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Mitigating Poverty:

Global Estimates of the Impact of Income Support during the Pandemic

by Johanna Fajardo-Gonzalez, George Gray Molina, María Montoya-Aguirre, Eduardo Ortiz-Juarez

UNDP GLOBAL POLICY NETWORK

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Global Estimates of the Impact of Income Support during the Pandemic

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Abstract

This paper reconstructs the full welfare distributions from household surveys of 160 countries, covering 96.5 percent of the global population, to estimate the pandemic-induced increases in global poverty and provide information on the potential short-term effects of income-support programmes on mitigating such increases. Crucially, the analysis performs a large-scale simulation by combining the welfare distributions with the database of social protection measures of Gentilini et al. (2021) and estimates such effects from 72 actual income-support programmes planned or implemented across 41 countries. The paper reports three findings: First, the projection of additional extreme poverty, in the absence of income support, ranges between **117 million people** under a distributive-neutral projection and **168 million people** under a distributive-regressive projection —which may better reflect how the shock impacted poor and vulnerable households. Second, a simulation of the hypothetical effects of a temporary basic income with an investment of 0.5 percent of developing countries' GDP, spread over six months, finds that this amount would mitigate to a large extent, at least temporarily, the increase in global poverty at both the $1.90- and $3.20-a-day thresholds, although poverty would still increase significantly in the poorest regions of the world. Third, the analysis of income-support programmes in 41 countries suggests that they may have mitigated, at least temporarily, the overall increase in poverty in **upper-middle income** countries but may have been insufficient to mitigate the increase in poverty at any poverty line in **low-income** countries. Income support likely mitigated 60 percent of the increase in poverty at the $3.20-a-day threshold and 20 percent at the $5.50-a-day threshold among **lower-middle-income countries**. This pattern is correlated with the amount of social assistance and social insurance per capita payments made in each country.

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1. Introduction

A key question arising from the pandemic policy response is: Was it robust enough to mitigate income and jobs losses around the world? While it is still early to adequately assess the welfare effects of multiple policy measures, this paper provides estimates of the potential influence of income support in mitigating, at least temporarily, increases in poverty headcount rates vis-à-vis a pure pandemic-induced shock scenario.[2] Clearly, policy responses around the world included more than income support—they included tax deferrals, service payment waivers and loans and guarantees, as well as various work furlough and employment insurance programmes, among other measures. But it is also evident that income support programmes were ubiquitous and made up a significant portion of the response.

Twelve months ago, two of the co-authors of this paper analysed the costs and implementation challenges of a temporary basic income (TBI) targeting poor and vulnerable people across the developing world (Gray Molina and Ortiz-Juarez, 2020). This paper revisits that exercise and provides counterfactual information on the potential short-term effects that income support has on mitigating the increase in poverty, and the associated financial costs, had countries implemented TBI schemes in response to the shock. To estimate the pandemic-induced increase in poverty and perform the simulations, the analysis retrieves the distributions of per capita income and consumption from household surveys in 160 countries (128 developing countries and 32 advanced economies) that covered about 96.5 percent of the world's population in 2019–2020. But the paper also dives into the actual response. Specifically, the analysis exploits these welfare distributions and the database of social protection measures of Gentilini et al. (2021) to undertake a systematic, large-scale assessment of the potential short-term effects on mitigating the increase in poverty of 72 cash-based programmes across 41 countries, which together concentrate a fourth of the global population and represent a fifth of the total number of countries that have planned or implemented income-support measures since March 2020.

There are three main findings derived from the simulations. First, spending equivalent to 0.5 percent of developing countries' GDP, for a monthly total of $58.1 billion (2011 PPP) spread over six months, would have sufficed to mitigate, at least temporarily, the increases in global poverty at the $1.90- and $3.20-a-day poverty lines. Despite the aggregate mitigation, the number of people pushed below these poverty lines because of the crisis could still be significant within the poorest regions of the world. It is important to emphasize that the estimates rely on a distribution-neutral economic contraction. This seems unlikely, and

[2] While this paper focuses on monetary poverty, it acknowledges that other dimensions of poverty such as education, employment, food security or safety are likely sensitive to the existence and timing of the income support provision.

it might well be that the incomes of some segments of the population contracted more than proportionally during the crisis; e.g., low- and middle-skill workers, women, or the informally employed (see, e.g., ILO 2020, 2021; IMF, 2021a). Although there is no consistent information available on the incidence of the income contraction across households, the analysis also simulated the mitigating effects of TBI schemes under an ad hoc regressive contraction that hits proportionally harder the bottom 60 percent of each country's population, which concentrates, on average across-countries, most of those living in poverty and at high-risk of falling into poverty (see section 4). The results suggest that the above investment could have helped to mitigate an important share of the increase in poverty, but certainly not all of it.

Second, actual income support programmes potentially mitigated the short-term increase in poverty in a sample of 41 countries. Although this result is driven by upper-middle-income countries that were able to roll out generous income support, the estimations suggest that low- and lower-middle-income countries may not have provided transfers large enough to fully mitigate the shock-induced increase in poverty and even experienced short-term increases in their headcount rates. Finally, although there has been substantial heterogeneity in the generosity and coverage of the social protection response across countries, mostly conditional on fiscal capacity and budget adaptation, the limited effectiveness observed in some poorer countries suggests that there is room for action even under significant constraints. Yet, again, the success of these moderate interventions in mitigating the increase in poverty is likely fragile under a scenario in which the income contraction is harder on those at the bottom.

Although with important caveats, the results presented in this paper provide some initial benchmarks on how the pandemic shock likely impacted poor and vulnerable households around the world, but also how important policy choices were in potentially mitigating those effects. The remainder of the paper is organized as follows. Section 2 reviews the evidence on the socioeconomic impacts of the COVID-19 pandemic and introduces the income support measures implemented as part of the governments' policy response to this crisis. Section 3 discusses the construction of the distributions of per capita income or consumption and measures the increases in poverty at different poverty lines. Section 4 estimates the potential magnitude of the mitigation of poverty increase from hypothetical and actual emergency income support around the world. Finally, Section 5 discusses some policy implications and provides a conclusion.

2. Looking back at the first pandemic year

At the onset of the pandemic, most developing countries were riven by pre-existing inequalities that would eventually threaten the lives and livelihoods of their most vulnerable citizens. A large share of workers in informal[3] and at-risk service sectors (construction, transportation, retail, tourism and hospitality), combined with absent safety nets, would soon reveal that any social distancing measures would prevent many people from earning their usual income or earning an income at all. Indeed, following the implementation of the first lockdowns, the earnings of informal workers were estimated to have contracted by 60 percent globally in the first month of the crisis, reaching an average contraction of 80 percent among the poorest countries, whereas estimates covering the whole of 2020 suggest that, relative to 2019, the loss of labour incomes had reached US$3.7 trillion globally as a result of working-hour losses (equivalent to more than 220 million full-time jobs), with lower-middle-income countries being the hardest hit (ILO, 2020a; ILO, 2021).

The rapid progression of the pandemic across developing countries and the immediate stringent disruptions to people's livelihoods that followed sounded the alarms of a potential immediate increase in global extreme poverty rates (see, e.g., Mahler et al., 2020a, 2020b; Sumner, Hoy and Ortiz-Juarez, 2020; Valensisi, 2020). While increased poverty is perhaps the most salient and visible negative economic consequence of the COVID-19 pandemic, and the focus of this paper, other critical, related indicators of social progress have also worsened. For starters, the pandemic-induced crisis has left more people food insecure worldwide. Some estimates suggests that it has pushed the number of acutely food insecure people to 270 million in 2020, an 82 percent increase compared to pre-pandemic projections (WFP, 2020). Studies using household survey data from developing countries suggest that the main reason for this increase in food insecurity is the loss of incomes resulting from strict lockdowns and restrictions to mobility,[4] while such an effect is compounded by disruptions to global and domestic markets and food value chains (see, e.g., Aggarwal et al., 2020; Amjath-Babu et al., 2020; Khan et al., 2021; Mahajan and Tomar, 2021).

Other analyses suggest that the effects of the pandemic are likely to exert important adverse effects on gender equality. More women than men lost their jobs or experienced a disproportionate decline in their incomes, resulting in a widening of gaps in labour market outcomes and opportunities (see, e.g., Adams-Prassl et al., 2020; Foucault and Galasso, 2020; Dang and Viet Nguyen, 2021; Montoya-Aguirre, Ortiz-Juarez and Santiago, 2021). There are at least two factors behind this disparity. First, in contrast with previous crises, the coronavirus pandemic has particularly affected sectors with high female employment shares (Alon et al., 2020; ILO, 2020b). Second, the demand for childcare has increased. In response to closures of schools and day-care centres, more mothers than fathers have reduced their working hours or shifted to unemployment or even inactivity (see, e.g., Andrew et al., 2020; Blundell et al., 2020; Collins et al., 2021; Sen, Zhengyun and Hao, 2020; Oreffice and Quintana-Domeque, 2021; Reichelt, Makovi and

[3] About 60 percent of total workers in developing countries make a living in non-agricultural informal markets (70 percent when including agriculture) (ILO, 2018; p 14).
[4] See, for example, evidence for China (Wang et al., 2021), Guatemala (Ceballos, Hernandez and Paz, 2021), Ethiopia (Hirvonen, de Brauw and Abate, 2021), Nigeria (Amare et al., 2020) and South Africa (Arndt et al., 2020).

Sargsyan, 2021); indeed, estimates suggest that the loss of women's jobs in 2020 could reach 64 million globally, with 86 percent moving completely into inactivity (ILO, 2021). A critical gendered outcome is that domestic violence against women was also exacerbated during the pandemic, with its rise being mainly associated to lack of employment, low social support, substance abuse, increased stress and poor mental health (see, e.g., Peterman and O'Donnell, 2020).

There are also potentially harmful, long-lasting consequences on human capital accumulation. Children have experienced learning losses across a range of subjects, grade levels and geographical regions due to school closures.[5] There is evidence that children have devoted less time to schoolwork, even though parents and schools are providing resources to support their learning process during the pandemic (see, e.g., Bacher-Hicks, Goodman and Mulhern, 2021; Jæger and Blaabæk, 2020; Maldonado and De Witte, 2020). Learning losses have also been amplified due to inadequate access to technical equipment for online schooling (see, e.g., Andrew et al., 2020b; Huber and Helm, 2020). Furthermore, learning delays are much more pronounced for primary-school students and students from low-income households, implying that educational inequalities may persist in the long term (see, e.g., Engzell, Frey and Verhagen, 2020; Gore et al., 2021; Tomasik, Helbling and Moser, 2020).

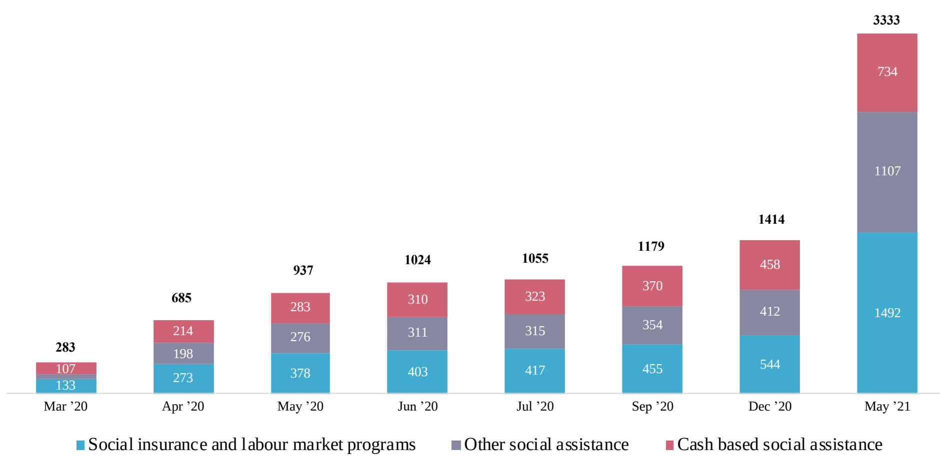
Finally, in terms of health-related indicators, some estimates suggest that the less advantaged groups of the population are likely to suffer high COVID-19-related infections and mortality rates in the future as they often lack access to basic services and good-quality health care, and they tend to live in contexts with persistent conditions of indoor and outdoor pollution and where malnutrition, infectious diseases and other comorbidities are more prevalent (see, e.g., Alkire et al., 2020; Brown, Ravallion and van de Walle, 2020; Walker et al., 2020). There are also indirect health effects that are yet to be fully addressed. Access to essential health services has been severely disrupted, presenting major threats to meeting general and special health-care needs. Krubiner et al. (2021) summarize the evidence and report that most providers diverted to COVID-19 activities and supply chains were seriously affected. For instance, focusing on HIV services, studies report that disruptions to treatment may increase HIV deaths by 10 percent over the next five years, with Sub-Saharan Africa being particularly affected (Hogan et al., 2020; Jewell et al., 2020). Maternal health services have been negatively affected, as well. Antenatal care visits and institutional deliveries declined markedly in Sub-Saharan Africa due to lockdowns (Shapira et al., 2021), while in some Asian countries the quality of intra- and post-partum care and immunization rates experienced major reductions following the containment measures (Headey et al., 2020; KC et al., 2020).

[5] Patrinos and Donnelly (2021) provide a systematic review of the evidence available for developed countries.

2.1 How did the world respond?

Since the start of the pandemic, an ever-increasing number of countries and territories embarked on an aggressive social protection response comprised by social assistance, social insurance and labour market measures. Data from the comprehensive tracker compiled by Gentilini et al. (2021) shows that by the end of March 2020, a total of 283 social protection measures were planned or implemented across 84 countries and territories, whereas by December 2020 their cumulative numbers had reached 1,414 and 215, respectively, and 3,333 measures worldwide by mid-May 2021. During 2020, about two-thirds of the total responses corresponded to social assistance, both cash-based and in-kind, with the former accounting for about a third of the total responses (Figure 1), and although social assistance still dominates in number of responses, the expansion in social protection measures after December 2020 comprised mostly social insurance and labour market programmes.

Figure 1. Evolution of the number of social protection measures, March 2020 to May 2021



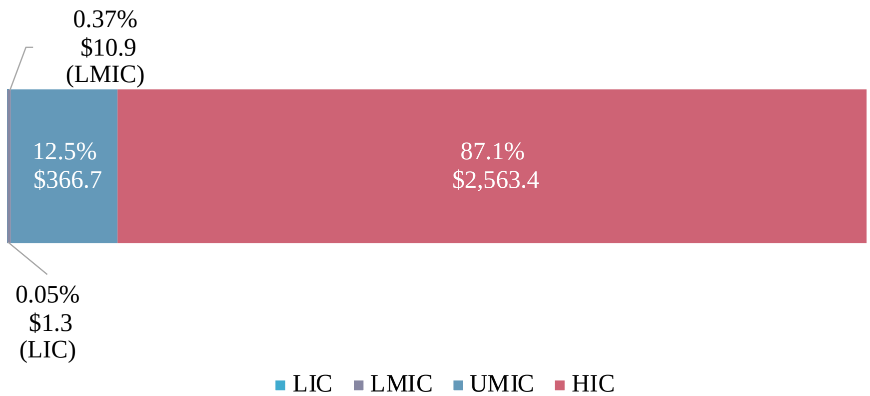
Sources: Authors' elaboration based on Gentilini, Almenfi and Orton (2020), Gentilini, Almenfi and Dale (2020a); Gentilini, Almenfi, Dale, Blomquist et al. (2020); Gentilini, Almenfi, Dale, Lopez, Mujica et al. (2020); Gentilini, Almenfi, Dale, Lopez and Zafar (2020); Gentilini, Almenfi, Dale, Palacios et al. (2020); Gentilini, Almenfi, and Dale (2020b); and Gentilini et al. (2021).

