Policy Research Working Paper 10300

Long COVID

The Evolution of Household Welfare in Developing Countries during the Pandemic

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Abstract

This paper examines the welfare impacts of the COVID-19 pandemic, using harmonized data from 343 high-frequency phone surveys conducted in 80 economies during 2020 and 2021, representing more than 2.5 billion people. The analysis focuses on the scarring effects of the initial losses of employment and income by examining their evolution over time across and within countries, as restrictions on mobility and economic activity were introduced and then gradually relaxed. The employment and welfare outcomes of some groups that were impacted to a greater degree initially—including women, informal workers, and those with less education—have been improving at a slower pace. The social protection response in lower-income economies was largely insufficient to protect households from the pandemic shock. Unmitigated welfare losses, as seen for example from the large share of households indicating income losses well into 2021, are highly correlated with food insecurity, which likely led some households to sell physical assets and deplete their savings. Without proper remediation, the uneven welfare impacts associated with COVID-19 may be amplified over the medium to long term, leading to future increases in poverty and inequality.

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 bbrunckhorst@worldbank.org.

Long COVID: The Evolution of Household Welfare in Developing Countries during the Pandemic*

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1 Introduction

Almost three years into the COVID-19 pandemic, the world is still recovering from disruptions in lives and welfare that are unprecedented in recent times. In 2020, economic activity contracted in nine out of ten economies – worse than during the Great Depression of the 1930s, World War II or the global financial crisis of 2007-08 – while global poverty increased for the first time since 1998, increasing the number of extreme poor by 70 million in 2020 (World Bank 2022b). Labor market impacts have been particularly severe with workplace disruptions due to social distancing requirements and global supply chain disruptions affecting many sectors and occupations. Recovery has been slow and challenging, impeded by inflationary pressures and the war in Ukraine.

Analysis of household phone surveys early in the pandemic suggested that the impact of COVID-19 on employment and incomes was large and unequal across and within economies. Employment and incomes dropped sharply almost everywhere but particularly in middle-income countries (MICs) during the first few months of the pandemic when governments adopted sweeping containment measures, including lockdowns, quarantines and social distancing. Within countries, restrictions on mobility and economic activity were associated with larger losses in employment and income among more vulnerable population groups, including those with lower levels of education, women, and urban informal workers (Bundervoet et al. 2022; Khamis et al. 2021; Kugler, Viollaz, et al. 2021).

The objective of this paper is to update the analysis of the early employment and income impacts of the pandemic over a considerably larger sample of countries,[1] and to describe how the welfare impact of the economic crisis associated with the COVID-19 pandemic evolved throughout 2020 and 2021. Toward those ends, we utilize a comprehensive database of high-frequency phone surveys (HFPS) that covers 80 economies in five out of six World Bank regions, representing a combined population of over 2.5 billion.[2] The HFPS database spans April 2020 through December 2021, with at least four survey rounds available in most economies represented. While this database is unique in its coverage, especially during a period when data collection efforts were halted in many countries at least temporarily, it also comes with a set of caveats. Biases associated with phone surveys were discussed extensively in previous papers. This paper discusses additional caveats related to the way phone survey data measure employment, which are important for interpretation of the evidence.

[1] For comparison, the analysis of initial impacts covered around 30 economies in earlier papers such as Bundervoet et al. (2022).

[2] While phone survey data also exist for countries in South Asia, they are dropped from the analysis because, at the time of writing, data was available only from one survey round and differences in the survey instrument prevented the construction of comparable employment indicators that are representative of the population.

One less known aspect of the COVID-19 pandemic, and the focus of this paper, is not only how large the shock has been but also how persistent, potentially affecting poverty and inequality in the medium term. We document that extensive work stoppages in the second quarter of 2020 persisted, to some degree, through 2020 and in most economies all the way through 2021. We confirm earlier findings that female workers and those with lower levels of education experienced more severe employment losses on account of the pandemic disproportionately impacting services sectors such as retail and hospitality and low-tech manufacturing sectors in which they tend to work. The uneven distribution of care responsibilities left women assuming the bulk of the increased needs of care for children following massive school closures. We also find women and those with lower levels of education have experienced smaller gains in employment through the second half of 2020 and 2021 following the initial shock.

While there is evidence of work restarting after initial job losses, one prominent feature of the recovery is the increased prevalence of self-employment relative to prepandemic patterns. It appears that the mass job displacement that was caused by the COVID-19 labor market shock was buffered partially by informal employment. Given that informal self-employment in developing economies tends to be concentrated in low-return activities, this may indicate that while employment improves, the new jobs may be of lower quality than those held prior to the pandemic. Similarly, participation in the agriculture sector in low-income countries (LICs) and lower middle-income countries (LMICs) also increased and acted as a buffer to absorb shocks. However, income losses remained quite widespread throughout the pandemic.

Beyond employment losses, the welfare impacts of the COVID-19 crisis have been much broader, especially when impacts remained largely unmitigated. Most economies implemented COVID-19 fiscal packages to counter the pandemic impacts on the economy and people, however there was wide variation in the scale of the response, with higher-income economies spending significantly more than lower-income economies on support to households and firms. A synthesis of available microsimulation studies shows that increases in poverty were only partly mitigated in poorer countries World Bank (2022b). While the phone surveys are an imperfect source of data to assess receipt of assistance, they point to benefits expanding in coverage over the course of the crisis, but not reaching many affected households, especially in LICs. Many income losses went unmitigated, as reflected in the strong correlation between income losses and high levels of food insecurity. Households adopted various coping strategies, including the use of savings and sales of assets, which could hurt their future productive capacity and ability to recover from the crisis, leading to higher future poverty and inequality, an economic version of “long COVID”.

The remainder of this paper is structured as follows. Section 2 provides a brief review of the existing studies on the welfare impacts of the COVID-19 pandemic and describes the contributions of this paper to the existing literature. Section 3 describes the data used in the analysis, defines the main variables that the study relies upon to examine the different dimensions of welfare impacts, and discusses some of the data-related caveats. Section 4 outlines the main findings related to the patterns of employment losses and subsequent dynamics across different countries and population groups. Section 5 looks at how the broader welfare impacts and the response to the shock could lead to scarring and reinforce inequality in the longer-term if the losses are left unmitigated. Section 6 concludes.

2 Welfare impacts of COVID-19: Existing evidence and knowledge gaps

A number of studies have documented the multifaceted welfare impacts of the COVID-19 pandemic both across and within countries, focusing primarily on the labor market impacts such as job and income losses. These resulted from the restrictions to mobility and economic activity that were imposed by governments in order to contain the spread of the coronavirus as well as the ensuing impact of global demand and supply shocks.[3] In developing countries, analyses mostly rely on HFPS data collected by the World Bank, as many countries had to put on hold the collection of household data through regular surveys such as Household Budget Surveys or Labor Force Surveys during 2020-2021. HFPS data revealed high levels of work stoppages early in the pandemic, particularly in the industry and services sectors, lack of payment for work performed, as well as income losses at the household level that correlate with the degree of stringency of the measures that were imposed to restrict mobility and economic activity (Bundervoet et al. 2022; Khamis et al. 2021; Kugler, Viollaz, et al. 2021). For instance, Bundervoet et al. (2022) find, based on a sample of 31 countries, that more than a third of respondents reported having stopped working since the onset of the pandemic, and almost two-thirds of households reported a decrease in total income. These job and income losses were associated with significantly higher levels of food insecurity at the household level.

The early analyses conclude that the welfare impacts precipitated by the economic crisis were not evenly distributed either across or within countries. Across countries, employment and incomes dropped sharply almost everywhere, and nearly all LICs and LMICs saw poverty increase in 2020. Globally, the pandemic led to a broad shock across the global income

[3] There is a substantive literature documenting the important benefits of public health policies to flatten the curve of COVID-19 contagion through masking, social distancing, contact tracing and vaccination in the context of developing countries that is beyond the scope and focus of this paper.

distribution, though households with per-capita incomes above $20 per day (in 2017 PPP) were much less affected than the rest (World Bank 2022).

Within countries, evidence suggests the brunt of the burden from the COVID-19 labor market shock was borne by women, less educated, and urban workers (Bundervoet et al. 2022; Kugler, Viollaz, et al. 2021). The disproportionate impact on these population groups has also been corroborated in a number of countries that continued standard survey data collection, including Türkiye (Aldan et al. 2021), South Africa (Köhler et al. 2023), Brazil (World Bank 2022a), Vietnam (Dang et al. 2023), and India (Deshpande 2020). Similar patterns are also observed in advanced economies. For instance, harmonized data from the EU Statistics on Income and Living Conditions (EU-SILC) show that in Q2 of 2020 the risk of temporary layoffs or reduced hours declines with household income. Chetty et al. (2020), based on data from the United States, find that employment losses between January and April 2020 decreased monotonically with income, from 37 percent in the bottom wage quartile to 14 percent in the top wage quartile.

These differential impacts across population groups are in part because the ability of workers to continue jobs remotely is higher among better-educated workers, as a result of the digital divide and the cognitive nature of work for high-skill occupations. In the case of developing countries, some studies have analyzed task characteristics across occupations to estimate the share of jobs that can be done at home. Dingel and Neiman (2020) find the share to be increasing with country income levels, with fewer than 25 percent of jobs in Mexico and Türkiye being amenable to working from home. World Bank (2020) uses data from India to estimate that less than 10 percent of jobs are amenable to working from home at the 70$^{\text{th}}$ and lower percentiles of the earnings distribution and suggests that the actual estimate is likely much lower because of constraints to accessing digital technology. Gottlieb et al. (2021) find that just 13.3 percent of urban workers in Brazil and 10.6 percent in Costa Rica were actually working from home during the pandemic. In addition to feasibility to work from home, there is also considerable evidence of the gender gap in the care responsibilities precipitated by the pandemic and accompanying school closures which may have led to a reduction in women's labor force participation (Albanesi and Kim 2021; Bau et al. 2022; Levine et al. 2021; Lee et al. 2021; Miguel and Mobarak 2022).[4]

Beyond the initial impact, there is also evidence that those who suffered the larger initial

[4] Evidence is more abundant in high-income countries. Sostero et al. (2020) find that in Europe three-quarters of employees in the top wage quintile were able to work remotely, compared to only 3 percent of those in the bottom quintile. Adams-Prassl et al. (2022) similarly find that in the UK workers with gross labor income above GBP 70,000 can accomplish some 60 percent of tasks remotely, compared to 20 percent among workers with gross labor income below GBP 10,000.

shocks – women, urban workers, and the low-educated – recovered more slowly during the initial relaxation of policy stringency measures during the summer of 2020 (Narayan et al. 2022). ILO (2021) using labor force survey data finds that the labor market recovery stalled during 2021, with little progress since the last quarter of 2020. Kim et al. (2021) using phone survey data from East Asian countries, find that employment impacts were widespread across the distribution when mobility restrictions were stringent, but it was more difficult for poorer workers to regain employment once stringencies had been relaxed. This pattern is also found in the US (Chetty et al. 2020; Lee et al. 2021), Colombia (Alvarez and Pizzinelli 2021), and India (Kugler and Sinha 2020).

This paper's first contribution is the use of a unique data source – arguably the most comprehensive data collection effort during the pandemic – to provide an analysis of the initial welfare impact, notably employment and income, and its evolution in the first two years of the pandemic, across and within countries.

Focusing solely on the levels of employment could obscure some of the welfare effects of the pandemic. In particular, transitions into agriculture and self-employment would likely be associated with lower quality informal jobs, yielding lower remuneration vis-à-vis prepandemic wage employment. For instance, Kugler, Viollaz, et al. (2021) document a fall in wage employment and an equivalent increase in the share of self-employment among younger workers during the early stages of the pandemic. Such coping strategies may be more prevalent among lower-income households, who lack access to safety nets and cannot sustain prolonged unemployment spells for fear of not being able to cover basic necessities. Therefore, another contribution of this paper is the analysis of employment transitions for different population groups during the pandemic to examine not only the scope of employment changes, but also changes in the quality of employment across different population groups.

Despite the uneven impact of the pandemic across population groups, the estimated short-run impacts of COVID-19 on aggregate within-country income inequality so far appear to be mixed (World Bank 2022b).[5] However, research on the inequality impacts of previous pandemics suggests that they could peak 4-5 years after the onset of the pandemic (Furceri et al. 2022). The impacts of the COVID-19 pandemic on inequality could worsen over time

[5] While traditionally vulnerable groups appear to have experienced greater losses as seen in group-wise comparisons, the final impact on within-country inequality depends on where these groups are located in the overall income distribution. In an analysis combining prepandemic household survey data with information from high-frequency phone surveys and macroeconomic growth projections, Mahler et al. (2022) estimate the change in the Gini index after COVID-19. These projections complement Ginis published by National Statistical Offices and estimates from the literature and household surveys conducted in 2020. The result shows a mix of positive and negative changes in within-country inequality, with the magnitude being small in most cases.

if the scarring effects of sustained employment and income losses as well as distress asset sales and learning disruptions for children in poorer households limit the recovery of poorer households relative to better off households over the medium-term (Kim et al. 2021; World Bank 2022b; Neidhöfer et al. 2021).

In this regard, the dynamics of income losses examined in this paper would reflect employment changes in the intensive as well as extensive margin and indicate the extent of unrecovered welfare losses throughout the pandemic. This paper goes on to argue that the wider welfare losses beyond job losses, if left unrecovered, could amplify inequality in the longer term. The pandemic has led to significant losses of productive assets and human capital, particularly in poorer countries. Households disposed of productive assets as a way of coping with the income shock since the social protection response was largely inadequate, often relied on inefficient means, and did not last long enough in many lower-income countries (World Bank 2022b). The loss of assets could hurt the productive capacity of those households that need it the most during the recovery.

3 Data and methods

The main data source for this paper is the November 2022 vintage of the World Bank's harmonized HFPS data which was collected to monitor the impact of the pandemic on households. The first surveys were conducted in April 2020, with data collection continuing into 2022 in some economies. Since questionnaires differed by economy and across survey waves, responses were harmonized globally to construct an internationally comparable dataset with up to half a million observations for a given indicator. Data used for analysis in this paper were collected from 80 countries in five of the six World Bank regions over 343 survey waves between April 2020 and December 2021. The breakdown of countries with harmonized survey data by income level, region and timing is shown in Table 1. More than half are LICs and LMICs, including 19 Fragile and Conflict-Affected Situations (FCS). Of the 80 countries with surveys, 53 are located in Latin America and the Caribbean (LAC) and Sub-Saharan Africa (SSA), so the country averages reported are strongly influenced by these regions (Figure 1).[6] Previous papers using the HFPS describe the harmonization process and dataset in more detail (Bundervoet et al. 2022; Khamis et al. 2021; Kugler, Viollaz, et al. 2021).

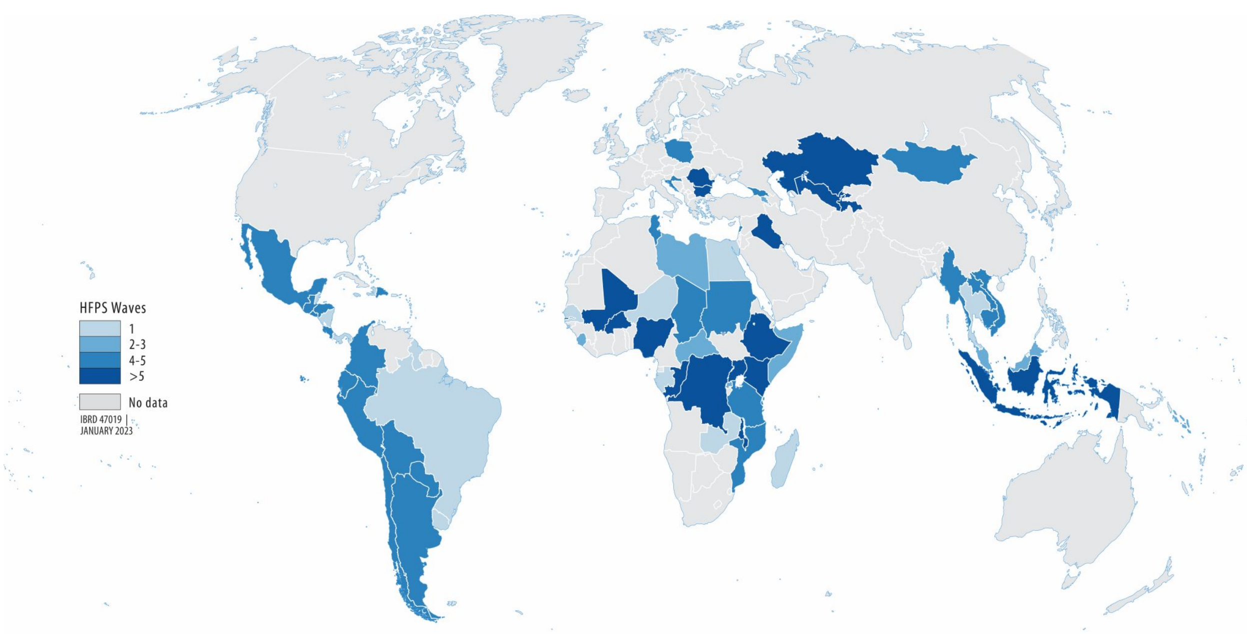
[6] Annex 1 provides more detail on the coverage and timing of surveys. Figure A1.1 shows countries with HFPS waves by the time periods used in the analysis, and Figure A1.2, by income level. Figure A1.3 lists all countries with HFPS data included in the analysis and the timing of HFPS waves between April 2020 and December 2021 at the country level.

Table 1. Sample composition across three periods of analysis

	Number of economies with HFPS				**Survey waves**
	Apr-Jun20	**Jul-Dec20**	**2021**	**Total**	
High income	5	5	7	8	26
Upper-middle income	14	18	24	26	90
Lower-middle income	19	19	17	26	112
Low income	13	18	12	20	115
East Asia and Pacific	7	8	10	11	40
Europe and Central Asia	5	9	9	9	77
Latin America and Caribbean	14	14	24	24	66
Middle East and North Africa	5	5	2	7	26
Sub-Saharan Africa	20	24	15	29	134
Fragile and Conflict-Affected	13	14	9	19	62
Total	51	60	60	80	343

Notes: Surveys are attributed to a period based on the mean month of data collection. Most surveys were conducted within two calendar months.

Figure 1. Number of HFPS waves across countries



Source: COVID-19 High-Frequency Phone Surveys.

