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Protecting Who? Optimal Social Protection Responses to Shocks with Limited Information

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ABSTRACT

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The literature on shock-responsive social protection focuses on operational features that improve the speed and reach of the response, but little is known about the optimal design of emergency social protection responses in terms of which programs to use, information about the people affected, and the extent of their losses. This paper studies optimal social protection responses to shocks, using microsimulations of different social assistance responses in Albania, Moldova, and North Macedonia. The paper shows that optimal design depends not only on the magnitude of the shock, but also on how the shock affects welfare rankings and on the parameters of the existing social assistance system, including the generosity of the schemes and how well they cover the poor. For given budgets, a universal transfer remains a suboptimal response. However, the extent to which existing programs should be expanded, as designed, to additional beneficiaries depends on the type of shock. When a shock tends to affect households homogeneously, increasing generosity and expanding the existing targeted social assistance program using established welfare metrics to assess eligibility is an effective response. When shocks affect households heterogeneously and bring some of them into extreme poverty, then pre-shock welfare indicators carry little information and policy makers should provide support through a new program or modified eligibility criteria, according to information on who suffered the shock. This analysis points to the importance of planning in advance for future crises and, within this, considering the optimal design of emergency social protection responses.

JEL Classification: D6, H5, I3, Q5

Keywords: social protection, adaptive social protection, disaster risk management, COVID-19, targeting

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1. Introduction

The COVID-19 pandemic spurred a massive wave of social protection responses across the globe. By January 2022, about 3,800 social protection and labor measures had been announced or implemented in 223 countries to help people cope with the economic downturn caused by the health emergency and the ensuing public health containment measures (Gentilini et al. 2020), amounting to 2 percent of countries' GDP on average.[2] Cash and food transfers, pension withdrawals, extended unemployment benefits, wage subsidies, and work sharing arrangements are some of the most common policy instruments governments deployed in an effort to reach different groups that were affected by the pandemic, from formal sector workers to poor and vulnerable individuals who do not work or were active in the informal sector.

Increasingly, studies are assessing the adequacy and impacts of these emergency social protection measures, but so far little is known about their efficiency.[3] Namely, there has been scant debate about whether the responses deployed to counter the pandemic-induced crisis were the most appropriate and cost-effective, although new evidence suggests there were considerable inefficiencies within specific programs.[4] Some evidence is also beginning to emerge on the effectiveness of different program designs. For example, Demirgüç-Kunt et al (2022) classify social protection measures into those that protected jobs as compared with those that protected household or individual income. The authors argue that job protection measures in Europe and Central Asia resulted in higher employment, less inactivity and lower poverty, in the short run, in countries with weaker pre-pandemic social insurance systems. However, while such analysis begins to provide insights that can be used to inform a response to a future large-scale pandemic, there is a need to develop a response framework that explains these differential effects and covers various types of shocks.

The lack of knowledge about an optimal social protection response to shocks extends beyond the COVID-19 pandemic. The literature on shock-responsive and Adaptive Social Protection (ASP) has mainly focused on operational features to enable a response through social protection programs to various types of shocks, such as setting out program procedures in advance (assessment, enrollment, payments, etc.), prepositioning financing to fund an increase in program size, and the use of social registries or geolocation to identify affected populations for program support (Bowen et al. 2020; O'Brien et al. 2018). Beyond the focus on building the capacity of a social protection program and its delivery systems to respond to future shocks, in countries with more robust social protection systems lies the question of

[2] Globally, social assistance makes up 61 percent of these response measures, followed by supply-side labor market programs (20 percent) and social insurance (19 percent).

[3] Reviews of the social assistance response to the COVID-19 pandemic mostly examine the target population, coverage rates, adequacy of benefits and speed of the response and highlight gaps in coverage and weaknesses in delivery systems. See for example Bastagli and Lowe (2021). Gentilini (2022) also discusses trends within the global cash transfers response to the COVID-19 pandemic.

[4] Autor et al. (2022), for instance, look at the "Paycheck Protection Program" in the US and find that while the program was deployed swiftly and had widespread take-up, its lack of targeting implied that only 23-34 percent of the spending went to workers who would have lost their jobs otherwise: similar results may thus have been obtained at a fraction of the cost.

which programs – across social assistance and social insurance – to select for such investments and why.[5]

The choice of which programs to use to respond to shocks and their specific design features can substantially influence impacts and efficiency. Shocks have heterogeneous distributional impacts (i.e., energy prices have different distributional impacts than earthquakes, floods or droughts), and these may vary with the economy's structure (e.g., COVID-19 pandemic affected tourism-dependent economies disproportionately), the robustness of existing social programs and their delivery systems (more informal economies may find it more challenging to reach affected people), or the containment measures applied (some countries restricted activity in more sectors than others to contain the pandemic). Ideally, emergency social protection responses should consider these factors and select precisely the program(s) to be expanded or modified that will reach the most affected groups with adequate and timely compensation.

In practice, however, countries often have varying levels of information about who is affected by shocks and their resulting losses. In countries with well-established social insurance systems, information on those shocks that affect the income of formal sector workers is readily available to policy makers and can then be used to quickly inform the design of an emergency social protection response. Data constraints rapidly emerge in terms of how shocks affect informal workers or other groups, which limit the ability of policy makers to launch an effective and timely response. The literature on ASP recognizes the central role that reliable data and robust information systems play in enabling an effective response to shocks.[6] However, the current lack of ex ante investments in data and information systems is resulting in suboptimal design response, as policy makers pragmatically use existing data to identify affected population or respond to political economy considerations.[7]

Such limitations call for a comparative analysis of different social protection response designs when policy makers have limited fiscal resources and limited information to identify the most affected groups, and therefore cannot ex-ante define a response measure that targets these groups accurately and provides adequate support. To fill this gap, we examine the efficiency of a range of social protection responses under shocks of diverse nature. In doing so we complement the knowledge on operational analyses of the responsiveness of delivery systems by looking into the trade-offs that policy makers face in determining how to allocate emergency financing across programs with different aims and target populations. In contrast to other studies that have considered the impact of different social protection responses to natural disasters (Baez, Kshirsagar, and Skoufias 2019) or the COVID-19 pandemic (Carraro and Marzi 2021; Lustig, Neidhöfer, and Tommasi 2020), this paper explicitly simulates the impact of different shocks and responses under incomplete information to derive lessons on

[5] We use the terms shock response and emergency social protection response interchangeably to describe a rapid response to protect households from the immediate effects of a shock.

[6] (World Bank 2021) explains that efforts to assess the flexibility and capacity of a social protection system to respond to shocks benefit from analyses of how the types of shocks affect the resulting need for support among the population.

[7] See for example Gentilini et al. (2020a), who show that responses to the pandemic crisis include a wide range of programs spanning from increasing the level of benefits to current social program beneficiaries (whether insurance or assistance) to introducing universal transfer schemes, but most of these responses were not selected under efficiency considerations, but rather followed operational or political criteria. See also Rigolini et al (2023).

how to design optimal social protection responses depending on the nature of the shock and who has been affected.

The paper's main contribution is to offer a simple framework to categorize shocks and optimal social protection responses according to the distributional implications of the shock and the information available to the policy maker. By doing so, it aims to motivate an emphasis on *ex ante* planning among governments in the design and management of their social protection systems by demonstrating the trade-offs implicit in the social protection responses to the COVID-19 pandemic. We begin by defining shock scenarios varying between those where the value of the losses and the people affected are both known (e.g., formal sector workers hit by job losses), to those where neither the affected groups nor the losses are identified precisely (e.g., informal, self-employed workers whose earnings may be reduced). Then, we discuss how different social protection response measures fare in compensating the actual losers, for a given budget envelope. For instance, in the first scenario, unemployment insurance would be an optimal response; while in the second case targeted cash transfers would be a better response, though who to reach and the generosity of support – two key design parameters - is crucial.

Next, we dive into the most challenging case for policy makers in terms of response design, namely the one where information about the magnitude of the loss and who is affected is limited. Empirically, this is a common case for shocks where those affected are working in the informal sector and may not be well-captured in administrative databases; it is also the case for many natural disasters, wherein the impacts may expand beyond the loss of formal labor income to assets and broader measures of wellbeing The crisis caused by the COVID-19 pandemic falls clearly into this category, as it hit wide groups within the population, including vulnerable (but not necessarily poor) informal workers in urban areas.

We then define shocks not in terms of their nature (i.e., droughts, floods, earthquakes, food or energy prices), but in terms of their distributional implications (i.e., whether a shock affects people's income homogeneously across the distribution, or some people substantially more than others). With the typology of shocks in place, the paper then proceeds to examine how, for given shocks, aggregate losses and response budgets, different response designs within social assistance fare in protecting the most affected groups from falling into poverty. We do so by means of microsimulations for Albania, Moldova, and North Macedonia. We limit the analysis to one form of social assistance (cash transfers) and modify key design features, namely, who is eligible for support,[8] the amount provided, and the size of the response. This allows us to adjust one aspect of a national social protection system to explore the implications of different design decisions, although these questions may apply equally when choosing to respond across social assistance and social insurance programs.[9] We do not consider behavioral responses or general equilibrium effects, so that we examine first-order effects only. Our main welfare measure, against which we gauge impacts, is the squared poverty gap, which not only counts people falling below the poverty line but also places higher weights on extreme poor households that are farther away from the poverty line (Lustig, Jellema, and Martinez Pabon 2021).

[8] Grosh et al. (2022) offer a thoughtful discussion of when and how to target in the face of a shock.

[9] We do not include administrative costs in the analysis as all three countries operate national social assistance programs, including cash transfers targeted to the poor, supported by established delivery systems, front-line staff, and operating budgets.

Our baseline case is the COVID-19 shock on labor income resulting from the early 2020 lockdowns and the actual social assistance response implemented, which aimed to provide rapid support to protect household wellbeing. From a distributional perspective, the COVID-19 shock has been relatively neutral: while it affected labor income across the income distribution, it did not change much income rankings across households. This feature of the COVID-19 shock is important to explain some of the findings.

We begin by assessing the impacts of the actual social assistance response with respect to other program design options. A frequently observed social assistance response – which Albania employed – has been to increase social assistance benefits to existing beneficiaries. While such a response can be seen as a pragmatic use of available information, it often delivers inferior poverty impacts than using the same budget to expand social assistance to new beneficiaries, who are selected using the existing targeting methods, which in these cases are all based on welfare metrics. The reason is relatively intuitive: for a given budget, all responses face a tradeoff between the generosity of the benefit and the coverage they provide; and when initial coverage is limited, expanding coverage to new poor households delivers greater welfare impacts for a given budget. On the other hand, expanding coverage may not be an optimal response anymore when coverage of the poor is already significant. In Moldova, for instance, the income threshold for the program is significantly below the extreme poverty level. Since the COVID-19 shock did not bring many non-poor households into extreme poverty, distributing larger transfers to the pre-shock extreme poor delivered higher welfare impacts than expanding the coverage to households that fell into moderate poverty after the shock, but still had higher income than most social assistance beneficiaries.

After having assessed the effectiveness of actual responses, we rank different design responses to our COVID-19 baseline shock in terms of poverty impacts. We consider two different budgets: countries' actual spending on the social assistance response, which was modest; and a more generous spending that we have set at 1 percent of GDP. We also consider three sets of program design alternatives (within these budgets) that may be realistically available to policy makers: distributing a flat transfer according to an existing welfare metric that has been calculated ahead of the shock[10]; distributing a flat transfer following an imperfect indicator of which household suffered the shock; and distributing a universal, flat transfer to all households.

