SOCIAL PROTECTION AND HUMANITARIAN CASH AND FOOD RESPONSES TO COVID-19: NEEDS, COVERAGE, AND GAPS

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September 2020

1 KEY MESSAGES AND RECOMMENDATIONS

The direct economic impacts of the COVID-19 pandemic and associated lockdowns are leading more people into poverty and hunger. Estimates to date on the impact of COVID-19 on poverty and food security are an important first step towards understanding the potential scale of need. However, they are mainly based on very high-level projections that apply uniform assumptions on impact, that simultaneously under-estimate the scale of needs and obscure who or where the needs are likely to be. At the same time, there have been some impressive efforts at compiling a detailed picture of social protection responses (Gentilini et al; IPC-IG), but the scattered and incomplete nature of the data makes it difficult to ascertain the extent to which coverage is expanding to meet the increase in needs.

This exercise aims to provide a more comprehensive look at needs, coverage, and gaps for 10 fragile and conflict-affected countries. It does this by undertaking detailed micro-simulations for three 'deep dive' countries (Bangladesh, Ethiopia, and Zimbabwe) and a more 'light touch' approach in the others (Afghanistan, Burkina Faso, Chad, DRC, OPT, Syria, and Yemen).

With respect to needs:

- Needs, as measured by those whose consumption falls below the national poverty line (which tends to be similar to the global 'extreme' $1.90/day line), are predicted to increase significantly as a result of anticipated COVID-19 recessions: in the 10 countries included here alone, *over 55 million additional people will be pushed into poverty.*
- This increase in need is disproportionately found in urban areas. For example, in Bangladesh urban poverty incidence increases by 124% compared to 43% in rural areas; and in Ethiopia 272% versus 29%.

- While number of people in need increased, the poverty gap is estimated to decrease on average, since many of the newly poor are closer to the threshold than the existing group already in poverty. However, many who started out already poor are also impacted by COVID-19 and fall even further below the poverty line, so even if the average poverty gap is decreasing overall, it will increase significantly for many households.
- Applying a micro-simulation model that accounts for greater levels of heterogeneity and differentiated impacts suggests that the number of those affected will be significantly higher than estimates to date. Approaches that assume a uniform impact across the board (which include most of the existing estimates) yield estimates of need that are significantly lower even for the same average impact than ones that account for heterogeneity. As an example, in Ethiopia alone, this would lead to an under-counting of the new poor by 8 million. This has major implications for the global estimates of COVID-19-induced poverty produced by the World Bank and others, suggesting great caution in their interpretation[1]. It also has major implications for our understanding of *who* is in need; these approaches tend to imply that it is those who were just above the poverty line who would be thrown into poverty as a result of COVID-19-induced recessions. Accounting for heterogeneity emphasises that many who started out far above the poverty line will be hit hardest.

With respect to coverage:

- Total coverage has increased in line with increases in poverty due to COVID-19 *on aggregate*, so that total coverage relative to the total poor stayed relatively constant across most of the countries included here. The combination of humanitarian transfers and on-going social protection programmes therefore suggests that the total number of targeted beneficiaries has scaled roughly in line with COVID-19-related needs. Or, put differently, post-COVID-19 coverage generally reflects the extent of coverage (or lack thereof) before the pandemic. However, coverage across countries is hugely disparate, and these 10 countries include a number of conflict countries that have relatively extensive support systems in place. Therefore, caution should be used before extrapolating these findings more broadly.
- *Beyond these total figures, however, effective* coverage of the poor (the poor who are actually covered) is much lower than total coverage would suggest, given high levels of targeting errors and programmes that are more universal in nature which mean that many of those covered are above the poverty line. This leaves nearly 42 million *additional* poor people uncovered as a result of COVID-19 in these 10 countries alone, for a total of 213 million poor people without either social protection or humanitarian cash or food assistance.

Implications for targeting COVID-19 responses:

- There is a need to urgently scale up coverage of social protection and humanitarian cash and food assistance to address both increasing levels of poverty and errors of exclusion, with particular attention to the urban poor.

[1] These may diverge for other reasons as well, including the specific assumptions used about the duration and size of the income shocks. The key point here, however, is that accounting for heterogeneity gives very different results, even holding other assumptions constant.

- New targeting approaches, including in some cases non-traditional measures, will be required to ensure exclusion errors are minimised. It is clear that much of the new caseload is likely to be very different from the existing one, and expanding horizontally using traditional methods - for example, using those on waiting lists, or increasing the eligibility threshold of existing proxy means tests – may be easier but will inherently leave out many of the newly poor. Creative measures such as community-based targeting and using networks of trusted affiliates to rapidly find the newly poor and minimise exclusion may be necessary.
- Carefully assess the adequacy of transfer size, in light of the magnitude of income losses, and accounting for potentially differentiated levels of transfers for cohorts who are just below the poverty line (as evidence by the decrease in the average size of the deficit) as well as we those who are in more extreme poverty.
- The scale of the response required means it is imperative that social protection and humanitarian systems work together to deliver a response, drawing on the key strengths of both.
- Whilst it is critical that response is timely, this analysis also highlights the importance of careful, but rapid assessments of need using micro-simulations wherever possible, accounting for heterogeneity of impacts and actual patterns of livelihoods strategies.
- These needs assessments must be joined-up efforts between humanitarian and development partners to ensure a coherent and coordinated response.
- Much better information sharing needs to be put in place for both social protection and humanitarian responses by all stakeholders, to enable a more global and more timely assessment of COVID-19-related needs, coverage, and remaining gaps.

2 INTRODUCTION

2.1 Background and context

The economic impacts of the COVID-19 pandemic and related lockdowns are leading more people into extreme poverty and hunger, and the number of people in need of social protection programming and other responses is increasing. At the same time, the fiscal space for response is under stress, including both domestic and international funding of social protection and humanitarian responses, given the challenging macro-fiscal environments in low- and middle-income countries and development partners alike. In response to the crisis, Humanitarian Response Plans (HRPs) have focused on the socio-economic impacts of COVID-19 and the role of cash and food assistance, and the World Bank and other development partners have been scaling up their investments in social protection.

Global estimates indicate a surge in the number of people being pushed into poverty as a result of COVID-19. For example, UNU WIDER estimates that 69 million people will fall back into extreme poverty[2]. The World Bank has very recently revised their estimates upwards based on new data, estimating that 88-115 million will be pushed under the $1.90 international 'extreme' poverty line[3] (revised upwards from the original estimate of 71-100 million[4]). However, these estimates are based on very high-level projections, for example taking estimates of reductions in GDP and estimates of inequality, and projecting those onto a total increase in the number of people below the poverty line (e.g. World Bank) or assuming that consumption will shrink by some percentage across the board (UNU-WIDER). Other approaches that take a more detailed approach (e.g. UNDP's simulations for some countries in SSA[5]) rely on very broad assumptions and tend to consider only more limited lockdown scenarios rather than on-going recessions.

These estimates are a very helpful first step towards estimating need. The analysis presented here seeks to build on this work by using detailed micro-simulations to provide a more nuanced estimate of heterogeneous needs. Further, this analysis seeks to advance the field by using the same microsimulations to estimate the extent to which resources have matched the level of need, and where the remaining gaps are.

2.2 Objectives

The objectives of this exercise were to assess the:

- Level and distribution of need both before and after COVID-19-induced recessions;
- Nature and distribution of cash transfers and food assistance, both before COVID-19 and in response to it to mitigate these effects;
- Gaps in provision: how many, who, and where?

The following sections describe the approach and methodology, and this is followed by sections that describe the key findings on needs, coverage and gaps.

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[2] Sumner et al (2020) "Impacts of COVID-19 on Global Poverty", WIDER Working Paper 2020/43 https://www.wider.unu.edu/publication/estimates-impact-COVID-19-global-poverty
[3] https://blogs.worldbank.org/opendata/updated-estimates-impact-COVID-19-global-poverty-effect-new-data
[4] https://blogs.worldbank.org/opendata/updated-estimates-impact-COVID-19-global-poverty
[5] https://www.undp.org/content/undp/en/home/coronavirus/socio-economic-impact-of-COVID-19.html

Annex A contains a more detailed description of the approach and methodology, and Annex B contains full data tables to support the findings summarised here.

3 SUMMARY OF THE APPROACH AND METHODOLOGY

3.1 Analytical approach

This section describes some of the more contextual issues that influenced the design of the simulation, followed by a more detailed breakdown of the methodology.

3.1.1 Building on existing approaches

A number of models have measured the potential impact of COVID-19 on poverty, including the UNU Wider and World Bank assessments described previously, as well as a range of country level studies, for example by UNDP[6]. As described previously, these methods typically assume that there will be an equivalent decrease in consumption across the board; the weakness of this approach is that it mis-represents the number of people who will be below the poverty line, because it is unable to take account of heterogeneity of impacts. Many of the country level estimates do not use simulations, or, where they do, tend to use very uniform and generalised assumptions. World Bank country estimates range from extremely detailed micro/macro-simulations (such as for Brazil) to very simple estimates based on an across-the-board decrease in consumption (such as Ethiopia)[7]. Estimates for humanitarian needs resulting from COVID-19, at least for the countries here, appear to have been based on extremely simplified assumptions (i.e. that needs will have increased by 10% from the HRP, or that 50% of the extreme poor will now need assistance).

Simulations that account for the full heterogeneity of actual impacts are still quite rare, and this analysis seeks to build on the work to date by offering a more nuanced look at differences in impact. The micro-simulation approach allows for fine-grain assessments of 'with' and 'without' COVID-19 need - excluding existing transfers – in order to assess the true level of need for social protection and/or humanitarian cash transfers or food aid. It also allows for a fuller accounting of the heterogeneous nature of COVID-19 economic shocks, in this case looking primarily at livelihood impacts, (where some households may lose all earnings, others will lose some, and many will remain unscathed), which is essential for estimating the true number of people who will require support.

