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The Short-Term Impacts of COVID-19 on Households in Developing Countries

An Overview Based on a Harmonized Data Set of High-Frequency Surveys

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Abstract

This paper combines 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 34 countries, accounting for a combined population of almost 1.4 billion, the findings show that in the average country, 36 percent of respondents stopped working in the immediate aftermath of the pandemic, over 64 percent of households reported decreases in income, and over 30 percent of children were unable to continue learning during school closures. Pandemic-induced loss of jobs and income translated into heightened food insecurity at the household level. The more stringent the virus containment measures were, the higher was the likelihood of loss of jobs and income. The pandemic's effects were widespread and highly regressive, disproportionally affecting vulnerable segments of the population. Women, youth, and lower-educated workers—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 in lower-income countries, and within countries for children in lower-income households with lower-educated parents and in rural areas. The unequal impacts of the pandemic across socioeconomic groups risk cementing inequality of opportunity and undermining social mobility and call for policies to foster an inclusive recovery and strengthen resilience to future shocks.

This paper is a product of the Poverty and Equity Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at tbundervoet@worldbank.org.

The Short-Term Impacts of COVID-19 on Households in Developing Countries: An Overview Based on a Harmonized Data Set of High-Frequency Surveys[1]

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[2] The World Bank Group, Poverty and Equity Global Practice.

1. Introduction

The COVID-19 pandemic is resulting in dramatic loss of life across the world. By March 14, 2021, over 2.6 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 4.4 percent in 2020 (IMF, 2020). 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 119 million to 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 partial 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 second wave impacts of the pandemic in both developed and developing countries (Lakner et al, 2021).

While high income countries have on average experienced sharper economic downturns in 2020 because of the pandemic,[3] 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. By September 2020, advanced economies had on average spent 7.4 percent of GDP on so-called "above the line" measures - budgetary fiscal support to people and firms in response to the pandemic.[4] 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 (up to 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 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 that were implemented in 34 countries following the onset of the pandemic.[5] 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 peak of the crisis, with the peak measured by the stringency of social distancing measures. As the questionnaires were tailored to specific country contexts, data was

[3] The economic contraction in 2020 is estimated at 5.8 percent for advanced economies, 3.3 percent for emerging markets and developing economies, and 1.2 percent for low-income developing countries. On a per capita basis, the contraction in low-income developing countries is projected to amount to -3.3 percent in 2020 (IMF, 2020).

[4] Calculated from the IMF's Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic (October 2020 version). https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19. Below the line measures (loans and equity stakes as well as guarantees) were even more important in advanced economies, amounting to 8.2 percent of GDP on average.

[5] COVID-19 high frequency surveys have been implemented in many more countries. This paper is however based on the 34 countries for which data have been harmonized and disclosure has been authorized.

harmonized by the World Bank to arrive at a harmonized micro-data set of 93 indicators.[6] 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 leaning 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 35.6 percent of respondents stopped working, either temporarily or permanently, in the immediate aftermath of the pandemic, over 64 percent of households reported a decrease in total income, and over 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 vulnerable segments of the population being disproportionally affected. Women, youth, and low-skilled workers 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 disproportionally affected children 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). 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.[7] 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 Eggers at al. (2021) but combines high-frequency survey data from a

[6] 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).

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

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 34 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 severity and 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 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.[8]

While the distributional impacts of the COVID-19-induced economic shock have been highly regressive in rich countries,[9] 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 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

[8] Draws from World Bank (2020c).

[9] See, for instance, Adams-Prassl et al. (2020), Bartik et al. (2020), Crossley at 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/graphics/2020/business/coronavirus-recession-equality/).

assets, which will be hard to rebuild even in the medium term; the effect of long school closures, disruptions to ECD 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.[10] The analysis presented in this paper is based on harmonized data from 34 countries and up to 47,000 respondents, 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 (12 countries), East Asia and the Pacific (7 countries), Middle East and North Africa (1 country) and Europe and Central Asia (3 countries). Thirty-one countries are low or middle-income countries, while the remaining three are high income. 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. 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.[11]

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 34 countries in the harmonized data set.

[10] 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.

[11] 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.

- 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.
- 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.
- 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.[12] 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.,

[12] https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker

relative to a pre-COVID baseline period.[13] 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 (Figure 1). In parallel, mobility sharply dropped and bottomed out in April 2020 (Figure 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 April or May 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.[14] The incidence of job losses follows an inverted U across country income level, being lowest in low-income countries and highest in upper middle-income countries, decreasing again in the high income countries in the sample (though this needs to be interpreted with caution given that there are only three high income countries in the sample). At the regional level, countries in Sub Saharan Africa (SSA) and East Asia and the Pacific (EAP) experienced the lowest job losses (27 percent and 22 percent respectively), 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, 42 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 40 percent reporting having lost their job compared to 28 percent of rural workers. In contrast, a largely similar share of less-educated (primary or less) vs more-educated (secondary or tertiary-educated) workers reported job losses. 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, 48 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 and Christiaensen, 2020). 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

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

[14] The Eggers 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.

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.[15] The descriptives in Table 1 indeed show that while job losses were relatively low in low-income countries, income losses were high: 68 percent of respondents reported that total household income had decreased since the start of the pandemic in their country. Self-reported income losses are high across the board, though they tend to be lower for high-income countries. Income losses were most frequently reported in SSA, likely linked to the dominance of self-employment in SSA countries. 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.[16] 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,[17] 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 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 four percentage points higher in households where the respondent has lost his/her job, and eight 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 though 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

[15] 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).

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

[17] 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?"