Phone surveys have the advantage of collecting data widely and rapidly and were the only option during the early peak of the COVID-19 crisis when nearly all face-to-face surveys ceased. However, there are important weaknesses to be considered. First, the surveys are representative of the phone-owning population only, which implies that households with limited or no access to phones will be underrepresented. Second, response rates are often quite low compared to in-person interviews and attempts to correct for nonresponse bias may not be perfect. Third, the scope and type of questions that can be asked is often limited compared to in-person surveys in order to keep the survey short and to minimize survey refusal.

Two main sampling strategies were used for the World Bank COVID-19 phone surveys, with important limitations intrinsic to the mode of data collection and leading to implications for the populations they were intended to represent. Surveys in 36 countries, especially those in LAC, used pure Random Digit Dialing (RDD) or assisted RDD. This method samples from all active landline and mobile phone numbers, such that RDD surveys would be representative of the population (over 18 years) with an active phone number if survey completion and response were perfect. On the other hand, surveys in 31 countries used a subsample drawn from a prepandemic nationally representative survey. The latter often collected the contact details of the household head, meaning that phone surveys using this sampling frame tend to overrepresent household heads and underrepresent members who are neither heads nor spouses. This means that individual level indicators such as employment outcomes may be biased due to respondent selection within households. The remainder of surveys use other pre-existing lists to identify the sampling frame.

To help correct for the non-representativeness of surveyed households, household sampling weights were calculated. These adjust for differential response rates among subgroups of the population, with the objective of obtaining estimates as close to nationally representative as possible.[7] Addressing the non-representative selection of individuals poses a greater challenge to generating statistics that are representative of individual level outcomes such as engagement in the labor market. Kugler, Viollaz, et al. (2021) examined this for five countries where surveys collected employment information for all household members and find that phone surveys overstate employment rates for the full population even once sampling weights are used. Encouragingly, their analysis suggests that phone surveys do reasonably well at tracking disparities and changes across gender, education, and urban/rural groups. However, for age group comparisons the bias was greater.[8]

We use household sampling weights for all our analysis. Household sampling weights are used even for respondent level employment indicators, so these should be interpreted as the share of households with a respondent having that employment outcome, rather than the share of individuals.[9] Countries are weighted equally such that summary statistics are

[7]Surveys in Democratic Republic of Congo, Central African Republic and Mozambique were conducted only in urban areas or the capital city and are not representative of the rural population.

[8]This paper does not make comparisons across age groups.

[9]Individual level sampling weights are only available in some countries with RDD surveys, and it would be

interpreted as averages of country averages, intended to represent a global picture of country experiences rather than the story of global population aggregates. The same approach to weighting is used for all regression analysis.

To keep the analysis tractable, we present descriptive statistics for three time periods broadly based on different stages of the pandemic, as shown in Figure 2, and the timing of surveys (Figure A1.3). The first period from April 2020 to June 2020 represents the initial impact of the pandemic, marked by stringent policy measures in many countries including lockdowns and school closures, as captured by the Oxford Covid-19 Government Response Tracker (OxCGRT) stringency index.[10] This corresponds with a substantial decrease in visits to workplaces and transit stations, while people spent more time in residential areas, as reflected in Google Community Mobility data. The second period, July 2020 to December 2020, is characterized by a gradual withdrawal of some containment measures and increased mobility following the initial shock, though there are regional differences. The third period covering 2021 is distinguished by stalled progress in many countries, with little change in policy stringency on aggregate, but some return to normal levels of mobility. More significant differences emerge between regions and countries in this latter period (Figure A1.4).

When countries fielded multiple surveys within one of these time periods, we select a single survey to include in the calculation of summary statistics for each period (Figure A1.3). For the initial period, we choose the survey month corresponding with the highest stringency index to measure peak welfare impacts at the onset of the pandemic. To look at subsequent recovery in welfare and employment outcomes, we use the survey month corresponding to the lowest stringency index in the second half of 2020, and the most recent survey collected in 2021 for the third period.[11]

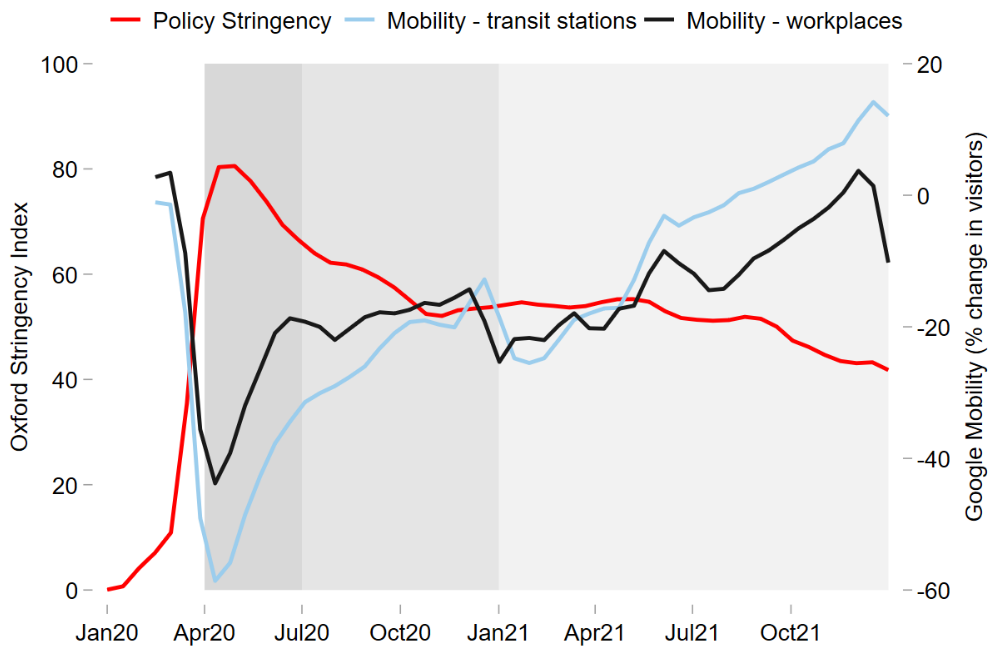
For employment outcomes, the sample is restricted to households in which the respondent was between 18 and 64 years old, since employment questions were only asked of the respondent. Survey waves were only included in the calculation of summary statistics if the indicator had a response rate of at least 50 percent. Table 2 describes welfare outcomes of interest related to employment, income, food security, assistance, and coping strategies. Annex 2 provides more detail on the construction of these indicators.

challenging to use these for cross-country comparisons with countries without individual level weights.

[10]The OxCGRT stringency index records the strictness of 'lockdown style' policies that primarily restrict people's behavior (Hale et al. 2021). It is calculated using 9 indicators including school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls.

[11]The main findings from the descriptive analysis are consistent if we instead pool surveys within each period. The regression analysis does not compare across time periods and uses all HFPS rounds (countries are weighted equally).

Figure 2. Policy stringency and mobility trends in economies studied



Source: Google COVID-19 Community Mobility Reports and Oxford COVID-19 Government Response Tracker.
Notes:The shaded regions represent the three time periods used for descriptive analysis. The OxCGRT stringency index is available in 76 out of 80 countries with HFPS data. Google Community Mobility data is available in 57 countries with HFPS data.

While HFPS data in principle allow us to compute estimates of the share of employed adults both prepandemic and in each subsequent HFPS round, comparisons between employment levels before and after the onset of the pandemic are made difficult by the fact that current and prepandemic employment are queried differently, and thus may not be strictly comparable. In particular, the HFPS estimates of prepandemic employment may overestimate actual employment level on account of recall bias. To minimize the impact of this recall bias, the analysis of employment losses in Section 4 draws primarily on estimates of net employment changes (losses and gains), computed in terms of differences between the employment status (working or not working) reported by the respondents in each survey round and their prepandemic recall. While prepandemic employment levels may be subject to a recall bias, we can still make internally valid comparisons across rounds by comparing estimates of net changes, if we assume that recall bias is constant across survey rounds.[12] Since prepandemic employment was queried in multiple survey rounds, we use an individual's earliest response and treat it as time invariant in our analysis by matching households

[12]Recall bias is subtracted out when comparing the difference in employment changes across time periods. Figure A3.1 illustrates a recall bias of unknown magnitude and its relationship with net employment changes over time.

Table 2. Harmonized welfare indicators

Topic	Indicator	Countries	N
Employment	Respondent was currently working at time of survey	77	471,967
	Respondent stopped/started working at time of survey relative to prepandemic	75	443,902
	Respondent changed job, sector or employment type relative to prepandemic, if working before the pandemic and at the time of survey	Job: 69 Sector: 54 Type: 43	184,324 115,828 96,152
	Respondent gained employment during the pandemic, if not working in a previous HFPS wave (panel respondents)	52	136,478
	Respondent recovered employment during the pandemic, if stopped working relative to prepandemic in a previous HFPS wave (panel respondents)	52	78,019
Income	Household income decreased relative to the prepandemic reference period	54	186,073
	Household received no or partial payment for wage work in the past week, if the respondent was a wage worker	47	36,421
	Household gained income during the pandemic since the date of the previous HFPS wave	29	102,091
	Household recovered income during the pandemic – income increased since the date of the previous HFPS wave – if the household reported income loss relative to prepandemic in a previous HFPS wave (panel households)	23	56,360
Food security	Household adults went a full day without eating in the last 30 days	61	309,457
Assistance and coping strategies	Household received any form of public assistance since the start of the pandemic	70	359,736
	Household reduced consumption of goods during the pandemic	49	229,090
	Household used money saved for emergencies to cover basic living expenses	52	285,059
	Household sold assets such as property to pay for basic living expenses	51	283,790

Notes: The number of observations includes all survey rounds; questionnaires varied across survey rounds and countries.

and individuals across panel survey rounds where possible. This both minimizes the recall period and reduces potential variation in recall bias across survey rounds. We observe that prepandemic employment estimates are stable across surveys, suggesting the constant recall bias assumption is valid in our data (Figure A3.2).

A further cross-check on employment statistics from HFPS can be provided by comparisons with labor force survey (LFS) data, primarily in UMICs and high-income countries (HICs) that continued to collect LFS after initial interruptions due to the pandemic. It should be noted that employment estimates from the two sources are not strictly comparable, and any differences may be the result of several factors, including the aforementioned recall bias, differences in the number, sequence and wording of questions, differences in the timing of surveys, and important distinctions between the populations represented.[13] More details on this comparison exercise can be found in Annex 4. The analysis suggests that despite some differences in magnitude, the HFPS and LFS capture similar employment dynamics in most countries with overlapping data (Figure A4.1). The share of respondents currently working in the HFPS is strongly correlated with the employment population rate reported in the ILO database (Pearson correlation coefficient=0.604, $p<0.001$; $R^2=0.869$ controlling for country fixed effects; see Figure A4.2). Furthermore, discrepancies in terms of how closely employment trends mirror each other at the country level tend to be less consequential in country or population group aggregates, which is the level of analysis in this paper (Figure A4.3). The number of LICs with LFS data remains very small, and as such HFPS data continue to be one of the few available sources of information for many developing countries throughout the pandemic.

4 Employment dynamics during the pandemic

This section uses the most comprehensive and up-to-date cross-country data available to (i) update the phone survey estimates of the initial impacts of the pandemic for a considerably larger set of countries vis-à-vis analysis in previous papers; (ii) trace the evolution of employment, work stoppages and acquisition of new jobs; and (iii) examine transitions across sectors and types of employment throughout 2020 and 2021, focusing on the question of the quality of the employment gains following initial losses.

4.1 What are the main patterns of initial employment losses and subsequent employment gains?

There are several ways through which labor market outcomes could be affected during the crisis. These include job losses, changes in jobs, and earnings losses which can be observed in

[13] For example, the HPFS question asking whether a respondent worked before the COVID-19 pandemic could be capturing broader recall of past employment which may or may not be coded as employment in a considerably more detailed LFS instrument. Respondents reporting not working in the HFPS after the onset of COVID-19 could still be classified as employed in the LFS as they are temporarily absent from work but believe they still have a job to go back to in the future. Differences in the magnitude of employment impacts are in line with expectations considering these factors. Also, the LFS available for comparison are conducted quarterly which does not line up with the timing of HFPS and therefore may not capture the same short-term disruptions to the labor market.

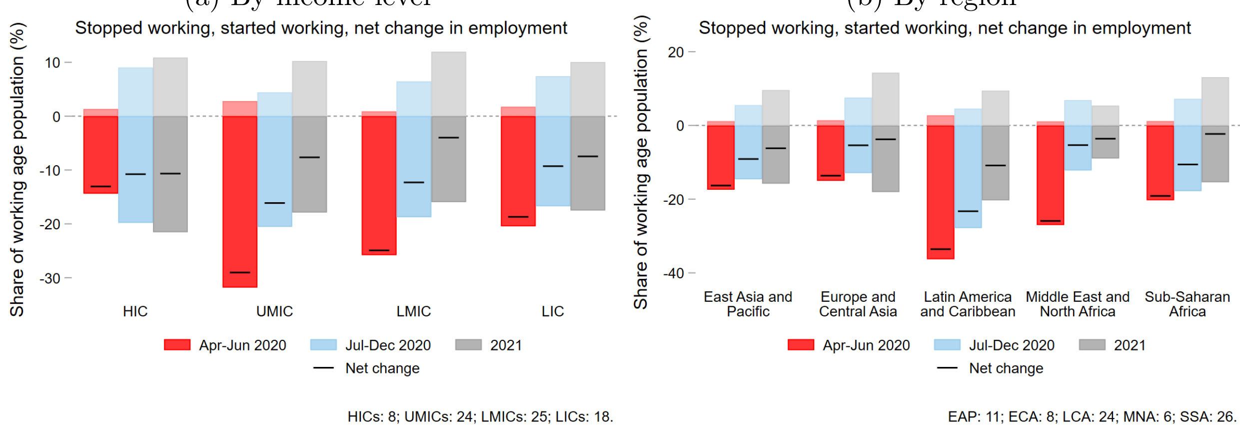
the data, albeit imperfectly. We focus on these outcomes here, since we can observe them in the HPFS data. However, some workers may also be temporarily absent from their job; job seekers may face worse job prospects while having to reduce their job search efforts due to the pandemic; some may decide to continue education instead. While plausible, these latter mechanisms are difficult to observe with the data at hand. Instead, this section mainly focuses on estimates of outright job and earnings losses and some, though not all, changes in jobs.

Figure 3 reports the evolution of employment for the overall HFPS sample by income group and region.[14] The estimates are based on the pooled sample including 75 countries that have at least one survey collecting relevant employment information in any of the three periods that we are reporting on. Taking the recall-based prepandemic employment status as our reference point, the net change in employment can be decomposed into the shares of working age population reporting job losses and starting new jobs. This decomposition shows that while the net changes in employment from April-June 2020 were almost entirely driven by sudden job losses, during the second half of 2020 and especially in 2021, the employment gains were driven not only by lower rates of job losses, but also by a higher share of previously unemployed adults starting work.

Figure 3. Employment dynamics across country groups

(a) By income level

(b) By region



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Consistent with earlier studies, the updated HFPS dataset confirms widespread initial

[14]In some countries, prepandemic employment variables were collected only for those not working at the time of the first survey wave. When questions were skipped for those working, we assume prepandemic employment variables (status, sector and employment type) are the same as their employment variables reported in the first survey, i.e., those working in the first wave did not only start working since the pandemic began. We find these assumptions hold true in 93-96 percent of cases in countries where prepandemic data was collected for those working in wave 1, and imputations appear to correct bias (Figure A5.2). Similar assumptions were made in previous studies using the HFPS data, but we now have sufficient data to conduct a robust validation. Details are provided in Annex 5.

labor market losses. Overall, the share of the working age population who reported being employed in April-June 2020 was, on average, 31 percent lower than prepandemic levels. However, as we note in the previous section, the absolute magnitudes of these initial job losses, inclusively in the earlier studies, should be interpreted with caution, as the magnitude of any recall bias associated with the framing of the prepandemic employment question in the HFPS is unknown.[15]

Given that many countries did not have a survey in all three periods, it is possible that dynamics of certain indicators across the three time periods may be a function of the composition of the sample within each time window. To address this concern, we also consider employment estimates for a sample restricted to countries with data points in all three periods, such that the sample composition remains constant across the three time periods. We attempt this whenever possible and include results for a "country panel" in Annex 6, however, data coverage varies significantly depending on the harmonized indicator. Overall, employment trends for a panel of 31 countries are similar to the full sample (Table A6.1).

Updated estimates reaffirm that the initial impacts, as well as the pace of the subsequent gains, varied considerably across country groups. MICs experienced the largest employment losses in the initial stage of the pandemic, followed by an increase in employment levels in the second half of 2020 and through 2021. Among a small sample of HICs, the initial magnitude of job losses was much smaller, but has been followed by a much slower pace of recovery. In LICs, losses of employment were subdued, compared to those reported in MICs. There could be several contributing factors behind lower employment losses in LICs. First, the extent of restrictions to mobility and economic activity, as measured by the OxCGRT stringency index, was somewhat lower on average in LICs. In addition, LICs have a much higher share of agricultural employment and a higher share of population residing in rural areas, which have not been affected as much by mobility restrictions as those living in urban areas. Finally, the HFPS data do not directly capture changes at the intensive margin, such as changes in hours worked which have been shown to have been affected significantly (ILO

[15]One possible estimate of recall bias within the HFPS is to compare a respondent's recalled employment status for the previous wave and their employment status reported in that wave (in countries asking both questions). Another estimate of recall bias is possible by comparing the HFPS estimate based on recall with prepandemic LFS data. This is likely to be an upper bound estimate because several other sources of error are expected to add to any recall bias when making this comparison. Using these methods, we estimate prepandemic employment levels in HFPS include recall bias less than zero, on average, in the first case (24 countries), and up to 6 percentage points using the upper bound LFS method (26 countries). Upper bound recall bias estimates remain smaller than employment losses in 2021 estimated from HFPS for 16 of the 21 countries with both data sources, suggesting evidence of unrecovered employment is quite robust (Figure A4.4).

2021). This may explain why a much larger share of households in LICs report to have lost income since the pandemic started. Employment recovery among LICs appears to stall in 2021, with gains driven only by new entrants and, unlike in MICs, the share of adults that had stopped working since the pandemic did not continue to fall between the second half of 2020 and 2021 (Table A6.2 and Table A6.3).

Across all regions, employment fell most in the early phase of the pandemic and was substantially lower in LAC compared to other regions. Employment levels recovered during the second half of 2020, most significantly in Europe and Central Asia (ECA), LAC and SSA, relative to prepandemic levels. The EAP region diverges from these patterns when considering results in a panel of five countries, where there is limited recovery from initial labor market losses throughout 2020 and into 2021. Results for a smaller but stable sample of countries also suggest little recovery in employment levels during 2021 in ECA and SSA (Table A6.1).

