



Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

The short-term impacts of COVID-19 on households in developing countries: An overview based on a harmonized dataset of high-frequency surveys

Tom Bundervoet*, Maria E. Dávalos, Natalia Garcia

The World Bank Group, USA



ARTICLE INFO

Article history:

Accepted 3 February 2022

Available online 8 February 2022

ABSTRACT

We combine new data from high-frequency surveys with data on the stringency of containment measures to examine the short-term impacts of the COVID-19 pandemic on households in developing countries. This paper is one of the first to document the impacts of COVID-19 on households across a large number of developing countries and to do so for a comparable time-period, corresponding to the peak of the pandemic-induced drop in human mobility, and the first to systematically analyze the cross- and within-country effects on employment, income, food security and learning. Using representative data from 31 countries, accounting for a combined population of almost 1.4 billion, we find that in the average country 36 percent of respondents stopped working in the immediate aftermath of the pandemic, 65 percent of households reported decreases in income, and 30 percent of children were unable to continue learning during school closures. Pandemic-induced jobs and income losses translated into heightened food insecurity at the household level. The more stringent the virus containment measures, the higher the likelihood of jobs and income losses. The pandemic's effects were widespread and regressive, disproportionately affecting vulnerable segments of the population. Women, youth, and workers without higher education – groups disadvantaged in the labor market before the COVID-19 shock – were significantly more likely to lose their jobs and experience decreased incomes. Self-employed and casual workers – the most vulnerable workers in developing countries – bore the brunt of the pandemic-induced income losses. Interruptions in learning were most salient for children from lower-income countries, and within countries for children from lower-income households with lower-educated parents and in rural areas. The unequal impacts of the pandemic across socio-economic groups risk cementing inequality of opportunity and undermining social mobility and calls for policies to foster an inclusive recovery and strengthen resilience to future shocks.

© 2022 Published by Elsevier Ltd.

1. Introduction

The COVID-19 pandemic is resulting in dramatic loss of life across the world. By December 8, 2021, a minimum of 5.3 million people had succumbed to the virus, with many more continuing to suffer from adverse longer-term health consequences of infection. Containment measures to curb the spread of the virus have exacted a large toll on the global economy, with worldwide economic output projected to have contracted by 3.5 percent in

2020 (IMF, 2021). Unlike the Great Recession, during which emerging and developing economies still recorded positive growth, the current pandemic has led to economic contraction in developing countries as well, with large consequences for poverty: the number of people living in extreme poverty is projected to have increased by between 119 million and 124 million in 2020, the first increase in global poverty since the Asian financial crisis of 1997/98 (World Bank, 2020a). In addition, while a strong economic rebound is expected for 2021, the estimated COVID-19-induced poor is projected to rise to between 143 million and 163 million in 2021, given the fairly low expected GDP per capita growth rates in countries accounting for the bulk of the global poor and the impacts of subsequent waves of the pandemic in both developed and developing countries (Lakner et al., 2021).

* Corresponding author.

E-mail address: tbundervoet@worldbank.org (T. Bundervoet).

While high income countries have on average experienced sharper economic downturns in 2020 because of the pandemic,¹ they have been able to provide unprecedented relief and stimulus in the form of cash transfers, expanded unemployment insurance, wage subsidies, deferral of tax obligations and social security contributions, etc. In 2020, advanced economies on average spent 8.5 percent of GDP on so-called “above the line” measures – budgetary fiscal support to people and firms in response to the pandemic.² These measures have helped to mitigate the worst socio-economic impacts of the crisis on households and workers, at least in the short-term. Governments in emerging markets and developing countries, however, had far less fiscal space to provide similar levels of relief: spending on above the line fiscal measures amounted to 2.9 percent of GDP in emerging markets and 1.7 percent of GDP in low-income developing countries. [Gentilini et al. \(2020\)](#) also show that COVID-related social protection spending was far higher in richer 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 who are unable to smooth consumption given the absence of sufficient savings or assets.

In this paper we analyze the short-to-medium term effects of the COVID-19 shock on the welfare of households and individuals in developing countries. The paper is based on data from high-frequency phone surveys from 31 low- and middle-income countries and over 41,000 households following the onset of the pandemic.³ To assess the immediate impact of the crisis in a comparable way across countries, we select survey waves within no more than two months of the first peak of the pandemic, with the peak measured by the stringency of social distancing measures. As the questionnaires were tailored to specific country contexts, data was harmonized by the World Bank to arrive at a harmonized micro-data set of 93 indicators.⁴ In this paper we mainly focus on four harmonized key indicators of household well-being: (i) job loss, whether the respondent to the phone survey had temporarily or permanently stopped working because of the pandemic; (ii) income loss, a self-reported measure of whether the household has experienced a reduction in income since the start of the pandemic; (iii) food insecurity, whether one or more adult household members had gone a whole day without eating because of lack of resources; and (iv), continued engagement in learning activities, whether the school-aged children of the household have continued to engage in learning activities during school closures. These four measures of household welfare in the immediate aftermath of the pandemic are examined in relation to households’ time-invariant socio-economic characteristics to assess the distributional nature of the crisis’ impacts, and in some cases to country-level variables including income level and the stringency of social distancing measures put in place.

We find that the pandemic has exacted a heavy toll on households in developing countries. Across countries, an average of 36.2 percent of respondents stopped working, either temporarily

or permanently, in the immediate aftermath of the pandemic, 65 percent of households reported a decrease in total income, and 30 percent of children did not continue in alternative learning activities as schools closed. The country-level stringency of containment policies was significantly correlated with job losses. Job and income losses were associated with significantly higher food insecurity at the household level, a pattern that does not seem to be due to pre-pandemic differences in food security. Despite substantial heterogeneity in the severity of impacts across countries, the impacts are found to be regressive, with more vulnerable segments of the population being disproportionately affected. Women, youth, and workers without tertiary education were significantly more likely to lose their job, and are also finding it harder to transition back into employment. The effects were also different by pre-pandemic sector of employment, with workers in manufacturing, commerce, and other services being more likely to have stopped working relative to those in agriculture. Self-reported income losses are high across the board but are highest for the non-farm self-employed, whose livelihoods depend on dense traffic and face-to-face interaction and have been heavily affected by lockdown-style measures. Learning interruptions have disproportionately affected children from poor households in lower-income countries, and children with lower-educated parents and in rural areas, further increasing the learning and opportunity gap across socio-economic groups.

The paper contributes to the growing literature on the household-level impacts of the COVID-19 shock. Most research so far has focused on the impact of COVID-19 in developed countries, where the labor market impacts of COVID are found to be highly regressive (see, for instance, [Adams-Prassl et al, 2020](#); [Crossley et al, 2021](#); [Chetty et al., 2020](#); [Miguel & Mobarak, 2021](#)). For developing countries, a substantial number of country-level impact monitoring reports have been produced based on high-frequency surveys that were fielded in the aftermath of the pandemic.⁵ [Egger et al. \(2021\)](#) is the first study to systematically combine post-pandemic surveys from nine developing countries in Africa, Asia and Latin America, and finds negative effects across countries in incomes and food security, with high heterogeneity in impacts. This paper is closest in spirit and approach to [Egger et al. \(2021\)](#) but combines high-frequency survey data from a larger number of countries with a broader geographical scope, and focuses more explicitly on the inequities in the pandemic’s economic impacts. By documenting and analyzing patterns across 31 low- and middle-income countries across Africa, East Asia and the Pacific, Latin America, Europe and Central Asia, and Middle East and Northern Africa, this paper adds to the knowledge on the impacts and the heterogeneity of impacts of the COVID-19 crisis on households in developing countries.

This paper proceeds as follows: [Section 2](#) describes a simple framework on how the COVID-19 pandemic can affect household welfare and introduces the data used in the analysis. The descriptive statistics and results of the regression analyses are presented in [Section 3](#), while [Section 4](#) discusses implications of the analytical results in terms of inequality and prospects of inclusive growth, and briefly summarizes the broad policy directions to foster an inclusive recovery and build resilience to future shocks. The final section concludes.

2. Framework and data

The COVID-19 pandemic is an aggregate shock to economic activity and can affect welfare and well-being at the household

¹ The economic contraction in 2020 is estimated at 4.5 percent for advanced economies and 2.1 percent for emerging markets and developing economies. Low-income developing countries experienced growth of 0.1 percent, which, given rapidly growing populations in these countries, translate into negative growth on per capita basis (IMF, 2021).

² Calculated from the IMF’s Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic (January 2021 version). <https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19>. This does not include direct spending on the health sector.

³ COVID-19 high frequency surveys have been implemented in many more countries. This paper is however based on the 31 countries for which data have been harmonized and disclosure has been authorized.

⁴ As of February 3, 2021. For more information, please consult the World Bank’s high frequency monitoring dashboard (<https://www.worldbank.org/en/data/interactive/2020/11/11/covid-19-high-frequency-monitoring-dashboard>).