(UN, 2020). Given the high returns to schooling in developing countries, learning losses and school dropouts would result in significant long-term welfare losses.[18]

The descriptives in Table 1 largely confirm the unequal learning effects of school closures. In low-income countries, 41 percent of children engaged in learning activities during school closures, compared to 91 percent of children in upper middle-income countries. 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:

$$P(Y_i = 1) = F(\alpha + \sum_k \beta_i X_i + \delta) \qquad (1)$$

Where Y is the variable of interest (alternatively: stop working, income loss, food insecurity, or continued learning) and $\sum_k \beta_i X_i$ 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 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(.) 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:

$$P(Y_i = 1) = F(\alpha + \sum_k \beta_i X_i + \sum \gamma_c Z_c + \theta) \qquad (2)$$

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[18] See Psacharopoulos and Patrinos, 2018. Azevedo at all (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).

[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).

Where $\sum \gamma_c Z_c$ 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 low-skilled workers. 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 (Figure 3). The pre-pandemic sector of employment played a large role in subsequent job losses, with workers in manufacturing, commerce, and other services being respectively 20, 16, and 17 percentage points more likely to have stopped working relative to workers in agriculture. Workers with school-aged children were also more likely to stop working, which may reflect the need to care for children as schools closed. The effect is however relatively small (2 percentage points), and does not significantly differ for male and female respondents (though the point estimate is higher for female respondents). Nevertheless, as presented in Cucagna and Romero (2021) using the same data source for three rounds of phone surveys in Latin American countries, the presence of school-age children in the household became a more relevant factor associated with loss of employment among women as the pandemic persisted. Once other factors are taken into account, urban location of the respondent is only marginally correlated with the likelihood of job loss.

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 assess the extent of the bias, Column (2) of Table 3 reports the results from Heckman's sample selection model (Heckman, 1979). In the first stage, we estimate the probability of working before the pandemic based on individual, household, and country-level covariates, including one variable that is not included in the actual outcome regression.[20] The second step estimates the probability of having stopped working after the pandemic, based on the independent variables used in Column (1) and the inverse Mills ratio from the first stage regression. Results are qualitatively similar: Men were 8.8 percentage points and tertiary-educated persons 9.9 percentage less likely to stop working relative to women and little-educated workers, respectively, and prime-workers were least likely to lose their jobs. Compared to regression (1), having a school-aged child ad urban location lose statistical significance.

To assess the effect of country-level factors, Column (3) 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$5,600 (in purchasing power parity terms) and decreasing thereafter. As discussed earlier, the lower likelihood of job losses in low-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

[20] Given that the high-frequency surveys were administered by phone, the questionnaires were kept as short as possible. As a result, there are not many variables that can be included in the selection regression. Household size is used in the selection regression and is significantly and inversely correlated with the probability of working before the pandemic. The pseudo R squared for the first stage regression is 0.238.

increase in the stringency index being associated with a 2.3 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 19.7 percent, compared to 43 percent in the country with the highest stringency level, all else equal (Figure 4 shows the marginal effects of stringency of containment measures).

Results from the income loss regressions are presented in Column (1) of Table 4. 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, less-educated workers and workers with school-aged children, who were more likely to have lost their jobs, were also more likely to 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 while those who work in family businesses (household enterprises) were 21 percentage points more likely to report income losses. 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 family businesses (and most low-income households) make their living. As a result, pandemic-induced income losses have hit the vulnerable the hardest. Running the income loss regression with regional dummies (Column (2) in Table 4) and country-level variables does not alter any of the results and shows a positive correlation between the stringency of measures and the likelihood of income loss (all else equal, the probability of reporting income losses increases by 19 percentage points as one moves from the lowest- to the higher-stringency country in the sample). The coefficients on GDP per capita are not significant, given the high correlation between the GDP variable and the variable capturing pre-pandemic employment type.[21]

Food security regressions are presented in Column (3) and Column (4) of Table 4. 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 15.3 percent. A concern here is that food security may already have been worse before the pandemic among households in which a respondent subsequently lost his/her job. 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. For these countries, pre-pandemic food security among households in which a respondent lost a job

[21] Running the same specification with employment type shows a non-linear concave association between GDP and the likelihood of decreased income, with the latter peaking at a per capita GDP level of (in PPP).

during the pandemic was not worse than in other households[22] (Annex 3). In Ethiopia, there were no discernible differences in pre-pandemic food security between households affected and non-affected by subsequent job losses. In Nigeria, pre-pandemic food security was better in households who were subsequently affected by job losses during the pandemic. While these limited country examples do not prove that the results are not driven by selection effects, they at least provide anecdotal evidence that the results are not driven by pre-existing differences in food security.[23] Column (4) replicates the analysis of Column (3) 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 percentage 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 4).

Finally, Columns (1) and (2) of Table 5 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 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 7.1 and 11.1 percentage points more likely to engage in learning activities during school closures relative to children of low-educated respondents, and children in urban areas were 6.3 percentage points more likely to continue learning, all else equal. Having lost a job following the pandemic, which was already more likely for lower-educated workers and women, is also significantly correlated with a lower likelihood of continued learning. Results (not shown) are robust to using different indicators of learning as an outcome variable.[24]

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. To test this, Column (2) in Table 5 restricts the sample to low and lower middle-income countries. Results indeed confirm that the influence of socio-economic characteristics in determining continued learning is stronger in lower-income countries: Children of tertiary-educated respondents were 15.1 percentage points more likely to continue learning relative to children with lower-educated parents, and children in urban areas were 10 percentage points more likely to continue learning relative to rural children. The pandemic risks further cementing inequality of opportunity in lower-income countries.