4.2 We're all in this together? Employment gains across different population groups

One of the main findings in studies of initial COVID-19 impacts described in Section 2 related to the uneven impacts of the pandemic on different population groups—those with lower levels of education, informal employment, and women have been impacted to a greater degree initially by job losses.

Table 3 reports the percentage change in employment across different population groups in 2020 and 2021, relative to each group's prepandemic employment level (based on recall), both for the full set of countries and for the country panel. Our main interest is in comparing the magnitudes of relative employment changes across different population groups over time. To make comparisons across countries in terms of education level, we define low education as primary or less in LICs and LMICs, and secondary or less in UMICs and HICs.

The estimates from the expanded HFPS sample confirm that the initial impacts of the pandemic on employment were more pronounced for women, urban workers, and those with lower levels of education. For instance, there was proportionally greater employment loss among women relative to prepandemic levels, and this gap persists into 2021 (Table 3). Work stoppages – the main component of net employment changes – decreased over time, but the rate of decrease tended to be lower among women, who report a higher incidence of work stoppages in the later part of the pandemic (Table A6.2). For a number of countries, particularly in the LAC region, women experienced larger proportionate declines in employment

Table 3. Evolution of employment across different population groups

	Net change in employment relative to prepandemic level (%)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	−30.6	−16.8	−8.2	75	246,618
Country panel	−31.0	−19.2	−12.0	31	140,798
Female	−33.6	−20.1	−10.0	73	103,900
	−35.8	−22.6	−13.0	31	60,950
Male	−27.2	−14.6	−7.4	73	139,142
	−27.7	−16.1	−10.4	31	79,353
Non-urban/Rural	−28.7	−15.1	−7.5	67	92,426
	−28.4	−16.6	−11.6	27	53,174
Urban	−31.5	−17.3	−9.3	69	135,127
	−31.3	−20.0	−14.2	27	73,999
Low education	−33.6	−19.4	−8.1	59	92,320
	−35.2	−22.5	−12.6	23	55,169
High education	−29.1	−17.8	−7.9	59	89,509
	−28.2	−20.7	−12.7	23	47,497

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

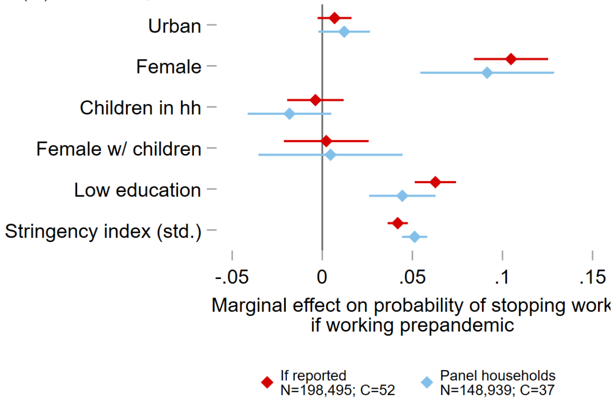
in the initial phase of the pandemic, and subsequent gains in employment either proceed at roughly the same pace among women and men, or gender disparities actually widened over time (Figure A6.1).

Employment also fell proportionately more among those with lower levels of education in April-June 2020, following the onset of the pandemic. Relative to prepandemic employment levels, this gap appears to close in subsequent HFPS waves, in the sample of all countries and in the country panel. However this is driven by previously unemployed workers in the low education group starting jobs at a faster rate, rather than those that stopped working since the pandemic returning to jobs more quickly (Table A6.2 and Table A6.3).

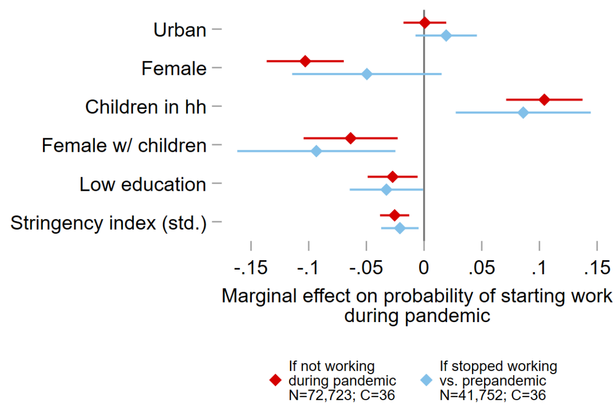
To get a cleaner picture of job losses and subsequent recovery, we employ the panel structure of the data to analyze the characteristics associated with employment loss and, separately, with employment recovery. In particular, we draw on a subsample of almost 40 countries with panel surveys to predict conditional probabilities that those who stopped working subsequently returned to work, as reported in a later HFPS wave. Figure 4a shows that those working before the pandemic were significantly more likely to stop working within each country if they were women, lower educated, and during a period of higher policy stringency. Workers in urban places were also marginally more likely to stop work. Figure 4b shows women were also less likely to gain or recover employment during the pandemic period, especially if they had children in their household. Those with lower education were also significantly less likely to recover employment after stopping work.

Figure 4. Characteristics associated with employment loss and recovery

(a) Employment loss *relative to prepandemic*



(b) Employment recovery *during the pandemic*



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: Regression results from a linear probability model with country and month fixed effects. Household sample weights are used within countries and countries are weighted equally. OxCGRT stringency index is matched to surveys at month level and standardized within countries across the period April 2020 to December 2021 so that figures show the effect of a one standard deviation increase in policy stringency. Standard errors are robust. 95% confidence intervals shown.

The estimated magnitudes of these effects are substantial. For example, less educated women with children were, on average, 14 percentage points more likely to stop working and 18 percentage points less likely to return to work, relative to more educated men with children (Table A6.4).[16] Taken together, the effects imply a widening gender and education employment gap over time, accentuated by the burden of childcare on women. We also estimate that those working in agriculture before the pandemic were 7 percentage points less likely to stop working, although there are no statistically significant differences in employment recovery during the pandemic by sector. The different types of employment transitions observed in HFPS data, and their welfare implications are discussed in more detail in Section 4.3.

More stringent containment policies are associated with higher rates of stopping work, and lower rates of employment recovery. By specifying a household panel regression model, we can probe whether the employment impacts associated with policy stringency varied across population groups. Since we control for time-invariant respondent characteristics in this model, the effects we observe are a result of variation in pandemic related impacts and containment policies over time, as captured by the stringency index, and any unobserved time varying factors with heterogeneous effects. If the latter, not captured by the stringency index, are relatively insignificant, this specification is closest to identifying the combined causal

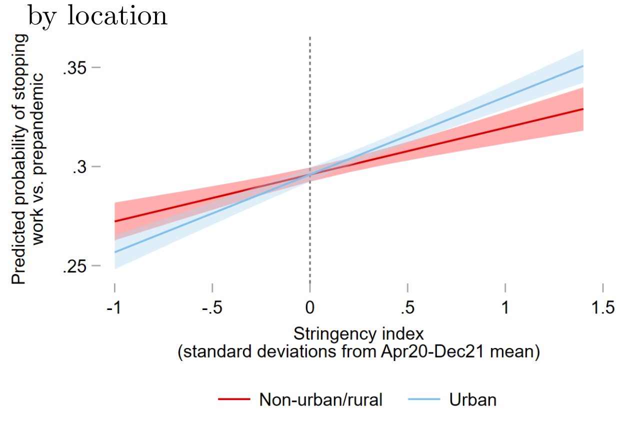
[16]Results are robust to alternate definitions of the outcomes or specifications of the model (logit, probit).

impact of the pandemic and related policies. We estimate that a policy stringency index value that is one standard deviation higher than the country mean between April 2020 and December 2021 increased the probability of stopping work by 3 percentage points, on average, and decreased the probability of subsequently recovering employment by 7 percentage points.

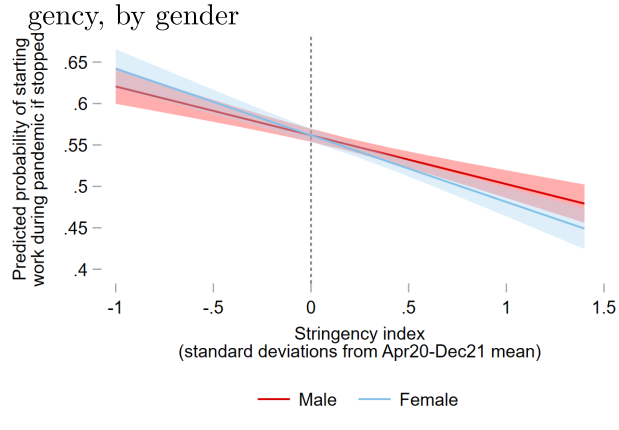
Moreover, the effect of policy stringency on employment outcomes varied by location, gender and education level. Figure 5a shows the probability of stopping work as a function of policy stringency which increased relatively more for urban dwellers. Women were both more likely to stop work as policy stringency increased, and less likely to recover employment as a function of stringency, relative to men, however the difference is only marginally significant at conventional levels (Figure 5b). We find more significant gendered effects when looking at particular containment measures included in the stringency index. For example, stay-at-home measures had stronger effects on employment loss for women relative to men, and public transport closures had a significant effect on reducing the probability of employment recovery for women, but not for men (Figure A6.2). In terms of employment loss, workers with lower education were in fact significantly less likely to stop work with increasing stringency compared to higher-educated workers.

Figure 5. Effect of policy stringency on employment loss and recovery from panel regressions

(a) Employment loss and policy stringency, by location



(b) Employment recovery and policy stringency, by gender

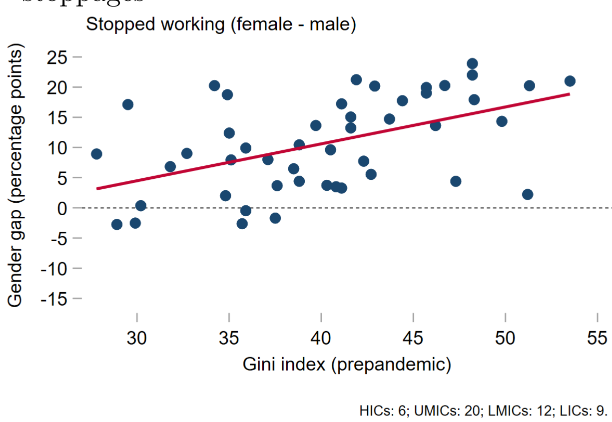


Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: The figures show predicted probabilities of employment loss and recovery as a function of policy stringency by location/gender, from a linear probability model with household fixed effects, controlling for differential effects of policy stringency by education level and gender/location. Results are reported in Table A6.5. Figure 5a includes respondents identified in at least two survey waves, whereas Figure 5b includes respondents identified in at least three survey waves, since construction of the employment recovery variable itself relies on two surveys. Household sample weights are used within countries and countries are weighted equally. Standard errors are robust. 95% confidence intervals shown.

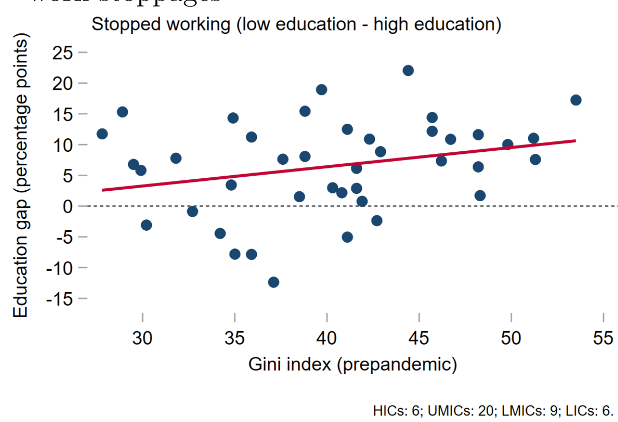
The differential initial impacts, and subsequent pace of recovery across population groups is at the core of the concerns related to the impact of the COVID-19 pandemic on global inequality (World Bank 2022b). One may also ask, at the same time, whether inequalities that were present before the onset of the pandemic can also mediate the heterogeneity of pandemic impacts. We probe this by plotting the average country-level gender gap in work stoppages from the most recent surveys in 2021 against the prepandemic Gini index of income inequality (Figure 6a) and observe a positive association between the two – that is, countries with higher levels of income inequality prior to the pandemic had relatively larger job losses among women compared to men. Figure 6b similarly plots prepandemic Gini against the gap in work stoppages among those with low education and high education, again showing a positive, albeit smaller gradient of COVID-19 impacts and prepandemic income inequality. While these correlations are only suggestive, they are nevertheless concerning, as they are consistent with negative feedback loops that may worsen future inequalities.

Figure 6. Prepandemic income inequality and gaps in employment loss

(a) Income inequality vs. gender gap in work stoppages



(b) Income inequality vs. education gap in work stoppages



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys and World Development Indicators.

4.3 Employment levels are increasing again, but are the new jobs of the same quality?

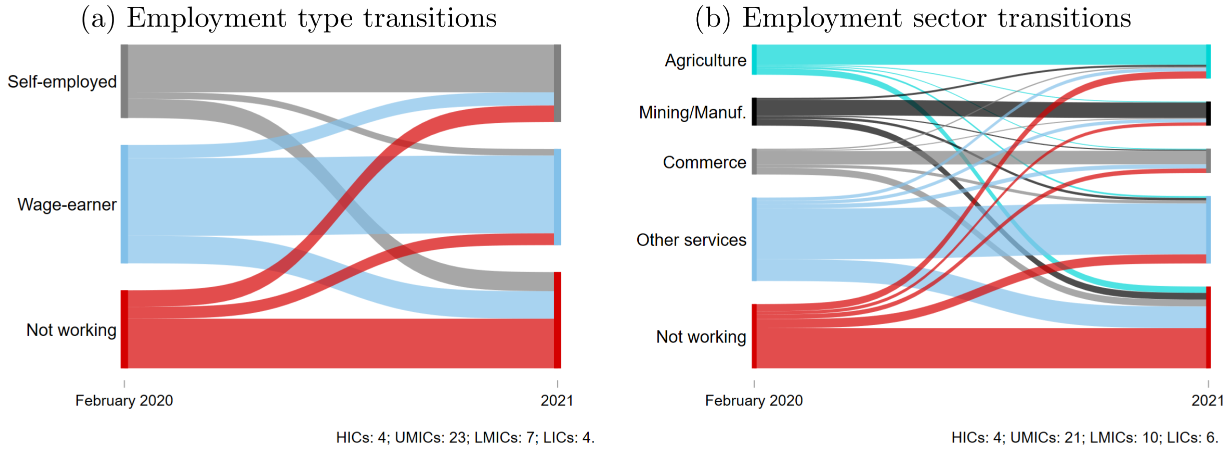
The employment gains observed throughout the second half of 2020 and in 2021, albeit incomplete and uneven across countries and population groups, are a welcome sign of the recovery. However, simply looking at employment levels may not represent the full picture. The next section documents widespread income losses, particularly in LICs, that have persisted for many households. In addition to employment changes at the intensive margin (changes in hours or remuneration) which we are not able to observe with the HFPS data, this raises a question of whether some of the people who regained employment now hold jobs that are inferior to their previous ones. This may be particularly concerning for low-income households, who cannot afford long unemployment spells, especially in the absence of support measures from the government and may need to maintain some means of livelihood to cover basic necessities (Franklin 2018).

We do not observe job quality directly in the HFPS data, so we rely on several proxies to analyze the quality of net employment changes. In particular, we examine transitions between sectors and types of employment (wage employment vs. self-employment) across different population groups before and after the onset of the pandemic. In the case of agriculture, in poorer countries the sector oftentimes acts as a shock absorber and workers unable to find work elsewhere may resort to jobs in the agriculture sector. As the economic fallout caused by the pandemic lingers over a longer period, households may rely on agricultural employment as a coping strategy. Since we observe the prepandemic sector of employment for each respondent, the analysis here relies on the plausible assumption that the movement from non-agricultural employment immediately preceding the COVID-19 pandemic to agricultural employment after the onset of the pandemic is a push factor related to the need to mitigate income losses, rather than a pull factor associated with better remunerated employment in agriculture. Similarly, self-employment which is oftentimes in the informal sector can serve as a buffer against the labor market shock, particularly among households who do not have access to formal or informal safety nets that would allow them to wait it out for a better job. As such, it could be argued that transitions from prepandemic wage employment to pandemic self-employment are primarily push factor transitions into immediate, but more precarious and lower-quality employment vis-à-vis the jobs held previously.

HFPS data record a significant share of workers changing jobs during the COVID-19 pandemic. In the early phase of the pandemic, a period also characterized by substantial work stoppages, an additional 9 percent of workers reported working in jobs different from their prepandemic employment. Over time, this figure rose to more than 20 percent of workers in the second half of 2020, before slowing in 2021, at which point around one in four workers reported having a different job than before the pandemic (Table A6.6). The incidence of job switches is particularly high in LICs, primarily on account of SSA countries, with 40 percent of workers reporting having changed jobs by 2021 since before the pandemic.

We construct transition matrices that trace changes in individuals' sector of activity or employment type. Because of limitations in the HFPS data, job changes within the same sector or within the same employment type are not captured. For example, the transition matrices would not capture workers who had a job in the services sector in February 2020 and switched jobs to a different services sector in 2021, but they would record a movement from services to agriculture, or from wage employment to self-employment. As such, job change estimates in the transition matrices are lower bound estimates of the total incidence of job changes that occurred during this period. Figure 7a and Figure 7b visualize transitions by employment type and sector between February 2020 (based on recall) and the most recent surveys in 2021.

Figure 7. Employment transitions, February 2020–2021



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: The width of categories is weighted by prepandemic employment share. Countries are weighted equally. "Other" employment type, accounting for 1 percent of prepandemic employment, is excluded.

There are several notable takeaways from these transition matrices. First, the pandemic led to an increase in lower-quality jobs in self-employment. Around 11 percent of prepandemic wage earners transitioned to self-employment, while 9 percent of the prepandemic self-employed report being wage employees in 2021 (Table A6.7). Considering a much higher share of the working-age population were wage employees before the pandemic in our sample, relative to self-employed, this indicates a stronger shift of the working-age population into self-employment (Figure 7a). In absolute terms, workers were twice as likely to transition from wage employment to self-employment. The transition was also more prevalent in lower-income countries, with upwards of 10 percent of workers entering self-employment, and relatively more common among women and those with lower education (Table A6.8).

Second, the prepandemic self-employed are slightly less likely to be working in 2021 compared to prepandemic wage employees (Table A6.7). This is consistent with greater employment impacts and slower employment gains in sectors such as commerce and other services where self-employment is more prevalent.