⁵ For an overview, see <https://www.worldbank.org/en/data/interactive/2020/11/11/covid-19-high-frequency-monitoring-dashboard>

and individual level through several channels. First, there is likely to be an impact on labor income due to the decline in aggregate demand, potential supply disruptions, and the associated decrease in employment and/or the returns to productive activities. Impacts will likely be felt first and foremost by those employed in vulnerable sectors, such as tourism and services (especially those services that require personal interaction), as well as by those in the gig economy and those unable to work remotely. Lost earnings could also result from the direct health impact of the outbreak on breadwinners. Second, non-labor income is likely to be negatively affected through a decline in remittances and domestic private transfers, and positively affected through a potential scale-up of public transfers and government-provided assistance. Third, disruptions in the functioning of markets could lead to price increases and/or rationing of basic consumption goods. Fourth, disruptions to service delivery, particularly health and education services, can have important long-run effects through the impact of health and education in childhood on future socio-economic well-being.⁶ In addition, school closures are likely to reduce labor supply of parents, particularly women, with potentially adverse effects on incomes.

While the distributional impacts of the COVID-19-induced economic shock have been highly regressive in rich countries,⁷ the short-run distributional impacts of the COVID-19 pandemic in developing countries are unclear ex-ante. In low and lower middle-income countries, the bulk of the poor reside in rural areas and are primarily engaged in own-account agriculture. This may minimize both the exposure to the virus (given the lower population density in rural areas) and its labor impacts, as self-employed or subsistence farmers are unlikely to stop working and/or be subject to strict lockdown measures. As such, the pandemic may have resulted in a temporary decrease in income inequality as better-off urban service workers have been more affected. As the pandemic-induced economic slowdown continues however, farm incomes may be adversely affected by reduced urban demand resulting from decreased purchasing power and the shutdown of urban hospitality services. In upper-middle income countries, where a large share of the poor work in low-skilled urban services and the “gig economy”, and particularly in settings with high share of informal jobs, impacts may be most felt by the poor, resulting in a highly regressive income shock. Given the high reliance of low-income households on public services and their limited capacity to smooth consumption, it is likely that despite substantial cross-country heterogeneity, the pandemic’s long-term effects will be particularly damaging to the poor and vulnerable. Income losses can quickly translate into the loss of productive assets, which will be hard to rebuild even in the medium term; the effect of long school closures, disruptions to early childhood development services, school nutrition programs, etc., are much higher on poor families and their children; and when they occur at critical ages, may not be recoverable for the cohort that suffers the temporary shock.

The data used in this paper are the result of an unprecedented data collection effort aimed at producing real-time information on the socioeconomic impacts of COVID-19 and the associated economic crisis on households and individuals in developing regions. Since the start of the outbreak, the World Bank has implemented or supported high-frequency phone household surveys in over 100 countries. As the contents of the questionnaires differed by country, data are being harmonized by the World Bank, resulting in a database currently containing 93 indicators and captured in

a publicly available dashboard. Additional survey waves and countries are being regularly added to the harmonized database.⁸ The analysis presented in this paper is based on harmonized data from 31 countries and over 41,000 respondents (for the variable that was asked in most of the countries), which corresponds to the December 2020 vintage of the harmonized database. The countries, which represent a combined population of almost 1.4 billion, are spread geographically across Sub-Saharan Africa (11 countries), Latin America and the Caribbean (11 countries), East Asia and the Pacific (6 countries), Middle East and North Africa (1 country) and Europe and Central Asia (2 countries). Annex 2 describes the countries in the harmonized database in more detail.

The high-frequency surveys were designed to be nationally representative. Though specific procedures differ by country, all data sets have been reweighted to adjust for differential response rates among subgroups of the population, with the objective of obtaining estimates as close to nationally representative as possible. However, several limitations inherent to conducting phone surveys need to be taken into account. First, groups with limited network coverage or no access to phones, mainly the poorest segment of the population, will be under-covered in the sample. Using data from four countries with pre-pandemic data, [Ambel et al. \(2021\)](#) show that phone survey respondents tend to be better off than the general population, and that reweighting schemes can substantially reduce bias. This reweighting scheme can only be used if a recent representative survey is available and hence cannot be used on our full dataset. For countries with pre-pandemic data however, reweighting does not qualitatively alter the results. Second, indicators that are measured at the individual level (such as employment and unemployment) will be biased due to respondent selection. In countries where the high-frequency surveys are sampled from an existing nationally representative (pre-pandemic) survey, the respondent to the phone survey was the household head, and particular characteristics related to being a household head (such as more likely to be male and older) mean that employment rates as measured from the high-frequency surveys would differ from those estimated by a conventional Labor Force Survey.⁹ These caveats need to be kept in mind when interpreting the results.

This paper mainly focuses on four key harmonized indicators that summarize the pandemic’s impact on household well-being across multiple dimensions: employment, income, food security, and continued learning. The indicators are defined as follows:

- **Stop working:** The harmonized indicator “stop working” is a dummy variable indicating whether or not the respondent to the phone survey stopped working after the pandemic. The indicator takes on the value 1 if the respondent was working before the pandemic and was not working in the first survey wave after the pandemic. This indicator is available for all 31 countries in our data set. The stop working variable does not capture reduced working hours due to the pandemic and is thus a lower bound of lost labor input.
- **Income loss:** The harmonized indicator “income decreased” is a dummy variable indicating whether the household’s total income (both labor and non-labor) decreased since the onset of the pandemic. This information is self-reported by the respondent and available for 24 countries. Additional data on changes in sources of income is also available, including on remittances, and farm and non-farm labor income.

⁶ Draws from World Bank (2020c).

⁷ See, for instance, [Adams-Prassl et al. \(2020\)](#), [Bartik et al. \(2020\)](#), [Crossley et al. \(2021\)](#), and [Chetty et al. \(2020\)](#). The Washington Post called the COVID-19 recession “the most unequal in modern U.S. history” (<https://www.washingtonpost.com/graph-ics/2020/business/coronavirus-recession-equality/>).

⁸ For more information on the harmonization process and the dashboard summarizing the indicators, please visit <https://www.worldbank.org/en/data/interactive/2020/11/11/covid-19-high-frequency-monitoring-dashboard>.

⁹ Individual-level questions were only asked to the respondent and not to all adult household members. Ongoing work is exploring reweighting schemes to partially control for these selection effects.

- Food security: The harmonized indicator “FS_day” is a dummy variable indicating whether any adult in the household went without eating for a whole day because of a lack of money or other resources in the last 30 days. This indicator is part of the standard Food Insecurity Experience Scale (FIES) and was asked in 24 countries. Alternative indicators of food insecurity, which are also part of the FIES, will be used to test robustness.¹⁰
- Continued learning: The harmonized variable “Educ_any” is a dummy variable indicating whether the household’s school-aged children (who were in school before the pandemic) have engaged in any learning or educational activities during school closures. Learning activities cover a wide range of options, including completing assignments provided by teachers, attending remote teaching sessions, watching educational TV programs and listening to educational programs on the radio. This question was asked in 29 countries.

Sample weights were calculated for all observations in the country-level high frequency surveys. Given that we work with the pooled country-level surveys, an important decision is how to scale the weights. Scaling the sample weights with each country’s population size would result in an equal probability of selection for all (phone-owning) households in the included countries but would give more weight to large countries, with the possibility that observed patterns would be driven by a small number of big countries. To avoid this, we re-scale household sampling weights to assign each country equal weight. Descriptive statistics should thus be interpreted as averages of country averages.

This paper focuses on the immediate impacts of the COVID-19 shock. Given that (i) surveys were implemented at different times in different countries and (ii) the timing and stringency of COVID containment measures was different by country, a key step in identifying the immediate COVID-19 crisis impacts is to define the timing of the peak of the COVID-induced socio-economic disruption in each country. To define this period of “peak disruption”, we use data from Oxford’s “Coronavirus Government Response Tracker” (OxCGRT). OxCGRT systematically collects information on several common policy responses that governments have taken to respond to the pandemic.¹¹ These policy responses are captured by 19 indicators, which are used to construct a set of four common indices. One of the indices, the stringency index, measures the strictness of lockdown-style policies that restrict people’s mobility and behavior. We use this index, which ranges from 1 to 100, to identify for each country the peak stringency of government measures. The survey wave which follows the moment of peak stringency, with a maximum distance to peak of two months, is then used to capture the immediate COVID-19 impacts.

One potential threat to the cross-country comparability of the stringency index is the extent to which lockdown measures are actually respected and enforced. To verify the validity of the stringency index, we cross-check its pattern with the Google mobility data. The Google mobility data show the trend in visits to places such as grocery stores, retail and recreational facilities, transit stations, workplaces, etc., relative to a pre-COVID baseline period.¹² While the stringency index summarizes the strictness of a country’s containment measures, the google mobility data summarizes what actually happens to human mobility. Overall, both data sets are strongly correlated: Most countries started introducing containment measures in March 2020 and the stringency of these measures

peaked in April 2020 (Fig. 1). In parallel, mobility sharply dropped and bottomed out in April 2020 (Fig. 2). Stringency tapered off starting May 2020, and mobility started to recover, though at different speeds for different countries. As a result, for most countries in our sample, the survey wave used to estimate the immediate impacts of the pandemic was implemented in May or June 2020.