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[22] These countries are Ethiopia and Nigeria, which are part of the Living Standards Measurement Study (LSMS) project. Nationally representative surveys were implemented in these countries in 2019 or early 2020 (before the pandemic), and the post-outbreak high frequency phone surveys recontacted the same households.

[23] 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.

[24] 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.

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 and less-educated workers, 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 an workers in household enterprises, 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). Given these patterns, income inequality in developing countries is likely to increase in coming years. Indeed, 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). 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, 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, largely inadequate to offset the pandemic's income effects (Gentilini et al., 2020).[25] 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 5). While the immediate labor market impact of the pandemic has been uneven, the recovery risks being uneven as well.[26] 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.[27]

The pandemic's impact on food security and learning risks further cementing inequality and opportunity and undermining social mobility (Hill and 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

[25] For comparison, average per capita spending in high income countries amounted to US$525.
[26] 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).
[27] See for example Bell and Blanchflower (2011); Cruces, Ham and Viollaz (2012); Heisz, Oreopoulus, and von Wachter (2012); Schmillen and Umkehrer (2018); Kahn (2010) and Petreski, Mojsoska-Blazevski & Bergolo (2017).

through lower incomes and rising food prices,[28] 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.[29] This would disproportionally 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 (Dabalen 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 and 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 and 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. 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 34 mainly low and middle-income countries, the results establish highly inequitable impacts of the pandemic in developing countries, with vulnerable segments of the population being disproportionally affected by the pandemic-induced economic crisis

[28] Global food prices, as measured by a World Bank food price index, increased by 14 percent in 2020.
[29] See, for instance, Almond and Currie (2011) and Alderman, Hoddinott and Kinsey (2006).

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.

References

Adams-Prassl, A., Boneva, T., Golin, M., and Rauh, C. (2020). "Inequality in the impact of the coronavirus shock: evidence from real time surveys". *Journal of Public Economics* 189.

Adaptive Social Protection : Building Resilience to Shocks (English). International Development in Focus Washington, D.C. : World Bank Group.

Alderman, H., Hoddinott, J., and Kinsey, B. (2006). "Long-term consequences of early childhood malnutrition". *Oxford Economic Papers* 58 (3): 450–474.

Almond, D. and Currie, J. (2011). Killing me softly: the fetal origins hypothesis. *Journal of Economic Perspectives* 25 (3): 153–172.

Banerjee, A. and 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., and 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. and Christiaensen, L. (2019). *Accelerating Poverty Reduction in Africa*. Washington, DC: World Bank.

Bell, David, and David Blanchflower. 2011. "Young People and the Great Recession." Oxford Review of Economic Policy 27 2: 241–267. doi: 10.1093/oxrep/grr011.

Bowen,Thomas Vaughan; Del Ninno,Carlo; Andrews,Colin; Coll-Black,Sarah; Gentilini,Ugo; Johnson, Kelly; Kawasoe,Yasuhiro; Kryeziu,Adea; Maher,Barry Patrick; Williams,Asha M..2020.

Chetty, R., Friedman, J., Hendren, N., and 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". National Bureau of Economic Research, Cambridge, MA.

Crossley, T., Fisher, P., and Low, H. (2021). "The heterogeneous and regressive consequences of COVID-19: Evidence from high quality panel data." *Journal of Public Economics* 193.

Cruces, G., A. Ham and M. Viollaz (2012), "Scarring effects of youth unemployment and informality. Evidence from Argentina and Brazil", La Plata, Centre for Distributive, Labour and Social Studies (CEDLAS0).

Cucagna, Emilia and Javier Romero (2021). The gendered impacts of COVID-19 on the labor market: Evidence from High-Frequency Phone Surveys in Latin America and the Caribbean. POLICY BRIEF. Washington, D.C. : World Bank Group.

D. Egger, E. Miguel, S. S. Warren, A. Shenoy, E. Collins, D. Karlan, D. Parkerson, A. M. Mobarak, G. Fink, C. Udry, M. Walker, J. Haushofer, M. Larreboure, S. Athey, P. Lopez-Pena, S. Benhachmi, M. Humphreys, L. Lowe, N. F. Meriggi, A. Wabwire, C. A. Davis, U. J. Pape, T. Graff, M. Voors, C. Nekesa, C. Vernot, Falling living standards during the COVID-19 crisis: Quantitative evidence from nine developing countries. Sci. Adv. 7, eabe0997 (2021).

Dabalen, A., Narayan, A., Saavedra-Chanduvi, J. and Hoyos Suarez, A. (2014). *Do African Children have an Equal Chance? A Human Opportunity Report for Sub-Saharan Africa*. Washington DC: The World Bank.

Gentilini, U., Almenfi, M. and 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., and 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): 1153-162.

Heisz, Andrew, Phil Oreopoulus, and Till von Wachter. 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. and 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, Lisa B. 2010 “The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy.” Labour Economics 17 (2): 303–16.

Lakner, C., Yonzan, N., Mahler, D., Aguilar, R., and 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

Nguyen, M., Yoshida, N., Wu, H. and 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]

Petreski, Marjan, Nikica Mojsoska-Blazevski & Marcelo Bergolo (2017) Labor-Market Scars When Youth Unemployment is Extremely High: Evidence from Macedonia, Eastern European Economics, 55:2, 168-196

Psacharopoulos, G. and Patrinos, H. (2018). Returns to investment in education: A decennial review of the global literature. *Education Economics*, 26(5): 445-458.