3.1.2 Focusing on recessions vs lockdowns

The estimates here are for on-going needs and gaps over the next year (and beyond) due to anticipated COVID-19-induced recessions induced by lockdowns and the global economic contraction that results. While lockdowns will generally cause more extreme curtailment of economic activities across the board, some of which would resume immediately once lockdowns were lifted, other sectors will continue to contract because of reductions in both

[6] https://www.undp.org/content/undp/en/home/coronavirus/socio-economic-impact-of-COVID-19.html
[7] https://blogs.worldbank.org/africacan/ethiopia-poverty-assessment-what-can-it-tell-us-about-likely-effects-coronavirus

local and global demand in the short- and medium-term[8]. The focus on recessions entails making assumptions of the likely impacts over the next year, even after lockdowns have lifted, and the coverage of programming that extends over a similar period.

3.1.3 Focusing on COVID-19-induced need

Although the end goal is to understand the level of need that will arise immediately and over the next year, it is important to also try to separate out how much of that need is specifically COVID-19-induced. In many countries the shocks from COVID-19 are taking place in addition to not only high levels of existing poverty, but also already-significant existing shocks in the form of desert locust infestations, conflict, drought, or other natural hazards. The approach here is to estimate as much as possible the 'without COVID-19' counterfactual so that we can attempt to attribute changes in needs to COVID-19 itself. The conceptual understanding of these COVID-19-specific shocks (as well as other existing shocks) is rooted in the livelihood's framework, which emphasises understanding the diversity of household livelihood strategies[9].

There are of course many different ways in which need could be defined. For the purposes of this exercise, in all countries included here, need is defined as those who are beneath the national general poverty line. This is determined by the cost of basic needs approach, reflecting the minimum amount required to meet both food (determined by caloric requirement) and non-food needs. The national poverty lines were chosen, rather than international lines such as the $1.90/day PPP, because they are consistent with official definitions of poverty in each country. (However, it should be noted that for many countries included here, the 'general' poverty line happens to be relatively close to the $1,90/day 'extreme' poverty line),

The accuracy of these assessments of need depends entirely on the level of detail in the approach; estimates for the 'deep dive' countries are much more robust than the other countries.

3.1.4 Understanding coverage

The focus here is on social protection and humanitarian responses that relate to cash, vouchers, and in-kind food aid. For social protection programming, we focus on social assistance, public works employment, and social pensions, and exclude fee waivers and stipends. Data on pre-COVID-19 coverage is drawn from, where available, Safety Nets Assessments published by the World Bank, DFID and World Bank programme reporting. There is unfortunately no existing database providing comprehensive information across countries[10], and individual programme data is often reported separately, so this was a multi-staged exercise to establish first what programmes were in place, and then to search for specific details on coverage and targeting for each programme. Information on new COVID-19 responses comes from the extremely useful databases such as the IPC-IG and Gentilini et al[11] - which provide some indication of what is being planned but without much detail in terms of

[8] For practical purposes, it would be difficult to disentangle the effects from lockdowns from those of the recessions that follow, and no attempt to do so is made here.
[9] For further elaboration, see Understanding the Economic Impacts of COVID-19 in Low- and Middle-Income Countries: Who, Where, How, and When?
[10] The World Bank's ASPIRE database aims to do this, but the data for most countries is extremely out of date and therefore not useful for this exercise.
[11] http://documents1.worldbank.org/curated/en/454671594649637530/pdf/Social-Protection-and-Jobs-Responses-to-COVID-19-A-Real-Time-Review-of-Country-Measures.pdf

who, where, or how much - and then supplemented wherever possible with additional programme documentation to glean more information about projected coverage, targeting, and timing. The focus here is on programming that goes beyond one-off interventions, so it excludes any one-off or very temporary measures during lockdowns. There may therefore be further programming in the pipeline that has yet to be reported that has not been included here.

Humanitarian coverage is drawn from Humanitarian Response Plans and Updates, as well as WFP and OCHA updates, where available. In most cases, these are unfortunately extremely limited in information with regards to actual number of people covered, the expected amounts or duration of transfers. Expected coverage is based on targets from the HRPs and Updates. Given the extreme uncertainty around exactly how much would be funded, for simplicity this assumes full funding of the HRPs (or that in the absence of full funding the same number would be reached with smaller/fewer transfers). It can therefore be seen to represent an upper bound of who is planned to be reached, and actual numbers will be smaller in the case of funding shortfalls[12].

In both cases, coverage entails not just total numbers reached but also the distribution of that coverage in order to assess how many of the *poor* are actually receiving assistance. Where possible based on available documentation, actual targeting efficiency information is used for these estimates. In other cases, assumptions are made based on international experiences with the particular kind of targeting approach employed[13].

3.2 Methodology

3.2.1 Select priority countries

The first step was to select a list of priority countries for the analysis. A longer list of 29 priority countries was selected with a view to balancing geographic and contextual coverage. Ideally, we would have included all low- and middle-income countries to gauge the overall flow of resources against needs, but the time and resources required for that global look are far beyond this exercise. Ten of these countries were selected for analysis based on availability and quality of data, both in terms of household level survey data as well as rapid/real-time assessments of the impacts of COVID-19 to underpin the assumptions used in the micro-simulation.

The analysis is based on the selection of these ten fragile and conflict-affected states where both humanitarian cash transfers and social protection are being provided, namely Afghanistan, Bangladesh, Burkina Faso, Chad, DRC, Ethiopia, OPT, Syria, Yemen, and Zimbabwe.[14] In three 'deep dive' countries (Ethiopia, Zimbabwe, and Bangladesh) the estimates of needs and impacts are based on full microsimulations of household survey data. In the remaining seven countries, estimates are based on much higher-level aggregated information, with assumptions informed by the 'deep dive' findings.

[12] In further estimates (not reported here), another scenario was estimated based on the share of funding for food aid in each HRP including COVID-19 updates, that had been received at the time of the analysis (in July 2020).

[13] See Kidd and Wylde (2011) "Targeting the Poorest: An Assessment of the Proxy Means Test Methodology" AusAID for some general trends in targeting efficiency by programme size for proxy means tests, for example.

[14] Brazil and Jamaica were also covered, but not included in the analysis here, as they are quite different in context from the others in the list.

3.2.2 Develop detailed micro-simulation models in the 'deep dive' countries

Detailed micro-simulations were undertaken for the three deep dive countries. The models provide the following simulation data:

- Pre- and post-COVID-19 consumption, before and after social protection/humanitarian transfers to allow estimates of pre- and post-COVID-19 poverty incidence, and depth of need;
- Estimates for both urban and rural households;
- Coverage (and hence gaps) in total and of the poor;
- The data reported is estimated against two different poverty lines - general poverty line, and a higher vulnerability line equivalent to 1.5 times the general line (see below for greater detail).

The micro-simulation models using household consumption and expenditure survey data were developed by:

I. Aging the datasets to represent 2020 by adjusting population weights to reflect population growth and urbanisation, adjusting for inflation, and adjusting for changes in poverty, and incorporating the effects of major events (e.g. drought in Zimbabwe, desert locust infestation in Ethiopia) on key household characteristics.

II. Backing out any existing social protection or humanitarian cash and food assistance that is reported, to assess what poverty would be in the *absence of any such programming*.

III. Determining 'need' pre-COVID-19, defined as those who would be below the general poverty line. Need was also estimated against a "vulnerability" threshold. This latter estimate is important, because (a) the general poverty line only covers the most basic food needs and therefore represents a bare minimum survival threshold, whereas a vulnerability line may be a more accurate reflection of a poor household's cost to maintain a basic minimum livelihoods standard; and (b) the vulnerability provides an estimate of the number of households who may be hovering just above the poverty line and who are high risk for falling into poverty should lockdowns/external shocks continue in this next year.

IV. Modelling the impact of the COVID-19 lockdown/recessionary impacts. The modelling relies on existing COVID-19 high frequency surveys as well as FEWSNET updates, to underpin a series of assumptions including agricultural price inputs (applies only to those households actually purchasing inputs); reductions in remittance income from domestic and international sources; reductions in wage earnings by sector and nature of employment (casual, permanent, or household enterprise), and price impacts. These assumptions are then used to simulate the impact of the COVID-19 lockdowns on households.

V. Modelling coverage, including targeting of existing and new programming. This involves an analysis of (a) who is already covered in the survey and then (b) scaling up to include additional households (where programmes had expanded since the survey was undertaken, and/or to account for any random under-sampling in the survey). This scale-up is based on either a proxy means test (where this is the targeting approach used by programmes in practice, for example Ethiopia's Urban PSNP) or based on a regression of likelihood of selection based on the characteristics of current beneficiaries (essentially allowing the model to mimic the current levels of targeting efficiency, using similar variables to those in a PMT). Humanitarian coverage is modelled using a similar approach, mimicking the distribution of coverage of any humanitarian programming in place at the time of the survey.

3.2.3 'Light touch' estimates

In the other 'light touch' countries, while it should be simple in theory to access estimates of poverty without COVID-19, in practice this is a challenge because available poverty estimates are several years old, and poverty assessments do not tend to provide the right kind of breakdowns in terms of livelihood strategies and consumption distribution that would be required to make an informed estimate of either non-COVID-19 shocks or COVID-19-specific impacts. The approach for these countries was much less rigorous than in the 'deep dive' countries. It starts with the most recent poverty estimates available, and then adjusts somewhat roughly as necessary (where, for example, countries faced poor harvests or worsening conflict in the intervening period since the latest poverty estimates). Where possible, information on targeting efficiency of existing programmes is based on the specific programmes, but in many cases, this is lacking, so assumptions are made about targeting errors, given the relative size of the programmes[15].

