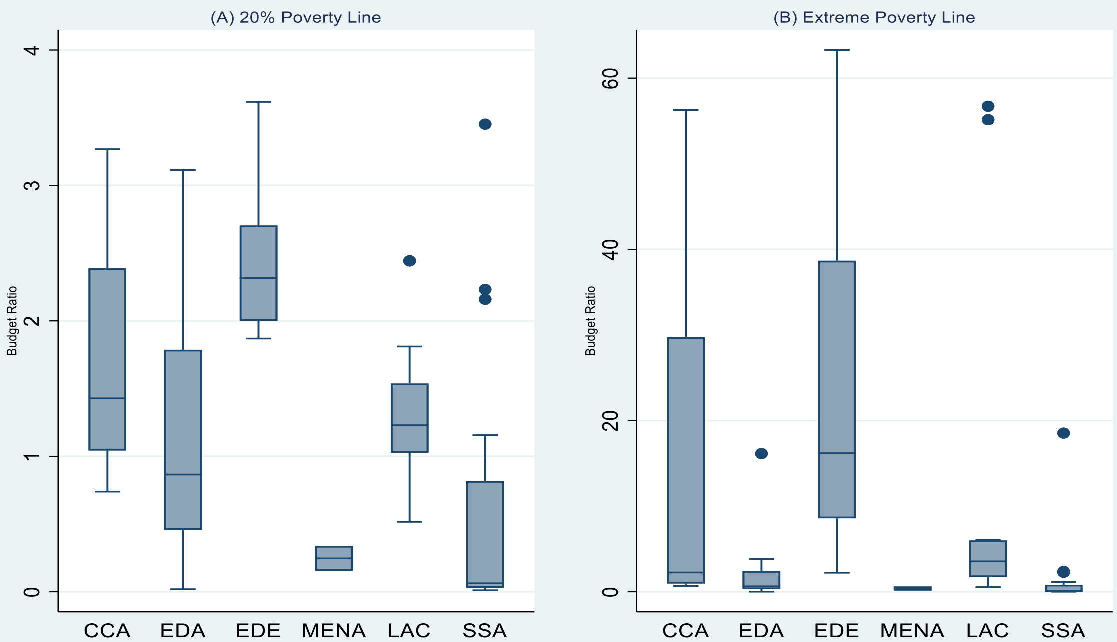
Appendix Figure 1. Distribution of PGI Impact by Region
(20% and Extreme Poverty Line)



Appendix Figure 2. Distribution of Targeting Efficiency by Region
(20% and Extreme Poverty Line)



Appendix Figure 3. Distribution of Budget Ratio by Region
(20% and Extreme Poverty Line)



Appendix Figure 4A. Distribution of Coverage of Poor by Region
(20% & Extreme Poverty)