Third, existing workers in agriculture were most likely to stay employed while the sector pulled in almost an additional 6 percent of the working age-population by 2021, on average, relative to before the pandemic (Figure 7b, Table A6.9). The highest incidence of these transitions occurred in LMICs and LICs (Table A6.10), where the importance of agriculture is typically higher. Across sectors, the share of prepandemic agricultural workers who were not working in 2021 was notably smaller in comparison with those who were employed in the commerce or other services sectors in February 2020 (Table A6.9), congruent with earlier evidence that rural areas and agricultural livelihoods were relatively less affected by pandemic-related restrictions and the impact of the crisis on the economy in comparison to the urban services sector. Among those who were employed before the pandemic, transitions from mining/manufacturing and commerce into other services sectors were relatively more prevalent than transitions from these two sectors into agriculture, which might reflect both the location and transferable skills of workers most affected.

Finally, the pace of employment gains appears to be particularly slow among those with low levels of education. Disaggregating the transition matrices by level of education shows that the largest difference along the socio-economic gradient is found in the transitions out of the labor market – among those with low education, 29 percent of prepandemic wage workers and self-employed had left the labor force by 2021, compared to 19-21 percent of higher educated workers with the same type of employment (Table A6.11). While the rates of transition from self-employment to wage work were similar by education level, low-educated wage workers were 3 percentage points more likely to transition to self-employment compared to their higher educated peers. In all sectors, those with lower education were more likely to transition to agriculture between February 2020 and 2021 (Table A6.12). In addition, low-educated workers in services sectors were especially more likely to exit the labor market, and those without work before the pandemic were less likely to start jobs (Figure A6.3).

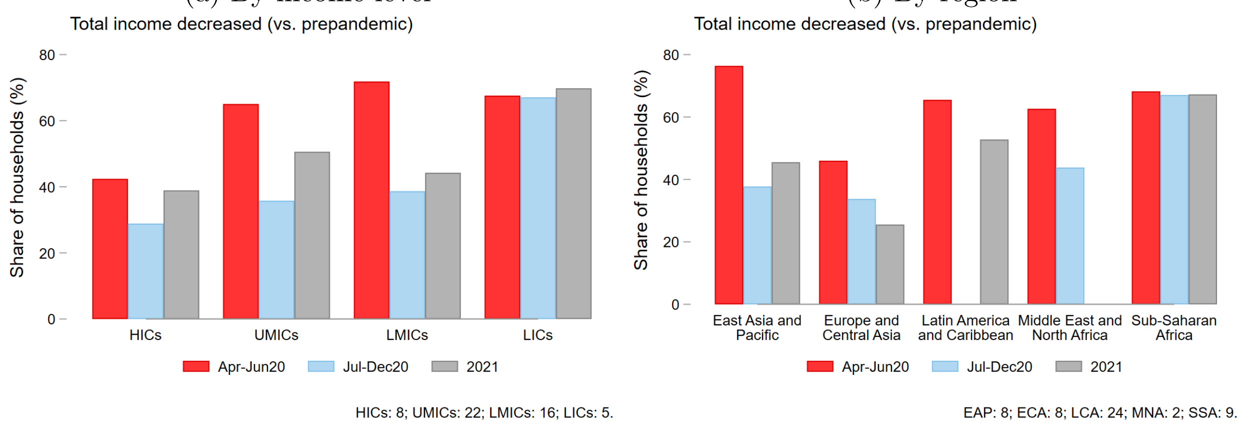
5 Beyond the labor market: Extensive income losses and weak safety nets led to heightened food insecurity and negative coping strategies

Outright job losses are but one of the ways in which household welfare was affected. Many workers ended up working fewer hours – and receiving smaller pay – even if they managed to hold on to their jobs throughout the COVID-19 pandemic. In poorer countries where formal wage employment is less common, informal workers may have continued to work while earning less. As such, many households could have experienced income losses on account of COVID-19 even without any household members losing their jobs. Relatedly, it has been documented that poor households are more exposed to underemployment risks. Therefore, vulnerable workers may have worse labor market outcomes not only in the extensive margin of employment, documented as job loss above, but also in the intensive margin by working fewer hours and thus experiencing a loss of income.

Income losses were considerable in the first few months of the pandemic but fell over time in most countries except for LICs. Figure 8 shows the evolution of income losses across country income groups and regions during the pandemic.[17] Total income decreased for about two-thirds of households in the second quarter of 2020 across most country groups, though rates were much smaller in ECA. The height of lockdowns early in the pandemic is associated with the highest incidence of income loss in most countries compared to later surveys. In the second half of 2020, as mobility restrictions started to be relaxed and supporting safety net programs reached more households, the share of households reporting a decrease in incomes vis-à-vis prepandemic fell considerably to around 40 percent in MICs but did not decrease in LICs (Table A6.13). It should be noted that the sample of LICs is rather small, and the overall lower number of countries with data on income losses makes it difficult to construct a country panel.

Figure 8. Share of households reporting income loss since the pandemic

(a) By income level (b) By region



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

The persistently high share of households reporting lower farm, nonfarm, and wage incomes mirrors the lack of recovery in overall incomes. Incomes were lost in both farm and nonfarm sectors (Table A6.14, Table A6.15 and Table A6.16). Among households that were receiving remittances before the pandemic, half reported losing at least part of that income source during the pandemic (Table A6.17). Over a quarter of wage workers in LICs and MICs reported losing some of their earnings in the early stages of the pandemic (Table A6.18). The same shares were significantly lower in HICs, many of which implemented wage subsidy schemes to support wage workers during the pandemic.

Lower earnings among wage workers may reflect an adjustment along the intensive margins, i.e., reduced work hours. For example, ILO (2021) estimates 8.8 percent of global

[17] Changes in income are reported using the full sample, as there are insufficient observations in the country panel.

working hours were lost in 2020 compared with the fourth quarter of 2019, a loss equivalent to 255 million full-time jobs. About half of the losses are estimated to have come from working hour reductions within employment. In fact, many more households reported losing incomes than households with a respondent stopping work, especially in lower income countries. This is consistent with the nature of the labor market in these countries where many workers are self-employed or hold otherwise informal jobs. Within countries, income losses were strongly correlated with work stoppages, job changes to self-employment, and sectoral transitions to agriculture (Figure A6.4).

During 2021, the share of households reporting that total incomes are below prepandemic levels remains very high – almost half of the households globally, and 70 percent of households in LICs are in this category. This may also be because the mitigating measures put forth by governments were largely limited in scope and duration (World Bank 2022b). While we do not have sufficient data to disaggregate trends by region and time window, it appears that apart from the ECA region, a relatively high share of households has still not recovered their lost incomes. The setback in 2021 could have been due to the emergence of new variants and re-imposition of partial lockdowns in several countries.

Evidence of "long COVID" effects on particular groups can be further seen by comparing characteristics associated with income loss and recovery using multivariate regressions. Similar to analysis of employment recovery, we draw on panel surveys in about 20 countries that collected information on income changes between survey waves during the pandemic, as well as recording initial income losses relative to before the pandemic. We can then identify which households reporting income loss relative to prepandemic were more likely to recover at least some income, as observed in a subsequent HFPS wave. Figure 9a shows that households were significantly more likely to lose income in each country if they were larger in size, less educated, the respondent stopped working, and during a period of higher policy stringency.[18] Figure 9b shows that some of the same households were less likely to gain income during the pandemic. Those who returned to work (or did not stop working) were more likely to recover income, implying that the same groups less likely to recover work (Figure 4b) were also less likely to recover income. Moreover, results are consistent with changes in income occurring at the intensive margin of employment, especially for households where respondents have lower education levels. Households with less access to education were significantly less likely to gain or recover income during the pandemic, whereas urban households were better off than rural households in terms of income recovery. Controlling for household characteristics, policy stringency remains a significant determinant of initial income losses and was

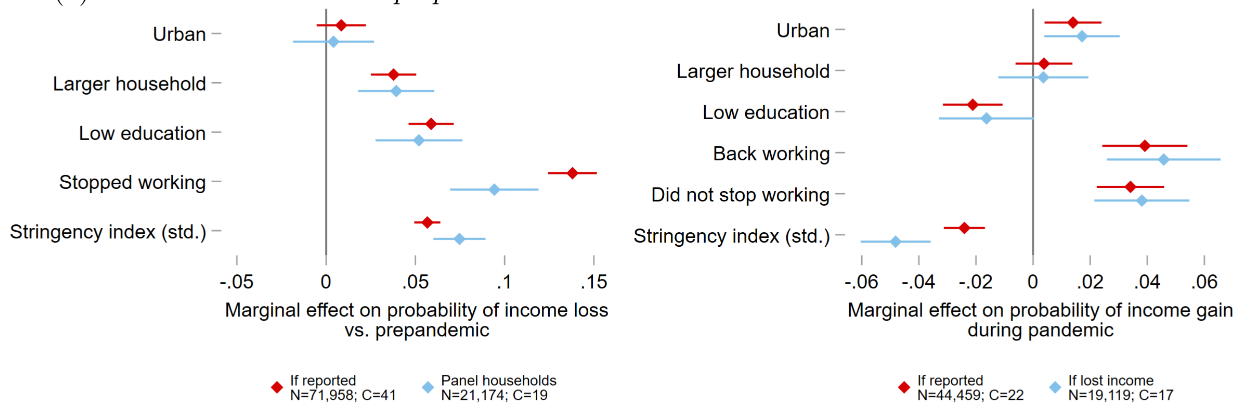
[18] Regression results are reported in Table A6.19. Results are robust to alternate definitions of the outcomes or specifications of the model (logit, probit).

associated with lower rates of recovery. Estimates for policy stringency are similar when controlling for all time-invariant characteristics in a household panel model.[19]

Figure 9. Characteristics associated with income loss and recovery

(a) Income loss *relative to prepandemic*

(b) Income gain or recovery *during the pandemic*



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: Regression results from a linear probability model with country fixed effects. Household sample weights are used within countries and countries are weighted equally. Larger household = above country median household size. OxCGRT stringency index is matched to surveys at month level and standardized within countries across the period April 2020 to August 2021 so that figures show the effect of a one standard deviation increase in policy stringency. Standard errors are robust. 95% confidence intervals shown.

Despite significant and widespread jobs losses, the fiscal response to support households was largely insufficient in most LICs and LMICs, given widespread income losses.[20] Available spending data on social protection and labor programs confirm large disparities in the amount of support provided to households, with average spending being significantly higher in HICs and MICs than in LICs.

HFPS data shows that public assistance appears to have fallen short or received with a delay, particularly in the poorest countries.[21] On average, the share of households that reported having received assistance from the government since the beginning of the pandemic

[19]We do not find significant heterogeneity in terms of the effect of policy stringency on income loss and recovery by location, household size or education in the panel household model. However, the panel household sample is much more limited for income outcomes compared to employment outcomes, including only 7 countries for income gain during the pandemic. Results are reported in Table A6.20.

[20]Sudden and widespread losses of livelihoods at the beginning of the pandemic led to a fiscal response of unprecedented scale around the world. According to the IMF COVID-19 fiscal policies database, countries have collectively spent over $13 trillion on mitigation measures since the beginning of the pandemic (IMF 2021). Nearly 4,000 social protection and labor measures were planned or implemented in 223 economies as of January 2022 (Gentilini et al. 2022). However, the magnitude and composition of the fiscal package varied across countries, with HICs on average spending significantly more, particularly on support toward households and firms (IMF 2021; Benmelech and Tzur-Ilan 2020; World Bank 2022b).

[21]Phone survey data are an imperfect source for assessing social assistance coverage during the pandemic. This is because the survey collected only a binary variable indicating whether assistance was received, and often times no distinction was made between assistance from pre-existing programs or new COVID-19-related initiatives. The wording of the questions was such that it usually included cash and in-kind

rose from 6 percent in LICs and 28 percent in UMICs during April-June 2020 to 19 percent and 52 percent respectively in 2021 (Table A6.21). While the number of beneficiaries increased over time, coverage likely fell short of the many households in need during the pandemic.

The difference in social assistance receipt tends to be relatively small across population groups (Table A6.21). Rural households were slightly more likely to benefit from assistance measures, though the difference with urban households remained small even later in the pandemic. Households where respondents had higher education were also less likely to receive assistance. Households with children were more likely to receive government assistance than households without any children, initially and also later in the pandemic as discussed in more detail in World Bank and UNICEF (2022).[22]

The inadequacy of safety nets to protect households and the extent of unmitigated losses from the pandemic shock are also seen from the sizable share of households that faced food insecurity during the pandemic.[23] In the HFPS, food security is commonly measured using a binary variable that indicates whether adults in the household went a day without food in the last 30 days.[24] Initially, LICs had a significantly higher share of households that reported food insecurity, compared with countries in higher income groups (Table A6.22). The situation improved somewhat over the next year, but food insecurity remained elevated in LICs and LMICs in 2021. Nationwide school closures that led to the suspension of school feeding programs may have further exacerbated households' lack of food access in some countries (Abay, Amare, et al. 2021). Bivariate regressions of food insecurity on a range of respondent characteristics show that within countries, respondents that were female and less educated

transfers, but was less likely to include support received in the form of subsidies or tax/payment exemptions. The timing of the survey is also not ideal for capturing the timing of support. Nevertheless, these phone surveys are a rare source of cross-country information on the extent to which some form of fiscal support reached households at different times over the pandemic.

[22] The challenges with targeting are in part due to existing constraints of the social protection system in poorer countries, in particular high levels of informality and the lack of a social registry which could be used to quickly reach those in need. In fact, cash transfers, the main form of income support provided during the pandemic, were directed at informal workers in 79 percent of programs. In contrast, wage subsidies which mainly benefit formal workers were the most common labor market policy directed at individuals in HICs (Kamran et al. 2023). Many governments relied on inefficient subsidies instead of targeted transfers to respond to the crisis (World Bank 2022b).

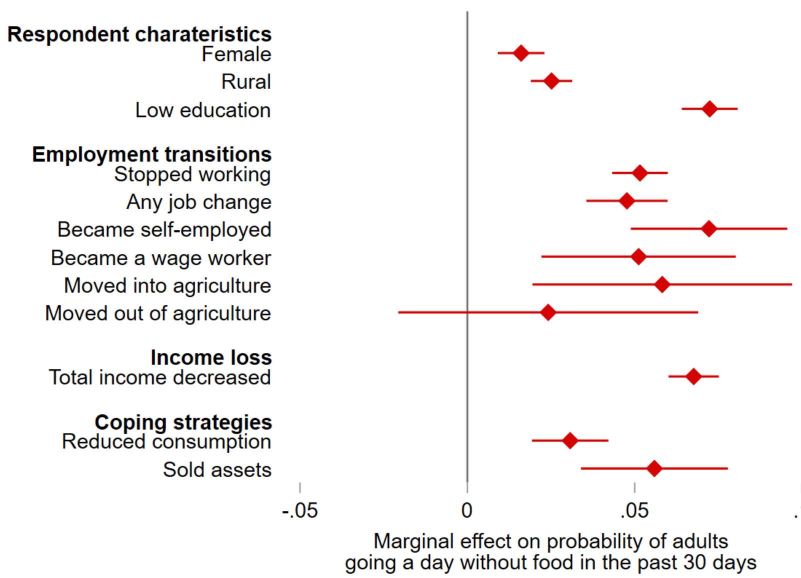
[23] In some countries, there is evidence that well-established cash transfer programs helped mitigate the impact. In Ethiopia, Abay, Berhane, et al. (2023) show that worsening food insecurity was offset for households participating in the country's flagship social safety net program. Aggarwal et al. (2022) presents similar findings in Liberia and Malawi in that receipt of cash transfers improved food security of rural households.

[24] This indicator is part of a set of self-reported questions that make up the Food Insecurity Experience Scale (FIES) and is associated with increased difficulties in accessing food due to resource constraints. The indicator was available for a total of 60 countries, including 4 HICs, 16 UMICs, 23 LMICs and 17 LICs.

were more likely to report food insecurity, as well as those living in rural households (Figure 10). Global averages may be masking important heterogeneities, however. For example, Rudin-Rush et al. (2022) find that food insecurity increased faster in rural areas in Burkina Faso, Ethiopia, Malawi and Nigeria, but Adjognon et al. (2021) find that urban households were more affected in Mali, leading the urban-rural food insecurity gap to disappear during the pandemic.

Unlike changes in labor market outcomes, it is difficult to attribute changes in food insecurity to the COVID-19 crisis, especially in poorer countries where it might have been prevalent even prior to the pandemic. One way to examine the impact of the crisis is to consider whether food insecurity is correlated with other pandemic-induced outcomes. These results are presented in Figure 10. Food insecurity is positively correlated with outcomes that can be plausibly attributed to the pandemic, such as job changes, income losses, or the use of adverse coping strategies including asset sales since the pandemic started.[25]

Figure 10. Within country correlates of food insecurity from bivariate regressions



Source: The sample includes all HFPS waves with response rates of at least 50 percent for the two variables included in the bivariate regression. Regressions control for country fixed effects. Sampling weights are used to weight observations within countries. Countries are weighted equally. Sample sizes range from 37,919 respondents in 25 countries (employment type transitions) to 296,962 respondents in 58 countries (urban/rural). Standard errors are robust. 95% confidence intervals are shown.

[25] That the pandemic-induced shortages of key food staples or loss of purchasing power, whether due to income losses or price effects, contributed to greater food insecurity has also been established in a few country-level studies. Although the impact on prices may not have been uniform across countries (Tabe-Ojong et al 2022), a few studies with information on food security prevalence before and after the pandemic confirm that households experienced greater insecurity after the pandemic (see for example, Adjognon et al. (2021) and Kansiime et al. (2021)). Amare et al. (2021) find higher levels of food insecurity in areas that were more affected by pandemic-related disruptions.

To counter the welfare shock from the COVID-19 crisis, some households resorted to adverse coping strategies. These are captured in the HFPS using questions about whether the household used emergency savings to cover necessities, reduced the consumption of goods, or sold assets such as property. A large share of households adopted some type of negative coping strategy, including in HICs (Table A6.23, Table A6.24 and Table A6.25). In particular, the sale of assets was more pronounced among households with lower access to education and those in rural areas. While the share of households resorting to adverse measures fell over time in most instances, even the temporary adoption of such negative coping mechanisms can have longer term implications as they could represent damages to human capital (for example, if reduced consumption leads to suboptimal nutrition levels) and reductions in productive capital (in the case of selling assets) that can impact future poverty and inequality if left unmitigated.

6 Concluding remarks

This paper analyzed the welfare impacts of the COVID-19 pandemic using the latest available harmonized global database of the World Bank's high-frequency phone surveys from 80 countries—the largest known source of data on households during the pandemic. Focusing on the scarring effects of the pandemic, we show that, while there have been some improvements in employment, the labor market impacts continue to be felt over two years into the pandemic. The dynamics of labor market outcomes suggest that the initial disparities that were observed early in the COVID-19 pandemic narrowed rather slowly over time and sometimes not at all, while women and the less educated continued to report a higher incidence of work stoppages than men and better educated groups.

