SPACE Social Protection Approaches to COVID-19: Expert Advice

Better responding to shocks through social protection: COVID-19 insights on identifying and responding to dynamic poverty

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Executive summary

The Coronavirus pandemic has affected substantial proportions of the population raising questions about how social protection systems could be used to respond. One of the key policy questions emerging is **how to deal with a sudden, large-scale increase in poverty levels.** This paper relies on pre-existing microsimulations of the pandemic impact on poverty in Bangladesh, Georgia, Mongolia, Pakistan, and Sierra Leone. It assesses what type of social protection interventions would provide adequate support to households badly affected by the shock. More specifically, the analysis assesses the following three questions.

Question 1: To what extent are 'vertical expansions' of pre-pandemic social protection programmes an adequate response to the COVID-19 shock? The analysis finds that these would not be effective in reaching the population that fell into poverty post-pandemic, except for situations of very high coverage (e.g. universally leaning categorical targeting approaches, such as focusing on children).

Question 2: To what extent do simulated programmes implementing different (commonly used) targeting approaches cover those made poor by the COVID-19 shock? The analysis finds no method performed particularly well to target the new poor. The drop in poverty targeting accuracy was particularly dramatic for PMT targeted programmes, because of their design tailored to reach the *chronic* poor. Categorical criteria (in this paper we look at children and vulnerable groups) show better results, linked to the fact that such programmes generally have relatively higher population coverage.

Question 3: What would be the hypothetical poverty-reducing impact of 'shock responsive' social assistance programmes that adopt different types of targeting approaches, at different budget ceilings? The findings suggest that:

- At a *low budget ceiling (1% of GDP)* the various targeting approaches achieve very similar outcomes in terms of overall poverty headcount reduction, while a PMT targeted programme (based on pre-crisis formula and data) is a bit more effective in reducing the poverty gap.
- At a *high budget ceiling (4% of GDP)* simulated PMT targeted programmes were more effective in reducing poverty in almost all countries – yet this comes with the important caveat that PMT coverage must increase to 40% or 50% for these effects to show. In other words, PMT-targeted programmes would need to be scaled up significantly to reduce poverty more than other demographically based transfers.
- Irrespective of the total budget, programmes targeted at children were the second-best performing in reducing the headcount, and often also poverty gaps, across the countries.

Important to note that these results hold for short-term impacts on poverty. In the medium term, social protection responses might require a more tailored approach conceived as a combination of different interventions, targeted in different ways.

Overall, the paper also finds that social protection interventions can have significant impacts on reducing poverty in response to shocks. It identifies two main strategic directions in the development of social protection policies to achieve this. First, the need to invest in social protection systems that can scale up rapidly through inclusive social registries or social protection floors. Second, the need to develop social registries, broader information systems, and approaches to determining eligibility that are more flexible and can capture chronic poverty as well as those affected by shocks.

Contents

1. Introduction

It is widely recognised that the COVID-19 pandemic is an unprecedented shock. Its scale, the speed at which it spread, and the severe mitigation measures implemented to curb it have all had a huge socio-economic impact. There has been a surge of social protection initiatives in response, attempting to reduce the impacts and promote a quicker economic recovery. Several data collection efforts are ongoing to monitor and document these responses (see for example ILO and Gentilini et al. 2020).

Social protection responses and approaches have differed by country in terms of:

- **Type of programmes**: 62% of global responses took the form of social assistance programmes, with cash transfers being the prevalent form of assistance. A quarter of responses consisted of social insurance interventions, and the rest of labour market programmes (Gentilini et al. 2020). Support was provided either through a vertical expansion of existing programmes (increasing level of existing support); through a horizontal expansion of existing programmes (including new beneficiaries); or the launch of entirely new programmes, often relying on pre-existing components of the social protection system.

- **Identification of beneficiaries:** Countries have selected a variety of methods to identify beneficiaries including categorical targeting, such as grants for children, the elderly or persons with disabilities. Some have expanded programmes using or adapting pre-existing targeting systems based on Proxy Means Tests (PMT)[1] and several countries, mostly high-income, have adopted social assistance measures that are 'universally leaning' in nature, directly or indirectly a large percentage of the population.

Sudden shocks affecting substantial proportions of a population raise questions about the way routine social protection systems should be organised to better respond to crises, i.e. be more 'Shock Responsive'. In these circumstances the reality and perspective on who might need support can change radically. This raises doubts on whether systems focusing too narrowly on supporting the extreme poor, or that concentrate on poverty correlates determined before the crisis, are adequate in times of shock. Indeed, the development of more inclusive social protection systems is advocated for in the Sustainable Development Goals and in the design of social protection floors. *The key policy question, therefore, is how to deal not only with chronic poverty 'at a specific point in time' but also with a sudden, large-scale increase in poverty levels.*

To address this fundamental question this paper relies on pre-existing microsimulations[2] of the short-term impact of the COVID-19 pandemic on income and consumption in five countries. This data is used to assess what type of social protection interventions could be employed to adequately identify households badly affected by this shock. The analysis exploits simulated; realistic changes due to the economic shock of the pandemic to make a comparative analysis on the appropriateness of different types of responses.

More specifically, income/consumption distribution data before and after the pandemic are used to answer the following three main questions:

1. To what extent are 'vertical expansions' of pre-pandemic social protection programmes an adequate response to the COVID-19 shock?

[1] The term "proxy means test" is used to describe a situation where information on household or individual characteristics correlated with welfare levels is used in a formal algorithm to proxy household income or welfare.

[2] The effect of the pandemic has been simulated using microdata from recent household surveys and information coming from different sources (national statistical agencies, household telephone surveys, national think tanks studies, etc.) on the impact of the shock on different economic sectors. The simulations tried to reproduce the reduction of income at the household level, considering the different household income sources and taking into account each household member employment income sources. Moreover, the simulations tried also to separate the 'effect' of the pandemic alone and the combined effect of the shock and governments' response. The microsimulations use the following household level surveys: 2018 Household Socio-Economic Survey for Mongolia, 2018 Household Incomes and Expenditures Survey for Georgia, 2015/2016 Household Integrated Economic Survey for Pakistan, 2016/2017 Household Income and Expenditure Survey for Bangladesh, 2018 Sierra Leone Integrated Household Survey for Sierra Leone.

2. To what extent do simulated programmes implementing different (commonly used) targeting approaches cover those made poor by the COVID-19 shock? *For this study, these commonly used techniques include categorical, poverty-based, and geographical.*
3. What would be the hypothetical poverty-reducing impact of 'shock responsive' social assistance programmes that adopt different types of targeting approaches, at different budget ceilings?

The countries included in the analysis are Bangladesh, Georgia, Mongolia, Pakistan, and Sierra Leone. Two methodological caveats are worth noting. First, it is important to clarify that the choice of countries was made based on expedience and does not follow a strategic choice: they were the subject of separate in-depth studies, and thus presented readily available data to compare a situation before and after the economic shock. More details on the specific analysis conducted in these countries can be found here for Bangladesh, Pakistan and Sierra Leone and here for Mongolia. Second, being based on the results of microsimulations, the study inherits all their methodological limitations. Most notably, the effect of the pandemic is estimated based on several assumptions that could well be inaccurate; moreover, the simulations represent only a short-term, partial equilibrium representation, i.e., no behavioural response from households is included.[3] Finally, the focus of the analysis is exclusively on the economic effects of the pandemic not accounting for the broader health and social consequences.

The findings of this primarily empirical investigation are used to provide some insights into the strategic policy choices required to identify vulnerability in times of shocks.

2. The COVID-19 shock and its impact on poverty and vulnerability in focus countries

This section provides an overview of the level of the COVID-19 shock in the five countries under analysis, summarising the simulated impact of the pandemic on poverty and inequality.

2.1 COVID-19 impact

The countries under analysis adopted measures with varying degrees of stringency to contain the spread of the pandemic. Sierra Leone used a relatively light-touch approach, with two, three-day lockdowns implemented in April and May 2020, plus a curfew and restrictions on internal movements. The latter were gradually removed by the end of June. Mongolia introduced an initial travel ban in January 2020 followed by a full border and school closure from March. Bangladesh, Pakistan, and Georgia all enforced a stringent lockdown from March-May 2020.[4]

All countries suffered economic losses because of the pandemic, with 2020 real GDP growth falling short of expectations. Pakistan and Bangladesh experienced a loss of roughly 4 percentage points for GDP growth forecasted. Bangladesh went from forecasted real GDP growth of 7.2% (World Bank, 2019) to real GDP growth of 3.2%.[5;] Pakistan's real GDP growth in 2020 was -0.4% against the projected growth of 3.9% and Sierra Leone's GDP growth loss was -2.2% in 2020 versus a predicted real GDP growth of 2.3–4% (World Bank, 2020b). For Mongolia and Georgia, both countries' growth was roughly 5% in real terms in 2019 and

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[3] This implies that households cannot respond to the crisis by for example changing household membership, changing job, etc

[4] While in Bangladesh the lockdown, in the form of a general holiday, was progressively extended till the end of May, Pakistan lifted the national lockdown at the beginning of May and moved to regional lockdowns in areas facing heavy caseloads. Finally, in Georgia the stringent lockdown lasted for two months between March 21 and May 22; afterwards, the country gradually reopened its economy. A second and more severe wave of the epidemic in the autumn triggered a new lockdown in December and January, but the analysis in this paper for Georgia focuses on the effect of the first wave and lockdown measures.

[5] Unless otherwise specified, estimates of real GDP growth are taken from the IMF (https://www.imf.org/en/Countries/BGD, PAK, SLE, MNG, and GEO).

faced a real GDP loss of 5.3% and 6.1% in 2020, respectively. Quarterly level losses during the year were even larger during the more stringent lockdown periods.

In response to these socio-economic impacts all the countries introduced social protection measures building off existing social protection systems. These are briefly summarised in Annex 1.

2.2 Simulated poverty impact of COVID-19: What are we seeing?

Countries under analysis experience different levels of poverty, which depend on measurement choices. Using an international comparable benchmark and World Bank estimates[6], the poverty headcount ratio at $3.20 a day[7] is 5% in Mongolia in 2018, 14.9% in Georgia in 2019, 35.7% in Pakistan in 2018, 52.3% in Bangladesh in 2016, and 76% in Sierra Leone in 2018. Poverty figures using official, nationally-set, poverty lines are much more similar, with all countries at around 20%[8], except for Sierra Leone, which has a substantially higher percentage of the population falling below the national poverty line at 57%.

For this paper, an arbitrary poverty line is used that identifies 30% of the poorest population in each country before the pandemic. This figure is calculated using per adult equivalent consumption aggregates[9]. The choice of artificially setting the same poverty level pre-pandemic is made to focus on the comparison of poverty dynamics and social assistance impact across countries. This should be kept in mind to avoid misinterpreting the results of the paper in terms of national and international poverty measures.