For the baseline COVID-19 shock, the most cost-effective response available to policy makers is to expand existing social assistance using the established assessment of household welfare, even if the latter has been constructed prior to the shock. The reason is simple: although people suffered income losses, the COVID-19 shock did not affect much their ranking within the income distribution: hence the welfare metric still provides valuable information on who are the poorest households that need support and, by extension, expanding the coverage of the current program (as designed prior to the shock) is an effective response. The remaining two program design alternatives deliver substantially inferior poverty impacts: a universal, flat transfer to all households leads to a much lower transfer to the poor, which in turn delivers much lower poverty impacts; and, for the COVID-19 shock, designing a new program that delivers support to households based on indicators about who suffered a loss are not

[10] In the simulations, we use a proxy means test (PMT) for simplicity given that Albania and Moldova currently employ a PMT, which in the case of Moldova is coupled with a means test. North Macedonia uses a means test.

very informative of poverty status since most households did suffer some form of losses and overall welfare rankings did not change substantially as a consequence of the shock.

These findings, however, hold under the COVID-19 shock: while it did not affect substantially rankings of the income distribution, some households were more impacted than others. Next, we compare the results with a fully homogeneous, "proportional loss" shock where each household loses the same share of their labor income. In addition to the COVID-19 shock, the "proportional loss" shock can also approximate other economy-wide shocks such as inflation or economic crises. To allow comparing results across shocks, we consider the same amount of aggregate labor income losses as in the COVID-19 shock, but we distribute these losses proportionally.

The results align with the findings under the COVID-19 shock. The simulations also underline the importance of option for program designs that expand coverage of cash transfers both horizontally (i.e., enrolling more beneficiaries) but also vertically (i.e., providing more generous transfers to existing beneficiaries) – especially if the emergency transfer is larger than the existing social assistance transfer. Two factors support this finding; first, existing beneficiaries are impacted by the shock, falling further into poverty and therefore requiring additional support. Second, the shock may not push some of the affected households as deep into poverty as some existing beneficiaries; hence, from a welfare perspective, providing more generous transfers to existing beneficiaries also delivers high impacts.

How much to expand horizontally and vertically depends however on initial conditions and the profile of existing beneficiaries of social assistance. All countries face a tradeoff between the number of people covered and the size of the transfer; but the optimal solution is country-specific and depends on initial conditions. In Moldova, for instance, the income threshold for the program is significantly below the extreme poverty level. A vertical expansion (e.g., giving more to existing beneficiaries) has therefore greater welfare impacts than significantly expanding coverage to new beneficiaries, because existing beneficiaries are substantially worse off than many households affected by the shock. In Albania and North Macedonia, instead, where fewer extreme poor households are covered by social assistance programs, horizontal expansions deliver instead greater impacts. However, excessive expansions (such as a universal flat transfer) deliver again inferior impacts because the budget is spread too thinly across the population.

Results differ substantially when we introduce a heterogeneous, "random loss" shock. Under this scenario, the same aggregate income loss as in the baseline shock is distributed randomly across the distribution; but people affected lose all their labor income. While in the aggregate, losses are equivalent across shock scenarios, the random loss shock is more extreme for people affected because they lose all their labor income and thus face a higher likelihood of falling into extreme poverty (especially for single-earner households). The random loss shock also substantially changes the rankings within the income distribution. This type of shock mimics what happens when disasters such as earthquakes or floods hit, disproportionately affecting differently households living nearby; and as a result, optimal responses change substantially from the ones for proportional income shocks. In all three countries, under the random shock loss, expanding support by using a loss indicator – even an imperfect one – delivers substantially higher impacts than an expansion through the existing programs that are based on the existing welfare metric. This is because the shock alters welfare rankings and many households affected by the shock fall into extreme poverty – hence the old welfare score carries little information about who the new extreme poor are as a result of the shock.

Similarly, assistance design based on a mix of a shock indicator and a welfare metric that is assessed prior to the shock also delivers lower results for the same reason. Even under the random shock scenario, however, delivering assistance through a universal, flat transfer remains an inferior option, with even lower impacts than using a welfare metric.

We conclude the analysis by looking at differences in impacts when targeting individuals instead of households (i.e., providing an equal transfer to each beneficiary household, independent from the household composition). From an implementation perspective, targeting individuals may be more complex; but since poorer households tend to be of larger size, targeting individuals could deliver, a priori, larger impacts. While in 2 out of 3 countries targeting individuals delivers higher impacts, in terms of magnitude gains seem relatively small (below a 10-percent difference in poverty impacts), suggesting that choosing the more practical approach has a low efficiency cost in emergency situations.

Summing up, our analysis aims to motivate a focus on planning for future shocks among governments, specifically to consider in advance the efficiency of different program design options to respond to shocks through national social protection systems. It does so by looking at the relative efficiency of social assistance design options, under a fixed budget allocation, to provide an immediate response to shocks with differing distributional impacts. The analysis shows that expanding the coverage of countries' last-resort income support programs is more efficient than providing a universal flat transfer. *How much* to expand these programs horizontally and vertically depends however on initial conditions and the profile of existing beneficiaries of social assistance. Additionally, the nature and extent of the shock influences the extent to which policy makers can expand their social assistance programs as designed. If the shock is homogeneous (in the sense that poor households and those around the poverty threshold are affected proportionally), expanding programs that identify people based on their welfare is an efficient tool to identify new beneficiaries. For heterogeneous shocks that alter the income distribution by impacting specific groups disproportionately, the eligibility criteria and targeting method will need to change, as the existing method carries little information about who has been affected, and alternative targeting methods, such as community-based targeting, geographical criteria, or gathering information about who has been affected by the shock, should be considered. Planning for future shocks by considering optimal program design should be complemented with efforts to "stress test" social protection systems, as set out in World Bank 2021 for cash transfers.

The paper proceeds as follows. Section 2 lays out the basic shock typology and reviews the responses we consider. Section 3 discusses the data and methodology for the microsimulations. Section 4 presents and discusses the results.

2. Classifying shocks and their responses – a simple framework

Shocks and social protection policy responses are often considered separately, although it is intuitively clear that optimal responses should incorporate a maximum amount of information about the nature of the shock, the characteristics of the people affected, and the losses they have incurred. However, in many instances, the information about the affected people and their losses is highly variable, incomplete, or nonexistent altogether, due to the structure and design of social protection programs and their delivery systems. This is most acute for the immediate response phase that aims to mitigate the impact of shocks on households. For instance, given the design of social insurance programs and existing databases, formal sector workers hit by unemployment are easy to identify and their losses (foregone wages) are relatively well-known; on the other hand, dismissed informal workers will go undetected and the information about foregone wages will be approximative at best. While both situations would in theory call for the same social protection response mechanism to mitigate the impact of job loss, in practice its ability to reach and compensate both types of workers effectively would be very different, as was seen during the COVID-19 pandemic.

As a thought experiment, we classify shocks and social protection policy responses that aim to mitigate the impact of shocks on individuals according to the information that is available to policy makers. In Table 1, we categorize shocks according to whether it is possible to know on an individual basis (1) who is affected; and (2) the value of each loss. Such categorization reflects one of the main challenges faced by policy makers, especially in low- and middle-income countries, in designing effective policy responses.[11] It is often relatively easier to estimate the total value of losses for localized shocks such as earthquake damages (through georeferenced simulations, for instance), or roughly identify the most affected population groups (e.g., agricultural households in a certain province). But even in cases where aggregate losses and affected groups of people are known, it is much more difficult – and at times impossible – to know with precision which households are affected and the exact value of their losses. The efficiency of the policy response (understood as its ability to compensate those affected adequately, for a given budget) will then depend on the heterogeneity of shocks across people and losses, and the more heterogeneous a shock, the more the response's efficiency will depend on how much it can be tailored.

[11] We recognize that the humanitarian system and, in some countries, the disaster risk management systems, have methods in place to collect some of this information. The speed and completeness with which this data is collected and made available to the social protection system varies, however.

Table 1: A simple taxonomy of shocks and social protection policy responses

		Who is affected: Known	Who is affected: Unknown
Value of individual loss	**Known**	Policy makers can easily identify affected people **AND** the value of losses is known, bounded or easily verifiable **Example:** Employment and demand shocks affecting formal sector workers **Example of responses:** Unemployment insurance, wage subsidies	Policy makers cannot easily identify affected people **BUT** the value of losses is known, bounded or easily verifiable **Example:** Disasters affecting informal urban settlements (i.e., loss is observable, but ownership is difficult to assess). **Example of responses:** Support through communities, (targeted) cash transfers, public works with self-targeting, expansion of social assistance
	Unknown	Policy makers can easily identify affected people **BUT** the value of their losses is not easily verifiable **Example:** Disasters affecting rural areas, such as through flooding or an earthquake **Example of responses:** Support through communities, Disaster Relief Funds; geographic targeting of social assistance benefits	Policy makers cannot easily identify affected people **AND** the value of their losses is not easily verifiable. **Example:** Disasters and **c**rises affecting incomes of informal sector workers or poor households out of the labor force **Example of responses** Support through communities, (targeted) cash transfers, public works with self-targeting, expansion of social assistance

The upper left quadrant in Table 1 represents the case where both the people affected, and the value of their loss can be relatively easily observed. A leading example would be shocks resulting in income or employment losses by formal sector workers, which can be supported through formal sector responses such as unemployment insurance or wage subsidies. The degree of information asymmetries increases when, for instance, affected people can be identified relatively easily, but not the degree of the loss (lower left quadrant). Think for instance of droughts or floods affecting informal rural areas – while it may be relatively easy to compile lists of landholders, assessing their losses may be more difficult, particularly in a time-sensitive manner. Conversely, in urban areas, it may be relatively easy to assess damages from, say, earthquakes; but – especially in informal settlements – it may be challenging to assess ownership, and hence whom should be compensated (upper right quadrant). Finally, the most complex case is when both the people affected, and the value of their loss are hard to identify (bottom right quadrant in Table 1). This is a frequent case as it covers most informal activity in urban areas (groups which are not extreme poor and thus are not captured by social assistance program rosters), where lack of information on employment, earnings and assets makes it difficult – if not impossible – to verify who lost employment or income, and the precise value of the loss to be able to adequately compensate affected people.

Because it is the most complex situation, we focus our analysis on the specific case where both (on an individual basis) who is affected from a shock and the value of the loss are unknown (or known without precision) by policy makers. The analysis focuses on critical design choices and their relation to the distributional characteristics of the shock that is affecting households, which will ultimately define the impact of the response. Rather than providing a formal, theoretical characterization between design choices and impacts, we use microsimulations based on household survey data for Albania, Moldova, and North Macedonia to illustrate important relations and trade-offs. Simulations also present the advantage to allow assessing the effectiveness of actual instruments available to policy makers (such as increasing the benefit paid through existing social programs or expanding coverage to different populations, as selected through varying targeting methods), something that would not be feasible with a theoretical model. In this case, we focus on different design options associated with one social protection instrument: cash transfers. We do not take into account behavioral responses or general equilibrium effects, so that we consider first-order effects only.

The policy relevance of bringing forward practical solutions for the design of social protection responses to shocks is high. Analyses of the social protection responses to the COVID-19 pandemic suggest that in many cases policy makers attempted to cover the informal sector using a variety of design "tweaks" to existing programs and their delivery systems. For instance, some countries topped-up benefits to existing beneficiaries (Kosovo), others expedited/automatized enrollment processes into existing programs (Moldova) or provided a one-off transfer to former beneficiaries or people in the program beneficiary registry (not current beneficiaries; Albania), while others provided a flat, universal transfer to ensure that informal sector workers are covered (Serbia).[12] Alas, the variety of designs is not the result of optimizing responses to a given type of shock (these were all responses to the same shock, hitting countries in similar ways), but rather of implementation challenges and political economy considerations faced by policy makers.

To illustrate the impact of these design choices while keeping the analysis tractable, we do not classify these covariate shocks by their origin (i.e., health, flood, drought, etc.) but rather by the distributional impacts they have on households. In particular, we distinguish between shocks that affect people's income or wealth proportionally, leaving the income distribution and income/wealth rankings unchanged, and those that affect some people substantially more than others and change the shape of the income distribution and its rankings.

