

# COVID-19 and Economic Inequality

## Short-Term Impacts with Long-Term Consequences

*Ambar Narayan*

*Alexandru Cojocaru*

*Sarthak Agrawal*

*Tom Bundervoet*

*Maria Davalos*

*Natalia Garcia*

*Christoph Lakner*

*Daniel Gerszon Mahler*

*Veronica Montalva Talledo*

*Andrey Ten*

*Nishant Yonzan*



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## Abstract

This paper examines the short-term implications of the COVID-19 pandemic for inequality in developing countries. The analysis takes advantage of high-frequency phone survey data collected by the World Bank to assess the distributional impacts of the pandemic through the channels of job and income losses, food insecurity, and children's education in the early days of the pandemic and subsequent period of economic recovery leading up to early 2021. It also introduces a methodology for estimating changes in income inequality due to the pandemic by combining data from phone surveys, pre-pandemic household surveys, and macroeconomic projections of sectoral growth rates. The paper finds that the pandemic had dis-equalizing impacts both across and within countries. Even under the assumption of distribution-neutral impacts within countries, the projected income losses are estimated to be higher in the bottom half of the global income distribution. Within countries,

disadvantaged groups were more likely to have experienced work and income losses initially and are recovering more slowly. Inequality simulations suggest an increase in the Gini index for 29 of 34 countries in the sample, with an average increase of about 1 percent. Although these short-term impacts on inequality appear to be small, they suggest that projections of global poverty and inequality impacts of COVID-19 under the assumption of distribution-neutral changes within countries are likely to underestimate actual impacts. Finally, the paper argues that the overall inequality impacts of COVID-19 could be larger over the medium-to-long term on account of a slow and uneven recovery in many developing countries, and disparities in learning losses during pandemic-related school closures, which will likely have long-lasting effects on inequality of opportunity and social mobility.

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# COVID-19 and Economic Inequality: Short-Term Impacts with Long-Term Consequences

Ambar Narayan, Alexandru Cojocaru, Sarthak Agrawal, Tom Bundervoet, Maria Davalos, Natalia Garcia, Christoph Lakner, Daniel Gerszon Mahler, Veronica Montalva Talledo, Andrey Ten, and Nishant Yonzan\*

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## 1. Introduction

The impact of the global coronavirus pandemic (COVID-19) was felt by the entire world, but not everyone was affected equally. The pandemic led to the largest global economic crisis since the Great Depression, with 95 percent of countries experiencing a contraction in output in 2020. It is estimated that the pandemic and the associated economic recession have led to an additional 97 million people in extreme poverty in 2020, resulting in the first increase in global poverty in nearly a quarter century (World Bank, 2020). This puts the Sustainable Development Goal of reducing global extreme poverty to 3 percent further out of reach. The actual impact of the pandemic on poverty may eventually be considerably more severe than this early estimate since it assumes that the pandemic has not increased inequality. For example, even a small increase (by one percentage point) in the Gini index of inequality<sup>2</sup> in every country could have increased the global poverty impact of the pandemic by around 35 percent in 2020 (Lakner et al, forthcoming).

As the pandemic is still unfolding, the degree to which its effects are dis-equalizing will not be known for some time, and they will also depend on the nature of inequalities that are being considered. For instance, Deaton (2021) shows that economic contractions, measured in terms of GDP per capita, were larger in richer countries, resulting in a reduction of unweighted between country inequality in 2020, while at the same time, in an increase in population-weighted inequality. Ferreira et al. (2021) similarly show that the mortality burden of COVID-19, in terms of the life years lost to the pandemic, are positively correlated with GDP per capita, with richer countries bearing a larger share of mortality burden. At the same time, emerging evidence from advanced economies shows that within those countries, households with lower socio-economic status and those with more precarious jobs have been more affected, in terms of job and income losses, by the restrictions aimed at containing the COVID-19 pandemic (Adams-Prassl et al., 2020; Chetty et al., 2020; Crossley et al., 2021).

Even when pandemic restrictions are disproportionately affecting jobs and incomes in low-income households, the impact on income inequality, at least in the short term, will also depend on the size and the effectiveness of the government response measures. Clark et al. (2021), based on data from five European countries, find that disposable income inequality fell between January and September of 2020, accounting for the government mitigation measures, but would have increased had those measures not been put in place. Finally, even when government response programs can mitigate short-term inequalities related to income losses, the COVID-19 pandemic can still have long-term effects related to differential losses in learning and human capital, or long-term unemployment effects.

Against this background, this paper aims to contribute to our understanding of the inequality effects of the COVID-19 pandemic by (i) extending the evidence base on the inequality impacts of the pandemic to emerging markets and developing economies (EMDEs); (ii) providing a first account of the impact of the pandemic on inequality for a large set of EMDEs; and (iii) analyzing the distributional patterns of early recovery related to the relaxation of the policy stringency measures. To address these questions, the paper pieces together empirical evidence on impact of the pandemic on inequality in EMDEs from existing pieces of research – updated in some cases with more recent data as they become available – along with evidence from past crises. To estimate the distributional impacts of COVID-19, the paper primarily draws on novel

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<sup>2</sup> This is of similar magnitude to the Great Recession increase in disposable income inequality in EU countries such as Greece, Italy, Portugal and Spain between 2010 and 2014, and considerably smaller than in countries like Bulgaria (2.2pp), Estonia (4.3pp), Cyprus (4.7pp), or Hungary (4.5pp) during the same period. (Data source: <http://appsso.eurostat.ec.europa.eu/nui/submitViewTableAction.do>)

data from the World Bank's high-frequency phone surveys (HFPS), complemented by simulations using official household surveys conducted before the pandemic.

To identify the long-term threats to inequality and social mobility, one is required to speculate, based on observable patterns in how the immediate impacts of the pandemic were distributed among households, on how the economic recovery is shaping up among households, and how the short-term impacts on children's education can affect human capital development. Simulations can be used to extrapolate how learning losses due to the pandemic pose a risk to social mobility of the current generation of children. The objective of the forward-looking simulations and extrapolations in this paper is not to predict the future. Rather, it is to identify the sources of risk of long-term inequality and quantify the potential impacts, so that the necessary policy packages can be designed and employed to prevent the risks from materializing.

As noted earlier in the introduction, the conclusions one may draw about the distributional impacts of the pandemic will depend on the types of welfare impacts and inequalities that are being considered. In this paper, we make inference on the welfare impacts by looking at distributional patterns for several indicators, including (i) job losses; (ii) income losses; (iii) food insecurity; and (iv) learning losses. This is primarily driven by the types of questions that are available in the HFPS data. Likewise, since HFPS data do not have detailed income or consumption modules that allow us to compute income or consumption deciles, we rely on data on educational attainment, area of residence, household size and types of jobs to identify households with characteristics that would commonly be more prevalent at the bottom of the income distribution, in order to assess the distributional implications of the pandemic and early recovery.

The remainder of the paper is structured as follows. Section 2 provides an overview of the existing evidence and simulations on the distributional impacts of the COVID-19 pandemic and a conceptual framework that draws out the implications for inequality of the initial impacts and of the recovery patterns. Section 3 provides details of the HFPS data that the bulk of the empirical analysis relies upon, as well as other sources of data, such as the Oxford Policy Stringency index, and data on the size and targeting of government policy response packages. Section 4 presents the main findings of the analysis of the distributional patterns of the initial impacts of the pandemic for the countries in the HFPS sample. Section 5 builds on the patterns observed in the HFPS data to present a first account of the global inequality impacts of the pandemic, based on a simulation exercise. Section 6 examines the distributional patterns associated with the early recovery by linking them to the evolution of the policy stringency measures. Section 7 concludes with some reflections on the longer-term impacts and the importance of having an equity lens for the building back better policy agenda.

## **2. How COVID-19 can amplify existing inequalities, with potential longer-term impacts**

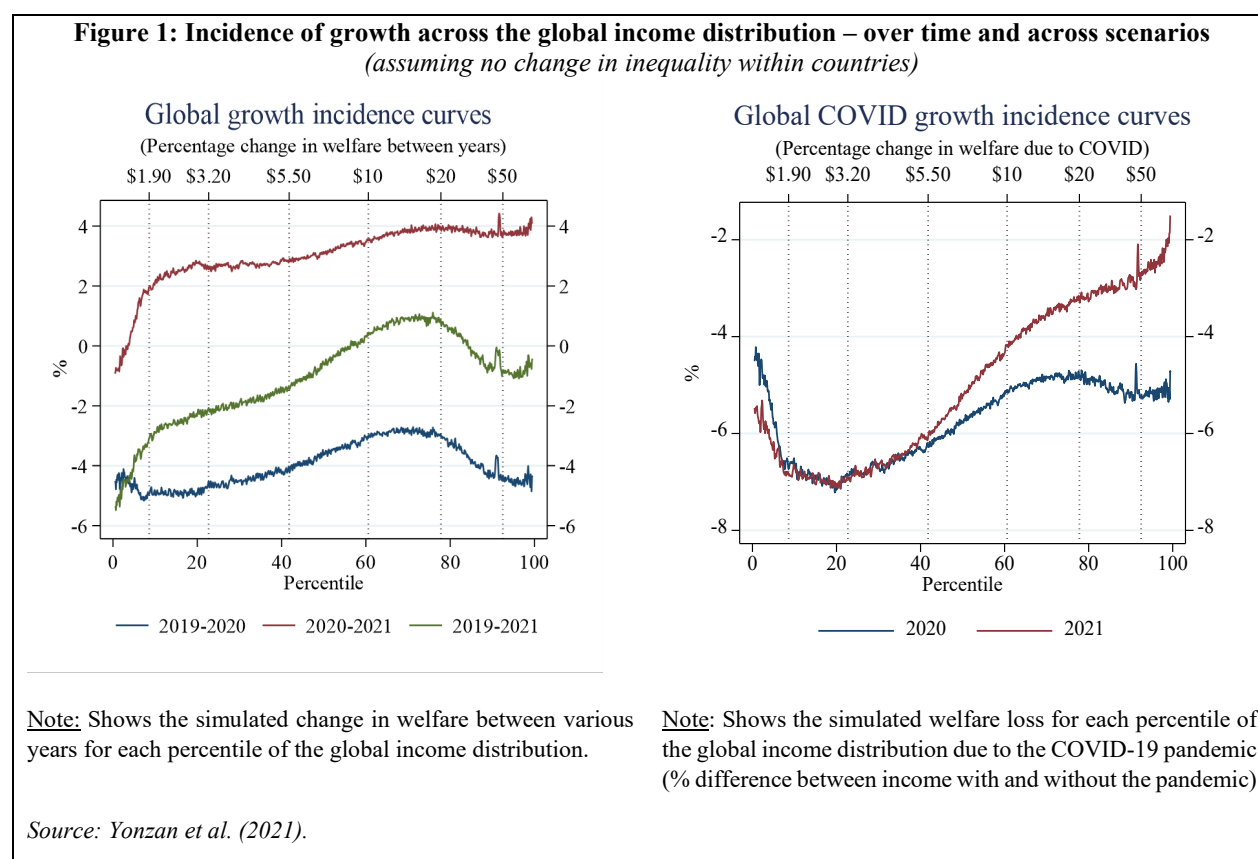
The impact of COVID-19 on the global income distribution is driven by its effects on inequality both *between* and *within* countries. On between-country inequality, simulations based on economic growth projections as well as the evidence from HFPS and other phone surveys suggests that household level socioeconomic impacts have been larger for poorer countries, widening the divide between households in rich and poor countries.

### **2.1. Impact on between-country inequality**

The incidence (or distribution) of income growth across the global income distribution can be simulated using projected GDP growth rates for countries, under the assumption of no change in inequality within countries since 2019. This assumption is necessary since income distribution within countries has not been observed in the data since the pandemic. Figure 1 shows the results based on simulations using distribution-

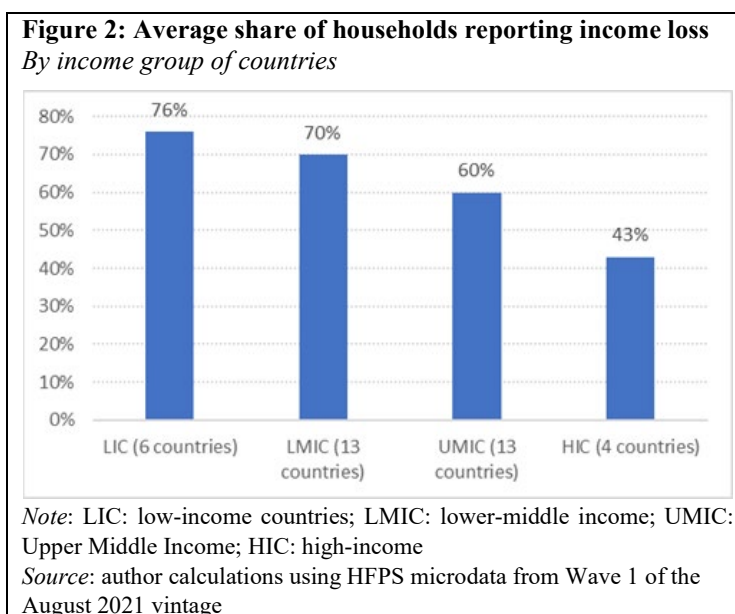
neutral GDP growth rates for all countries for 2020 and 2021. The left panel shows the effect of COVID-19 on incomes (the income difference between scenarios with and without COVID-19 for each centile of the distribution) for each year, while the right panel shows the projected change in income for each centile between different years.

Even with the assumption of no change in income distribution within countries, the growth incidence curves show projections of higher global inequality because of the pandemic, which would have led to a rise in inequality from 2019 to 2021. This is less due to the initial impact of the crisis and more due to incomes of the poorest 40 percent not recovering in 2021 while incomes of the top 60 percent are, with the largest improvements seen for the top 20 percent (Figure 1 right panel). Those with per capita income between \$1.90 and \$5.50 were hit the hardest. By 2021, average income of the top 40 percent would have almost returned to pre-COVID levels, while average income of the bottom 40 percent would be around 2 percent smaller than what it was before the pandemic (Figure 1 left panel). Notably, these distributional impacts are entirely attributable to differences in growth of (per capita) GDP across countries, given that income distribution within every country is held unchanged in the simulations.



Household level impacts measured by phone surveys find patterns across countries that are consistent with the rise in between-country inequality suggested in Figure 1. The Gallup World Poll data from 117 countries shows greater economic damage to households in low-income countries, with workers without a college degree in these countries faring the worst, even though low-income countries appear to have a much lower death toll from COVID-19 than high-income countries at the time of data collection. In the HFPS data, income losses relative to pre-pandemic income were reported by a higher share of households in low- and lower-middle income countries than in upper-middle and high-income countries (Figure 2). Poorer

countries also had higher shares of children who were unable to participate in any form of learning activities during school closures (Bundervoet et al 2021).



Data from these surveys as well as the projections in Figure 1 thus seem to present a stronger dis-equalizing effect of the COVID-19 pandemic compared to Deaton (2021), who found population-weighted between-country income inequality in 2020 to have increased only marginally. This reflects, in part, the fact that Figure 1 is based on updated growth projections that are different those available earlier, reflecting a more pessimistic outlook for EMDEs relative to advanced economies in 2021. When it comes to phone surveys on which Figure 2 is based, any direct comparison with GDP-based projections is difficult as the surveys reflect income losses reported by households as a response to a question with three categories (income loss, income gain, no change). The response is also likely to reflect the difference in availability of social programs across countries, including the massive direct transfers by rich country governments to households that developing countries have not been able to provide (see section 4.4).