The first step in the simulation is the estimation of the impact of the pandemic on poverty headcount and poverty gap[10], assuming no social protection intervention. Table 1 summarises these results showing the indexes before and after the shock across countries at national and geographical level (urban and rural areas). What emerges is that:

- Unsurprisingly**, post-COVID-19 there are significantly more people in poverty due to the shock**. Pakistan experiences the highest increase in poverty, going from 30% to 62%, and Mongolia the lowest, going from 30% to 39%.
- **The shock disproportionally affects households that are not traditionally classified as poor or vulnerable**, e.g. informal workers, urban households. This tallies with other work conducted under SPACE (see Wylde, Carraro and Mclean 2020). The only exception is Mongolia, where the increase in poverty is similar in urban and rural areas as border closures affected cashmere farmers.

The analysis of poverty dynamics by geographical and demographical characteristics[11] shows that in all countries some of the household categories that are often classified among the most vulnerable are impacted less severely by the pandemic. This includes larger households with many children, households with one or more elderly members, and households with one or more widowed or separated women. Moreover, in Mongolia, Georgia, and Sierra Leone, households with one or more member with a

[6] Data retrieved from the World Development Indicators using the "wbopendata" command in STATA.
[7]2011 Purchasing power parity.
[8] More precisely the percentage of poor under the national poverty line is 24% for Pakistan, 18% for Bangladesh, 20% for Georgia and 28% for Mongolia.
[9] Equivalence scales adopted for Bangladesh, Pakistan, and Sierra Leone are as follows: 0.5 for children below 6, 0.8 for children between 6 and 14, and 1 for individuals above 14 years old. In Mongolia the first adult member of the household counts as 1, a second adult as 0.7 and a child under 14 as 0.5, but persons with disabilities have a higher equivalence scale by a factor of 1.4. For Georgia a child under 13 is counted as 0.7 and a person with disabilities as 1.4 and all other members count as one, the adult equivalised household size is then corrected by the power of 0.75 to correct for economies of size.
[10] The poverty headcount is the percentage of the poor population, whereas the poverty gap index measures the intensity of poverty as the consumption shortfall from the poverty line. The latter is expressed as a percentage of the poverty line and averaged across the whole population (this is the Foster-Greer-Thorbecke index with alfa equal to 1 correcting for the fact that the gap is sensitive to the number of per adult equivalents).
[11] Disaggregated results have been produced as part of the simulations but are not presented in detail in the paper.

disability are also proportionally less impacted by the pandemic[12]. Households headed by women, which are generally considered more vulnerable to poverty, are impacted differently across countries. For example, in Mongolia and Georgia, where they display a higher poverty rate at baseline, they are impacted less severely by the pandemic than households headed by men. In Pakistan, Sierra Leone and Bangladesh, where they are not poorer pre-COVID-19, they are impacted equally or slightly more strongly than male-headed households. **In all countries, households composed of working-age adults only, or by working-age adults with one or two children, are the household categories experiencing the highest relative increase in poverty.**

Table 1. Poverty headcount and poverty gap before and after the pandemic and % increase post-COVID-19, by country and geographical area.

	Mongolia			Georgia			Pakistan			Bangladesh			Sierra Leone		
Poverty headcount	**Pre**	**Post**	**Δ%**	**Pre**	**Post**	**Δ%**	**Pre**	**Post**	**Δ%**	**Pre**	**Post**	**Δ%**	**Pre**	**Post**	**Δ%**
Overall	30	39	30%	30	54	79%	30	62	107%	30	50	68%	30	48	59
Urban	28	37	29%	26	54	109%	24	53	120%	14	43	209%	13	39	208
Rural	33	44	31%	36	54	48%	37	68	81%	37	53	46%	43	54	25
Poverty Gap	**Pre**	**Post**	**Δ%**	**Pre**	**Post**	**Δ%**	**Pre**	**Post**	**Δ%**	**Pre**	**Post**	**Δ%**	**Pre**	**Post**	**Δ%**
Overall	5	8	51	7	17	163	5	21	311	6	16	169	6	13	111
Urban	5	8	52	6	18	217	4	18	389	3	15	490	2	11	427
Rural	6	8	49	8	16	103	6	22	245	7	17	124	9	14	53

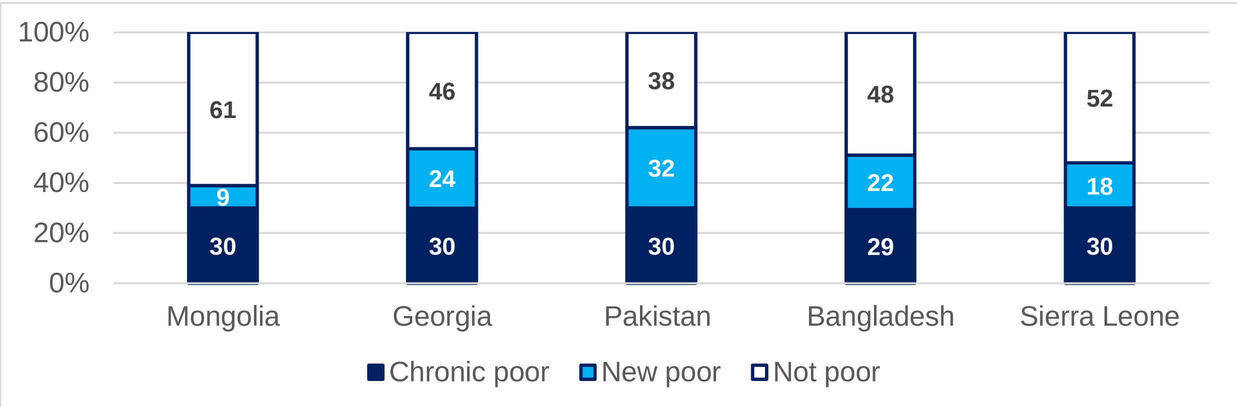
Source: Authors based on results of microsimulations.

Whilst the scale of impact is generally greater amongst those not traditionally assumed to be vulnerable, those who were poor pre-shock were also pushed deeper into poverty. Figure 1 below provides an overview of poverty dynamics based on the arbitrary poverty line used for this study for the populations classified as:

- **'Chronic poor'** – people poor before the pandemic and still in poverty after the pandemic (note that usually chronic poverty would require an assessment across many years, but in this case the definition is simply related to the measures before and after the pandemic).
- **'New poor'** – people not in poverty before COVID-19 but who become poor after the shock.
- **'Not poor'** - people not in poverty pre- and post-pandemic.

In summary, those who were poor pre-COVID-19 remain so post-COVID-19[13] and a new segment of the population has also been pushed into poverty, at least in the short term. The increases vary by country but reach a high of 32% in Pakistan and a low of 9% in Mongolia.

Figure 1. Poverty dynamics due to COVID-19 shock by country (% of the population).



Source: Authors based on results of microsimulations.

[12] There is no information on disability status for Pakistan, while data from Bangladesh suggests that households with one or more member living with a disability are marginally more impacted by the pandemic than other households.

[13] Only a very small number of households who were poor pre-pandemic exit poverty after the pandemic. Since this group is not statistically significant, and in all countries represents less than 1% of the population. Separate statistics for this group are not presented.

3. To what extent are ‘vertical expansions’ of pre-pandemic social protection programmes an adequate response to the COVID-19 shock?

Vertical expansions are the “temporary increase of the value or duration of an intervention to meet beneficiaries' additional needs” during a shock (O’Brien et al, 2018). As such, they target the same beneficiaries as routine programmes and are only effective response to shocks if they have good coverage of those most affected by that specific shock.

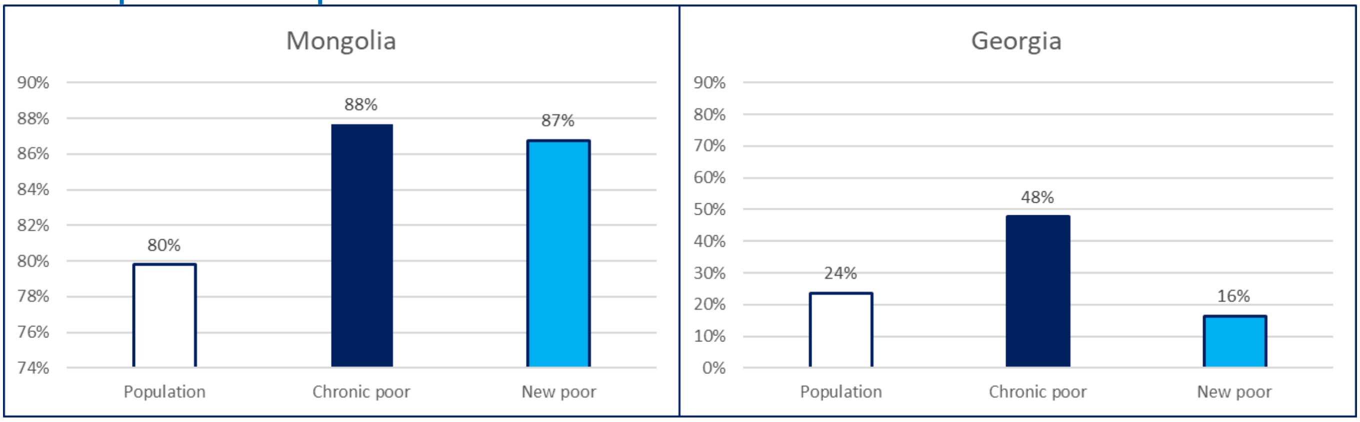
This section simulates the targeting performance of the vertical expansions of a selection of routine social assistance programmes[14] in reaching the population of new poor post-COVID. Specifically, programmes analysed include a universal child-targeted programme in Mongolia, a poverty targeted child grant in Georgia, social pensions in Mongolia and Georgia, and poverty targeted programmes in Mongolia, Georgia, and Pakistan[15].

In general, the analysis suggests that vertically expanding social assistance programmes as a response to the COVID-19 shock is not fully effective in reaching the newly poor. Population coverage along with coverage of the chronically poor and new poor of routine programmes are presented in Figures 2, 3 and 4 for the programmes under review (child grants, social pensions, and poverty targeted programmes). The key findings that emerge from the analysis are the following;

- **Unsurprisingly, only routine programmes covering a large share of the population through <u>universal categorical targeting</u> are likely to reach the new poor**. This is the case for the Mongolian child transfer programme for all children under 18 and to a smaller extent for the social pension programme in Georgia.
- **The performance of <u>poverty targeted programmes</u> deteriorates significantly in a post-COVID scenario and a simple vertical expansion would not be effective in reaching the new poor.** This is the case in all the selected PMT targeted programmes and for the poverty targeted child grant in Georgia.
    - However, in the case of Georgia, it is important to stress that in reality the PMT targeting system has a dynamic nature and it allows **on-demand applications**. Indeed, the coverage of the targeted social assistance programme increased by 22% from January to December 2020, thus showing the possibility to cover the new poor with the right system in place.
- **The difference in the ability of these programmes of covering the new poor reflects their different social protection objectives**, i.e., addressing chronic poverty versus broader inclusion of large population groups who are commonly recognised as vulnerable.