The distinction is subtle, but important. If shocks affect incomes uniformly, then existing programs and their targeting mechanisms, such as those that assess welfare through means tests or proxy means tests, can relatively easily identify a significant share of people who fell into poverty because of the shock, as many of them would have been near the poverty line even before the shock hit – hence an increase in benefits with possibly some program expansion to cover the "new" poor may be close to an optimal response. On the other hand, if a shock affects some people substantially more than others, the "new" poor may have a different profile than the "old" poor, and effective responses may require an approach that differs from increases in benefits or expanding the program using the existing welfare metric

[12] See Gentilini et al. (2020a) for a more detailed account.

to select beneficiaries to cover households that were just above the eligibility threshold before the shock. In reality, shocks often consist of a combination of these two extremes.

We also focus on social assistance programs that aim to mitigate the immediate impact of the shocks on households through an emergency or rapid response, leaving aside the broader range of programs along the disaster risk management continuum that extends from preparedness through response into recovery (Macdonald et al 2015). This is to ensure that we are comparing the relative efficiency of different design options to achieve the same objective. Our focus on the poor and poverty reduction leads us to restrict the analysis to social assistance programs, specifically cash transfers, leaving aside for the moment the question of the relative effectiveness of a response through social insurance programs and their delivery systems.

In what follows, we anchor our analysis to the COVID-19 shock and subsequent social protection response. Accordingly, we consider as a "baseline" shock the COVID-19 pandemic-induced crisis that affected all countries in the world, but whose impact within each country varied depending on the movement and economic restrictions imposed to contain the spread of the virus. To simulate the social protection response, we use World Bank microsimulations of the impacts of the shock and subsequent responses in Albania, Moldova, and North Macedonia during the first COVID-19 wave (World Bank 2020c, 2020b, 2020a) as the starting point. We chose these countries because they are all upper middle-income countries of relatively the same size in Europe and Central Asia, with established social protection systems.

Next, for a fixed budget and for each type of shock, we consider different compensatory strategies in the form of cash transfers. We focus on the most common responses and program expansions observed during the pandemic, and on additional responses that could be easily implemented by policy makers. Again, our baseline scenario is the actual social assistance response to the first wave of the COVID-19 pandemic in Albania, Moldova, and North Macedonia. To analyze the quality of responses, we consider various alternatives under equivalent budgets, presented in Table 2. In summary, we consider broadly three types of shocks: the baseline "COVID-19" shock; a homogeneous, "proportional" shock reducing all labor incomes but maintaining the income distribution unchanged; and a heterogeneous, "random" shock altering the labor income distribution. For each shock, we study the quality of different responses by comparing post-response welfare measures including the poverty headcount, the squared poverty gap and the Gini coefficient.

Table 2: Social Assistance responses considered in the simulations

	Social Assistance Response Distributing an additional fixed budget to:
1a.	Pre-shock beneficiaries of Social Assistance programs
1b.	Actual post-shock beneficiary expansion (if any)
2	All households identified as poor before the shock hit
3.	All households identified as poor after the shock hit
4.	All households (i.e. universal, flat transfer)
5.	All households ranked according to a Proxy Means Test, up to the point where the number of beneficiaries corresponds to the number of pre-shock poor
6.	All households ranked according to a Proxy Means Test, up to the point where the number of beneficiaries corresponds to the number of post-shock poor
7.	All households identified as having suffered a shock (Perfect Indicator)
8.	All households identified as having suffered a shock (Imperfect Indicator)
9.	All households in (5) and households having faced a shock according to a perfect indicator
10.	All households in (6) and households having faced a shock according to a perfect indicator

Responses 1a and 1b simulate the policies deployed as a response to the COVID-19 shock, hence we assess the welfare impact of actual program responses in the three countries. Specifically, we model response 1 of Table 2 by distributing a fixed budget to all the pre-shock beneficiaries of Social Assistance programs. The payment is *in addition* to all the payments that these beneficiaries were receiving before the shock occurred. In response 1b we do the same but consider the actual expansion of beneficiaries that occurred in North Macedonia - the only country among the three that enacted a major expansion of the beneficiary base to respond to the crisis.

Responses 2 and 3 are hypothetical benchmarks as they assume perfect identification of the poor – something that is only possible under perfect means testing – an ideal that we simulate to establish a “first-best” response. In response 2 we identify in the survey all poor households *before* the shock and distribute the same fixed budget to all of them; and in response 3 we do the same but consider instead all households identified as poor *after* the shock hit. The payments simulated here are added to any pre-shock transfer that households may have reported. It is important to note that due to data limitations this simulation does not include other types of transfers that were implemented in response to the COVID-19 shock, such as wage subsidies or new unemployment benefits. Doing this would have required extreme assumptions about how transfers to firms would eventually be channeled to households and about the households affected by shock-related unemployment. It is also important to note that unemployment insurance programs in these countries have very low coverage and thus are not well captured in household surveys.

Response 4 reflects a pragmatic choice – i.e., a universal, flat transfer that divides the fixed budget equally among all households, independently from their income and from whether they suffered an income shock. This scenario captures the absence of any information on which to target resources during an emergency.

Responses 5 and 6 are more realistic versions of 2 and 3. Specifically, pre-shock poverty status is estimated using a proxy-means test indicator (PMT scores) that ranks households’ welfare according to observable characteristics that are correlated with income. In response 5 we distribute equally the fixed budget to all households below PMT threshold, up to the point where the number of beneficiaries corresponds to the number of pre-shock poor; while in response 6 we do the same, but up to the point where the number of beneficiaries corresponds to the number of post-shock poor (so that there will be more beneficiaries, but the transfer will be lower).[13] Once again payments are in addition to any pre-shock transfer that households may have received but exclude households that may have benefitted from other COVID-19 support programs.

Note that, while the proxy-means indicator may be relatively efficient in identifying pre-shock poor, it may not necessarily be a good indicator of *new* poor because asset holdings may not change immediately nor predict vulnerability to the shock, and PMT scores are usually not recalculated in the aftermath of a shock. Hence, accurate identification of post-shock beneficiaries using a pre-shock PMT index may vary substantially according to the nature of the shock, depending on whether the shock affected distributional rankings.

At times, however, policy makers may be able to make use of an indicator identifying which households may have suffered a shock. For instance, following a drought one may not be able to perfectly identify the value of the loss, but a good approximation could be obtained by estimating households' land holdings. Similarly, information of an informal workers' sector of activity could provide some indication of the extent of the income loss she may have suffered during a crisis.

To reflect the availability of this "imperfect" information, we consider two additional responses (7 and 8). In response 7 we distribute the fixed budget among households that suffered the shock with certainty. We call this a "perfect loss" indicator. In response 8, we introduce an exclusion error of 25% to mimic the case of imperfect information.

The final two responses (9 and 10) combine the PMT indicators with the "perfect loss" indicator. We then distribute the fixed budget to all households ranked low according to each Proxy Means Test *or* whose indicator shows they suffered a shock. By combining the two indicators we make sure that both the poor and those that suffered a shock receive support. The rationale behind using the perfect loss indicator and not the imperfect one is understanding how access to the best possible information during a crisis can improve proxy-means testing.

3. Data and methodology

For the microsimulations, in Albania and North Macedonia we rely on data from the Survey of Income and Living Conditions (SILC – 2018 for Albania and 2019 for North Macedonia). The SILC collects annual information on household incomes, including public and private transfers. It collects information about household's annual income for the year before the survey, as such incomes for Albania and North Macedonia refer to the years 2017 and 2018, respectively. In Albania the total number of households covered was 772,197 and the number

[13] This is a scenario where the number of individuals affected is known, but what remains unknown is which individuals were effectively affected or what the value of their loss is.

of individuals is 2,870,315. In the case of North Macedonia, the total number of households covered was 567,753 and the number of individuals was 2,076,247. In both cases we nowcast incomes to what would be observed in 2019 levels using official GDP per capita growth and passthrough rates for each country.[14] For Moldova we use the 2019 Household Budget Survey (HBS), which is a nationally representative household survey conducted annually that captures information on income, expenses, and consumption in addition to demographic and social indicators. The 2019 HBS covered 4,408 households containing 11,355 individuals.

In the simulations we use an expenditure-based poverty threshold of $5.5 per day; and the same threshold is used to calculate the poverty gap squared, our main welfare indicator. The estimated poverty rates for each country before the shocks are 32%, 12% and 17% for Albania, Moldova, and North Macedonia, respectively. The poverty gap squared indexes are 6.7, 1.3 and 3.5, while the Gini indexes are 0.37, 0.32 and 0.33.

Methodology

To determine the poverty and distributional impacts of alternative responses to shocks, we use survey-based microsimulations (Bourguignon and Spadaro 2006). We consider three types of shocks and assess the impacts of the different responses described in Table 2 for each type of shock. As a baseline shock we use the first wave of the Covid-19 Pandemic shock as simulated by World Bank (2020d, 2020b, 2020a), where individuals were exposed to the shock to varying degrees depending on the industry where they work and the type of workers they are. We then simulate two additional shocks of the same magnitude (i.e., with the same aggregate labor income losses), but with different distributional impacts. The second shock consists of a proportional loss of income that is equal for all workers who report labor income. This is an extreme case that wants to assess optimal responses under shocks that do not affect welfare rankings across the population; the third shock is the opposite – it affects fewer households, randomly, but workers affected lose all their labor incomes. Under the third shock there will therefore be households who suddenly become extreme poor and drop to the bottom of the income distribution – a case that many common targeting methodologies, such as Proxy-Means Tests, are not able to capture.[15]

Specifically, the algorithm for the simulations loops over three layers: the type of shock, the overall budget of the social assistance response, and the different ways to identify (target) program beneficiaries. The first layer in the simulation is the shock. Once each shock is modeled and income losses have taken place, we proceed to the second layer and iterate over two social assistance package budgets. Given a shock and budget, we proceed to distribute each budget equally for each of the ten targeting cases in Table 2, one at a time. Once the budget is distributed equally among the chosen beneficiaries, we compute poverty and inequality indexes, as well as statistics regarding the average value of transfers, the

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[14] Official GDP per capita growth rates are from WDI. Albania: 3.9% (2017), 4.3% (2018); North Macedonia: 2.8% (2018). Passthrough rates are 1 and 0.87 percent for Albania and North Macedonia, respectively.

[15] We acknowledge that the two modeled shocks (besides the “COVID-19” one) may not be very realistic, as most shocks are not random –even those considered exogenous such as natural disasters. Indeed, most shocks hit groups that share common characteristics, whether geographic, demographic or socio-economic. To some extent, the COVID-19 shock already captures these differential impacts as it varies according to the type of employment and sector of the worker. The other two shocks are extreme in nature but help to set certain bounds to the analysis of the quality of responses.

number of beneficiaries and coverage of populations of interest. Because shocks affect households randomly, and we also need to attribute some individual characteristics which we do not observe in the data,[16] we bootstrap each simulated case to estimate the averages of all statistics collected. Each combination of shock, package and targeting mechanism is bootstrapped 50 times to account for the randomness that is introduced in modeling the shocks and different responses. In total we simulate 120 scenarios in Albania and Moldova, and 132 in North Macedonia.[17] The main results show simulations where the transfer is delivered at the household level; however, we also discuss below differences when the transfer targets individuals.

Next, we describe in greater detail each shock, budget and target populations considered. The baseline shocks in all countries simulate the losses that households faced during the first wave of the COVID-19 pandemic in 2020, which led to widespread lockdowns. The simulations identify sectors that, due to imposed mobility restrictions, border closures, etc., were moderately or highly affected, and assign income losses depending on individuals' sector of activity employment status, and to some extent, formality. This captures the fact that wage-employees in formal firms were better protected because they could benefit from some types of government support, whereas informal workers and self-employed were not targeted by any support measures, unless they were already beneficiaries of social assistance programs. Namely, self-employed individuals face twice the labor income loss than salaried workers (employees) in the same industries; and individuals in highly affected industries (which are country specific) face a loss of income twice as high as those in moderately affected ones. We also assume that workers in unaffected industries do not suffer income losses (see Table 3).