Another contribution of this paper is on the findings related to broader labor market impacts, beyond adjustments at the extensive margin. Analysis of job transitions throughout the pandemic show significant churning in the labor market, including significant shifts from wage employment to self-employment and from non-agriculture sectors to agriculture, likely reflecting a rise in informal and more precarious employment accompanied by lower earnings. Lower socio-economic groups, as proxied by the respondent's level of education, were more likely to transition into these lower-quality jobs, while also being less likely to recover lost employment. This is consistent with income losses being more prevalent among households with less educated respondents, higher dependency ratios and greater incidence of labor market disruptions. Beyond labor market impacts, and likely reflecting that safety nets were insufficient to mitigate the full extent of the pandemic-induced shock, we observe heightened food insecurity and a high share of households resorting to negative coping strategies, especially in the form of reduced consumption and drawdown of savings, with only slow improvements through the second year of the pandemic.

In addition to the short-term impacts analyzed in this paper, one of the key pathways of longer-term welfare impacts will be through the learning inequalities that have been accentuated by school closures. It is estimated that globally, about 1.6 billion students in over 190 countries were affected over the pandemic (Munoz-Najar et al. 2022). While a detailed investigation of learning losses throughout the pandemic is beyond the scope of this paper, the HFPS data also show that in LICs, children stopped learning in more than half of households where children had been enrolled prior to the pandemic, in contrast to much lower figures for UMICs where governments and households had more resources available to support distance learning or facilitate in-person learning with containment measures (Table A6.26). Over 20 percent of students in LICs and LMICs had not returned to school in 2021. Moreover, children were less likely to access education if household adults had lower levels of education (Figure A6.6). Evidence from COVID-19 indicates these same households are more vulnerable to economic crises, consistent with negative feedback loops that may worsen future inequalities. The loss in human capital could be detrimental for future poverty among the poorest. Azevedo et al. (2022) estimate that the share of children with more years of education than their parents – a measure of absolute inter-generational mobility – could decline by 8 percentage points or more in UMICs, with the largest declines in the Latin America region.

In conclusion, unrecovered and unmitigated welfare losses from the COVID-19 crisis could worsen inequality in the longer term, an economic version of "long COVID". Jobs and income losses went largely unmitigated, as reflected in the strong correlation between income losses and food insecurity. The adoption of negative coping strategies during the pandemic, including the use of savings and sale of assets, could hurt households' productive capacity and ability to recover from the crisis. Combined with the impact of the unequal learning losses, which by some estimate could result in a total of $17 trillion of lost lifetime earnings, equivalent to 14 percent of today's global annual GDP, the full impact of the crisis may only be seen over the long term.

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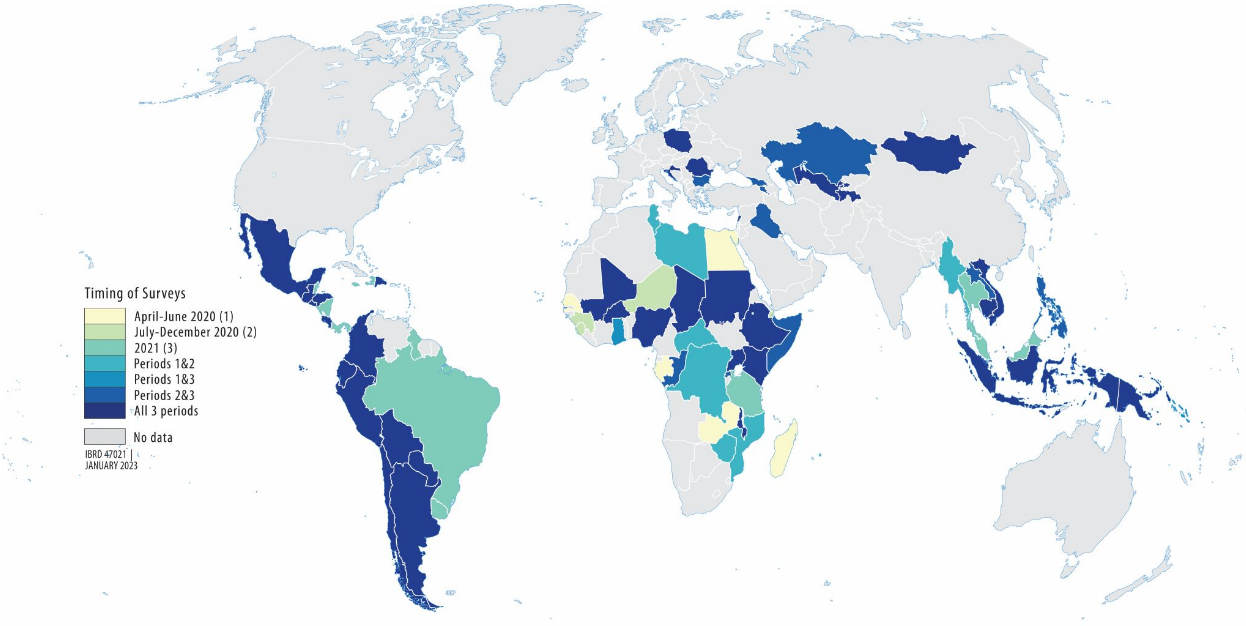
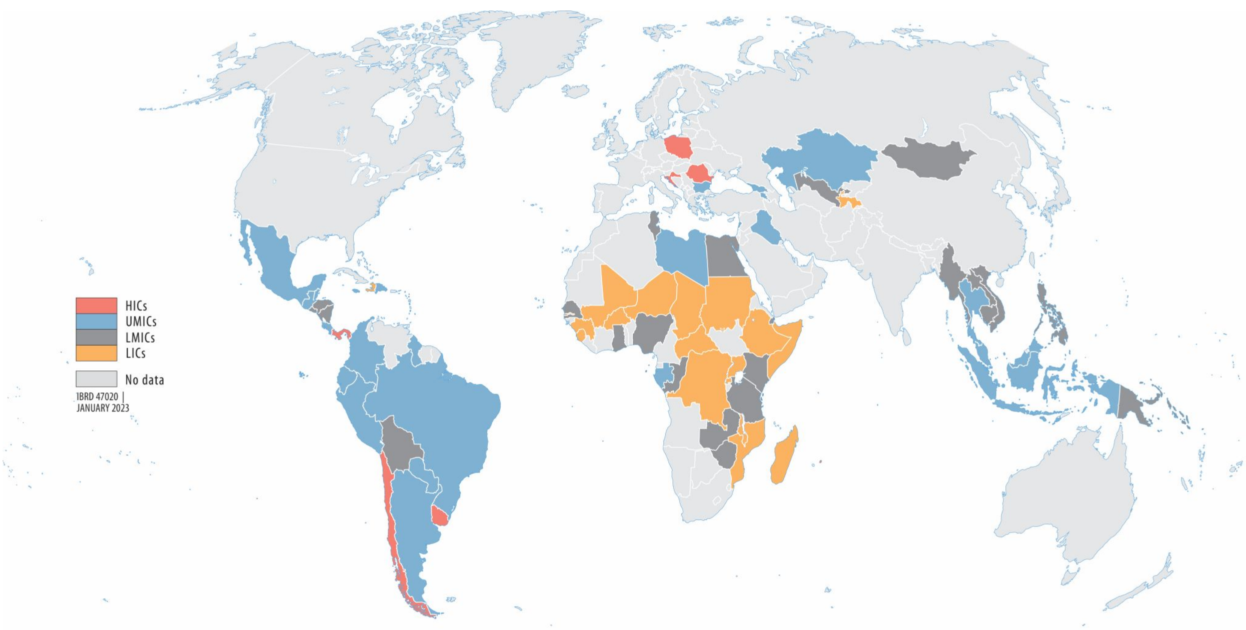
Annex 1 Country coverage, survey timing and policy stringency

Figure A1.1. Countries with HFPS waves by time period in the analysis



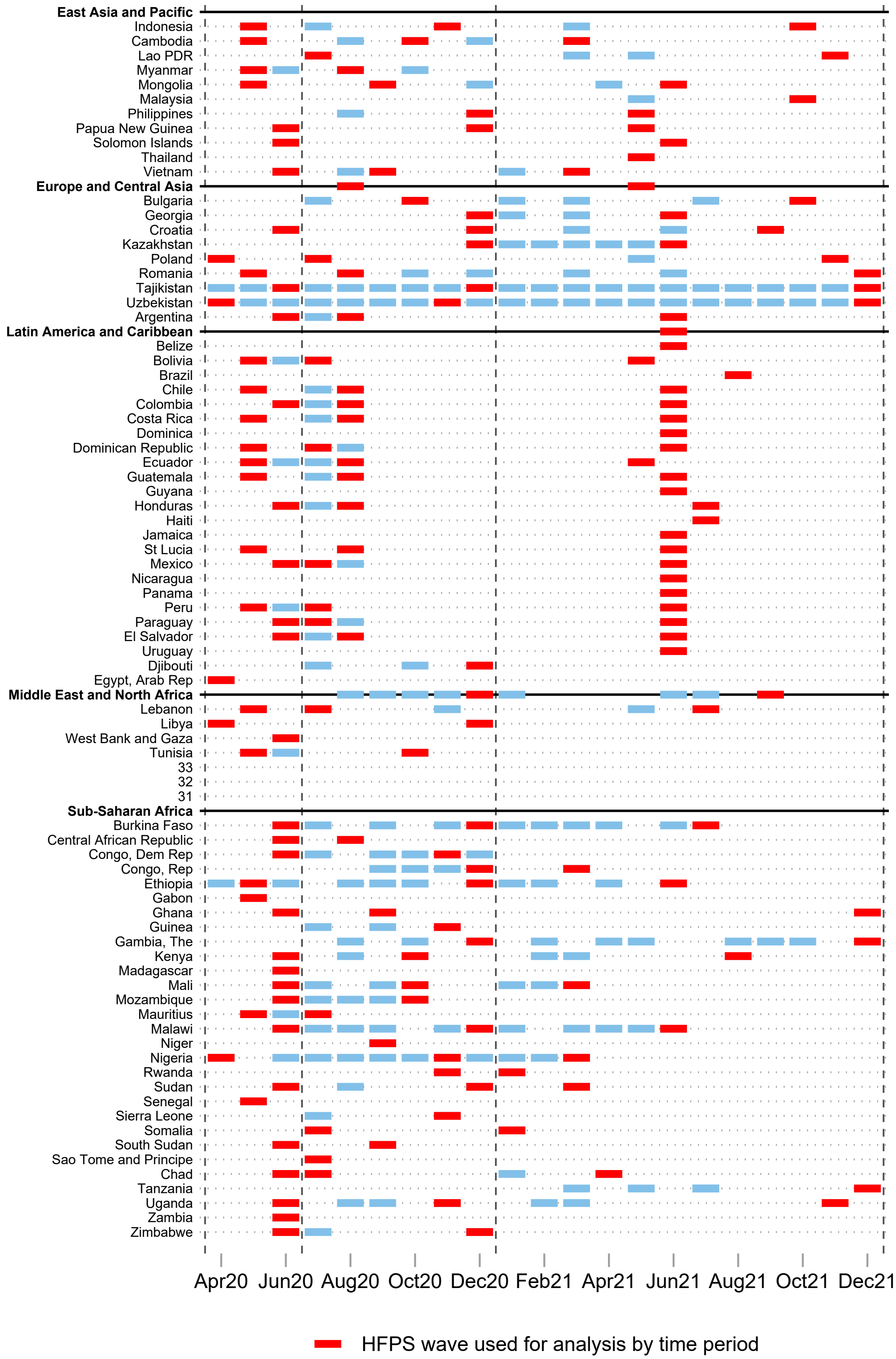
Source: COVID-19 High-Frequency Phone Surveys.

Figure A1.2. Countries with HFPS waves by income level



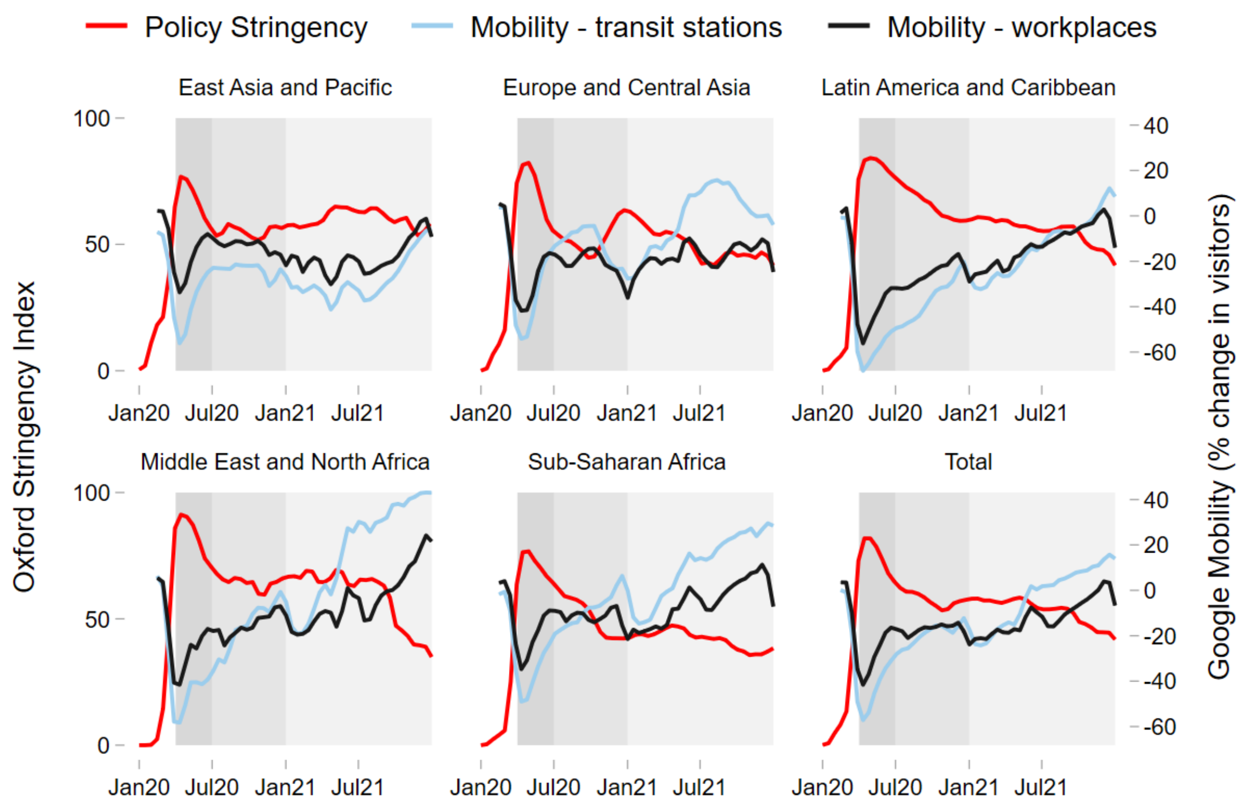
Source: COVID-19 High-Frequency Phone Surveys.

Figure A1.3. Timing of HFPS waves by country, sorted by region



Source: COVID-19 High-Frequency Phone Surveys.
Notes: Surveys were attributed to the mean month of data collection.

Figure A1.4. Policy stringency and mobility trends over time in countries included in analysis, by region



Source: Google COVID-19 Community Mobility Reports and Oxford COVID-19 Government Response Tracker.

Annex 2 Harmonized welfare indicators

Table A2.1: Harmonized welfare indicators

Topic	Indicator	Description	Countries	N
Employment	Currently working	Indicates the respondent was working at the time of the survey. The sample is the working age population.	77	471,967
	Stopped working/ started working	Stopped working indicates the respondent was working before the pandemic (based on recall) and was not working at the time of the survey. Started working indicates the respondent was not working before the pandemic (based on recall) and was working at the time of the survey. The sample is the working age population.	75	443,902
	Changed job	Indicates the respondent directly reported that they had changed jobs since the pandemic if this question was asked, or they were working in a different sector/ type of employment before the pandemic (based on recall) compared to at the time of the survey and provided sector/employment type information for both. The sample is the working age population that was working before the pandemic and at the time of the survey.	69	184,324
	Changed sector	Indicates the respondent was working in a different sector before the pandemic (based on recall) compared to at the time of the survey and provided information for both. The sample is the working age population that was working before the pandemic and at the time of the survey.	54	115,828
	Changed employment type	Indicates the respondent had a different employment type before the pandemic (based on recall) compared to at the time of the survey and provided information for both. The sample is the working age population that was working before the pandemic and at the time of the survey.	43	96,152
	Started work during pandemic	Indicates the respondent was working at the time of the survey for the sample of working age respondents that were not working in a previous pandemic era survey and were recontacted in a subsequent survey wave. Unlike the back to work indication, this variable does not rely on a prepandemic recall question (used for stopped working) and has greater country coverage.	52	136,478
	Back to work during pandemic	Indicates the respondent was working at the time of the survey for the sample of working age respondents that stopped working (see above) in a previous pandemic era survey relative to prepandemic survey and were recontacted in a subsequent survey wave.	52	78,019
Income	Total income decreased	Indicates the household's total income has decreased relative to the prepandemic reference period. The sample is all households, however questions on specific income sources were asked in more countries.	54	186,073
	Farm income decreased	Indicates the household's farm income has decreased relative to the prepandemic reference period. The sample is all households with this income source.	55	40,357
	Non-farm income decreased	Indicates the household's non-farm income has decreased relative to the prepandemic reference period. The sample is all households with this income source.	59	67,685
	Wage income decreased	Indicates the household's wage income has decreased relative to the prepandemic reference period. The sample is all households with this income source.	54	76,680

Continued on next page

Table A2.1: Harmonized welfare indicators (Continued)