The magnitude of the emergency social protection response is unprecedented. Available data on actual investment for about 15 percent of the 3,333 measures amounts to a world total of about $2.9 trillion (current US dollars) invested since the start of the pandemic (Gentilini et al., 2021).[6] However, the lion's share of this effort has been accounted for by high-income economies that have spent about $2.6 trillion, or 87

[6] All monetary figures in this paragraph are expressed in current US dollars. From Section 3 onward, unless otherwise stated, all monetary figures are expressed in international dollars adjusted by purchasing power parity at 2011 prices (2011 PPP).

percent of the world's total (Figure 2). When considering social assistance alone, low- to middle-income countries have allocated $79.6 billion in cash-based and in-kind measures, equivalent to 4.6 percent of the world's total spending of $1.7 trillion on these measures. This staggering heterogeneity in the capacity to respond is dramatic in per capita terms: while high-income countries have allocated an average of $545 in social assistance and of $847 if social insurance and labour market programmes are added, low- and middle-income countries have spent a per capita average of just $26 in social assistance and $124 in total social protection—among low-income countries only, the amounts per capita are as low as $4. The capacity to respond to the crisis was not only smaller among poorer countries, but further, not all of them were able to provide any income support to mitigate the short-term effects on income losses.

Figure 2. Spending on social protection measures by income group ($billion, US dollars), March 2020 to May 2021



Source: Authors' elaboration based on Gentilini et al. (2021). ***Notes***: LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income.

The evidence summarized in this section reveals how the COVID-19 pandemic has negatively affected households worldwide and how governments have provided a sizeable response to protect the livelihoods of the most vulnerable individuals. However, important questions remain. First, had countries around the world implemented temporary basic income schemes, what could have happened in terms of mitigating the increase in poverty? Second, what has been the potential magnitude of mitigating the increase in poverty from the *actual* investment in emergency cash support programmes among those countries that implemented them? The next section presents the analytical approach followed in this paper to answer these questions.

3. Estimating the pandemic-induced increase in poverty

3.1 Data and the counterfactual approach to measuring poverty

To address the questions presented at the end of the last section, this paper built a cross-country comparable dataset to estimate the potential magnitude of the increase in poverty headcount rates resulting from the economic shock induced by the COVID-19 pandemic. To do so, the analysis exploited the latest version of the World Bank's online dataset of harmonized household income and consumption surveys, which is the main data source to report comparable indicators of monetary-based poverty at the regional and global levels (Arayavechkit et al., 2021).[7] The user of this dataset cannot observe per capita income or consumption at the household level, but rather can retrieve the distributions of those indicators for each country and year (see, e.g., Dykstra, Dykstra and Sandefur, 2014) using an algorithm applied to the dataset's application programming interface (Castañeda Aguilar et al., 2019; Zhao, 2019).[8]

Specifically, the analysis focused on the most recent household surveys for 160 countries containing about 96.5 percent of the world's population in 2019–2020.[9] To retrieve each country's distribution, the algorithm computed the cumulative share of the population with per capita income or consumption below an array of poverty lines that change in value every $0.10 a day per person (2011 PPP),[10] starting from $0.10 up to a maximum value that covers 99.9 percent of the population. From these cumulative shares, individuals within each $0.10-bin were isolated and then assigned the middle value of their bin as their daily amount of per capita income or consumption. That is, for those individuals located within the interval [$0, $0.10], each one holds $0.05; for those within the interval [$0.10, $0.20], each one holds $0.15, and so on. Since not all household surveys were collected in a year that is common to all 160 countries, a distribution-neutral extrapolation of per capita income or consumption, while adjusting for population growth, was performed between each distribution's actual year and the year 2019, just before the start of the pandemic, in those countries where data collection occurred before this year.

The extrapolation follows the approach of Prydz et al. (2019),[11] in which each value of the distribution is multiplied by a factor $\left(\frac{n_{t+1}}{n_t}\right)$ that represents the annual per capita growth rate between the years t and $t+1$ at constant prices of two potential indicators from national accounts: household final consumption expenditure per capita (HFCE) and gross domestic product (GDP) per capita. Notice that applying the same

[7] PovcalNet March 2021 global poverty update. Household income or consumption surveys are collected on a country-by-country basis and tend to differ in key methodological aspects as well as in the criteria for open access. The World Bank has led the task of homogenizing national surveys for consistent and comparable cross-country analyses on monetary-based poverty.
[8] The code, written in the R software, is available from the authors upon request.
[9] The average and median years among these surveys are 2015 and 2017, respectively. In the dataset, 114 surveys covering 70 percent of the population are for the period 2015-2019; 37 surveys covering 29 percent of the population are for the period 2010-2014, and the remaining 9 surveys covering 1 percent of the population are for before 2010. See the Appendix for further details and the list of countries included in the analysis.
[10] From here onward and unless otherwise stated, all monetary figures are expressed in international dollars adjusted by purchasing power parity at 2011 prices (2011 PPP).
[11] See also World Bank (2018a), Appendix A, and World Bank (2020), Chapter 1. The latter presents specific details on the extrapolation of per capita consumption in India, as captured by the latest available survey from 2011. This country is included in the analysis of this paper.

annual growth rate to each value of the country's distribution changes its mean value only, while holding its shape constant; i.e., there are no changes in income or consumption inequality. As noted in Prydz et al. (2019), HFCE is conceptually closest to the households' economic activity captured by surveys and, hence, it is adopted as the preferred source for extrapolation in all countries with the available indicator. In countries where HFCE is scarce or not available, mainly in Sub-Saharan Africa, the extrapolation uses the annual growth rate of GDP per capita. To verify the quality and consistency of this exercise, Figure A1 in the Appendix plots the extrapolated means in each country's retrieved distribution against the corresponding survey means extrapolated by the World Bank, suggesting a virtually perfect match between the two exercises.

By pooling together the 160 distributions lined up to 2019, poverty headcount rates can be estimated globally and by groups of countries (Table 1) simply by comparing the monetary values associated with each bin with typical international thresholds, using the size of the population within each bin as weights. In particular, an individual is identified as poor if her daily per capita income or consumption is below the following poverty lines per person: $1.90 a day, equivalent to the median value of the national poverty lines among low-income countries (LIC) and used for global estimates and comparisons of extreme poverty, and $3.20 and $5.50 a day, or the median values of the national poverty lines among, respectively, lower-middle-income (LMIC) and upper-middle-income countries (UMIC) (for further details on these lines, see Jolliffe and Prydz, 2016). Additionally, the analysis identifies those people living below a vulnerability threshold of $13 a day per person, which is associated with a low probability, 10 percent or less, to fall into poverty at the $5.50 poverty line.[12]

Table 1. Number of countries in the dataset and their combined population by aggregates

[12] This threshold of $13 a day per person is the updated value (2011 PPP) of the cut-off of $10 a day per person (2005 PPP) identified by Lopez-Calva and Ortiz-Juarez (2014) as the dividing line between vulnerability to poverty and economic security in three Latin American countries (Chile, Mexico and Peru) and is consistent with the value estimated for countries in Europe and Central Asia by Bussolo et al. (2018).

Group	Countries' distributions	Population 2019 (million)
Advanced economies	**32**	**1,020.1**
Developing countries	**128**	**6,304.7**
East Asia and Pacific (EAP)	19	2,031.0
Europe and Central Asia (ECA)	24	466.1
Latin America and the Caribbean (LAC)	23	591.6
Middle East and North Africa (MNA)	11	362.0
South Asia (SAS)	7	1,779.9
Sub-Saharan Africa (SSA)	44	1,074.1
Income group		
Low-income (LIC)	23	561.2
Lower-middle-income (LMIC)	49	2,868.3
Upper-middle-income (UMIC)	46	2,775.6
High-income [/a] (HIC)	42	1,119.7
By welfare indicator		
Per capita consumption	99	5,653.0
Per capita income	61	1,671.8
Total in dataset	**160**	**7,324.9**
World's total (countries and territories)	217	7,592.0
Total in dataset (% of world's total)	**74%**	**96.5%**

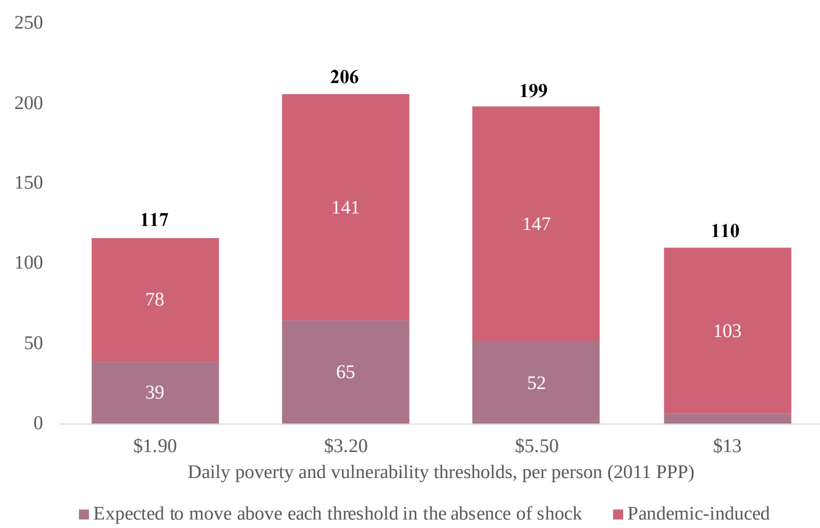
Source: Authors' elaboration based on World Bank's PovcalNet (March 2021 global poverty update) for the distributions of per capita income or consumption and World Development Indicators (May 2021 update) for the world's total. ***Notes***: [/a] Includes the following 10 countries not classified as advanced economies: Chile, Croatia, Hungary, Mauritius, Panama, Poland, Romania, Seychelles, Trinidad and Tobago, and Uruguay.

To capture the potential effect of the pandemic on poverty in 2020, the analysis implemented the counterfactual approach used in Mahler et al. (2020a, 2020b) and Lakner et al. (2020a, 2021), which involves projecting forward the 160 lined up welfare distributions under two different scenarios. The first scenario uses the country-specific forecasts, as of October 2019, of GDP per capita growth that would have prevailed in 2020 in the absence of the pandemic (IMF, 2019), while the second uses the corresponding forecasts, as of April 2021, after taking into account the economic contraction (IMF, 2021b). In the two scenarios, the analysis followed the standard practice in the above studies that only 85 percent of the growth in national accounts is passed through to household income or consumption vectors (see Lakner et al., 2020b for further details on the estimation of this value). Therefore, the 160 distributions lined up to 2019 were projected for 2020 at 0.85 times the growth rate in GDP per capita between 2019 and 2020, accounting for the demographic change between both years and assuming, as before, no changes in inequality. The analysis has thus produced three per capita welfare distributions: 2019 (lined up) and 2020 with and without the pandemic-induced economic shock (see Figure A2 in the Appendix).

3.2 Immediate increases in poverty and welfare losses

Following the counterfactual approach, the increase in poverty that may be attributable to the pandemic-induced shock is given by the difference between the two welfare distributions in 2020. Figure 3 shows that the number of people falling into poverty reaches 117 million at the $1.90-a-day poverty line, 206 million at $3.20 a day, and 199 million at $5.50 a day,[13] whereas the increase in the number of those falling under the vulnerability threshold reaches 110 million. The total increase can be broken down into those people who were expected to leave poverty or move above the vulnerability line between 2019 and 2020 had the pandemic not occurred and those falling below each threshold between 2019 and 2020 after accounting for the shock. The main finding is that, had the pre-pandemic trends continued, the number of people in poverty was expected to reduce in 2020 by between 39 million and 65 million people, depending on the poverty line.

Figure 3. Increases in global poverty (million people), 2020



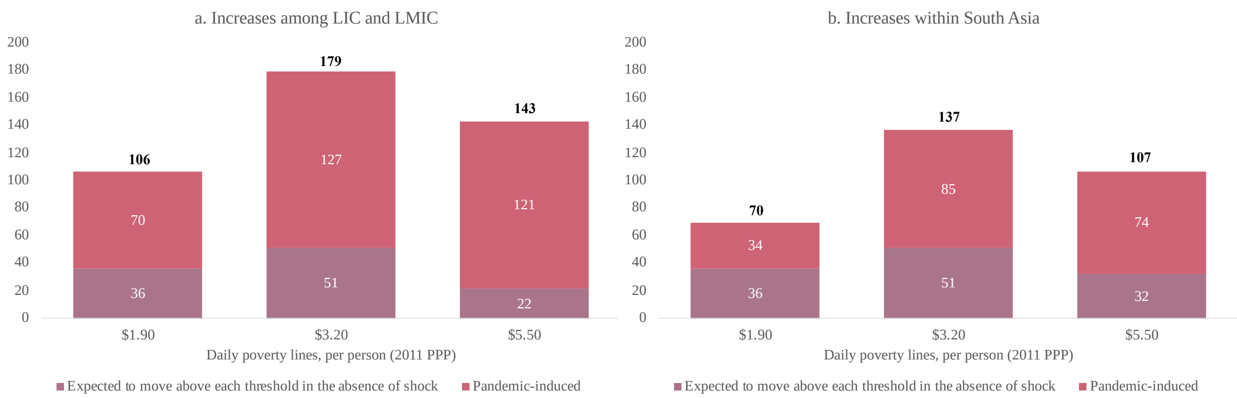
Source: Authors' calculations. ***Notes***: The breakdown of the number of people falling into poverty is inspired by Figure 1 in Lakner et al. (2021).

The estimates reveal that most of the increase in the number of poor people is accrued by LIC and LMIC and mainly driven by South Asia, which emerges as the hardest hit region by any poverty standard. Figure

[13] These results are consistent in orders of magnitude with those reported in Lakner et al. (2021), who estimate an increase of at least 119 million at $1.90 a day, 228 million at $3.20 a day, and 201 million at $5.50 a day. The differences between the two sets of estimates may be attributable to i) the source of GDP per capita growth rates to project the dataset to 2020, with and without the shock (Lakner et al. use the Global Economic Prospects of January 2020 and 2021, whereas this paper relies on the IMF's World Economic Outlook of October 2019 and April 2021); ii) the value of individuals' per capita welfare, which, in this paper, corresponds to the middle value of each $0.10-bin; and iii) the number of countries or territories in the dataset (the analysis in this paper excluded Guinea-Bissau, Nauru, Somalia, Suriname, Taiwan, United Arab Emirates and Syrian Arab Republic, either because it was not possible to retrieve the welfare distributions or because no data was found to perform the required projections to 2020 for those countries).