Table 3: Distribution of income losses in the baseline shock

Shock Depth		Worker Type	
		Employee	Self-Employed
Sector	Highly Affected	-0.25	-0.5
	Mildly Affected	-0.125	-0.25
	Unaffected	0	0

Note: The table shows the percentage loss of annual labor income under the baseline, COVID-19 shock.

We then estimate the total value of labor income losses, and model two additional shock scenarios holding the same level of aggregate losses constant (for comparability purposes).

[16] Such as formality status, which affects households' likelihood of receiving formal sector support and would exclude them from social assistance support.

[17] The extension of benefits (response 2 in Table 2) was only modeled in North Macedonia since in Albania and Moldova there was no expansion of social assistance coverage.

The second shock is a *Proportional loss shock*, where all individuals experience the average loss faced under the baseline scenario (i.e., the COVID-19 shock). A potential real-life example may be an inflationary crisis, which tends to affect incomes proportionally. Note that a proportional shock preserves the ranking of individuals along the labor income distribution. Finally, the third shock is the opposite – i.e., a *Random loss shock*. In this scenario the shock only affects a fraction of individuals randomly, but they lose their full year's labor income. This shock is akin to an idiosyncratic shock that forces some individuals out of employment. Note that a random loss shock affects the ranking of individuals along the income distribution. In both cases we ensure that the aggregate level of income losses is the same as in the baseline (COVID-19) scenario.[18]

Next, we simulate the responses. In terms of budget/fiscal envelope, we consider two levels of response: the cost of the actual social assistance responses in Albania and North Macedonia, as well as a 0.05 percent of GDP response in Moldova;[19] and a larger package that amounts to 1 percent of GDP in each country. We estimate the total value of transfers in Albania and North Macedonia to have been 0.05 percent and 0.09 percent of GDP, respectively (note that this amount only covers the social assistance response to the first COVID-19 wave – countries spent much more in total on a variety of policy measures).[20] As we shall see, given the limited amount allocated to the responses their impacts on poverty remain quite limited; therefore, we will devote most of the discussion to the more ambitious but simulated response of 1 percent of GDP.

To study the effectiveness of different expansion mechanisms we then test ten different responses for each of the three shocks and the two budgets/fiscal envelopes, as highlighted in Table 2. For each response, once beneficiaries are identified we split the available budget equally across beneficiary households. Since poor households tend to be larger, as a robustness exercise, we do also split the available budget equally across all eligible beneficiaries, but we shall see that results do not change significantly. Simulation details for each response are as follows:

Pre-shock beneficiaries of social assistance programs (column 1a in the tables). This scenario reflects Albania's choice of a temporary doubling of social assistance benefits for existing beneficiaries. In our simulations we do not double benefits necessarily but distribute equally the additional budget envelope across existing social assistance beneficiaries. Social Assistance beneficiaries are identified through dedicated questions present in the surveys.

Actual post-shock beneficiary expansion (column 1b in the tables). This scenario is only modeled for North Macedonia, which expanded benefits to 15,500 households that were previously not covered by the Guaranteed Minimum Income program. To maintain some

[18] Due to the randomness involved in modeling the shock and sampling weights in the surveys, we can only guarantee to be close enough to the baseline level of losses. We ensure that absolute aggregate differences are no larger than 0.02% relative to the baseline level of losses.

[19] The actual direct social assistance response in Moldova was too small to properly identify impacts – hence we model a package of 0.05 percent of GDP.

[20] Since the values of both total transfers and total losses are needed for the modeling exercise across scenarios, we did not rely on administrative data to assess the total value of the baseline program. Rather, we estimated the total value of the baseline program by aggregating the value of transfers to households simulated in the baseline program following the rules regarding eligibility, amount, and the frequency of transfers to beneficiaries. We considered any extensions in time and expansions in eligibility of the program response for each country that took place during 2020.

equity between original and new beneficiaries, under the original spending scenario of 0.09% of GDP we only give the funds to new (15,373) beneficiaries, but under the 1% of GDP spending scenario we give the additional funds to both old and new (33,112) beneficiaries.

All households identified as poor before/after the shock hit (columns 2 and 3 in the tables). We distribute the additional budget equally across households whose income per capita (according to the surveys) falls below the poverty line prior to/after the shock. While in real terms it is not possible to identify precisely poor households, these scenarios provide a good benchmark of the effectiveness of an ideal "perfect targeting" scenario.

All households (i.e., universal, flat transfer; column 4 in the tables). We assign the budget equally among all households in the country regardless of income or losses.

All households ranked low according to a Proxy Means Test (PMT), up to the point where the number of beneficiaries corresponds to the number of pre-shock/post-shock poor (columns 5 and 6 in the tables). For this scenario, we estimate first a PMT indicator using information available in the surveys (see the Annex for more details). We then distribute the additional budget among households with a low PMT score, up to the point where the number of beneficiaries matches the share of the population living below the poverty line before/after the shock.

All households suffering a shock (columns 7 and 8 in the tables). For this scenario we generate an indicator that takes the value of 1 if the household suffered an income shock. We also estimate an imperfect version of this indicator, where we randomly exclude 25% of households that suffered a shock to add uncertainty to the indicator. We distribute the budget only among households that have been affected by the shock according to the indicator.

All households ranked low according to a Proxy Means Test or a perfect indicator of having faced a shock (columns 9 and 10 the tables). Finally, we combine each PMT and the perfect indicator, to ensure that both the poor and those who experienced a shock receive transfers. We have selected the perfect shock indicator to capture an upper bound of how well-functioning information systems can work alongside PMTs.

4. Impacts of social protection responses

We now discuss the impacts of the different social protection responses. Because of the high number of cases and simulations, we have harmonized the way we report and compare responses as presented in Table 4, which shows the poverty impacts of the various responses for the baseline (i.e., COVID-19) shock in Albania. The first row in Table 4 indicates the shock we are considering (in this case the COVID-19 shock). In the next row, the table shows whether benefits are given per household, or per individual. We will discuss the results based on benefits given to households, which is how most cash transfers operates, but we will then review differences in giving benefits to individuals. Next, each column considers a different response scenario, as described in Table 2. We then present results for two different poverty indicators, the poverty headcount and the poverty gap squared, to take into consideration the fact that the headcount index does not consider distributional changes among the poor and fails to put a greater weight on the welfare of the extreme poor (Lustig et al. 2021). For each welfare measure and type of response we then show the impacts of a response based on two budgets – the actual budget spent on the COVID-19 response, and a response budget of 1 percent of GDP.

Given that the poverty impacts of actual responses remain small, to ease the comparison we focus the discussion on the more ambitious response of 1 percent of GDP; but again, results remain very similar as they seem to depend more on the choice of coverage of beneficiaries, than on budget. Similarly, because we would like to give more weight on the impacts of the extreme poor, we focus the discussion on the impacts captured by the poverty gap squared, which at times differ substantially from the impacts as captured by the poverty headcount indicator.[21] Finally, to facilitate further the reading of the results, we also color-coded the responses from dark red (most effective response) to dark blue (least effective).

Baseline (COVID-19) shock

Not surprisingly, the most impactful responses in Table 4 (baseline shock for Albania) are when the poor can be perfectly identified (either before or after the shock), because the funds are distributed to the most vulnerable (columns 2 and 3). Interestingly, when the poverty gap squared indicator is considered, distributing the funds to all ex-ante poor households delivers higher impacts than covering all the post-shock poor households. This is because the simulated baseline COVID-19 shock only has a moderate impact on extreme poverty, and by distributing the same budget to more people the extreme poor receives a lower amount. Note, also, that the choice of indicator matters: the poverty headcount indicator, which only looks at the number of people below the poverty line and ignores how far households are from the poverty line, would suggest that covering the post-shock poor (column 3) would deliver higher poverty impacts than only covering the pre-shock poor (column 2).

[21] Our choice to focus on the poverty gap squared also reflects policy maker's concerns about how crisis response resources should be distributed among the poorest and/or most affected by the shock, and time-bound, in light of binding fiscal constraints.

Table 4: Albania, baseline shock: poverty and inequality impacts

	Baseline Shock									
Targeting →	Household									
	Eligibility ↓									
Budget ↓	Original Beneficiaries	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Pefect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Perfect Loss Indicator
	(1a)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Poverty Rate	**Pre-shock: 0.320; Post-shock: 0.373**									
(1) 0.05% GDP	-0.005	-0.006	-0.008	-0.005	-0.005	-0.005	-0.006	-0.006	-0.006	-0.006
(2) 1.0% GDP	-0.027	-0.049	-0.067	-0.024	-0.031	-0.028	-0.029	-0.025	-0.028	-0.027
Poverty Gap Sqr.	**Pre-shock: 6.721; Post-shock: 7.715**									
(1) 0.05% GDP	-0.373	-0.486	-0.468	-0.341	-0.410	-0.402	-0.328	-0.329	-0.352	-0.352
(2) 1.0% GDP	-1.522	-3.346	-3.127	-1.282	-2.249	-2.154	-1.010	-0.982	-1.447	-1.450
Gini	**Pre-shock: 0.371; Post-shock: 0.375**									
(1) 0.05% GDP	-0.002	-0.003	-0.003	-0.002	-0.003	-0.003	-0.002	-0.002	-0.002	-0.002
(2) 1.0% GDP	-0.013	-0.031	-0.030	-0.009	-0.020	-0.020	-0.008	-0.007	-0.011	-0.012
Coverage										
(1) Average Transfer	$ 105.1	$ 70.3	$ 60.6	$ 18.7	$ 70.3	$ 60.7	$ 37.7	$ 49.7	$ 28.1	$ 27.2
(2) Average Transfer	$ 1,946.5	$ 1,301.7	$ 1,123.4	$ 345.5	$ 1,302.4	$ 1,123.6	$ 698.7	$ 925.8	$ 521.2	$ 503.3
Beneficiaries	137,071	204,973	237,496	772,197	204,856	237,471	381,857	289,901	511,939	530,157
Ex-ante poor	0.28	1.00	1.00	1.00	0.60	0.65	0.40	0.31	0.78	0.81
Ex-ante non-poor	0.13	0.00	0.08	1.00	0.17	0.22	0.62	0.46	0.70	0.72
Ex-ante Vulnerable	0.17	0.00	0.12	1.00	0.25	0.32	0.60	0.46	0.73	0.76
Post-shock poor	0.27	0.86	1.00	1.00	0.55	0.59	0.48	0.36	0.81	0.83

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact). Not all households declare labor income.

The next best (simulated) response (and the first best response for a policy maker who cannot perfectly identify the poor) is to use a Proxy Means test and distribute the additional budget to the poorest households (columns 5 and 6). Again, in the case of Albania, and under the baseline shock, it looks like the better response would be to distribute the additional resources to only the pre-shock poor as identified through the PMT, because the shock did not affect much extreme poverty. Note, also, that while using the PMT is an effective, practical response, exclusion errors become substantial – less than 60 percent of the post-shock poor would be covered by the transfer.

The third-best response would be to distribute additional benefits to existing social assistance beneficiaries (column 1a), which is the actual government response. Because the social programs do not cover all the poor, this remains however an inferior response than a more generous coverage which, even if the transfer per household remains lower, would cover all the pre-shock poor.

Next, the fourth- and fifth- best responses would be to cover all the poor classified as such through a PMT, plus people who suffered a loss as identified through an indicator (columns 9 and 10). Again, this remains a worse response than just covering the pre-shock poor because the specific shock we considered did not affect much extreme poverty.

Note also that while a universal transfer would be the only way to guarantee that all the poor would be covered, providing a universal, flat transfer to all households would deliver extremely low poverty impacts (column 4), because to ensure that all the poor are covered the transfer would have to be given to all non-poor households as well, which lowers substantially the amount given to each poor household. There is therefore an important tradeoff between equity considerations (i.e., covering all the poor), and poverty impacts.