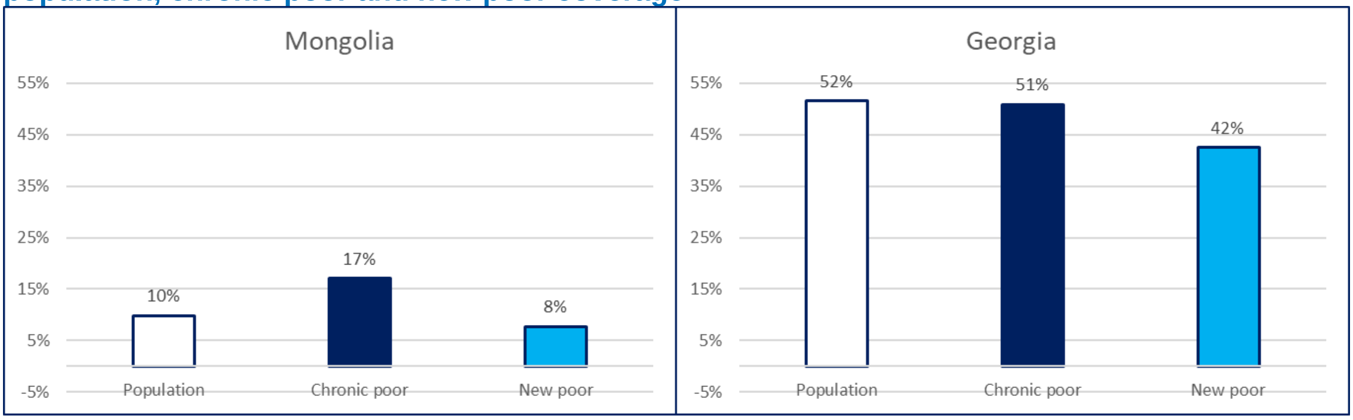
[14] In other words, these were routine programmes operating before COVID-19, they were not created to respond to the shock (same targeting criteria, same caseload).
[15] Pre-existing cash transfer allowances programmes in Bangladesh are not included in the analysis due to very low population coverage at baseline, while for Sierra Leone no significant social assistance programme was already in place before the pandemic.

Figure 2. Coverage of *child grant programmes* in Mongolia and Georgia as % of the population, chronic poor and new poor



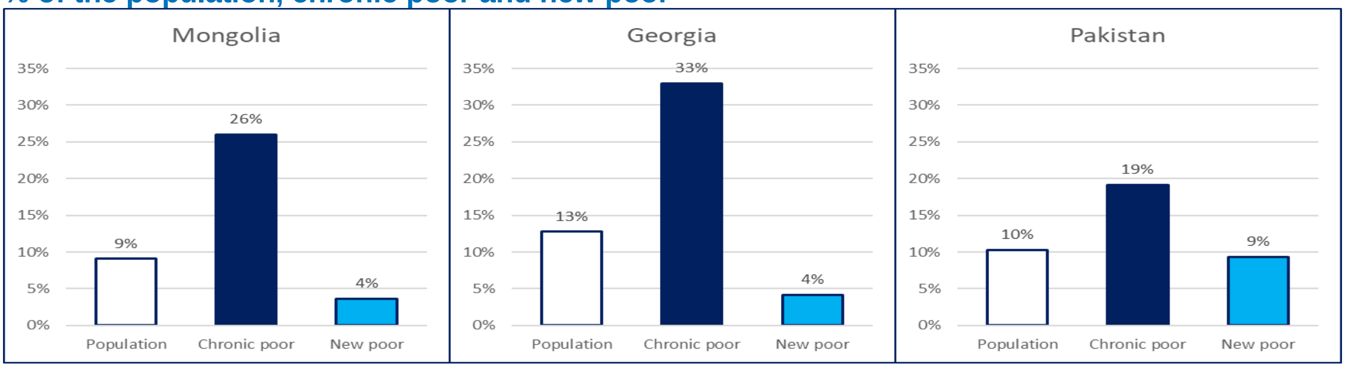
Source: Authors based on results of microsimulations. Notes: Child Money Programme in Mongolia and poverty targeted Child Grant programme in Georgia.

Figure 3. Coverage of social pension programmes in Mongolia and Georgia as % of the population, chronic poor and new poor coverage



Source: Authors based on results of microsimulations

Figure 4. Coverage of PMT targeted pension programmes in Mongolia, Georgia, and Pakistan as % of the population, chronic poor and new poor



Source: Authors based on results of microsimulations. Notes: Food Stamp Programme in Mongolia, Targeted Social Assistance in Georgia, Benazir Income Support Programme in Pakistan.

Importantly, this finding tallies with and quantitatively reinforces previous research, before COVID-19 and COVID-specific.

4. To what extent do simulated programmes implementing different (commonly used) targeting approaches cover those made poor by the COVID-19 shock?

Having assessed the performance of existing programmes (and their simulated vertical expansions) in each country above, this section simulates the effectiveness of using different targeting approaches to identify the new poor across all countries.

Specifically, the simulation uses a range of categorical, poverty, and geographical beneficiary selection mechanisms that are based on criteria commonly used in the countries under analysis[16]. These are:

- **Categorical:**
  - Child-based targeting – beneficiaries are all individuals whose age is below a given age threshold. Depending on the demographic structure of each country, different age thresholds are usually selected because of caseload and budget consideration.
  - Targeting of vulnerable groups – beneficiaries are all individuals who belong to one or more of pre-selected categories considered as vulnerable in the countries under analysis (elderly, widowed or separated women, persons with a disability).
- **Poverty targeting** – beneficiaries are all individuals ranked as among the poorest based on a PMT score computed based on household-level information *collected before the shock*[17]. In Mongolia, Pakistan and Georgia, there is a social registry that collects household-level information used in a PMT that scores and ranks households based on the estimated welfare level; these scores are used for the simulation[18]. In Sierra Leone and Bangladesh, this information is not available and so a regression based PMT is estimated for the simulation using the pre-pandemic consumption data.
- **Geographical targeting** - beneficiaries are all individuals who live in geographical areas (provinces, regions, districts, etc.) with higher-than-average poverty rates, as assessed *before the shock*[19]. Geographical targeting is common in many low-income and middle-income countries and often used in combination with other selection criteria to prioritise vulnerable areas in a context of limited resources.

To conduct the simulation we have selected one criterion for each of the four methods mentioned above. These will help us to comparatively illustrate the likely targeting performance of these methods in response to a shock. The simulated section criteria are:

- Child-based targeting aimed at children under 5 years.

[16] The paper does not address effectiveness of community-based selection methods.

[17] In other words, this assumes no changes to the composition of the PMT formula or to the data it assesses eligibility on.

[18] However, there are significant differences in the way the PMT operates in these three countries. In fact, in Georgia the rules for the PMT were estimated in 2015, but they are applied through an on-demand system and information is regularly updated. In Mongolia, the latest bulk of information was collected in 2017 using PMT rules updated in 2016. In Pakistan there was a relatively recent data collection exercise, but most current beneficiaries entered the programme based on information that is more than ten years old. In all these countries the current PMT rules have been applied and reproduced in the data available in the household surveys.

[19] As above, this assumes no refinement of geographical targeting criteria to reflect changes in poverty induced by the shock. This is contrary to many experiences in response to COVID-19, where urban areas were prioritised, for example.

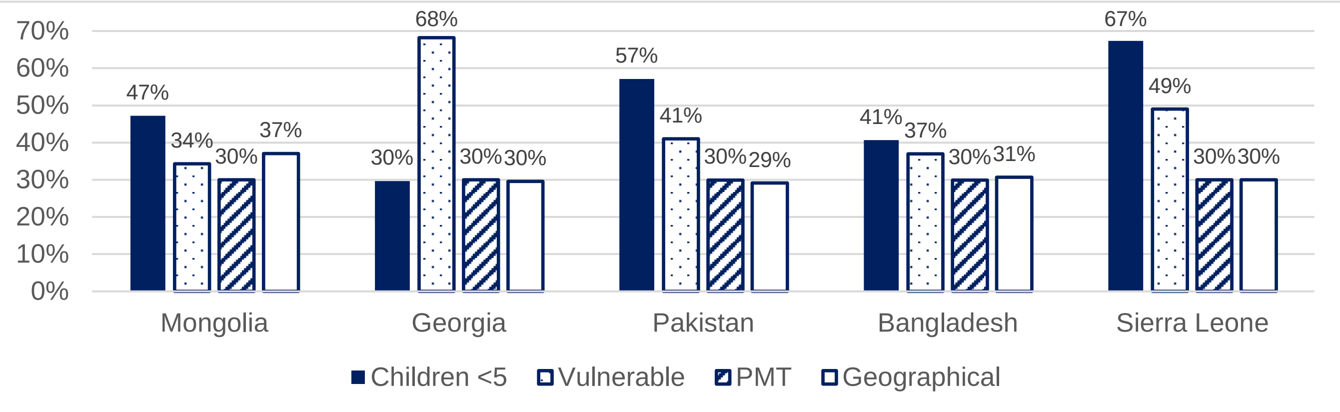
- Targeting aimed at population groups commonly considered as vulnerable (elderly, widows and separated women, and persons with a disability).[20]
- Poverty targeting aimed at the poorest 30% of the population based on the PMT score (pre-pandemic).
- Geographical targeting aimed at the poorest 30% of the population (pre-pandemic).[21]

In terms of assessing targeting effectiveness, the initial concern is with the ability to reach the newly poor. We do this in two stages:

First, we look at overall population coverage. A large population coverage increases the probability of better coverage of the poor, but a fixed budget implies also a lower benefit when compared to a mechanism with smaller population coverage. This is due to the inevitable trade-off between coverage and adequacy of support.

Figure 5 below shows the percentage of the country population that would be covered using each of the selected criteria/method[22]. Supporting children under 5 would have the highest reach of population, except for Georgia, where supporting vulnerable groups would cover the highest percentage of the population.

Figure 5. Percentage of population covered by different targeting approaches



Source: Authors based on results of microsimulations.

Second, we look at the coverage of the poor after the pandemic, which can be further disaggregated into coverage of the chronic poor and that of the new poor.

For each simulated targeting approach, Figures 6 and 7 look at a post-pandemic scenario, showing the percentage of the poor, chronic poor, and the new poor that would be covered. Results are presented for Mongolia first, to help the reader to interpret the results for other countries**Error! Reference source not found.**[23]. In the case of Mongolia, overall coverage of the poor post-pandemic would be the highest using the PMT (57%), followed by children under 5 (55%), vulnerable groups (37%) and geographic (only 23%). The PMT approach would also have the advantage of covering an overall lower percentage of the population at 30% compared to other methods (see Figure 5). However, some mechanisms are much more biased towards the chronic poor (those poor before *and* after a shock), than the new poor. In particular the PMT would cover 68% of the chronic poor, but only 22% of the new poor, whereas supporting children under 5 would have a similar coverage of chronic poor and new poor.