4 shows that, of the 117 million people pushed by the pandemic into extreme poverty, 106 million (91 percent) live in LIC and LMIC, with 70 million (60 percent) alone living in South Asia. For higher poverty lines, LIC and LMIC concentrate the equivalent of 72–87 percent of the global increase, whereas South Asia accounts for 54–66 percent. Another revealing finding is that, had the economic shock induced by the pandemic not occurred, these groups of countries comprise most of the total number of people that was expected to move out of poverty at $1.90 and $3.20 a day and about half of those expected to leave poverty at the standard of $5.50 a day.

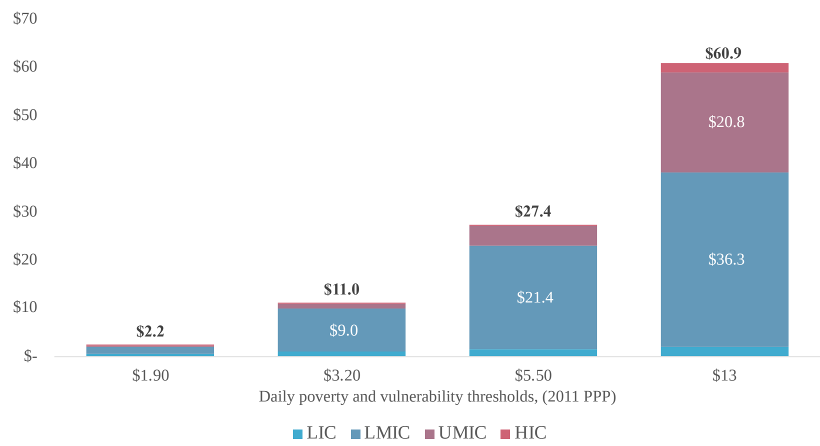
Figure 4: Increases in poverty in LIC, LMIC, and South Asia (million people), 2020



Source: Authors' calculations. ***Notes***: The breakdown of the number of people falling into poverty is inspired by Figure 1 in Lakner et al. (2021). LIC = low-income; LMIC = lower-middle-income. Due to rounding, some totals may not correspond with the sum of the separate figures.

The welfare losses induced by the economic contraction are sizeable and disproportionate among the poorest countries in the world. After examining the groups of people comprised by those already living below the poverty lines and those who fell into poverty after the shock, we find the estimates reveal that the short-term loss of per capita income or consumption could have reached the equivalent of $2.2 billion per month among those below the $1.90-a-day poverty line and $11–27 billion per month among those living on less than $3.20 and $5.50 a day, with LIC and LMIC accounting for between 84 and 94 percent of the total welfare loss, depending on the poverty line (Figure 5). Among those identified as living below the $13-a-day threshold globally, the welfare loss could have reached a staggering $61 billion per month, with almost two-thirds being accounted for by LMIC. In per capita terms, the monthly loss among those in extreme poverty reached $3.2, on average, whereas among those in poverty at $3.20 and $5.50 a day, it reached an average of $5 and $7.5, respectively, and among those below the vulnerability threshold it reached $12.6.

Figure 5. Monthly welfare losses among those living below each threshold after the shock by income group ($billion, 2011 PPP), 2020



Source: Authors' calculations. ***Notes***: LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income.

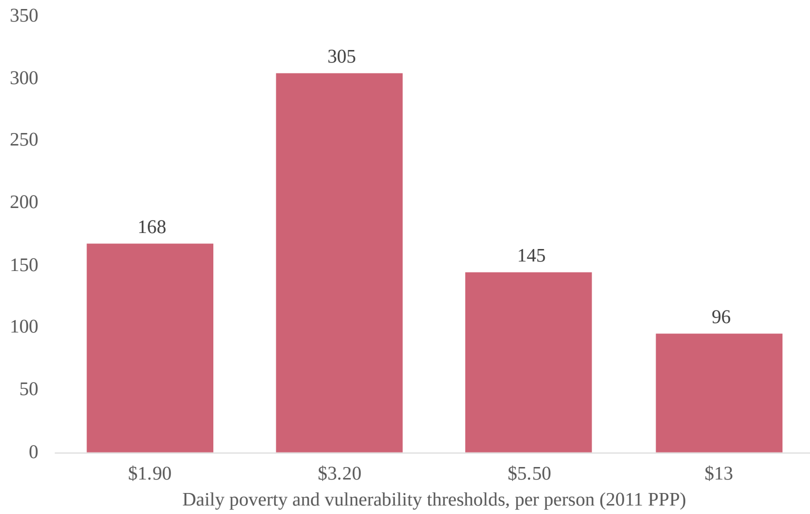
It is hard to tell yet for how long these welfare losses have persisted, whether they have caused assets depletion leading households to acute states of material deprivation, or whether the increases in global poverty have been rather transitory. Evidence from previous crises, however, suggests that the loss of incomes is especially hard during the shock and tends to persist with a low recovery well beyond the end of the crisis (e.g., Davis and von Wachter, 2011). More recent estimates from telephone surveys collected from April to June 2020 across households in nine LMIC suggest that the drop in living standards persisted for at least three months after the start of the pandemic and, crucially, that households' coping strategies and even some government assistance proved insufficient to compensate for the losses (Egger et al., 2021).

It is also unclear how the contraction in income was allocated across households, as this depends on their relative position in the distribution—and, perhaps, this will never be known with certainty, as the collection of robust survey data was severely hampered in most countries during 2020. Yet, given the interaction between pre-existing conditions of inequality and exclusion with stringent lockdowns, the closure of non-essential service sector activities and reduced mobility in most developing countries, there is no harm in presuming that the contraction in incomes may have hit harder low- and middle-skill workers, women and the informally employed (see, e.g., ILO 2020, 2021; IMF, 2021a), who are usually found towards the bottom of the distribution. While this paper acknowledges that the assumption of a distribution-neutral economic contraction is highly uncertain, with no more consistent information available, the previous estimates of the increase in global poverty are used as the baseline for the empirical analysis conducted in the next sections.

Box 1. A hypothetical regressive contraction

For illustrative purposes, Figure B1 presents the results of a hypothetical exercise of the increase in poverty by simulating an additional 60 percent hit among those people at the bottom 60 percent of the distribution, which comprises a large share of those living either in poverty or at high risk of it across developing countries (see Figure 6 below)—with a proportional adjustment among the top 40 percent, thus making the economy-wide contraction remain unchanged while allowing for inequality to increase slightly.[14] The results suggest that this regressive contraction could increase the number of people in poverty at $1.90 and $3.20 a day by 168 million and 305 million, respectively, which implies an additional 51–99 million relative to the distribution-neutral contraction (see Figure 3 above). Notice that the global increase at higher thresholds is less pronounced than in the baseline, which is driven by the proportionally less severe contraction for the top 40 percent that would benefit UMIC in particular.

Figure B1. Increases in global poverty and vulnerability in a hypothetical scenario of a regressive economic contraction (million people), 2020



Source: Authors' calculations.

4. Estimating the poverty-mitigating effect of temporary basic incomes

4.1. The counterfactual case

As noted in Section 2, even though the world has witnessed a massive response in emergency social protection and assistance since the start of the pandemic, the lion's share has been accounted for by high-

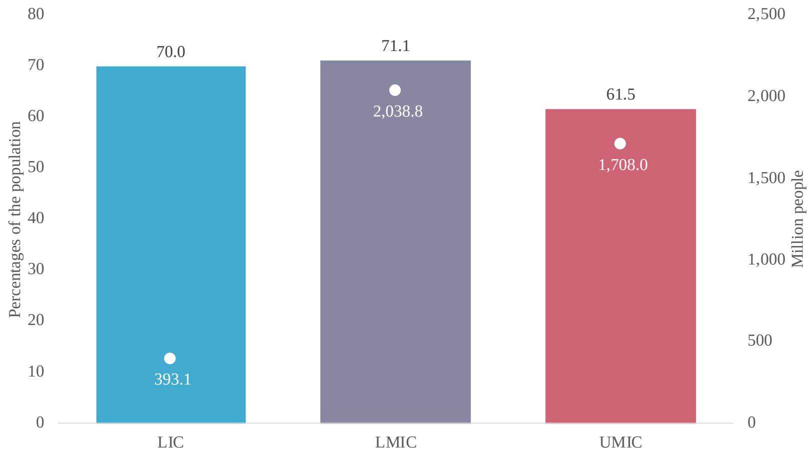
[14] For instance, instead of assuming that a contraction of, say, 2 percent passes through homogeneously to all households as in the distribution-neutral scenario, the additional hit will lead such contraction to reach 3.2 percent among the bottom 60 percent, but only 0.2 percent among the top 40 percent. The adjustment excludes those 13 countries that recorded positive rates of GDP per capita in 2020: Bangladesh, China, Egypt (Arab Republic of), Ethiopia, Guinea, Guyana, Iran (Islamic Republic of), Ireland, Myanmar, Tajikistan, Turkey, Tuvalu and Vietnam. This hypothetical regressive contraction would imply an increase in the global Gini coefficient of about 0.48 percent, relative to the distribution-neutral case.

income countries, which have invested a per capita amount in social assistance that is more than 20 times larger, on average, than the amount spent by developing countries. Not all developing countries, which account for 99–100 percent of the increase in poverty depending on the poverty line, were able to either deliver cash support or to provide it for an extended period, considering the duration of the crisis, while others were able to roll out only in-kind assistance or waivers on utility bills. The pressing question is: Had developing countries implemented schemes of temporary basic incomes (TBI), what could have been the magnitude of the mitigation effect on poverty-increase and its fiscal cost?

In a paper released four months into the pandemic, Gray Molina and Ortiz-Juarez (2020) discussed the implementation challenges and costs of TBI schemes that may have had the potential to benefit up to 2.8 billion people based on varying scenarios of per capita transfers, including top-ups up to a minimum income threshold and even a share of countries' median income. While the authors argued for the affordability of some of those schemes, depending on the duration of the assistance and each country's living standards, the progression of the pandemic would have eventually exhausted health systems and severely limited fiscal space in some contexts, making the delivery of relatively generous cash support schemes prohibitive, especially in poorer and populous countries. More than one year after the outbreak of COVID-19, instead of simulating the poverty-mitigating effect of those TBI schemes, the analysis in this subsection focuses on schemes whose total cost is equivalent to a portion of GDP that is homogeneous across countries and, arguably, proportional to each country's fiscal capacity. Similar to Gray Molina and Ortiz-Juarez (2020), it is assumed that such schemes are delivered on an individual basis, regardless of household composition.

The target population for the TBI is those living below vulnerability thresholds, which change in value depending on each country's income level. For starters, the $13-a-day threshold was originally computed in UMIC contexts (see, e.g., Lopez-Calva and Ortiz-Juarez, 2014; Bussolo et al., 2018), where poverty is typically measured with the $5.50-a-day poverty line. While such a threshold may be as informative for global comparisons as measuring poverty with the $1.90-a-day poverty line even in high-income countries (HIC), it may be very demanding in both LIC and LMIC for targeting purposes. In some countries of the latter group, where the typical poverty line equals $3.20 a day, a recent estimate suggests that $5.50 a day is associated with a low vulnerability to poverty (World Bank, 2018b), which is adopted in this paper as the threshold among all LMIC. As for LIC, where poverty is typically measured at $1.90 a day and with no known information of an associated vulnerability threshold, it is simply assumed that those at high risk of poverty at this level are those living below the next international poverty line, i.e., $3.20 a day. Figure 6 shows the percentages and number of people living below such thresholds in 2019 by income group, which reach 61–71 percent and a combined population of about 4.1 billion people.

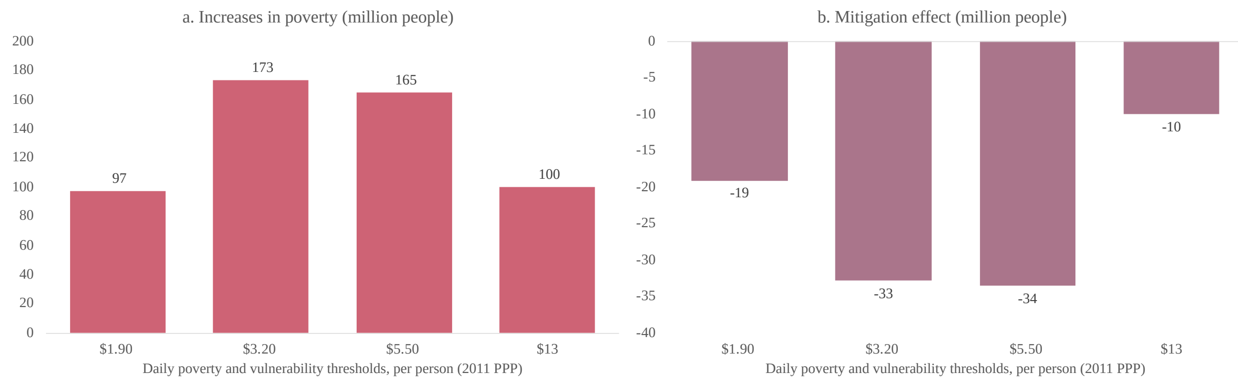
Figure 6. Population living below context-adjusted vulnerability lines, 2019



Source: Authors' calculations. ***Notes***: The vulnerability threshold per day, per person, used among LIC equals $3.20, among LMIC equals $5.50 and among UMIC equals $13. The latter group includes the following 10 developing countries classified as HIC: Chile, Croatia, Hungary, Mauritius, Panama, Poland, Romania, Seychelles, Trinidad and Tobago, Uruguay. LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income.

In all the simulated schemes, the monthly costs of TBI are derived under the assumption that all developing countries deliver cash support for at least six months, backed by the above evidence of welfare loss persistence and slow recovery, with no TBI schemes implemented in advanced economies. The focus on developing countries is intended to capture the magnitude of the mitigation of poverty increases driven by these countries only, given the low participation of advanced economies in global poverty rates: less than 0.1 percent at $1.90 and $3.20 a day, and 0.8 percent at $5.50 a day. A first scheme assumes that each developing country has invested 0.10 percent of its 2019 GDP (2011 PPP) and spread this investment over six months, which is equivalent to monthly spending of 0.017 percent of the annual GDP, or $11.6 billion globally—enough to compensate for the monthly loss of $11 billion among those living below $3.20 a day in 2020 (see Figure 5 above). Relative to the increase in poverty presented in Figure 3 above, this investment could have prevented 19 million people from falling into extreme poverty at $1.90 a day, about 33–34 million from falling into poverty at either $3.20 or $5.50 a day, and 10 million from falling below the $13-a-day threshold (Figure 7).