Finally, giving the transfer only to households who suffered a shock, as identified through a perfect/imperfect indicator (columns 7 and 8) would deliver even worse poverty impacts than a universal transfer. This is strongly related to the nature of the shock, which did not bring as many households into extreme poverty, and to the fact that existing social-assistance transfers are relatively modest, so that covering the pre-shock poor can deliver greater impacts than covering households affected by the shock: we discuss below how this finding stops holding for other types of shocks.

Note that the rankings of impacts are strikingly similar between the two generosity levels (i.e., 1% of GDP and 0.05% pf GDP). This provides a useful insight in terms of optimal response design: unless the shock affects substantially extreme poverty, the optimal response – independently from budget – should also cover the extreme poor, even if they have not been affected by the shock, because they remain in worse economic conditions that many households that have been affected by the shock.

Observe also that the impacts on inequality remain very similar to the impacts on poverty: this is because the more the transfer covers the lower tail of the distribution, the more it will reduce the Gini coefficient.

Table 5: Moldova, baseline shock: poverty and inequality impacts

	Baseline Shock										
Targeting →	Household										
	Eligibility ↓										
Budget ↓	Original Beneficiaries	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Pefect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Perfect Loss Indicator
	(1a)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Poverty Rate	**Pre-shock: 0.120; Post-shock: 0.129**									
(1) 0.05% GDP	0.000	-0.002	-0.002	0.000	-0.001	-0.001	0.000	0.000	0.000	0.000
(2) 1.0% GDP	-0.015	-0.034	-0.039	-0.005	-0.010	-0.010	-0.004	-0.004	-0.008	-0.008
Poverty Gap Sqr.	**Pre-shock: 1.344; Post-shock: 1.410**									
(1) 0.05% GDP	-0.073	-0.040	-0.038	-0.005	-0.016	-0.015	-0.002	-0.002	-0.006	-0.006
(2) 1.0% GDP	-0.789	-0.614	-0.587	-0.097	-0.285	-0.262	-0.040	-0.033	-0.107	-0.104
Gini	**Pre-shock: 0.320; Post-shock: 0.317**									
(1) 0.05% GDP	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(2) 1.0% GDP	-0.009	-0.008	-0.008	-0.002	-0.005	-0.005	-0.001	-0.001	-0.002	-0.002
Coverage										
(1) Average Transfer	$ 124.95	$ 41.71	$ 38.90	$ 5.09	$ 42.15	$ 39.34	$ 14.98	$ 20.29	$ 11.45	$ 11.39
(2) Average Transfer	$ 2,499.04	$ 834.28	$ 777.96	$ 101.73	$ 842.91	$ 786.76	$ 299.59	$ 400.19	$ 229.00	$ 227.82
Beneficiaries	109,169	327,009	350,683	2,681,733	323,663	346,758	910,650	672,277	1,191,328	1,197,498
Ex-ante poor	0.29	1.00	1.00	1.00	0.49	0.48	0.16	0.11	0.59	0.57
Ex-ante non-poor	0.00	0.00	0.01	1.00	0.07	0.08	0.36	0.27	0.42	0.42
Ex-ante Vulnerable	0.01	0.00	0.02	1.00	0.13	0.14	0.28	0.21	0.39	0.40
Post-shock poor	0.27	0.93	1.00	1.00	0.46	0.45	0.22	0.16	0.62	0.60

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact). Not all households declare labor income.

Table 5 shows the results of the same simulations (i.e., baseline shock) for Moldova. In full similarity with Albania results are very similar between the two spending scenarios. Nevertheless, the simulations show that, in the case of Moldova, distributing the budget only to existing beneficiaries of social assistance (column 1a) seems to deliver the highest impacts when measured with the poverty gap squared (though not with the poverty headcount). This is because the Moldova social assistance program is relatively small and is focused on the extreme poor; and since the shock as simulated did not bring too many households into extreme poverty, the most effective poverty alleviation strategy remains to cover the extreme poor, even if the response may not cover many households that have been affected from the shock. Again, we shall see that this result will change substantially when other shocks are considered – stressing further the importance of adapting the design of the response to the nature of the shock.

The remaining impacts follow a similar ranking as for Albania. If a policy maker would be able to perfectly identify the poor (either pre- or post-shock, columns 2 and 3), it would be the best response; and again, under the baseline shock focusing on the pre-shock poor delivers higher impacts (when measured with the poverty gap squared) because the extreme poor would receive a higher transfer. Using a PMT remains the best response available to a policy maker, while a universal transfer, or selecting beneficiaries through an indicator of losses suffered, deliver worse impacts.

Table 6 shows the results of the same simulations for North Macedonia. Note that there is one additional column (column 1b), which reflects the actual expansion of beneficiaries implemented by the government. To maintain some equity between original and new beneficiaries, under the original spending scenario of 0.09% of GDP we only give the funds to new (15,373) beneficiaries, but under the 1% of GDP spending scenario we give the additional funds to both old and new (33,112) beneficiaries.

In full similarity with Albania and Moldova results are very similar between the two spending scenarios, and the best impacts are delivered by covering all the poor (columns 3 and 4). Again, covering only the pre-shock poor deliver slightly higher impacts because the shock did not affect substantially extreme poverty, and by distributing the budget to less people the average transfer is higher, delivering higher impacts on extreme poverty.

Table 6: North Macedonia, baseline shock: poverty and inequality impacts

	Baseline Shock										
Targeting →	Household										
	Eligibility ↓										
Budget ↓	Orginal Beneficiaries	Expansion	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Perfect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Pefect Loss Indicator
	(1a)	(1b)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Poverty Rate	**Pre-shock: 0.169; Post-shock: 0.241**										
(1) 0.09% GDP	-0.028	-0.025	-0.031	-0.034	-0.030	-0.029	-0.035	-0.028	-0.030	-0.028	-0.030
(2) 1.0% GDP	-0.048	-0.085	-0.102	-0.119	-0.044	-0.068	-0.060	-0.049	-0.047	-0.050	-0.044
Poverty Gap Sqr.	**Pre-shock: 3.523; Post-shock: 4.547**										
(1) 0.09% GDP	-1.025	-1.119	-1.202	-1.127	-0.807	-1.029	-1.025	-0.849	-0.783	-0.826	-0.879
(2) 1.0% GDP	-1.601	-2.200	-3.556	-3.347	-1.413	-2.799	-2.580	-1.422	-1.365	-1.596	-1.550
Gini	**Pre-shock: 0.330; Post-shock: 0.344**										
(1) 0.09% GDP	-0.012	-0.013	-0.013	-0.014	-0.012	-0.013	-0.013	-0.012	-0.011	-0.012	-0.013
(2) 1.0% GDP	-0.022	-0.035	-0.044	-0.045	-0.018	-0.034	-0.031	-0.020	-0.019	-0.021	-0.021
Coverage											
(1) Average Transfer	$ 1,415.8	$ 1,640.2	$ 345.8	$ 243.3	$ 44.4	$ 346.9	$ 243.3	$ 63.2	$ 85.4	$ 58.3	$ 56.5
(2) Average Transfer	$ 15,041.3	$ 8,096.3	$ 3,673.7	$ 2,584.4	$ 471.3	$ 3,685.7	$ 2,584.7	$ 671.4	$ 902.4	$ 619.0	$ 600.1
Beneficiaries	17,790	(1) 15,355 (2) 33,051	72,839	103,538	567,743	72,601	103,526	398,575	294,899	432,268	445,932
Ex-ante poor	0.15	0.30	1.00	1.00	1.00	0.59	0.68	0.61	0.46	0.89	0.91
Ex-ante non-poor	0.01	0.03	0.00	0.09	1.00	0.08	0.12	0.79	0.58	0.81	0.82
Ex-ante Vulnerable	0.02	0.06	0.00	0.22	1.00	0.15	0.22	0.78	0.57	0.82	0.84
Post-shock poor	0.11	0.27	0.70	1.00	1.00	0.48	0.57	0.73	0.55	0.92	0.94

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact). Not all households declare labor income.

Interestingly however, and in contrast with Albania, which chose to increase benefits to existing beneficiaries, the government expansion, while small (0.09% of GDP), delivered the first best response for a policy maker who is not able to perfectly identify the poor (column 1b). For the actual budget of 0.09% of GDP the response was in fact slightly more effective than covering the poor by relying on a PMT score (columns 5 and 6). Relying on the PMT score keeps delivering however higher impacts than a universal transfer (column 4) or including an indicator of who suffered a shock in the process of identifying beneficiaries (columns 7-10). Moreover, relying on a PMT score also delivers higher impacts for the 1% of GDP scenario – highlighting the fact that response designs also need to take into consideration the available budgetary envelope. Finally, note again that ranking of impacts for inequality remain very similar than ranking of impacts for the poverty gap squared.

Proportional loss shock

Next, we analyze best responses when the shock affects all workers' labor incomes proportionally, so that the shape of the income distribution and households' welfare rankings (insofar labor income is concerned) remain the same. Overall, the ranking of responses remains similar to the one for the baseline COVID-19 shock, which reflects in part the fact that the way the baseline shock was simulated had limited impacts on the poor's welfare rankings, making it very similar to a proportional loss shock.

Table 7 : Albania – Proportional loss shock

	Proportional Loss Shock										
Targeting →	Household										
	Eligibility ↓										
Budget ↓	Original Beneficiaries	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Perfect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Perfect Loss Indicator
	(1a)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Poverty Rate	**Pre-shock: 0.320; Post-shock: 0.361**									
(1) 0.05% GDP	-0.008	-0.007	-0.010	-0.006	-0.007	-0.007	-0.007	-0.007	-0.006	-0.006
(2) 1.0% GDP	-0.029	-0.045	-0.071	-0.025	-0.034	-0.033	-0.027	-0.027	-0.026	-0.026
Poverty Gap Sqr.	**Pre-shock: 6.721; Post-shock: 7.493**									
(1) 0.05% GDP	-0.196	-0.314	-0.293	-0.164	-0.235	-0.227	-0.160	-0.158	-0.167	-0.168
(2) 1.0% GDP	-1.336	-3.243	-2.973	-1.086	-2.091	-2.004	-1.012	-0.982	-1.149	-1.153
Gini	**Pre-shock: 0.371; Post-shock: 0.367**									
(1) 0.05% GDP	0.000	-0.001	-0.001	0.000	-0.001	-0.001	0.000	0.000	0.000	0.000
(2) 1.0% GDP	-0.011	-0.029	-0.028	-0.008	-0.019	-0.018	-0.007	-0.007	-0.008	-0.008
Coverage										
(1) Average Transfer	$ 105.1	$ 70.3	$ 62.5	$ 18.7	$ 70.3	$ 62.6	$ 23.1	$ 30.5	$ 21.1	$ 20.9
(2) Average Transfer	$ 1,946.5	$ 1,301.7	$ 1,158.1	$ 345.5	$ 1,302.4	$ 1,159.3	$ 428.8	$ 562.6	$ 391.4	$ 388.0
Beneficiaries	137,071	204,973	230,390	772,197	204,856	230,155	622,231	471,915	681,636	687,644
Ex-ante poor	0.28	1.00	1.00	1.00	0.60	0.63	0.83	0.63	0.96	0.97
Ex-ante non-poor	0.13	0.00	0.06	1.00	0.17	0.21	0.90	0.69	0.93	0.94
Ex-ante Vulnerable	0.17	0.00	0.10	1.00	0.25	0.30	0.88	0.66	0.93	0.93
Post-shock poor	0.26	0.89	1.00	1.00	0.57	0.61	0.85	0.63	0.96	0.97

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact). Not all households declare labor income.