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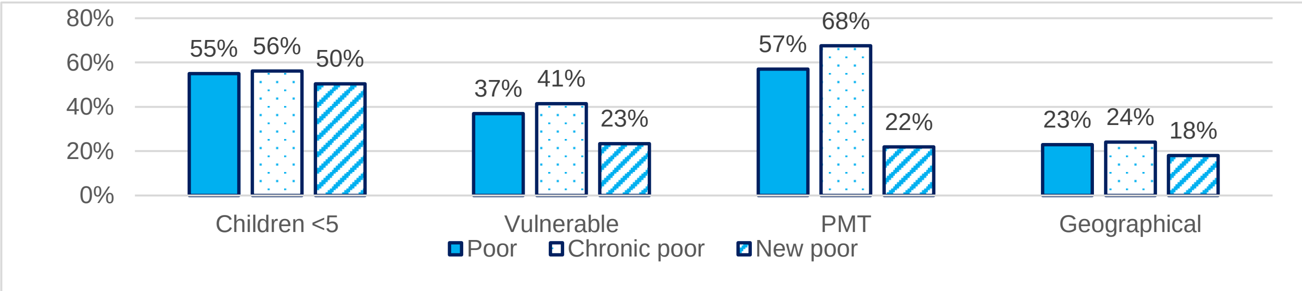
[20] The choice of assessing a range of heterogenous vulnerabilities as a single group is made in order to deal with a population group of reasonable size and to reflect the fact that in most countries' programmes did try to cover all these groups together.

[21] Note that the exact percentage of the population covered through geographical targeting can differ from 30% due to the differences in population distribution across geographical regions in the country.

[22] This includes direct and indirect beneficiaries, where indirect beneficiaries are individuals living with one or more direct beneficiary.

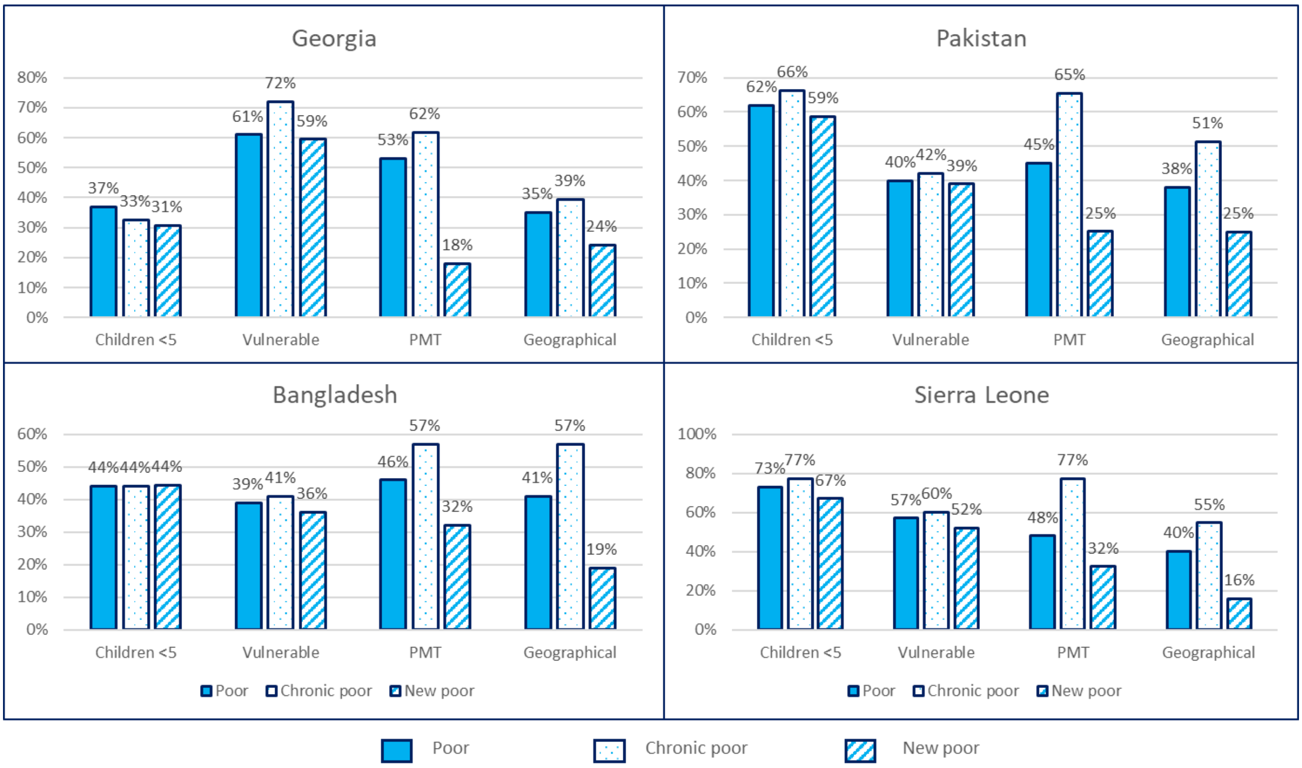
[23] See Table 4 in Annex 2 for an overview of coverage of each selection criteria by consumption quintiles as well.

Figure 6. Poor, chronic poor and new poor coverage of different targeting approaches in Mongolia



Source: Authors based on results of microsimulations.

Figure 7. Poor, chronic poor and new poor coverage of different targeting approaches by country



Source: Authors based on results of microsimulations.

In all countries and across all beneficiary selection methods, coverage of the chronic poor is higher than the relative coverage of the new poor (see Figure 6 and Figure 7). This suggests that all simulated targeting criteria are more effective in identifying individuals (or households) that were poor pre-pandemic rather than those who become poor due to the shock.

Breaking this down to look specifically at performance identifying the new poor, the following results emerge:

- **Geographical targeting aimed at poverty 'pockets' pre-pandemic has the lowest coverage among the new poor.** This is somehow expected since the impact of the shock is stronger in urban settings while most of the poor pre-pandemic are likely to be resident in rural areas.
- **The largest difference in coverage of chronic poor versus new poor occurs for the PMT criteria.** This is because pre-pandemic coverage of the chronic poor is very high relative to the overall population coverage, but then given the extent of the shock and the fact that proxies are better suited to measure chronic poverty, the loss of accuracy is significant.
- **Categorical criteria selecting children and the vulnerable show the smallest deterioration in poverty coverage**. This is partly explained by the relative higher population coverage of categorical criteria. It should be highlighted though that while the probability of covering the chronic and new poor is higher for criteria reaching a larger percentage of the population, the potential level of the transfer would also likely be lower in a context of limited resources.

5. What would be the hypothetical poverty-reducing impact of 'shock-responsive' social assistance programmes that adopt different types of targeting approaches, at different budget ceilings?

Section 4 **looked at differential coverage among those made poor by the shock, based on different targeting** approaches. **This section goes one step further, aiming to assess hypothetical poverty-reducing impacts of different programme designs. To do this realistically, it sets two different budget ceilings (1% and 4% of GDP)** and simulates programmes that use different targeting approaches to stay within these budget ceilings to respond to the COVID-19 shock. The comparison is therefore on comparable GDP spending, using different approaches to achieve intended outcomes (poverty reduction).

The analysis enables comparisons across different countries in terms of impacts on poverty headcount and poverty gap, at 1 and 4% of GDP budget ceilings, by:

- Bringing issues of '**adequacy'** (transfer values) into the picture. Each of the two budget scenarios (1% and 4%) are divided by the number of beneficiaries identified by the various beneficiary selection criteria which are used to determine transfer value[24]. The total value allocated to each household is then added to its post-COVID-19 shock income to determine consumption and poverty status.
- Setting out **more realistic targeting approaches and criteria** across the different countries (e.g. compared to the analysis in the previous section), taking into account each countries' population pyramid and together with the budget ceilings discussed above. These are:
  - **Universal targeting** – a universal benefit is simulated, given that some countries have adopted this type of response.
  - **Categorical**
    - **Child-based targeting –** beneficiaries are all individuals whose age is below 18 in Georgia and Mongolia and all those whose age is under 10 in the other countries.
    - **Targeting of vulnerable groups –** beneficiaries are all individuals who are elderly, widowed or separated women, persons with a disability, or children below 10 in Georgia and Mongolia or children below 5 in the other countries.
  - **Poverty targeting –** the selected PMT thresholds in terms of expected population coverage varies by country and GDP scenario. Each is set based on country reality (the de-facto formula) or context (a realistic formula). Importantly, both the composition of the formula and the data used to inform simulation of eligibility are from *before the shock*[25].
  - **Geographical targeting –** with the possibility to cover about 20 - 30% of the population, depending on the country population structure and poverty concentration, etc. Importantly,

[24] Transfer value is assigned based on per adult equivalent scales (see Table 2 in Annex 2 for an overview of the resulting benefit level as a percentage of national poverty lines for the options presented in the report).
[25] In other words, this assumes no changes to the PMT to reflect new drivers of poverty and no new data collection.

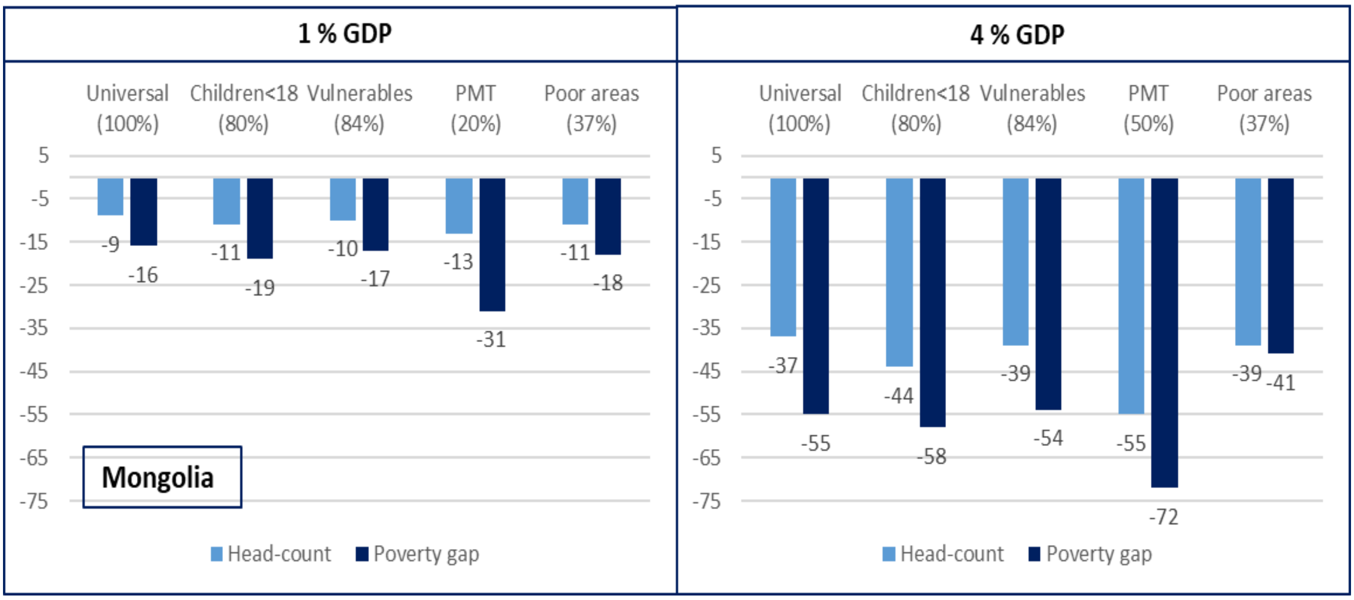
geographic targeting is simulated based on the distribution of poverty at a geographical level *before the shock*[26].