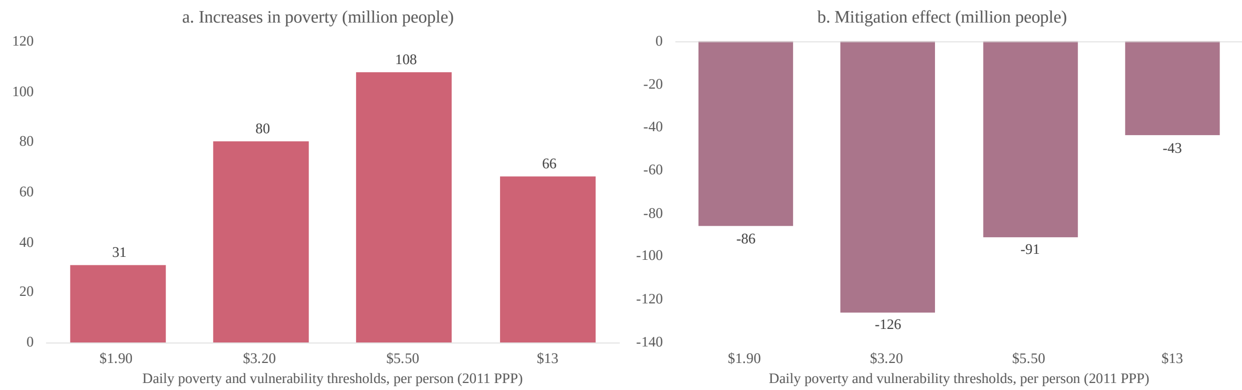
Figure 7. Poverty increases and mitigation effect had developing countries delivered a monthly TBI to 4.1 billion people equivalent to 0.017 percent of their GDP, 2020



Source: Authors' calculations. ***Notes***: The figures in panel a correspond to the increases in poverty after accounting for the pandemic-induced shock and the delivery of a monthly TBI equivalent to 0.017 percent of developing countries' GDP ($11.6 billion)—or 0.10 percent of GDP ($69.8 billion) over a period of six months. The figures in panel b are the corresponding differences between the increases in panel a and those presented in Figure 3. Due to rounding, some totals may not correspond with the sum of the separate figures.

A second scheme assumes that government investment amounts to 0.30 percent of developing countries' GDP spread over six months, equivalent to 0.05 percent of GDP or $34.9 billion per month, which seems enough to compensate for the monthly loss of $27 billion among the global poor at $5.50 a day (see Figure 5 above). Having rolled out this TBI scheme, global extreme poverty would have increased by almost 31 million after the pandemic-induced shock instead of the 117 million reported previously, which implies that the scheme could have potentially prevented 86 million people from falling into poverty (Figure 8). Although the increase in global poverty at $3.20 and $5.50 a day would still be sizeable (80 million and 108 million, respectively), the magnitude of the mitigated increase in poverty at these levels could have reached 126 million and 91 million people, respectively, relative to the scenario with no TBI in place. Finally, the number of people entering the group of those below $13 a day would have reduced by 43 million, in comparison to the scenario with no TBI in place.

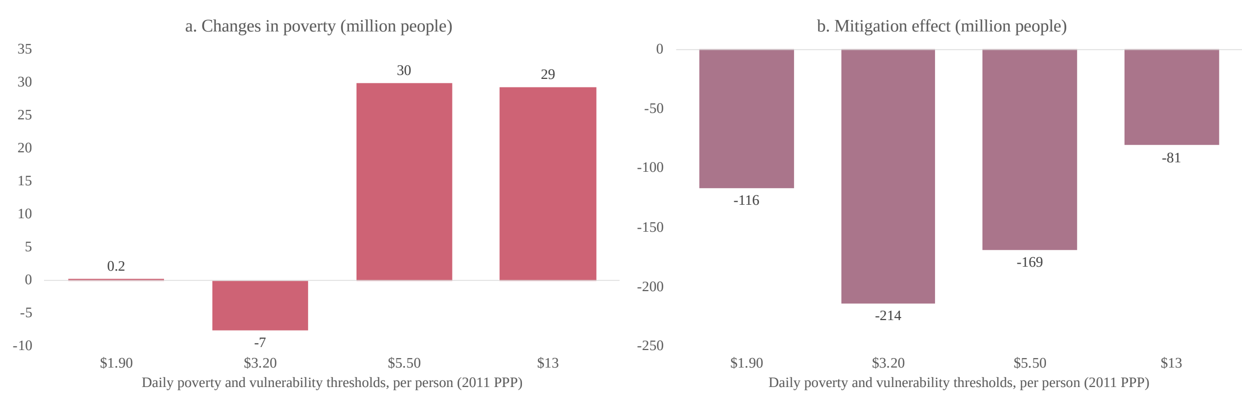
Figure 8. Poverty increases and mitigation effect had developing countries delivered a monthly TBI to 4.1 billion people equivalent to 0.05 percent of their GDP, 2020



Source: Authors' calculations. ***Notes***: The figures in panel a correspond to the increases in poverty after accounting for the pandemic-induced shock and the delivery of a monthly TBI equivalent to 0.05 percent of developing countries' GDP ($34.9 billion)—or 0.30 percent of GDP ($209.3 billion) over a period of six months. The figures in panel b are the corresponding differences between the increases in panel a and those presented in Figure 3. Due to rounding, some totals may not correspond with the sum of the separate figures.

A third and final scheme assumes that all developing countries have delivered a TBI equivalent to 0.5 percent of their GDP spread over six months, equivalent to monthly spending of 0.083 percent of GDP or $58.1 billion—almost enough to compensate for the monthly loss of $60 billion among those living with less than $13 globally (see Figure 5 above). Figure 9 shows that this magnitude of investment could have mitigated almost entirely the increases in global poverty at the lowest poverty lines, at least temporarily, despite the economic contraction. Moreover, this TBI scheme could have prevented 169 million people from falling into poverty at $5.50 a day.

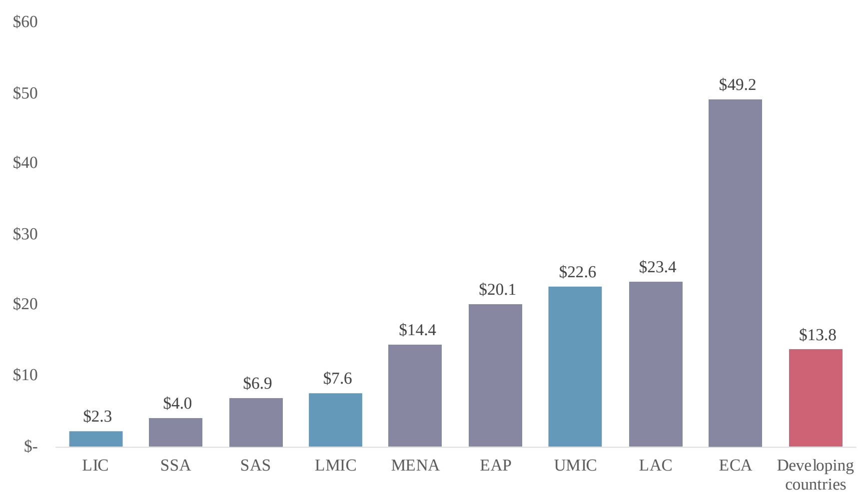
Figure 9. Poverty changes and mitigation effect had developing countries delivered a monthly TBI to 4.1 billion people equivalent to 0.083 percent of their GDP, 2020



Source: Authors' calculations. ***Notes***: The figures in panel a correspond to the changes in poverty after accounting for the pandemic-induced shock and the delivery of a monthly TBI equivalent to 0.083 percent of developing countries' GDP ($58.1 billion)—or 0.50 percent of GDP ($348.8 billion) over a period of six months. The figures in panel b are the corresponding differences between the changes in panel a and those presented in Figure 3. For the $3.20-a-day threshold, the figure of -214 million people in panel b results from the sum of the mitigated increase of 206 million people (Figure 3) and additional poverty reduction impact of 7 million people (panel a). Due to rounding, some totals may not correspond with the sum of the separate figures.

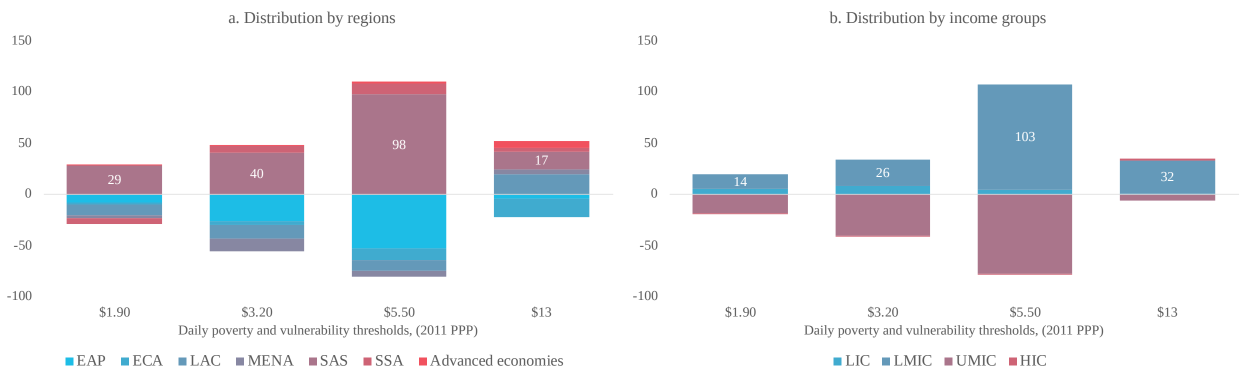
These results show that a global investment of $58.1 billion per month to benefit 4.1 billion poor and vulnerable people—or a cumulative of $348.8 billion over six months, equivalent to 0.5 percent of each developing country's GDP in 2019—could have had the potential to cushion the worst immediate economic effects among the less advantaged groups of the global population. In per capita terms, the investment under this scheme is equivalent to a developing world's average transfer of $13.8 per month, ranging from less than $10 in LIC and LMIC to more than $20 in UMIC (Figure 10). It is important to emphasize that although the increase in poverty at $1.90 and $3.20 a day could have been mitigated at a global scale by the third TBI scheme, the number of people pushed below these poverty lines by the pandemic-induced shock could still be significant in South Asia, increasing by 29 and 40 million people, respectively (Figure 11, panel a). In fact, the aggregate mitigation of poverty at these levels results from an additional reduction of poverty beyond the mitigation effect in the remaining regions. This scenario would give less cause for celebration, as the needed effort to compensate for the welfare losses would require proportionally more resources in South Asia—and in Sub-Saharan Africa at the $3.20-a-day poverty line—relative to the rest of the developing countries.

Figure 10. Monthly per capita transfer under a TBI scheme in which developing countries invest 0.083 percent per month of their GDP, by regions and income groups (2011 PPP)



Source: Authors' calculations. ***Notes***: The figures on each bar correspond to the weighted average within each group of the per capita transfer under a TBI scheme in which each developing country invests 0.083 percent of GDP ($58.1 billion) per month—or 0.5 percent ($348.8 billion) over a period of six months. Income group: LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income. Developing regions: EAP = East Asia and Pacific; ECA = Europe and Central Asia; LAC = Latin America and the Caribbean; MNA = Middle East and North Africa; SAS = South Asia; SSA = Sub-Saharan Africa.

Figure 11. Absolute distribution of the changes in poverty after the pandemic-induced shock and a monthly TBI equivalent to 0.083 percent of developing countries' GDP (million people), 2020

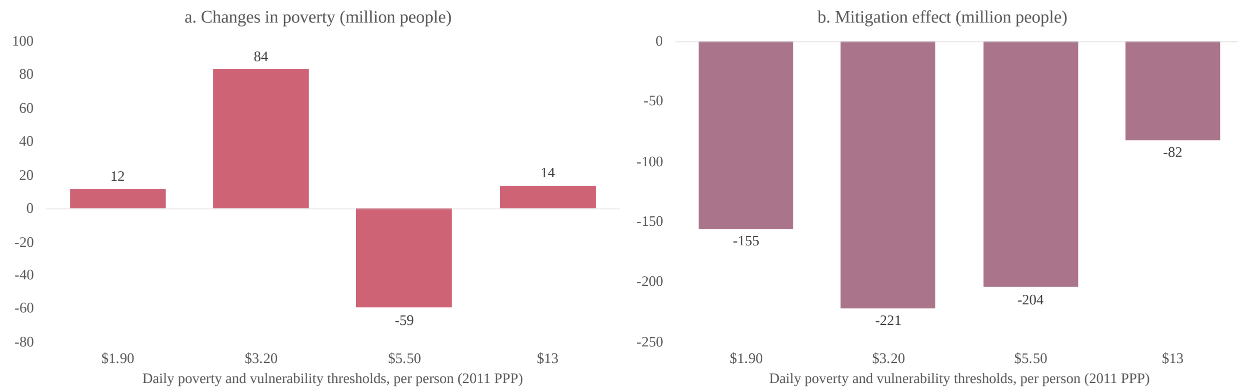


Source: Authors' calculations. ***Notes***: The differences between the positive and negative figures in each bar yield the results presented in Figure 9, panel a, for the corresponding poverty and vulnerability thresholds. The simulated monthly TBI is equivalent to 0.083 percent of developing countries' GDP ($58.1 billion)—or 0.50 percent of GDP ($348.8 billion) over a period of six months. Income group: LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income. Developing regions: EAP = East Asia and Pacific; ECA = Europe and Central Asia; LAC = Latin America and the Caribbean; MNA = Middle East and North Africa; SAS = South Asia; SSA = Sub-Saharan Africa. Advanced economies as classified by the International Monetary Fund (IMF 2021a).

Box 2. Would the monthly TBI of 0.083 percent of GDP mitigate the increase in poverty in the short term under the hypothetical scenario of a regressive contraction?

The results shown in Figure B2 suggest that a monthly investment of 0.083 percent of developing countries' GDP (0.5 percent over six months), or $58.1 billion, could have helped to mitigate about 90 percent (155 million) and 70 percent (221 million) of the 168 million and 305 million people falling into poverty at $1.90 and $3.20 a day (see Box 1) in the absence of cash support and under a regressive contraction. As the contraction among those located at the top 40 percent of the population was proportionally adjusted to be less severe, together with the provision of cash relief, global poverty at $5.50 a day would have been further reduced by 59 million people on top of having mitigated the increase of 145 million in the absence of cash assistance.

Figure B2. Poverty changes and mitigation effect had developing countries delivered a monthly TBI to 4.1 billion people equivalent to 0.083 percent of their GDP in a hypothetical scenario of a regressive economic contraction, 2020



Source: Authors' calculations. ***Notes***: The figures in panel a correspond to the changes in poverty after accounting for a regressive contraction induced by the pandemic and the delivery of a monthly TBI equivalent to 0.083 percent of developing countries' GDP ($58.1 billion)—or 0.50 percent of GDP ($348.8 billion) over a period of six months. The figures in panel b are the corresponding differences between the changes in panel a and those presented in Figure B1. For the $5.50-a-day threshold, the figure of -204 million people in panel b results from the sum of the mitigated increase of 145 million people (Figure B1) and additional poverty reduction impact of 59 million people (panel a). Due to rounding, some totals may not correspond with the sum of the separate figures.

Although hypothetical, the results from the simulations presented earlier suggest substantial, albeit temporary, effects of TBI schemes on mitigating increases in poverty. The next subsection focuses on an arithmetic simulation that estimates the potential magnitude of the mitigation effect of actual income support measures planned or implemented in a subsample of countries that allocated benefits based on the standing of the population in the welfare distribution.