3.2.4 Limitations

A major limitation was the availability and quality of data to underpin the analysis. The simulations use the best data available, but there is a need to continue to update and refine this analysis as new data becomes available:

- Although informed as much as possible by existing data, the assumptions used in the micro-simulation models inevitably depend on assumptions based on the best available data. Given how much uncertainty exists about how lockdown experiences will ultimately translate into experiences during COVID-19-induced recessions, the modelling should be seen as a next step to build the field but applied with caution and updated as new data becomes available. Further, the estimates are primarily based on heterogeneous shocks to livelihoods/income. The model could be expanded and refined further to include heterogeneous impacts by sex and age, for example.
- With respect to humanitarian caseloads, the estimates of need published in humanitarian response plans, particularly with respect to COVID-19, do not appear to be based on sufficiently robust assessment of the evidence. For example, in Zimbabwe, the June Update to the HRP simply assumes that 10% of the population of Harare and 10% of the extreme poor will be affected by COVID-19. In Ethiopia, similarly, the HRP Update assumed that 50% of the extreme poor would be affected by COVID-19, with no reference to the evidence or assumptions used, or how actual need compares to actual coverage of existing social protection and humanitarian programmes.
- As shown in the analysis here, careful, detailed assessments are required in order to estimate with any degree of accuracy the numbers in need and, crucially, *who* is in need. These must be rooted in a livelihood's framework, based on evidence on income sources, the extent of consumption from people's own production, use of agricultural inputs like modern seed and chemical fertilizers, receipt of remittances, etc. This analysis can be further disaggregated in terms of certain characteristics, such as gender, age, disability

[15] Assuming estimates are similar to what would be expected using a Proxy Means Test for an equivalently-sized programme.

status that have an impact on a household's vulnerability and ability to cope with the shock.[16]

- Outside of humanitarian responses, highly aggregated estimates of needs and gaps are available for some countries[17], but these are both inaccurate and unhelpful in providing insight into either the *level* of un-addressed need or *where* the greatest needs in fact are. As illustrated above, while COVID-19 impacts will be wide-ranging, they will be nevertheless be highly heterogenous, with some people even in hard-hit industries relatively unscathed in terms of income loss, and others losing nearly everything. This means that applying average effects can lead to vast misrepresentations of the scale and depth of the impacts on poverty.
- On the coverage side, there is almost no publicly available information on humanitarian cash transfer and food assistance responses in terms of breakdowns of numbers reached by different modalities and different partners, or on actual numbers reached compared to those targeted in appeals[18]. There are scattered reports (such as WFP or FAO updates, OCHA updates, etc) but they do not provide specific information on reach by programme, either in terms of targeted or actual numbers, making it impossible to track coverage relative to the targets in the HRPs on aggregate, let alone separating out cash/in-kind provision from, say, school feeding.
- Data on coverage of social protection responses to COVID-19 also remains a very big challenge, as there is little publicly available information on what is in the pipeline, especially including details about how many are reached, details of targeting approaches, duration and nature of programming, etc.

While the estimates here provide some indications that many of the global estimates produced are likely to be vastly under-stating the impacts of COVID-19 on poverty, it is important to be careful in extrapolating the findings here with respect to trends in coverage and remaining gaps to other contexts.

This assessment was relatively rapid, which limited the scope of what could be done. This analysis could be expanded to:

I. Include more countries;

II. Undertake scenario analysis to test the impact of the assumptions on the final conclusions;

III. Expand the urban/rural differentiation to also look at data disaggregated by age, sex, etc;

IV. To model behavioural effects, particularly related to the use and implications of different household coping strategies.

4 FINDINGS

4.1 The number of people in need

[16] There are of course some major limitations on the extent to which household survey data can provide insight into some of these aspects, as they do not distinguish between the distribution of consumption within households, for example, and the instruments for assessing disability might not be comprehensive.
[17] See, for example, UNDP's estimates for a large number of countries here https://www.undp.org/content/undp/en/home/coronavirus/socio-economic-impact-of-COVID-19.html
[18] In theory the Periodic Monitoring Reports should have filled some of this gap, but none were available for the countries included here as of July.

It is estimated that over 55 million people will have been pushed into poverty due to COVID-19, in just the 10 countries included in this exercise alone. The impact of COVID-19 across these countries is, however, highly varied; in some conflict areas, dependence on assistance was already very high so the relative impact of COVID-19 economic shocks is estimated to be smaller. Similarly, the drought and extremely high levels of underlying poverty in Zimbabwe meant that poverty incidence pre-COVID-19 was already estimated at 75% and the majority of the poor are rural subsistence producers, so the COVID-19-specific impact on poverty incidence is relatively small.

In Bangladesh, by contrast, the level of structural transformation is much greater as is the market dependence of even rural households, and hence the likely effects of COVID-19 are quite large, increasing poverty incidence overall by 45%. The impact on poverty incidence is estimated to be similar in Ethiopia, with an increase overall by around 50%. (It is, however, important to note that outside of the three 'deep dive' countries here with more robust estimates, the estimates for the 'lighter touch' countries are based on assumptions rather than detailed modelling; numbers may be found to be even higher if more accurate estimation approaches are used).

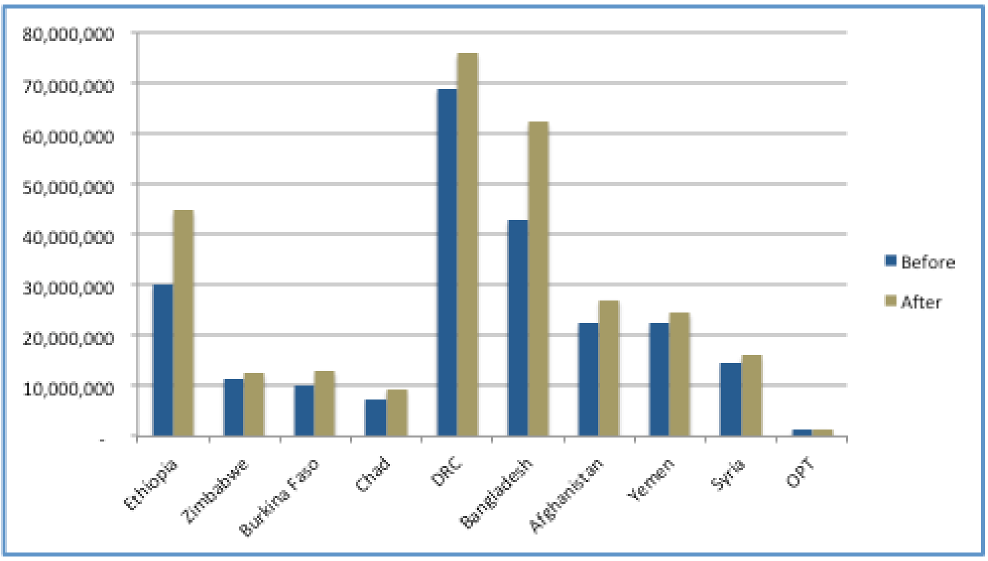

Figure 1. Estimated number of people living in poverty, before and after COVID-19

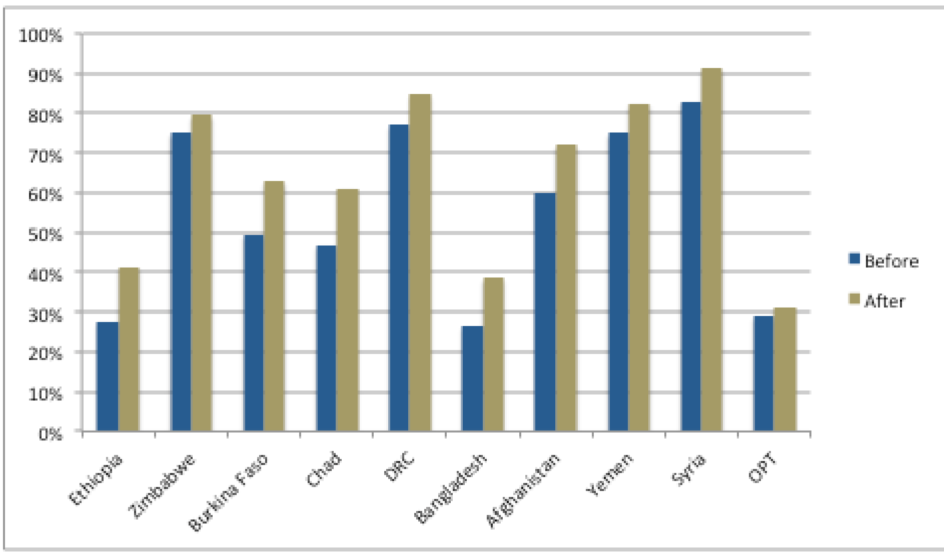

Figure 2. Estimated poverty incidence, before and after COVID-19

This increase in need is disproportionately large in urban areas. For example, in Bangladesh urban poverty incidence increases by 124% compared to 43% in rural areas; and in Ethiopia 272% versus 29%. This illustrates how crucial it is for expansions in coverage to focus on increases in need in urban areas. Given that the majority of existing programmes are focused on rural poverty, serious questions need to be asked for each country context about whether scaling existing programmes will be sufficient. Pre-existing criteria based on proxy means tests, for example, are likely to miss out many of the newly poor who are not the 'usual suspects' for social protection (since scoring systems were developed based on pre-COVID-19 profiles of poverty that tend to be skewed towards rural areas and also tend to be based on many indicators like the quality of the dwelling that will not reflect sudden decreases in incomes).

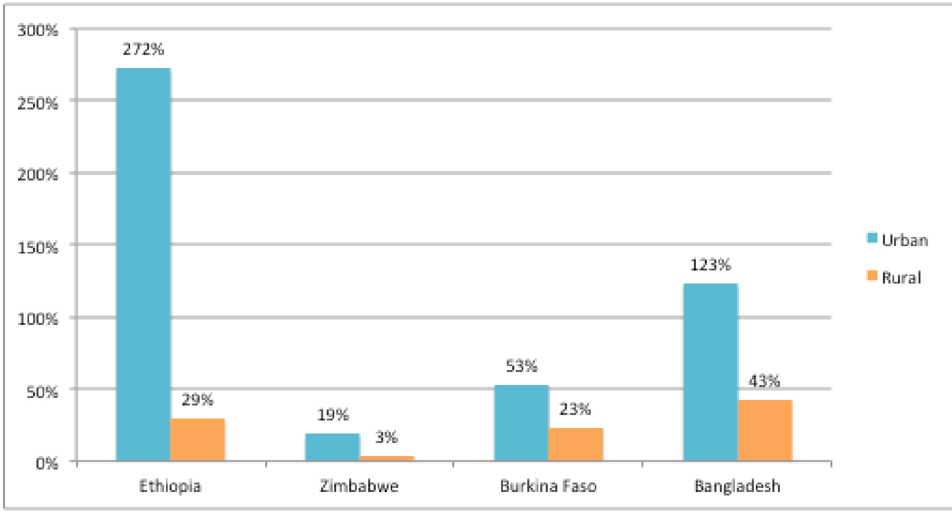

Figure 3. Increase in Poverty Incidence, Urban vs Rural

Importantly, this data is assessed against the poverty line. The micro-simulation was also run for a vulnerability threshold – defined as 1.5 times the poverty line – to capture an estimate of the additional number of people who are at risk of falling below the poverty line if COVID-19 and other impacts persist. The findings are quite disparate. Bangladesh presents the most worrying case, with an additional 45 million people, equivalent to an additional 72% of the existing caseload post COVID-19, at risk of being added to the caseload. In Ethiopia, an additional 21 million people, equivalent to 46% of the existing caseload post COVID-19, are at risk. And in Zimbabwe an additional 1.4 million people, or 11% of the existing caseload post COVID-19, are at risk.