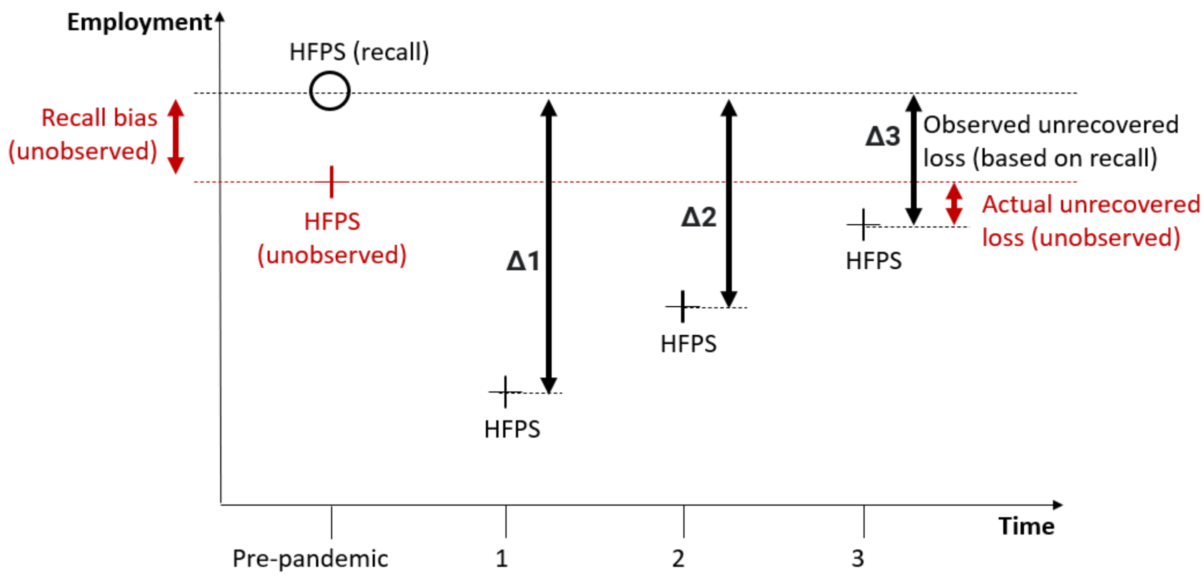
Topic	Indicator	Description	Countries	N
Income	Remittances decreased	Indicates the household's income from remittances has decreased relative to the prepandemic reference period. The sample is all households with this income source.	52	38,285
	Wage workers received no or partial payment	Indicates the respondent received no or partial payment in the last week and is a wage worker. The sample is respondents who were working and confirm their employment type as a wage worker.	47	36,421
	Total income increased during pandemic	Indicates the household's total income increased relative to the previous pandemic era survey. The sample is all panel households where the question was asked relative to the previous pandemic era survey wave.	29	102,091
	Total income recovered during pandemic	Indicates the household's total income increased relative to the previous pandemic era survey for the sample of households that reported income loss (Total income decreased) relative to prepandemic in a previous pandemic era survey and were recontacted in a subsequent survey wave.	23	56,360
Food security	Adults went day without eating	Indicates adults in the household went a full day without eating in the last 30 days. The sample is all households.	61	309,457
Assistance and coping strategies	Received public assistance	Indicates the household received any form of public assistance since the start of the pandemic. The sample is all households.	70	359,736
	Reduced consumption	Indicates the household reduced consumption of goods during the pandemic. These goods could include essential and non-essential items. The sample is all households.	49	229,090
	Used savings	Indicates the household used money saved for emergencies to cover basic living expenses. The sample is all households.	52	285,059
	Sold assets	Indicates the household sold assets such as property during the pandemic to pay for basic living expenses. The sample is all households.	51	283,790
Child education	Children stopped learning / continued learning	Stopped learning indicates school age children in the household were learning before school closures and stopped learning after school closures. This includes any type of learning such as completing assignments provided by the teacher, using mobile learning apps, watching educational TV programs, listening to educational programs on radio or meeting with a tutor. Continued learning is the inverse of stopped learning. The sample is all households with previously enrolled school age children.	69	161,710

Source: COVID-19 High-Frequency Phone Surveys.

Notes: The number of observations includes all survey rounds; questionnaires varied across survey rounds and countries.

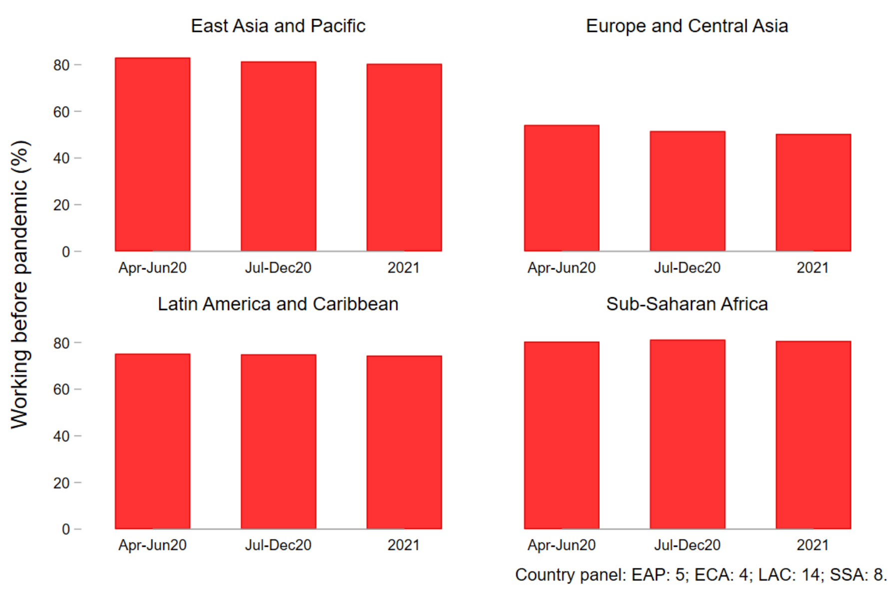
Annex 3 Assessing recall bias in HFPS employment measures

Figure A3.1. Illustration of recall bias and employment dynamics over time



Source: Authors' illustration.

Figure A3.2. HFPS estimates of prepandemic employment across time periods for a country panel, by region



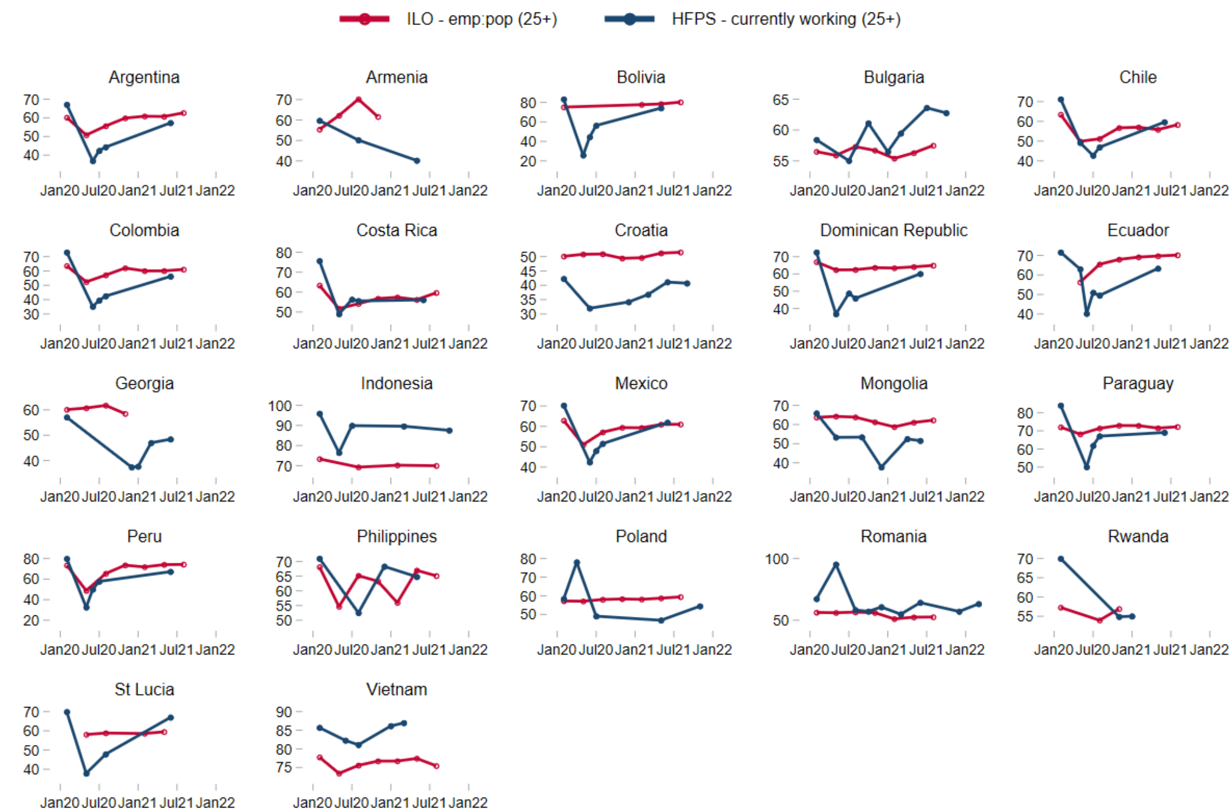
Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Annex 4 Comparison of employment measures in HFPS and Labor Force Surveys

A preliminary analysis of labor market outcomes using HFPS and LFS shows that in terms of shares of adults employed, the largest differences are found in the baseline (pre-COVID-19) estimates which are higher in the HFPS in the majority of countries and similarly in the larger jobs losses found in the HFPS. There are several possible reasons for these differences. First, the HPFS question of whether a respondent worked before the COVID-19 pandemic, used to establish the prepandemic baseline, could be capturing broader recall of past employment which may or may not be coded as employment in a considerably more detailed LFS dataset. Second, some of the respondents reporting not working in the HFPS after the onset of COVID-19 could still be classified as employed in the LFS as they are temporarily absent from work but believe that they still have a job to go back to in the future. For instance, in 2020, Eurostat was recording those who were absent from work for up to 3 months for technical or economic reasons as employed, before the regulations were updated at the beginning of 2021 to reclassify these individuals as inactive. OECD reports that in Q2 of 2020 a large share of the total reduction in hours worked was on account of zero hours employment (OECD, 2021). In the case of Italy, this revision of definitions increases the measured job losses between February and December 2020 by 80 percent. Despite these differences, we find that trends in employment are qualitatively similar in most countries with both sources of data (Figure A4.1 and Figure A4.2). This is particularly evident when considering aggregates as is the case in this paper, including by population groups (Figure A4.3). Employment gaps by location, gender, and employment type display similar dynamics during the pandemic across the two sources of data, even though they are not strictly comparable and each subject to measurement error.

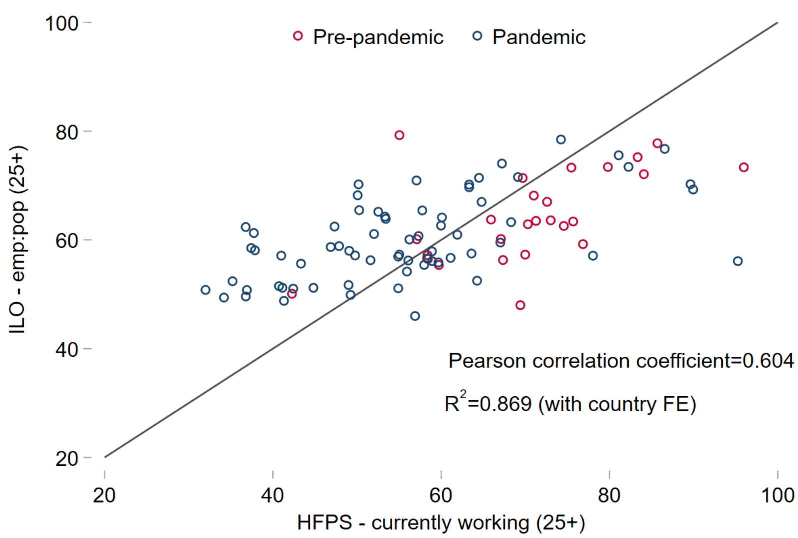
These differences in methodology are important, but the primary goal of this paper is not to compare across HFPS and LFS data points, but rather to compare, within the HFPS data, the patterns of job losses and recovery across different population groups, with everyone's prepandemic and subsequent employment throughout 2020-2021 captured by the same survey instrument. Furthermore, the number of countries with LFS estimates of employment in low-income countries remains very small, and as such HFPS data continue to be one of the few available sources of data with global coverage throughout the COVID-19 pandemic.

Figure A4.1. Comparisons of ILO vs HFPS currently working, by country



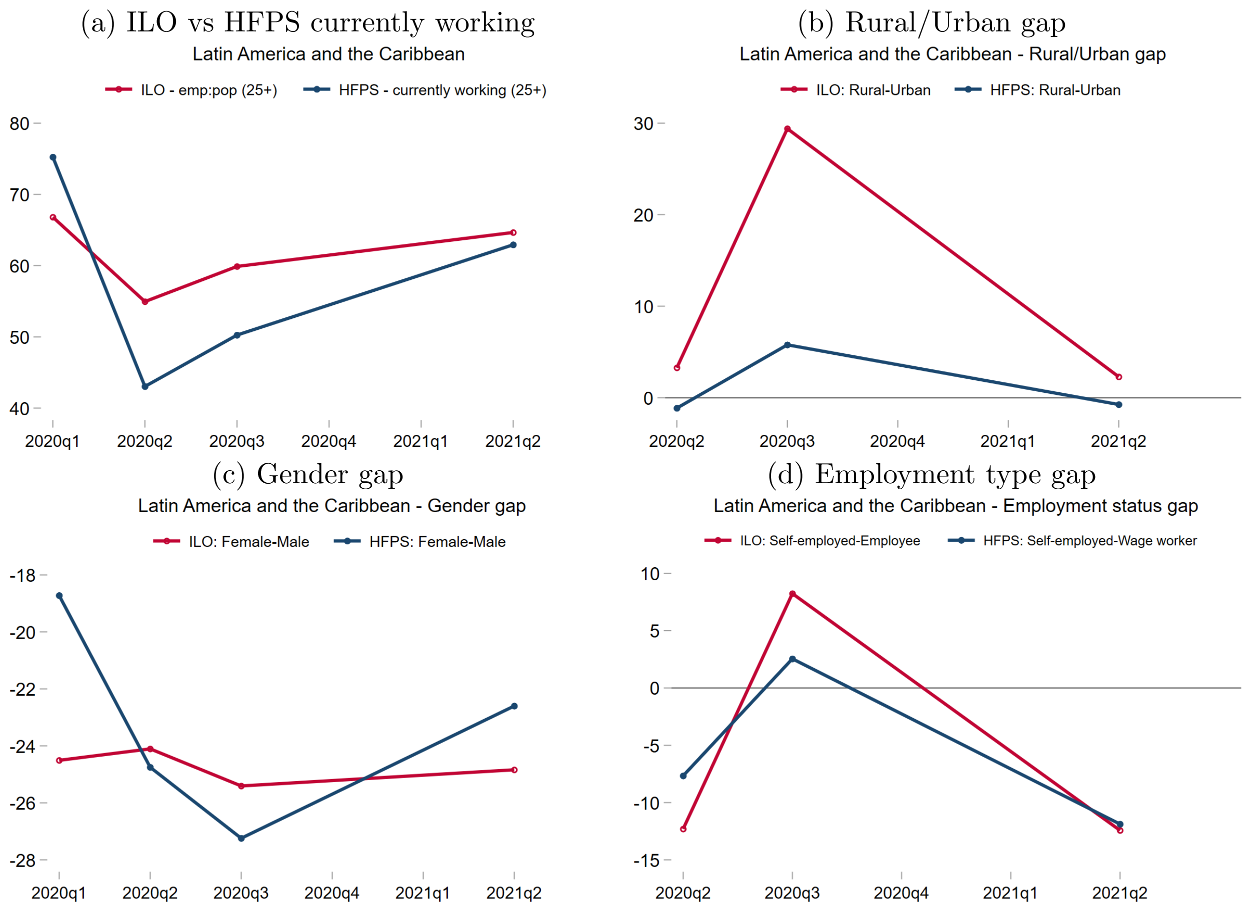
Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys and ILOSTAT.

Figure A4.2. Correlation between ILO and HFPS currently working



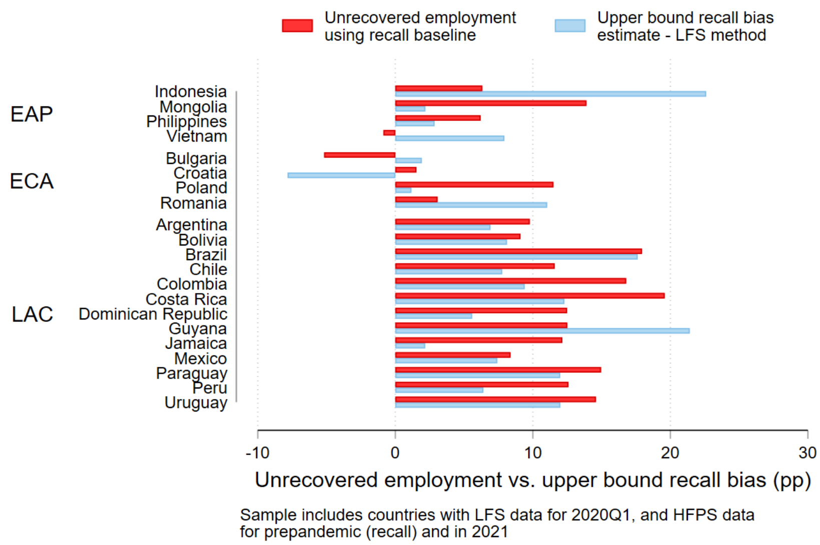
Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys and ILOSTAT.
Notes: The sample includes 94 matched datapoints in 28 economies. HFPS data are matched to ILO data at quarter level. Sources of error include differences in sampling, timing of surveys, and questions asked in surveys, including recall bias for the prepandemic baseline collected in HFPS.

Figure A4.3. LAC averages of ILO and HFPS currently working



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys and ILOSTAT.
Notes: LAC average for 9-11 countries with data collected in the same quarter.

Figure A4.4. Unrecovered employment loss in 2021 relative to upper bound estimate of recall bias (based on LFS) in HFPS prepandemic employment levels



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys and ILOSTAT.
Notes: Sample includes countries with LFS data for 2021Q1 and HFPS data for prepandemic (recall) and from surveys in 2021.

Annex 5 Prepandemic work assumptions in HFPS

Problem: prepandemic labor variables are missing for some countries because the question was skipped for those currently working in the first HFPS wave, and only asked of those not working. Without correction, this causes bias in some prepandemic employment variables, e.g. less than 40 percent prepandemic employment in Ethiopia, because the question was only asked to those not working in the first HFPS wave (at the height of pandemic impacts).

Proposed solution: assume prepandemic labor variables = labor variables in wave 1 surveys for those currently working, if the question was skipped only for those currently working. In other words, assume those working at the peak of the pandemic were working before the pandemic (in the same sector and job type, if applicable).

Proxy for question skipped if currently working: the first survey wave has less than 20 percent response rate if currently working and more than 80 percent response rate if not currently working.