4.2 The actual case: Potential mitigation of poverty increases from 72 planned or implemented schemes of emergency cash-based social assistance across 41 countries

Previous studies have analysed the effects of cash assistance in mitigating the short-term consequences of the pandemic-induced shock by focusing either on specific programmes or on a reduced number of countries. For instance, Blofield, Lustig and Trasberg (2021) and Lustig, Neidhöfer and Tommasi (2020) simulate the impact of the economic contraction on income inequality and poverty, as well as the mitigating poverty and inequality effects of the social assistance programmes implemented during the crisis in Argentina, Brazil, Colombia and Mexico. Except for the latter country, where there was virtually no expansion of emergency social assistance, the findings suggest that the introduction of cash relief might have more than offset the negative effect on incomes in all countries, especially in Argentina and Brazil, due to their large expansion in emergency social assistance. In turn, Younger et al. (2020) simulate the poverty impacts of COVID-19 in Uganda in the presence of temporary transfers. Without social assistance, the authors estimate an aggregate income loss equivalent to 9.1 percent of monthly GDP and a poverty-rate increase of 7.9 percentage points. Their calculations indicate that expanding the two largest existing social programmes would reduce poverty by 1.6 percentage points, and that to offset about two-thirds of the increase in poverty, the government would need to transfer about 0.7 percent of their monthly GDP to targeted poor households.

In another study, Egger et al. (2021) use telephone-based surveys collected across nine countries in Africa, Asia and Latin America and assess the impacts of the pandemic on income losses as well as the effects of social assistance in reducing food insecurity. Their results show that although a sizeable share of respondents benefited from social support (at a median of 11 percent), this was insufficient to maintain pre-pandemic living standards and, hence, to prevent food insecurity. While these estimates provide a useful characterization of the immediate reach of social support programmes in these countries, the surveys were conducted over the first three months of the pandemic, well before the bulk of social assistance and cash transfers were rolled out worldwide.

The analysis in this subsection exploited the database of social protection measures of Gentilini et al. (2021) to undertake a systematic, large-scale assessment of the potential short-term effects of the cash-based social assistance planned or implemented by governments through 72 programmes in a sample of 36 developing countries and five advanced economies, which together comprise 1.95 billion people or a fourth of the global population in 2020, and represent a fifth of the total number of countries that have planned or implemented cash assistance measures since March 2020 (the list of countries included in the analysis is presented in the Appendix).

Most of the 72 cash-based programmes are new (78 percent) and only 16 of them are scaled up based on existing schemes. The information provided by Gentilini et al. (2021) allowed for the identification of the number of potential beneficiaries by income level and, hence, the allocation of individual cash benefits using the retrieved distributions of per capita income or consumption (see section 3). For each program, the transfer amount and its periodicity were identified from the database and corroborated with the programme description and other official sources to determine the total transfer that individuals would have received in 2020. For transfers delivered to households, or to one household member, the analysis assumed equal sharing within the household, and the transfer was then divided by the average household size to estimate the per capita benefit.

To allocate the potential cash transfers, the per capita amounts were converted from local currency units to international dollars at 2011 prices (2011 PPP), and the number of beneficiaries was identified according to income level or relative position in the country's welfare distribution before the COVID-19 shock, i.e., the distributions lined up to 2019 (see subsection 3.1). The allocation followed four different approaches depending on each programme's target population:

1. Universal transfers were assigned to all individuals irrespective of their income level.

2. Transfers targeted to people living in poverty, or to beneficiaries of existing social assistance programmes, were allocated from the bottom tail of the distribution and upward until the total number of beneficiaries was reached.

3. Programmes that explicitly exclude beneficiaries of existing social assistance schemes but are still aimed at low-income people were allocated to individuals just above the corresponding poverty line (depending on country's income level) and upward until the total number of beneficiaries was reached.

4. Those transfers targeting self-employed, informal workers or other vulnerable groups that are not necessarily poor were assigned to individuals just below the context-specific vulnerability thresholds (see previous subsection) and downward until the total number of beneficiaries was reached.[15]

In this sample of 41 countries, the estimated pre-pandemic poverty rates for 2020 are 7 percent (137 million), 17.8 percent (346.3 million), 34.3 percent (669.1 million) and 59.5 percent (1,159.8 million), at the $1.90-, $3.20-, $5.50- and $13-a-day thresholds, respectively. Using the welfare distributions projected to 2020 with and without the pandemic-induced shock, the counterfactual approach to poverty (i.e., the difference between the two projected distributions; see subsections 3.1 and 3.2) estimates a potential increase in extreme poverty of 15 million people using the $1.90-a-day line, and an increase in poverty of 26 million people at $3.20 a day and of 42 million at $5.50 a day (Figure 12). Using the $13-a-day threshold, the pandemic-induced shock would result in an increase of 29 million people—notice from the breakdown that about 10 million people were already expected to fall below this threshold in the absence of the pandemic.

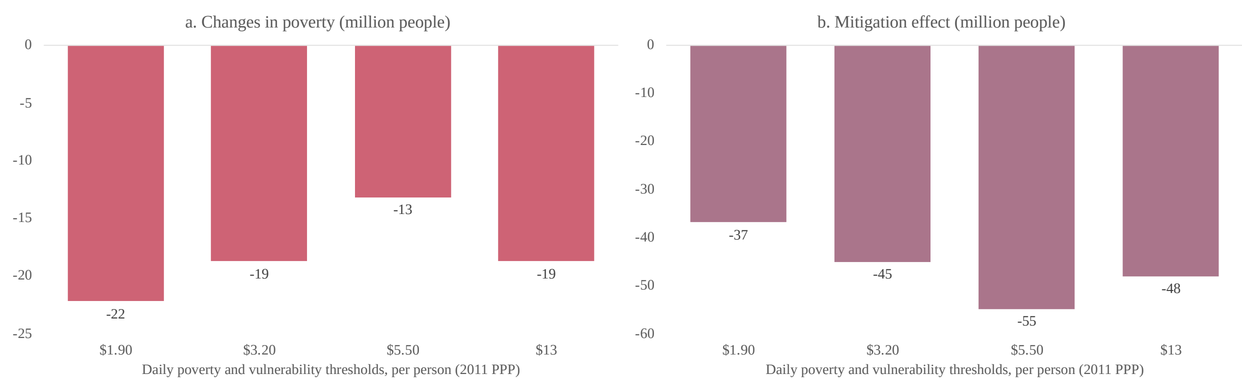
Figure 12. Increases in poverty in the sample of 41 countries (million people), 2020

[15] In the case of the five advanced economies in the sample (Australia, Israel, Korea, Republic of, United Kingdom and United States), the threshold was set at $21.7 a day per person, which corresponds to the median value of the poverty lines among high-income countries (Jolliffe and Prydz, 2016).

Source: Authors' calculations. ***Notes*****:** The breakdown of the number of people falling into poverty is inspired by Figure 1 in Lakner et al. (2021).

After adding the per capita amounts of the planned or implemented cash assistance, the increases in poverty rates are likely fully mitigated when looking at the group of 41 countries together (Figure 13). Specifically, the estimated increase of 15 million people in extreme poverty appeared fully mitigated, and extreme poverty may have been reduced in an additional 22 million people amid a severe crisis. Similarly, the increases in the number of people below the $3.20- and $5.50-a-day poverty lines are potentially fully mitigated by income support and reduced by an additional 19 million and 13 million, respectively. Since most of the cash assistance programmes are new, we caution the reader to interpret these estimates as the potential effect of pandemic-induced cash assistance while holding unchanged the social protection already in place before the pandemic.

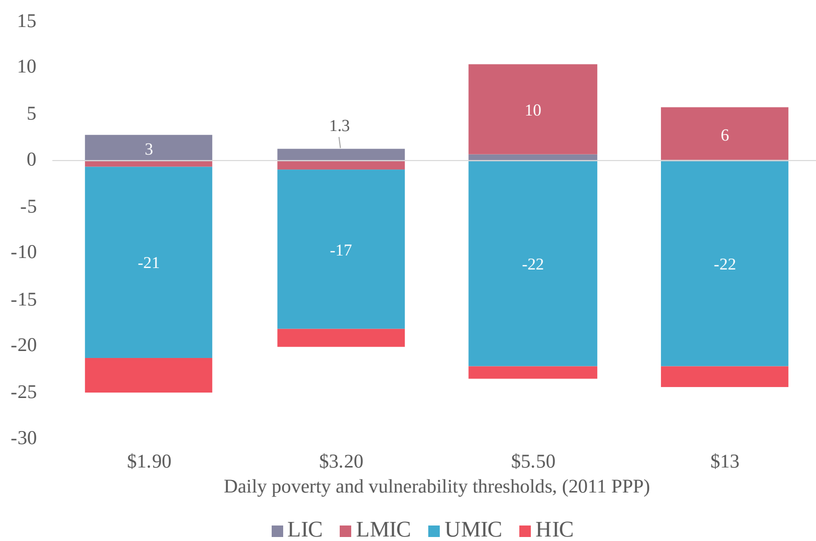
Figure 13. Poverty changes and mitigation effect after the pandemic-induced shock and actual income support in the sample of 41 countries, 2020



Source: Authors' calculations. ***Notes***: The figures in panel a correspond to the changes in poverty after accounting for the pandemic-induced shock and the delivery of income support. The figures in panel b are the corresponding sums of additional poverty reduction (panel a) and the mitigated increases in poverty (those in Figure 12). For the $1.90-a-day threshold, for instance, the figure of -37 million people in panel b results from the sum of the mitigated increase of 15 million people (Figure 12) and additional poverty reduction impact of 22 million people (panel a). Due to rounding, some totals may not correspond with the sum of the separate figures.

Yet, this potential effect of mitigating the aggregate increase in poverty in the whole sample is driven by a few countries where income support was or was planned to be so generous that it further lifted a significant share of their population out of poverty, at least temporarily, thus likely mitigating the poverty increases in countries where transfers were smaller. Indeed, looking at the absolute distribution of changes in poverty, Figure 14 reveals that, while the number of people below each threshold is significantly reduced in the UMIC and HIC in the sample, it potentially increased among the LIC and LMIC in the sample, even after the delivery of income support. Among the LIC, poverty at $1.90 and $3.20 a day increased by about 3 million and 1.3 million people, respectively, whereas among LMIC, poverty at $5.50 a day increased by 10 million people.

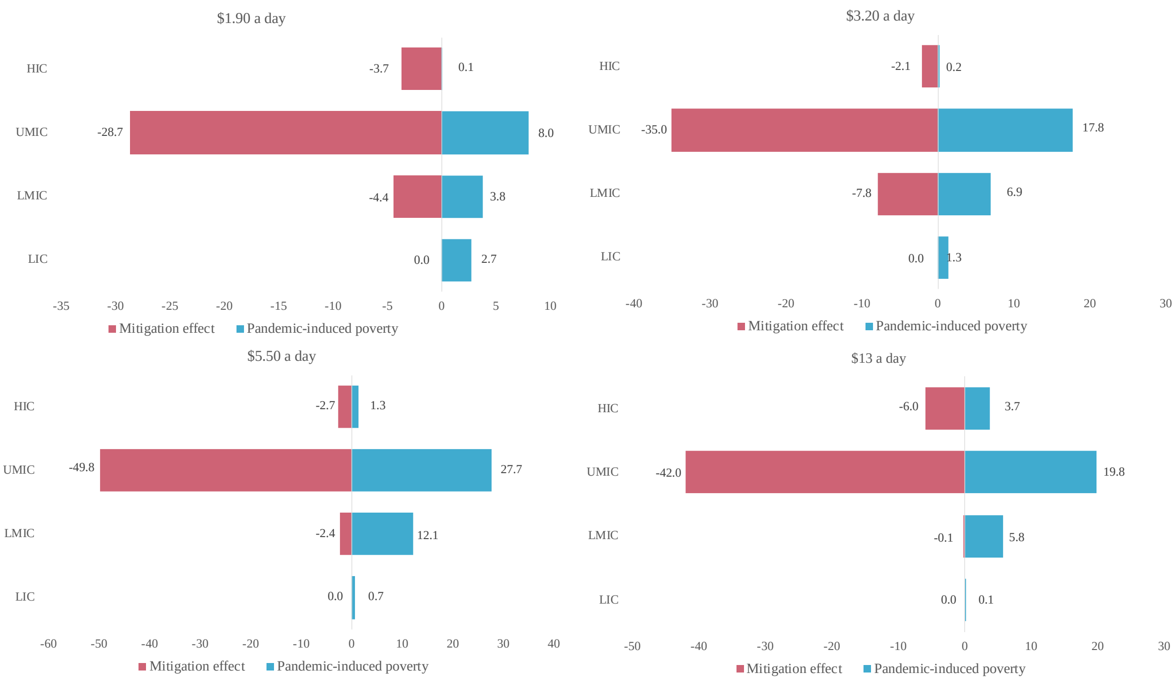
Figure 14. Absolute distribution of the changes in poverty and vulnerability after the pandemic-induced shock and actual income support in the sample of 41 countries (million people), 2020



Source: Authors' calculations. ***Notes***: The differences between the positive and negative figures in each bar yield the results presented in Figure 13, panel a. LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income.

Furthermore, a breakdown of the changes in the number of people below the poverty thresholds after the shock and income support reveals that cash assistance in LIC was likely insufficient to mitigate the increase in poverty at any poverty line (Figure 15). Cash relief among LMIC, on the other hand, possibly prevented all the pandemic-induced increases in extreme poverty and poverty at $3.20 a day, although it was less effective at the higher poverty line of $5.50 a day. The generosity and poverty-reducing effect of planned or implemented cash assistance in UMIC is notable: it appeared to have mitigated all the pandemic-induced increase in poverty by more than twice, regardless of the poverty line. The same is true for HIC, although the increase in poverty they experienced during the pandemic is of a much smaller magnitude than that in UMIC.

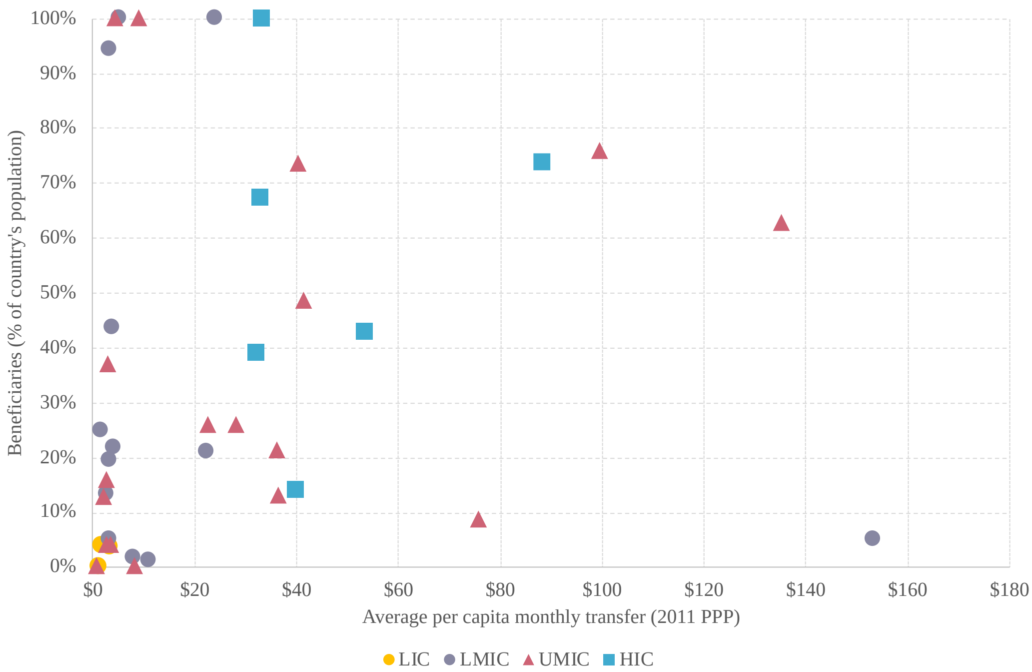
Figure 15. Breakdown of the changes in poverty after the pandemic-induced shock and actual income support in the sample of 41 countries (million people), 2020



Source: Authors' calculations. ***Notes***: LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income.