Schmillen, Achim; Matthias Umkehrer (2018). The scars of youth: Effects of early-career unemployment on future unemployment experience. International Labour Review, Vol. 156, No. 4 (2018), S. 465-494.

UN. 2020. Education during COVID-19 and beyond. Policy Brief New York: The United Nations.

Wieser, C., Ambel, A. Bundervoet, T., and Haile, A. (2020a, b). “Monitoring covid-19 impacts on households in Ethiopia: Results from a high-frequency phone survey of households”. (Vols. 2 and 3), World Bank, Washington, DC.

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.

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	35.6	64.3	15.3	67.9
By income group					
Low income	19.3	16.8	67.5	22.7	41.0
Lower middle income	41.1	37.2	64.9	14.1	67.9
Upper middle income	31.5	46.4	67.5	12.4	91.3
High income	7.1	30.0	44.2	5.3	83.7
By region					
SSA	29.5	26.7	70.7	19.8	46.8
EAP	22.7	22.2	56.5	12.0	60.1
LAC	38.6	51.3	67.0	12.3	94.5
ECA	5.9	34.5	47.6	na	62.8
MNA	3.3	26.8	51.7	na	62.2
By location					
Urban	49.5	39.8	62.7	14.7	72.7
Rural	50.5	27.9	64.9	16.0	55.5
By gender respondent					
Female	41	41.8	65.9	15.5	73.2
Male	59	30.6	64.1	15.2	65.1
By Education					
Primary or less	31.8	37.7	66.6	21.8	55.5
Secondary	40.2	40.5	66.2	15.9	70.9
Tertiary	28	37.4	58.8	7.2	82.4
By age					
Under 30	22.4	38.5	65.4	19.5	64.6
30 and over	77.6	34.8	64.0	13.8	68.1
By stringency of measures					
Below median stringency	48.7	22.9	62.3	11.9	62.0
Above median stringency	51.3	47.7	65.5	17.5	72.1
N		46,244	42,036	47,031	33,008

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.

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

	Food insecurity (% yes)
Lost job	18.3
	[0.004]
Did not lose job	14.4
	[0.003]
Mean difference	-4.1***
Income declined	16.6
	[0.003]
Income did not decline	8.7
	[0.003]
Mean difference	-7.9***

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.

Table 3: Correlates of having lost a job in the immediate aftermath of the pandemic

VARIABLES	(1) Stop working	(2) Stop working (Heckman)	(3) Stop working
male	-0.0935***	-0.0881***	-0.0942***
	(0.00702)	(0.0149)	(0.00710)
Age	-0.383***	-0.277*	-0.425***
	(0.0625)	(0.152)	(0.0646)
Age sq.	0.203***	0.172**	0.225***
	(0.0312)	(0.0875)	(0.0324)
Has school-aged child	0.0200**	0.0138	0.0126
	(0.00818)	(0.00922)	(0.00787)
Urban	0.0134*	0.0136	0.00764
	(0.00795)	(0.00907)	(0.00801)
Secondary-educated	-0.0129	-0.0137	-0.0140
	(0.00950)	(0.0103)	(0.00939)
Tertiary-educated	-0.0924***	-0.0994***	-0.0904***
	(0.0101)	(0.0133)	(0.00999)
Minig/Manuf.	0.202***	0.120***	0.211***
	(0.0143)	(0.0174)	(0.0144)
Commerce	0.160***	0.0953***	0.183***
	(0.0127)	(0.0160)	(0.0127)
Other services	0.170***	0.0873***	0.176***
	(0.0110)	(0.0145)	(0.0109)
Ln(GDP/capita)			18.82***
			(1.010)
Ln(GDP/capita Sq.)			-10.02***
			(0.531)
Stringency			0.227***
			(0.0187)
Country dummies	Yes	Yes	No
Region Dummies	No	No	Yes
Heckman correction	No	Yes	No
Pseudo R Sq.	0.142	0.143	0.136
Observations	30,589	35,254	29,836

Notes: Dependent variable takes on 1 if respondent stopped working following the outbreak 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. ***: Statistically significant at 1%; **: Statistically significant at 5%. *: Statistically significant at 10%.

Table 4: Correlates of income loss and food insecurity

	(1)	(2)	(3)	(4)
VARIABLES	Income decreased	Income decreased	Food insecurity	Food insecurity
male	-0.0336***	-0.0361***	-0.000882	-0.0164***
	(0.00941)	(0.00949)	(0.00593)	(0.00609)
Age	0.0870	0.131	-0.0387	-0.0284
	(0.0852)	(0.0856)	(0.0479)	(0.0448)
Age sq.	-0.0726*	-0.0907**	-0.00463	-0.00764
	(0.0429)	(0.0431)	(0.0234)	(0.0222)
Has school-aged child	0.0471***	0.0266***	0.0148**	0.00133
	(0.00994)	(0.00986)	(0.00664)	(0.00656)
Urban	0.0141	-0.00123	0.00125	-0.0212***
	(0.0106)	(0.0106)	(0.00665)	(0.00666)
Secondary-educated	0.00594	0.0179	-0.0417***	-0.0506***
	(0.0129)	(0.0125)	(0.00841)	(0.00874)
Tertiary-educated	-0.0511***	-0.0370***	-0.117***	-0.123***
	(0.0144)	(0.0141)	(0.00837)	(0.00854)
Minig/Manuf.	0.0963***	0.112***		
	(0.0209)	(0.0210)		
Commerce	0.110***	0.124***		
	(0.0197)	(0.0198)		
Other services	0.0521***	0.0632***		
	(0.0184)	(0.0185)		
Self-employed	0.182***	0.181***		
	(0.0129)	(0.0130)		
Family business	0.213***	0.243***		
	(0.0194)	(0.0176)		
Seasonal/temporary	0.219***	0.230***		
	(0.0767)	(0.0737)		
Stopped working			0.0390***	
			(0.00635)	
Income decreased				0.0639***
				(0.00744)
Ln(GDP/capita)		-1.039		
		(1.476)		
Ln(GDP/capita Sq.)		0.139		
		(0.795)		
Stringency		0.149***		
		(0.0396)		
Country dummies	Yes	No	Yes	Yes
Region Dummies	No	Yes	No	No
Pseudo R Sq.	0.108	0.093	0.176	0.098
Observations	14,823	14,823	22,949	20,191