### 2.1. Impact on within-country inequality

The impact on global inequality would be different from what is shown in Figure 1 if the pandemic were to affect inequality within countries. From the outset, the economic impacts of the pandemic within a country were expected to be highly correlated with differences in people's circumstances – socioeconomic factors like income, education, location, occupation, and individual attributes like age, gender and race. For instance, economic impact was expected to be higher for those who work outside of the home but are less able to work remotely. In the United States, for example, just 37 percent of jobs can be performed entirely at home, with significant variation across cities and industries (Dingell and Neiman, 2020).

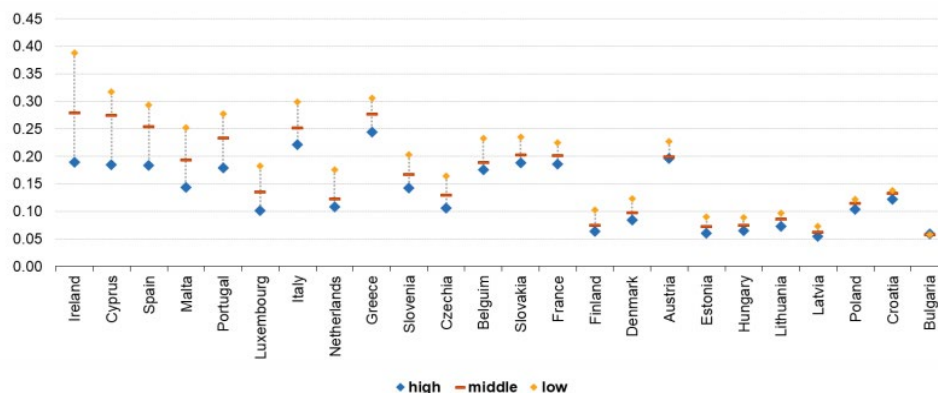
Furthermore, the ability to work remotely increases as one moves up the wage distribution, with three-quarters of employees in the top wage quintile in Europe being able to work remotely, compared to only 3 percent of those in the bottom quintile (Sostero et al., 2020). Estimates from the UK suggest that some 60 percent of tasks can be accomplished remotely by those with gross labor income above GBP 70,000, compared to 20 percent of tasks among workers with gross labor income below GBP 10,000 (Adams-Prassl et al., 2020). As a result, the scope for maintaining (or increasing) pre-pandemic levels of productivity while



working remotely is lower among low-income workers (Etheridge et al., 2020; Bartik et al., 2020). In the US, workers in high-physical-proximity jobs in urban areas experienced greater declines in employment; these workers tend to be less educated, have lower incomes, fewer liquid assets relative to income, and are more likely to be renters (Mongey et al., 2020). Bick et al. (2021), based on real-time population survey data designed to be representative of the US population, find that while roughly 8 percent of employees across all education levels worked from home every day in February 2020, in May 2020 the share among those with high education was 50 percent, compared to only 14.6 percent among those with low education; moreover, among those with low education who were working from home in before the onset of the pandemic, 40 percent were no longer employed in May 2020. Compared to only 14.8 percent of those with high education. In other words, labor demand considerations were also at play.

**Figure 3: Higher probability of temporary layoffs or reduced hours, and loss of jobs, among low income employees**

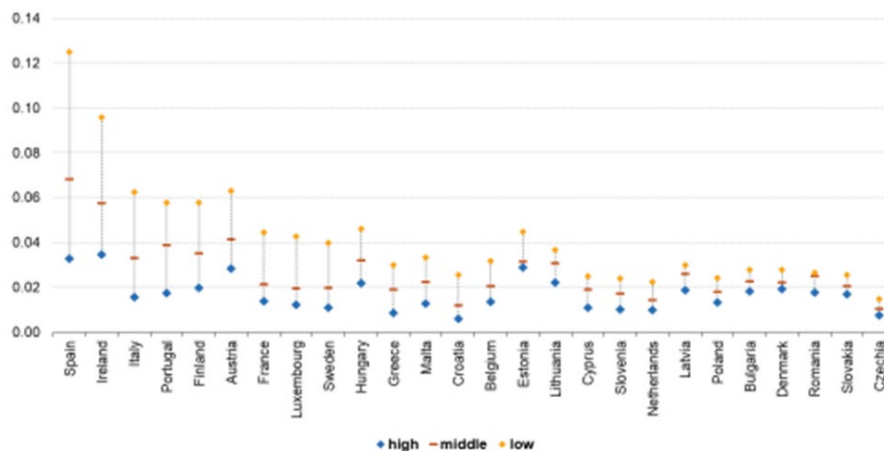
**Risk of layoff/reduced hours by income from work**  
(measured as probability from 0 to 1)



Data not available for Germany  
Source: Eurostat

eurostat

**Risk of losing job by income from work**  
(measured as probability from 0 to 1)



Data not available for Germany  
Source: Eurostat

eurostat

Source: [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=COVID-19\\_labour\\_effects\\_across\\_the\\_income\\_distribution&stable=0#A\\_more\\_in-depth\\_cross-country\\_analysis](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=COVID-19_labour_effects_across_the_income_distribution&stable=0#A_more_in-depth_cross-country_analysis)



Harmonized data from the EU Statistics on Income and Living Conditions (EU-SILC) show that in Q2 of 2020 across all EU countries for which data is available, the risk of temporary layoffs or reduced hours declines with household income. Moreover, in several countries in Southern Europe and in Ireland, the probability of employment loss is considerably higher for low-income households (Figure 3). Chetty et al (2020) similarly find that employment loss between January and April 2020 decreased monotonically with income, from 37 percent in the bottom wage quartile to 14 percent in the top wage quartile.

The within-country socio-economic disparities in access to remote work is mirrored by patterns across countries, with richer countries more likely to have a higher share of urban jobs that can be performed from home (Hatayama *et al.*, 2020). This is largely because the share of self-employed workers, whose occupations are less conducive to working from home, tends to be large in poor countries (Gottlieb *et al.*, 2020). Jobs in poor countries tend to be more intensive in physical/manual tasks, less intensive in ICT use, and workers do not always have as good internet connectivity at home (Hatayama *et al.*, 2020). This means that urban areas in poorer countries were likely to be harder hit by lockdown policies and aversion behavior.

The impact of the shock is likely to have amplified some of the pre-existing inequalities within countries. The differences in losses across socio-economic groups are driven at least to some extent by structural inequalities in the labor market – in terms of how jobs before the pandemic were distributed by type among individuals with different circumstances. Crises tend to have a larger impact on households that have lower access to markets, capital, and basic services.<sup>3</sup> This implies that all other things being equal, crises would have larger distributional impacts in economies with greater pre-existing inequality of opportunities – in access to basic services, and to jobs, markets, and capital – that are also drivers of high income inequality. There is some evidence for this from the Gallup World Poll data: the socio-economic gap in job losses (difference in job-loss rate between those with college education and those without) due to COVID-19 tends to be significantly lower for countries with lower income inequality before the pandemic (Rothwell, 2021).

To what extent a shock widens pre-existing inequalities depends on who is exposed to the shock, to what extent, and for how long.<sup>4</sup> In the case of COVID-19, exposure to the economic risks has been disproportionately high among certain groups, relative to others. The distribution of impacts also depends on the adequacy (or lack thereof) of policies that support those who are affected, and how they might have adjusted their behavior to cope with the shock. Certain factors could alleviate the dis-equalizing effects in the short-run. In low-income countries, income inequality may be dampened by the initial impacts being lower on the poorest (who are often in rural areas and in agriculture in developing countries, which tend to be less affected by restrictions on economic activity) than among the less poor (who are employed in urban services and manufacturing). In middle-income countries, the moderating effect might come from social assistance provided by the government to temporarily replace incomes of poorer households. While the net short-term impact on income inequality is uncertain and varies widely across countries, simulations by the International Monetary Fund (IMF) estimated an increase in inequality across EMDEs by an average of 2.6 percentage points as a result of the crisis (IMF, 2020).

The short-term dis-equalizing effects could in turn lead to a more unequal recovery process, with worse implications for inequality of opportunities over time. As disadvantaged groups suffer larger, longer-lasting shocks, they are also more likely to adopt coping mechanisms (such as running down their savings and selling assets) that are harmful to their future economic prospects. Learning losses caused by education

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<sup>3</sup> Dercon, 2004; Lybbert et al., 2004; Thirumurthy et al., 2008; Hill and Porter, 2016.

<sup>4</sup> For example, the financial crisis of 2008 often affected workers in the manufacturing sector the most in some middle-income countries, whereas the poorest tend to be in rural areas, which meant that inequality did not increase appreciably in these countries.

disruptions can be another source of longer-term impacts on inequality. A recent study estimates in a sample of 157 countries that COVID-19 could lead to a loss of between 0.3 and 0.9 years of schooling adjusted for quality (Azevedo et al 2020). When such losses occur disproportionately among children from vulnerable social groups, such as households with lower education levels and in rural areas, this can affect the accumulation of human and physical capital, reducing socioeconomic mobility across generations and cause disparities in inequality and wealth to persist and even widen over time. Neidhoefer et al (2021) simulate the effects of school closures and other lockdown policies on intergenerational persistence of education in 17 Latin American countries and find likely adverse impacts. In particular, the likelihood of children from low educated families to attain a secondary schooling degree could fall substantially.

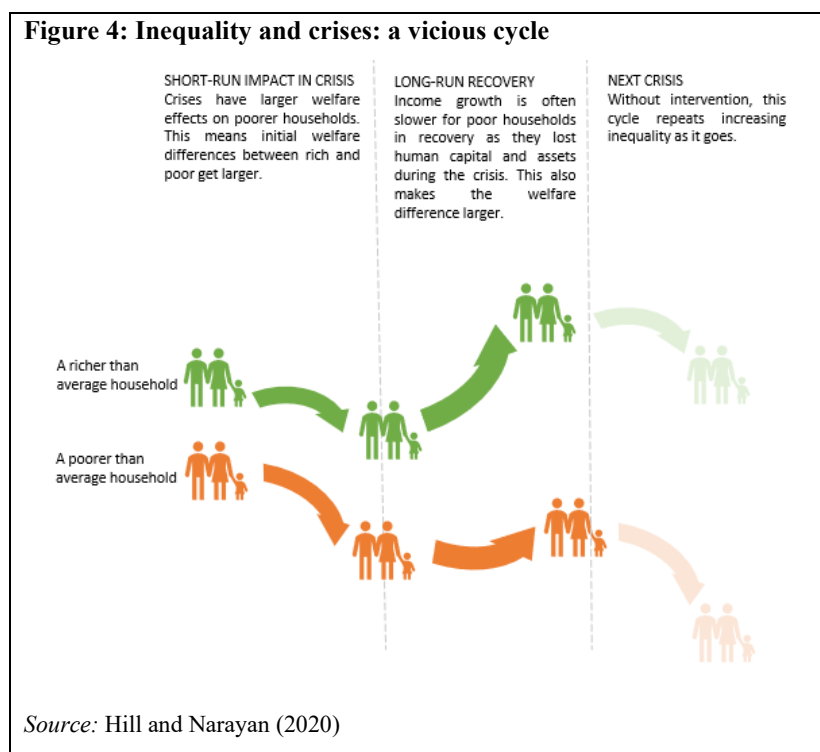


Figure 4 provides an illustration of the vicious cycle of inequality and crises showing how pre-existing inequalities can result in unequal impacts of the crisis, which can, in turn, lead to disparities in recovery and increase further the vulnerability of disadvantaged groups to future crises.

### 3. Description of data and caveats

Since in-person data collection efforts, including official surveys conducted by national statistical offices, were suspended in most countries at the onset of the pandemic, phone surveys are often the only source of observational data on the pandemic's impacts on people and firms. The HFPS data used extensively in this paper is the product of an unprecedented effort undertaken by the World Bank – in over 100 developing countries, sometimes in partnership with official statistical agencies and development partners – to monitor the socioeconomic impacts of COVID-19 on households and individuals. As the questionnaires were adjusted to fit individual country contexts, the data needed to be harmonized to make them comparable across countries. This resulted in a database of key harmonized indicators that are visualized in a publicly

available interactive dashboard.<sup>5</sup> The dashboard and its underlying microdata, henceforth referred as the harmonized HFPS data, is the basis for much of the evidence presented in this paper. The paper draws on the findings of several recent publications, some of which are updated with additional data and/or complemented with additional analysis of harmonized HFPS data.

Since phone surveys like the HFPS cannot collect reliable data on income or consumption, the analysis relies on proxy indicators, such as self-reported job or income losses, missed meals (as a proxy for food insecurity), and so on. While the HFPS are designed to be nationally representative (using reweighting methods to adjust for differential response rates among subgroups of the population), several limitations arise because of the inherent nature of phone surveys in developing country setting.<sup>6</sup> Three sources of potential inaccuracies are particularly important. First, groups with limited network coverage or no access to phones, who are also likely to be among the poorest, are likely to be under-represented in the sample – a bias that may not be fully corrected by sample re-weighting that can be only done using observable characteristics of households. Second, individual level indicators, such as employment and unemployment, are likely to have been overestimated in the HFPS relative to the full population, since the respondents to phone surveys were household heads in most countries, who are more likely to be male and older (and if a woman, more likely to be working than the general population of women in a country).<sup>7</sup> Third, the share of missing values in indicators of interests is at times quite high, and regularly higher than in household surveys. Since the reweighting has not factored variable-specific missing values into account, if indicator values are not missing at random, estimates may be biased.

These biases suggest the need for caution in interpreting the findings from HFPS data. In particular, direct comparisons between employment and labor force participation rates in HFPS with those obtained from conventional surveys can be problematic. However, the caveats are less of a concern when it comes to tracking indicators like job and income losses over time among those who were working before the pandemic and comparing these losses across different population groups. Using evidence from five countries, Kugler et al (2021) show that the bias is of similar magnitude across gender, education, and urban/rural groups, meaning that HFPS data does give accurate picture of group disparities in employment rates following the onset of the pandemic. Thus, for all its flaws, HFPS data is a valuable source for identifying and measuring inequalities in the socioeconomic impact of the pandemic on households.

#### **4. Short-term impacts on inequality – what we know from phone survey data**

In addition to widening gaps in well-being across countries (see Section 2 above), the pandemic might have affected global inequality through its short-term impact on within-country inequality in developing countries. To understand the distribution of economic impacts within countries in the first three months of the pandemic, we present evidence below on the distribution of job and income losses, food insecurity, and continued learning, based on harmonized HFPS data from 52 developing countries and up to 47,000 respondents. The findings are based on an update of earlier work by Bundervoet et al (2021), which was

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<sup>5</sup> <https://www.worldbank.org/en/data/interactive/2020/11/11/covid-19-high-frequency-monitoring-dashboard>. The dashboard currently includes 126 indicators covering 15 topics for 64 countries, with multiple rounds of data for some countries.

<sup>6</sup> See Bundervoet et al (2021) and Kugler et al (2021) for detailed discussions.

<sup>7</sup> The respondents were household heads in all countries where the phone surveys were sampled from a nationally-representative pre-pandemic survey.

based on a smaller sample of 34 countries, complemented by select findings from a few other studies.<sup>8</sup> We consider four primary outcome variables, defined below, on which the impacts of the pandemic are measured. The number of countries for which that outcome variable is available is in parentheses, since all variables are not available for every country.