The impressive results of potential poverty reduction for the aggregate of the sample (see Figure 13) are not surprising given the magnitude of the planned or implemented cash assistance. The population who benefited from the transfers, directly and indirectly, amounts to almost 835 million people, equivalent to 43 percent of the population in the sample. Moreover, the monthly per capita transfer averaged $64 (2011 PPP), which is more than the monthly equivalent of the $1.90-a-day poverty line ($57.8). Nonetheless, there is substantial heterogeneity in the size and coverage of cash support across countries (Figure 16)—and even within income groups, except for LIC where transfers are distinctively minimal.

Figure 16. Transfer generosity and coverage of actual income support in the sample of 41 countries, 2020



Source: Authors' elaboration. ***Notes***: The figures correspond to the average monthly transfer (2011 PPP) in each country and the total number of beneficiaries of cash assistance as a percentage of each country's population. The data for Israel (average of $420 and universal coverage) is omitted for visual purposes. LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income.

Some emergency cash assistance schemes that were actually implemented and offered generous transfers to a substantial share of the population might be thus responsible, to a large extent, for the magnitude of potential mitigation of poverty increases and further poverty reduction (at least in the sample analysed). The furthest-reaching cash relief programme implemented in the sample was undertaken by Israel, with a universal transfer of $402 per month. Universal and quasi-universal schemes, although comprising less generous amounts (under $33 per month, i.e., less than the monthly equivalent of the $1.90-a-day poverty line), were also implemented in Korea (Republic of) and in middle-income countries such as Tuvalu, Timor-Leste, Mongolia, Iran (Islamic Republic of) and Bolivia. In addition to Israel, only three countries in the sample (Brazil, Argentina and the United States) actually delivered transfers that guaranteed a temporary income of at least the value of the extreme poverty line and engaged in broad coverage, reaching between 60 percent and 80 percent of their total population.

Other countries' implemented programmes were more modest in terms of their coverage and generosity but still managed to likely mitigate most of the pandemic-induced increase in poverty. For instance, transfers in South Africa averaged $40 per month and reached three-fourths of the population, which was enough to mitigate the increases in poverty at $1.90 and $3.20 a day and about one-fifth of the increase at $5.50 a day.

Similarly, Chile delivered a relatively modest transfer of $53 per month for about 43 of the population, but it contributed to mitigating, at least temporarily, all the poverty increases caused by the pandemic at all thresholds, except for the $13 vulnerability line, for which it prevented only about 31 percent of the increase. Interventions in other countries were significantly narrower in scope, although they worked well to potentially mitigate increases in poverty. For instance, Colombia, Panama and the Dominican Republic benefited less than half of their populations with monthly transfers of around $30, and this was enough to temporarily mitigate all poverty increases at $1.90 and $3.20 a day, and even a sizeable share of the increase at $5.50 a day. Finally, although cash transfers in Algeria reached only about 5 percent of the population, they still managed to mitigate the entire increase in extreme poverty at $1.90 a day.

When contrasting the short-term mitigation effect of the actual income support vis-à-vis the TBI schemes simulated in subsection 4.1 for the sample of 41 countries, the results show a substantial variation across both countries and poverty lines. Table 2 compares the magnitudes of the estimated mitigation of poverty increases and highlights the heterogeneity in fiscal constraints and the impact of the shock across countries. It shows that countries that rolled out (or planned to roll out) the most generous programmes, mostly UMIC, likely achieved a more significant magnitude of short-term mitigation and further short-term poverty reduction in comparison to what they would have achieved with the largest TBI scheme, suggesting a non-trivial investment in emergency relief. By contrast, among the LIC in the sample, both their actual income support and the most generous TBI scheme would have had virtually no impact on short-term poverty mitigation.

Table 2. Short-term poverty mitigation (and further short-term poverty reduction) with hypothetical TBI schemes and actual income support in the sample of 41 countries (million people)

		$1.90 a day			
Group	**Poverty increase**	**Poverty mitigation**			
		TBI 0.017%	TBI 0.05%	TBI 0.083%	Actual support
Income group					
Low-income (LIC)	2.7	0.0	0.0	-0.7	0.0
Lower-middle-income (LMIC)	3.8	-1.0	-7.6	-10.1	-4.4
Upper-middle-income (UMIC)	8.0	-6.3	-16.2	-22.2	-28.7
High-income [/a] (HIC)	0.1	-0.1	-0.1	-0.1	-3.7
Total in sample	**14.6**	**-7.4**	**-23.9**	**-33.1**	**-36.8**
		$3.20 a day			
Group	**Poverty increase**	**Poverty mitigation**			
		TBI 0.017%	TBI 0.05%	TBI 0.083%	Actual support
Income group					
Low-income (LIC)	1.3	0.0	0.0	0.0	0.0
Lower-middle-income (LMIC)	6.9	-1.8	-14.5	-16.9	-7.8
Upper-middle-income (UMIC)	17.8	-9.2	-20.6	-37.1	-35.0
High-income [/a] (HIC)	0.2	-0.1	-0.3	-0.4	-2.1
Total in sample	**26.3**	**-11.1**	**-35.4**	**-54.4**	**-45.0**
		$5.50 a day			
Group	**Poverty increase**	**Poverty mitigation**			
		TBI 0.017%	TBI 0.05%	TBI 0.083%	Actual support
Income group					
Low-income (LIC)	0.7	0.0	0.0	0.0	0.0
Lower-middle-income (LMIC)	12.1	-1.3	-8.0	-16.0	-2.4
Upper-middle-income (UMIC)	27.7	-8.2	-20.0	-35.4	-49.8
High-income [/a] (HIC)	1.3	-0.2	-0.7	-1.0	-2.7
Total in sample	**41.7**	**-9.6**	**-28.8**	**-52.4**	**-54.9**
		$13 a day			
Group	**Poverty increase**	**Poverty mitigation**			
		TBI 0.017%	TBI 0.05%	TBI 0.083%	Actual support
Income group					
Low-income (LIC)	0.1	0.0	0.0	0.0	0.0
Lower-middle-income (LMIC)	5.8	0.0	0.0	0.0	-0.1
Upper-middle-income (UMIC)	19.8	-0.3	-3.0	-6.9	-42.0
High-income [/a] (HIC)	3.7	0.0	-0.2	-1.0	-6.0
Total in sample	**29.3**	**-0.3**	**-3.2**	**-7.9**	**-48.1**

Source: Authors' calculations. ***Notes***: The percentages for each TBI scheme are per month, relative to countries' annual GDP in 2019 (2011 PPP). Income group: LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income. Developing regions: EAP = East Asia and Pacific; ECA = Europe and Central Asia; LAC = Latin America and the Caribbean; MNA = Middle East and North Africa; SAS = South Asia; SSA = Sub-Saharan Africa. Advanced economies as classified by the International Monetary Fund (IMF, 2021a).

While this exercise does not consider the entirety of the social protection responses implemented in these countries, it covers their largest income support schemes. In general, the results suggest that such schemes, whose targeting was based on income level or vulnerability status, likely had the potential of protecting the livelihoods of those who remain out of the scope of traditional, contributory social insurance, of those who are in informal activities and of those who are self-employed or engaged in activities that were hit hardest by containment measures. Although other cash-based measures were implemented (or planned to be implemented) by some countries in the sample, they were excluded from the exercise because their targeting mechanism could not be reasonably linked to the welfare distributions used in the analysis.

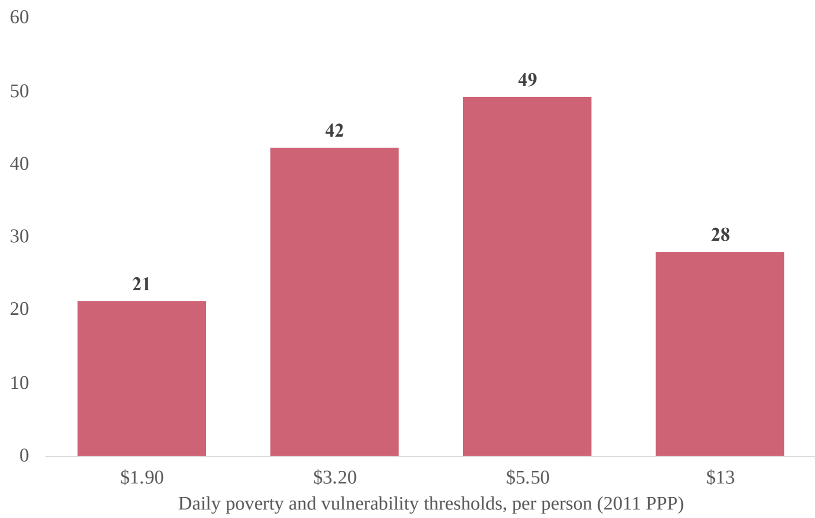
It is important to highlight that the measures included in the analysis consider only the additional social assistance that was planned or implemented as part of an emergency response during the pandemic. The size of the assistance is also conditional on a country's capacity to adapt their budget and provide a tailored response. Therefore, the estimates presented above should be interpreted as the potential effect of pandemic-induced cash assistance while holding unchanged the social protection already in place before the pandemic. Importantly, although the results offer valuable information on the potential magnitude of temporary mitigation of poverty increases from emergency cash support amid a severe health and economic crisis, they should be interpreted with caution and within those limits and should not be used to evaluate the adequacy of the overall government response in the countries under analysis. This is because the magnitude of the mitigation effect largely depends on how the income contraction was simulated; i.e., the overall income contraction and its incidence across the distribution are likely endogenous. As noted previously, with no consistent information available, the assumption of a distribution-neutral contraction is highly uncertain.

The hypothetical exercise of a stronger contraction at the bottom 60 percent of the distribution is also tested for illustrative and sensitivity purposes on the sample of 41 countries (see Box 3). In general, the results suggest that although actual income support may have mitigated a sizeable share of the poverty increases in the short term, especially in UMIC and HIC, this should not be understood as a sign of excessive spending on social protection in these countries. The pandemic caused not only income losses but substantial health costs and human development losses that could harm both the recovery of economic growth at the macro level and the income-generating capacities of households. As such, the estimates presented in this subsection can shed light only on the potential of actual income support in protecting people's livelihoods temporarily.

Box 3. Would actual income support also mitigate poverty in the short term under the hypothetical scenario of a regressive contraction?

Figure B3.1. Increases in poverty in the sample of 41 countries under a regressive contraction (million people), 2020

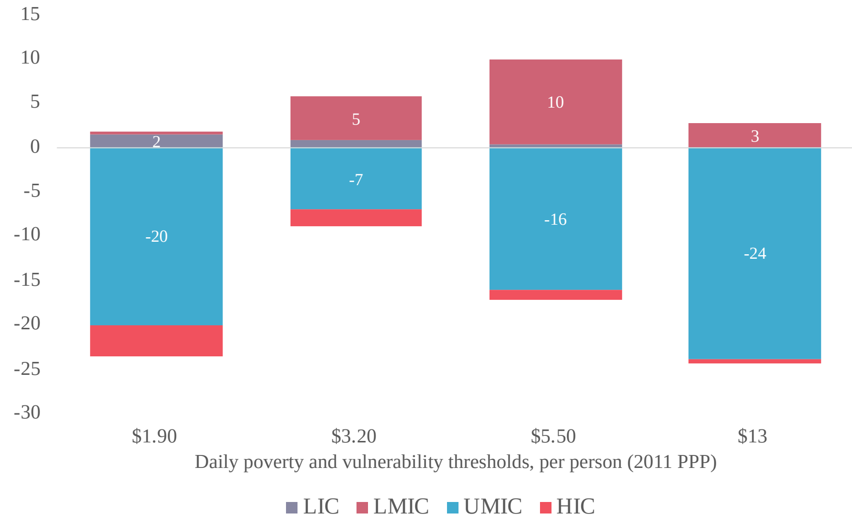
Under a stronger income contraction at the bottom 60 percent, Figure B3.1 shows that extreme poverty would have increased by 21 million people, 7 million more than in the baseline (see Figure 12 above), whereas poverty at $3.20 and $5.50 a day would have increased by 42 million and 49 million people, respectively, suggesting an additional 16 million and 7 million people above the baseline.



Source: Authors' calculations.

Figure B3.2 shows that the potential power of income support to mitigate these increases in poverty is reduced under this regressive scenario, in comparison to the distribution-neutral baseline results presented in Figure 14 above. The additional hit at the bottom 60 percent of the distribution worsens the performance of income support among LMIC considerably: While the number of people below the $3.20-a-day poverty line is estimated to have reduced in the baseline scenario on top of having mitigated the pandemic-induced increase, such a number would likely increase by 5 million people, even after income support, under a regressive contraction. In UMIC and HIC, the number of people falling below each poverty threshold is still reduced after the increase in poverty is potentially mitigated, but this occurs in a smaller magnitude than in the baseline, most notably at $3.20 and $5.50 a day. For instance, after the pandemic-induced increase in poverty at $3.20 a day, income support in UMIC could likely reduce poverty in an additional 17 million people in the baseline, while such reduction reaches only 7 million under the regressive contraction scenario.

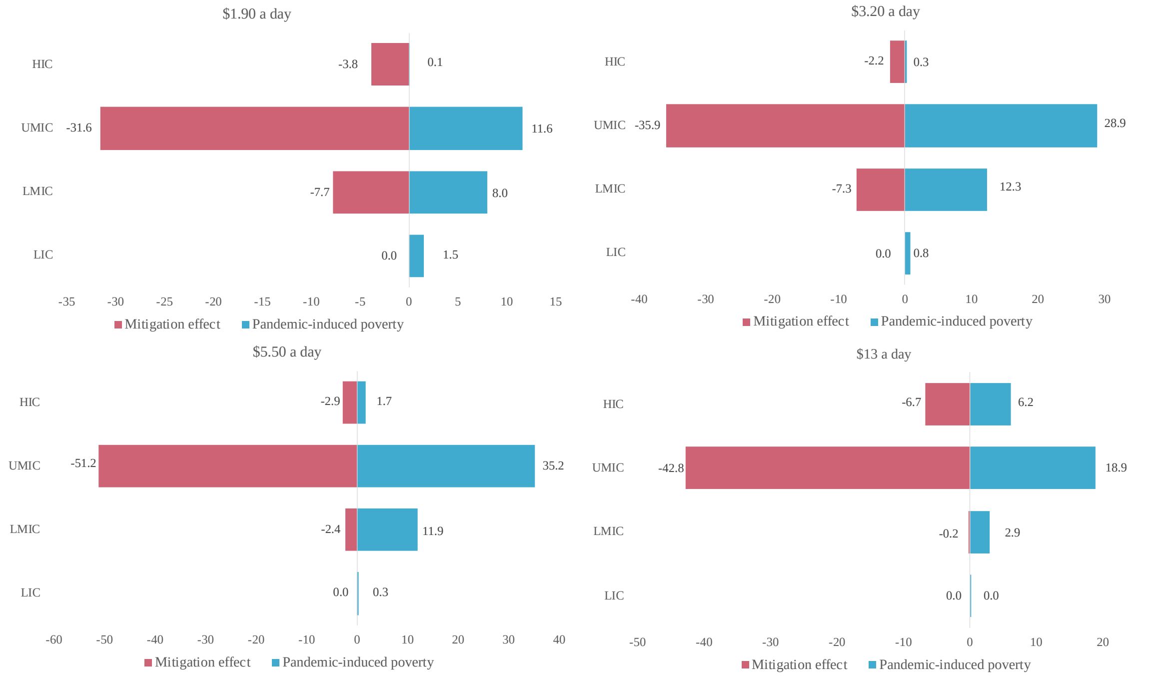
Figure B3.2. Absolute distribution of the changes in poverty after the hypothetical pandemic-induced shock of an additional 60 percent hit at the bottom and actual income support in the sample of 41 countries (million people), 2020



Source: Authors' calculations. *Notes*: LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income.