Once again, results are presented first for just one country, Mongolia, to support the interpretation of the Figures for the other countries. Figure 8 thus summarises the results in terms of reduction in poverty headcount and poverty gap with respect to the post-COVID-19 scenario. For each budget option, reduction in head-count poverty and poverty gap concerning the post-COVID rates (see Annex 2 Table 2) are shown for each programme type together with an indication of the programme overall population coverage (in brackets below the programme name).

- **In the case of a 1% GDP budget in Mongolia the highest poverty impact (-13% headcount, -31% poverty gap) is obtained by a programme selecting beneficiaries using PMT criteria with a coverage of 20% of the population.** The better performance of the PMT, compared to other targeting modalities, is more evident in the case of the poverty gap and so crucially depends on what Atkinson has categorised as 'sharpness of objectives'. That is, it would not be enough to say that the best approach is selected based on the reduction of poverty, but that there is a need to qualify what is meant by poverty, i.e., the percentage of poor falling below the poverty line, or reducing the distance to the poverty line, or even inequality amongst the poor[27].
- **PMT targeting achieves the best performance also when looking at interventions that use a budget of 4% of GDP.** However, while for the other types of interventions the best performance is obtained by selecting the same eligible population in both budget scenarios, in the case of PMT the selected population changes based on the budget available. With a budget of 1% of GDP, population coverage of 20% is most efficient, whereas with 4% of GDP the best performance is obtained by covering 50% of the population – a percentage that is much higher than any 'routine' PMT.

In the case of Mongolia, the results suggest that poverty correlates pre-pandemic remain relatively good as criteria to reduce poverty post-pandemic, with the fundamental caveat that there should be the flexibility to significantly increase population coverage. However, it should be kept in mind that Mongolia is the country that saw a relatively smaller poverty increase.

Figure 8 Impact on poverty headcount and poverty gap for selected interventions and budget level for Mongolia.



Source: Authors based on results of microsimulations. Notes: Underneath each intervention type, population coverage is reported. Transfers targeted at vulnerable categories cover the following: widows, elderly, people with a disability, and children below 10.

[26] As above, this assumes no refinement of geographical targeting criteria to reflect changes in poverty induced by the shock. This is contrary to many experiences in response to COVID-19, where urban areas were prioritised, for example.

[27] As part of the same argument, it should also be clarified how poverty would need to be defined and measured.

An overview of poverty impact results for the other countries is offered in Figure 9. The key findings that emerge from the analysis are the following:

- **For a comparatively low total budget (1% of GDP) the various targeting approaches achieve very similar outcomes in terms of overall poverty headcount reduction**. However, in all countries a PMT targeted programme (based on pre-crisis formula and data) is a bit more effective in reducing the poverty gap, but differences are not as large as in the case of Mongolia.
- **For a comparatively high total budget (4% of GDP** – higher than most de-facto social protection responses in low-middle income countries) **PMT targeted programmes are more effective in reducing poverty in almost all countrie**s (except for Sierra Leone), however PMT coverage must increase to 40% or 50% for these effects to show[28]. Moreover, once again the differences between PMT and other methods are not stark as in the case of Mongolia.
    - Overall, when the country can provide a relatively large response to the crisis, **PMT based programmes** (that are based on a pre-crisis formula and data) **would need to be scaled up significantly to reduce poverty more than other demographically based transfers**.
- **Programmes targeted at children are the second-best performing in reducing the headcount, and often also poverty gaps, irrespective of the total budget**, but differences in performance are even smaller. Their relative better performance could be related to the fact that households with young children are more likely to be households with younger working-age adults who are more likely to have lost employment and thus have been affected disproportionally more by the pandemic.
- **In Georgia and Sierra Leone universal targeting is the second, if not the first, most effective in the 4% GDP scenario**, depending on which poverty measure one considers more relevant.
- **Except for Pakistan, relying on geographic targeting that is based on pre-shock poverty distributions provides the worst results in terms of poverty reduction**, and this is once again partly explained by the pandemic affecting urban areas, which were significantly less poor before the shock and the relatively lower overall population coverage even in the case of the 4% budget scenario. This is unsurprising and is the reason why many countries that adopted geographical targeting as a first layer ensured these were updated to the pandemic scenario – e.g. with a focus on urban areas.
- **In Sierra Leone, all approaches appear to perform similarly and, especially at the lower budget level, interventions have a much higher impact on poverty reduction compared to other countries**. Moreover, unlike in other countries, the impact on headcount and poverty gap are quite similar. This is explained by the fact that the country has the lowest post-COVID-19 poverty gap and, even more importantly, the lowest inequality among the poor[29].

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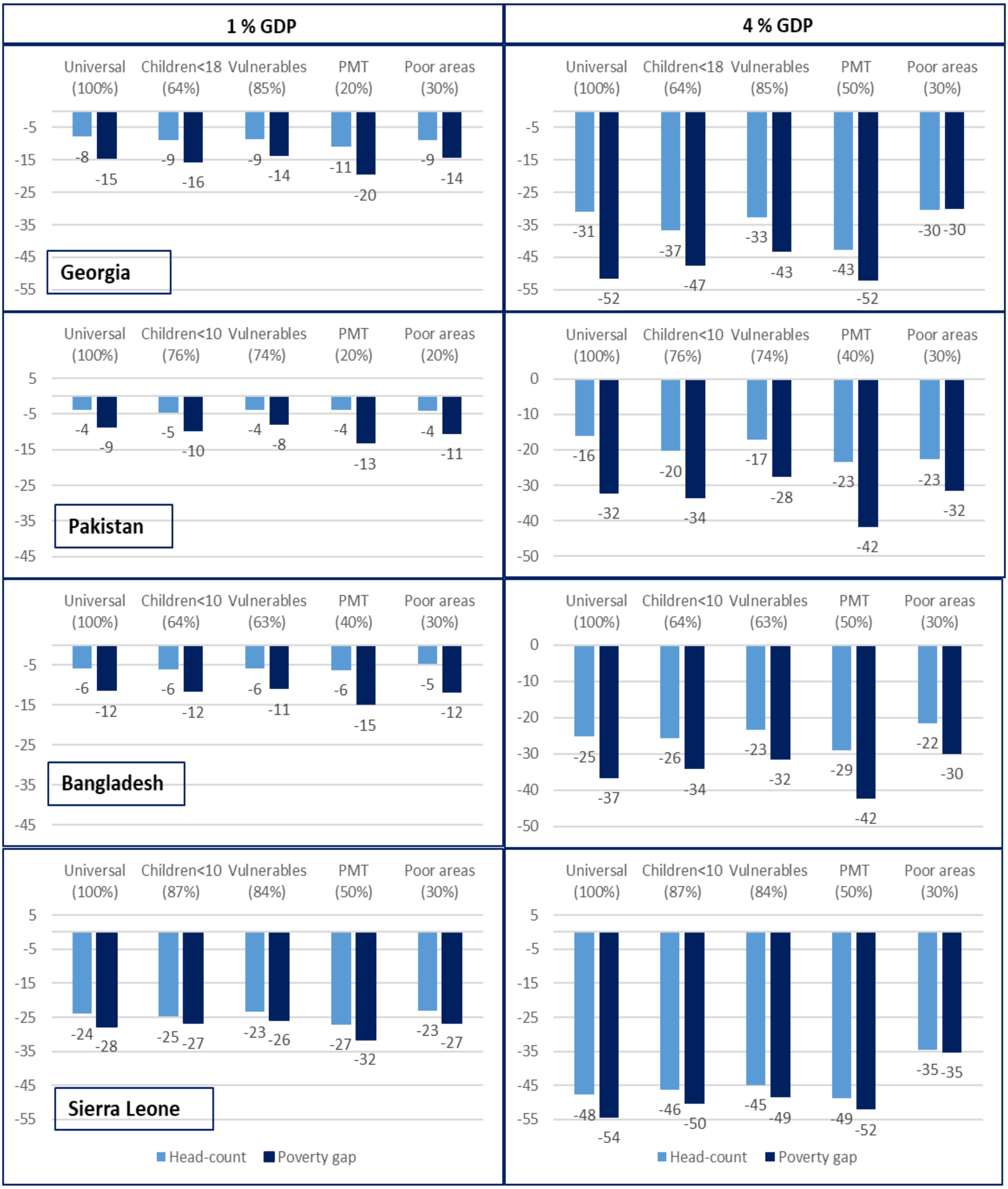
[28] Table 4 in Annex 2 further explores the relative effectiveness of PMT transfers targeting 20%, 30% and 50% of the population with respect to a relatively low and high total transfer budget. The results suggest that post-shock PMT targeted programmes with a small budget have a relatively higher impact on both poverty headcount and poverty gap when targeted to a smaller percentage of the population. On the contrary, when the available budget increases, higher coverage PMT programmes are more effective than lower coverage ones in reducing headcount poverty and poverty gap.

[29] Table 7 in Annex 2 shows the squared poverty gap before and after the COVID-19 shock for all countries. The squared poverty gap captures the level of inequality among the poor.

Figure 9 Impact on poverty headcount and poverty gap for selected interventions by budget level.



Source: Authors based on results of microsimulations. Notes: Underneath each intervention type, population coverage is reported. Transfers targeted at vulnerable categories cover the following: widows, elderly, people with a disability, and children below 10 for Georgia; widows, elderly, people with a disability, and children below 5 for Bangladesh and Sierra Leone; and, widows, elderly, and children below 5 for Pakistan.

6. Discussion and policy implications

6.1 What is the data telling us?

This section summarises the results of the microsimulations of the short-term impact of the pandemic on income and consumption in five countries (Bangladesh, Georgia, Mongolia, Pakistan, and Sierra Leone), including the simulation of the effectiveness of different targeting approaches to adequately support households that were badly affected by the COVID-19 shock. Specifically, it focuses on the three key research questions posed at the beginning of the paper and draws some policy implications.

All of the findings rest on the fundamental principle (substantiated by extensive evidence) that individuals and households most affected by COVID-19 were not the same as the 'usual suspects' that were supported by routine social assistance. In fact, in all the countries analysed some of the household categories that are often classified among the most vulnerable were impacted less severely by the pandemic.

6.1.1 To what extent are 'vertical expansions' of pre-pandemic social protection programmes an adequate response to the COVID-19 shock?

The targeting performance of simulated vertical expansions of a selection of pre-existing social assistance programmes was assessed (i.e. accompanied by no expansion of coverage). The main findings suggest that:

- **Vertical expansions are not an adequate response to COVID-19 except for situations of very high coverage.**
- **There is a stark difference in the ability of pre-pandemic social assistance programmes to protect the new poor depending on the type of targeting routinely used.** Poverty targeted programmes are largely unable to support the new poor through vertical expansion whereas universally leaning categorical targeting approaches, such as focusing on children, are much better placed. This in part is due to their relatively broader coverage under routine social protection.