3. Impacts of the crisis

3.1. Descriptives

Table 1 presents the descriptive statistics of the four main indicators. In the average country in the sample, 36 percent of respondents stopped working in the immediate aftermath of the peak of government-imposed virus containment measures.¹³ The incidence of job losses increases with country income level, being lowest in low-income countries and highest in upper middle-income countries. At the regional level, countries in Sub Saharan Africa (SSA) and East Asia and the Pacific (EAP) experienced the lowest job losses (at approximately 23 percent), reflecting in part the lower job losses among low-income countries, which are predominantly located in those regions. Latin America and the Caribbean experienced the highest job losses: In the average country, over half of respondents reported having lost their job either temporarily or permanently.

At the individual level, women and young workers were most likely to have stopped working because of the pandemic. On average across countries, 43 percent of women lost their job, compared to 31 percent of men. The age difference is less salient though still statistically significant at the 1% level. As expected, urban workers were hit harder by the short-term economic fallout from the pandemic, with 41 percent reporting having lost their job compared to 28 percent of rural workers. Less-educated workers (primary education or less) were somewhat less likely to report job losses compared to more-educated (secondary or tertiary-educated) workers, likely due to low-skilled workers’ overrepresentation in own account agriculture. Finally, the stringency of containment policies, as measured by the aggregate score on the Oxford stringency index, was significantly correlated with job losses: In countries with above median stringency, 45 percent of workers lost their job, compared to 23 percent in below-median stringency countries.

The lower job losses in low-income countries is likely explained by an employment structure that is dominated by agriculture and own-account work. Even in the non-farm sector, most workers in low-income countries tend to be self-employed in a myriad of small-scale business activities, especially in the services sector (Beegle & Christiaensen, 2019). While strictly speaking these people may not have lost their job because of the pandemic, it is likely that their incomes have been severely affected by lockdown measures and stay-at-home orders. In addition, the nature of self-employment in lower-income countries is such that it cannot be performed from home (Gottlieb et al., 2020). Many self-employed workers in urban areas of low-income countries depend on dense foot traffic and close personal interaction to make a living, and reduced mobility is bound to hit their livelihoods hard.¹⁴ The descriptives in Table 1 indeed show that while job losses were relatively low in low-income countries, income losses were high: Over 53 percent of respondents in low-income countries reported that total household income had decreased since the start of the pan-

¹⁰ The full FIES is used to estimate a population prevalence of food security and hence is not useful at a household level.

¹¹ <https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker>

¹² The baseline period is the 5- week period Jan 3–Feb 6, 2020. <https://www.google.com/covid19/mobility/>

¹³ The Egger et al (2021) study finds a median share of job loss across samples of 30 percent. The corresponding share in our sample is 32.8 percent.

¹⁴ Household enterprises, which are a key livelihood strategy for lower-income households in urban areas, have been hit particularly hard by lockdown measures. In both Nigeria and Ethiopia, 85 percent of respondents reported that income from non-farm household enterprises declined or entirely disappeared in the immediate aftermath of the pandemic (Wieser et al, 2020; World Bank, 2020b).

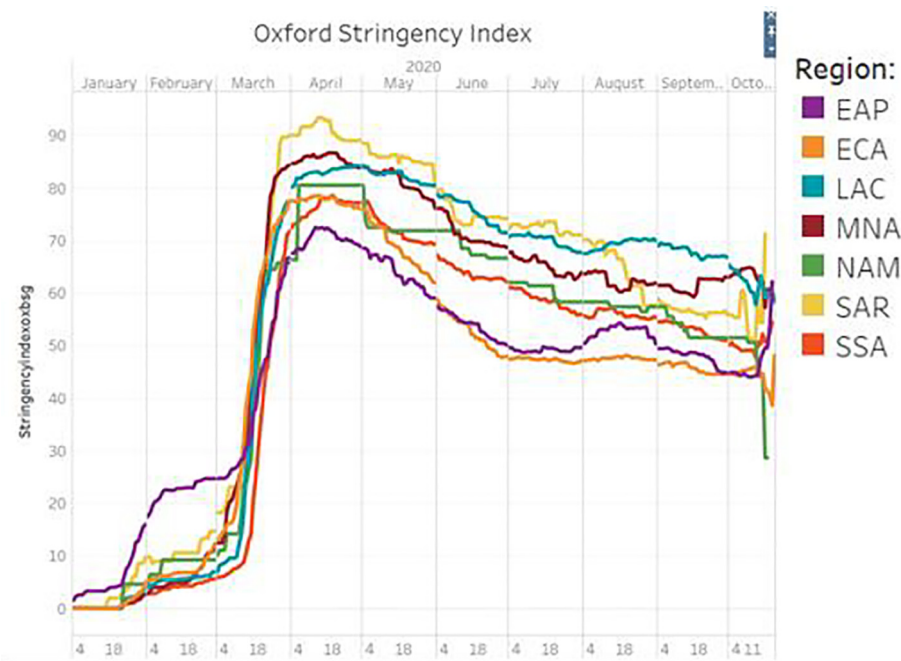


Fig. 1. Stringency of containment measures by region and month.

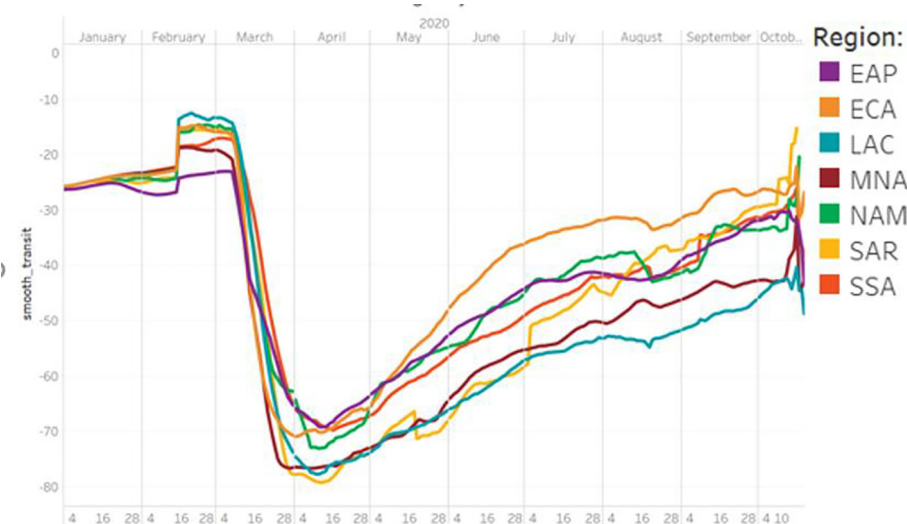


Fig. 2. Changes in human mobility relative to pre-pandemic baseline, by region and month.

demic in their country. Self-reported income losses are high across the board, and highest for upper-middle income countries. Income losses were most frequently reported in SSA and LAC, likely linked to the dominance of self-employment and informal employment in those regions. These patterns are in line with self-reported falls in labor income that are, on average, higher among nonfarm self-employed workers (across countries, an average of 63 percent of respondents report a decrease in income), compared to that of wage and farm workers (44 percent and 54 percent, respectively). They are also in line with estimates from other studies.¹⁵ Moreover, data from the high frequency surveys also shows that among remittances-

recipient households, that source of income also declined at the onset of the crisis.

While the stop working and income loss variables can be directly linked to the pandemic, this is not the case for the food security variable. The food security questions were administered with a 30-day reference period and did not explicitly refer to COVID-19,¹⁶ and for most countries there is no systematic and comparable pre-pandemic data available that would allow identifying its effect on food security. The incidence of food insecurity in the data thus cannot be attributed directly to the pandemic, especially as food insecurity is pervasive in lower-income countries even in normal

¹⁵ In their smaller sample of countries, Egger et al. (2021) find that the across-sample median share of respondents reporting a decrease in income amounts to 70 percent.

¹⁶ The question we use was phrased as follows: “In the last 30 days, did you or any other adult in your household go without eating for a whole day because of a lack of money or other resources?”

Table 1
Descriptive statistics.