Figure B3.3 presents the breakdown of the changes in the number of people falling below each threshold, suggesting that cash assistance in LMIC in the sample may not be enough to mitigate the totality of the pandemic-induced increases in extreme poverty and poverty at $3.20 a day, although it could have been sufficient in the baseline scenario (see Figure 15 above). The magnitude of the potential mitigation of poverty-increase as a result of the generous (planned or implemented) income support in HIC and UMIC in the sample is still larger in the regressive scenario; however, such a magnitude is significantly smaller than that estimated in the baseline scenario, most notably at $3.20 a day for UMIC and $13 a day for HIC.

Figure B3.3. Breakdown of the changes in poverty after the hypothetical pandemic-induced shock of an additional 60 percent hit at the bottom after income support in the sample of 41 countries (million people), 2020



Source: Authors' calculations. *Notes*: LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income.

5. Conclusions and implications

What have we learned from these counterfactual simulations and estimates? Three results stand out from the analysis. First, policy choices potentially led to significant yet temporary poverty-mitigation effects in a subset of 41 countries that planned or implemented income support programmes. The strongest results were estimated for high- and upper-middle-income countries, and mostly for the lower-threshold poverty lines ($1.90 and $3.20 a day). While richer countries provided generous and far-reaching support, in low-income countries, income support was likely insufficient to mitigate poverty increases at any poverty line. Among lower-middle-income countries, cash assistance potentially mitigated 60 percent of new poverty at $3.20 a day, under a regressive projection, but was less effective at the $5.50-a-day poverty line, as it mitigated only 20 percent of new poverty.

This analysis has two major caveats. The first caveat relates to the temporary nature of most cash assistance and implies that the road to recovery for poor and vulnerable households is not guaranteed. In the absence of well-funded and universal social insurance and social assistance programmes, poor and vulnerable households can lapse back into situations of poverty in the future. The second caveat is fiscal: The key difference between advanced economies and low- and middle-income countries is their financial capacity to cope with the crisis. Many countries could not implement 'whatever it takes' strategies and opted, instead, to maximize the impact of their programmes under difficult budget constraints. While the analysis presented in this paper does not delve into the likely multiplier effects of the actual cash assistance provided during the pandemic, it acknowledges that income support programmes may well have had indirect effects on the economy, in addition to their direct effects on household income. With high fiscal multipliers and high productive capacity, public spending, even in the short run, increases aggregate demand, thus raising consumption and private investment, which in turn increases employment and income. Also, in terms of fiscal space, as aggregate demand rises, tax revenues increase and new opportunities to spend emerge. We argue, therefore, that the poverty-increase in low-income countries was not mitigated likely because of both low fiscal multipliers and limited fiscal space, in contrast with higher-income countries. Further country-specific evidence is yet to be provided.

A second result is borne out by the counterfactual simulations for 160 countries that indicate that an investment of 0.5 percent of developing countries' GDP, spread over six months, would have sufficed to mitigate, at least temporarily, the increase in global poverty at both $1.90 and $3.20 a day—but not equally everywhere. While the simulations illustrate the powerful effects of a quasi-universal and far-reaching policy, the poorer, hardest hit regions of the world would require additional financial effort, beyond their fiscal capacities, to compensate for the welfare losses relative to the rest of the developing countries. The simulations also illustrate the real-world constraints faced by actual social assistance programmes that face administrative and digital constraints in enrolling new benefit holders, expanding their administrative registries and setting up digital payment systems for largely invisible informal sector workers as well as unpaid care and domestic workers. This is a real-world challenge for countries around the developing world.

A third result is that the size of the pandemic was massive and threatened to push between 117 million people and 168 million people back into extreme poverty. Distributive assumptions are crucial for this reassessment. Early evidence on distributive impact suggests that the distribution of the COVID-19 shock on jobs and incomes was neither random nor neutral—it impacted the poor and vulnerable in disproportionate numbers. We will understand the true poverty and income effects only in a few years, as official poverty statistics are normally standardized with a two-year lag. An added caveat is that for some countries, we may never understand the true impact of the pandemic because of the difficulty of deploying accurate household surveys during the lockdown period itself. It is important to note that there is no simple arithmetic rule that would have mitigated the increase in poverty: The depth of income losses was idiosyncratic and left many households in negative numbers. In other words, incomes losses were higher than available income, which could only be compensated through borrowing, selling assets or deploying other income-smoothing strategies. This paper has tried to capture some of these non-trivial effects on income.

There are some additional caveats and considerations to bear in mind. First, our initial set of estimates of pandemic-induced poverty (117 million new poor people) relied on a distribution-neutral economic contraction, which we then corrected for a distribution-regressive scenario (168 million new poor people). Neutrality is unlikely, and it might well be that the incomes of some segments of the population contracted more than proportionally (e.g., workers in the non-essential services sector), whereas in other segments, incomes did not seem especially affected (e.g., workers who were able to transition to work-from-home arrangements). To begin with, distribution-neutrality is particularly restrictive for the extrapolation of the welfare distributions used in the analysis, from the actual year of survey data collection to 2019 (see section 3). Although most household surveys are relatively recent (67 of the 160 surveys are for 2018 and 2019, while 114 are for the period 2015-2019), the assumption that inequality has remained unchanged over time within countries is, at least, highly uncertain. Second, for the simulation exercise, the cost of TBI schemes is assumed to be equivalent to a proportion of a country's GDP but ignores issues related to institutional capacity in implementation or delivery, and whether the population has access to bank or mobile money accounts. Third, for the estimation of the mitigation effects on poverty increases of actual social assistance programmes, the analysis assumes that the targeting of such programmes is solely based on relative income. A more careful calculation would require detailed household and individual information for each country to fully account for other characteristics of beneficiaries. Fourth, the effects estimated in this paper are likely short-lasting, and it is unclear whether poverty will revert to its pre-pandemic levels once the crisis has subsided. Finally, the only dimension of poverty considered in this study is monetary. Potential effects of social assistance and protection measures on multidimensional poverty are yet to be uncovered.

What are the key implications looking forward? A first implication is empirical. As more actual data becomes available, researchers will be able to dive deeper into actual cases and also discern more counterfactual simulations across the distribution. If anything, we have learned that the impacts of large-scale shocks are not bound by the arbitrary thresholds used to measure poverty or well-being. We need to understand how shocks affect the full distribution of income, above and beyond $1.90 a day or even $13 a day, as well as across other human development metrics. The links to future research on climate change mitigation and adaptation are evident. Some of the most difficult development problems for a carbon-neutral transition are distributive. There is much to learn from this historic—but probably not unique—set of shocks.

A second implication is policy-oriented, with effects on labour markets and social protection systems. This paper's opening question asks: What difference did income support make? The unqualified answer is 'a big difference'. By both TBI counterfactual simulation and measured impact of actual cash assistance, income support policies that extended vertically (with higher payments) and horizontally (to more people) likely mitigated poverty increases across various poverty lines—and were most effective at the bottom of the distribution. Looking forward, countries face choices on how to move beyond temporary income support programmes: They can either strengthen existing social insurance or social assistance programmes or extend their policy ambition to universal basic income policies or universal job guarantees. Most countries will supplement their existing social protection programmes with state-contingent social insurance, thus adding a counter-cyclical mechanism to a typical life-cycle welfare system.

Policy choices mattered during the COVID-19 pandemic. Although we still need to unearth the unexpected effects and quantify the welfare impacts on poor and vulnerable households more precisely, temporary income support schemes mitigated poverty increases; looking forward, social protection systems will need to evolve to incorporate these lessons into a robust and successful policy response.

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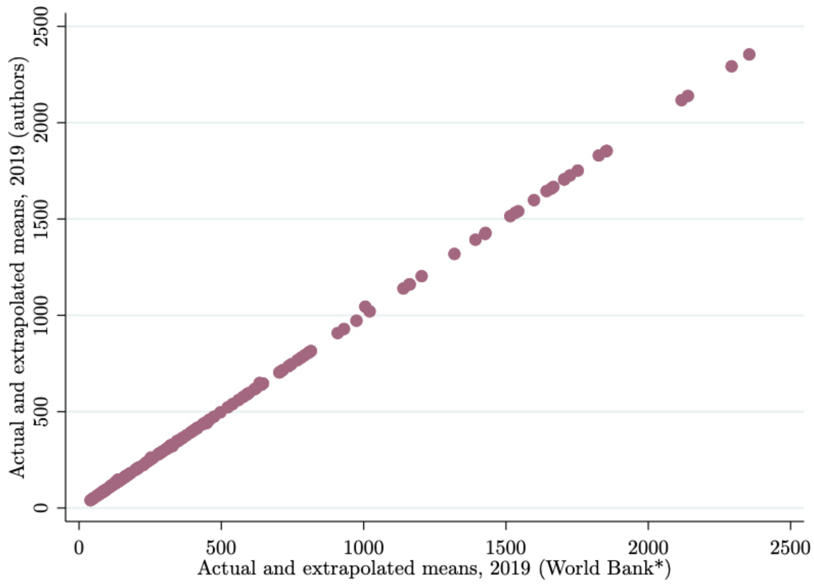
Appendix

A. Extrapolated welfare distributions

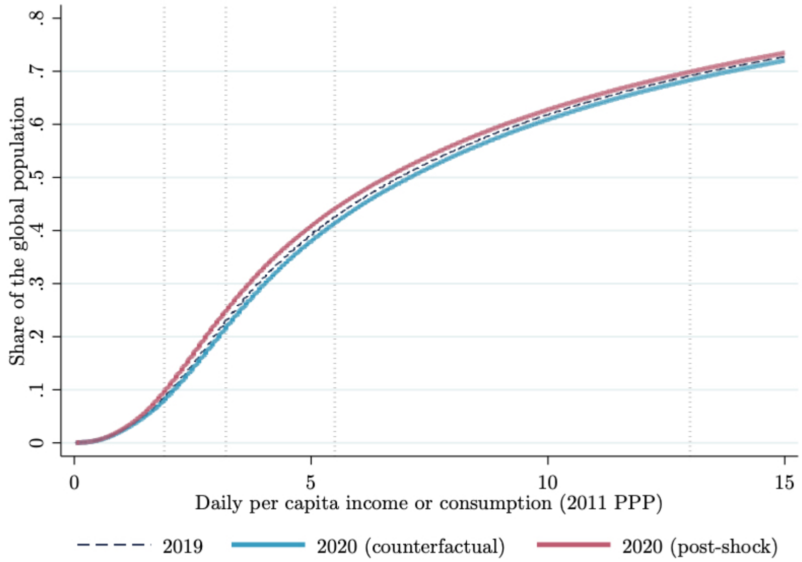
Figure A1. Comparison of actual and extrapolated survey means of per capita income or consumption (monthly $, 2011 PPP), 2019



Source: Authors' calculations based on World Bank, PovcalNet (March 2021 global poverty update). ***Notes***: * Downloaded from PovcalNet under the heading "Download economies table".

The distribution lined up to 2019 at a global scale, after pooling together the 160 countries' extrapolated distributions, is plotted as a dashed curve in Figure A2, which shows the daily per capita income or consumption on the horizontal axis and the cumulative share of the global population on the vertical axis. The figure also includes four vertical dotted lines indicating the values of the poverty and vulnerability lines, i.e., starting from the left-hand side, $1.90, $3.20, $5.50 and $13 a day. This figure also plots the two projected distributions in 2020 pooled together at a global scale. The fact that they lie entirely below (counterfactual) and above (post-shock) the distribution lined up to 2019 is the result of projecting per capita welfare to, respectively, an expansion or a contraction, while assuming no changes in inequality between 2019 and 2020. The location of the curves also indicates that the share of the population living below each poverty line in 2020 would have reduced (counterfactual) or increased (post-shock) relative to 2019.

Figure A2. Empirical distribution functions of welfare, 2019 and 2020



Source: Authors' calculations. ***Notes***: The distributions are capped at $15 for visual purposes.

B. Countries for which the welfare distribution was retrieved

Country	Income group	Developing region	Welfare measure	Survey year
Developing countries				
Albania	UMIC	ECA	Consumption	2017
Algeria	LMIC	MNA	Consumption	2011
Angola	LMIC	SSA	Consumption	2018
Argentina	UMIC	LAC	Income	2019
Armenia	UMIC	ECA	Consumption	2019
Azerbaijan	UMIC	ECA	Consumption	2005
Bangladesh	LMIC	SAS	Consumption	2016
Belarus	UMIC	ECA	Consumption	2019
Belize	UMIC	LAC	Income	1999
Benin	LMIC	SSA	Consumption	2015
Bhutan	LMIC	SAS	Consumption	2017
Bolivia	LMIC	LAC	Income	2019
Bosnia and Herzegovina	UMIC	ECA	Consumption	2011
Botswana	UMIC	SSA	Consumption	2016
Brazil	UMIC	LAC	Income	2019
Bulgaria	UMIC	ECA	Income	2018
Burkina Faso	LIC	SSA	Consumption	2014
Burundi	LIC	SSA	Consumption	2014
Cabo Verde	LMIC	SSA	Consumption	2015
Cameroon	LMIC	SSA	Consumption	2014
Central African Republic	LIC	SSA	Consumption	2008
Chad	LIC	SSA	Consumption	2011
Chile	HIC	LAC	Income	2017
China	UMIC	EAP	Consumption	2016
Colombia	UMIC	LAC	Income	2019
Comoros	LMIC	SSA	Consumption	2014
Congo, Democratic Republic of	LIC	SSA	Consumption	2012
Congo, Republic of	LMIC	SSA	Consumption	2011
Costa Rica	UMIC	LAC	Income	2019
Cote d'Ivoire	LMIC	SSA	Consumption	2015
Croatia	HIC	ECA	Income	2018
Djibouti	LMIC	MNA	Consumption	2017
Dominican Republic	UMIC	LAC	Income	2019
Ecuador	UMIC	LAC	Income	2019
Egypt, Arab Republic of	LMIC	MNA	Consumption	2018
El Salvador	LMIC	LAC	Income	2019
Eswatini	LMIC	SSA	Consumption	2016
Ethiopia	LIC	SSA	Consumption	2016
Fiji	UMIC	EAP	Consumption	2013
Gabon	UMIC	SSA	Consumption	2017
Gambia, The	LIC	SSA	Consumption	2015
Georgia	UMIC	ECA	Consumption	2019
Ghana	LMIC	SSA	Consumption	2017
Guatemala	UMIC	LAC	Income	2014