- *Work stoppage or job loss*: The share of respondents who stopped working during the pandemic out of those who were working pre-pandemic (46 countries).
- *Income loss*: The share of respondents who report a decrease in total household income compared to pre-pandemic (30 countries).
- *Food insecurity*: The share of households in which at least one adult went without eating for a whole day due to lack of resources (37 countries).<sup>9</sup>
- *Continued learning*: Share of households with children in school prior to the pandemic who reported their children engaging in any learning activity during pandemic-induced school closures (38 countries)

#### 4.1. Inequality in job and income losses

The rate of job loss in the first three months of the pandemic (April-June 2020) was much higher among women, younger workers, and workers with lower levels of education. Taking simple averages across countries, women were 8 percentage points more likely than men to stop working in the initial phase of the crisis, and gender disparities were larger than gaps by age, education, and location (urban versus rural) (Figure 5).<sup>10</sup>

Regressions that consider the effects of all these factors taken together confirm that women and low-skilled (education of primary level or less) workers were significantly more likely to stop working relative to men and workers with college education (Figure 6a). The probability of job loss was higher for younger and older workers and lowest for prime-age workers (Figure 6b). Those working in manufacturing, commerce, and other services before the pandemic were significantly more likely to have stopped working than those in agriculture.<sup>11</sup> A greater share of urban workers lost jobs compared to rural workers, but this is the result of spatial differences in employment composition – when the effects of other factors like sector of

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<sup>8</sup> The countries included in the updated results for Bundervoet et al (2021) are from Sub-Saharan Africa (21 countries), Latin America and the Caribbean (13 countries), East Asia and the Pacific (8 countries), Middle East and North Africa (5 countries) and Europe and Central Asia (5 countries). Grouped by per capita GDP, the sample consists of 4 high-income, 12 upper-middle income, 21 lower-middle income, and 15 low-income countries. The data corresponds to the April 2021 vintage of the harmonized database. To assess the immediate impact of the crisis in a comparable way across countries, the authors select survey waves (between April and July 2020) that are no more than two months of the peak of the economic crisis, with the peak measured by Google mobility data when available or by policy index of social distancing measures, available from Oxford's "Coronavirus Government Response Tracker" (OxCGRT).

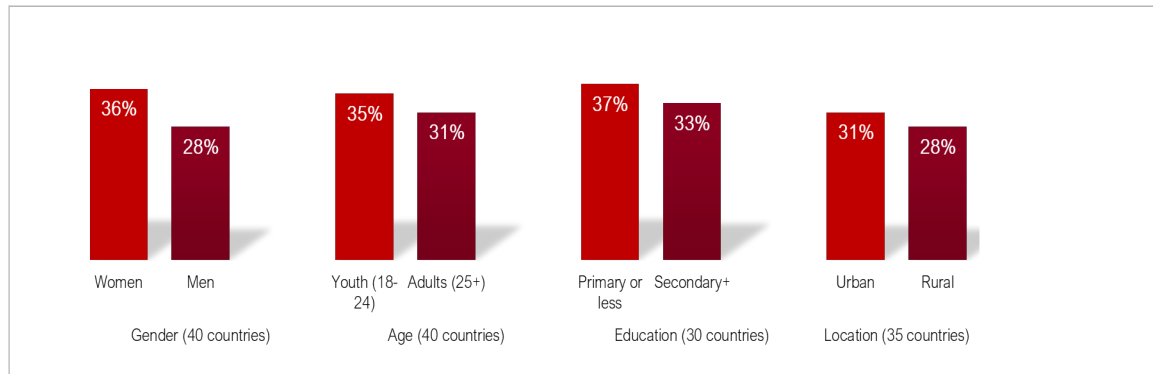
<sup>9</sup> This indicator is part of the standard Food Insecurity Experience Scale (FIES) and was included in the surveys for a subset of countries.

<sup>10</sup> Kugler et al (2021), with sample of countries that may not exactly match those used by Bundervoet et al.

<sup>11</sup> Having a school-age child in the household, which could affect labor force participation due to additional childcare responsibilities during school closures, did not significantly affect the likelihood of work stoppage. However, Cucagna and Romero (2021), using the same data source for three rounds of phone surveys in Latin American countries, find that the presence of school-age children in the household developed a greater association with loss of employment among women as the pandemic persisted, suggesting that childcare burden may affect labor force participation of women more as school closures stretched on.

employment are included in regressions, urban location of the respondent did not have a significant effect on the probability of job loss (Figure 6a).<sup>12</sup>

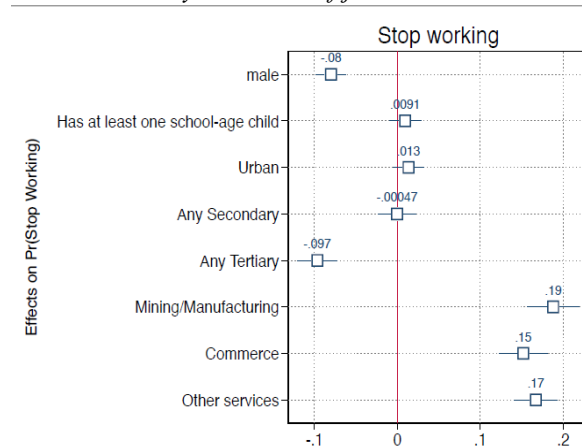
**Figure 5: Rate of work stoppage by group in first wave of phone surveys**  
(simple averages of shares across countries)



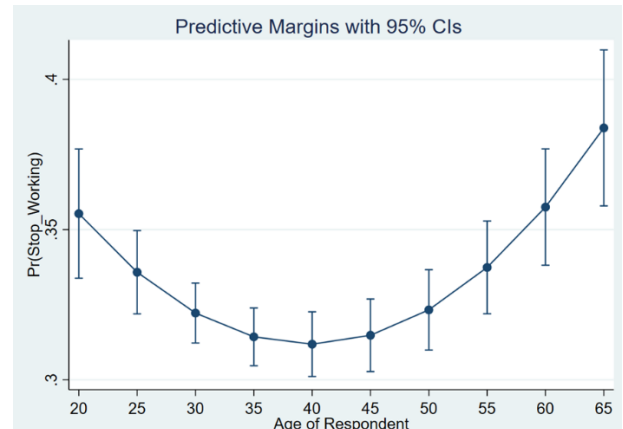
Source: Kugler et al (2021)

**Figure 6: Likelihood of work stoppage in the early aftermath of the pandemic's onset**

(a) Gender, (college) education and sector of prior work are key correlates of job losses



(b) The young and the old have higher likelihood of job losses



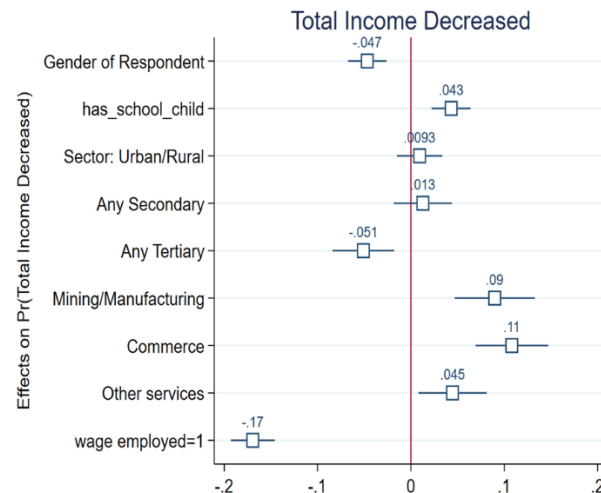
Note: Based on logistic regression of “stop working” variable (sample limited to individuals who were working before the pandemic) on several covariates and country dummies

Source: Based on Bundervoet, Garcia and Davalos (2021), updated by the authors with April 2021 version of HFPS data

<sup>12</sup> When sample selection bias (due to the fact that job losses are only observed by those who were working before, which is a non-random sample of the working age population) is corrected using a Heckman sample selection method, the effects of gender, (college) education and age on the probability of job loss remain similar and significant, whereas the effects of having school-age children and being in urban areas become insignificant.

**Figure 7: Likelihood of income loss in the early months of the pandemic**

*Gender, (college) education, sector of employment and wage employment are key correlates of income loss*



*Note:* Based on logistic regression of whether a household report income loss after the pandemic on several covariates with country dummies. “Gender of respondent” refers to the respondent being a woman.

*Source:* Based on Bundervoet et al (2021), updated by the authors with April 2021 vintage of harmonized HFPS data

The pattern of losses for (self-reported) income is consistent with those observed for job losses. Women, less-educated workers, and workers with school-aged children were more likely to report reductions in total household income (Figure 7). Workers in non-farm sectors were more likely to report income losses than workers in agriculture. Moreover, self-employed workers and those working in family businesses were significantly more likely than wage-employment workers to report income losses, which suggests that regular wage employment protected workers to some extent. Formal wage employment, especially in the public sector, is typically associated with greater protection for workers against layoffs and wage reductions in developing countries. Moreover, some developing countries introduced temporary measures to support formal firms in retaining their staff or prohibited them from laying off employees. Thus, income losses were disproportionately suffered by casual workers and self-employed in the non-farm sector, whose livelihoods depend on dense traffic and face-to-face interaction that are most directly affected by measures that reduce mobility.

Across countries, the likelihood of job loss has an inverted U-shaped relationship with GDP per capita – rising with GDP per capita till a certain point, peaking at around US\$5,600 (in purchasing power parity terms) and decreasing thereafter. Countries with higher stringency of containment measures were likely to experience more job losses (see Annex, Figure A-1). The overall patterns of disparities in impacts within countries vary considerably between countries at different levels of development (as measured by per capita GDP) (Annex, Figure A-3). The most common gap in job losses across countries is the gender gap, which is however much narrower for low-income countries than for upper-middle and high-income countries. Interestingly, the education gap in job losses (more losses among those with lower levels of education) is reversed for low-income countries. This may be because workers with higher education in low-income countries are more likely to be employed in urban industry and services that were more affected by the pandemic, whereas those with low levels of education tend to be self-employed in agriculture and were thus somewhat more insulated from the pandemic-related restrictions on economic activity.

Thus, at least for this sample of countries, employment impacts of the pandemic in upper-middle and high-income countries appear to be associated with gender and education level of workers, with women and low-skilled workers being most affected. In low and low-middle income countries, location (urban vs rural) and gender (to some extent) are the key contributors to inequality.

These patterns raise the question whether micro and small enterprises, which are more likely to employ less-skilled workers, have been disproportionately affected by the pandemic. Estimates based on harmonized data from Business Pulse Surveys (BPS) – phone surveys of firms – conducted in 51 countries by the World Bank reveal that the COVID-19 pandemic has affected smaller firms to a greater degree. In particular, larger firms have a lower probability of falling into arrears and can cover their costs with cash at hand for a longer period than small and micro firms (Apedo-Amah et al., 2020). Data from World Bank Enterprise Survey (WBES) COVID-19 Follow-up surveys across 35,496 firms in 40 countries similarly reveal a higher incidence of permanent firm closures among firms of smaller size (Karalashvili and Viganola, 2021).

#### 4.2. Unequal impact on food security

Food insecurity after the pandemic was higher for countries with lower per capita income, and particularly high in some low-income countries, with more than 30 percent of households in some countries in Sub-Saharan Africa reporting going without food for at least one full day in the last month due to lack of resources.<sup>13</sup> Since food insecurity is pervasive in poorer countries even in normal times, its observed incidence in the data cannot be attributed directly to the pandemic, unlike work stoppages and income loss, which are based on questions in HFPS that link these losses to the pandemic. Instead, it is possible to explore whether pandemic-induced jobs and income losses are associated with worsening food security, which would suggest that the pandemic has affected food security via its economic impacts on households (Bundervoet et al., 2021).

Regressions controlling for demographic characteristics and country dummies show that respondents who had lost their job or suffered some income losses were significantly more likely to report that an adult in their household had gone a whole day without eating due to lack of resources in the last 30 days (see Annex, Figure A-2). One cannot rule out, however, that rather than food insecurity being associated with job or income losses, pre-pandemic food security was already lower among households who were more likely to experience income or job losses. This does not appear to have been the case for two countries (Ethiopia and Nigeria) where information on households' pre-pandemic food security status is available (Bundervoet et al., 2021). This does not necessarily address the concern for all countries in the sample but lends support to the view that widespread food insecurity seen in (mostly) low-income countries in the early months of the pandemic was at least in part attributable to economic distress caused by the crisis.

#### 4.3. Unequal impact on education of children

At the peak of the pandemic, temporary school closures in more than 180 countries kept nearly 1.6 billion students out of school (Azevedo et al, 2020). As classroom education was increasingly replaced by remote learning, children in poorer households, including most children in low-income countries, had minimal access to internet, computers, or even television or radios at home. The digital gaps, combined with the uneven quality of online instruction in many developing countries, are likely to have widened pre-existing

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<sup>13</sup> This can be seen from the World Bank's [COVID-19 High Frequency Monitoring Dashboard](#), which uses harmonized data from HFPS.

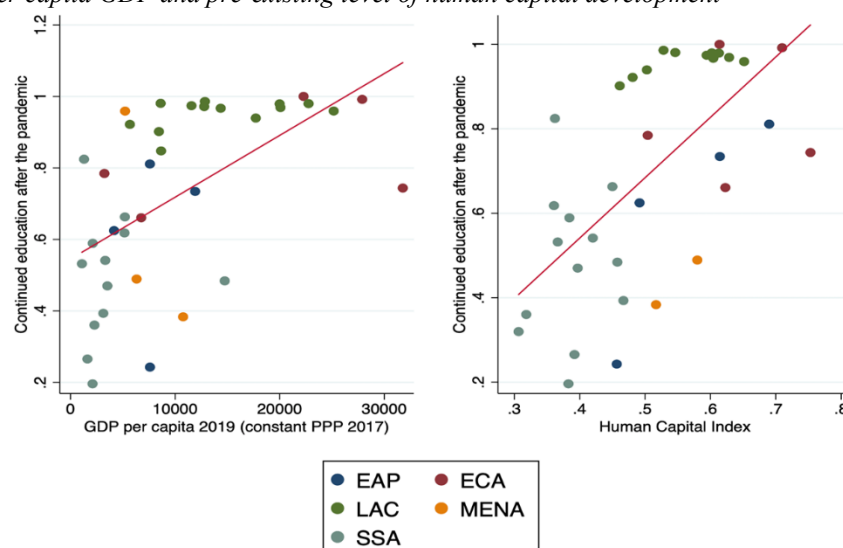


learning inequalities between advanced and developing countries and between socioeconomic groups within countries.

Across countries in the harmonized HFPS data, an average of 66 percent of households with children in school prior to the pandemic reported their children engaging in any learning activity during pandemic-induced school closures. This share tends to be higher for countries with higher levels of (pre-pandemic) per capita income and human capital development (as measured by the Human Capital Index) (Figure 8). Among developing regions, children were least likely to continue learning in countries in Sub-Saharan Africa, a region that was already lagging in learning achievements before the pandemic.