Notes: "Income decreased" takes on 1 if the respondent reported a decrease in income in aftermath of the pandemic. "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. "Learning" takes on 1 if the households' children continued to engage in learning activities during school closures. 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. ***: Statistically significant at 1%; **: Statistically significant at 5%; *: Statistically significant at 10%.

Table 5: Correlates of continued learning

VARIABLES	(1) Continued learning	(2) Continued learning
male	-0.00979	-0.0108
	(0.00872)	(0.0135)
Age	0.157**	0.190*
	(0.0743)	(0.112)
Age sq.	-0.0655*	-0.0788
	(0.0359)	(0.0539)
Urban	0.0625***	0.0992***
	(0.00907)	(0.0140)
Secondary-educated	0.0710***	0.0907***
	(0.0112)	(0.0169)
Tertiary-educated	0.111***	0.151***
	(0.0133)	(0.0204)
Stopped working	-0.0325***	-0.0483***
	(0.00995)	(0.0156)
Country dummies	Yes	Yes
Pseudo R Sq.	0.383	0.195
Observations	12,884	9,699

Notes: "Continued Learning" takes on 1 if the households' children continued to engage in learning activities during school closures. 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. ***: Statistically significant at 1%; **: Statistically significant at 5%; *: Statistically significant at 10%.

Figure 1: Stringency of containment measures by region and month

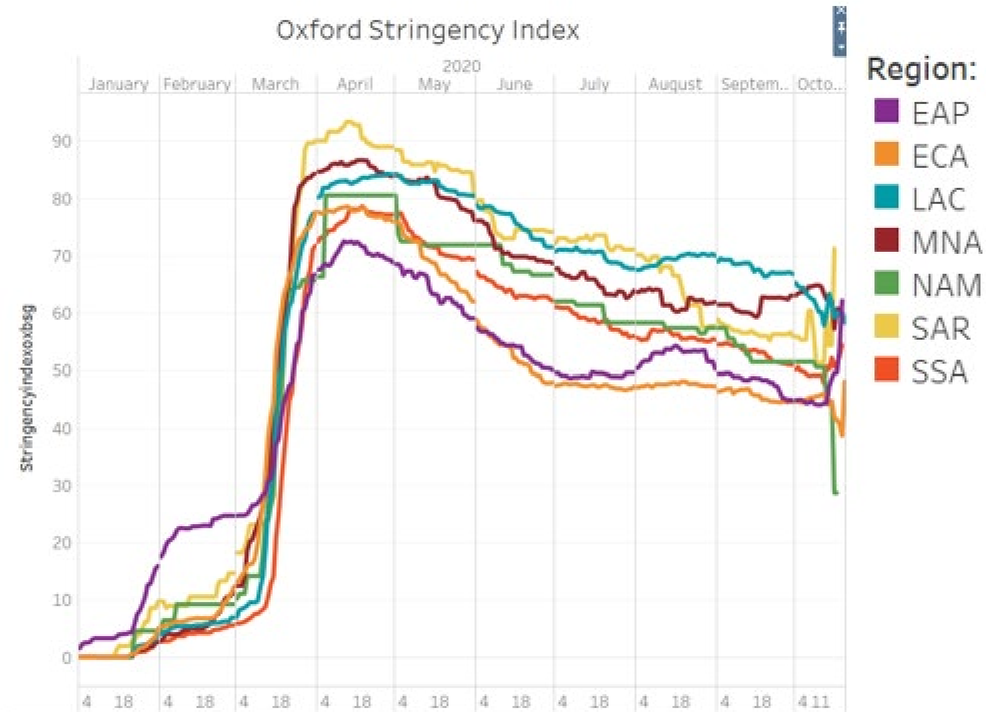


Figure 2: Changes in human mobility relative to pre-pandemic baseline, by region and month