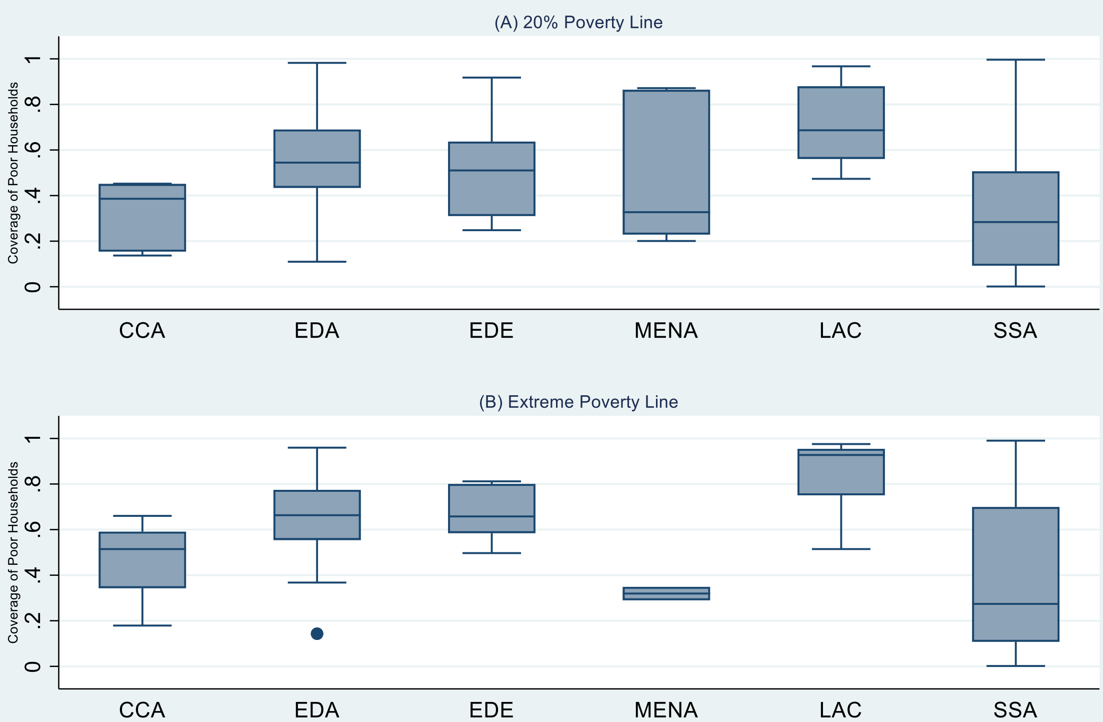
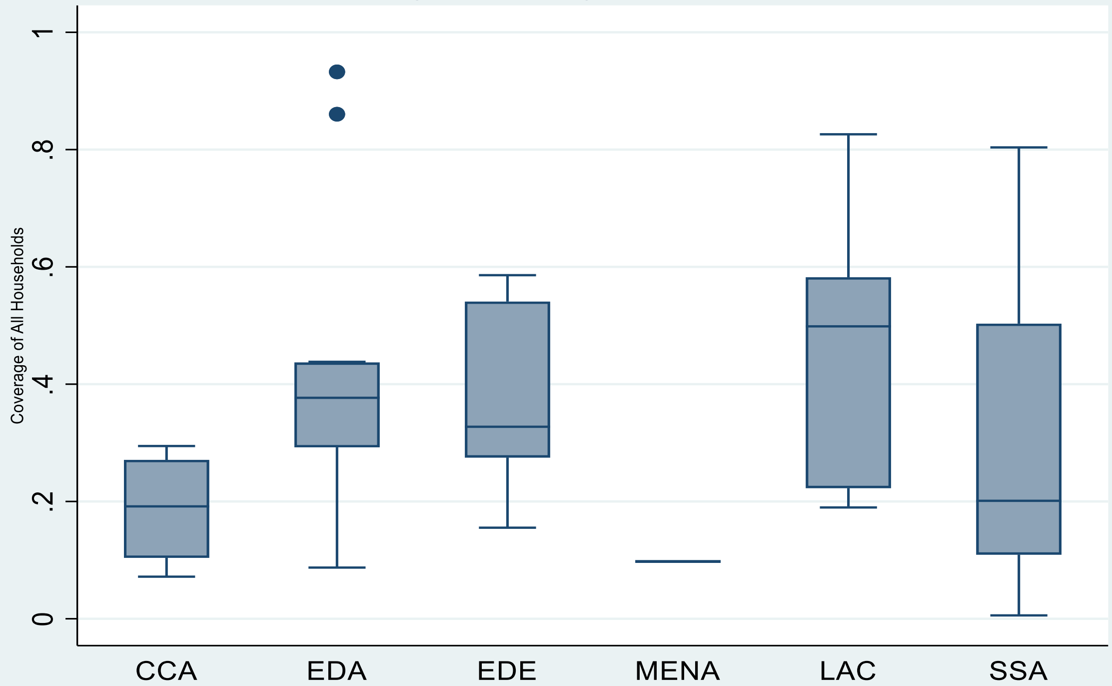
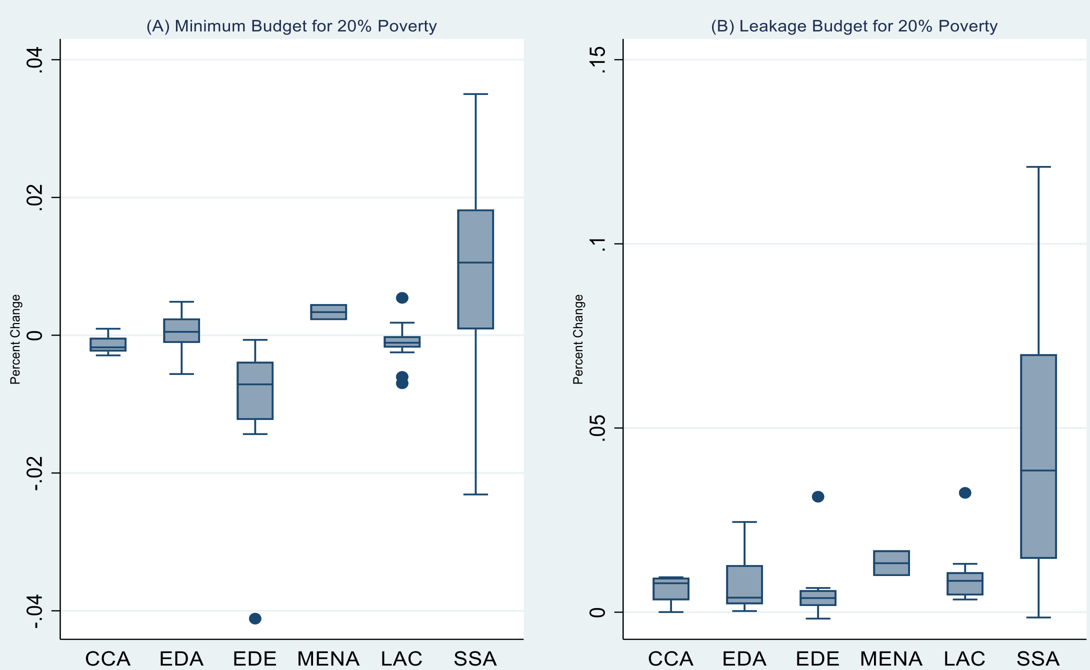