For Albania (Table 7), ranking of impacts as captured by the poverty gap squared remain similar across the two spending scenarios. Again, impacts that remain the closest from being able to perfectly identify the pre- or post-shock poor (columns 2 and 3) are achieved using a PMT score (columns 5 and 6). Just distributing the additional budget to existing beneficiaries (column 1a) remains a second-best response. However, it delivers still higher impacts than a universal, flat transfer (column 4). Finally, under a proportional loss shock, using an indicator of which households suffered a shock (columns 7-10) does not deliver any additional impacts as all households are affected: when income ranks do not change because of a shock, the best responses continue to be to support households according to their pre-shock poverty status.[22]

Table 8 : Moldova – Proportional loss shock

	Proportional Loss Shock									
Targeting →	Household									
	Eligibility ↓									
Budget ↓	Original Beneficiaries	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Perfect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Perfect Loss Indicator
	(1a)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Poverty Rate	**Pre-shock: 0.120; Post-shock: 0.128**									
(1) 0.05% GDP	0.000	-0.001	-0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(2) 1.0% GDP	-0.014	-0.034	-0.039	-0.005	-0.010	-0.010	-0.004	-0.003	-0.005	-0.005
Poverty Gap Sqr.	**Pre-shock: 1.344; Post-shock: 1.402**									
(1) 0.05% GDP	-0.073	-0.040	-0.038	-0.005	-0.017	-0.015	-0.002	-0.002	-0.004	-0.004
(2) 1.0% GDP	-0.787	-0.616	-0.587	-0.097	-0.286	-0.268	-0.042	-0.044	-0.075	-0.074
Gini	**Pre-shock: 0.320; Post-shock: 0.316**									
(1) 0.05% GDP	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(2) 1.0% GDP	-0.009	-0.008	-0.008	-0.002	-0.005	-0.005	-0.001	-0.001	-0.001	-0.001
Coverage										
(1) Average Transfer	$ 124.95	$ 41.71	$ 39.11	$ 5.09	$ 42.15	$ 39.45	$ 7.58	$ 10.26	$ 6.80	$ 6.84
(2) Average Transfer	$ 2,499.04	$ 834.28	$ 782.12	$ 101.73	$ 842.91	$ 789.01	$ 151.51	$ 204.31	$ 136.03	$ 136.71
Beneficiaries	109,169	327,009	348,817	2,681,733	323,663	345,773	1,800,685	1,329,764	2,005,571	1,995,577
Ex-ante poor	0.29	1.00	1.00	1.00	0.49	0.48	0.43	0.33	0.74	0.71
Ex-ante non-poor	0.00	0.00	0.01	1.00	0.07	0.08	0.70	0.51	0.74	0.74
Ex-ante Vulnerable	0.01	0.00	0.02	1.00	0.13	0.14	0.58	0.42	0.66	0.66
Post-shock poor	0.28	0.94	1.00	1.00	0.47	0.46	0.46	0.36	0.75	0.73

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact). Not all households declare labor income.

Results for Moldova (Table 8) also remain very similar to the ones for the baseline, COVID-19 shock, suggesting again that the nature of the COVID-19 shock was very similar to a proportional loss shock. In terms of ranking of impacts, they remain basically the same than for the rankings of the COVID-19 shock discussed in Table 5.

Finally, results for North Macedonia (Table 9) show again that using pre-shock indicators of poverty status to determine coverage, such as a PMT (columns 1b-3, 5, 6), is an effective response when the shock does not affect substantially the poverty rankings; and again, going universal (column 4) or focusing the response only on households affected by the shock (columns 7 or 8) delivers worse impacts.

In contrast to the baseline shock, however, the actual expansion of beneficiaries does not deliver much higher impacts than relying on a PMT score; for the 1% of GDP scenario, it delivers actually lower impacts. This, on the one hand, shows the importance of tailoring the

[22] Note that, because some households do not declare any labor income in the survey, coverage of the transfer under a proportional shock is not universal even when selection is based on an indicator of households who suffered a shock (i.e., column 7).

response to the nature of the shock; but, also, it shows that providing all/most extreme poor households with a lower transfer (i.e. columns 5 and 6) tends to deliver higher impacts than providing a more generous transfer to only a subset of them (columns 1a and 1b), even when poor households cannot be perfectly identified (i.e. need to rely on a PMT score).[23]

Table 9 : North Macedonia – Proportional loss shock

	Proportional Shock										
Targeting →	Household										
	Eligibility ↓										
Budget ↓	Orginal Beneficiaries	Expansion	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Perfect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Perfect Loss Indicator
	(1a)	(1b)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Poverty Rate	**Pre-shock: 0.169; Post-shock: 0.219**										
(1) 0.09% GDP	-0.021	-0.023	-0.024	-0.035	-0.027	-0.027	-0.027	-0.025	-0.025	-0.022	-0.024
(2) 1.0% GDP	-0.048	-0.088	-0.097	-0.110	-0.037	-0.061	-0.059	-0.042	-0.045	-0.040	-0.045
Poverty Gap Sqr.	**Pre-shock: 3.523; Post-shock: 4.205**										
(1) 0.09% GDP	-0.851	-0.816	-0.997	-0.906	-0.604	-0.851	-0.832	-0.594	-0.601	-0.670	-0.629
(2) 1.0% GDP	-1.410	-1.760	-3.439	-3.164	-1.219	-2.665	-2.492	-1.193	-1.166	-1.306	-1.318
Gini	**Pre-shock: 0.330; Post-shock: 0.331**										
(1) 0.09% GDP	-0.009	-0.010	-0.010	-0.011	-0.009	-0.010	-0.010	-0.009	-0.008	-0.008	-0.010
(2) 1.0% GDP	-0.019	-0.031	-0.042	-0.042	-0.015	-0.031	-0.029	-0.016	-0.016	-0.017	-0.017
Coverage											
(1) Average Transfer	$ 1,413.1	$ 1,634.5	$ 345.1	$ 267.2	$ 44.3	$ 346.3	$ 267.3	$ 52.6	$ 71.1	$ 50.0	$ 49.4
(2) Average Transfer	$ 15,041.3	$ 8,057.8	$ 3,673.7	$ 2,844.0	$ 471.3	$ 3,685.7	$ 2,845.3	$ 560.2	$ 759.9	$ 532.5	$ 525.6
Beneficiaries	17,790	(1) 15,380 (2) 33,208	72,839	94,088	567,743	72,601	94,045	477,689	353,594	502,500	509,066
Ex-ante poor	0.15	0.35	1.00	1.00	1.00	0.59	0.66	0.79	0.61	0.98	0.98
Ex-ante non-poor	0.01	0.02	0.00	0.06	1.00	0.08	0.11	0.93	0.67	0.94	0.94
Ex-ante Vulnerable	0.02	0.04	0.00	0.16	1.00	0.15	0.20	0.94	0.66	0.96	0.96
Post-shock poor	0.12	0.31	0.77	1.00	1.00	0.50	0.57	0.84	0.62	0.98	0.99

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact). Not all households declare labor income.

Random loss shock

To conclude, we analyze best responses when the shock affects some workers randomly, albeit in a profound and radical manner: whenever a worker is hit by a shock, her labor income drops to zero. Note that such a shock has the potential to profoundly change rankings of the income distribution, with some households – especially the ones with one main breadwinner – facing a significantly higher risk of falling into extreme poverty. Note also that not all households who are hit by a shock will face zero labor income: the shock is given to individuals, hence if there is more than one worker in a household the likelihood of labor income falling to zero is lower.

[23] In practical terms there may be however limits on how much one can "spread thinly". The poverty gap squared measure is concave, hence the marginal gains in welfare are inversely proportional to the transfer amount. In reality, however, there may be a transfer threshold below which the marginal welfare impacts are minimal. If this is the case, limiting the number of beneficiaries may deliver greater welfare gains.

Table 10: Albania – Random loss shock

Targeting →	Random loss Shock										
	Household										
	Eligibility ↓										
Budget ↓	Original Beneficiaries	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Perfect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Perfect Loss Indicator
	(1a)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Poverty Rate	Pre-shock: 0.320; Post-shock: 0.370									
(1) 0.05% GDP	-0.007	-0.009	-0.008	-0.005	-0.007	-0.007	-0.005	-0.005	-0.005	-0.005
(2) 1.0% GDP	-0.027	-0.061	-0.056	-0.020	-0.030	-0.029	-0.018	-0.019	-0.022	-0.022
Poverty Gap Sqr.	Pre-shock: 6.721; Post-shock: 16.720									
(1) 0.05% GDP	-0.473	-0.584	-0.637	-0.460	-0.518	-0.509	-0.522	-0.516	-0.515	-0.511
(2) 1.0% GDP	-1.709	-3.517	-4.572	-1.812	-2.582	-2.478	-2.777	-2.689	-2.727	-2.658
Gini	Pre-shock: 0.371; Post-shock: 0.422									
(1) 0.05% GDP	-0.001	-0.002	-0.002	-0.001	-0.002	-0.002	-0.001	-0.001	-0.002	-0.002
(2) 1.0% GDP	-0.013	-0.029	-0.031	-0.010	-0.020	-0.019	-0.013	-0.013	-0.016	-0.016
Coverage										
(1) Average Transfer	$ 105.1	$ 70.3	$ 60.0	$ 18.7	$ 70.3	$ 60.1	$ 64.9	$ 87.0	$ 38.2	$ 35.9
(2) Average Transfer	$ 1,946.5	$ 1,301.7	$ 1,112.4	$ 345.5	$ 1,302.4	$ 1,112.8	$1,201.8	$ 1,568.3	$ 708.6	$ 664.8
Beneficiaries	137,071	204,973	239,848	772,197	204,856	239,772	222,010	165,599	376,548	401,350
Ex-ante poor	0.28	1.00	1.00	1.00	0.60	0.65	0.27	0.22	0.71	0.75
Ex-ante non-poor	0.13	0.00	0.07	1.00	0.17	0.22	0.33	0.25	0.45	0.49
Ex-ante Vulnerable	0.17	0.00	0.08	1.00	0.25	0.33	0.35	0.26	0.53	0.58
Post-shock poor	0.26	0.87	1.00	1.00	0.54	0.59	0.36	0.29	0.75	0.78

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact). Not all households declare labor income.

Under this shock, results and optimal responses change substantially. In both Moldova and North Macedonia, covering the pre-shock poor either through perfect means testing or using a PMT indicator (columns 2 and 5) becomes a suboptimal response (again, using the poverty gap squared as a metric). If the post-shock poor could be perfectly identified (column 3) covering them would still remain an optimal response, but now the use of a PMT delivers poor impacts because the PMT cannot identify well the new poor who fell into poverty as a consequence of the shock. In contrast, in both countries the use of an indicator of who suffered losses (either perfect or imperfect, columns 7 and 8) provides now greater poverty impacts than the use of a PMT; in fact, mixing the use of a loss indicator with the PMT does provide slightly lower impacts than using just the loss indicator, reflecting the fact that households affected by the random shock loss lose all their labor income and fall into deeper poverty than the average for the ex-ante poor. Using a flat, universal transfer remains, again, among the options delivering the lowest impacts.

Results for Albania, while overall similar, present some subtle differences. Using a loss indicator delivers slightly better impacts than using the PMT, but differences remain small. This is consistent with the fact that, if one would distribute the emergency budget to the ex-ante poor (column 2), one would still achieve the second-highest impacts among all design alternatives – something that does not hold for Moldova and North Macedonia. A contributing factor is that labor income as reported in the survey is only one source of income for many Albanian households, and despite many households losing all their labor income from the random shock, there are still many households in extreme poverty that remain poorer than the average household affected by the shock.