B. Countries for which the welfare distribution was retrieved (cont.)

Country	Income group	Developing region	Welfare measure	Survey year
Guinea	LIC	SSA	Consumption	2012
Guyana	UMIC	LAC	Income	1998
Haiti	LIC	LAC	Consumption	2012
Honduras	LMIC	LAC	Income	2019
Hungary	HIC	ECA	Income	2018
India	LMIC	SAS	Consumption	2011
Indonesia	UMIC	EAP	Consumption	2019
Iran, Islamic Republic of	UMIC	MNA	Consumption	2018
Iraq	UMIC	MNA	Consumption	2012
Jamaica	UMIC	LAC	Consumption	2004
Jordan	UMIC	MNA	Consumption	2010
Kazakhstan	UMIC	ECA	Consumption	2018
Kenya	LMIC	SSA	Consumption	2016
Kiribati	LMIC	EAP	Consumption	2006
Kosovo	UMIC	ECA	Consumption	2017
Kyrgyz Republic	LMIC	ECA	Consumption	2019
Lao People's Democratic Republic	LMIC	EAP	Consumption	2018
Lebanon	UMIC	MNA	Consumption	2012
Lesotho	LMIC	SSA	Consumption	2017
Liberia	LIC	SSA	Consumption	2016
Madagascar	LIC	SSA	Consumption	2012
Malawi	LIC	SSA	Consumption	2016
Malaysia	UMIC	EAP	Income	2016
Maldives	UMIC	SAS	Consumption	2016
Mali	LIC	SSA	Consumption	2010
Mauritania	LMIC	SSA	Consumption	2014
Mauritius	HIC	SSA	Consumption	2017
Mexico	UMIC	LAC	Income	2018
Micronesia, Federated States of	LMIC	EAP	Consumption	2013
Moldova	LMIC	ECA	Consumption	2018
Mongolia	LMIC	EAP	Consumption	2018
Montenegro	UMIC	ECA	Income	2016
Morocco	LMIC	MNA	Consumption	2014
Mozambique	LIC	SSA	Consumption	2014
Myanmar	LMIC	EAP	Consumption	2017
Namibia	UMIC	SSA	Consumption	2015
Nepal	LMIC	SAS	Consumption	2010
Nicaragua	LMIC	LAC	Income	2014
Niger	LIC	SSA	Consumption	2014
Nigeria	LMIC	SSA	Consumption	2019
North Macedonia	UMIC	ECA	Income	2018
Pakistan	LMIC	SAS	Consumption	2019
Panama	HIC	LAC	Income	2019
Papua New Guinea	LMIC	EAP	Consumption	2010
Paraguay	UMIC	LAC	Income	2019

B. Countries for which the welfare distribution was retrieved (cont.)

Country	Income group	Developing region	Welfare measure	Survey year
Peru	UMIC	LAC	Income	2019
Philippines	LMIC	EAP	Consumption	2018
Poland	HIC	ECA	Consumption	2019
Romania	HIC	ECA	Income	2018
Russian Federation	UMIC	ECA	Consumption	2018
Rwanda	LIC	SSA	Consumption	2017
Samoa	UMIC	EAP	Consumption	2013
Sao Tome and Principe	LMIC	SSA	Consumption	2017
Senegal	LMIC	SSA	Consumption	2011
Serbia	UMIC	ECA	Consumption	2018
Seychelles	HIC	SSA	Income	2018
Sierra Leone	LIC	SSA	Consumption	2018
Solomon Islands	LMIC	EAP	Consumption	2013
South Africa	UMIC	SSA	Consumption	2015
South Sudan	LIC	SSA	Consumption	2017
Sri Lanka	LMIC	SAS	Consumption	2016
St. Lucia	UMIC	LAC	Income	2016
Sudan	LIC	SSA	Consumption	2014
Tajikistan	LIC	ECA	Consumption	2015
Tanzania	LMIC	SSA	Consumption	2018
Thailand	UMIC	EAP	Consumption	2019
Timor-Leste	LMIC	EAP	Consumption	2014
Togo	LIC	SSA	Consumption	2015
Tonga	UMIC	EAP	Consumption	2015
Trinidad and Tobago	HIC	LAC	Income	1992
Tunisia	LMIC	MNA	Consumption	2015
Turkey	UMIC	ECA	Consumption	2019
Turkmenistan	UMIC	ECA	Consumption	1998
Tuvalu	UMIC	EAP	Consumption	2010
Uganda	LIC	SSA	Consumption	2017
Ukraine	LMIC	ECA	Consumption	2019
Uruguay	HIC	LAC	Income	2019
Uzbekistan	LMIC	ECA	Consumption	2003
Vanuatu	LMIC	EAP	Consumption	2010
Vietnam	LMIC	EAP	Consumption	2018
West Bank and Gaza	LMIC	MNA	Consumption	2017
Yemen, Republic of	LIC	MNA	Consumption	2014
Zambia	LMIC	SSA	Consumption	2015
Zimbabwe	LMIC	SSA	Consumption	2019
Advanced economies				
Australia	HIC		Income	2014
Austria	HIC		Income	2018
Belgium	HIC		Income	2018
Canada	HIC		Income	2017
Cyprus	HIC		Income	2018

B. Countries for which the welfare distribution was retrieved (cont.)

Country	Income group	Developing region	Welfare measure	Survey year
Czech Republic	HIC		Income	2018
Denmark	HIC		Income	2018
Estonia	HIC		Income	2018
Finland	HIC		Income	2018
France	HIC		Income	2018
Germany	HIC		Income	2016
Greece	HIC		Income	2018
Iceland	HIC		Income	2017
Ireland	HIC		Income	2017
Israel	HIC		Income	2016
Italy	HIC		Income	2017
Japan	HIC		Income	2013
Korea, Republic of	HIC		Income	2016
Latvia	HIC		Income	2018
Lithuania	HIC		Income	2018
Luxembourg	HIC		Income	2018
Malta	HIC		Income	2018
Netherlands	HIC		Income	2018
Norway	HIC		Income	2018
Portugal	HIC		Income	2018
Slovak Republic	HIC		Income	2018
Slovenia	HIC		Income	2018
Spain	HIC		Income	2018
Sweden	HIC		Income	2018
Switzerland	HIC		Income	2018
United Kingdom	HIC		Income	2017
United States	HIC		Income	2018
Mean year				**2015**
Median year				**2017**

Notes: Income group: LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income. Developing regions: EAP = East Asia and Pacific; ECA = Europe and Central Asia; LAC = Latin America and the Caribbean; MNA = Middle East and North Africa; SAS = South Asia; SSA = Sub-Saharan Africa. Advanced economies as classified by the International Monetary Fund (IMF 2021a).

C. List of countries included in the simulation of actual income support in Section 4

Country	Income group	Developing region
Developing countries		
Algeria	LMIC	MNA
Angola	LMIC	SSA
Argentina	UMIC	LAC
Bolivia	LMIC	LAC
Brazil	UMIC	LAC
Cabo Verde	LMIC	SSA
Chile	HIC	LAC
Colombia	UMIC	LAC
Congo, Republic of	LMIC	SSA
Costa Rica	UMIC	LAC
Dominican Republic	UMIC	LAC
Ecuador	UMIC	LAC
Fiji	UMIC	EAP
Honduras	LMIC	LAC
Indonesia	UMIC	EAP
Iran, Islamic Republic of	UMIC	MNA
Iraq	UMIC	MNA
Jamaica	UMIC	LAC
Jordan	UMIC	MNA
Kenya	LMIC	SSA
Lebanon	UMIC	MNA
Madagascar	LIC	SSA
Malaysia	UMIC	EAP
Mongolia	LMIC	EAP
Montenegro	UMIC	ECA
Mozambique	LIC	SSA
Niger	LIC	SSA
Pakistan	LMIC	SAS
Panama	HIC	LAC
Paraguay	UMIC	LAC
South Africa	UMIC	SSA
Timor-Leste	LMIC	EAP
Tuvalu	UMIC	EAP
Uzbekistan	LMIC	ECA
Vietnam	LMIC	EAP
West Bank and Gaza	LMIC	MNA
Advanced economies		
Australia	HIC	
Israel	HIC	
Korea, Republic of	HIC	
United Kingdom	HIC	
United States	HIC	

Notes: Income group: LIC = low-income; LMIC = lower-middle-income; UMIC = upper-middle-income; HIC = high-income. Developing regions: EAP = East Asia and Pacific; ECA = Europe and Central Asia; LAC = Latin America and the Caribbean; MNA = Middle East and North Africa; SAS = South Asia; SSA = Sub-Saharan Africa. Advanced economies as classified by the International Monetary Fund (IMF, 2021a).

D.1 Poverty increase and mitigation effect in the sample of 160 countries had developing countries delivered a monthly TBI to 4.1 billion people equivalent to 0.083 percent of their GDP, 2020

Neutral contraction

Group	Poverty increase	TBI 0.083% Poverty mitigation	TBI 0.083% Total effect
$1.90 a day			
Income group			
Low-income (LIC)	18.4	-12.9	5.4
Lower-middle-income (LMIC)	87.9	-73.9	14.0
Upper-middle-income (UMIC)	10.1	-28.9	-18.8
High-income [/a] (HIC)	0.2	-0.7	-0.4
Total in sample	**117**	**-116**	**0.2**
$3.20 a day			
Income group			
Low-income (LIC)	11.8	-3.83	8.0
Lower-middle-income (LMIC)	166.9	-141.24	25.7
Upper-middle-income (UMIC)	26.8	-67.14	-40.4
High-income [/a] (HIC)	0.62	-1.39	-0.8
Total in sample	**206**	**-214**	**-7**
$5.50 a day			
Income group			
Low-income (LIC)	4.5	0.0	4.5
Lower-middle-income (LMIC)	138.3	-35.0	103.3
Upper-middle-income (UMIC)	53.2	-130.4	-77.2
High-income [/a] (HIC)	2.6	-3.3	-0.6
Total in sample	**199**	**-169**	**30**
$13 a day			
Income group			
Low-income (LIC)	0.6	0.0	0.6
Lower-middle-income (LMIC)	33.4	-1.1	32.3
Upper-middle-income (UMIC)	64.5	-70.0	-5.6
High-income [/a] (HIC)	11.6	-9.5	2.1
Total in sample	**110**	**-81**	**29**

Regressive contraction

Group	Poverty increase	TBI 0.083% Poverty mitigation	TBI 0.083% Total effect
$1.90 a day			
Income group			
Low-income (LIC)	16.3	-10.9	5.4
Lower-middle-income (LMIC)	136.4	-112.5	23.9
Upper-middle-income (UMIC)	14.5	-31.3	-16.8
High-income [/a] (HIC)	0.4	-0.7	-0.4
Total in sample	**168**	**-155**	**12**
$3.20 a day			
Income group			
Low-income (LIC)	9.7	-4.9	4.73
Lower-middle-income (LMIC)	252.7	-144.1	108.58
Upper-middle-income (UMIC)	41.6	-70.7	-29.04
High-income [/a] (HIC)	1.0	-1.6	-0.60
Total in sample	**305**	**-221**	**84**
$5.50 a day			
Income group			
Low-income (LIC)	0.5	0.0	0.5
Lower-middle-income (LMIC)	72.7	-73.3	-0.6
Upper-middle-income (UMIC)	67.9	-127.1	-59.2
High-income [/a] (HIC)	3.6	-3.5	0.1
Total in sample	**145**	**-204**	**-59**
$13 a day			
Income group			
Low-income (LIC)	0.2	0.0	0.2
Lower-middle-income (LMIC)	18.3	-1.1	17.2
Upper-middle-income (UMIC)	58.9	-72.6	-13.6
High-income [/a] (HIC)	18.2	-8.2	10.0
Total in sample	**96**	**-82**	**14**

Source: Authors' calculations**.**

D.2 Poverty increase and mitigation effect in the sample of 41 countries with actual income support, 2020

Neutral contraction

$1.90 a day			
Group	**Poverty increase**	**Actual income support**	
		Poverty mitigation	Total effect
Income group			
Low-income (LIC)	2.7	0.0	2.7
Lower-middle-income (LMI	3.8	-4.4	-0.6
Upper-middle-income (UMI	8.0	-28.7	-20.6
High-income [a] (HIC)	0.1	-3.7	-3.7
Total in sample	**15**	**-37**	**-22**

$3.20 a day			
Group	**Poverty increase**	**Actual income support**	
		Poverty mitigation	Total effect
Income group			
Low-income (LIC)	1.3	0.0	1.3
Lower-middle-income (LMI	6.9	-7.8	-0.9
Upper-middle-income (UMI	17.8	-35.0	-17.2
High-income [a] (HIC)	0.2	-2.1	-1.9
Total in sample	**26**	**-45**	**-19**

$5.50 a day			
Group	**Poverty increase**	**Actual income support**	
		Poverty mitigation	Total effect
Income group			
Low-income (LIC)	0.7	0.0	0.7
Lower-middle-income (LMI	12.1	-2.4	9.7
Upper-middle-income (UMI	27.7	-49.8	-22.1
High-income [a] (HIC)	1.3	-2.7	-1.4
Total in sample	**42**	**-55**	**-13**

$13 a day			
Group	**Poverty increase**	**Actual income support**	
		Poverty mitigation	Total effect
Income group			
Low-income (LIC)	0.1	0.0	0.1
Lower-middle-income (LMI	5.8	-0.1	5.6
Upper-middle-income (UMI	19.8	-42.0	-22.2
High-income [a] (HIC)	3.7	-6.0	-2.2
Total in sample	**29**	**-48**	**-19**

Regressive contraction

$1.90 a day			
Group	**Poverty increase**	**Actual income support**	
		Poverty mitigation	Total effect
Income group			
Low-income (LIC)	1.5	0.0	1.5
Lower-middle-income (LMI	8.0	-7.7	0.2
Upper-middle-income (UMI	11.6	-31.6	-20.0
High-income [a] (HIC)	0.1	-3.8	-3.7
Total in sample	**21**	**-43**	**-22**

$3.20 a day			
Group	**Poverty increase**	**Actual income support**	
		Poverty mitigation	Total effect
Income group			
Low-income (LIC)	0.8	0.0	0.8
Lower-middle-income (LMI	12.3	-7.3	5.1
Upper-middle-income (UMI	28.9	-35.9	-7.0
High-income [a] (HIC)	0.3	-2.2	-1.9
Total in sample	**42**	**-45**	**-3**

$5.50 a day			
Group	**Poverty increase**	**Actual income support**	
		Poverty mitigation	Total effect
Income group			
Low-income (LIC)	0.3	0.0	0.3
Lower-middle-income (LMI	11.9	-2.4	9.5
Upper-middle-income (UMI	35.2	-51.2	-16.1
High-income [a] (HIC)	1.7	-2.9	-1.2
Total in sample	**49**	**-57**	**-7**

$13 a day			
Group	**Poverty increase**	**Actual income support**	
		Poverty mitigation	Total effect
Income group			
Low-income (LIC)	0.0	0.0	0.0
Lower-middle-income (LMI	2.9	-0.2	2.8
Upper-middle-income (UMI	18.9	-42.8	-23.9
High-income [a] (HIC)	6.2	-6.7	-0.5
Total in sample	**28**	**-50**	**-22**

Source: Authors' calculations.