4.2 COVID-19 impacts on poverty gaps

It is also important to recognise that poverty incidence – the number in need – tells only part of the story. COVID-19 recessions will also have major impacts on poverty gaps, or *how far* below the poverty line household consumption is for the poor.

Interestingly, the average poverty gap amongst the poor actually reduces at the same time as poverty incidence is increasing. For Ethiopia, the poverty gap would fall from 31% of the poverty line on average to 8%, while in Bangladesh it would fall from 40% to 26%, although in Zimbabwe it will fall much less, from 49% to 46%. In all three countries, this is because many of the newly poor would fall just below the poverty line, thereby bringing up the average, as illustrated in Figure 4 below for Bangladesh.

However, many who started out already poor will also be impacted by COVID-19 and fall even further below the poverty line. In other words, it is essential, again, to consider the heterogeneity of outcomes in terms of magnitude, with implications for the *size of transfers* required to maintain an adequate standard of living, and how these are differentiated in terms of groups affected.

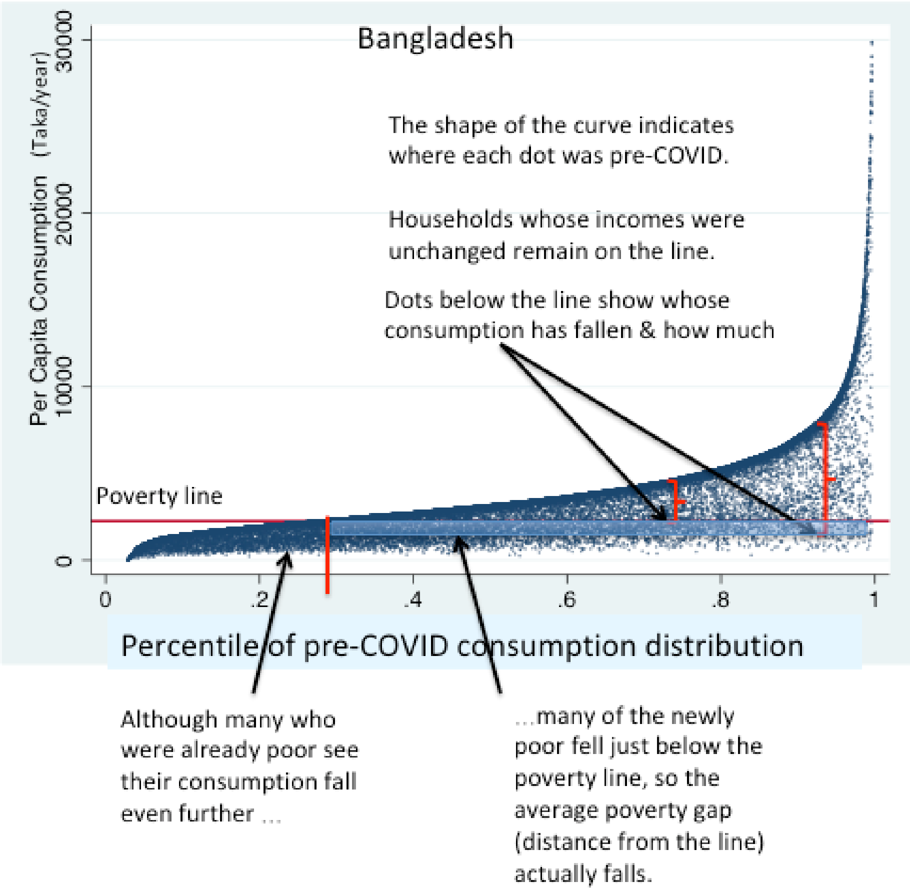

Figure 4. Consumption (and Poverty) Pre- and Post-COVID-19, without social protection or humanitarian assistance, Bangladesh

4.3 Aggregate coverage

The total number of targeted beneficiaries post-COVID-19 has scaled more or less in line with increases in poverty in these 10 countries. The biggest exception is Bangladesh, where pre-COVID-19 the total number actually covered by social protection and humanitarian programmes (amongst the Bangladeshi population[19]) was equal to 55% of the poor, whereas post-COVID-19 it is estimated to be just 41%.

However, as the following section demonstrates, the aggregate figures hide high levels of poor who remain uncovered. Further, it is important to remember that the starting point was

[19] The analysis here focuses on the Bangladeshi population (including humanitarian programming for host communities) and excludes Rohingya refugees.

hugely varied, with coverage relative to the number of poor at only around 10% in Burkina Faso and DRC compared to over 100% in OPT[20].

It is important not to extrapolate these findings beyond this specific sample, however, as this is a fairly unique group that includes, on the one hand, conflict-affected countries with very extensive humanitarian programmes already in place and, on the other hand, those with relatively wide social protection coverage pre-COVID-19, including Ethiopia and Bangladesh, where there have been recent expansions[21]. A wider look across sub-Saharan Africa and South Asia as a whole would likely reveal even greater gaps in coverage. Furthermore, it is important to remember that even the 'general' poverty lines used here represent quite high levels of deprivation (just enough to cover basic caloric needs plus the most necessary of other basic needs), and there is a very large share of the population that lives just above these poverty lines and who are therefore extremely vulnerable to poverty (See Annex B for estimates using the vulnerability line, defined as 1.5 times the poverty line, for Bangladesh, Ethiopia, and Zimbabwe).

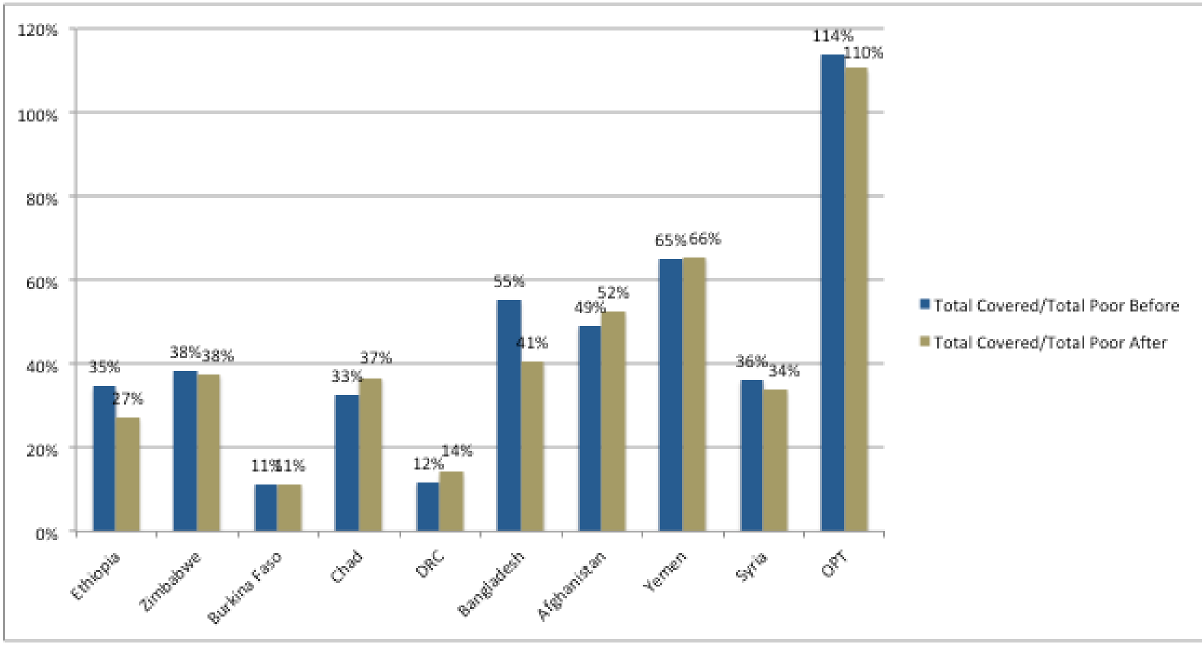

Figure 5. Total number of people covered by transfers as a share of the total poor, before and after COVID-19

4.4 Coverage of the poor

Aggregate numbers mask significant disparities in coverage of those below the poverty line. Looking at total coverage relative to the total number of poor people is misleading, as it vastly overstates the effective coverage of the poor because targeting errors are significant (for those programmes that do target based on poverty) and other programmes may be categorical based on lifecycle vulnerability and therefore are more universal by nature. So, while actual coverage of the poor (the number of *poor* people covered divided by the total

[20] This relatively high levels of coverage for OPT likely reflects the fact that the poverty line is set relatively low. At the $5.50/day line in 2016 (the latest available) poverty incidence was 23%; in the absence of more recent data this was increased to 29% here based on WFP's estimate of food insecurity. However, if the incidence of food insecurity is greater than the poverty incidence, the poverty line is more likely to reflect extreme rather than general poverty.

[21] In Bangladesh, it is also important to note that although coverage is fairly wide, many of the existing programmes such as the old age and widow's allowance provide relatively small transfer values.

number of poor) has also scaled more or less in line with COVID-19 impacts, similar to the total numbers covered, the *levels* of coverage are much lower than the total would suggest. For example, if we compare total coverage in Ethiopia, it looks like coverage was sufficient to reach 35% of the poor before COVID-19 falling to 27% after. However once actual targeting is considered, we find that in fact only 14% of the poor were actually covered before, and 13% after COVID-19.

This illustrates why it is essential to look at effective coverage of the poor, not simply the total number of people who are covered relative to the number of people in poverty. Targeting errors are significant in practice[22], and these must be carefully considered in the assessment of the adequacy of the response, underlying again the importance of understanding *who* not just *how many*.