	Share of observations in sample	Stopped working (% yes)	Total income decreased (% yes)	Food insecurity (% yes)	Children continued to learn (% yes)
Full sample	100	36.2 (0.249)	65.0 (0.268)	14.7 (0.173)	70.3 (0.266)
<i>By income group</i>					
Low income	22.6	18.0 (0.500)	53.2 (0.834)	18.2 (0.346)	42.5 (0.628)
Lower middle income	45.2	35.2 (0.334)	64.1 (0.356)	14.1 (0.242)	70.3 (0.361)
Upper middle income	32.3	45.7 (0.478)	67.5 (0.470)	12.4 (0.358)	91.8 (0.320)
<i>By region</i>					
SSA	35.5	23.2 (0.382)	68.1 (0.467)	18.8 (0.255)	45.3 (0.440)
EAP	19.4	23.4 (0.346)	57.0 (0.530)	12.0 (0.422)	65.7 (0.517)
LAC	35.5	51.1 (0.531)	68.2 (0.441)	12.9 (0.318)	94.4 (0.305)
ECA	6.5	34.5 “(0,	40.1 (1.136)	1.5 (0.350)	72.6 (1.112)
MNA	3.2	26.8 (1.304)	na	na	78.8 (1.257)
<i>By location</i>					
Urban	48.7	41.2 (0.263)	65.4 (0.376)	14.8 (0.238)	74.1 (0.377)
Rural	51.3	27.5 (0.356)	62.2 (0.420)	14.5 (0.271)	59.2 (0.424)
<i>By gender respondent</i>					
Female	46	42.8 (0.406)	66.0 (0.4060)	15.0 (0.268)	75.6 (0.375)
Male	54	31.4 (0.310)	64.3 (0.372)	15.0 (0.234)	66.7 (0.381)
<i>By education</i>					
Primary or less	36.5	35.1 (0.461)	65.7 (0.561)	18.6 (0.325)	59.1 (0.558)
Secondary	40	41.0 (0.444)	70.4 (0.489)	15.2 (0.293)	73.3 (0.506)
Tertiary	23.5	38.8 (0.537)	62.7 (0.608)	7.5 (0.271)	83.0 (0.570)
<i>By age</i>					
Under 30	22.8	37.3 (0.538)	66.0 (0.611)	18.9 (0.378)	65.6 (0.663)
30 and over	77.2	35.9 (0.281)	64.7 (0.298)	13.3 (0.193)	71.6 (0.288)
<i>By stringency of measures</i>					
Below median stringency	48.4	22.7 (0.299)	58.1 (0.380)	10.5 (0.228)	65.6 (0.385)
Above median stringency	51.6	44.5 (0.374)	68.6 (0.381)	17.5 (0.247)	71.6 (0.368)
N		37,243	31,668	41,697	29,597

Notes: Food insecurity is measured by following indicator: In the past 30 days, did you or any adult in the household go a whole day without eating due to lack of resources? Sample size differs across indicator as not all questions were asked in every country. Data are weighted by sample weights that are re-scaled to give each country in the sample equal weight. Standard errors in parentheses.

times. Rather, the main objective is to explore whether the pandemic has affected food security through its direct effect on the labor variables, that is, whether pandemic-induced jobs and income losses have translated into worsening food security. In a bivariate fashion, this appears to indeed be the case, with the incidence of food insecurity being five percentage points higher in households where the respondent has lost his/her job, and seven percentage points higher for households who experienced a decrease in total income (Table 2). The regression analysis below will explore to what extent this relationship is robust for the inclusion of control variables.

The interruption of schooling is a key channel through which the pandemic risks having an adverse long-term distributional effect. At the peak of the pandemic, temporary school closures in more than 180 countries have kept nearly 1.6 billion students out of school (Azevedo et al., 2020). As schools across the world closed, classroom education was progressively replaced by remote learning, at least in more developed countries. Yet many of the world's children – particularly those in poorer households – do not have

internet access, personal computers, TVs or even a radio at home, amplifying existing learning inequalities between richer and poorer countries and between better-off and worse-off households within countries. Azevedo et al. (2020) estimate that COVID-19 could result in a loss of 0.6 year of schooling adjusted for learning quality. In addition to learning loss, the severe economic impact of the pandemic is expected to increase early drop-out, especially among low-income households in lower-income countries (UN, 2020). Given the high returns to schooling in developing countries, learning losses and school dropouts would result in significant long-term welfare losses.¹⁷

¹⁷ See Psacharopoulos and Patrinos, 2018. Azevedo et al (2020) estimate that COVID-19, through its impact on learning, may lead to an average reduction in expected annual earnings US\$ 872 (in 2017 PPP terms). Next to the impact on expected earnings, school closures may also affect child mental health and may, in certain settings, put girls at higher risk of sexual violence.

Table 2
Incidence of food insecurity, by job or income loss.

	Food insecurity (% yes)
Lost job	18.7 [0.004]
Did not lose job	13.5 [0.003]
Mean difference	-5.2***
Income declined	15.6 [0.003]
Income did not decline	8.4 [0.003]
Mean difference	-7.2***

Notes: Food insecurity is measured by following indicator: In the past 30 days, did you or any adult in the household go a whole day without eating due to lack of resources? Data are weighted by sample weights that are re-scaled to give each country in the sample equal weight. Standard errors in brackets. ***: Statistically significant at the 1% level.

The descriptives in Table 1 largely confirm the unequal learning effects of school closures. In low-income countries, 43 percent of children engaged in learning activities during school closures, compared to 92 percent of children in upper middle-income countries.¹⁸ In countries in SSA, where human capital was already lagging before the pandemic, children were least likely to continue learning. The cross-country inequalities extend to the household level, where children in rural households and children in households with less-educated respondents were significantly less likely to continue learning. The few countries for which comparable pre-pandemic data on the same households are available confirm the highly regressive effects of school closures.¹⁹ This may further lower intergenerational mobility in education, which had been stagnating in developing countries even before the pandemic (World Bank, 2018).

While the descriptive statistics presented in this subsection are illustrative, they do not control for other factors which may influence the variables of interest. The next subsection will present the results of a series of regressions, controlling for country effects and covariates at the household and individual level. The focus of the regression analyses is on identifying the factors that mediate the pandemic’s impact on the outcomes of interest to assess the potentially regressive impacts of the pandemic on well-being of households in developing countries.

3.2. Regression results

In this section, we present results of logistic regressions of the four main indicators on a set of explanatory variables and country or region dummies. The basic specification is the following:

$$P(Y_i = 1) = F(\alpha + \sum_k \beta_k X_i + \delta) \tag{1}$$

where Y is the variable of interest (alternatively: stop working, income loss, food insecurity, or continued learning) and $\sum_k \beta_k X_i$ is a vector of respondent and household characteristics mediating the impact of the COVID-19 shock, consisting of age, gender, and education of the respondent, pre-pandemic sector of employment of the respondent, rural vs. urban location of the household and

¹⁸ There is one important weakness in the variable measuring continued learning during school closures. If a household has several school-aged children who were attending school prior to the pandemic, and during the pandemic only some of the children continued learning, this will not be captured. This household would be considered as a household in which children continued learning.

¹⁹ In Ethiopia, 14.6 percent of children in the lowest consumption quintile engaged in learning activities during school closures, compared to 37.1 percent in the top quintile (Wieser et al. 2020). In Nigeria, these figures amounted to 57.3 percent for the bottom quintile and 71.6 percent for the top quintile (World Bank, 2020b).

whether there are school-aged children in the household. δ denotes country dummies and pick up all observed and unobserved country-level characteristics that may influence the outcome of interest. $F(\cdot)$ is the logistic function $F(z) = \exp(z)/(1 + \exp(z))$. Specification (1) thus estimates the average within-country partial correlation between respondent and household characteristics and the outcome of interest.

While specification (1) is the preferred specification, a disadvantage is that it does not allow exploring the effects of relevant country-level variables such as country income levels and the severity of containment measures. To assess the effects of these variables, we also estimate an alternative specification with regional instead of country dummies:

$$P(Y_i = 1) = F(\alpha + \sum_k \beta_k X_i + \sum_c \gamma_c Z_c + \theta) \tag{2}$$

where $\sum_c \gamma_c Z_c$ is a vector of variables at the country level, including pre-pandemic per capita GDP levels as a squared term and the stringency of containment measures in the country, and θ are regional dummies. This specification is only estimated for the labor market variables (stop working and income loss).