Countries where question was skipped based on proxy:

- prepandemic work: COD, ETH, LCA, LAO, MLI, MNG, MOZ, MUS, MWI, NER, NGA, RWA, SDN, SEN, SOM, STP, TCD, UGA, ZMB;
- prepandemic sector: GIN, LAO, LCA, MNG, MUS, NGA, SDN, RWA, SLE, SOM, UGA, ZMB;
- prepandemic employment type: ETH.

The first HFPS wave was conducted by November 2020 in all countries that skipped questions.

Validation: we can use surveys that do have prepandemic labor information to validate assumptions and choose parameters.

How accurate are the assumptions in countries with data?

- Working prepandemic if working in first wave: true in 96 percent of cases for 2020 surveys (N=51,186)
- Prepandemic sector is same as sector in first wave, if working in first wave: true in 93 percent of cases for 2020 surveys (N=23,045)
- Prepandemic employment type is same employment type in first wave, if working in first wave: true in 95 percent of cases in 2020 surveys (N=14,966)

How does timing of first HFPS wave affect accuracy of assumptions?

- Assumptions are valid in more than 90 percent of cases most months (Figure A5.1)

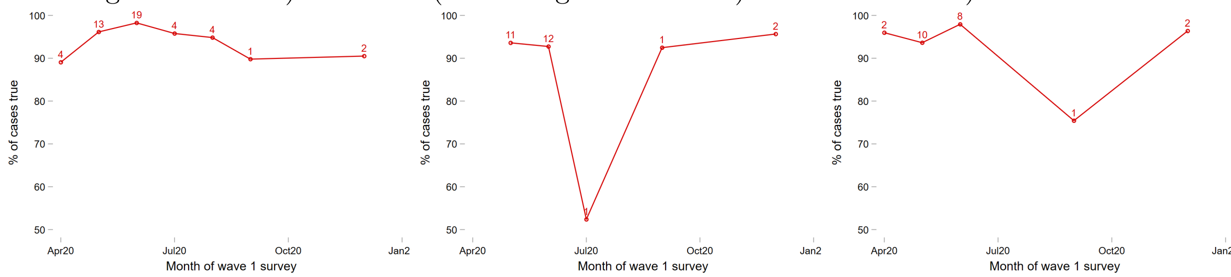
- Similar results hold for SSA, which represents most countries that skipped questions

Figure A5.1. Validation of prepandemic work assumptions in countries where data was collected, by month of first HFPS wave

(a) Working prepandemic (if working in first wave)

(b) Same prepandemic sector (if working in first wave)

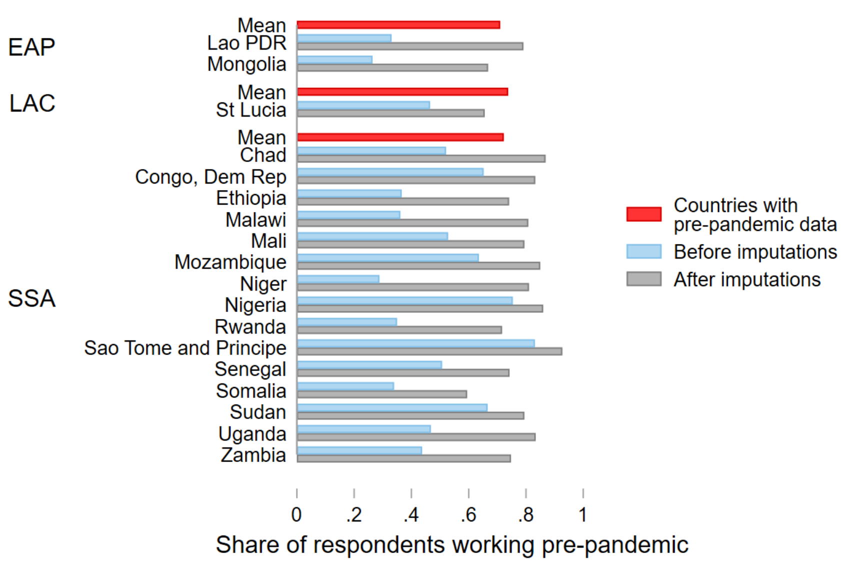
(c) Same prepandemic employment type (if working in first wave)



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: Labels on each data point show the number of countries with a wave 1 survey included in calculations for a given month.

Decision: Given the high probability assumptions hold based on data from other countries, apply in countries where question was skipped for those working in the first HFPS wave in 2020. Figure A5.2 shows prepandemic employment in each country where assumption is applied before and after imputations, and relative to the regional average in countries with data. Imputations appear to correct bias.

Figure A5.2. Prepandemic employment before and after imputations



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys and ILOSTAT.

Annex 6 Descriptive tables and additional analysis

Table A6.1. Net change in employment relative to prepandemic levels, by country group

	Net change in employment relative to prepandemic level (%)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	−30.6	−16.8	−8.2	75	246,618
Country panel	−31.0	−19.2	−12.0	31	140,798
High income	−18.0	−17.9	−15.3	8	18,740
	−17.9	−17.9	−14.2	4	15,719
Upper-middle income	−38.6	−22.1	−7.7	24	74,561
	−38.6	−27.7	−15.0	12	48,113
Lower-middle income	−33.8	−16.0	−4.6	25	92,293
	−36.3	−19.5	−11.3	9	41,511
Low income	−23.2	−11.8	−9.8	18	61,024
	−16.6	−2.7	−5.6	6	35,455
East Asia and Pacific	−20.2	−12.0	−7.3	11	54,933
	−15.2	−15.8	−11.1	5	36,142
Europe and Central Asia	−22.3	−10.3	−0.5	8	32,724
	−22.3	−11.6	−15.6	4	16,735
Latin America and Caribbean	−44.5	−31.0	−14.8	24	52,550
	−44.5	−31.0	−14.6	14	41,119
Middle East and North Africa	−37.3	−7.2	−6.6	6	21,441
	−24.3	−17.2	−10.0	1	5,991
Sub-Saharan Africa	−24.3	−13.3	−0.3	26	84,970
	−21.3	−2.6	−5.6	7	40,811

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.2. Stopped working relative to prepandemic (% of working age population)

	Stopped working vs. prepandemic (% of working age population)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	24.8	18.8	17.8	75	246,618
Country panel	25.9	20.9	17.9	31	140,798
High income	14.4	19.8	21.5	8	18,740
	14.9	19.8	22.0	4	15,719
Upper-middle income	31.8	20.6	17.9	24	74,561
	31.8	24.8	18.9	12	48,113
Lower-middle income	25.8	18.8	16.0	25	92,293
	28.9	20.8	16.6	9	41,511
Low income	20.5	16.7	17.5	18	61,024
	16.9	13.9	15.0	6	35,455
East Asia and Pacific	17.4	14.6	15.8	11	54,933
	14.1	16.4	15.5	5	36,142
Europe and Central Asia	15.0	12.9	18.1	8	32,724
	15.0	15.8	21.1	4	16,735
Latin America and Caribbean	36.3	27.8	20.3	24	52,550
	36.3	27.8	20.0	14	41,119
Middle East and North Africa	27.0	12.2	9.0	6	21,441
	21.2	18.1	9.3	1	5,991
Sub-Saharan Africa	20.3	17.8	15.4	26	84,970
	20.5	13.5	14.8	7	40,811
Female	23.6	20.3	19.3	73	103,900
	26.0	22.3	19.1	31	60,950
Male	24.7	17.8	16.1	73	139,142
	26.0	19.4	16.3	31	79,353
Non-urban/Rural	23.6	18.4	17.9	67	92,426
	24.5	20.7	18.1	27	53,174
Urban	25.1	19.0	18.2	69	135,127
	25.7	21.0	19.1	27	73,999
Low education	27.4	20.2	19.0	59	92,320
	29.5	22.8	19.3	23	55,169
High education	24.8	19.4	16.8	59	89,509
	25.2	21.7	18.0	23	47,497

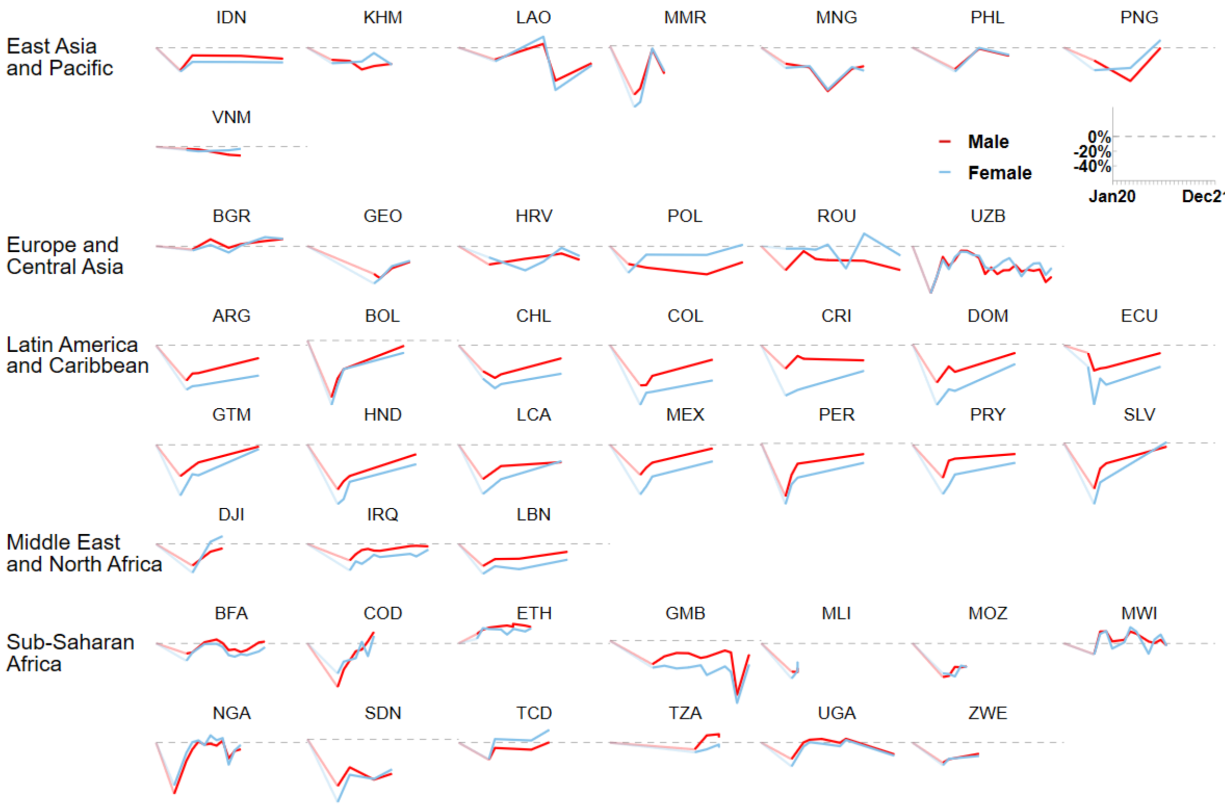
Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.3. Started working relative to prepandemic (% of working age population)

	Started working vs. prepandemic (% of working age population)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	1.6	6.3	10.8	75	246,618
Country panel	2.2	6.8	9.2	31	140,798
High income	1.3	9.0	10.9	8	18,740
	1.7	9.0	12.8	4	15,719
Upper-middle income	2.8	4.4	10.2	24	74,561
	2.8	4.2	7.7	12	48,113
Lower-middle income	0.9	6.5	12.0	25	92,293
	1.3	6.2	9.0	9	41,511
Low income	1.8	7.4	10.0	18	61,024
	2.8	11.5	10.1	6	35,455
East Asia and Pacific	1.1	5.5	9.6	11	54,933
	0.8	4.5	6.4	5	36,142
Europe and Central Asia	1.4	7.5	14.3	8	32,724
	1.4	10.0	12.7	4	16,735
Latin America and Caribbean	2.7	4.6	9.5	24	52,550
	2.7	4.6	9.1	14	41,119
Middle East and North Africa	1.1	6.9	5.4	6	21,441
	4.4	5.4	4.7	1	5,991
Sub-Saharan Africa	1.2	7.2	13.1	26	84,970
	2.4	11.2	10.0	7	40,811
Female	1.7	7.3	12.0	73	103,900
	2.3	8.1	11.0	31	60,950
Male	1.7	5.6	9.4	73	139,142
	2.2	5.9	7.8	31	79,353
Non-urban/Rural	2.0	7.5	11.4	67	92,426
	2.8	8.7	9.5	27	53,174
Urban	1.2	5.9	10.2	69	135,127
	1.6	6.1	8.4	27	73,999
Low education	2.3	6.6	12.0	59	92,320
	3.0	7.2	10.4	23	55,169
High education	1.8	5.1	9.3	59	89,509
	2.3	5.3	8.0	23	47,497

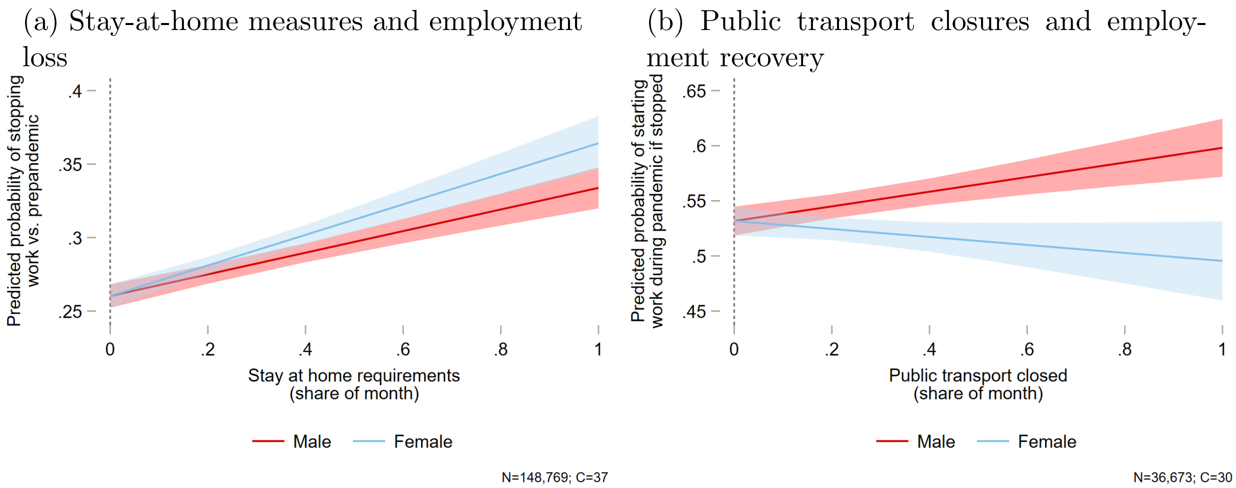
Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Figure A6.1. Percentage change in employment relative to prepandemic levels across surveys, by gender



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: The figure includes all countries with at least 3 HFPS waves.

Figure A6.2. Effect of containment policies on employment, by gender



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.4. Characteristics associated with stopping work (if working prepandemic), and starting or recovering work during the pandemic

	Stopped working if working prepandemic				**Started working during pandemic (panel)**		
	Full sample		Panel households		If not working in any previous HFPS wave	If stopped working in any previous HFPS wave	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Urban	0.007	−0.000	0.012*	0.009	0.001	0.019	−0.003
	(0.005)	(0.007)	(0.007)	(0.010)	(0.009)	(0.014)	(0.020)
Female	0.105***	0.105***	0.091***	0.080***	−0.103***	−0.050	−0.009
	(0.010)	(0.014)	(0.019)	(0.023)	(0.017)	(0.033)	(0.040)
Has children	−0.004	−0.020**	−0.018	−0.038***	0.104***	0.086***	0.140***
	(0.008)	(0.010)	(0.012)	(0.015)	(0.017)	(0.030)	(0.040)
Female × Has children	0.002	0.006	0.005	0.024	−0.064***	−0.093***	−0.131***
	(0.012)	(0.016)	(0.020)	(0.027)	(0.021)	(0.035)	(0.044)
Low education	0.063***	0.072***	0.044***	0.058***	−0.027**	−0.033**	−0.047**
	(0.006)	(0.008)	(0.009)	(0.012)	(0.011)	(0.016)	(0.019)
Stringency index (std.)	0.042***	0.044***	0.051***	0.063***	−0.026***	−0.021**	−0.025***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)	(0.008)	(0.009)
Mining/ Manufacturing		0.078***		0.077***			0.008
		(0.015)		(0.023)			(0.039)
Commerce		0.071***		0.069**			0.002
		(0.018)		(0.027)			(0.030)
Other services		0.069***		0.053***			0.025
		(0.013)		(0.020)			(0.028)
Country FE	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓
R^2	0.08	0.09	0.09	0.10	0.16	0.12	0.11
N	198,487	146,364	148,936	106,392	72,723	41,752	31,321
Countries	52	46	37	31	36	36	30

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: Regression results from a linear probability model. Household sample weights are used within countries and countries are weighted equally. OxCGRT stringency index is matched to surveys at month level and standardized within countries across the period April 2020 to December 2021. The baseline sector (not shown) is agriculture. Standard errors are robust. 95% confidence intervals shown. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6.5. Effect of policy stringency on employment loss and recovery by population group

	Stopped working if working prepandemic		**Started working during pandemic (panel)**			
			If not working in any previous HFPS wave		If stopped working in any previous HFPS wave	
	(1)	(2)	(3)	(4)	(5)	(6)
Stringency index (std.)	0.033***	0.026***	−0.063***	−0.062***	−0.067***	−0.064***
	(0.002)	(0.006)	(0.003)	(0.010)	(0.005)	(0.017)
Urban × Stringency index (std.)		0.016***		−0.005		−0.004
		(0.005)		(0.009)		(0.014)
Female × Stringency index (std.)		0.009		−0.018**		−0.022
		(0.005)		(0.009)		(0.013)
Low education × Stringency index (std.)		−0.011**		0.022**		0.014
		(0.005)		(0.009)		(0.014)
Household FE	✓	✓	✓	✓	✓	✓
R^2	0.60	0.62	0.68	0.68	0.64	0.63
N	249,993	148,768	120,927	62,387	70,030	36,673
Countries	51	37	42	30	42	30

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: Linear probability model with household fixed effects, controlling for differential effects of policy stringency by education level and location. Household sample weights are used within countries and countries are weighted equally. OxCGRT stringency index is matched to surveys at month level and standardized within countries across the period April 2020 to December 2021. Standard errors are robust. 95% confidence intervals shown. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6.6. Changed job relative to prepandemic (if working before and during pandemic)

	Changed job vs. prepandemic (% of working age population employed before and during pandemic)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	8.6	21.9	23.6	67	110,810
Country panel	9.7	28.2	25.4	23	52,796
High income	1.4	19.9	16.7	7	5,077
	4.1	31.7	14.1	1	1,538
Upper-middle income	8.9	18.2	21.6	24	42,742
	8.9	21.1	20.6	12	29,233
Lower-middle income	6.8	27.3	23.1	23	38,611
	7.9	35.9	28.7	7	10,788
Low income	13.9	20.5	36.2	13	24,380
	19.4	37.2	41.0	3	11,237
East Asia and Pacific	6.9	23.5	23.2	11	30,440
	6.5	24.7	26.1	3	12,443
Europe and Central Asia	7.0	9.1	13.3	7	10,017
	14.0	18.0	21.9	1	1,063
Latin America and Caribbean	8.8	27.8	21.5	24	28,697
	8.8	27.8	22.3	14	22,005
Middle East and North Africa	2.2	21.4	20.5	6	11,446
	9.0	9.5	3.2	1	2,915
Sub-Saharan Africa	11.2	20.3	40.8	19	30,210
	14.5	39.2	42.3	4	14,370
Female	8.2	20.8	23.3	65	38,859
	9.7	26.2	25.6	23	18,320
Male	9.3	23.1	23.7	65	70,503
	9.8	29.3	25.2	23	34,297
Non-urban/Rural	9.6	20.8	24	61	39,533
	11.3	27.3	27.8	19	15,602
Urban	8.3	20.0	25.2	62	62,385
	9.3	26.8	27.0	19	30,329
Low education	8.2	21.8	22.6	55	40,699
	9.9	29.3	24.3	17	21,885
High education	7.7	19.7	19.5	55	42,626
	7.3	25.6	20.4	17	19,614

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.7. Employment type transition matrix, February 2020 – 2021

Prepandemic employment type	**Share of working age population prepandemic (%)**	**Share of prepandemic employment in 2021 (%)**			
		Self-employed	Wage-earner	Other	Not working
Self-employed	27	65	9	0	26
Wage-earner	44	11	65	0	23
Other	1	20	21	30	30
Not working	29	21	15	1	63

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes:Row percentages across current employment types add to 100 for each prepandemic employment type. Countries are weighted equally. The sample includes 4 HICs, 23 UMICs, 7 LMICs, and 4 LICs.