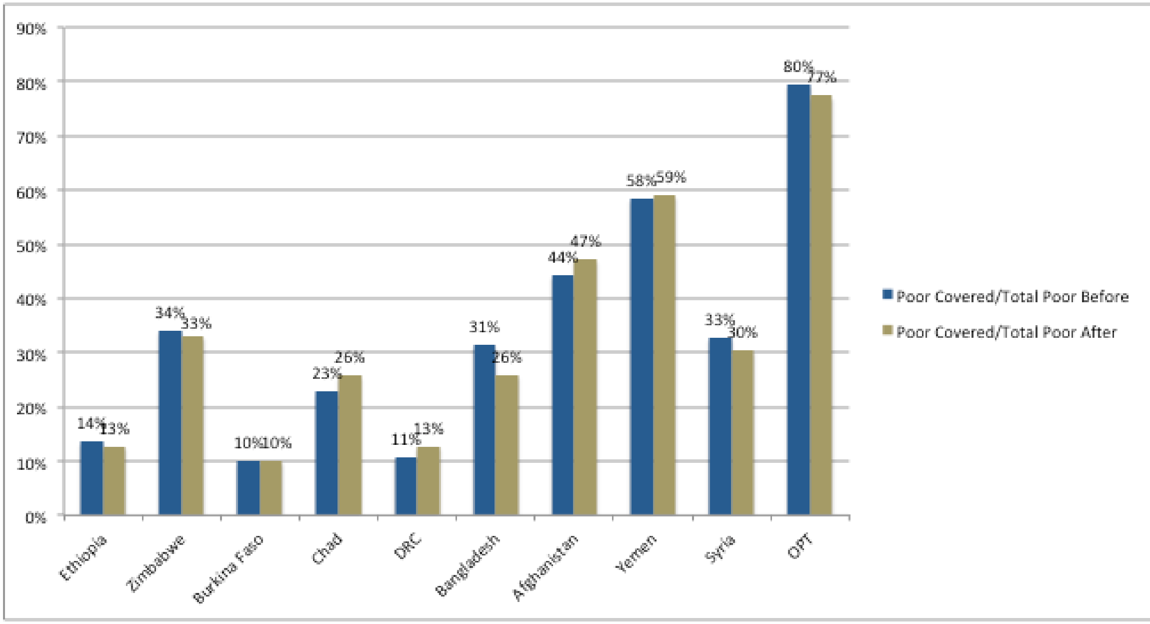

Figure 6. Total number of poor people covered by transfers as a share of the total poor, before and after COVID-19

4.5 The gap between need and coverage

Given the large increases in poverty incidence resulting from COVID-19-induced recessions, even if programming is increasing as a share of the poor, in absolute terms this means tens of millions of people will be left without any response at all, and many of those will be pushed into extreme deprivation. **For the small number of countries included in this exercise alone, there are an estimated 213 million who will be below the poverty line, without any social protection or humanitarian coverage, compared to 171 million before COVID-19, an increase of nearly 42 million without coverage (out of the additional 55 million in need).**

Table 1 Poor people not covered by any social protection or humanitarian cash transfer or food assistance response (Number and as % of population)

[22] Of course, some of those targeting errors might help to pick up the previously non-poor who were pushed into poverty as a result of COVID-19, but in practice, as discussed above, because most of the newly poor as a result of COVID-19 are in urban areas, where there was very little coverage of programming to start with, the existing errors of inclusion are unlikely to help reach those who have been pushed into poverty now.

	Before		After		Increase	
	Number	As % of total pop	Number	As % of total pop	Number	As % of total pop
Ethiopia	25,960,938	23%	39,005,334	34%	13,044,396	11%
Zimbabwe	7,527,927	51%	8,447,593	57%	919,666	6%
Burkina Faso	9,045,778	44%	11,533,682	56%	2,487,905	12%
Chad	5,612,602	36%	7,025,282	45%	1,412,680	9%
DRC	61,578,370	69%	65,094,167	73%	3,515,797	4%
Bangladesh	29,485,031	18%	46,163,212	28%	16,678,181	10%
Afghanistan	12,570,387	33%	14,301,387	38%	1,731,000	5%
Yemen	9,289,589	31%	10,086,536	34%	796,947	3%
Syria	9,779,372	56%	11,112,667	63%	1,333,295	8%
OPT	278,610	6%	331,710	7%	53,100	1%
Total	171,128,602		213,101,569		41,972,967	

4.6 Comparison of findings with other estimates

This analysis aims to use a more heterogeneous and nuanced approach to understanding the impacts of COVID-19. The figure below illustrates how large a difference the methodology used makes to the total estimates using Ethiopia as an example.

- Panel A on the left shows the estimates of COVID-19 impacts on consumption using the micro-simulation approach, where households are ordered by their pre-COVID-19 percentile in the consumption distribution. Those dots that have fallen below the original consumption line are those who are anticipated to have their consumption reduced due to the impacts of COVID-19. Two things are striking from these findings: (i) many of those whose incomes (and hence consumption) are reduced are certainly poorer than before but not pushed below the poverty line; and (ii) many of those pushed into poverty started off relatively well-off.
- By contrast, methods that assume an equivalent decrease in consumption across the board (i.e. an average effect of the same size as in Panel A) shift the entire consumption distribution downwards, as in Panel B on the right. This approach results in two significant errors: (i) mis-representing the number of people who will be below the poverty line (either over- or under-estimating need depending on the shape of the distribution); and (ii) implying that those in need will be those who started out closest to the poverty line.

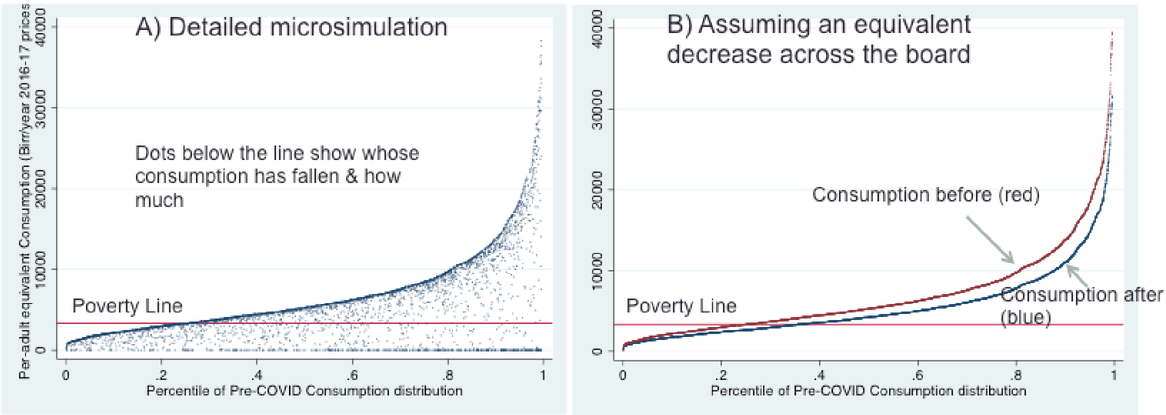

Figure 7. Estimates of Pre- and Post-COVID-19 Consumption (and Poverty) using different methods, Ethiopia

In terms of magnitudes of impact, the 'uniform' approach of estimating need in Panel B would conclude that poverty in Ethiopia would increase from 28% to 34% due to COVID-19 (in the absence of any social protection or humanitarian assistance), whereas the micro-simulation approach in Panel A estimates that poverty will rise significantly to 41% (47 million people). This equates to a difference of over *8 million people that would be under-counted using the 'uniform' approach* in Ethiopia alone.

This also has major implications for understanding *who* will be in need and how to ensure they are covered:

- If, as in Panel B, the assumption is that those who were just above the poverty line before COVID-19 are most affected, it might be reasonable to assume that expanding existing systems (where they exist) would be a good approach, since the profile of the new caseload would be fairly similar to the existing one.
- However, with a much more detailed and nuanced view from Panel A, it is clear that much of the new caseload is likely to be very different from the existing one, and expanding horizontally using existing mechanisms (for example, using those on waiting lists, or increasing the eligibility threshold of existing proxy means tests) will inherently leave out many of the newly poor. Unfortunately, these kinds of simple expansions appear to be more common amongst the existing responses in both social protection and humanitarian programming, with fewer countries developing new or expanded options specifically geared to those who will be most affected by COVID-19.

This illustrates how essential it is that more of this kind of in-depth livelihoods micro-simulation work is undertaken for individual countries, to improve the accuracy of estimates of both total numbers in need as well as who is in need and where and how to locate them. This should be supplemented with more real-time quantitative and qualitative information, particularly from 'pulse taking' type surveys to ensure these reflect as best as possible the experiences of different groups on the ground, in particular to better understand the gendered nature of impacts that cannot be captured with much detail by the micro-simulation approach.