Table 11: Moldova – Random loss shock

	Random Loss Shock									
Targeting →	Household									
	Eligibility ↓									
Budget ↓	Original Beneficiaries	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Perfect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Perfect Loss Indicator
	(1a)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Poverty Rate	**Pre-shock: 0.120; Post-shock: 0.152**									
(1) 0.05% GDP	0.000	-0.002	-0.002	0.000	-0.001	-0.001	0.000	0.000	-0.001	-0.001
(2) 1.0% GDP	-0.015	-0.037	-0.034	-0.005	-0.011	-0.012	-0.009	-0.009	-0.011	-0.012
Poverty Gap Sqr.	**Pre-shock: 1.344; Post-shock: 3.095**									
(1) 0.05% GDP	-0.072	-0.040	-0.057	-0.009	-0.017	-0.016	-0.092	-0.089	-0.037	-0.032
(2) 1.0% GDP	-0.779	-0.613	-0.959	-0.172	-0.289	-0.274	-1.210	-0.979	-0.661	-0.592
Gini	**Pre-shock: 0.320; Post-shock: 0.337**									
(1) 0.05% GDP	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(2) 1.0% GDP	-0.009	-0.008	-0.008	-0.002	-0.005	-0.005	-0.008	-0.007	-0.006	-0.006
Coverage										
(1) Average Transfer	$ 124.95	$ 41.71	$ 32.96	$ 5.09	$ 42.15	$ 33.23	$ 116.20	$ 154.05	$ 31.14	$ 26.33
(2) Average Transfer	$ 2,499.04	$ 834.28	$ 659.26	$ 101.73	$ 842.91	$ 664.65	$ 2,323.91	$ 3,484.51	$ 622.86	$ 526.60
Beneficiaries	109,169	327,009	413,824	2,681,733	323,663	410,471	117,396	88,551	438,007	518,077
Ex-ante poor	0.29	1.00	1.00	1.00	0.49	0.55	0.02	0.01	0.51	0.56
Ex-ante non-poor	0.00	0.00	0.04	1.00	0.07	0.10	0.05	0.03	0.12	0.14
Ex-ante Vulnerable	0.01	0.00	0.04	1.00	0.13	0.17	0.04	0.03	0.17	0.21
Post-shock poor	0.23	0.79	1.00	1.00	0.39	0.45	0.23	0.14	0.61	0.65

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact). Not all households declare labor income.

Note, again, the importance of focusing attention on the right indicator. In particular, the use of the poverty headcount indicator delivers misleading results: in Albania, for instance, under the poverty headcount welfare metric using a PMT indicator would still indicate larger impacts than using a loss indicator. This is because the excessively simple metric used by the poverty headcount indicator, which focusses on an extremely narrow section of the income distribution around the poverty line, ignores any distributional impacts that happen below the line.

Table 12: North Macedonia – Random loss shock

Targeting →	Random Shock										
	Household										
	Eligibility ↓										
Budget ↓	Orginal Beneficiaries	Expansion	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Perfect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Pefect Loss Indicator
	(1a)	(1b)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Poverty Rate	**Pre-shock: 0.169; Post-shock: 0.256**										
(1) 0.09% GDP	-0.014	-0.010	-0.019	-0.015	-0.013	-0.013	-0.014	-0.015	-0.016	-0.015	-0.015
(2) 1.0% GDP	-0.042	-0.038	-0.081	-0.064	-0.024	-0.045	-0.038	-0.024	-0.028	-0.030	-0.030
Poverty Gap Sqr.	**Pre-shock: 3.523; Post-shock: 32.396**										
(1) 0.09% GDP	-2.860	-5.666	-3.513	-3.817	-3.294	-2.926	-3.038	-3.533	-3.280	-3.660	-3.404
(2) 1.0% GDP	-3.989	-13.951	-6.361	-12.499	-5.435	-5.478	-5.114	-7.668	-7.523	-7.428	-6.910
Gini	**Pre-shock: 0.330; Post-shock: 0.439**										
(1) 0.09% GDP	-0.014	-0.017	-0.016	-0.015	-0.014	-0.014	-0.015	-0.016	-0.014	-0.016	-0.016
(2) 1.0% GDP	-0.029	-0.045	-0.047	-0.050	-0.024	-0.038	-0.034	-0.030	-0.030	-0.032	-0.031
Coverage											
(1) Average Transfer	$ 1,409.8	$ 1,622.6	$ 344.3	$ 210.8	$ 44.2	$ 345.5	$ 210.9	$ 114.5	$ 156.1	$ 96.3	$ 86.6
(2) Average Transfer	$ 15,041.3	$ 8,038.0	$ 3,673.7	$ 2,248.8	$ 471.3	$ 3,685.7	$ 2,249.8	$ 1,221.8	$ 1,646.1	$ 1,027.5	$ 924.3
Beneficiaries	17,790	(1) 15,457 (2) 33,290	72,839	118,990	567,743	72,601	118,937	219,010	160,677	260,437	289,491
Ex-ante poor	0.15	0.15	1.00	1.00	1.00	0.59	0.70	0.46	0.33	0.78	0.82
Ex-ante non-poor	0.01	0.05	0.00	0.11	1.00	0.08	0.15	0.38	0.28	0.42	0.47
Ex-ante Vulnerable	0.02	0.04	0.00	0.10	1.00	0.15	0.26	0.40	0.30	0.49	0.57
Post-shock poor	0.11	0.22	0.66	1.00	1.00	0.40	0.49	0.64	0.46	0.85	0.88

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact). Not all households declare labor income.

Targeting households vs. individuals

Our simulations provide an equal transfer to each beneficiary household, independent from the household composition. However, although more complex to implement, providing an equal transfer to each individual could in principle deliver higher poverty impacts, because often poorer households tend to be larger in size. We test this hypothesis below.

Differences in impacts reported in Table 13, Table 14 and Table 15 only partially support this hypothesis. In Albania, targeting individuals delivers higher impacts across shocks and coverage scenarios; in North Macedonia, targeting individuals delivers higher impacts for the baseline and proportional shocks, but not for the random loss shock; and in Moldova, targeting households delivers higher impacts across shocks. These country differences would call for a careful analysis of the country-specific demographic, and on how it interacts with the shock. However, in terms of magnitudes, differences appear to remain relatively small (less than a 10 percent difference in poverty impacts), so that in emergency responses efficiency and speed considerations should dictate the choice of covering households vs. individuals.

Note, also, that the choice of targeting households vs. individuals does not seem to significantly impact the rankings in beneficiary selection methods: increasing benefits of current beneficiaries, as well as universal transfers, remain suboptimal strategies, while using the PMT remains a solid option if shocks do not affect substantially welfare rankings, in which case introducing an indicator of who may have been affected by a shock delivers higher impacts. All the results discussed in the previous sections remain therefore valid.

Table 13: Targeting households vs Individuals (Albania)

Budget ↓		Eligibility ↓ Original Beneficiaries	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Perfect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Perfect Loss Indicator
		(1a)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline Shock (Poverty Gap Squared)										
1.0% GDP	Households	-1.522	-3.346	-3.127	-1.282	-2.249	-2.154	-1.010	-0.982	-1.447	-1.450
	Individuals	-1.741	-3.477	-3.230	-1.505	-2.467	-2.363	-1.142	-1.130	-1.637	-1.635
	Proportional Loss Shock (Poverty Gap Squared)										
1.0% GDP	Households	-1.336	-3.243	-2.973	-1.086	-2.091	-2.004	-1.012	-0.982	-1.149	-1.153
	Individuals	-1.551	-3.370	-3.075	-1.303	-2.307	-2.205	-1.166	-1.143	-1.326	-1.330
	Random loss Shock (Poverty Gap Squared)										
1.0% GDP	Households	-1.709	-3.517	-4.572	-1.812	-2.582	-2.478	-2.777	-2.689	-2.727	-2.658
	Individuals	-1.932	-3.643	-4.587	-2.061	-2.829	-2.709	-2.936	-2.881	-2.923	-2.846

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact).

Table 14: Targeting households vs Individuals (Moldova)

Budget ↓		Eligibility ↓ Original Beneficiaries	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Perfect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Perfect Loss Indicator
		(1a)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline Shock (Poverty Gap Squared)										
1.0% GDP	Households	-0.789	-0.614	-0.587	-0.097	-0.285	-0.262	-0.040	-0.033	-0.107	-0.104
	Individuals	-0.794	-0.603	-0.578	-0.094	-0.278	-0.256	-0.039	-0.050	-0.105	-0.102
	Proportional Loss Shock (Poverty Gap Squared)										
1.0% GDP	Households	-0.787	-0.616	-0.587	-0.097	-0.286	-0.268	-0.042	-0.044	-0.075	-0.074
	Individuals	-0.792	-0.605	-0.578	-0.093	-0.279	-0.262	-0.041	-0.054	-0.073	-0.072
	Random loss Shock (Poverty Gap Squared)										
1.0% GDP	Households	-0.779	-0.613	-0.959	-0.172	-0.289	-0.274	-1.210	-0.979	-0.661	-0.592
	Individuals	-0.784	-0.603	-0.941	-0.166	-0.281	-0.267	-1.184	-1.365	-0.644	-0.575

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact).

Table 15: Targeting households vs Individuals (North Macedonia)

Budget ↓		Eligibility ↓ Original Beneficiaries	Expansion	Means Testing (Ex-Ante Poor)	Means Testing (Post Shock Poor)	Universal	PMT Ex-ante	PMT Post Shock	Perfect Loss Indicator	Imperfect Loss Indicator	PMT Ex-ante or Perfect Loss Indicator	PMT Post Shock or Perfect Loss Indicator
		(1a)	(1b)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline Shock (Poverty Gap Squared)											
1.0% GDP	Households	-1.601	-2.200	-3.556	-3.347	-1.413	-2.799	-2.580	-1.422	-1.365	-1.596	-1.550
	Individuals	-1.493	-2.299	-3.666	-3.420	-1.571	-2.914	-2.811	-1.370	-1.375	-1.643	-1.659
	Proportional Loss Shock (Poverty Gap Squared)											
1.0% GDP	Households	-1.410	-1.760	-3.439	-3.164	-1.219	-2.665	-2.492	-1.193	-1.166	-1.306	-1.318
	Individuals	-1.404	-1.888	-3.613	-3.275	-1.415	-2.845	-2.767	-1.238	-1.263	-1.401	-1.417
	Random loss Shock (Poverty Gap Squared)											
1.0% GDP	Households	-3.989	-13.951	-6.361	-12.499	-5.435	-5.478	-5.114	-7.668	-7.523	-7.428	-6.910
	Individuals	-2.480	-12.287	-4.911	-10.340	-3.810	-3.942	-3.905	-6.642	-6.495	-6.153	-5.815

Note: impacts are color-coded from dark red (highest impacts) to dark blue (lowest impact).

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Annexes

Overview of poverty-targeted social assistance programs in Albania, Moldova and North Macedonia

Albania: The Ndihma Ekonomike (*Economic Assistance*) program is the main cash transfer program providing support to poor households and the vulnerable population in Albania. Transfers are provided monthly through banks or post office branches and the value is based on household size and composition. In 2020, transfers amounted to 1800 Albanian lek (ALL) for the first family member according to the order in the family certificate, 1260 ALL for other family members over the age of 18, and 900 ALL for members under 18 years old. Based on administrative data, in 2020, the NE covered 8.9 percent of the population, compared to 8.8 percent in 2019 and 8.1 in 2018. Initial analysis of survey data from EU SILC suggests an improvement in coverage among the poorest people, with coverage of the poorest decile reaching 37 percent in 2019, up from 32.6 in 2017 (World Bank 2022b).

Moldova: The Ajutor Social (AS), the country's national cash transfer program, aims to contribute to poverty reduction and guarantee equal opportunities to disadvantaged households. The program was established in December 2008, initially opening to households with disabled members, then to those with children, and finally from July 2009 to all households. Eligibility is determined based on income (through a means test) and then checked through a proxy means test (PMT) that verifies that households' living standards are below a set threshold. To encourage taking up employment, the guaranteed minimum income threshold is set substantially below the subsistence minimum. Households must re-apply every 12 months; if there are no household members who are of working age, then the benefit is granted for 2 years. In 2020 the program covered more than 53,000 households (World Bank 2022a).