Column (1) of Table 3 presents the results of the regression of stop working using specification (1). The results confirm that the pandemic had an outsized effect on those who were already disadvantaged on the labor market to begin with: Women, youth, and workers without tertiary education. Relative to men, women were 9 percentage points more likely to have lost their job in the immediate aftermath of the pandemic’s onset, and relative to tertiary-educated workers, low-skilled workers (primary or less) were 9 percentage points more likely to stop working. Both young and old workers bore the brunt of the pandemic’s jobs impact, with the probability of job loss being highest for 20- and 60-year-old workers and lowest for prime-age workers. Workers with school-age children were more likely to stop working, likely due to increased time constraints given school closures. We find however no evidence in our dataset that having school-aged children affected male and female workers differently. The pre-pandemic sector of employment played a large role in subsequent job losses, with workers in manufacturing, commerce, and other services being respectively 21, 17, and 19 percentage points more likely to have stopped working relative to workers in agriculture.²⁰ Once other factors are taken into account, urban location of the respondent is only marginally correlated with the likelihood of job loss.²¹

To assess the effect of country-level factors, Column (2) of Table 3 shows the results of specification (2). There is a non-linear association between per capita GDP levels and the likelihood of job loss, rising at low levels of GDP per capita, peaking at around US\$7200 (in purchasing power parity terms) and decreasing thereafter.²² As discussed earlier, the lower likelihood of job losses in low-

²⁰ In countries where a large share of employment is in agriculture, one may be concerned about the effects of seasonality. If, by chance, the start of the pandemic coincided with the start of the lean season, we would observe sharp drops in employment which are not necessarily linked to the pandemic. This is however unlikely to be a concern in our analysis given the large number of countries included and, hence, large variation in agricultural calendars. In addition, results show that job losses were lowest in agriculture, which is inconsistent with seasonality-driven drops in agricultural employment.

²¹ The stop working regression can only be estimated for respondents who were working before the pandemic. Respondents who were not working before the pandemic are not observed in the stop working equation, which will introduce bias through non-random sample selection. To correct for this, we also ran a two-stage Heckman sample selection model (Heckman, 1979). Results (not shown here but available on request) were qualitatively similar.

²² Testing for a non-linear association between GDP and the likelihood of job loss using a non-parametric approach yields similar results, with the likelihood of job loss first increasing with GDP and then decreasing at GDP per capital levels around US \$7,000 – US\$8,000 in purchasing power parity terms.

Table 3
Correlates of job and income loss in the immediate aftermath of the pandemic.

Variables	(1) Stop working	(2) Stop working	(3) Income decreased	(4) Income decreased
Male	-0.0947*** (0.0114)	-0.0908*** (0.0115)	-0.0263** (0.0128)	-0.0298** (0.0129)
Age	-0.287*** (0.0824)	-0.302*** (0.0816)	-0.0493 (0.1097)	0.0160 (0.1099)
Age sq.	0.160*** (0.0403)	0.169*** (0.0400)	-0.0033 (0.0541)	-0.0357 (0.0540)
Has school-aged child	0.0286*** (0.0106)	0.0262** (0.0103)	0.0562*** (0.0129)	0.0381*** (0.0128)
Urban	0.0182* (0.0110)	-0.000734 (0.0111)	0.0118 (0.0155)	0.00793 (0.0155)
Secondary-educated	0.00250 (0.0136)	0.000655 (0.0141)	0.00145 (0.0183)	0.0105 (0.0183)
Tertiary-educated	-0.0908*** (0.0141)	-0.0858*** (0.0143)	-0.0565*** (0.0193)	-0.0444** (0.0192)
Mining/Manuf.	0.212*** (0.0193)	0.202*** (0.0200)	0.123*** (0.0281)	0.124*** (0.0281)
Commerce	0.166*** (0.0176)	0.174*** (0.0182)	0.116*** (0.0241)	0.114*** (0.0241)
Other services	0.187*** (0.0158)	0.178*** (0.0168)	0.0638*** (0.0239)	0.0592** (0.0238)
Self-employed			0.180*** (0.0149)	0.182*** (0.0149)
Seasonal/temporary			0.203 (0.171)	0.190 (0.179)
Stopped working			0.0796*** (0.0154)	0.0833*** (0.0154)
Ln(GDP/capita)		25.91*** (2.008)		19.30*** (3.583)
Ln(GDP/capita Sq.)		-13.29*** (1.046)		-9.73*** (1.885)
Stringency		0.242*** (0.09238)		-0.0072 (0.09238)
Country dummies	Yes	No	Yes	No
Region Dummies	No	Yes	No	Yes
Pseudo R Sq.	0.153	0.136	0.088	0.074
Observations	22,524	22,889	10,413	10,413

Notes: "Stop working" takes on 1 if respondent stopped working following the outbreak of the pandemic. "Income decreased" takes on the value 1 if household income decreased since the start of the pandemic. Results are marginal effects for discrete variables (the percentage point change in the likelihood of stop working if the discrete indicator is true) and semi-elasticities for continuous variables (dyex: the percentage point change in the likelihood of stop working for a 1 percent change in the independent variable). Data are weighted by sample weights that are re-scaled to give each country in the sample equal weight. Standard errors are robust. ***: Statistically significant at 1%; **: Statistically significant at 5%; *: Statistically significant at 10%.

income countries is likely due to the higher prevalence of agriculture and own-account work in these countries. The stringency of virus containment measures is also significantly related to job losses, with a 10 percent increase in the stringency index being associated with a 2.4 percentage point increase in the probability of job loss. To illustrate, the average probability of job loss in the country with the lowest stringency level in our sample amounts to 18.8 percent, compared to 42 percent in the country with the highest stringency level, all else equal.²³ In line with the regression with country dummies, respondents in households with school-aged children were more likely to stop working in the aftermath of the pandemic.

The finding that groups who were disadvantaged on the labor market to begin with (women, youth, and workers without higher education) were more likely to stop working in the immediate aftermath of the pandemic does not necessarily mean that job losses were concentrated among poor households. The extent to which different welfare groups were affected by job losses partly depends on the income level and economic structure of the country. In very low-income countries, where most of the poor are engaged in own-account agriculture, we expect job losses to be

²³ The lowest value of the stringency index observed in our sample is 20.4, while the highest value is 97.2. Most of the stringency values are however concentrated at higher values (half of households in the sample live in countries where the stringency index exceeds 80).

higher among the relatively better-off, as they actually have wage jobs they can lose. In middle-income countries, where agriculture's share of employment is lower and many of the poor work in the informal non-farm sector, we expect job losses to be more equally distributed among welfare groups. Descriptive data for a limited number of countries for which pre-pandemic data on the same households is available supports this hypothesis: In Ethiopia, Malawi and Uganda, three low-income countries, the probability of job loss was highest among respondents in the top consumption quintile.²⁴ In Nigeria, a middle-income country, job losses were higher overall and fairly uniformly distributed across welfare groups (Table 4).

Results from the income loss regressions are presented in Column (3) of Table 3. In this regression, we add pre-pandemic type of employment as an independent variable to explore whether the employment type of the respondent plays a role in mitigating income losses (regular wage employment is the reference category). Results of the income loss regression are largely similar to those of the stop working regressions. Women, workers without higher education, and workers with school-aged children, who were more likely to have lost their jobs, were also more likely to

²⁴ For Uganda, Mahmud and Riley (2021) also find that lockdowns affected wealthier households most, as these households are more reliant on enterprise and salaried income.

Table 4
Probability of job loss by pre-pandemic consumption quintile (%).

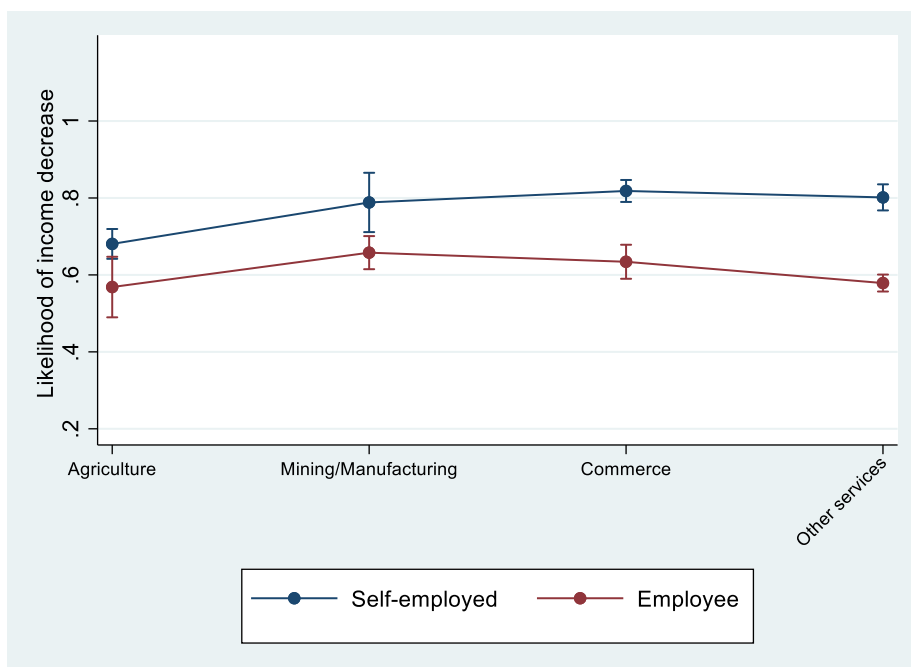
	Q1	Q2	Q3	Q4	Q5
Ethiopia	1.6	7.5	7.6	9.0	16.5
Malawi	6.0	8.0	8.0	8.0	15.0
Nigeria	57.1	50.9	44.1	51.2	48.8
Uganda	13.3	13.8	10.1	17.9	24.4