Figure 4B. Coverage of All Households



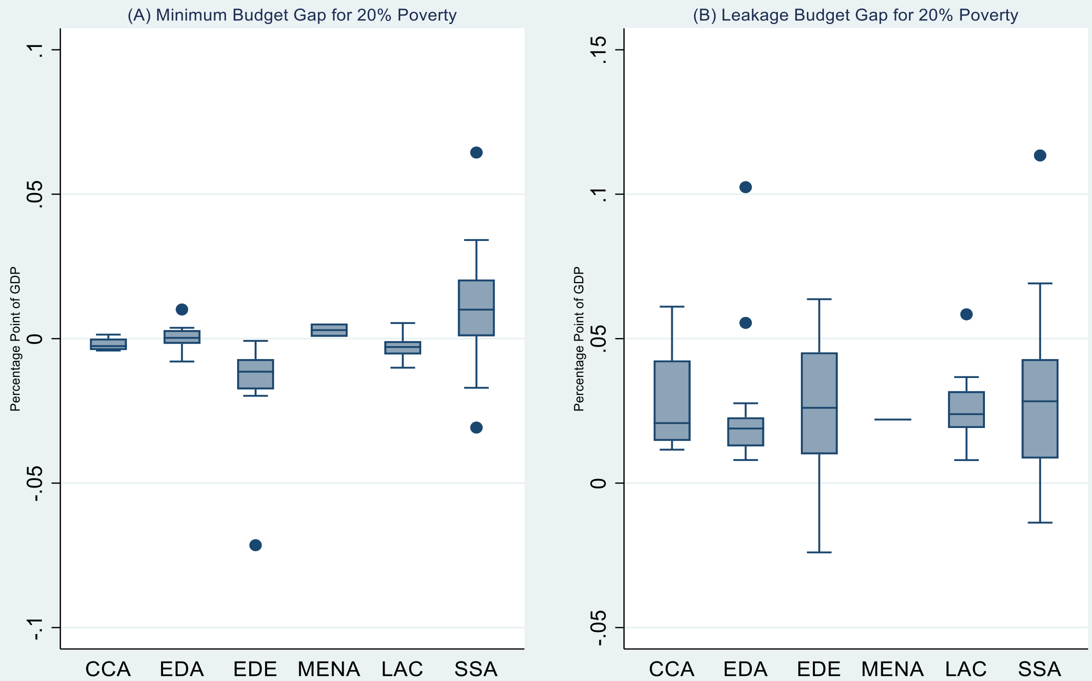
Appendix Figure 5. Distribution of 20% Poverty Budget Gaps by Region

(For Minimum and Leakage Budget Gaps)



Appendix Figure 6. Distribution of 20% Poverty Budget Gaps by Region

(For Minimum and Leakage Budget Gaps)



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Challenges Facing SSNs in Emerging and Developing Economies:
An Illustration Using the World Bank's ASPIRE Database
Working Paper No. WP/2024/096