5 RECOMMENDATIONS

- There is a need to urgently **scale up coverage of social protection and humanitarian cash and food assistance to address both increasing levels of poverty and errors of exclusion, with particular attention on the urban poor.**
- **New targeting approaches, including in some cases non-traditional measures, will be required to ensure exclusion errors are minimized.** It is clear that much of the new caseload is likely to be very different from the existing one, and expanding horizontally using traditional methods - for example, using those on waiting lists, or increasing the eligibility threshold of existing proxy means tests – may be easier but will inherently leave out many of the newly poor. Creative measures such as community-based targeting and using networks of trusted affiliates to rapidly find the newly poor and minimise exclusion may be necessary.
- **The donor and response community must also carefully assess the adequacy of transfer size**, in light of the magnitude of income losses, for both old and new beneficiaries, and importantly accounting for potentially differentiated levels of transfers for cohorts who are just below the poverty line (as evidence by the decrease in the average size of the deficit) as well as we those who are in more extreme poverty. This will of course have implications for the number of beneficiaries that can be reached where there are fixed budgets, so it will be important to assess all of the possible trade-offs including transfer size versus coverage against overall value for money.
- **The scale of the response required means it is imperative that social protection and humanitarian systems work together to deliver a response, drawing on the key strengths of both.** Social protection provision supported by governments and development partners, complemented by humanitarian actors where they have a comparative advantage, whether because they are better positioned to reach those in need or because they can respond more quickly to urgent needs, will be essential to building strong shock responsive social protection systems.
- **Whilst it is critical that response is timely, this analysis also highlights the importance of careful, but rapid assessments of need using micro-simulations wherever possible, accounting for heterogeneity of impacts and actual patterns of livelihoods strategies.** It is critical that any assessment accounts for both the impact of COVID-19 as well as other co-variate shocks such as drought, locusts, or conflict that may exacerbate needs.
- **These needs assessments must be joined-up efforts between governments, the World Bank and OCHA (along with the wider UNCT including especially WFP) and other development and humanitarian partners to ensure a more coherent and coordinated response.** Solid, joint, evidence-based modelling of the COVID-19-related needs for 2021 as well as other existing crises, taking account of the actual social protection and humanitarian responses in place or being planned, should be prioritised. This should reflect disaggregated micro-data approaches based on a nuanced understanding of livelihoods, rather than aggregated assumptions.
- **Much better information sharing needs to be put in place for both social protection and humanitarian responses, within countries but also globally.** For the UN, consolidated information on reach by type of response should be provided systematically and made publicly available as part of regular updates, i.e. by cash/voucher/food, type of

recipient (IDPs, non-displaced population), etc, comparing targeted numbers against actuals at least quarterly if not monthly[23]. More visibility is needed on social protection programming in the pipeline across all partners, but in particular the World Bank given its relative scale and scope. It would also be helpful to have an updated, consolidated, database of social protection coverage by programme and by country (actual/forecast)[24].

[23] Ideally coordinated by OCHA's Information and Analysis Unit for the COVID-19 response
[24] This information is currently available in scattered Implementation and Completion Reports and Project Appraisal Documents, but it is currently time-consuming to gather all the disparate information across countries.

6 ANNEXES

Annex A – Approach and Methodology

The approach here was driven by a desire for accuracy on one hand, and the limited time and resources for a fairly 'light touch' exercise on the other. As a result, it takes a differentiated approach, taking a detailed 'deep dive' into three countries (Ethiopia, Bangladesh, and Zimbabwe) while using a more aggregated approach for the remaining seven countries.

Detailed micro-simulation approach in the 'deep dive' countries

For these three countries, the approach is very detailed, based on a micro-simulation of household survey data. Micro-simulation is a kind of policy simulation – allowing for 'ex ante' evaluation of potential policy and programme impacts - that relies on micro data, in this case a representative household survey (see Table 2), in contrast to macro models that rely on a 'representative agent'. They are especially useful where the distributional impact is important and where there is a wide diversity of experiences across and within households in terms of living conditions. They are also able to replicate the complexity of policy structures and programme eligibility criteria (such as those used by social protection targeting) and allow for detailed scenario analysis or "what if" testing of different options.

Table 2: Datasets used for micro-simulation

Country	Dataset
Bangladesh	Household Income and Expenditure Survey (HIES) 2017
Ethiopia	Ethiopia Socio-economic Survey (ESS) 2015/16
Zimbabwe	Poverty, Income, Expenditure, and Consumption Survey (PICES) 2017

Given the fairly small scale of this exercise, the model here is static, looking mainly at first-round impacts without making assumptions about second-round behaviour effects (further work could extend this to account for behavioural effects including the use and implications of different coping strategies).

This entails the following general steps:

I. 'Aging' the household survey datasets to correspond to February 2020. This includes adjusting population weights to reflect population growth and urbanisation, adjusting for inflation, as well as adjusting for changes in poverty in the period between the survey and early 2020 where necessary. Population growth and urbanisation was estimated using the World Population Prospects (2019 Revision) and World Urbanisation Prospects (2018 Revision) respectively. These were used to estimate the rate of change in both urban and rural households, and then these inflation factors were applied to the survey population weights. As such, small divergences with the total population estimates from the UN data remain in the model, due to divergences in the original weights (i.e. the population estimates from the survey data do not align exactly even for the original survey year, which is not surprising since the UN estimates make small adjustments from the census data which is normally used as sampling frames for the household surveys). These divergences are small in magnitude, around 2% of the UN estimates.

Prices are adjusted using CPI data from the IMF, so that the current value of transfers is deflated to reflect real prices at the time of the survey.

Poverty adjustments were especially important to consider for Zimbabwe, which was (and is) undergoing a severe drought. This was accounted for by assessing the scale and scope of the drought impacts, based on comparisons of FEWS NET updates from 2017 (the year of the survey) and 2020. This is modelled as a reduction in crop earnings by an average of 25% since 2020 (crop earnings are expected to be 25% below the 5-year average; modelled probabilistically as a normal distribution with a mean and standard deviation of 25% to reflect heterogeneity in outcomes). The survey year, 2017, was a bumper crop, but those surveyed early in the year would be reflecting consumption from the 2016 harvest, which was also far below normal, so this introduces some natural heterogeneity of impacts into the estimates as well. It also includes some price impacts based on early warning market data, showing increases in food prices across the country (modelled as a 10% decrease in real food consumption). Similarly, Ethiopia is undergoing a desert locust infestation that is expected to have significant impacts on yields. However, in this case, the survey year 2015/16 was a very poor harvest due to the effects of el Niño, and while not identical, the areas affected by the locust invasion are similar to those hit hardest by the drought in 2015/16, so the analysis assumes that the snapshot in the survey is a reasonable approximation for conditions pre-COVID-19 (see comparison of the two years in the figure below).

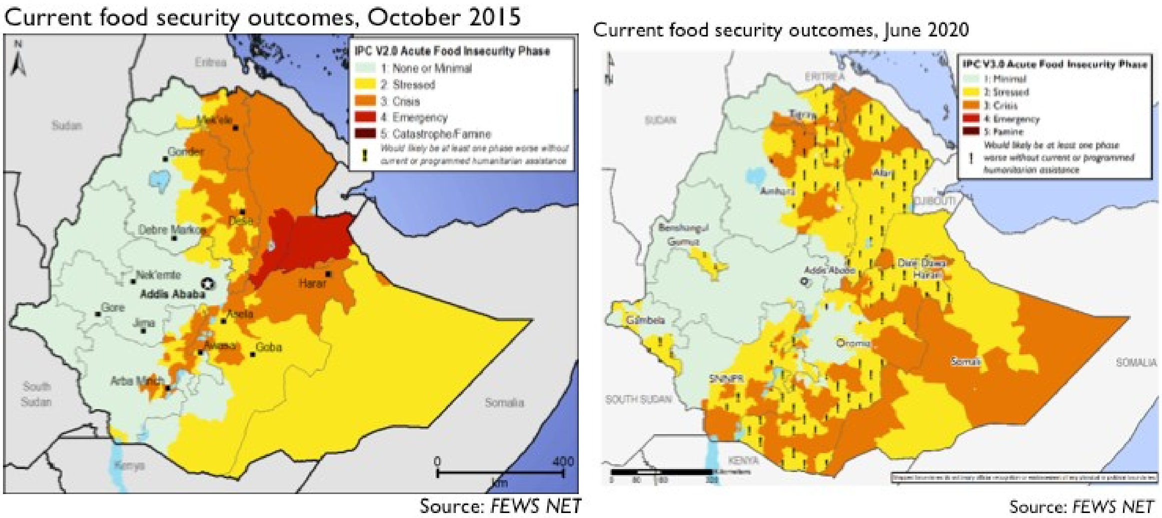

Figure 8. Food security outcome estimates 2015 vs 2020, FEWS NET

In Bangladesh, as in urban areas of Ethiopia and Zimbabwe, it is likely that poverty would have fallen since the survey, however without any better information, we simply take the survey situation as our 2020 baseline. This will be somewhat conservative but should not unduly influence the assumptions since the data are still relatively recent.

I. **Backing out any existing social protection or humanitarian cash and food assistance that is reported, to assess what poverty would be in the *absence of any such programming*. This gives as accurate a picture as possible of needs pre-COVID-19, to which SP/humanitarian programmes should respond.** The social protection/humanitarian assistance can then be added back in in subsequent rounds of analysis to model the effect on the overall caseload, and in particular to estimate the degree to which existing systems may have helped to mitigate some of the impacts of COVID-19.

II. **Modelling the COVID-19-induced recession.** This is done across many different channels, including agricultural price inputs (applies only to those households actually purchasing inputs); reductions in remittance income from domestic and international sources; reductions in wage earnings by sector and nature of employment (casual, permanent, or household enterprise), and price impacts. The following text describes existing estimates of the impact of COVID-19 that were then used to underpin the assumptions used in the micro-simulation models.

The precise assumptions are informed by the COVID-19 high frequency survey in Ethiopia[25] and a similar survey in Bangladesh, as well as information from FEWS updates on prices. The second survey for Ethiopia covered the lockdown period, but it is expected to provide a reasonable baseline for an L—shaped recession, given the nature of Ethiopia's lockdown (which was not 100%), and firms were not allowed to lay off workers, so post-lockdown there should be an uptick in some activity but at the same time also some lay-offs that had been prevented previously, so here it is assumed that these effects cancel each other out. This is indeed what the third round of the survey has found, with results post-lockdown almost identical to those during, in terms of changes in household incomes and remittances.[26]

There was somewhat more detail provided in the second-high frequency survey by sector, which helps to inform the model here. In terms of outright job losses, casual workers were nearly twice as likely as private sector wage workers (those who are more 'permanent' workers) to report having lost their job (38% of casual vs 20% of 'permanent'). Job losses were greatest in hospitality (38%); personal services, construction and trade (around 30%); manufacturing 23%; transport 17%; and only 5% in agriculture.

Only 11% of the self-employed reported losing their job, but this could be a definitional issue, with many expecting to resume their activities eventually, rather than having 'lost' them entirely as with employees. This is reinforced with the finding that, with respect to changes in incomes, the self-employed had the highest share reporting losses, with 28% having total loss of income and another 58% reporting some kind of reduction. By contrast, only 12% of wage employees faced a total loss of income compared to 23% reporting some kind of reduction. Remittance earnings from abroad were lost entirely by 40% who had received them, and another 24% reported a reduction, while remittances from within Ethiopia collapsed completely for 12% of those who had received them and reduced for a further 33%.