6.1.2 To what extent do simulated programmes implementing different (commonly used) targeting approaches cover those made poor by the COVID-19 shock?

The paper used simulations to compare different standardised targeting methods (namely child-based, vulnerable groups, PMT, and geographic), to see which would have more success in covering the new poor (given COVID-19 impacts). Findings suggest that:

- **Across all methods and countries, the relative coverage of the chronic poor is higher than the relative coverage of the new poor** (i.e. all methods perform better to identify those who were poor pre-pandemic rather than those who become poor due to the shock).
- **PMT has the largest difference in coverage between chronic and new poor (i.e. it significantly loses accuracy in identifying the new poor)**, which is unsurprising as the proxies within PMTs are specifically correlated with the characteristics of those who are chronically poor in any given country.
  - **Even though PMT has the largest drop in performance, overall it remains relatively effective in reaching the poor considering the percentage of population covered**, but this is dependent on the relative size of the new poor compared to the chronic poor.
- **Child-based targeting approaches perform better than all other approaches to identify the new poor** – primarily because of their higher coverage overall. This can be very positive for effective shock-response if it does not come at the expense of an adequate transfer level.

6.1.3 What would be the hypothetical poverty-reducing impact of 'shock-responsive' social assistance programmes that adopt different types of targeting approaches, at different budget ceilings?

Further expanding the above simulation and comparing different budget ceiling scenarios (1% and 4%) for cash transfers that use the different selection methods[30], the paper evaluated which approaches had the largest poverty reduction impacts in the situation created by the pandemic.

- <u>**Low total budget (1% of GDP)**</u>
  - **The various targeting approaches achieve very similar outcomes in terms of overall *poverty headcount* reduction**.
  - **In all countries, a PMT targeted programme** (based on pre-crisis formula and data) **is slightly more effective in reducing the *poverty gap***, with large differences only in the case of Mongolia (as it has the lowest percentage of new poor).
- <u>**High total budget (4% of GDP**</u> – higher than most de-facto social protection responses in low-middle income countries).
  - **PMT targeted programmes are more effective in reducing poverty in almost all countries** (except for Sierra Leone), even when they are based on a pre-crisis formula and data).
    - This comes with the important **caveat** that **PMT coverage must increase to 40% or 50% for these effects to show. In other words, PMT-targeted programmes would need to be scaled up significantly to reduce poverty more than other demographically based transfers.** Also, relative bias towards the pre-pandemic poor would most likely remain with larger coverages.

Importantly, irrespective of the total budget, programmes targeted at children were the second-best performing in reducing the headcount, and often also poverty gaps, across the countries.

More broadly, the study also shows that social protection interventions can have very significant impacts in reducing poverty and supporting living standards when responding to shocks. In all countries, the simulated social protection responses contribute significantly to reducing the increase in poverty due to the pandemic, to the extent that, in some countries, interventions could completely reverse the negative effects of the economic shock. Of course, all simulations have assumed a seamless implementation, which is never the case – yet these insights are confirmed by emerging literature (see for example Parekh and Bandiera).

6.2 What are the policy implications of these findings?

Overall it is clear that in a situation of large disruption such as the one generated by the pandemic, programmes that target large categorical groups become legitimate responses, achieving very similar poverty results as PMT targeted programmes.

A few further considerations that are important for the 'targeting' of future shocks emerge from the simulations results and the response to COVID-19 worldwide**.**

First, while the simulation assumes perfect implementation of all selection mechanisms, real-world challenges reduce the precision of the selection process, especially in the case of poverty targeted programmes. PMT targeted programmes, in particular, are usually more complex to implement than categorical programmes – especially if new data is required for post-shock ranking. This further suggests that universal transfers and categorical transfers (particularly for children) present a reasonable strategy to respond to a major crisis and protect the new poor – by covering a large percentage of the population. However, as the case of Mongolia shows, this is conditional to the effect of the shock in each country.

[30] Note these differed from the standardised approaches used for Q2 as the comparison focused on comparable budget expenditure and realistic targeting designs for each country, given their GDP, population structure, etc. It also included a focus on transfer adequacy.

Second, **in the context of shocks, simple, transparent and widely understood targeting criteria make a difference** - increasing take-up by lowering barriers to access, simplifying processes and informational requirements (and thus enhancing the timeliness of the response), and enhancing understanding and trust in government.

Third, distributional changes resulting from microsimulations (such as those conducted in this paper) **change over the course of a crisis. In the medium-long term, social protection responses require a more tailored – and sequenced – approach**. In the case of the pandemic shock, some income losses due to a lockdown are likely to disappear once restrictions are fully lifted and economic activities re-start. As an example, the manufacturing sector that was specifically hit during the first lockdowns found ways to re-start and continue activities during the second waves of the pandemic and subsequent restrictions. This implies that for some economic sectors the distributional changes resulting from the microsimulations are likely to be true only in the short-term, while other sectors might experience a more long-term disruption (for example in the hospitality and tourism industry). Social protection response should be conceived as a combination of different interventions. Indeed, this was the case in many countries that tried to combine different approaches.

Fourth, it is clear that future shocks will not have the same characteristics, and distributional impacts, as COVID-19. However, the analysis and findings from this paper do have some important implications for future strategic directions in the development of social protection policies in the context of large covariate shocks:

- When crises are as strong as the pandemic, the social protection response needs to be able to cover large percentages of the population to mitigate the poverty increase.
- The development of social registries, broader information systems, and approaches to determining eligibility that is more dynamic and that hold information that is more sensitive to changes induced by shocks and are not exclusively focused on the chronic poor.

6.2.1 Investment in social protection measures and systems that can cover large percentages of the population

Effective social protection response to large shocks significantly altering the income distribution requires covering large percentages of the population, even when using poverty targeting approaches. In turn, this raises the question of how different countries can build systems that would allow achieving this result. The simulation work points to two different possible trajectories:

1. Investing in high coverage social protection floors (across a range of programmes catering to different needs) that would allow a quick and simple vertical expansion in times of crisis.

2. Building inclusive social protection information systems, that can inform high coverage poverty *and* categorical targeting in response to shocks: building on social registries alongside interoperability and data sharing with other government entities including civil registration, tax authorities, informal worker registration databases, etc. To truly support high-coverage responses to shocks, these would need to focus far beyond the 'chronic poor' (and would need to be operationally 'ready' to inform rapid expansions). See more below.

It should be stressed that the two approaches not only represent different philosophical approaches to social assistance but also offer alternative solutions for countries with very different levels of development and capacities to gradually achieve universal social protection.

6.2.2 Development of social registries, broader information systems, and approaches to determining eligibility that are more dynamic and better capture information about vulnerability

In many countries the primary purpose of social registries – and broader information systems serving the social protection sector[31] – is to collect information required to conduct PMT assessments for the targeting of one or more social assistance interventions. There is, however, scope to expand their function far beyond: to

[31] See Chirchir and Barca (2020)

inform more universally leaning routine programming and to play a stronger role to support responses to covariate shocks. We focus here on the second.

In the simulations used for this paper we assumed no changes to the composition of the PMT formula or to the data it assessed eligibility on. However, this does not have to be the case.

On one hand, for routine information systems to play a better role in informing shock responses, they would ideally collect information ‘dynamically’:

- Utilising on-demand application approaches, rather than static census sweeps. This renders routine assistance intrinsically shock responsive – though it is not easy to implement in low-capacity countries[32].
- Leveraging existing data from other, more dynamic, government data sources. For example, in countries such as Georgia and Mongolia (but also in a wide array of other countries that used existing data to target their pandemic response), information on formal sources of income via tax data could be easily collected as well as information on the sector of work (e.g. within the informal sector). In these cases, PMT approaches to poverty targeting could become closer to means tests.
- Combining ad-hoc data collection exercises with routine administrative data from social registries and beyond in strategic ways. This is the case in Chile, for example.[33]

On the other hand, where information cannot be collected dynamically, there is also the scope to ensure that PMT assessments (and other targeting strategies) are more responsive to shocks, by collecting data and including variables that are more sensitive to changes in circumstances over time – or ensuring these are modified in response to different shocks.

Ultimately, information that can be used to predict *vulnerability* to poverty depends largely on the type of shock and it is easier to factor for recurring shocks, for example in drought-prone areas. Indeed, several countries have started to introduce “disaster and climate aware/smart targeting” (see examples reported in Barca and Beazley 2019). Research comparing the role of PMT and Household Economy Analysis in Niger has shown a degree of complementarity between different targeting approaches and scope to combine the type of information collected to be useful in response to recurrent crises (Schnitzer, 2016).

There is significantly more work to be done on this, but the pandemic could provide the push and the foundations for more strategic approaches to targeting in the context of covariate shocks – ensuring the sector fully lives up to its aspiration of protecting people from poverty and vulnerability, no matter how these are generated.

[32] See Barca and Hebbar, 2020 for more details.
[33] See Barca and Beazley, 2019.

Annex 1: The COVID-19 Response in the five countries analysed

Social protection responses to the pandemic varied significantly by country.

Pakistan's main response was a household-level, one-off cash transfer of PKR 12,000 through the '*Ehsaas Emergency Cash Programme*'. [34] The value of the transfer represents approximately 2.6 times the monthly, national poverty line[35] and is equal to the value of six month's-worth of transfers under the largest pre-existing cash transfer programme in Pakistan. Ehsaas is mainly financed by the Federal Government with support from provincial governments and aims at covering 16.9 million households (around half of the country's population (Nishtar, 2020)). Beneficiaries were selected using a mix of proxy means testing, geographical targeting, and wealth-profiling exclusion criteria. In total, PKR 203 billion (about 1% of 2020 forecasted GDP) was allocated to support 16.9 million poor and vulnerable families (Lone and Shakeel).

Bangladesh invested mostly in the activation of pre-existing social safety net programmes. The estimated reach is 77 million beneficiaries, equivalent to around 47% of the population. The programmes activated include the '*Gratuitous Relief Programme'* and the '*Open Market Sales'* programme. The former is an on-demand programme allocating cash and food transfers in rural areas, while the latter is a subsidised food distribution programme operating in urban areas. At the same time, the country horizontally expanded existing cash-based allowance programmes covering individuals who had been on a waiting list to receive support, including;

- 500,000 new beneficiaries were included in the '*Old age Allowance programme'* – a monthly allowance of BDT 500[36] - representing 17% of the monthly national poverty line[37].
- 350,000 were added to the '*Allowance programme for widows and other vulnerable women*' which provides a monthly allowance of BDT 500.
- 255,000 to the allowance programme for persons with disabilities (the '*Financially Insolvent Disabled programme'*) – a monthly allowance of BDT 750 (25% of the monthly national poverty line).

Moreover, Bangladesh introduced two new cash-based, countrywide programmes covering informal sector workers. The Prime Minister's one-off cash support scheme of BDT 2,500 (84% of the monthly national poverty line) targeted 5 million beneficiary households, and a new transfer for workers in export-oriented industries with a target of 1 million households. The transfer for workers in export-oriented industries took the form of a monthly transfer of BDT 3,000 (100% of the monthly national poverty line) for a maximum of three months (Hebbar et al.).