**Figure 8: Share of households with continued learning activity among children during school closures**

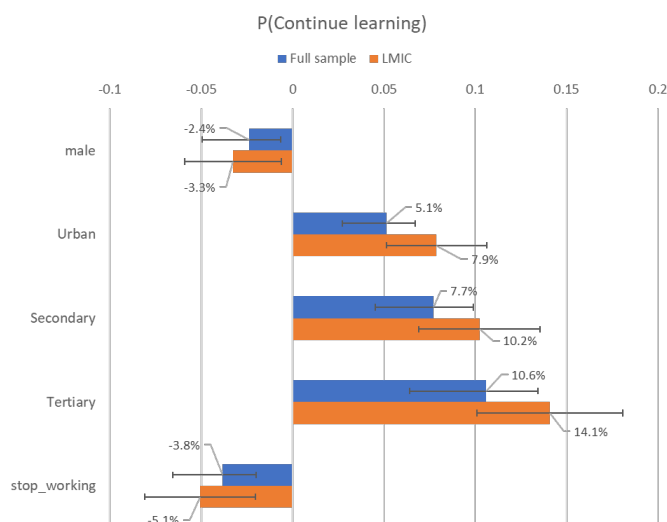
*Increases with per capita GDP and pre-existing level of human capital development*



Source: Based on Bundervoet et al (2021), updated by the authors with April 2021 vintage of harmonized HFPS data

**Figure 9: Likelihood of continued learning among children during school closures**

*Education of household respondent, location (urban/rural) and job losses are key correlates*



*Note:* Based on logistic regression of whether a household reports continued learning among children on several covariates with country dummies; sample limited to households with children going to school before the pandemic  
*Source:* Based on Bundervoet et al (2021), updated by the authors with April 2021 vintage of harmonized HFPS data

Children in rural areas and from households with lower levels of education were significantly less likely to continue learning during school closures, widening the pre-existing learning gap with urban children and children from better-off households (education of household head is a good proxy for socioeconomic status of a household) within countries (Figure 9). Children living in households with secondary- and tertiary-educated respondents were nearly 8 and 11 percentage points more likely to continue learning during school closures relative to children in households with primary-educated respondents. Children in households with job loss during the pandemic, which were typically higher among the less-educated, were also less likely to continue learning. Interestingly, there is a small significant negative association of a household head (respondent) being a man and likelihood of continued learning among children, which might indicate the positive influence of mothers on their children's education when they are also the main decision-maker of the household. Notably, all the gaps were larger for children in low and lower middle-income countries, where pre-existing inequalities are already larger, than for the full sample of countries.<sup>14</sup>

#### 4.4. Adequacy of policy response

By September 2020, advanced economies had on average spent 7.4 percent of GDP on “above the line” measures in the form of budgetary fiscal support to people and firms in response to the pandemic (Bundervoet et al, 2021). These measures, which include cash transfers, expanded unemployment insurance, wage subsidies, and deferral of tax obligations, utility payments and social security contributions, have helped to mitigate the socio-economic impacts of the crisis on households and workers. Governments in EMDEs, however, have been able to spend far less on relief measures because of limited fiscal space. Spending on above the line fiscal measures by September 2020 amounted to 3.8 percent of GDP in emerging markets and 2.4 percent of GDP in low-income developing countries. As a result, though the economic downturn was on average less severe in lower-income countries, the impact on households and individuals may have been far worse, especially for the poor and vulnerable.

The vast gap in adequacy of relief measures between advanced and developing economies is apparent from social protection expenditures that are critical for protecting households, even though many developing countries have extended existing safety net programs and/or introduced temporary new ones. Low-income countries have spent an average of US\$4 per person in COVID-19 social protection responses, compared to US\$30 in lower middle-income and US\$156 in upper middle-income countries (Annex, Figure A-4). Spending on social protection measures is especially low in South Asia and Sub-Saharan Africa (Gentilini et al., 2020). In the HFPS data, the share of households who report receiving public assistance in April-July 2020 rises with per capita GDP, with coverage rates of less than 10 percent seen for most low-income countries in Sub-Saharan Africa (Figure 10a). Coverage among those who lost jobs during the pandemic is also strongly correlated with per capita GDP – a large share of those affected in low-income countries did not receive public assistance, at least during the first few months of the crisis (Figure 10b).

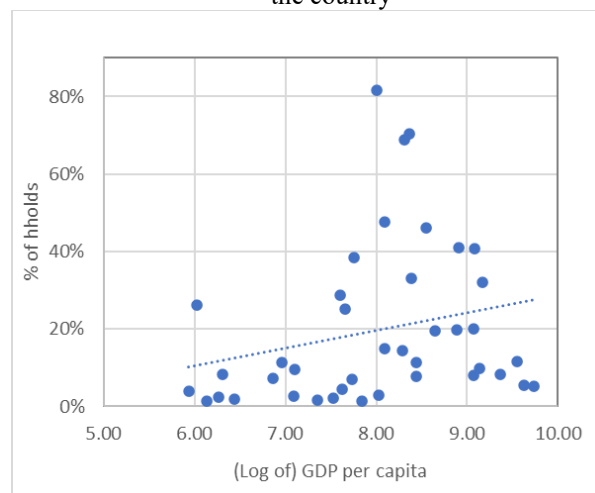
Thus, by all indications, public social assistance in the early months of the pandemic was highly inadequate in most developing countries and particularly so in low-income countries. Within countries, those receiving assistance were more likely to have reported job and income loss during the pandemic and have low socio-economic status (lower education level and larger household size). This suggests that for countries in our

<sup>14</sup> While the indicator used here is whether the child engaged in any learning activities during school closures, using alternative outcome variables that specify the kind of learning activity the child was engaged in (completing homework provided by teacher, watching educational TV programs, meeting with teacher or private tutor) shows similar results.

sample, public assistance appears to have been targeted toward the vulnerable who were more likely to suffer economic losses during the pandemic.<sup>15</sup> Inadequate coverage, however, would have meant that the effect of public transfers on mitigating the distributional impacts of the crisis is likely to have been low.

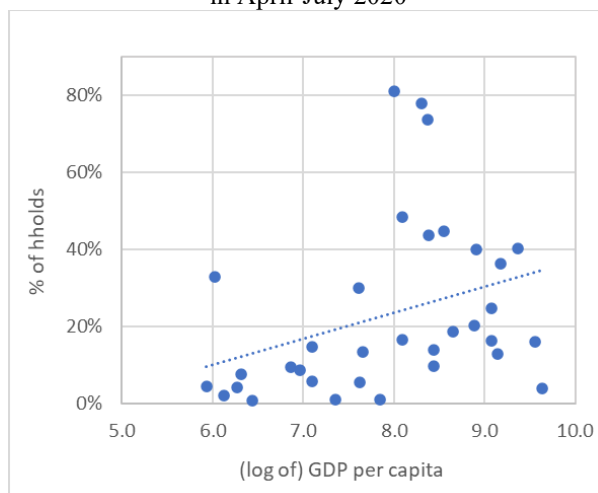
**Figure 10: Lower coverage of public assistance in poorer countries during the pandemic (April-July 2020)**

(a) % receiving assistance, among all households in the country



Correlation: 0.23

(b) % receiving assistance, among those who lost jobs in April-July 2020



Correlation: 0.33

Source: Authors' calculations using harmonized HFPS data and World Development Indicators

#### 4.5. Unequal impacts are compounded by coping strategies that households need to adopt

In the absence of adequate social protection measures, when faced with large and sustained income losses, households are forced to use coping mechanisms, such as reducing consumption (including food), using savings, selling assets and borrowing, which compound the unequal impacts of the pandemic with potential long-term consequences. Past evidence suggests that reducing food consumption is most frequently used as a coping strategy after a fast onset shock, whereas sale of productive assets seems to be largely a coping strategy of last resort.<sup>16</sup>

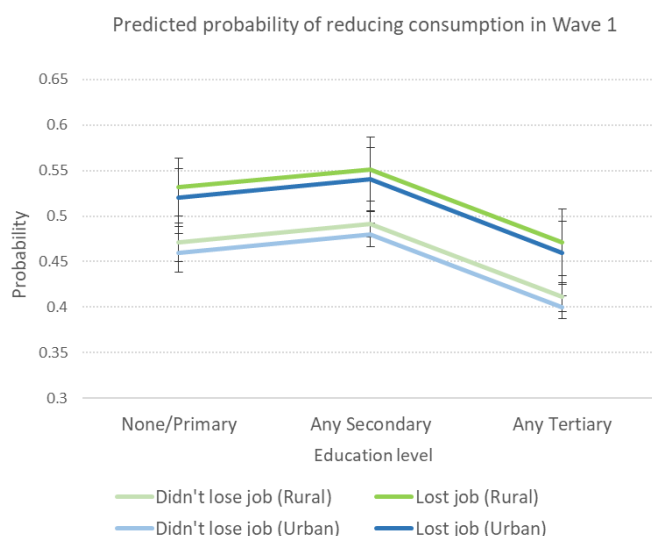
The harmonized HFPS data show that the coping strategies adopted by households in the early months of the pandemic followed the pattern consistent with past evidence. Households who suffered job or income losses were much more likely to adopt one or more coping strategies. Reducing consumption was the most common measure adopted, followed by drawing down of emergency savings; while selling assets to cope with the shock was relatively rare (reported by an average of 6 percent of households). Moreover, selling assets and reducing consumption are much more likely among households with lower socioeconomic status and in rural areas, probably due to lower access to financial services (particularly credit) among these

<sup>15</sup> Based on regressions using harmonized HFPS data – of whether a household reports receiving social assistance on household characteristics (education levels, gender and age of household head) and indicators of job or income loss during April-July 2020, controlling for country fixed effects (for samples of 20,000 or more households pooled across countries).

<sup>16</sup> See Hill and Narayan (2020) for a review of the evidence.

groups.<sup>17</sup> Notably, while those with job losses are more likely to have reduced consumption for every level of education, the lowest likelihood is observed among those with tertiary education in urban areas (Figure 11). Such patterns suggest that coping strategies might add to the risk of worsening inequality if these are strategies with potential long-term adverse consequences for households.

**Figure 11: Those with job losses are more likely to reduce consumption, for every level of education**



*Note:* Results from (unweighted) logistic regressions with interaction terms using HFPS data for 10 countries with reliable data on all variables considered above

The high rate of adoption of coping strategies among those with job and income losses may affect their future ability to weather economic shocks and generate income. Reducing consumption, particularly for mothers and young children, can lead to long-lasting impacts on health, nutrition, and human capital development of future generations. Distress sale of assets or using emergency savings could imply the loss of productive assets, depending on the type of assets and savings that are being depleted. Using assets and savings for consumption-smoothing in the face of shocks is common in developing countries. But the depth and scale of the impact of this pandemic increases the extent to which the coping strategies need to be used by vulnerable households, which increases the risk of longer-lasting effects on the productivity and economic mobility of these households.

## 5. The short-run impact of COVID-19 on income inequality – results from simulations

How do the impacts of COVID-19 on job and income losses translate to income inequality within developing economies? We cannot directly estimate the income distribution within countries during the pandemic with the data we have. Instead, we draw on the preliminary results from microsimulations of the impact of the pandemic for 2020 (Mahler <sup>(r)</sup> et al., forthcoming). This exercise triangulates three data

<sup>17</sup> Based on regressions using harmonized HFPS data – of whether a household reports adopting a certain coping strategy on household characteristics (education levels, gender and age of household head) and indicators of job or income loss during April-July 2020, controlling for country fixed effects (for samples of 19,000 or more households pooled across countries). Reducing consumption was more likely among households that are larger, located in rural areas, and with survey respondents (usually household heads) who are female, older and less than college-educated. Selling assets shows similar patterns, with one key difference – it is more likely among male-headed households.

sources – the latest household survey for each country, the World Bank’s HFPS, and national accounts data – to get around the lack of income or consumption data from surveys conducted during the pandemic. The exercise as of now covers 34 countries, which are a mix of all developing regions of the World Bank other than South Asia, and countries at different levels of development.<sup>18</sup>

Briefly, the simulation methodology is as follows (see Annex B for more details): (a) using the last household survey available for each country (mostly pre-2019) to estimate the income distribution for 2019, assuming all households’ welfare have grown in accordance with growth in national accounts till 2019; (b) using a variable in HFPS indicating whether a household lost income in 2020 to predict the probability of households experiencing an income loss based on their characteristics (education, demographic, urban/rural); (c) merging these probabilities with the household survey data for 2019 to predict for each household a probability of experiencing an income loss in 2020, based on which an income loss is stochastically assigned; and (d) using sectoral growth figures from national accounts and assumptions mapping sectoral income growth to rural/urban to determine the size of income loss for each household. The exercise produces a distribution of household income in 2019 (pre-COVID-19) and 2020 (with COVID-19) for all 34 countries in the sample, using which poverty can be projected for these years.

To assess the impact of the pandemic on inequality and poverty, comparisons are made with a counterfactual 2020 income distribution, which is produced by using the last pre-pandemic sectoral GDP forecast for 2020. To isolate the impact of changes in inequality on poverty projections, another counterfactual scenario is created assuming that COVID-19 hit all households equally, by adjusting all households’ income in 2019 with the growth rate of 2020.

The estimated probability of changes in income for rural and urban households by country are shown in Annex A (Figure A-5). On average, 62 percent of rural households and 61 percent of urban households had a decline in income due to the pandemic; 31 percent and 32 percent respectively had no change in their income; and 7 percent had an increase in income in both areas. In this sample of 34 countries, the countries in SSA fared the worst where 76 percent of rural and 71 percent of urban households had an income decline. Countries in EAP and ECA fared the best with around 40 percent of households with income declines.

According to the simulations, income losses in 2020 were likely regressive in most countries – more likely for bottom 40 percent (or b40) of the distribution than for top 60 percent (or t60) in 26 out of 33 countries (Figure 12, right panel).<sup>19</sup> The gap was also larger for urban areas than for rural areas in most countries (Figure 12, left and center panels). On average, the b40 in rural areas had a 1.7 percent higher probability of experiencing a decrease in their income compared to the t60, compared to a 4.5 percent difference for urban areas. A comparison between the top and bottom income quintiles shows similar patterns. The likelihood of income loss was higher for the bottom quintile than the top quintile for 27 countries, and the average gap was 2.5 percent for rural areas versus 6.9 percent for urban areas. Thus, on the average, inequality may have increased more in urban areas than in rural areas.

The simulations project an increase in income (or consumption) inequality for most countries, albeit by a small amount. The Gini index for income in 2020 with COVID-19 is higher than what it would have been without COVID-19 for 29 out of 34 economies (Figure 13). The average expected increase in the Gini due

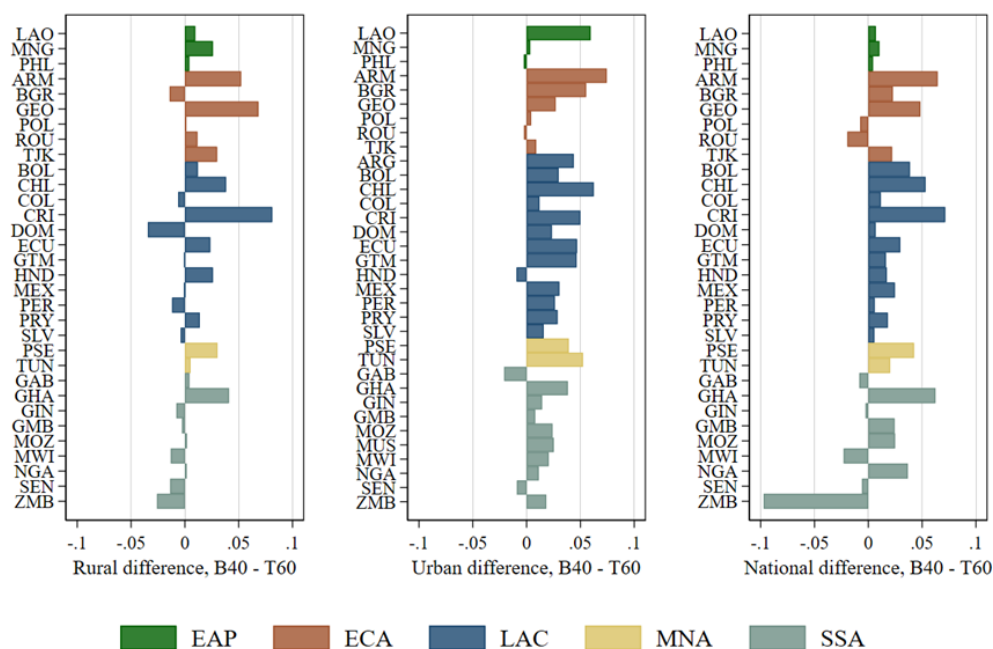
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<sup>18</sup> The 34 countries are from EAP (3), ECA (6), LAC (13), MNA (2) and SSA (10). The simulations are based on country-specific sectoral growth estimates from MPOs (April 2021) and harmonized HFPS data (as of July 2021). Results may change as growth estimates updated with the next round of MPOs (October 2021) and HFPS data are updated with surveys for more countries.