Source: Aguta et al., 2020; Wieser et al., 2020; Chikoti et al., 2020; Siwatu et al., 2020.

report reductions in total household income in the immediate aftermath of the pandemic. Workers in non-farm sectors (manufacturing, commerce, and other services), who were more likely to have lost their jobs, were more likely to report income losses relative to workers in agriculture. Regular wage employment, which is relatively rare in low-income countries, protected workers from income losses: Relative to wage-employment workers, self-employed workers were 18 percentage points more likely to report a decrease in income. Formal sector wage employment, especially in the public sector, comes with fairly high levels of job protection, insulating formal wage workers to an important extent from dismissal and income losses. In addition, many developing countries put in place temporary measures to help formal enterprises weather the pandemic and keep on their staff or even outrightly prohibited formal firms from laying off employees. Similar measures tended not to be extended to the informal sector, where most of the self-employed (and most lower-income households) make their living. As a result, pandemic-induced income losses have hit self-employed workers hard, especially those working in the mostly informal commerce and services sectors (interacting pre-pandemic employment sector and employment type shows that self-employed workers in commerce, services and manufacturing bore the brunt of the income losses – Fig. 3. As expected, job loss

had an effect on income loss, with respondents who lost their job due to the pandemic being eight percentage points more likely to report income losses. Running the income loss regression with regional dummies (Column (4) in Table 4) and country-level variables does not alter any of the results and suggests the absence of any association between the stringency of measures and the likelihood of income loss. As with job loss, GDP per capita is non-linearly related to the likelihood of income loss, with this likelihood peaking at a GDP per capita around US\$10,000 (in purchasing power parity terms).

Food security regressions are presented in Column (1) and Column (2) of Table 5. Here, the objective is to assess whether the pandemic-induced jobs and income losses translated into worsening food security at the household level. Overall, controlling for demographic characteristics and country dummies, respondents that had lost their job were 3.9 percentage points more likely to report that an adult in their household had gone a whole day without eating due to lack of resources. The magnitude of this effect is substantial given that the prevalence of the food security variable in the sample is 14.7 percent. Column (2) replicates the analysis of Column (1) but uses self-reported income loss instead of stop working as a proxy for the pandemic’s impact. All else equal, households that reported a decrease in income were 6.4 percent-



Notes: Graph shows the likelihood of income losses based on the income loss regression of Column (3) of Table 3 where pre-pandemic employment type and employment sector have been interacted. 95% confidence intervals are included.

Fig. 3. The likelihood of income losses by pre-pandemic employment sector and employment type. Notes: Graph shows the likelihood of income losses based on the income loss regression of Column (3) of Table 3 where pre-pandemic employment type and employment sector have been interacted. 95% confidence intervals are included.

Table 5
Correlates of food insecurity.

Variables	(1) Food insecurity	(2) Food insecurity
Male	-0.000882 (0.00593)	-0.0164*** (0.00609)
Age	-0.0387 (0.0479)	-0.0284 (0.0448)
Age sq.	-0.00463 (0.0234)	-0.00764 (0.0222)
Has school-aged child	0.0148** (0.00664)	0.00133 (0.00656)
Urban	0.00125 (0.00665)	-0.0212*** (0.00666)
Secondary-educated	-0.0417*** (0.00841)	-0.0506*** (0.00874)
Tertiary-educated	-0.117*** (0.00837)	-0.123*** (0.00854)
Stopped working	0.0390*** (0.00635)	
Income decreased		0.0639*** (0.00744)
Country dummies	Yes	Yes
Region Dummies	No	No
Pseudo R Sq.	0.176	0.098
Observations	22,949	20,191

Notes: "Food insecurity" takes on 1 if at least one adult in the household did not eat for a whole day due to a lack of resources. Results are marginal effects for discrete variables (the percentage point change in the likelihood of the dependent variable if the discrete indicator is true) and semi-elasticities for continuous variables (dyex: the percentage point change in the likelihood of the dependent variable for a 1 percent change in the independent variable). Data are weighted by sample weights that are re-scaled to give each country in the sample equal weight. Standard errors are robust. ***: Statistically significant at 1%; **: Statistically significant at 5%; *: Statistically significant at 10%.

age points more likely to have experienced food insecurity (measured by one or more adults in the household not eating for a whole day because of lack of resources). The food security results are robust to using different indicators of household food insecurity (Annex 3).

For the food security analysis, a concern is that food security may already have been worse before the pandemic among households in which a respondent subsequently lost his/her job and/or lost income. While this cannot be tested for the full data, it can be tested for countries for which pre-pandemic data on the same households are available and can be merged with common identifiers (Ethiopia and Nigeria, the two most populous countries in Sub-Saharan Africa). For these two countries, we append the data and run a difference-in-differences regression on our preferred indicator of food security. Results, presented in Table 6, show that (i) food insecurity worsened across the board after the pandemic, (ii) households who experienced income losses experienced still higher increases in food insecurity (significant interaction term in Column (2)), but (iii) job losses were not significantly associated with worse food security. While these limited country examples do not prove that the results are not driven by selection effects, they at least provide some evidence that the results, at least for income losses, are not driven by pre-existing differences in food security.²⁵

Finally, Columns (1) and (2) of Table 7 present the results on continued engagement in learning activities during school closures. The regression results confirm the highly unequal effects of the pandemic on learning activities of children affected by school closures. Children with lower-educated parents – a robust proxy for household welfare – and children in rural areas – where

²⁵ Egger et al. (2021) also find that that levels of food insecurity observed in their data after the pandemic greatly exceeded the levels usually observed at the same time of year.

Table 6
Difference-in differences analysis of food insecurity in Ethiopia and Nigeria.

Variables	(1) Food insecurity	(2) Food insecurity
Post pandemic	0.122*** (0.0172)	0.0737*** (0.0266)
Stopped working	0.0109 (0.0248)	-0.0284 (0.0448)
Post-pandemic*Stopped working	0.00402 (0.0276)	
Income decreased		0.0134 (0.0248)
Post-pandemic*Income decreased		0.0555* (0.0302)
Country dummies	Yes	Yes
Subnational dummies	Yes	Yes
Pseudo R Sq.	0.121	0.127
Observations	8263	9943

Notes: "Food insecurity" takes on 1 if at least one adult in the household did not eat for a whole day due to a lack of resources. This variable was observed both before and after the pandemic. Results are marginal effects for discrete variables (the percentage point change in the likelihood of the dependent variable if the discrete indicator is true). Other variables included in the regressions are household size, education, sex and age of the respondent, urban vs rural location, and a dummy indicating whether or not the household is below the poverty line. Data are weighted by sample weights that are re-scaled to give each country in the sample equal weight. Standard errors are robust. ***: Statistically significant at 1%; **: Statistically significant at 5%; *: Statistically significant at 10%.

Table 7
Correlates of continued learning.

Variables	(1) Continued learning	(2) Continued learning
Male	-0.0178* (0.0104)	-0.0144 (0.00924)
Age	0.164** (0.0833)	0.0878 (0.0700)
Age sq.	-0.0751 (0.0392)	-0.0383 (0.0333)
Urban	0.0711*** (0.00968)	0.0597*** (0.00888)
Secondary-educated	0.0606*** (0.0131)	0.0278** (0.0127)
Tertiary-educated	0.0936*** (0.0182)	0.0906*** (0.0132)
Stopped working	-0.0396*** (0.0109)	
Income decreased		0.0124 (0.00961)
Food insecurity	-0.0332*** (0.0125)	-0.0162 (0.0115)
Country dummies	Yes	Yes
Pseudo R Sq.	0.349	0.407
Observations	11,803	8,145

Notes: "Continued Learning" takes on 1 if the households' children continued to engage in learning activities during school closures. "Food insecurity" takes on 1 if at least one adult in the household went a whole day without eating due to lack of resources. Results are marginal effects for discrete variables (the percentage point change in the likelihood of the dependent variable if the discrete indicator is true) and semi-elasticities for continuous variables (dyex: the percentage point change in the likelihood of the dependent variable for a 1 percent change in the independent variable). Data are weighted by sample weights that are re-scaled to give each country in the sample equal weight. Standard errors are robust. ***: Statistically significant at 1%; **: Statistically significant at 5%; *: Statistically significant at 10%.

the bulk of the poor live – were significantly less likely to continue learning during school closures, widening the pre-existing learning gap with children from better-off households and urban children. The magnitude of the effects is substantial: Children of secondary- and tertiary-educated respondents were 6 and 9 percentage points more likely to engage in learning activities during

Table 8
Likelihood of continued learning by pre-pandemic consumption quintile (%).