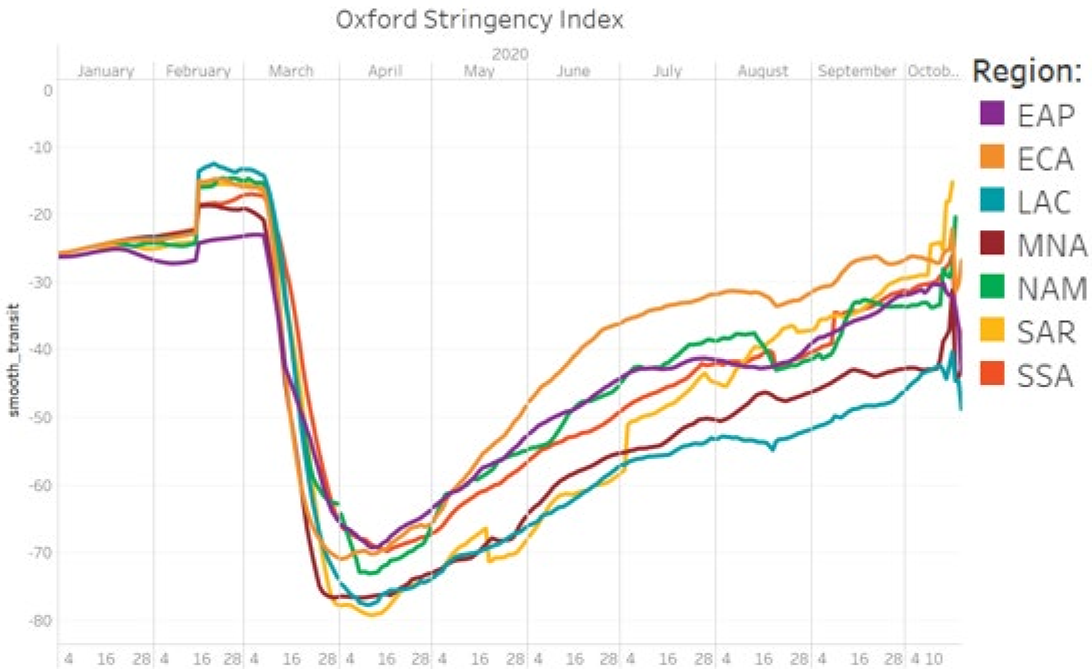


Figure 3: The marginal effects of age on the likelihood of stop working

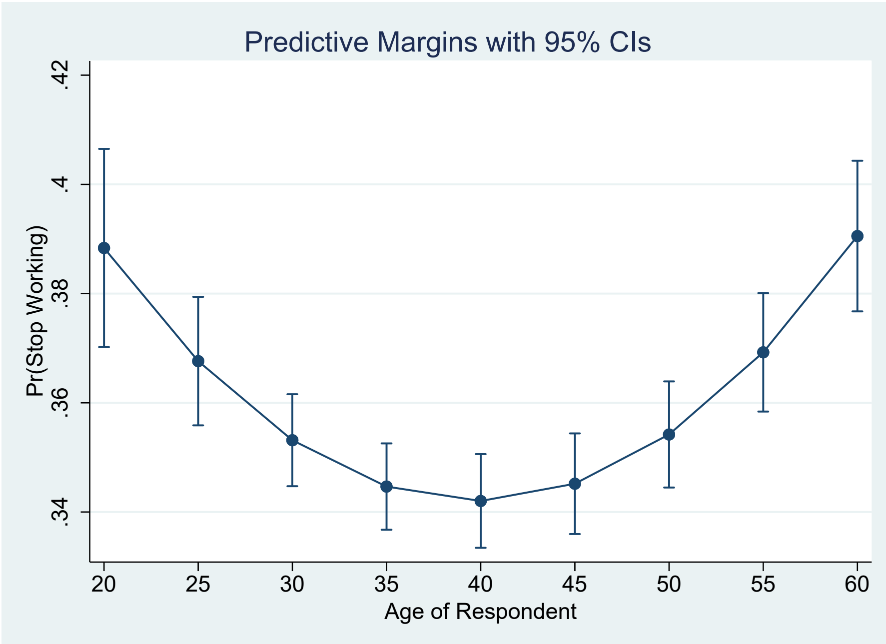
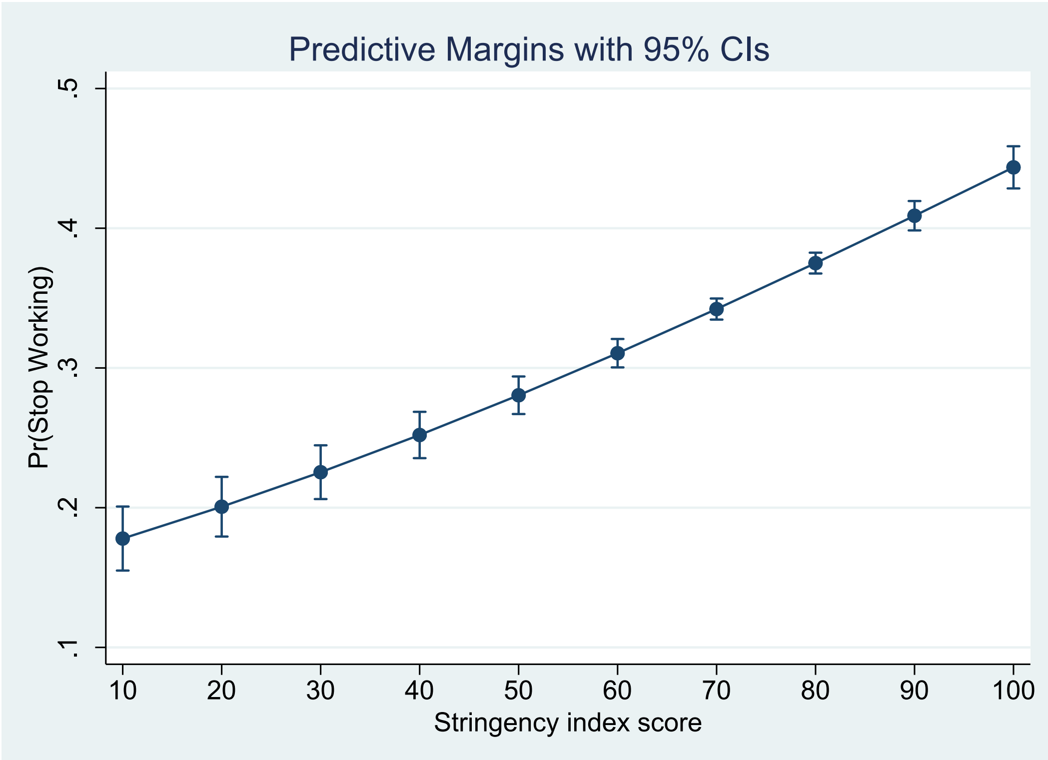