Sierra Leone's response included:

- One-off cash transfer of SSL 250,000[38] (62% of the monthly national poverty line[39]) and in-kind handouts to extremely poor persons with disabilities.
- A one-off emergency cash transfer of SLL 1,309,000 (3 times the monthly national poverty line) targeted at informal sector workers, low-wage workers in the services sector, and workers in small and micro enterprises (to reach 29,000 households).
- The poverty-targeted social safety net programme, which was in the process of being introduced in the country, was also horizontally expanded to cover an additional 65,000 households (around 5% of the total population). The design of the programme was modified to deliver a total of SSL 2,659,000 (almost 8 times the monthly national poverty line) over nine months (Yusuf et al.).

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[34] Average exchange rate between April and June 2020 was 163.5 PKR for 1 USD, 180.2 PKR for 1 Euro.
[35] Estimate based on Pakistan monthly per adult equivalent poverty line.
[36] Average exchange rate between April and June 2020 was 84.9 BDT for 1 USD, 94.1 BDT for 1 Euro.
[37] Estimate based on Bangladesh monthly national per capita poverty line.
[38] Average exchange rate between April and June 2020 was 9,523 SLL for 1 USD, 10,495 SLL for 1 Euro.
[39] Estimate based on Sierra Leone monthly per adult equivalent poverty line.

Mongolia adopted a significant and relatively swift response to the crisis. The overall package of support between April and September 2020 was equivalent to about 5% of the 2018 GDP. The country increased the benefit amount of some of the main social assistance programmes that existed in the country before the pandemic (vertical expansion), including;

- The '*Child Money Programme'*, generally provided to all children under 18, was increased from 20,000 MNT to 100,000 MNT[40] per month which is equivalent to more than half of the official national monthly poverty line. Monthly transfers were provided from April through to June 2021.
- Social welfare pensions, which are normally provided to around 9% of households in the country[41], were also increased from 180,000 MNT to 280,000 MNT from May to September 2020.
- Food stamps, which are usually provided to approximately 8% of the population identified through a poverty-targeted approach (PMT), were also doubled in value for five months (between May and September).

Other significant support measures have included the exemption of the payment of social security contributions and the payment of personal income tax, as well as support to herders through a subsidy for each kilogram of cashmere.

Georgia's response to the first wave of the epidemic was also substantial. For six months, the overall budget of support was equivalent to about 2.15% of the 2018 GDP. Responses included several top-ups, horizontal expansions, and new benefits using the information in the available social registry.

- The amount of the cash transfers for persons with disabilities was increased and households in the social registry who are above the eligibility threshold for the main '*Targeted Social Assistance'* programme, but still relatively poor, also received special support. Moreover, families with three or more children under 16 who are in the social registry and are classified as being relatively poor also received new support. In all these cases the cash support lasted for 6 months for an amount equal to 100 GEL[42] per month per household which is about two-thirds of the official monthly poverty line. It is estimated that these transfers reached about 12% of households in the country.
- The number of beneficiaries of the 'Targeted Social Assistance' programme increased by almost 22% from January to December 2020 thanks to the simplification of some of the social registry registration procedures. Simplifications included the reduction in registration checks, automatic extension of the validity of applications, and waiving of some of the asset tests.
- Two new measures were introduced to address rising unemployment. Firstly, all employees in the formal sector who lost their job received up to six, monthly payments of 200 GEL per month. Also, self-employed and informal workers that could demonstrate a loss of work as a result of the pandemic received a one-off transfer of 300 GEL. These measures could have reached, respectively, 21% and 16% of households in the country.
- Tax exemptions for a period of six months were granted to people receiving low incomes, and utility subsidies (for gas and electricity) were given for three months to households with low kilowatt consumption. These measures reached around 40% of the population for tax exemptions and 80% for utility subsidies.

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[40] Average exchange rate between April and June 2020 was approximately 2800 MNT for 1 USD, 3100 MNT for 1 Euro.

[41] Eligible group include persons with disabilities without social insurance, senior citizens who are not entitled to pension benefits from social insurance, orphaned or half-orphaned children and single parents with four or more children.

[42] Average exchange rate between April and June 2020 was about 3.11 GEL for 1 USD and 3.45 GEL for 1 Euro.

Annex 2: Simulated transfer value

Table 2. Simulated transfer value as % of the national poverty line, by target population, total budget, and country.

	Total Budget (% GDP)	0.5%	1%	2%	4%
Target population	Transfer (% National Poverty line)				
Universal	Mongolia	2%	5%	10%	20%
	Georgia	4%	9%	18%	36%
	Pakistan	2%	5%	10%	19%
	Bangladesh	2%	3%	7%	14%
	Sierra Leone	1%	1%	2%	4%
Children < 18	Mongolia	5%	15%	30%	61%
	Georgia	13%	93%	185%	370%
Children < 10	Pakistan	13%	25%	50%	100%
	Bangladesh	12%	24%	48%	95%
	Sierra Leone	3%	5%	10%	21%
Vulnerables (Widows/Elderly/Children<10)	Mongolia	5%	13%	26%	51%
	Georgia	6%	14%	28%	55%
Vulnerables (Widows/Elderly/Children<5)	Pakistan	10%	19%	38%	76%
	Bangladesh	7%	15%	29%	58%
	Sierra Leone	2%	4%	7%	15%
PMT (20%)	Mongolia	13%	26%	52%	103%
	Georgia	23%	46%	92%	185%
	Pakistan	13%	25%	50%	101%
	Bangladesh	9%	18%	35%	71%
	Sierra Leone	3%	6%	11%	23%
PMT (30%)	Mongolia	9%	17%	34%	68%
	Georgia	15%	31%	61%	122%
	Pakistan	8%	17%	34%	67%
	Bangladesh	6%	12%	24%	47%
	Sierra Leone	2%	4%	8%	15%
PMT (40%)	Mongolia	6%	13%	25%	51%
	Georgia	11%	23%	46%	91%
	Pakistan	6%	13%	25%	50%
	Bangladesh	4%	9%	18%	35%
	Sierra Leone	1%	3%	6%	11%
PMT (50%)	Mongolia	5%	10%	20%	40%
	Georgia	9%	18%	36%	73%
	Pakistan	5%	10%	20%	40%
	Bangladesh	3%	7%	14%	28%
	Sierra Leone	1%	2%	5%	9%
Geographical (30%)	Mongolia[a]	7%	13%	27%	53%
	Georgia	15%	30%	60%	119%
	Pakistan	8%	17%	34%	68%
	Bangladesh	6%	11%	22%	45%
	Sierra Leone	2%	4%	8%	15%
Geographical (20%)	Pakistan	12%	24%	47%	95%

Notes: Geographical coverage for Mongolia is 37% of the population.

Table 3. Squared poverty gap before and after the pandemic and % increase post-COVID-19, by country

	Mongolia			Georgia			Pakistan			Bangladesh			Sierra Leone		
Squared Poverty Gap	Pre	Post	Δ	Pre	Post	Δ	Pre	Post	Δ	Pre	Post	Δ	Pre	Post	Δ
Overall	1.93	3.34	73%	2.96	11.15	276%	1.26	6.02	376%	1.76	4.44	153%	1.86	3.30	77%

Source: Authors based on results of microsimulations.

Table 4. Potential coverage of a selection of simulated categorical, PMT, and geographically targeted programmes before and after the pandemic.

	Children Under 5		Vulnerable[a]		PMT		Geography	
Mongolia								
% population	47		34		30		37	
% chronic poor	56		41		68		45	
% new poor	50		23		22		40	
Consumption quintiles	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Q1	57	58	44	37	76	70	46	44
Q2	52	51	37	37	43	43	44	44
Q3	47	46	34	34	19	24	39	40
Q4	44	45	30	33	9	10	33	33
Q5	36	37	28	30	2	3	23	25
Georgia								
% population	30		68		30		30	
% chronic poor	33		72		62		39	
% new poor	31		59		18		24	
Consumption quintiles	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Q1	34	34	71	54	70	42	39	28
Q2	30	32	74	74	40	48	37	37
Q3	29	27	71	75	24	33	33	33
Q4	28	29	63	73	12	21	23	29
Q5	27	26	61	65	4	7	16	21
Pakistan								
% population	57		41		30		29	
% chronic poor	66		42		65		51	
% new poor	59		39		25		25	
Consumption quintiles	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Q1	67	63	42	35	72	53	56	38
Q2	64	62	43	43	45	50	38	42
Q3	58	63	42	42	23	33	27	33
Q4	54	55	41	45	7	12	15	21
Q5	42	43	40	42	1	2	9	11
Bangladesh								
% population	41		37		30		31	
% chronic poor	44		41		57		57	
% new poor	44		36		32		19	
Consumption quintiles	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Q1	44	46	42	39	62	54	62	44
Q2	44	44	38	38	41	46	41	41
Q3	42	42	37	38	28	29	26	32
Q4	39	38	37	37	14	15	15	22
Q5	34	34	31	33	4	5	10	15
Sierra Leone								
% population	67		49		30		30	
% chronic poor	77		60		64		55	
% new poor	67		52		24		16	
Consumption quintiles	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Q1	80	74	63	59	71	55	59	42
Q2	72	74	54	56	46	48	40	40
Q3	71	70	48	49	24	27	30	34
Q4	64	66	41	41	8	16	16	24
Q5	49	52	37	39	2	4	5	10

Source: Authors based on results of microsimulations. Notes: Table 4 shows for each beneficiary selection criteria: the percentage of the country population that a programme using the above targeting method would cover[43], the percentage of chronic poor population and new poor that would be covered, and the coverage by consumption quintile pre- and post-pandemic. [a] For Pakistan this category does not include people living with a disability due to the lack of information in the survey data.

[43] This includes direct and indirect beneficiaries, where indirect beneficiaries are individuals living with one or more direct beneficiary.

Table 5. Post transfer poverty headcount and poverty reduction with respect to post-COVID-19 estimates, by transfer type, total budget, and country.