	Q1	Q2	Q3	Q4	Q5
Ethiopia	14.6	14.2	18.1	25.7	37.1
Malawi	7.0	15.0	18.0	17.0	25.0
Nigeria	57.3	53.0	62.2	61.5	71.6
Uganda	44.0	48.8	57.0	65.8	74.0

Source: Aguta et al., 2020; Wieser et al., 2020; Chikoti et al., 2020; Siwatu et al., 2020.

school closures relative to children of low-educated respondents, and children in urban areas were 7 percentage points more likely to continue learning, all else equal. Having lost a job following the pandemic is also significantly correlated with a lower likelihood of continued learning. Food insecurity, which also increased during the pandemic, is also significantly related with the likelihood of continued learning, with children in households where an adult went without eating for a whole day (due to lack of resources) being three percentage points less likely to continue learning. Results (not shown) are robust to using different indicators of learning as an outcome variable.²⁶

Heightened economic stress in the household following job losses may also result into permanent school drop-out, as households cut back on expenditures to cope with the income shock or require additional income from child labor. As argued by Hill and Narayan (2020), the role of socio-economic circumstances in determining continued learning during the pandemic is likely highest in low- and lower middle-income countries, where pre-existing inequality of opportunity is highest. Pre-pandemic data confirms the highly regressive impact of the pandemic on children's schooling: Children in households in the highest consumption quintile were up to three times more likely to continue learning compared to children in the poorest consumption quintile (Table 8). The pandemic risks further cementing inequality of opportunity in lower-income countries.

4. Discussion

The results presented in the previous section suggest that, similar to rich countries, the impacts of the COVID-19 pandemic in the developing world have not been felt the same way by everyone. Women and young workers and those without higher education, who were at a disadvantage on the labor market to begin with, were significantly more likely to lose their job in the immediate aftermath of the pandemic. Self-employed workers in commerce and services, who in urban areas of developing countries often hail from lower-income or vulnerable households, reported the highest pandemic-induced income losses, while the wage-employed and the tertiary-educated were relatively more resilient (wage-employment in developing countries is often a privilege for better-off households). Nevertheless, labor income among the wage-employed still declined significantly, on average, in line with firm-level surveys in 51 countries that report that job adjustments took place less through lay-offs, and most often through leave of absence and reduction in hours or wages (World Bank, 2020c,d). While the pandemic's impact on short-term income inequality is unclear,²⁷ the long-term effects are likely to be inequality-increasing given the pandemic's disproportionate impact on educa-

tion of poor children. In addition, beyond an increase in the number of poor, the shock is likely to alter the profile of the poor: Relative to the pre-pandemic poor, the new poor are expected to be more urban, slightly more educated and more concentrated in non-agricultural sectors (Nguyen et al., 2020).

Recovery in incomes of vulnerable groups in developing countries will depend, alongside a general improvement in the global health environment and the rate of vaccination, on the pace at which they can transition back into employment and the adequacy of safety nets. While many developing countries have extended existing safety net programs and/or introduced temporary new ones, their adequacy has generally been low. Low-income countries have on average spent US\$6 per person on social protection COVID-19 responses, compared to US\$26 per person in lower middle-income countries and US\$58 in upper middle-income countries (Gentilini et al., 2020).²⁸ Fajardo-Gonzalez et al. (2021) find that while these measures were fairly effective in mitigation increases in poverty in upper middle-income countries, they were not effective in low-income countries, hardly surprising given the low volume of support. Pre-existing inequalities can also mean that employment recovery will be slower for disadvantaged groups. Analysis on the harmonized database, only for those countries with several survey waves in the database and data on all required X-variables, suggests that this has indeed been the case. While employment rates among respondents recovered between Wave 1 and Wave 2, the likelihood of transitioning back into employment by W2 (conditional on having lost a job between the pandemic onset and Wave 1) was significantly higher for men, tertiary-educated workers, and prime-age workers (see Annex 4). While the immediate labor market impact of the pandemic has been uneven, the recovery risks being uneven as well.²⁹ For youth, for instance, there is ample literature on the scarring effects on employment opportunities and earnings that unemployment spells can have on young labor market entrants.³⁰

The pandemic's impact on food security and learning risks further cementing inequality and opportunity and undermining social mobility (Hill & Narayan, 2020). Job and income losses due to the pandemic, which were skewed towards lesser-educated and more vulnerable workers, were associated with increased food insecurity at the household level. To the extent that worsening food security persists through lower incomes and rising food prices,³¹ and affects diets of children, the pandemic could have long-term effects through the causal impact of early childhood malnutrition on educational and socio-economic outcomes later in life.³² This would dispropor-

²⁸ For comparison, average per capita spending in high income countries amounted to US\$525.

²⁹ In its seventh monitor, the ILO warns of the possibility of a K-shaped recovery, whereby sectors and workers hit hardest by the pandemic could be left behind in the recovery (ILO, 2021).

³⁰ See for example Bell and Blanchflower (2011); Cruces, Ham and Viollaz (2012); Heisz, Oreopoulos, and von Wachter (2012); Schmillen and Umkehrer (2018); Kahn (2010) and Petreski, Mojsoska-Blazevski & Bergolo (2017).

³¹ Global food prices, as measured by a World Bank food price index, increased by 14 percent in 2020.

³² See, for instance, Almond and Currie (2011) and Alderman, Hoddinott and Kinsey (2006). Leroy and Frongillo (2019) however argue that the relation between early childhood malnutrition (measured by stunting) and worse outcomes later in life is not causal.

²⁶ The main education outcome variable we use is whether the child engaged in any learning activities during school closures. "Any" spans a wide variety of potential learning activities. 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.

²⁷ The IMF projects that income inequality in emerging markets and developing economies has increased by 2.6 percentage points in 2020 alone because of the pandemic (IMF, 2020).

tionally affect children in poor and vulnerable households, jeopardizing their future trajectories and prospects for upward social mobility. Arguably the biggest threat to social mobility stems however from the pandemic's inequitable impact on learning. The data suggest learning losses will be highest for children from lower-educated parents, in rural areas, and among the bottom welfare quintile. These dimensions (household location, wealth, and education of caregivers) were already the main contributors to inequality of opportunity in education in lower-income countries before the pandemic (Dabalén et al., 2014). The pandemic has further strengthened the salience of these dimensions in determining access to opportunities, with potentially adverse consequences for intergenerational mobility.

Appropriate policies can counter, at least partially, the pandemic's effect on inequality. In the post-crisis phase, policies should focus on fostering an inclusive recovery and building the resilience to future shocks, particularly among the poor and vulnerable (Hill & Narayan, 2020). This will require closing the currently large gaps in access to opportunities across socio-economic groups, by focusing on spatially-blind investments in health and education, designing additional support for vulnerable groups, and providing support to parents and children to transition back into school as schools reopen to prevent early drop-out. It will also require helping those who lost their job during the pandemic to transition back into employment, with special support for disadvantaged workers through appropriate active labor market policies. For women, in particular, the pandemic and the resulting school closures have likely exacerbated pre-crisis barriers in the burden of family and household responsibilities, that could limit their opportunities to join or rejoin the labor market. The stronger resilience of wage-employed workers highlights the importance of addressing barriers to the creation of formal wage jobs in developing countries, where the employment structure is currently dominated by informal self-employment, even in the non-farm sector. The development of a more resilient middle class is indeed highly associated with the growth of wage work (Banerjee & Duflo, 2008). Market reforms to strengthen competition and level the playing field and improvements in the business environment can help in creating wage-employment for the rapidly growing youth cohorts in these countries. Finally, the crisis has shown that despite strong progress in social protection over the past decades, safety nets in developing countries are for the most part not yet flexible enough to respond to sudden shocks. While most developing countries operate one or more social protection programs, few have systems that can adapt or scale rapidly in the face of changing circumstances. The pandemic's disproportionate impact on incomes of the informally self-employed is a reminder that this large vulnerable segment of the population is currently not well covered by social protection schemes. Investing in the design of national systems that can provide quick support in case of a severe income shock should be a priority (Bowen et al., 2020).

5. Conclusion

This paper descriptively analyzed a harmonized database of high-frequency surveys that were fielded in the aftermath of the pandemic in developing countries to assess the welfare impacts of the COVID-19 pandemic and inform policy responses. Using data from 31 low and middle-income countries, the results establish inequitable impacts of the pandemic in developing countries, with vulnerable segments of the population being disproportionately affected by the pandemic-induced economic crisis and mobility-reducing lockdown measures. The effects of the pandemic risk undoing years of development progress.

As the immediate crisis period ebbs in many developing countries, at least the least-developed ones, policies need to focus on fostering an inclusive recovery and strengthening resilience to future shocks. Closing the opportunity gaps across different socio-economic groups in developing countries and investing in flexible and scalable safety nets are among the priorities to increase resilience to future shocks, health or otherwise.

CRedit authorship contribution statement

Tom Bundervoet: Formal analysis, writing. **María E. Dávalos:** Formal analysis, writing. **Natalia García:** Formal analysis, Data curation.

Conflict of interest statement

The authors have no conflicts of interest.