Figure 4: The marginal effects of the stringency index score on the likelihood of stop working



Annex 1: Variable description

Variable	Description
Stopped working	Dummy variable that takes a value of 1 if the respondent stopped working since the pandemic and 0 otherwise
Total income decreased	Dummy variable that takes the value of 1 if the respondent's total household income (both labor and non-labor) decreased since the onset of the pandemic and 0 otherwise
Food insecurity	Dummy variable that takes the value of 1 if 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 and 0 otherwise
Children continued to learn	Dummy variable that takes the value of 1 if the household's school-aged children (who were in school before the pandemic) have engaged in any learning or educational activities since school closures
Urban	Dummy variable that takes on value 1 if the respondent lives in an urban area, and 0 for non-urban/rural
Male	Dummy variable that takes on value 1 if the respondent is male
Education level: No education, Primary or less; Secondary; Tertiary	Dummy variables that take on the value of 1 for the level of education attained by the respondent, and 0 for the other three variables
Age	Numeric continuous variable on age of the respondent
Under 30	Dummy variable that takes on value 1 if the respondent is under 30 years of age
30 and over	Dummy variable that takes on value 1 if the respondent is 30 years of age or older
Has school-aged children	Dummy variable that takes on the value 1 if there are school-age children in the household (defined as children ages 6–18).
Sector: Mining/Manufacturing, Commerce, Other Services, Agriculture	Dummy variables that take the value 1 for the respondent's pre-pandemic sector of employment, and zero for the other three variables

Annex 2: Country-level indicators

Annex Table 1: Country-level indicators and descriptives (34 countries)

Country	Population ('000)	GDP per capita	Stopped working (%)	Income decreased (%)	Food insecurity (%)	Continued learning (%)
Burkina Faso	20,000	476	11.6%			87.6%
Bolivia	12,000	2,296	69.9%	70.0%	13.7%	84.8%
Chile	19,000	9,090	32.8%	53.9%	5.3%	95.9%
Colombia	50,000	4,538	53.9%	71.7%	14.2%	96.7%
Costa Rica	5,000	7,940	38.7%	63.1%	7.5%	96.9%
Djibouti	974	1,623	26.8%			78.8%
Dominican Republic	11,000	5,749	51.1%	59.2%	15.7%	93.9%
Ecuador	17,000	3,682	48.5%	73.8%	11.5%	97.4%
Ethiopia	110,000	486	13.7%	54.5%	13.9%	19.6%
Gabon	2,200	2,993	60.9%	63.1%		48.4%
Ghana	30,000	1,409	28.9%	77.4%	8.9%	60.7%
Guatemala	17,000	3,661	42.5%	69.9%	15.4%	90.2%
Honduras	9,700	2,014	53.7%	68.1%	20.0%	92.2%
Croatia	4,100	8,171	29.6%	28.6%		62.8%
Indonesia	270,000		23.4%			
Kenya	53,000	1,205	61.7%		11.4%	66.6%
Cambodia	16,000	1,031	14.0%			62.5%
Lao PDR	7,200		12.8%	44.5%		24.3%
Madagascar	27,000	353	7.8%		4.2%	26.6%
Mexico	130,000	6,317	42.3%	60.0%	6.4%	97.9%
Myanmar	54,000		56.6%	53.5%	2.1%	
Mongolia	3,200	2,743	18.9%		5.1%	73.4%
Malawi	19,000	381	11.7%	80.6%	34.3%	17.0%
Nigeria	200,000	1,815	49.8%	78.4%	25.4%	61.8%
Peru	33,000	4,281	60.2%	81.4%	18.1%	97.2%
Papua New Guinea	8,800	1,064	22.1%		28.9%	
Paraguay	7,000	3,840	42.6%	64.5%	10.4%	98.6%
Romania	19,000	8,406	25.3%	37.8%		
El Salvador	6,500	3,393	57.5%	68.8%	9.4%	98.1%
South Sudan	11,000	38	39.4%		72.6%	32.0%
Uganda	44,000	545	18.8%		9.7%	58.9%
Uzbekistan	34,000	1,051	50.1%	60.7%		
Vietnam	96,000	1,789	3.4%	69.5%		81.1%
Zambia	18,000	675	26.1%	54.9%	16.5%	47.0%

Notes: Data on stopped working, income decreased, food insecurity and continued learning come from the country-level high frequency surveys. Data on population and GDP per capita (in constant 2010 US$) come from the World Development Indicators. A blank cell means that the indicator was not included in the country's high frequency survey.

Annex 3: Pre-pandemic food security situation in countries with pre-pandemic data

Annex Table 2 presents the pre-pandemic differences in food security between households in which the respondent lost a job due to the pandemic and households which were not affected by job losses in Ethiopia. Overall, there were no statistically significant differences in food security in 2019 between the two groups of households. In the aftermath of the pandemic however, Ethiopian households that were affected by job losses had a higher incidence of food insecurity (21.5 percent) relative to non-affected households (14 percent), a difference statistically significant at the 1% level.