	Budget = 1% GDP										Budget = 4% GDP									
Transfer type	**Mongolia**		**Georgia**		**Pakistan**		**Bangladesh**		**Sierra Leone**		**Mongolia**		**Georgia**		**Pakistan**		**Bangladesh**		**Sierra Leone**	
Universal	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ
Overall	35.3	-9%	49.5	-8%	59.7	-4%	47.7	-6%	36.0	-24%	24.4	-37%	37.1	-31%	52.1	-16%	37.9	-25%	24.8	-48%
Urban	33.3	-9%	49.9	-7%	50.3	-4%	40.5	-7%	33.4	-14%	23.5	-36%	38.8	-28%	44.2	-15%	32.9	-24%	25.7	-34%
Rural	39.1	-10%	48.8	-9%	64.8	-4%	50.7	-5%	38.1	-30%	26.1	-40%	34.6	-35%	56.4	-16%	39.9	-26%	24.0	-56%
Children[a]	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ
Overall	34.7	-11%	48.9	-9%	59.2	-5%	47.6	-6%	35.7	-25%	21.8	-44%	33.9	-37%	49.5	-20%	37.7	-26%	25.5	-46%
Urban	32.8	-10%	49.4	-8%	50.3	-4%	40.3	-7%	33.6	-14%	21.1	-42%	35.3	-34%	44.1	-16%	32.3	-26%	27.3	-30%
Rural	38.4	-12%	48.2	-10%	64.1	-5%	50.6	-6%	37.2	-31%	23.4	-46%	31.8	-41%	52.3	-23%	39.9	-26%	24.0	-56%
Vulnerables[b]	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ
Overall	35.2	-10%	49.0	-9%	59.7	-4%	47.6	-6%	36.3	-23%	23.6	-39%	36.1	-33%	51.5	-17%	38.8	-23%	26.2	-45%
Urban	33.1	-10%	49.2	-8%	50.5	-3%	40.6	-7%	33.9	-13%	22.3	-39%	37.7	-30%	45.3	-13%	33.8	-22%	27.7	-29%
Rural	39.3	-10%	48.6	-9%	64.6	-4%	50.5	-6%	38.2	-29%	26.2	-40%	33.9	-37%	54.8	-19%	40.9	-24%	25.0	-54%
PMT[c]	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ
Overall	33.8	-13%	47.8	-11%	59.8	-4%	47.5	-6%	34.6	-27%	17.4	-55%	30.7	-43%	47.6	-23%	36.0	-29%	24.3	-49%
Urban	30.7	-16%	50.8	-5%	51.7	-1%	40.4	-7%	35.9	-8%	16.0	-56%	36.9	-31%	46.7	-11%	31.9	-27%	32.2	-17%
Rural	39.9	-8%	43.4	-19%	64.1	-5%	50.4	-6%	33.5	-38%	20.3	-53%	21.8	-59%	48.0	-29%	37.7	-30%	18.2	-66%
Geograhic[d]	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ
Overall	34.7	-11%	48.9	-9%	59.5	-4%	48.2	-5%	36.5	-23%	23.8	-39%	37.3	-30%	48.0	-23%	39.7	-22%	31.0	-35%
Urban	34.6	-6%	52.3	-2%	51.7	-1%	43.0	-1%	38.9	0%	29.3	-20%	47.9	-11%	48.6	-7%	41.0	-6%	38.9	0%
Rural	34.9	-20%	43.9	-18%	63.7	-6%	50.4	-6%	34.6	-36%	13.0	-70%	22.0	-59%	47.6	-29%	39.2	-27%	25.0	-54%

Source: Authors based on results of microsimulations. Notes: a Beneficiaries are all children below 5 years old in all country except Mongolia where all children below 10 benefit. b Beneficiaries are elderly above 60 years old, children below 5 years old, widowed/separated women, and people with a disability (for Pakistan the last category cannot be targeted). A special equivalence scale is used to account for disability with beneficiaries with a disability receiving 50% higher transfers than the other categories. c Beneficiaries are all individuals with a PMT score among the 30% lowest. d Beneficiaries are all individuals residing in the poorest 30% geographical areas in each country.

Table 6. Post transfer poverty gap and poverty gap reduction with respect to post-COVID-19 estimates, by transfer type, total budget, and country.

	Budget = 1% GDP										Budget = 4% GDP									
Transfer type	**Mongolia**		**Georgia**		**Pakistan**		**Bangladesh**		**Sierra Leone**		**Mongolia**		**Georgia**		**Pakistan**		**Bangladesh**		**Sierra Leone**	
Universal	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ
Overall	6.8	-16%	14.6	-15%	19.0	-9%	14.4	-12%	9.1	-28%	3.7	-55%	8.3	-52%	14.1	-32%	10.3	-37%	5.7	-54%
Urban	6.7	-15%	15.7	-14%	16.7	-8%	12.7	-16%	9.4	-16%	3.8	-52%	9.2	-49%	12.7	-30%	9.2	-39%	6.7	-40%
Rural	6.9	-18%	13.0	-16%	20.3	-9%	15.1	-10%	8.9	-35%	3.4	-59%	6.9	-55%	14.9	-34%	10.7	-36%	5.0	-64%
Children[a]	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ
Overall	6.6	-19%	14.4	-16%	18.8	-10%	14.4	-12%	9.2	-27%	3.4	-58%	9.0	-47%	13.8	-34%	10.7	-34%	6.3	-50%
Urban	6.5	-18%	15.5	-15%	16.7	-8%	12.7	-16%	9.6	-14%	3.4	-57%	9.7	-47%	13.2	-27%	9.7	-36%	7.4	-34%
Rural	6.7	-19%	12.8	-17%	19.9	-11%	15.0	-10%	8.9	-35%	3.5	-59%	7.9	-49%	14.2	-37%	11.1	-34%	5.4	-61%
Vulnerables[b]	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ
Overall	6.7	-17%	14.7	-14%	19.2	-8%	14.5	-11%	9.3	-26%	3.7	-54%	9.7	-43%	15.1	-28%	11.1	-32%	6.5	-49%
Urban	6.6	-17%	15.9	-13%	16.9	-6%	12.8	-15%	9.7	-13%	3.7	-54%	10.6	-42%	13.9	-23%	10.0	-34%	7.6	-32%
Rural	6.9	-18%	13.1	-15%	20.4	-9%	15.2	-9%	9.1	-34%	3.7	-55%	8.3	-46%	15.7	-30%	11.6	-31%	5.6	-59%
PMT[c]	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ
Overall	5.6	-31%	13.7	-20%	18.1	-13%	13.8	-15%	8.6	-32%	2.3	-72%	8.2	-52%	12.1	-42%	9.4	-42%	6.0	-52%
Urban	5.2	-35%	16.0	-12%	17.2	-5%	12.3	-19%	10.0	-10%	2.2	-72%	10.8	-41%	13.9	-23%	8.7	-43%	8.7	-22%
Rural	6.4	-23%	10.5	-32%	18.5	-17%	14.4	-14%	7.5	-45%	2.4	-71%	4.4	-71%	11.2	-50%	9.7	-42%	3.9	-71%
Geograhic[d]	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ
Overall	6.6	-18%	14.6	-14%	18.6	-11%	14.3	-12%	9.3	-27%	4.7	-41%	11.9	-30%	14.3	-32%	11.4	-30%	8.2	-35%
Urban	7.2	-9%	17.3	-5%	17.6	-3%	13.8	-9%	11.2	0%	6.1	-23%	16.2	-11%	16.1	-11%	12.9	-15%	11.2	0%
Rural	5.6	-33%	10.8	-30%	19.2	-14%	14.6	-13%	7.8	-44%	2.1	-75%	5.8	-63%	13.3	-41%	10.8	-36%	5.8	-58%

Source: Authors based on results of microsimulations. Notes: a Beneficiaries are all children below 5 years old in all country except Mongolia where all children below 10 benefit. b Beneficiaries are elderly above 60 years old, children below 5 years old, widowed/separated women, and people with a disability (for Pakistan the last category cannot be targeted). A special equivalence scale is used to account for disability with beneficiaries with a disability receiving 50% higher transfers than the other categories. c Beneficiaries are all individuals with a PMT score among the 30% lowest. d Beneficiaries are all individuals residing in the poorest 30% geographical areas in each country.

Table 7. Post transfer poverty headcount and poverty reduction with respect to post-COVID-19 estimates, by total budget and country for three potential PMT targeting coverage.

	Budget = 1% GDP										Budget = 4% GDP									
Transfer type	Mongolia		Georgia		Pakistan		Bangladesh		Sierra Leone		Mongolia		Georgia		Pakistan		Bangladesh		Sierra Leone	
PMT (20%)[a]	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ
Overall	34	-13%	48	-11%	60	-4%	48	-6%	38	-21%	23	-42%	37	-30%	47	-25%	40	-22%	33	-29%
Urban	31	-16%	51	-5%	52	-1%	40	-7%	37	-4%	18	-50%	43	-19%	48	-9%	33	-24%	36	-7%
Rural	40	-8%	43	-19%	64	-5%	51	-5%	38	-30%	31	-28%	29	-46%	46	-31%	42	-21%	31	-42%
PMT (30%)[b]	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ
Overall	34	-13%	49	-9%	60	-4%	48	-6%	36	-23%	17	-55%	32	-40%	46	-26%	37	-26%	29	-39%
Urban	31	-15%	51	-5%	52	-1%	40	-7%	37	-4%	14	-63%	39	-27%	47	-10%	32	-26%	35	-10%
Rural	39	-10%	45	-16%	64	-5%	51	-5%	36	-34%	25	-43%	23	-58%	46	-33%	39	-26%	25	-55%
PMT (50%)[c]	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ	H0	Δ
Overall	34	-13%	49	-9%	60	-4%	47	-7%	35	-27%	17	-55%	31	-43%	48	-22%	36	-29%	24	-49%
Urban	32	-14%	50	-6%	51	-2%	40	-7%	36	-8%	16	-56%	37	-31%	46	-12%	32	-27%	32	-17%
Rural	38	-12%	46	-13%	64	-5%	50	-6%	34	-38%	20	-53%	22	-59%	50	-27%	38	-30%	18	-66%
PMT (20%)[a]	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ
Overall	5.6	-31%	13.7	-74%	18	-13%	14	-14%	9	-25%	4.0	-50%	12.0	-78%	14	-33%	11	-31%	8	-34%
Urban	5.2	-35%	16.0	-70%	17	-5%	12	-20%	11	-5%	3.4	-57%	14.6	-73%	16	-14%	10	-36%	10	-10%
Rural	6.4	-23%	10.5	-80%	19	-17%	15	-12%	9	-38%	5.3	-37%	8.1	-85%	13	-42%	12	-29%	7	-49%
PMT (30%)[b]	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ
Overall	5.7	-29%	13.8	-74%	18	-13%	14	-15%	9	-29%	2.9	-64%	10.0	-81%	13	-40%	10	-37%	7	-42%
Urban	5.4	-32%	15.9	-70%	17	-6%	12	-19%	10	-7%	2.4	-70%	12.9	-76%	15	-20%	9	-40%	10	-13%
Rural	6.3	-24%	10.7	-80%	19	-17%	14	-14%	8	-44%	4.0	-52%	5.7	-89%	11	-49%	11	-36%	5	-60%
PMT (50%)[c]	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ	Pgap	Δ
Overall	6.0	-25%	14.0	-74%	18	-12%	14	-15%	9	-32%	2.3	-72%	8.2	-85%	12	-42%	9	-42%	6	-52%
Urban	5.9	-25%	15.7	-71%	17	-7%	12	-18%	10	-10%	2.2	-72%	10.8	-80%	13	-26%	9	-43%	9	-22%
Rural	6.2	-25%	11.6	-78%	19	-15%	14	-14%	8	-45%	2.4	-71%	4.4	-92%	11	-49%	10	-42%	4	-71%

Source: Authors based on results of microsimulations. Notes: a Beneficiaries are all individuals with a PMT score among the 20% lowest. b Beneficiaries are all individuals with a PMT score among the 30% lowest. c Beneficiaries are all individuals with a PMT score among the 50% lowest.

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