The findings on agricultural earnings are somewhat surprising, with 40% reporting a reduction., however, this could be picking up normal seasonal variation and/or the effects of the Desert Locust Invasion.

In Bangladesh, the lockdown was more comprehensive, with many more people citing complete reductions in earnings[27], so it is not assumed that the lockdown findings will continue into the L-shaped recession in the same way as Ethiopia. In addition, the survey for Bangladesh sampled urban and rural poor households, so is not representative of the population as a whole. Nevertheless, the findings were stark; 54% of rural main earners and 72% of urban ones were economically inactive in April

[25] Wieser et al (2020)" Monitoring COVID-19 Impacts on Households in Ethiopia: Results from a High-Frequency Phone Survey of Households". World Bank Report Number 1, 4 June 2020.
[26] Wieser et al (2020)" Monitoring COVID-19 Impacts on Households in Ethiopia: Results from a High-Frequency Phone Survey of Households". World Bank Report Number 3, 11 August 2020.
[27] Rahman et al (2020) "Livelihoods, Coping, and Support During COVID-19 Crisis" PPRC-BIGD Rapid Response Research

(although it is not clear how many were active just before lockdown, and particularly in rural areas there could be some seasonality influencing the numbers). Incomes fell by 75% in urban slums and 62% amongst the rural poor, with little regional variation. As in Ethiopia, those in more permanent jobs (including the ready-made garment sector, manufacturing, security, cleaners/sweepers) had lower drops in earnings compared to those in more informal occupations (daily labour, rickshaw pullers, restaurant workers). Those in agriculture reported relatively lower reductions in earnings (which, again, could be reflecting seasonal variation rather than only COVID-19-related effects).

For Zimbabwe there was no COVID-19 high frequency survey data available, so assumptions are based on FEWS NET monitoring as well as modifying some of the assumptions from the Ethiopia data.

For the model here, all earnings-related shocks are modelled as probability distributions to capture heterogeneity. In practice, earnings data does not correspond perfectly to consumption, so the assumption here is that shocks translate into consumption poverty proportionately (so a 50% reduction in earnings translates into a 50% reduction in purchased consumption; own—produced consumption is excluded from the COVID-19 shock).

For earnings shocks, the model is stochastic to capture the heterogeneity of impacts. This has two components: first is a binary, which is the likelihood of any earnings shock, and the second is the % of earnings lost, which is modelled as a normal distribution. These are disaggregated by sector and by type of employment. For example, in Ethiopia, the hardest-hit sectors are assumed to be construction, trade, and hospitality, with 50% of casual workers in hospitality experiencing any kind of income loss during the recession, and of those who do lose earnings, the average reduction will be 50% (this is slightly higher than the findings in the High Frequency survey, on the assumption that the hospitality sectors will continue to contract as international tourism is severely restricted throughout the rest of 2020 and likely 2021). In general, it is assumed that across sectors, those with permanent jobs will be half as likely as casual workers to have any earnings loss (as found in the High Frequency Survey). Household enterprises, by contrast, are assumed to be 2-3 times as likely to lose any earnings than casual workers, and the average reduction to be similarly 2-3 times higher. This diverges somewhat from the High Frequency Survey, which found the self-employed only half as likely to have lost their job, but this is because more nuance is needed than the survey itself provides; here we are interested in capturing not just those who have lost their jobs entirely (which will be relatively low amongst the self-employed because very few can afford to be fully un-employed; many will continue to try to eke out some kind of earnings even if it is very low) but also those experiencing any loss of earnings. This is captured here by the high likelihood of some income loss, but also with much greater variability for the self-employed.

The assumptions for sector-specific wage and self-employment earnings were fairly similar across countries aside from a few notable exceptions: in Zimbabwe the model assumes greater impacts on transport and trade sectors, given Zimbabwe's interdependence with South Africa where COVID-19 impacts are currently very high, and also for much larger disruptions in the agricultural sector compared to Ethiopia and Bangladesh for similar reasons; in Bangladesh the phone survey revealed that agriculture was hit relatively hard during the lockdown compared to Ethiopia, perhaps because of the greater market integration amongst smallholder farmers there in general, so the impacts, while still low compared to other sectors, is assumed to have double the effect of the assumptions for Ethiopia.

The model also considered shocks to remittances, using a similar approach to modelling, first the probability that a household faces any reduction, and then the degree of the reduction itself, modelled as a normal distribution with a specified mean value. These are the same in all three countries (Table 3), and both the probability of a shock and the degree are higher for remittances from abroad (60%) compared to domestic remittances, whether urban or rural (40%).

In terms of agricultural production, the models included COVID-19-induced shocks to productive inputs. This is done through assuming increases in the cost of purchased inputs (seeds, fertiliser, labour) by 20% in Ethiopia and 5% in Bangladesh, which will reduce agricultural profits. In practice, only a better-off minority of producers uses any purchased inputs, so this approach will capture the distributional effects. The price increase is assumed to be much higher in Ethiopia because of reports from FEWS monitoring that there were particular limits on movements of goods and people that were affecting the agricultural sector[28], whereas this was not reported for Bangladesh. For Zimbabwe, production losses are modelled more explicitly, given the need to adjust for the drought in step 1, where output was assumed to have fallen by 25% from 2017 levels (using a normal distribution, with mean and standard deviation of .25). In the COVID-19 context, losses are assumed to be even greater than they would be without COVID-19, because of mobility restrictions on agricultural labour and the availability and price of inputs at key points in the production cycle, as reported by FEWS NET[29]. The COVID-19 impact is therefore to reduce production by 30% (again modelled using a normal distribution, with mean and standard deviation of .3).

Finally, the model assumes there will be price rises above wages in urban areas, with a real impact of 10% in Ethiopia and Zimbabwe (where the additional effects of desert locust infestations and droughts respectively increase the likelihood of urban food price increases) and 5% in Bangladesh.

It is important to note that, while these assumptions are based on as much information as possible from the COVID-19 impact monitoring, as well as our general understanding of livelihoods dynamics, they are based on a context with high levels of uncertainty and hence the findings should be viewed with caution and revised as more data is gathered. The point here is to provide an initial look at what the recessions might mean for earnings and poverty, and then ideally these can be refined over time with more data, and with further scenario analysis to test the extent to which the assumptions impact the conclusions and to establish some likely ranges of outcomes where considerable uncertainty remains.

Table 3: Key assumptions for COVID-19-related economic shocks for micro-simulations

Assumption	Bangladesh	Ethiopia	Zimbabwe
Agricultural production	5% increase in the price of inputs (fertiliser, seed, labour)	20% increase in the price of inputs (fertiliser, seed, labour)	Assumes greater production losses due to COVID-19. Whereas pre-COVID-19 production was assumed to fall by 25% on average

[28] While more recent reports have not shown input prices to be a particular issue in general, in both Ethiopia and Zimbabwe restrictions on the movement of labour has been reported to have impacted crop production to some extent, and earlier reported issues with input availability and prices during key points in the agricultural cycle will have already impacted annual expenditure on inputs.
[29] https://fews.net/southern-africa/zimbabwe/food-security-outlook/june-2020

			compared to the 2017 production values (using a normal distribution with mean and standard deviation of .25); COVID-19 reductions increase to 30% (again using a normal distribution)
Wage and self-employment earnings	'Permanent' jobs (which are the minority of all wage employment) are assumed to be hit half as hard as casual labour, whereas household enterprises (self-employment) are hit 2-3 times as hard as casual labour. The probability of any earnings loss and, if a loss occurs, the share lost is detailed in the table below for Ethiopia. Assumptions for Zimbabwe are similar but with slightly higher percentages for trade and transport sectors, while in Bangladesh it is assumed that 20% of casual workers were impacted.		
Remittances	See Table 3 below		
Price increases	Urban 10%	Urban: 5%	National: 20% increase in food prices; 10% non-food

III. Modelling coverage. This is done based on (a) who is already covered in the survey and then (b) scaling up to include additional households (where programmes had expanded since the survey was undertaken, and/or to account for any random under-sampling in the survey). This scale-up is based on either a proxy means test (where this is the targeting approach used by programmes in practice, for example Ethiopia's Urban PSNP) or based on a regression of likelihood of selection based on the characteristics of current beneficiaries (essentially allowing the model to mimic the current levels of targeting efficiency, using similar variables to those in a PMT). Humanitarian coverage is modelled using a similar approach, mimicking the distribution of coverage of any humanitarian programming in place at the time of the survey. Levels of programme coverage are based on whatever information on actuals could be gleaned from Implementation Completion Reports and Project Appraisal Documents by the World Bank, DFID Annual Reviews, or other programme reporting available online.

IV. Estimating impacts. With both the pre-COVID-19 level of consumption and programme coverage articulated, the model can then estimate both pre- and post-COVID-19 consumption, before and after social protection/humanitarian transfers to allow estimates of pre- and post-COVID-19 poverty incidence (and depth), coverage in total and of the poor, and gaps. It does this using three different poverty lines (food poverty, general poverty reported in this note, and a higher vulnerability line equivalent to 1.5 times the general line).

'Lighter touch' estimates

In the 'light touch' countries, the approach is much less rigorous. It starts with the most recent poverty estimates are available, and then adjusts using rules of thumb as necessary (so, for example, in Afghanistan the latest estimate is from 2017 but 2018 and 2019 were bad years, so it is assumed poverty increased from 55% to 60%). Programme coverage numbers are gleaned from available documentation (HRPs, OCHA and WFP updates, and World Bank and DFID project reporting), and these are scaled to capture individuals covered using average household size, wherever reporting is based on households. Where possible, information on targeting efficiency is based on the specific programmes, but in many cases, this is lacking, so assumptions are made about targeting errors, given the relative size of the programmes. It is assumed that errors generally follow the pattern that would be expected if a PMT were used (so errors are much lower once coverage is quite high and poverty levels are also high, as in Yemen and Syria).

Burkina Faso was an exception, using a 'middle way'. It did not involve a full micro-simulation, but did use disaggregated, detailed data from the recent (2017) Poverty Assessment and (2019) Safety Net Assessment, to estimate the impacts on rural poverty separately for insecure vs secure parts of the country and urban areas.