North Macedonia: In May 2019, the Ministry of Labor and Social Policy (MLSP) introduced a comprehensive social safety net reform aimed at increasing the coverage of the poorest quintile by consolidating social assistance benefits and introducing a new Guaranteed Minimum Income (GMI) program. The GMI provides a level of support that equals the difference between the household income of the applicant and the established threshold, which is set at a maximum MKD 10,000 a month (US$177) for a five-member family, using an equivalence scale. Eligibility to the GMI is determined using a means-test, which was modified to enable an expansion to additional poor households during the COVID-19 pandemic. As of 2020, the GMI covered more than 32,000 beneficiaries (World Bank 2022c).

Government responses to the COVID-19 shock in Albania, Moldova and North Macedonia

This section provides a brief description of the initial social assistance responses to the COVID-19 pandemic in Albania, Moldova, and North Macedonia. A detailed description of all the measures that were implemented in the three countries can be found in Gentilini et al. (2020a); and World Bank (2020b, 2020a). Globally, these social protection responses included social assistance measures like cash transfers, food vouchers, and utility waivers; social insurance measures like paid sick leave, health insurance, unemployment benefits and subsidized social security contributions; and labor market responses including wages subsidies and reduced work time among others. These three countries employed a sub-set of these measures, building on their existing social insurance system and assistance schemes.

All three countries harnessed their social assistance schemes to protect poor and vulnerable citizens, although to varying degrees. Albania doubled the value of payments made to beneficiaries of the Ndihma Ekonomike (*Economic Assistance*) program, its only poverty targeted social assistance program, for three months (April, May and June 2020).[24] Moldova similarly increased the amount paid to existing beneficiaries by raising the threshold for the minimum guaranteed income amount (1107 to 1300 Lei) during the emergency period (April and May 2020) and modifying the equivalence formula as it applied to children. North Macedonia opted to make no changes to the minimum guaranteed income threshold. Albania, Moldova and North Macedonia waived the requirement for existing beneficiaries to reapply in person for their benefits (for example, automatically extending these during the state of emergency in the case of Moldova) and suspended the required home visit for any new or repeat application. Albania also allowed for applications to be submitted electronically or through the post office (World Bank 2020b, 2022b, 2022c, 2022a).

In contrast, efforts to expand access of these programs to additional poor households was mixed. North Macedonia modified the legislation for its Guaranteed Minimum Income (GMI) program, changing the eligibility criteria to allow additional poor people, who were negatively affected by the pandemic, to enter the program. This included assessing household income of applicants for the previous month only instead of the normal three-month period and eliminating eligibility criteria that are relevant during normal periods but do not apply during emergencies, such as asset and property ownership. These changes extended the coverage of the GMI by nearly 25%, allowing more than 7,210 new households to join the program, although some delays were experienced in registering these people for the GMI, given staff shortages in the Centers for Social Work. The increase in the GMI threshold in Moldova naturally extended access to additional people who were previously not eligible for support. This support was quickly allocated to people who were registered in the management information system and who were found to be eligible. However, the closure of Centers for Social Work and a lack of outreach to potential beneficiaries resulted in few new people, who had lost jobs or income due to the pandemic, applying for support. The payment to people registered in the management information system resulted in an instant increase in coverage from 47,981 families in March 2020 to 71,802 families in April, as well as significant increase

[24] This increase in benefit amount was subsequently extended in Albania. We do not discuss these here given the focus of the simulations on the initial response to the COVID-19 pandemic.

in benefit amount (about 34% increase in average benefit). In contrast, Albania did not change the eligibility criteria to expand the coverage of the NE; though the government also used the management information system to identify households who were vulnerable: in the second half of April 2020, the government approved a one-off benefit (16,000 Albanian lek, equivalent to US$156) for all the families that had applied to the NE between July 2019 and April 2020 but were not currently receiving NE benefits, with 4,524 families receiving this payment.

Simulations of the COVID-19 social protection responses

Albania. Out of all the measures implemented by Albania, we only take a subset to the data as shown in Table 16. These measures were modeled similar to how they were implemented, as two packages.[25] The first package is mostly a social assistance package; however, it includes a 3-month, minimum wage subsidy of 26,000 ALL to formal workers of small formal firms.[26] The second package is a one-time wage subsidy transfer of 40,000 ALL to formal workers in highly affected sectors, in hospitality and in moderately affected sectors.[27] When modeling different responses, our microsimulations maintain the wage subsidy part fixed and only modify the portion of package 1 that corresponds to Ndihma Ekonomike beneficiaries (the highlighted part in Table 16). As such, these modifications capture alternative ways of distributing the same social assistance resources to different populations while holding the rest of the overall country response constant.

Table 16 Response measures modeled in simulations. Albania

Beneficiaries of Decision	Model in SILC	Benefit assigned
	Package 1	
Workers in business entities with annual income up to 14,000,000 ALL	Select 65,565 employees/self-employed/unpaid family workers, excluding employers, individuals working in the public sector, and recipients of social assistance. Exclude those with wages above the 90% percentile to roughly capture those in firms below 14 million in annual income.	26,000 ALL (for three months)
Individuals who receive payment of economic assistance (Ndihma Ekonomike)	Current beneficiaries of social assistance.	Double the current amount (for three months)
Individuals who benefit from the payment of income from unemployment	Current beneficiaries of unemployment insurance.	Double the current amount (for three months)
	Package 2	
Workers in affected entities with annual income up to 14,000,000 ALL in affected sectors including hospitality	Select share of employees/self-employed/unpaid family workers in highly affected sectors including hospitality. Exclude those with wages above the 90% percentile to roughly capture those in firms below 14 million in annual income. Exclude if received package #1.	40,000 ALL (For 3 months)
Workers in unaffected entities with annual income up to 14,000,000 ALL	Select share of formal employees/self-employed/unpaid family workers from less affected sectors. Exclude those with wages above the 90% percentile to roughly capture those in firms below 14 million in annual income. Exclude if received package #1.	40,000 ALL

Source: Based on World Bank (2020b, 2022b).

[25] The data does not allow us to identify who lost their job due to the COVID-19 shock. As such, we can identify pre-shock beneficiaries of social assistance measures, but not those eligible because they suffered a shock. Likewise, measures that rely on information about the company where an individual works are difficult to model since there is no information about the company in our data. These include the value of their sales, social security contributions, paid leave, or reduced work hours.

[26] By December 2020, of 125,053 individuals on whose behalf employers applied, 65,632 had received the benefits (corresponding to 39,020 employers).

[27] By December 2020, of 210,705 individuals on whose behalf employers applied, 173,019 had received the payment (corresponding to 43,410 employers).

Moldova. As part of the emergency response to the COVID-19 pandemic, the Moldovan government implemented a social assistance package to protect the poor and vulnerable for a period of two months, beginning on March 17th and expiring at the end of the state of emergency on May 16th of 2020. To simulate the government's response, the individuals who were receiving the unemployment benefit were assigned the difference between the new unemployment benefit of MDL 2,775 /month and their current unemployment benefit. Unemployment benefits of MDL 2,775 /month were extended to the 45,050 individuals predicted to lose their jobs in the labor simulation as well as 4.3% of the 15,800 simulated return migrants in the migrant simulation based on the reports on the proportion of return migrants who have received the unemployment benefit. The child coefficient in the GMI benefit formula was modified from 0.5 to 0.75 and the effect of the Guaranteed Minimum Income (GMI) on poverty was computed by assigning individuals the difference between their income and the total GMI adult equivalent of MDL 1,300 if their simulated income under the combination of the remittances, migrant, social assistance (including the new unemployment benefit and the existing Ajutor Social benefit) and labor simulations is less than the GMI (World Bank 2020a).

North Macedonia. In North Macedonia four responses were simulated: The GMI program, wage subsidies, the home payment card, and the tourism and home improvement card. Again, when modeling different responses, our microsimulations only modify the portion that corresponds to the GMI (the highlighted part in Table 17). To model the expansion of the GMI, we first select the pool of individuals working in impacted sectors who were not beneficiaries of social assistance, wage subsidy or recipients of tourism and home improvement vouchers. We select the poorest 15,500 households where these individuals live and transferred 7,000 denars (US$124) for six months per household.

Table 17 Response measures modeled in the baseline scenario. North Macedonia.

Cash transfers (SA)	Model in SILC
Expanding coverage to informal self-employed individuals who became unemployed with a per capita household income below the threshold of eligibility and who are not receiving program. The benefit is 7,000 denars (US$124) per household for 6 months.	Identify working individuals in impacted sectors that did not receive GMI (Social Allowances in SILC) , WS or V2. Identify the households these eligible individuals belong to. Select the poorest 15.5k households and transfer 7000 denars per household for 6 months.
Firm support (WS)	**Model in SILC**
Private support to private sector employers for the months of April-July (not for employees with salaries above MKD 39,900). Viable firms are eligible to a minimum net wage subsidy of up to 14,500 denars per employee (about 124k individuals). Viable firms in transport, tourism, and catering. receive 50% of contributions (on average 3000 denars)	Randomly select formal workers using formality rates by sector. Select self-employed and wage employees in all sectors of the economy. Select those who are not working in public sector (Public Admin. and Education). Select those with earning less than 39,900 denars in 2019. Randomly select 127K individuals. Transfer 14,500 denars for 4 months Transfer is the minimum between transfer and wage shock to avoid giving employee individual a higher wage than baseline.

	Beneficiaries of WS cannot be beneficiaries of SA.
Domestic tourism and home payment card	**Model in SILC**
Vouchers for tourism worth MKD 6k and home payment card worth MKD 3k. Beneficiaries are about 100k employees with low monthly income (below MKD 15k).	Select employed (self-employed, wage employees and family businesses) in non-affected sectors with household labor income < MKD 15k before covid. Select employed in affected sectors (excluding self-employed in highly impacted sectors who are assumed unemployed after covid) with household labor income < MKD 15k after covid (shocked based on our covid simulations). Randomly select 100k individuals Transfer MKD 9,000 to their total household income They cannot be beneficiaries of the SA and Home payment card to unemployed

Source: based on World Bank (2020b, 2022c).

Proxy Means Testing

In this section we explain the methodology used to estimate a proxy-means score for the PMT for Albania, Moldova, and North Macedonia. Proxy Means Testing provides an estimate of a family's welfare using a score that is based on observable characteristics, like education, household composition, location, and the physical characteristics of the dwelling, among others. The score is usually derived from weights that result from the estimation of a model using a survey or administrative data (Bowen et al. 2020). The word "proxy" reflects the fact that observable characteristics are considered proxies for actual incomes or consumption (Lindert et al. 2020). Albania and Moldova use PMTs to assess eligibility for their social assistance programs. Although North Macedonia does not use a PMT, for comparative purposes, we use the same set of variables that are available in Albania's survey to estimate a PMT for North Macedonia.

The first step is to estimate a linear regression model of income or consumption as a function of the available variables in the survey for each country. The dependent variable is the household's disposable income net of income support and other cash benefits. The idea is to capture the income that households can use to consume net of the social assistance programs that are in place. One common issue that arises is that many households do not have any other sources of income other than social assistance, therefore our dependent variable can take zero or negative values. Since the standard practices is to transform incomes to the logarithmic scale for estimation, this implies that households with zero or negative income will not be part of the estimation sample.

Once a model has been estimated, the second step is to predict the expected log income per capita for each household. At this step each household, including those that had negative, zero or missing income, provided they have all the variables used in the model, will have a predicted log income per capita.

The third step is to estimate the empirical income distribution based on the income prediction. Specifically, we rely on the cumulative density function (CDF) to determine each household's position on the overall distribution. This is a key component of our analysis since we need to determine the precise position of each household along the distribution to reproduce the official poverty rate in each country before any shock takes place.

The final step is to classify as beneficiaries those households below the exact percentile of the CDF that matches the target poverty rate, either before or after the shock. For example, if the initial poverty rate is 10 percent, we would select as beneficiaries the bottom 10 percent of the estimated income distribution. If the shock increases poverty to 12 percent, we would go up to this point in the estimated CDF to include those households as well.