Annex Table 2: Pre- and post-pandemic food security in Ethiopia

	Lost job		
	No	Yes	Mean difference
Pre-pandemic data:			
In the last 12 months, have you been faced with a situation when you did not have enough food to feed the household?	13.8	13.1	-0.70
Number of days in past 7 days that the household:			
Limited portion sizes for meals	0.58	0.44	-0.14
Reduced number of meals per day	0.44	0.47	0.03
Restricted consumption for adults	0.32	0.26	-0.06
Had no food of any kind in the household	0.05	0.05	0.00
Went a whole day and night without eating	0.03	0..03	0.00
Number of meals per day	2.95	2.95	0.00
Post-pandemic data:			
At least one adult in household did not eat for a whole day due to lack of resources	14.1	21.5	7.40***
N	1,919	433	

Notes: Pre-pandemic data come from the fourth wave of the Ethiopia LSMS. Post-pandemic data comes from the first wave of the Ethiopia High Frequency Survey, which sampled from the LSMS survey. Data are weighted by sampling weights. ***: Statistically significant at 1%;

Annex Table 3 presents the same differences for Nigeria. Overall, the 2018 food security situation was better among households affected by job losses during the pandemic than household that were not affected. In the aftermath of the pandemic however, Nigerian households that were affected by job losses had a higher incidence of food insecurity relative to non-affected households.

Annex Table 3: Pre-and post-pandemic food security in Nigeria

	Lost job		
	No	Yes	Mean difference
Pre-pandemic data:			

In the last 30 days, did the household:			
Worry about not having enough food to eat	57.1	51.5	-5.60
Run out of food	41.6	39.3	-2.30
Go hungry and did not eat	41.2	31.7	-9.50***
Go without eating for a whole day	15.0	13.0	-2.00
Restrict consumption for adults so that children could eat	33.8	27.6	-6.20*
Post-pandemic data:			
At least one adult in household did not eat for a whole day due to lack of resources	21.7	30.9	9.20***
N	848	840	

Notes: Pre-pandemic data come from the Nigeria LSMS, implemented in 2018. Post-pandemic data comes from the second wave of the Nigeria High Frequency Survey, which sampled from the LSMS survey. Data are weighted by sampling weights. ***: Statistically significant at 1%; *: Statistically significant at 10%;

Annex 4: Robustness check for the food security findings

The main findings in the paper use the following indicator of food insecurity: "In the past 30 days, did you or another adult in the household go a whole day without eating due to lack of resources?" The harmonized database contains other indicators of food security as well: whether the household ran out of food in the past 30 days due to a lack of money or other resources ("ran out") and whether In the last 30 days, any adult in the household was hungry but did not eat because of lack of money or other resources for food ("hungry"). Annex Table 4 repeats regression (3) of Table 4 using these alternative indicators of food security. Results are robust: Losing a job because of the pandemic is associated with 8.9 percentage point increase in the "ran out" variable and a 7.7 percentage point increase in the "hungry" variable.

Annex Table 4: Correlates of food insecurity

	(1)	(2)
VARIABLES	Ran out	Hungry
male	-0.0305***	-0.0189**
	(0.00763)	(0.00768)
Age	-0.0363	-0.0996
	(0.0647)	(0.0648)
Age sq.	-0.0264	0.00641
	(0.0319)	(0.0319)
Has school-aged child	0.0453***	0.0467***
	(0.00838)	(0.00851)
Urban	-0.0321***	-0.0187**
	(0.00857)	(0.00870)
Secondary-educated	-0.0544***	-0.0638***
	(0.0104)	(0.0106)
Tertiary-educated	-0.186***	-0.166***
	(0.0108)	(0.0111)
Stopped working	0.0923***	0.0812***
	(0.00799)	(0.00823)
Country dummies	Yes	Yes
Pseudo R Sq.	0.15	0.145
Observations	22,189	17,734

Notes: Data are weighted by sample weights that are re-scaled to give each country in the sample equal weight. ***: Statistically significant at 1%; **: Statistically significant at 5%; *: Statistically significant at 10%.

Annex 5: Preliminary findings on employment recovery

The December 2020 vintage of the harmonized database that is used in this paper contains 22 countries with two post-pandemic survey waves. However, only 13 countries have data on all X-variables required to estimate the correlates of transitioning back into employment following job loss. For these 13 countries, we estimate following regression:

$$P(Back\ in\ employment\ W2) = \alpha + \sum_k \beta_i X_i + \delta + \varepsilon$$

Where X includes age (as a squared term), education, gender, and location of the respondent, and whether the respondent has a school-age child; δ are country dummies. The sample only consists of respondents who had lost their job between the onset of the pandemic and Wave 1 – we estimate the probability of being back in employment by Wave 2 conditional on having lost employment by Wave 1. Results are shown in Annex Table 5. Conditional on having lost a job in the immediate aftermath of the pandemic, men were 17 percentage points and tertiary-educated workers 11 percentage points more likely to have transitioned back into employment by Wave 2. Secondary-educated workers were also more likely than less-educated workers to transition back into work. Prime-age workers (around age 40) were most likely to transition back into employment, while both young and older workers were least likely to do so.

Annex Table 5: Correlates of transitioning back into employment following job loss

	(1)
VARIABLES	Back to work
male	0.169***
	-0.0165
Age	0.5419***
	0.1553
Age sq.	-0.3122***
	0.0781
Has school-age child	-0.0107
	-0.0182
Urban	-0.0467**
	-0.0206
Secondary educated	0.0397*
	-0.0213
Tertiary educated	0.109***
	-0.0247
Country dummies	Yes
Pseudo R sq.	0.063
Observations	3,664

Notes: Data are weighted by sample weights that are re-scaled to give each country in the sample equal weight. ***: Statistically significant at 1%; **: Statistically significant at 5%; *: Statistically significant at 10%.