<sup>19</sup> Argentina is not included for rural-urban breakdowns, since only urban data is available in the official household survey.

to COVID-19 is about 1 percent. The Gini is expected to rise for 29 economies from 2019 to 2020, compared to 11 (that was expected) in the absence of COVID-19. For the countries expected to have an increase in inequality from 2019 to 2020, the average increase in the Gini index was projected to be 0.29 percent without the pandemic and 0.93 percent with the pandemic.

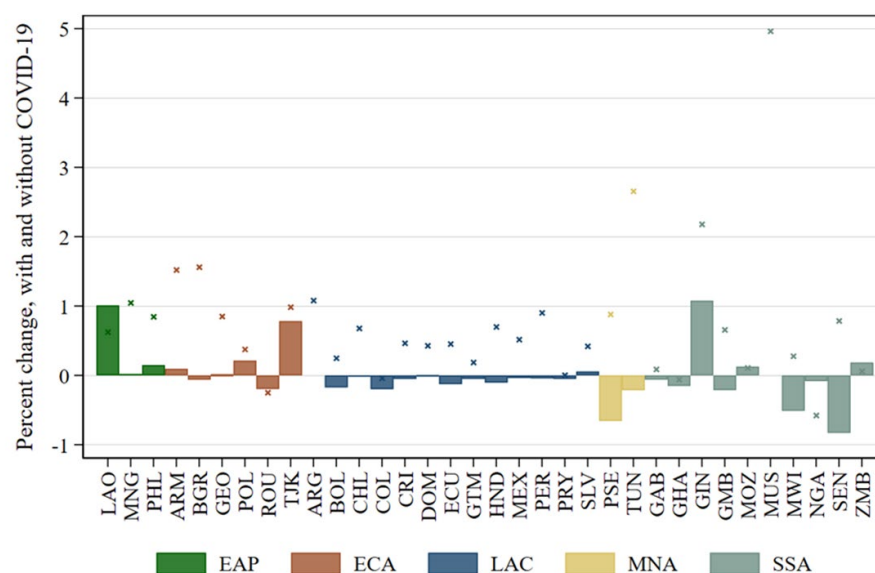
**Figure 12: Difference in probability of decline in income, bottom 40% minus top 60%**



Note: Difference > 0: higher prob of loss for bottom 40% relative to top 60%

Source: Mahler <sup>(r)</sup> et al. (forthcoming).

**Figure 13: Impact of COVID-19 on income Gini**



Note: The bars report the expected percent change in the Gini index from 2019 to 2020 before the COVID-19 pandemic and the dots represent the expected change with the pandemic

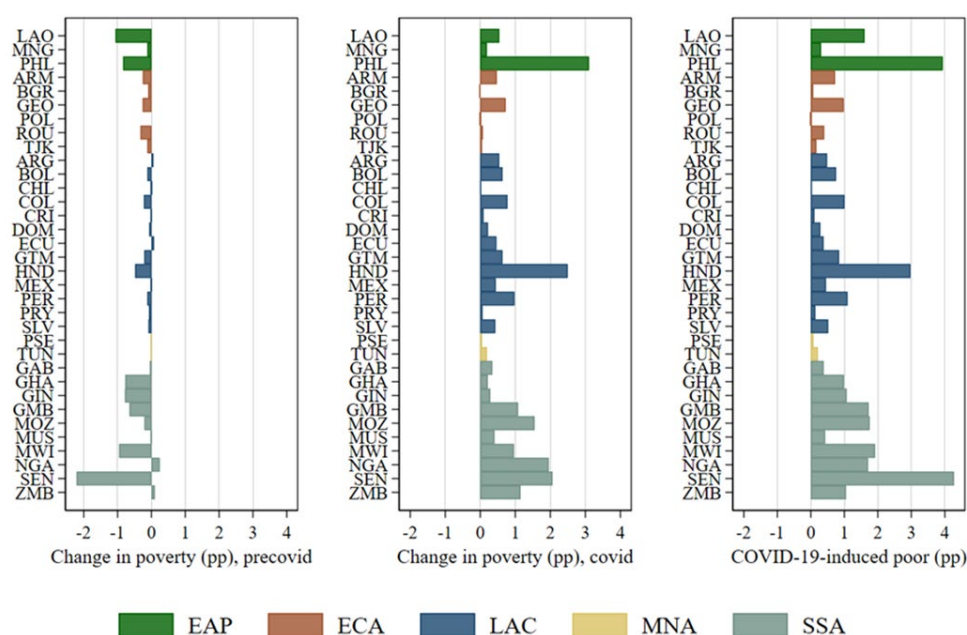
Source: Mahler <sup>©</sup> al. (forthcoming).

The simulations yield higher extreme poverty due to COVID-19 for all 34 economies (Figure 14). Only one economy is now expected to have a decline in extreme poverty from 2019 to 2020, compared to 29 of 34 expected to have so without the pandemic. The poverty rate is now expected to increase by an average of 0.68 percentage points (pp), compared to a decline by 0.29 pp without the pandemic. Accounting for population growth, this implies 15 million additional extreme poor due to COVID-19 in these 34 economies, which represents a 7.5-fold increase over the pre-COVID-19 scenario.

How much difference does it make to include inequality impacts of the pandemic, for projections of poverty impact? Incorporating distributional changes leads to a higher projected poverty impact of COVID-19 for most countries. Extreme poverty projections with distributional changes are larger than or equal to those with distribution-neutral changes for 25 of the 34 countries (Annex A, Figure A-6). The differences are small, given the relatively small size of inequality impacts. For these countries, incorporating distributional changes leads to 0.19 pp higher poverty rates on average.

If the results of the simulation for these 34 countries are representative of patterns across most developing countries, one would expect the impact of COVID-19 on global inequality to be higher than what was suggested earlier by the simulations based on distribution-neutral GDP growth projections (Figure 1). But one would expect the difference to be small, based on what we see from the average size of the simulated impacts on within-country inequality.

Figure 14: Impact of COVID-19 on extreme poverty



Note: Right panel: impact of covid on poverty, which is the difference in poverty rates in 2020 with covid and without COVID

Source: Mahler <sup>©</sup> al. (forthcoming).



## 6. Inequality in the early phase of economic recovery and long-term inequality impacts

COVID-19 struck in a world where inequality was pervasive and socioeconomic mobility was not improving in most of the developing world since the 1960s-born generation (Narayan et al, 2018). As described above, the shock led to a widening of pre-existing gaps in capabilities and endowments in many countries, as well as a small increase in average income inequality within countries for 2020, as seen from the simulations conducted for 34 developing countries. The small within-country inequality impacts would have added to the increase in global inequality projected earlier (Figure 1), which were based on differences in GDP growth rates across countries due to the pandemic. The increase in income inequality also occurred because unlike advanced economies, most low- or middle-income countries could not ramp up social assistance to compensate the vulnerable for the income losses they suffered.

Moreover, the processes triggered by these impacts could have continued widening gaps between privileged and vulnerable groups even when economic activities are on the rebound. The limited evidence available from past epidemics suggests that events of this kind are associated with long-run increases in income inequality. Furceri et al. (2020) estimate the distributional impacts of five major events over the five years following each event and find that on average, the Gini coefficient of income in affected countries increased steadily.<sup>20</sup> The impact on inequality tends to be higher when the crisis leads to significant contraction in economic activity, as it happened on a large scale with COVID-19. This is also consistent with evidence from past *economic* crises suggesting that larger shocks are associated with higher inequality over time. Economies with larger output and employment losses in the initial aftermath of the global financial crisis registered greater increases in income inequality compared with their pre-crisis average, as the employment rate of those with basic levels of education fell significantly in the medium term, while the employment rate of those with intermediate or higher levels of education was not affected (IMF 2018).

While the long-term impacts of COVID-19 on inequality cannot be known yet, waves of HFPS data can be used to identify patterns that provide clues about the trajectory of economic recovery. As economic activity starts to return where policies are becoming less stringent, an unequal recovery may foreshadow the risk of higher long-term inequality.

### 6.1. Channels of potential impact on long-term inequality and social mobility

It is useful to reflect on what past crises suggest about the channels of longer-term impact on inequality, so that the analysis of recovery can focus on these channels to assess long-term risks to inequality.<sup>21</sup> First, loss of jobs and business can leave lasting impacts on vulnerable workers. An unemployment spell for a new job market entrant can lead to lower lifetime earnings due to the lost time of (potential) experience, skills depreciation, and scarring effects. Compared with youth in well-off households, who can afford to postpone entry and use the time to get more education or experience through internships, youth from disadvantaged backgrounds may have little option but to enter the labor market even when it is in a depressed state. Higher rate of job losses among women can also have a persistent impact on women's employment and wages.<sup>22</sup> Moreover, large-scale closures of small and micro enterprises can lead to erosion of entrepreneurial capital and jobs, which disproportionately affect the youth, low-skilled workers and those without access to capital.<sup>23</sup>

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<sup>20</sup> These epidemic or pandemic events are SARS (2003), H1N1 (2009), MERS (2012), Ebola (2014) and Zika (2016).

<sup>21</sup> See Hill and Narayan (2020), Section 3 for a detailed review of the evidence.

<sup>22</sup> See Narayan *et al.* (2018), Chapter 6 for a discussion.

<sup>23</sup> This is in addition to the efficiency costs imposed on society. See Didier *et al.* (2020), who refer to 'inefficient bankruptcies'.

Employment shocks caused by firm closures and mass layoffs can lead to lower economic mobility within and across generations. Studies have found that workers who are displaced by unexpected firm closures experience significant and long-lasting reductions in earnings.<sup>24</sup> The long-term impacts of unexpected job loss can extend beyond the effect on one's own income to the eventual labor market outcomes of offspring, reducing intergenerational mobility. Oreopoulos et al (2008), using Canadian data that follows more than 39,000 father-son pairs from 1978 to 1999, find that sons with fathers whose jobs were displaced by firm closures have significantly lower earnings than similar individuals whose fathers did not experience an employment shock, with the effects driven by families in the bottom quartile of the income distribution.<sup>25</sup> These effects are probably due to the impact of permanent reductions in family income caused by employment shocks on human capital development of children, with other non-monetary costs (such as stress in families) of unexpected job losses likely playing a role as well.

Second, large income losses often compel households to use coping mechanisms with potential longer-run impacts on nutrition, indebtedness, and at times, (the loss of) productive assets. As described in Section 4, the size of the shock and lack of adequate income-replacement programs led to many households, particularly the poor and the vulnerable, to adopt such strategies. Reducing consumption could increase nutritional deprivation for children and mothers, with damaging long-term consequences. High rates of indebtedness can lead to poverty traps, as the poor often pay higher interest rates for emergency loans than do better off households. The sale of productive assets to cope with shocks can be highly damaging when it is adopted, as it can adversely affect a household's income-generating potential and ability to cope with future shocks.

Third, disruptions to schooling can widen learning gaps between children from different socioeconomic strata, reducing intergenerational mobility. In most low-income countries covered by HFPS, children in fewer than 66 percent of households participated in any continued learning when the schools were closed. Learning losses can have irreversible long-term costs for individuals and society alike. Evidence from past disasters suggests that disrupted schooling and the trauma of shocks can adversely affect learning among children that are observable years later.<sup>26</sup> These effects increase educational inequality, as suggested by early data from high-income countries (Belgium and the Netherlands). As children learn from home, social inequalities become more salient. To compound this effect, as vulnerable households in developing countries suffer income losses, some may also be less likely to send children back to school after a long period of closure. The closure of schools could thus widen already existing gaps in education between children born into different socioeconomic strata.

Fourth, long-term effects on inequality can also occur due to the interruption of critical health services caused by the pandemic, including maternal and child health care, which can leave lasting impacts on the health of future generations from vulnerable families. Elston et al (2017) find that in areas affected by the 2014–15 Ebola outbreak in West Africa, maternal and delivery care, malaria admissions for children under the age of 5, and vaccination coverage fell significantly. Such disruptions to health care, as well as to nutrition, could undo decades of gains in health outcomes in many low- and middle-income countries.

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<sup>24</sup> Jacobson, LaLonde, and Sullivan (1993) and Stevens (1997). They argue that firm closings can be thought of as exogenous employment shocks after conditioning on pre-displacement earnings.

<sup>25</sup> The adult earnings of men whose fathers were displaced from their jobs due to firm closures are estimated to be 9 percent lower than earnings of similar individuals whose fathers did not experience an employment shock, after accounting for fathers' pre-displacement earnings, initial region of work, industry, and firm size (Oreopoulos et al, 2008).

<sup>26</sup> See, for example, Andrabi et al (2020), who finds significant impacts of an earthquake in Pakistan on children's learning outcomes four years later.

## 6.2. Early signs of an uneven jobs recovery

A key area of concern about the impacts of a shock is that economic recovery may occur more slowly among those who were most affected by it, thus exacerbating inequality over a longer term (as illustrated by the conceptual framework in Figure 4). This appears to be the case globally (see section 2) as recovery in 2021 appears to be concentrated in the upper part of the global income distribution, while the lower end of the distribution who suffered the greatest losses in 2020 fall further behind (Figure 1). In 2021, the top 60 percent are projected to return to pre-COVID welfare levels, while the bottom 40 percent will have incomes 2 percent smaller than that before the pandemic. In these distribution-neutral simulations, the widening gap during recovery is the consequence of GDP growth in low-income countries lagging growth rates in advanced economies in 2021.<sup>27</sup>

What can we discern about the pattern of early recovery *within* countries? Analysis of harmonized HFPS data from surveys conducted since July 2020, in those developing economies where policy restrictions became less stringent, allows an early look at the pattern of recovery across different groups in the population to provide some indication of what is likely to happen when economies rebound. To our knowledge, this is the only database that allows analysis of changes over time in the pandemic period in a consistent manner across many developing countries.

We study the recovery between May-June 2020 (Round 1) and August-September 2020 (Round 2) — periods chosen in a way that maximizes the number of countries in our HFPS sample with at least one wave in each round, while ensuring that the two surveys of each country are roughly equidistant. Around 40 percent of the countries (23 out of 59) with harmonized HFPS data have survey rounds conducted within the Round 1 and Round 2 windows.<sup>28</sup> To focus on the patterns associated with economic recovery, we restrict our attention to 20 countries where policy stringency declined between Round 1 and Round 2.<sup>29</sup> For the average country in our sample, policy restrictiveness — measured by the Oxford Stringency index — fell from 77 to 68 between rounds 1 and 2, where higher values indicate greater stringency.<sup>30</sup> Our findings are thus reflective of countries covered by HFPS where policies became more favorable toward economic activity between May and September 2020, and do not reflect what happened during subsequent months that included a second wave of the pandemic in some countries.