Acknowledgements

The authors thank Ambar Narayan, Benu Bedani, and Carolina Sánchez-Páramo for helpful comments on an earlier version of this paper. The authors are indebted to the fantastic work of the World Bank's COVID-19 data harmonization team, without which this paper would not have been possible.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.worlddev.2022.105844>.

References

- Aguta, D., Atamanov, A., Ilukor, J., Kilic, T., Mupere, A., Ponzini, G., & Ssenono, V. (2020). *Monitoring COVID-19 impacts on households in Uganda: Findings from the first round of the high-frequency phone survey*. Washington, D.C.: World Bank Group <http://documents.worldbank.org/curated/en/538251597678748650/Findings-from-the-First-Round-of-the-High-Frequency-Phone-Survey>.
- Ambel, A., McGee, K., & Tsegay, A. (2021). Reducing bias in phone survey samples. Effectiveness of reweighting techniques using face-to-face surveys as frames in four African countries. *World Bank Policy Research Working Paper* 9676. Washington DC: The World Bank.
- Adams-Prassl, A., Boneva, T., Golin, M., & Rau, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics*, 189, 104245. <https://doi.org/10.1016/j.jpubeco.2020.104245>.
- Alderman, H., Hoddinott, J., & Kinsey, B. (2006). Long-term consequences of early childhood malnutrition. *Oxford Economic Papers*, 58(3), 450–474.
- Almond, D., & Currie, J. (2011). Killing me softly: The fetal origins hypothesis. *Journal of Economic Perspectives*, 25(3), 153–172.
- Azevedo, Joao Pedro, Hasan, Amer, Goldemberg, Diana, Syedah Aroob, Iqbal, & Geven, Koen (2020). *Simulating the potential impacts of Covid-19 school closures on schooling and learning outcomes: A set of global estimates*. Washington DC: The World Bank Group.
- Banerjee, A., & Duflo, E. (2008). What is middle class about the middle classes around the world? *Journal of Economic Perspectives*, 22(2), 3–28.
- Bartik, A., Cullen, Z., Glaeser, E., Luca, M., & Stanton, C. (2020). What jobs are being done at home during the covid-19 crisis? Evidence from firm-level surveys. Working Paper 27422, National Bureau of Economic Research, Cambridge, MA.
- Beegle, K., & Christiaensen, L. (2019). *Accelerating Poverty Reduction in Africa*. Washington, DC: World Bank.
- Bell, D., & Blanchflower, D. (2011). Young people and the great recession. *Oxford Review of Economic Policy*, 27(2), 241–267. <https://doi.org/10.1093/oxrep/grr011>.
- Bowen, T.V., Del Ninno, C., Andrews, C., Coll-Black, S., Gentilini, U., Johnson, K., Kawasoe, Y., Kryeziu, A., Maher, B. P., Williams, A. M. (2020).
- Chetty, R., Friedman, J., Hendren, N., & Stepner, M. (2020). *How did covid-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data*. Cambridge, MA: National Bureau of Economic Research.
- Chikoti, L., Vundru, W., Fuje, H., Ilukor, J., Kanyanda, S., Kanyuka, M., ... Yoshida, N. (2020). *Monitoring COVID-19 Impacts on Households in Malawi: Findings from the First Round of the High-Frequency Phone Survey*. Washington, D.C.: World Bank Group. <http://documents.worldbank.org/curated/en/591551597706342578/Findings-from-the-First-Round-of-the-High-Frequency-Phone-Survey>.

- Crossley, T. F., Fisher, P., & Low, H. (2021). The heterogeneous and regressive consequences of COVID-19: Evidence from high quality panel data. *Journal of Public Economics*, 193, 104334. <https://doi.org/10.1016/j.jpubeco.2020.104334>.
- Egger, D., Miguel, E., Warren, S. S., Shenoy, A., Collins, E., Karlan, D., ... Vernot, C. (2021). Falling living standards during the COVID-19 crisis: Quantitative evidence from nine developing countries. *Science Advances*, 7, eabe0997.
- Dabalen, A., Narayan, A., Saavedra-Chanduvi, J., & Hoyos Suarez, A. (2014). *Do African children have an equal chance? A human opportunity report for Sub-Saharan Africa*. Washington DC: The World Bank.
- Fajardo-Gonzalez, J., Molina, G., Montoya-Aguirre, M., & Ortiz-Juarez, E. (2021). *Mitigating poverty: Global estimates of the impact of income support during the pandemic*. New York: United Nations Development Programme.
- Gentilini, U., Almenfi, M., & Dale, P. (2020). Social protection and jobs responses to COVID-19: A real-time review of country measures. Living paper version 14 [accessed on 3 February 2021].
- Gottlieb, C., Grobovšek, J., & Poschke, M. (2020). Working from home across countries. *Covid Economics*, 1(8), 71–91.
- Heckman, J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1): 1153–1162.
- Heisz, A., Oreopoulos, P., & von Wachter, T. (2012). The short- and long-term career effects of graduating in a recession: Hysteresis and heterogeneity in the market for college graduates. *American Economic Journal: Applied Economics*, 4(1), 1–29.
- Hill, R., & Narayan, A. (2020). COVID-19 and Inequality: A review of the evidence on likely impacts and policy options. Centre for Disaster Protection Working Paper 3.
- ILO (2021) *COVID-19 and the world of work. Seventh edition*. ILO Monitor. Geneva: The International Labor Organization. Accessed at https://www.ilo.org/wcmsp5/groups/public/-dgreports/-dcomm/documents/briefingnote/wcms_767028.pdf.
- IMF (2020). *World economic outlook: A long and difficult ascent*. Washington DC: The International Monetary Fund.
- Kahn, L. B. (2010). The long-term labor market consequences of graduating from college in a bad economy. *Labour Economics*, 17(2), 303–316.
- Lakner, C., Yonzan, N., Mahler, D., Aguilar, R., & Wu, H. (2021). Updated estimates of the impact of COVID-19 on global poverty: Looking back at 2020 and the outlook for 2021. Data Blog, World Bank Blogs, 11 January 2021, [accessed 11 February 2021], <https://blogs.worldbank.org/opendata/updated-estimates-impact-covid-19-global-poverty-looking-back-2020-and-outlook-2021>.
- Leroy, J., & Frongillo, E. (2019). Perspective: What does stunting really mean? A critical review of the evidence. *Advances in Nutrition*, 10(2), 196–204.
- Mahmud, M., & Riley, E. (2021). Household response to an extreme shock: Evidence on the immediate impact of the Covid-19 lockdown on economic outcomes and well-being in rural Uganda. *World Development*, 140, 1–21.
- Nguyen, M., Yoshida, N., Wu, H., & Narayan, A. (2020). Profiles of the new poor due to the COVID-19 pandemic. <http://pubdocs.worldbank.org/en/767501596721696943/Profiles-of-the-new-poor-due-to-the-COVID-19-pandemic.pdf>. [Accessed 3 February 2021]
- Miguel, Edward, & Mobarak, Ahmed Mushfiq (2021). The Economics of the COVID-19 Pandemic in Poor Countries. *National Bureau of Economic Research* 29339.
- Petreski, M., Mojsoska-Blazevski, N., & Bergolo, M. (2017). Labor-market scars when youth unemployment is extremely high: Evidence from Macedonia. *Eastern European Economics*, 55(2), 168–196.
- Psacharopoulos, G., & Patrinos, H. (2018). Returns to investment in education: A decennial review of the global literature. *Education Economics*, 26(5), 445–458.
- Schmillen, A., & Umkehrer, M. (2018). The scars of youth: Effects of early-career unemployment on future unemployment experience. *International Labour Review* 56(4), S. 465–494.
- Siwatu, G., Palacios-Lopez, A., Mcgee, K., Amankwah, A., Vishwanath, T., & Azad, M. (2020). *Impact of COVID-19 on Nigerian Households: Baseline results*. Washington, D.C.: World Bank Group. <http://documents.worldbank.org/curated/en/781421591886886760/Baseline-Results>.
- UN (2020). Education during COVID-19 and beyond. Policy Brief New York: The United Nations.
- Wieser, C., Ambel, A., Bundervoet, T., & Haile, A. (2020). *Monitoring covid-19 impacts on households in Ethiopia: Results from a high-frequency phone survey of households (Vols. 2 and 3)* Washington, DC: World Bank.
- World Bank (2020c). Unmasking the Impact of COVID-19 on Businesses Firm Level Evidence from Across the World. Policy Research Working Paper 9434. Washington DC: The World Bank.
- World Bank (2018). *Fair progress? Economic mobility across generations around the world*. Washington DC: The World Bank.
- World Bank (2020a). *Poverty and shared prosperity 2020: Reversals of fortune*. Washington DC: The World Bank.
- World Bank (2020b). *Nigeria COVID-19 Impact Monitoring, May 2020*. Washington DC: The World Bank.
- World Bank (2020c). Poverty and distributional impacts of COVID-19: Potential channels of impact and mitigating policies. Brief.