Table 4. Ethiopia Earnings Shock Assumptions by sector

		Casual wage		Permanent wage		Household Enterprise	
Employment sectors		% any loss	% reduction mean	% any loss	% reduction mean	% any loss	% reduction mean
I.	Agriculture, (Hunting, Forestry and Production of Related Products and Services)	5%	10%	3%	5%	15%	30%
II.	Fishing, Fish Farms and Service Activities Incidental to Fishing	5%	10%	3%	5%	15%	30%
III.	Mining and Quarrying	20%	20%	10%	10%	60%	60%
IV.	Manufacturing (For example Manufacturing of Food Products Including Processing, Caning and Preservation	30%	20%	15%	10%	90%	60%
V.	Electricity, Gas, Steam and Hot Water Supply	0%	0%	0%	0%	0%	0%
VI.	Construction, (contractor, Site Preparation, Land Clearing, building/ home construction)	40%	30%	20%	15%	80%	60%
VII.	Trade (Wholesale and Retail Trade)	40%	30%	20%	15%	80%	60%
VIII.	Hotels and Restaurants/ Hotels (With Hotel Rooms); Camping Sites and Other Provision of Short-Sta	50%	50%	25%	25%	100%	100%
IX.	Transport, Storage and Communications/ Land Transport? People and Merchandise	15%	20%	8%	10%	45%	60%
X.	Financial Intermediation (Except Insurance and Pension Funding)	20%	20%	10%	10%	60%	60%
XI.	Real Estate, Renting and Business Activities)	20%	20%	10%	10%	60%	60%
XII.	Public Administration and Defense	0%	0%	0%	0%	0%	0%
XIII.	Education	0%	0%	0%	0%	0%	0%
XIV.	Health and Social Work	0%	0%	0%	0%	0%	0%
XV.	Other Services	0%	0%	0%	0%	0%	0%
XVI.	Private Households with Employed Persons	20%	20%	10%	10%	60%	60%
XVII.	Extra-Territorial Organisations and Bodies including International Organisations and NGOs	0%	0%	0%	0%	0%	0%

Table 5. Assumed impacts on remittance income, Bangladesh, Ethiopia, and Zimbabwe

Remittances	% any loss	% reduction mean
Abroad	60	60
Urban	40	40
Rural	40	40

Annex B: Micro-simulation estimates

Table 6: Number of poor vs Number covered, general poverty line and 'vulnerability' line (1.5 times the poverty line)

		Urban		Rural		Total	
		Pre-COVID-19	Post-COVID-19	Pre-COVID-19	Post-COVID-19	Pre-COVID-19	Post-COVID-19
Bangladesh	Estimated population	63,040,067	63,040,067	98,760,142	98,760,142	161,800,196	161,800,196
	N Covered by SP	6,930,420	7,346,063	16,519,555	17,266,138	23,449,976	24,612,201
	N Covered Humanitarian	183,583	250,340	134,181	420,044	317,764	670,384
	N Covered Total	7,114,003	7,596,403	16,653,736	17,686,182	23,767,739	25,282,586
	General Poverty Line						
	N Poor	12,459,996	18,717,628	30,472,418	43,609,036	42,932,414	62,326,664
	N Covered by SP/ N Poor	55.6%	39.2%	54.2%	39.6%	54.6%	39.5%
	N Covered by Hum/ N Poor	1.5%	1.3%	0.4%	1.0%	0.7%	1.1%
	Total Covered/Total Poor	57.1%	40.6%	54.7%	40.6%	55.4%	40.6%
	Vulnerability line						
	N Vulnerable	30,626,694	36,139,072	61,594,736	71,210,176	92,221,430	107,349,248
	N Covered by SP/ N Vulnerable	22.6%	20.3%	26.8%	24.2%	25.4%	22.9%
	N Covered by Hum/ N Vulnerable	0.6%	0.7%	0.2%	0.6%	0.3%	0.6%
	Total Covered/Total Vulnerable	23.2%	21.0%	27.0%	24.8%	25.8%	23.6%
Ethiopia	Estimated Population	24,645,232	24,645,232	83,262,971	83,262,971	107,908,203	107,908,203
	N Covered by SP	769,058	1,308,708	8,028,132	8,759,554	8,797,190	10,068,262
	N Covered Humanitarian	1,418	298,860	1,596,449	1,777,707	1,597,867	2,076,567
	N Covered Total	770,476	1,607,568	9,624,581	10,537,261	10,395,057	12,144,829
	General Poverty Line						
	N Poor	2,405,103	8,952,534	27,609,106	35,748,988	30,014,209	44,701,522
	N Covered by SP/ N Poor	32.0%	14.6%	29.1%	24.5%	29.3%	22.5%
	N Covered by Hum/ N Poor	0.1%	3.3%	5.8%	5.0%	5.3%	4.6%
	Total Covered/Total Poor	32.0%	18.0%	34.9%	29.5%	34.6%	27.2%
	Vulnerability Line						
	N Vulnerable	5,166,546	12,217,703	47,596,596	53,108,352	52,763,142	65,326,055
	N Covered by SP/ N Vulnerable	14.9%	10.7%	16.9%	16.5%	16.7%	15.4%
	N Covered by Hum/ N Vulnerable	0.0%	2.4%	3.4%	3.3%	3.0%	3.2%
	Total Covered/Total Vulnerable	14.9%	13.2%	20.2%	19.8%	19.7%	18.6%
Zimbabwe	Estimated Population	4,640,217	4,640,217	9,921,955	9,921,955	14,562,173	14,562,173
	N Covered by SP	23,474	24,177	119,212	124,361	142,686	148,538
	N Covered Humanitarian	285,780	498,851	3,927,125	4,099,888	4,212,904	4,598,738
	N Covered Total	309,253	523,028	4,046,337	4,224,248	4,355,590	4,747,276
	General Poverty Line						
	N Poor	2,004,909	2,484,048	9,415,242	10,130,346	11,420,151	12,614,394

		Urban		Rural		Total	
	N Covered by SP/ N Poor	1.2%	1.0%	1.3%	1.2%	1.2%	1.2%
	N Covered by Hum/ N Poor	14.3%	20.1%	41.7%	40.5%	36.9%	36.5%
	Total Covered/Total Poor	15.4%	21.1%	43.0%	41.7%	38.1%	37.6%
	Vulnerability Line						
	N Vulnerable	3,173,405	3,562,232	9,942,747	10,492,119	13,116,152	14,054,351
	N Covered by SP/ N Vulnerable	0.7%	0.7%	3.8%	3.8%	3.1%	3.0%
	N Covered by Hum/ N Vulnerable	9.0%	14.0%	39.5%	39.1%	32.1%	32.7%
	Total Covered/Total Vulnerable	9.7%	14.7%	43.3%	42.9%	35.2%	35.7%

Table 7. Number and % of poor individuals actually covered by SP/Humanitarian transfers, General Poverty Line and Vulnerability Line

		Pre-COVID-19	Post-COVID-19	Change
Bangladesh	General Poverty Line			
	N Poor	42,932,414	62,326,664	19,394,250
	N Poor Covered by SP	13,447,383	16,163,452	2,716,069
	As %	31%	26%	
	N Poor not covered	29,485,031	46,163,212	16,678,181
	Vulnerability Line			
	N Vulnerable	92,221,430	107,349,248	15,127,818
	N Vulnerable covered by SP	19,656,589	21,996,532	2,339,943
	As %	21%	20%	
	N Vulnerable Not Covered	72,564,841	85,352,716	12,787,875
Ethiopia	General Poverty Line			
	N Poor	30,014,209	44,701,522	14,687,313
	Poor Covered Total	4,053,271	5,696,188	1,642,917
	Poor Covered by SP	3,651,165	4,989,480	1,338,315
	Poor Covered by Humanitarian	402,106	706,708	304,602
	Poor Covered by SP (%)	12.2%	11.2%	
	Poor Covered by Humanitarian (%)	1.3%	1.6%	
	Poor not covered	25,960,938	39,005,334	13,044,396
	Vulnerability Line			
	N Vulnerable	52,763,142	65,326,055	12,562,914
	Vulnerable Covered Total	5,996,640	7,369,180	1,372,540
	Vulnerable Covered by SP	5,327,727	6,365,852	1,038,125
	Vulnerable Covered by Humanitarian	668,913	1,003,328	334,415
	Vulnerable Covered by SP (%)	10.1%	9.7%	
	Vulnerable Covered by Humanitarian (%)	1.3%	1.5%	
	N Vulnerable Not Covered	46,766,502	57,956,875	11,190,373
Zimbabwe	General Poverty Line			
	Poor	11,420,151	12,614,394	1,194,243
	Poor Covered Total	3,892,224	4,166,801	274,577
	Poor Covered by SP	366,425	387,963	21,537
	Poor Covered by Humanitarian	3,525,799	3,778,839	253,040
	Poor covered Total %	34%	33%	
	Poor Covered by SP (%)	3.2%	3.1%	
	Poor Covered by Humanitarian (%)	30.9%	30.0%	
	Poor not covered	7,527,927	8,447,593	919,666
	Vulnerability Line			
	N Vulnerable	13,116,152	14,054,351	938,199
	Vulnerable Covered Total	3,931,867	4,174,417	242,550
	Vulnerable Covered by SP	378,061	394,516	16,455
	Vulnerable Covered by Humanitarian	3,553,806	3,779,900	226,094
	Vulnerable Covered by Total (%)	30.0%	29.7%	
	Vulnerable Covered by SP (%)	2.9%	2.8%	
	Vulnerable Covered by Humanitarian (%)	27.1%	26.9%	
	N Vulnerable Not Covered	9,184,285	9,879,934	695,649

ACKNOWLEDGEMENTS AND DISCLAIMER

This document was developed as part of SPACE - Social Protection Approaches to COVID-19: Expert advice, implemented by the UK Foreign, Commonwealth & Development Office (FCDO) and Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH, and funded by UK Aid and the German Federal Ministry for Economic Cooperation and Development (BMZ). SPACE is managed by DAI Europe Ltd contracted through the FCDO framework agreement EACDS Lot B service 'Strengthening resilience and response to crises', and the advice is provided by independent consultants contracted by FCDO, GIZ and other partners.

Published by FCDO and GIZ