Since we are focusing on changes in three outcome variables that were the focus of the analysis of the initial impacts of COVID-19 — income loss, employment, and food security — over time, and disaggregating by several sociodemographic characteristics, the sample of countries varies because of differences in coverage of variables across surveys and quality of data. Our total sample of countries includes two countries in the World Bank's Europe and Central Asia region, two in East Asia and Pacific, eight in Latin America and the Caribbean, and eight in Sub-Saharan Africa. Of these, seven are low-income countries, seven are lower-middle-income, and six are either upper-middle-income or high-income countries. Eight countries fall under the World Bank's IBRD lending classification and 12 under the IDA category (including those

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<sup>27</sup> Note that LICs account for most of the lower end of the global income distribution.

<sup>28</sup> Survey waves were fielded at different times in each country. Therefore, these rounds do not necessarily correspond to waves 1 and 2 for all countries but can also correspond to waves 1 and 3.

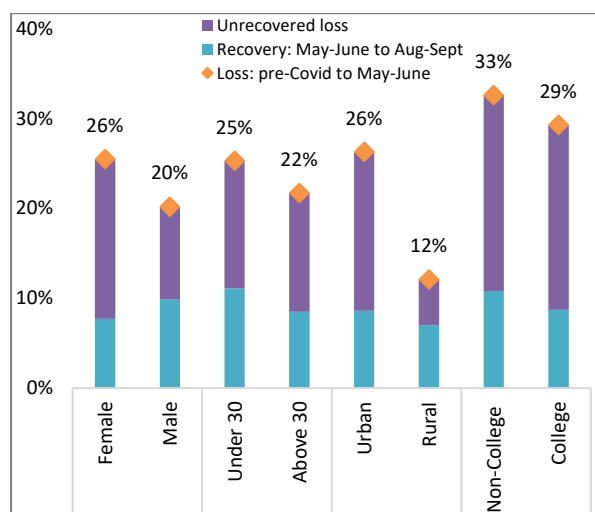
<sup>29</sup> Countries are Argentina Burkina Faso, Colombia, Costa Rica, Dominican Republic, Ethiopia, Guatemala, Honduras, Kenya, Cambodia, Mali, Mongolia, Mozambique, Malawi, Nigeria, Paraguay, El Salvador, Tajikistan, Uganda, and Uzbekistan. Please see Annex A for further details. Chile and Mexico witnessed a rise in the Oxford Stringency index in this period and are hence omitted for our analysis. We exclude St. Lucia because of lack data on policy stringency.

<sup>30</sup> The Oxford stringency index is also highly correlated with Google mobility data, which is another commonly used indicator of the impact of COVID related restrictions. For further details, see Bundervoet et al (2021).

classified as “Blend”). All results presented below are simple country averages in which each country carries the same weight (but workers and households within countries are weighted appropriately).

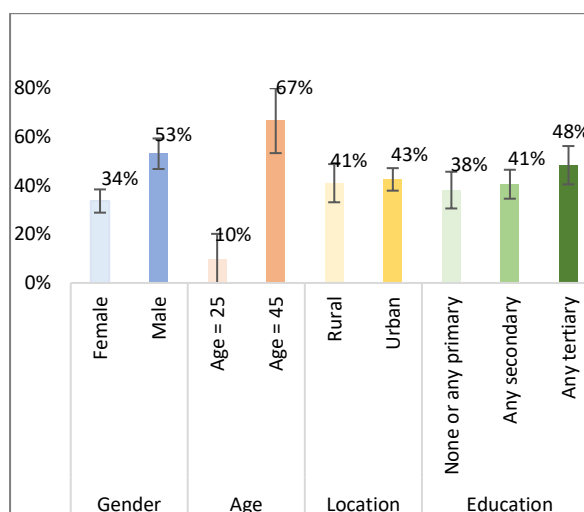
The HFPS data reveal that while falling policy stringency was accompanied by a recovery in both employment and incomes, these were still well below pre-pandemic levels in September 2020. Across 17 countries, employment recovered to only 83 percent of its pre-pandemic average by August-September after falling to 71 percent in May-June. While an average of 63 percent of households in a country reported a fall in income in May-June, 58 percent continued to have lower incomes in August-September compared to pre-COVID levels.

**Figure 15: Decline in employment rates between pre-COVID and May-June (pp) & share of loss recovered by August-September**



Note: Results for 14-17 countries. All changes measured in percentage points (pp) terms. Loss in employment from pre-pandemic to May-June is split into (i) recovery in employment between May-June and Aug-Sep, and (ii) “unrecovered loss”.

**Figure 16: Predicted probability of recovering job lost during the pandemic, by August-September 2020**



Note: Results for 6 countries from logit models where the dependent variable indicates whether the individual is working again in Aug/Sep 2020 (for those who had a job pre-pandemic but lost it in May/June 2020). 95% confidence intervals shown for each bar.

Within countries, those who suffered the larger initial shocks – women, younger workers, urban workers, and the low-educated – either recovered more slowly compared to their counterparts or did not recover fast enough to significantly reverse initial disparities in losses (Figure 15). By August-September, the recovery in female employment lagged behind that in male employment — men recovered 49 percent of their initial employment losses while women recouped 30 percent, after the initial shock was more unfavorable to women by 6 percentage points (pp).<sup>31</sup> Urban workers, hardest hit in the immediate aftermath of the crisis, similarly lagged behind rural workers in recovering their initial losses — while rural workers recovered 58 percent of initial losses by August-September, those living in urban areas recovered only a third of their

<sup>31</sup> There are several ways to compare the rate of recovery in employment between groups, including: (i) percentage point change in employment rate of each group between post-pandemic rounds 1 and 2; and change between rounds 1 and 2 as a share of (ii) employment rate in round 1, (iii) pre-pandemic employment rate, and (iv) initial decline (between pre-pandemic and round 1). We use (iv) as our metric to compare employment gains of different groups in Figure 1, as it has an intuitive interpretation: 100% would indicate that all losses suffered by a group (e.g. women) since the pandemic has been recovered, and the comparison of two rates (e.g. between men and women) would indicate how far away each group is, relative to the other, from its pre-pandemic employment rate.

initial losses.<sup>32</sup> Although the recovery was slightly faster in percentage point terms for workers below age 30 and those without college education than for older and non-college educated workers, the difference was not enough to significantly reduce the gaps in job losses by age and education. Analysis for a smaller set of countries suggests that the likelihood of job recovery among those who lost jobs during the pandemic was lower for female, younger and non-college educated workers, compared to male, older and college-educated workers in these countries (Figure 16).<sup>33</sup>

Self-employment accounted for a large share of the recovery in employment for workers with lower levels of education, who tend to be the vulnerable group. In seven countries, 71 percent of the increase in employment rates from May-June to August-September occurred in self-employment for primary educated workers, compared to 46 percent and 60 percent respectively for workers with secondary and tertiary education.<sup>34</sup> In these countries, self-employment also accounted for a large share of the recovery in employment for women (44 percent of the increase, compared to 0.3 percent for men) and urban workers (49 percent, compared to a fall in the share of self-employment for rural workers).<sup>35</sup> Self-employment in developing economies tends to be informal and insecure in nature, which suggests that the job recovery in some countries may be occurring with a rise in more insecure forms of employment.

Initial job and income losses due to COVID-19 were associated with rising food insecurity. While government policies across many countries tried to limit the damage, safety nets in low-income countries were insufficient to mitigate a rise in food insecurity.<sup>36</sup> As restrictions were scaled back, the average share of food-insecure population in 16 countries fell from 13 percent to 9 percent.<sup>37</sup> Job recovery was associated with rising food security (Figure 17). For households across the socioeconomic spectrum, food insecurity became less of a concern by August-September, but improvements were more pronounced for households with college-educated members.<sup>38</sup>

Extending the time window of the analysis to January 2021 for a smaller set of 8 countries, we observe continuing signs of uneven recovery in labor markets, along with some signs of stalling.<sup>39</sup> Women and those living in urban areas continued to experience a slower recovery in employment towards the end of 2020 and beginning of 2021 as a proportion of the initial losses suffered — while employment among men reached 95 percent of its pre-pandemic level by January 2021, women's employment was only at 89 percent. Employment recovery also continued lagging for urban areas (Annex. Figure A-7). Moreover, overall recovery in employment seemed to have stalled for the 8 countries since September 2020, even though

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<sup>32</sup> Furthermore, Batana et al. (2021) find, based on city-level panel data from Ethiopia and from Kinshasa, DRC, that households from large, densely populated cities (and, within cities, vulnerable households residing in remote areas), suffered greater COVID-19 related losses and recovered at a slower rate.

<sup>33</sup> This analysis could be done for a subset of 6 countries from the original sample of 20 countries, because it requires data on all the characteristics of workers and households, namely age, gender, location and education.

<sup>34</sup> These 7 countries are: Argentina, Costa Rica, Ethiopia, Guatemala, Mongolia, Paraguay, and El Salvador.

<sup>35</sup> Data on respondents' urban/rural status is not available for Guatemala and El Salvador.

<sup>36</sup> While public safety nets were scaled up, they were largely inadequate in lower income countries. Average per capita spending on COVID-19 social protection by LICs and LMICs was 3 percent and 19 percent, respectively, that of UMICs (that spent US \$156 per capita).

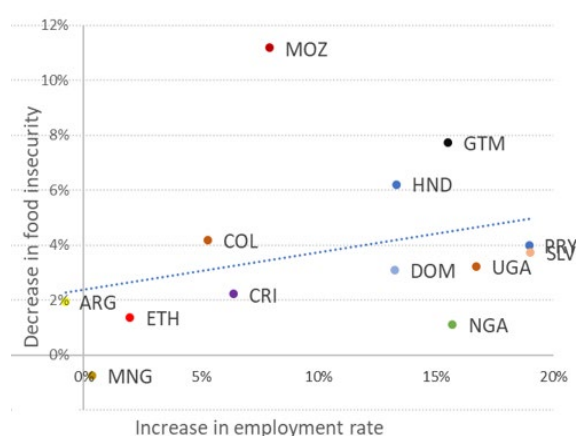
<sup>37</sup> We measure food insecurity as the proportion of households with hungry adults who went without at least one meal in the last 30 days before the survey. Our results are based on a sample of 16 countries where policy stringency fell between May-June and Aug-Sep. 13 of these countries are also used in the employment analysis.

<sup>38</sup> This data is for 13 countries, for which overall food insecurity fell from 12.6% to 9.3% during the same period.

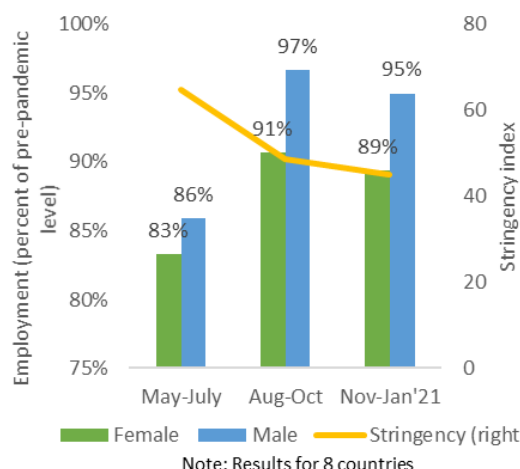
<sup>39</sup> We use a sample of 8 countries with at least one wave in each of the following time periods: May-July, Aug-Oct, and Nov-Jan'21. Stringency did not necessarily decrease for all countries in this sample, although it did on average. These 8 countries are Burkina Faso, Bulgaria, Democratic Republic of Congo, Cambodia, Mongolia, Malawi, Uganda, and Uzbekistan.

policy stringency continued to improve through January 2021 (Figure 18). While the sample of countries is too small to generalize, the findings suggest that the rate of jobs recovery since September 2020, in addition to being uneven across different segments of the population, slowed in some countries.

**Figure 17: Food security and employment dynamics between 1st and 2nd survey rounds (pp)**



**Figure 18: Employment dynamics by gender**



Source: Authors' calculations using harmonized HFPS data.

## 7. Conclusion

The restrictions on mobility and economic activity that were put in place to mitigate the health impacts of the COVID-19 pandemic had an unequal impact both across and within countries, with vulnerable populations within developing countries being affected disproportionately. The evidence presented in this paper suggests that household level impacts have been larger for poorer countries, widening the divide between households in rich and poor countries, with implications for global inequality. The projected losses due to the pandemic, even with an assumption of no change in inequality within countries, are estimated to be higher for the bottom half of the global income distribution (that is comprised predominantly of households from developing countries) than the top half, which would imply higher global inequality.

In addition, COVID-19 may have amplified pre-existing inequalities within developing countries. In advanced economies, that seems to have been the case before social transfers were ramped up – income and job losses due to COVID-19 were greater among lower income households (Bernstein and Rothstein, 2020) and lockdowns increased inequality (Palomino et al., 2020). In contrast, social transfers in low- and lower-middle income countries, which were a small fraction of what was deployed in upper-middle and high-income countries, were insufficient to mitigate the impacts of income losses among the vulnerable.

In developing countries, observational data collected through phone surveys have largely validated the *ex ante* expectations about unequal distribution of job and income losses. The World Bank's HFPS data indicate that the pandemic hit vulnerable groups in EMDEs – those with low education, informal employment in urban areas, and women and youth – particularly hard in the first few months, a finding that is also consistent with patterns in the Gallup World Poll data. Simulations based on these impacts suggest that income losses were mildly regressive and raised income inequality in 2020 in 29 of 34 developing economies. The average impact on inequality within countries was small, and greater for urban than rural areas. The within-country impacts, *if* they turn out to be broadly representative of developing countries,

would imply that projections (of global impact) using distribution-neutral GDP growth rates of countries are likely to mildly understate the pandemic's aggregate impact on global poverty and income inequality.

Inequality impacts of the pandemic should not be seen only through the lens of income inequality, but rather as a spectrum of dis-equalizing effects on multiple dimensions of well-being, some of which are likely to be harmful for social mobility and long-run inequality. COVID-19 struck in a world with already high structural inequality and low socioeconomic mobility in most of the developing world. As the shock led to a widening of pre-existing gaps in opportunities and incomes in many countries, it may have triggered processes that continue widening gaps between privileged and vulnerable groups even as economic growth rebounds. This is the reason why major epidemics in the last two decades have been associated with higher within-country inequality five years later (Furceri et al., 2020). While the long-term impacts of COVID-19 on inequality in developing countries cannot be known yet, HFPS data for some countries from the early days of economic recovery can be used to identify patterns in the trajectory of household well-being. An inequitable recovery would foreshadow a higher long-term risk to inequality and social mobility.

As economic activity starts to return where policies are becoming less stringent, there are reasons to be concerned about the pandemic's more lasting consequences for inequality and social mobility. Globally, the recovery in 2021 appears to be concentrated in the upper half of the global income distribution, while the lower end of the distribution who suffered the most losses in 2020 fall further behind as growth outlook for many developing countries lags the recovery in richer economies. On the positive side, across a sample of 17 developing countries with comparable HFPS data between May-June and August-September (2020) where policies became more conducive to economic activity, significant improvements in employment, incomes and food security are observed. However, the employment recovery appears to be both slow and uneven. Employment among those who suffered larger initial shocks – women, non-college-educated, and urban workers – did not recover enough to close the gap caused by initial disparities in losses. More recent data for 8 countries up to January 2021 suggest that these disparities have persisted even as recovery in employment seems to have stalled, that too at levels that are well short of the pre-pandemic state. There are indications that self-employment, which is often lower-quality employment in developing countries, is accounting for a high share of the employment that is coming back.

Beyond its effects on jobs and incomes of the current generation of workers, the pandemic could reduce economic mobility across generations through its impacts on human capital development of children. Past research suggests that intergenerational mobility can be constrained by unexpected job losses caused by firm closures and mass layoffs, due to their long-lasting impacts on family incomes that in turn affect education of children in low-income families (Oreopoulos et al 2008). In the context of this pandemic, the income effect of job losses is compounded by the large and inequitable impacts of learning losses. A large share of children in poorer families, particularly in low-income countries, had almost no access to learning opportunities during school closures, resulting in disparities in learning losses that could persist over time and further reduce intergenerational mobility. The simulations by Neidhoefer et al (2021) suggest that despite the mitigation policies adopted in some countries, loss of instruction from school closures is likely to affect the education of the children from vulnerable households most seriously, and particularly secondary school attainment of children in less-educated families.

Making our societies more equitable and resilient to future crises requires taking on structural inequalities today, to help women, low-skilled workers, and urban informal sector workers recover from the deep losses they suffered, so that they do not fall further behind even as economies recover. Moreover, a global shortage of COVID-19 vaccines adds to the risks of an uneven recovery, with vaccination rates in low-income countries remaining very low compared to advanced economies. Thus, an important policy priority is ensuring adequate and equitable access to vaccines in developing countries. Governments also need to help



children and parents transition back to school and facilitate re-entry of workers who are most at risk of not rejoining work. Older and low-educated workers might also require more support to deal with the consequences of rapid technological change that can exacerbate existing inequalities and slow their recovery. Gender disparities pre-dating COVID-19 widened throughout this crisis, reversing which will require a concerted effort to empower women and girls worldwide across the different dimensions of gender equality. The pandemic has underscored the need for building an effective and equitable public health system and investing in safety nets and social insurance, and fiscal policy to raise resources in a fair and efficient way to finance these investments.

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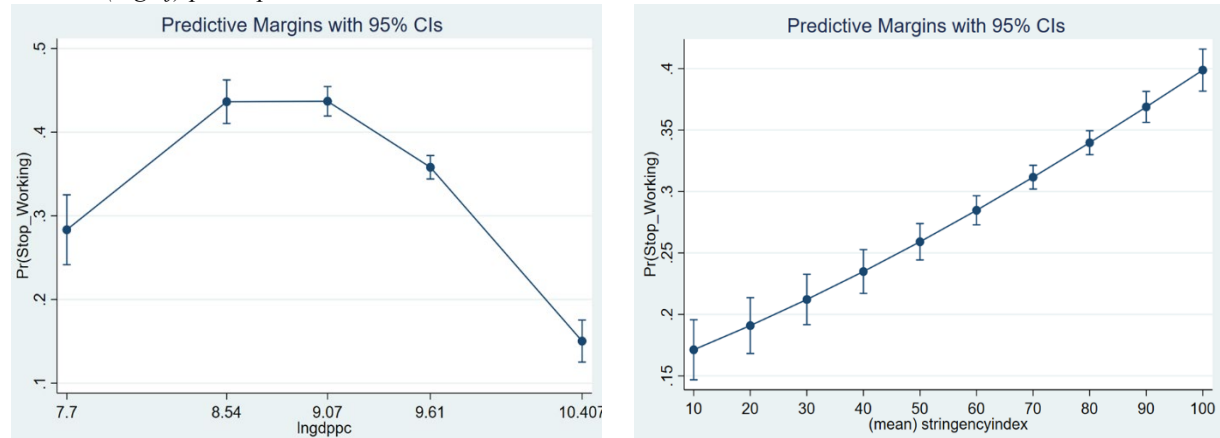
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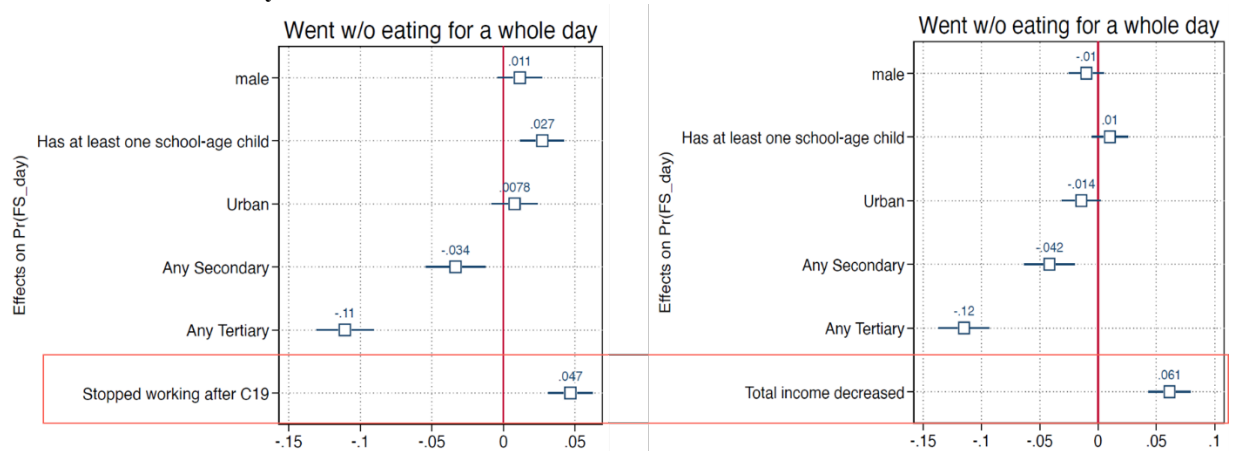
## Annex A

**Figure A-1: Country-level correlates of self-reported job losses in 3 months after the onset of the pandemic**  
 (a) *Inverted U-shaped relationship between job loss and (log of) per capita GDP* (b) *Higher policy stringency associated with more job losses*



*Note:* Policy stringency is measured by the stringency index, which measures the strictness of lockdown-style policies that restrict people's mobility and behavior, available from Oxford's "Coronavirus Government Response Tracker" (OxCGRT)  
*Source:* Based on Bundervoet, Garcia and Davalos (2021) – updated by the authors with April 2021 vintage of harmonized HFPS data

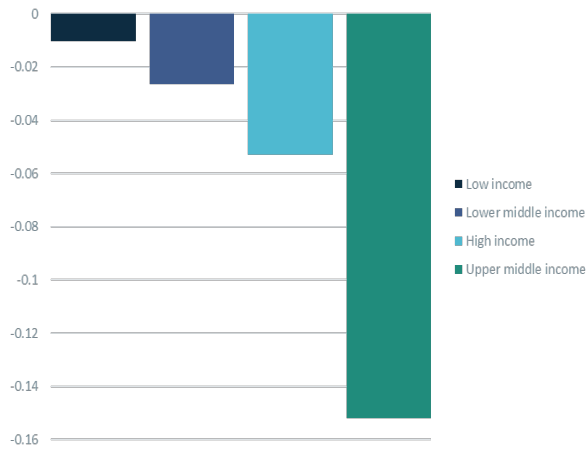
**Figure A-2: Controlling for other factors, households affected by job or income losses experienced higher levels of food insecurity**



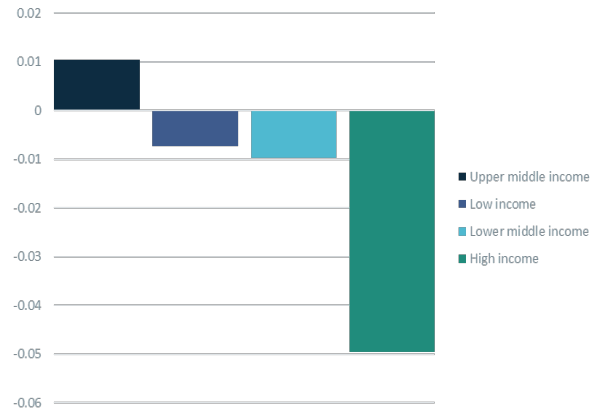
*Note:* Based on logistic regressions of whether a household reports being food insecure with country dummies. Overall incidence of food insecurity is 17%, so the effects are sizable. Other indicators of food insecurity show similar results.  
*Source:* Based on Bundervoet et al (2021), updated by the authors with April 2021 vintage of harmonized HFPS data

**Figure A-3: Pattern of (inequality) in employment impacts can vary across types of countries (income groups)**

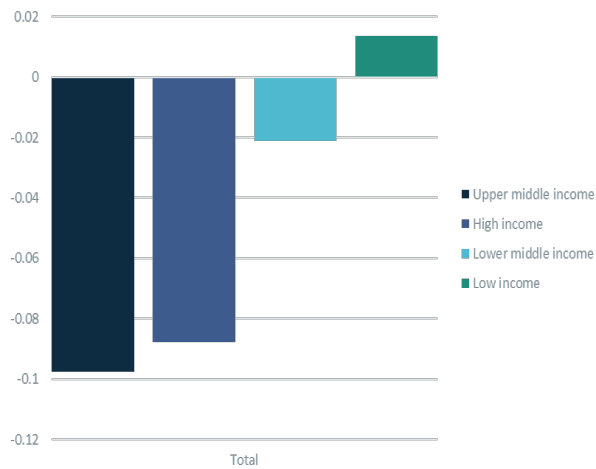
(a) Gender gap (male–female): share of respondents who stopped working permanently or temporarily (%)



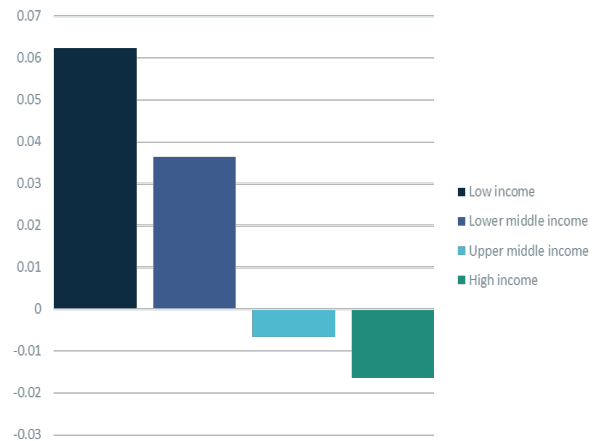
(b) Age gap (older–younger): share of respondents who stopped working permanently or temporarily (%)



(c) Education gap (higher–lower educated): share of respondents who stopped working, perm or temp (%)



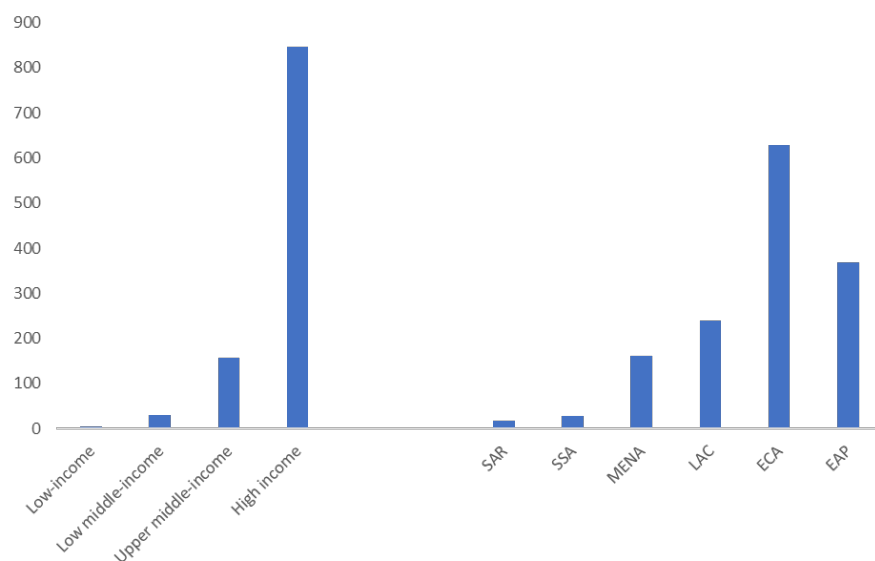
(d) Urban-rural gap: share of respondents who stopped working permanently or temporarily (%)



*Note:* averages for income groups are simple averages across countries in each group for which data is available, unweighted by population

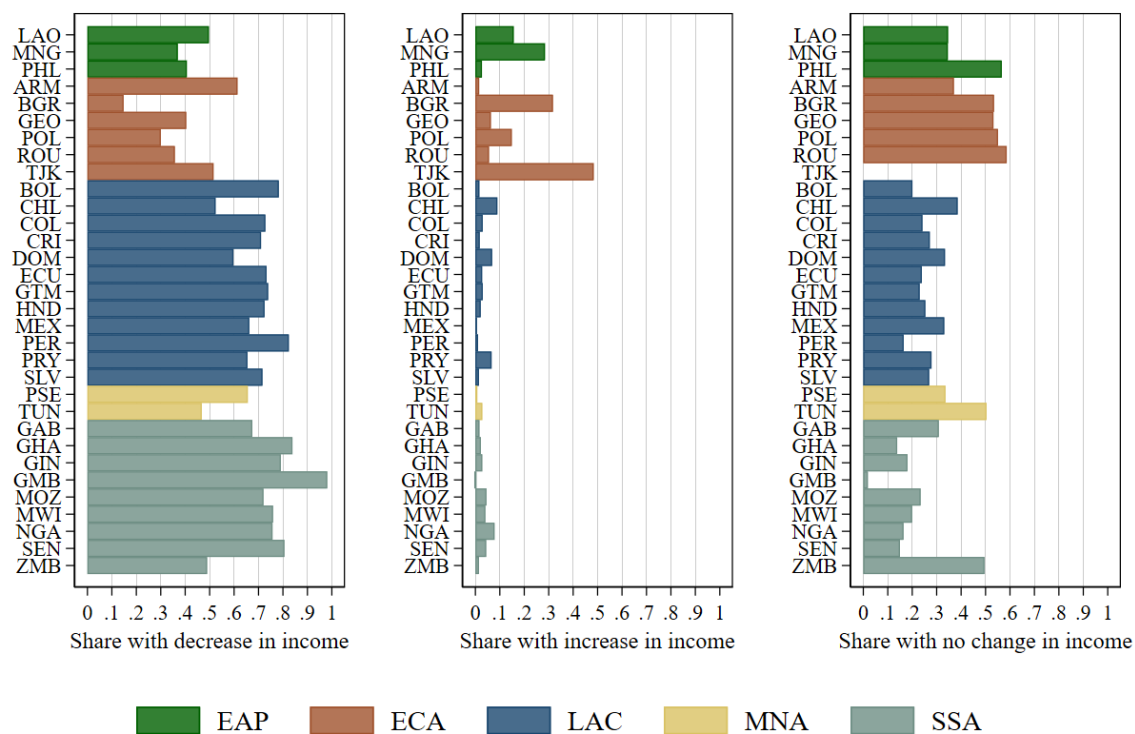
*Source:* Based on Bundervoet, Garcia and Davalos (2021) – updated by the authors with April 2021 vintage of harmonized HFPS data

**Figure A-4: Average spending per capita on COVID-19 social protection (US \$)**



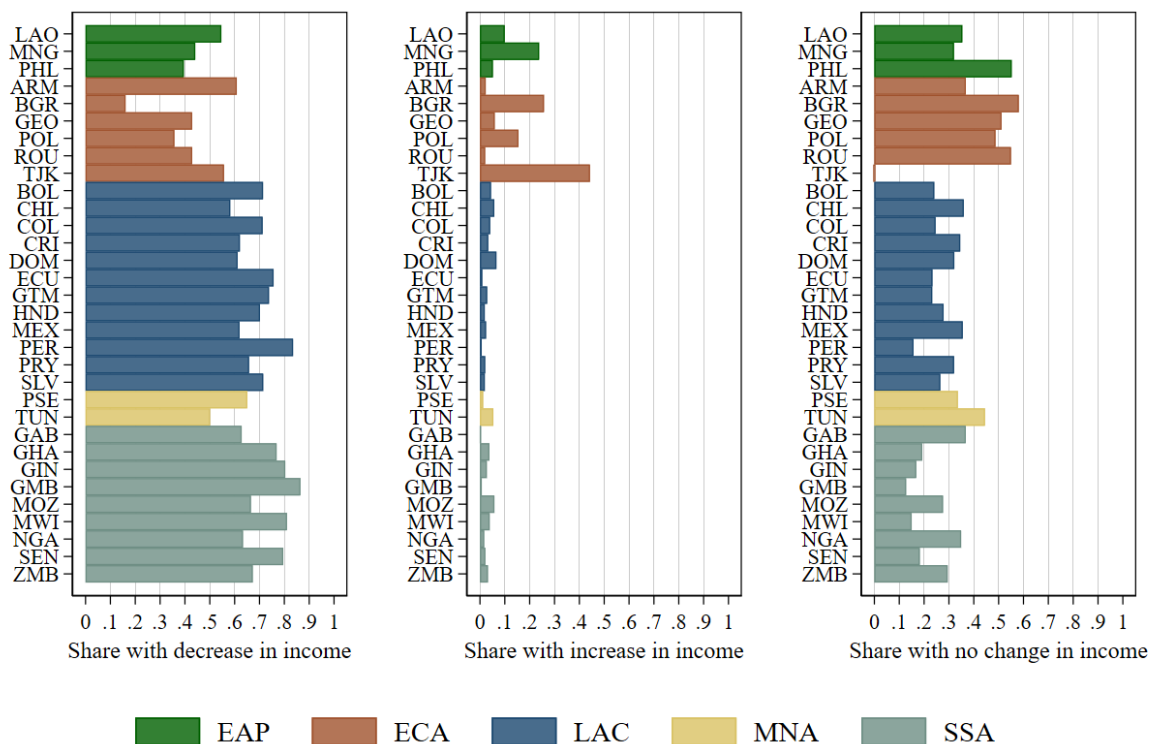
Source: Based on Bundervoet et al (2021) using Gentilini et al (June 2021), updated by the authors

**Figure A-5: (a) Probability of change in income, Rural Households**



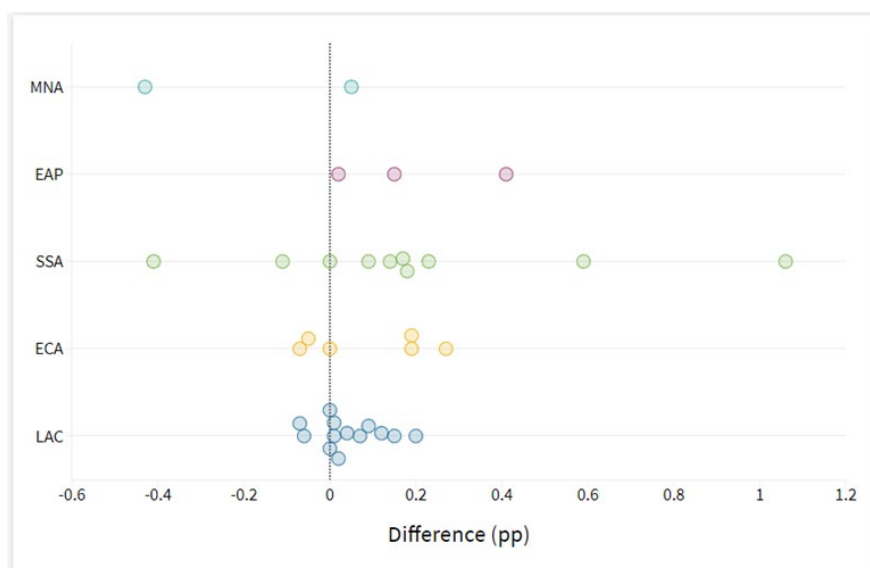


**(b) Probability of change in income, Urban Households**



Source: Mahler (R) al. (forthcoming)

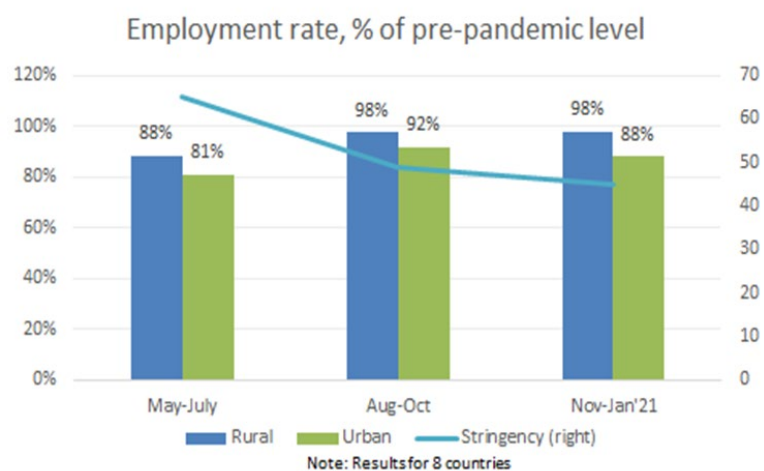
**Figure A-6: Difference in poverty rate between the distribution-sensitive and distribution-neutral scenario**



Note: difference between the distribution-sensitive poverty rates and poverty rates assuming distributional-neutrality

Source: Mahler (R) al. (forthcoming)

**Figure A-7: Employment dynamics by rural/urban**



Source: Own calculations using harmonized HFPS data

## Annex B: Inequality simulations methodology

To estimate the impact of the pandemic on poverty and inequality we triangulate three data sources: the latest household survey for each country, the World Bank's High-Frequency Phone Surveys (HFPS), and national accounts data. To start with, we need to know the level of poverty and inequality before COVID-19. Most countries do not have annual household surveys and hence lack a poverty estimate for 2019. To circumvent this, we use the last household survey available for each country, and assume that since this survey was collected, all households' welfare has grown in accordance with growth observed in national accounts. Hence, the method shifts the entire distribution by a given factor.

To estimate the impact of COVID-19 on these distributions we utilize a variable from the HFPS indicating whether a household lost, gained, or had no change to their income since the start of the pandemic. We use this variable to predict the probability that households experienced a change in income based on certain characteristics such as their education, demographic characteristics, and urban/rural residence. We merge these probabilities with the household surveys for 2019 such that each household is assigned an income loss, gain, or no change with a certain probability. Suppose for example that the phone survey of a particular country revealed that 75% of urban households where the head has less than primary education experienced a decrease in income in 2020, 20% experienced no change, and 5% experienced an increase in incomes. We find all urban households where the head has less than primary in the latest household survey, and randomly select 75% of them to experience a decrease in incomes, 20% to have their incomes kept constant, and 5% to have an increase in incomes.

National growth in per capita GDP,  $g^{nat}$ , can be attributed to rural and urban areas using the following identity:

$$(1A) \ g_t^{nat} = g_t^{rur} y_{t-1}^{rur} + g_t^{urb} y_{t-1}^{urb},$$

where  $g_t$  represents growth in rural and urban areas and  $y_{t-1}$  is the share of national income pertaining to rural or urban areas. Note that the contribution to national growth from rural areas is defined as  $g_t^{c,rur} = g_t^{rur} y_{t-1}^{rur}$ . Likewise, urban contribution is  $g_t^{c,urb} = g_t^{urb} y_{t-1}^{urb}$ .

From the phone surveys we do not know the size of the income losses and increases. However, we want to assure that the total income decreases and increases we assign in rural and urban areas match the aggregate GDP per capita growth from national accounts as in equation (1A).<sup>40</sup> The growth of rural households that have experienced an increase, decrease, and zero change in income,  $g_t^{rur+}$ ,  $g_t^{rur-}$ , and  $g_t^{rur0}$ , and the share of income pertaining to rural households that have experienced an increase, decrease or no change in income,  $s_{t-1}^{rur+}$ ,  $s_{t-1}^{rur-}$ , and  $s_{t-1}^{rur0}$  (and similarly for urban), should aggregate such that:

$$g_t^{rur} = g_t^{rur+} s_{t-1}^{rur+} + g_t^{rur-} s_{t-1}^{rur-} + g_t^{rur0} s_{t-1}^{rur0}$$

and,

$$g_t^{urb} = g_t^{urb+} s_{t-1}^{urb+} + g_t^{urb-} s_{t-1}^{urb-} + g_t^{urb0} s_{t-1}^{urb0}.$$

Hence, we may rewrite equation (1A) as:

<sup>40</sup> In practice, we only assume that 85% percent of growth in national accounts pass through to growth rates observed in household surveys, following historical evidence presented in Lakner et al. (forthcoming). Hence, whenever growth rates in national accounts are referred to here, we are working with 0.85 times the growth rate.

$$(1B) \ g_t^{nat} = (g_t^{rur+} s_{t-1}^{rur+} + g_t^{rur-} s_{t-1}^{rur-} + g_t^{rur0} s_{t-1}^{rur0}) \times y_{t-1}^{rur} \\ + (g_t^{urb+} s_{t-1}^{urb+} + g_t^{urb-} s_{t-1}^{urb-} + g_t^{urb0} s_{t-1}^{urb0}) \times y_{t-1}^{urb}$$

We know that  $g^{rur0} = g^{urb0} = 0$ , but the remaining four growth terms on the right-hand side of equation (1B) are unknown, hence, more assumptions are needed.

First, we assume that the sectoral growth rates from national accounts can be allocated to rural and urban areas. Denote the contribution to growth from agriculture, industry, and services as  $g_t^{c,agr}$ ,  $g_t^{c,ind}$ , and  $g_t^{c,ser}$ , then total growth is given by  $g_t^{nat} = g_t^{c,agr} + g_t^{c,ind} + g_t^{c,ser}$ . We assume that the growth in agricultural incomes pertain to rural households, that the growth in industry income applies to urban households, and that growth in the services sector is distributed to urban and rural households based on their population shares. In other words, we assume the rural contribution to national growth,  $g_t^{c,rur} = g_t^{c,agr} + \frac{pop_{t-1}^{rur}}{pop_{t-1}^{nat}} g_t^{c,ser}$  and the urban contribution to national growth,  $g_t^{c,urb} = g_t^{c,ind} + \frac{pop_{t-1}^{urb}}{pop_{t-1}^{nat}} g_t^{c,ser}$ . We can now split equation (1B) into two:

$$(2R) \ g_t^{c,rur} = g_t^{c,agr} + \frac{pop_{t-1}^{rur}}{pop_{t-1}^{nat}} g_t^{c,ser} = (g_t^{rur+} s_{t-1}^{rur+} + g_t^{rur-} s_{t-1}^{rur-}) \times y_{t-1}^{rur}$$

and

$$(2U) \ g_t^{c,urb} = g_t^{c,ind} + \frac{pop_{t-1}^{urb}}{pop_{t-1}^{nat}} g_t^{c,ser} = (g_t^{urb+} s_{t-1}^{urb+} + g_t^{urb-} s_{t-1}^{urb-}) \times y_{t-1}^{urb}$$

We still have two unknowns in each equation: the growth rate of rural (urban) households experiencing an income decline or increase. To progress, we first set the size of the income increases to match the growth projections prior to COVID-19. To make sense of this, notice that all the equations above can be written based on the most recent growth estimate – which we refer to without any additional notation – as well as based on what was expected prior to COVID-19 spreading. We refer to those equations by adding ‘preCOVID’ as a subscript. Keep in mind that the time of the growth estimates still refer to 2020, only now they were estimated before COVID-19 spread. In practice, this means we assume that

$$g_t^{rur+} = g_{t,preCOVID}^{c,agr} + \frac{pop_{t-1}^{rur}}{pop_{t-1}^{nat}} g_{t,preCOVID}^{c,ser} \text{ and } g_t^{urb+} = g_{t,preCOVID}^{c,ind} + \frac{pop_{t-1}^{urb}}{pop_{t-1}^{nat}} g_{t,preCOVID}^{c,ser}.$$

We now have only one unknown in equations (2R) and (2U),  $g_t^{rur-}$  and  $g_t^{urb-}$ , and can find these by isolation:

$$g_t^{c,agr} + \frac{pop_{t-1}^{rur}}{pop_{t-1}^{nat}} g_t^{c,ser} = \left\{ \left( g_{t,preCOVID}^{c,agr} + \frac{pop_{t-1}^{rur}}{pop_{t-1}^{nat}} g_{t,preCOVID}^{c,ser} \right) s_{t-1}^{rur+} + g_t^{rur-} s_{t-1}^{rur-} \right\} \times y_{t-1}^{rur} \leftrightarrow \\ (3R) \ g_t^{rur-} = \frac{\left( g_t^{c,agr} + \frac{pop_{t-1}^{rur}}{pop_{t-1}^{nat}} g_t^{c,ser} \right) / y_{t-1}^{rur} - \left( g_{t,preCOVID}^{c,agr} + \frac{pop_{t-1}^{rur}}{pop_{t-1}^{nat}} g_{t,preCOVID}^{c,ser} \right) s_{t-1}^{rur+}}{s_{t-1}^{rur-}}$$

Similar calculations for urban households yield that

$$(3U) \ g_t^{urb-} = \frac{\left( g_t^{c,ind} + \frac{pop_{t-1}^{urb}}{pop_{t-1}^{nat}} g_t^{c,ser} \right) / y_{t-1}^{urb} - \left( g_{t,preCOVID}^{c,ind} + \frac{pop_{t-1}^{urb}}{pop_{t-1}^{nat}} g_{t,preCOVID}^{c,ser} \right) s_{t-1}^{urb+}}{s_{t-1}^{urb-}}$$

To foster some intuition, suppose for the moment that all growth rates in equation (3R) and (3U) are negative, except for the ones with a preCOVID subscript. The income declines of rural households are then driven by three factors (with a similar intuition for urban households):

1. [The first two terms in the numerator of (3R)]: The larger decline in agricultural and service sector growth, the larger drops rural households assigned to an income loss will have.
2. [The remaining terms of the numerator in (3R)]. The greater growth in agriculture and services expected before COVID-19, and the more rural households experiencing income increases, the larger drops rural households assigned to an income loss will have.
3. [The denominator of (3R)]: The more rural households experiencing a decrease in incomes, the smaller decrease the rural households assigned to an income loss will have.

With this procedure, for all the countries in our sample, we have a distribution of households' income in both 2019 and 2020. To assess the impact of COVID-19 we create a counterfactual 2020 estimate using the last pre-pandemic sectoral GDP forecast for 2020. We assume that had COVID-19 not occurred, all rural households' income would have grown by the growth in agricultural income from these forecasts (plus their share of service sector growth, i.e.  $g_{t,preCOVID}^{c,ind} + \frac{pop_{t-1}^{rur}}{pop_{t-1}^{nat}} g_{t,preCOVID}^{c,ser}$ ) and similarly for urban households with industrial income. We also create a scenario which assumes that COVID-19 hit all households equally to isolate the impact of changes in inequality on the increase in poverty. This scenario scales the 2019 distributions with the published GDP growth for 2020, i.e. it adjusts all households' income with the growth rate  $g_t^{nat}$ .