Table A6.8. Transitions into self-employment (if working before and during pandemic)

	Became self-employed (% of working age population employed before and during pandemic)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	3.6	7.3	9.3	42	53,877
Country panel	4.3	8.6	11.2	17	28,141
High income	1.8	4.3	8.3	4	2,676
	1.8	4.3	5.5	1	1,375
Upper-middle income	4.4	7.2	8.5	22	29,745
	4.3	9	10.9	9	13,691
Lower-middle income	2.6	8.7	9.3	11	10,153
	3.6	10.6	10	5	5,497
Low income	3.9	3.8	14.1	5	11,303
	7.6	3.8	18.6	2	7,578
East Asia and Pacific	3.7	7.3	3.6	5	10,559
	1.6	7.2	3.9	1	917
Europe and Central Asia	1.7	2.8	5.7	3	3,590
	1.7	5.9	8.9	1	1,063
Latin America and Caribbean	4.2	9.6	10.3	24	24,596
	4.2	9.6	10.8	13	18,583
Middle East and North Africa	0	6.6	2.7	5	3,875
	.	.	.	0	0
Sub-Saharan Africa	3.9	2.6	14.6	5	11,257
	7.6	3.8	18.6	2	7,578
Female	4.1	8.1	10.2	41	19,728
	4.7	9.7	12.5	17	10,441
Male	3.6	6.9	8.6	41	33,347
	4.1	7.9	10	17	17,521
Non-urban/Rural	4.4	7.4	10.1	39	16,072
	5.4	8.2	12.9	14	6,805
Urban	3.2	5.7	8.8	39	33,432
	3.9	6.6	9.4	14	17,803
Low education	3.8	8	9.1	36	22,537
	4.4	9.6	10.9	13	10,105
High education	2.8	6.6	7.2	36	21,014
	3.4	7.7	8.3	13	11,643

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.9. Employment sector transition matrix, February 2020 – 2021

Prepandemic sector	**Share of working age population prepandemic (%)**	**Share of prepandemic employment in 2021 (%)**				
		Agriculture	Mining/Manuf.	Commerce	Other services	Not working
Agriculture	13	67	3	3	6	21
Mining/Manuf.	12	7	56	4	9	24
Commerce	11	5	4	53	12	27
Other services	36	4	4	5	61	26
Not working	28	11	5	7	14	62

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: Row percentages across current sectors add to 100 for each prepandemic sector. Countries are weighted equally. The sample includes 4 HICs, 21 UMICs, 10 LMICs, and 6 LICs.

Table A6.10. Transitions into agriculture (if working before and during pandemic)

	Changed sector to agriculture (% of working age population employed before and during pandemic)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	1.3	5.2	5	52	73,806
Country panel	1.5	6.6	5.6	19	32,343
High income	0.1	2.5	2	6	3,726
	0.2	2.5	1.1	1	1,324
Upper-middle income	1.9	3.4	3.8	20	27,146
	1.6	4.1	3.9	10	13,804
Lower-middle income	0.8	8	6.1	17	24,939
	1.5	11.1	8.4	6	9,081
Low income	2.2	5.2	8.8	9	17,995
	1.4	7.5	8.2	2	8,134
East Asia and Pacific	1.3	4.9	4.6	9	17,484
	0	8	6.6	2	2,621
Europe and Central Asia	0	0.3	0.7	3	3,215
	.	.	.	0	0
Latin America and Caribbean	1.8	4.6	3.8	24	23,962
	1.8	4.6	4.1	14	18,455
Middle East and North Africa	0	.	.	3	6,122
	.	.	.	0	0
Sub-Saharan Africa	1.2	8.3	11.5	13	23,023
	1	14.9	12	3	11,267
Female	0.9	4.2	4.4	51	24,693
	1.1	4.8	5.3	19	11,380
Male	1.6	5.8	5.3	51	48,807
	1.6	7.5	5.8	19	20,963
Non-urban/Rural	2.2	8.5	7.3	49	25,228
	2.6	11.3	8.3	16	9,213
Urban	0.4	2.2	3.1	49	43,815
	0.5	3.1	3.5	16	19,826
Low education	1.6	6.3	5	45	26,605
	2.2	8	6.1	15	10,371
High education	1.7	2.5	2.7	45	30,709
	1.3	2.9	3.3	15	15,445

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.11. Employment type transition matrix by education level, February 2020 – 2021

Prepandemic employment type	Education level	Share of working age population prepandemic (%)	Share of prepandemic employment in 2021 (%)			
			Self-employed	Wage-earner	Other	Not working
Self-employed	Low	28	62	8	0	29
	High	21	70	9	0	21
Wage-earner	Low	39	11	60	0	29
	High	55	8	72	0	19
Other	Low	1	18	21	32	29
	High	1	16	20	31	32
Not working	Low	32	20	13	1	67
	High	23	18	21	1	61

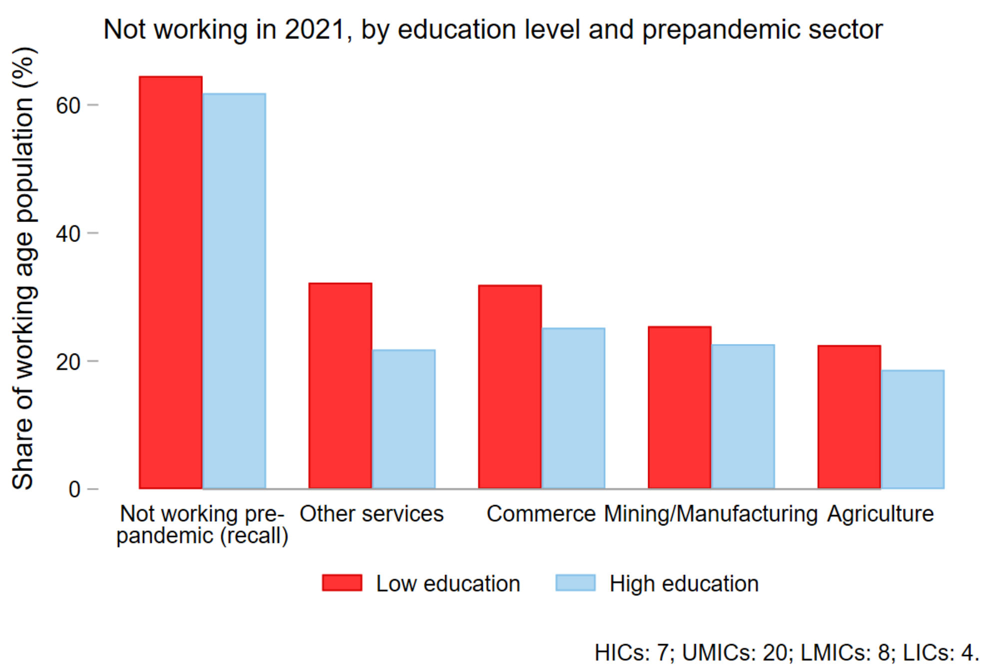
Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.12. Employment sector transition matrix by education level, February 2020 – 2021

Prepandemic sector	Edu. level	Share of working age population prepandemic (%)	Share of prepandemic employment in 2021 (%) Agri.	Min./Manu.	Commerce	Oth. serv.	Not working
Agriculture	Low	14	68	3	3	6	21
	High	6	72	3	2	7	16
Mining/Manu.	Low	13	6	54	3	12	25
	High	11	3	61	3	8	24
Commerce	Low	11	4	4	49	9	33
	High	11	2	3	61	10	24
Other services	Low	30	4	4	4	56	32
	High	48	2	3	4	69	21
Not working	Low	32	11	5	7	12	65
	High	24	7	5	8	20	60

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Figure A6.3. Share of working age population who are not working in 2021, by level of education and prepandemic employment sector



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.13. Total income decreased since pandemic (share of households)

	Total income decreased since pandemic started (% of households)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	64.7	42.8	48.1	51	120,349
High income	42.4	28.9	38.9	8	13,972
Upper-middle income	65	35.8	50.6	22	44,138
Lower-middle income	71.8	38.7	44.2	16	47,787
Low income	67.6	67	69.8	5	14,452
East Asia and Pacific	76.4	37.7	45.5	8	20,561
Europe and Central Asia	46	33.7	25.5	8	24,665
Latin America and Caribbean	65.5	.	52.8	24	41,922
Middle East and North Africa	62.6	43.8	.	2	10,271
Sub-Saharan Africa	68.2	67	67.2	9	22,930
Non-urban/Rural	67	38.7	48.7	49	43,755
Urban	64.2	40.3	47.4	49	70,399
Low education	63.6	45.9	49.6	44	47,210
High education	58.3	42.3	45.2	44	44,778

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.14. Farm income decreased since pandemic (share of households)

	Farm income decreased since pandemic started (% of households with income source)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	60.4	56.4	56.3	53	35,582
High income	51.4	.	55.2	4	243
Upper-middle income	65.7	.	60.6	19	4,670
Lower-middle income	60.3	56.9	44.7	14	11,307
Low income	54.6	56.2	64.3	16	19,362
East Asia and Pacific	50.8	49.8	46.4	8	6,774
Europe and Central Asia					
Latin America and Caribbean	63.2	.	57.3	24	4,747
Middle East and North Africa					
Sub-Saharan Africa	60.4	57.7	64.6	21	24,061
Non-urban/Rural	61.9	56.4	57.5	48	20,701
Urban	61.3	56.3	54.8	47	12,111
Low education	62.3	65	56.2	43	12,530
High education	59.7	56.2	52.6	36	11,818

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.15. Nonfarm income decreased since pandemic (share of households)

	Nonfarm income decreased since pandemic started (% of households with income source)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	70.2	54.5	63	59	48,788
High income	69.5	.	61.8	4	1,734
Upper-middle income	75.4	52.3	64.5	20	14,822
Lower-middle income	64.4	45.6	57.8	19	17,654
Low income	73.1	59.7	71.3	16	14,578
East Asia and Pacific	51.3	48.3	58.2	11	10,543
Europe and Central Asia	87.1	56.5	56.7	1	1,751
Latin America and Caribbean	72.3	.	62.8	24	18,336
Middle East and North Africa	.	39.4	.	2	143
Sub-Saharan Africa	76	59.7	74.5	21	18,015
Non-urban/Rural	68.9	55.9	63.4	53	16,573
Urban	72.9	59.3	62.8	57	29,189
Low education	69.4	57.2	64.9	45	15,803
High education	70.8	55.1	59.5	47	19,229

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.16. Wage income decreased since pandemic (share of households)

	Wage income decreased since pandemic started (% of households with income source)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	49.1	37.6	49.9	54	57,239
High income	62	81.8	51.4	5	4,218
Upper-middle income	53.6	.	52.8	18	23,889
Lower-middle income	47.1	29.5	43.7	15	15,749
Low income	43.1	35.3	47.4	16	13,383
East Asia and Pacific	39.8	25.2	28.1	5	4,827
Europe and Central Asia	58.8	48.2	27.4	2	3,045
Latin America and Caribbean	52.8	.	54.7	24	31,996
Middle East and North Africa	.	15.1	.	1	265
Sub-Saharan Africa	46.4	40	48.1	22	17,106
Non-urban/Rural	48.9	41.4	51.7	49	16,640
Urban	47.3	35.2	48.8	51	36,661
Low education	54.6	44	55	41	20,646
High education	43.7	34.2	45.1	42	25,374

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.17. Income from remittances decreased since pandemic (share of households)

	Remittance income decreased since pandemic started (% of households with income source)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	49.6	32.9	46.7	50	25,870
High income	37.7	.	45.5	4	618
Upper-middle income	44.6	28.8	48.3	18	7,543
Lower-middle income	52.8	30	38.4	13	8,908
Low income	53.7	35.2	54.8	15	8,801
East Asia and Pacific	46	27.8	29.3	7	7,920
Europe and Central Asia	55.3	68.7	56.6	3	1,567
Latin America and Caribbean	45.5	.	47.8	24	9,239
Middle East and North Africa					
Sub-Saharan Africa	56.4	31.6	49.7	16	7,144
Non-urban/Rural	53	38.8	47.8	41	9,462
Urban	45.5	31.2	46.3	45	14,113
Low education	46.3	35.3	46	40	10,396
High education	45.5	26.5	46.8	38	11,841

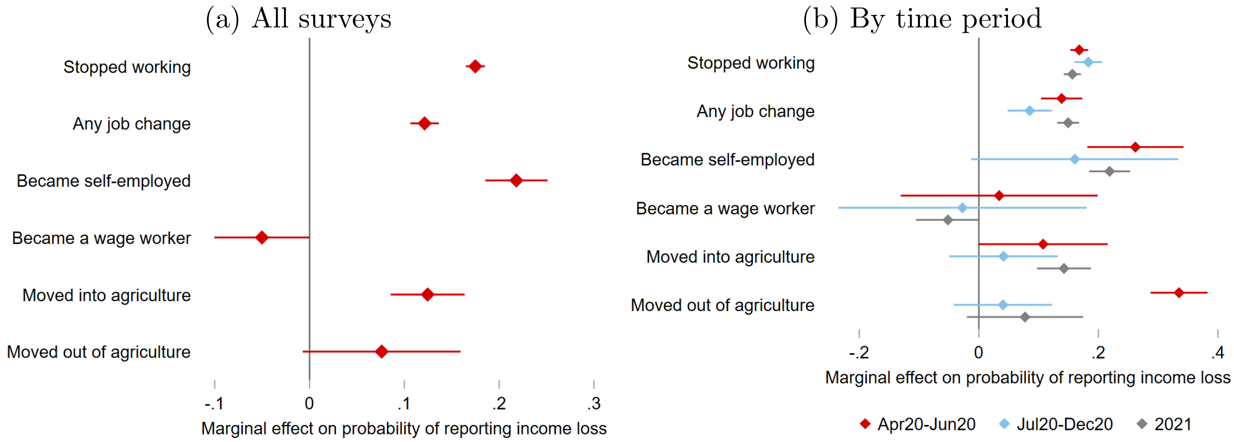
Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.18. Wage workers received no or partial payment in past week (share of households)

	Wage workers received no or partial payment in past week (% of households with wage worker)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	25.5	19.3	8.6	27	17,733
High income	15.9	11.2	.	1	640
Upper-middle income	26.3	20.7	9.7	11	6,127
Lower-middle income	29.7	15.4	8.5	11	8,501
Low income	14.4	28.1	7.8	4	2,465
East Asia and Pacific	34.7	16.7	8.6	5	5,218
Europe and Central Asia					
Latin America and Caribbean	21.7	20.3	.	13	5,613
Middle East and North Africa	50.3	4.4	.	3	4,210
Sub-Saharan Africa	14.4	24.5	8.7	6	2,692
Non-urban/Rural	29.7	22.6	9	23	4,768
Urban	25.4	19.6	7.1	23	11,192
Low education	26.2	24.3	13.5	19	4,612
High education	19.2	18.6	7.2	21	6,492

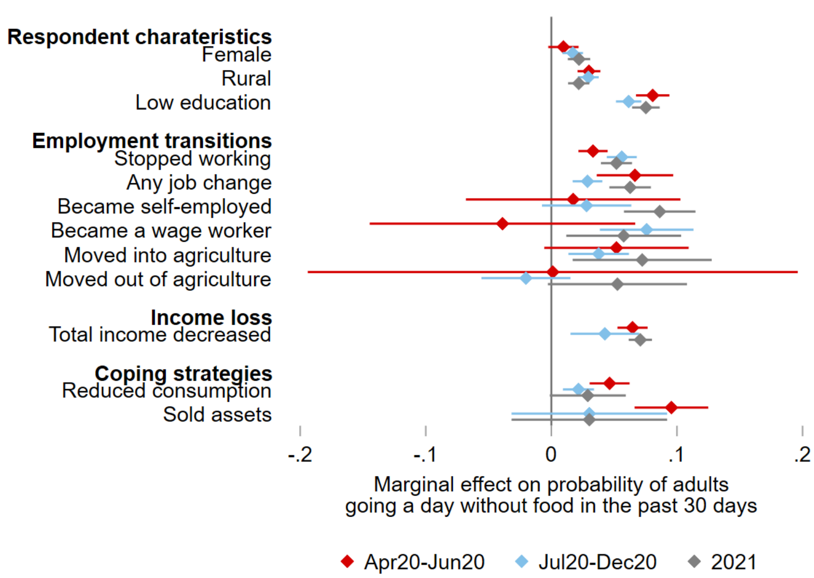
Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Figure A6.4. Relationship between employment transitions and income loss within countries from bivariate regressions



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: The sample includes all HFPS waves with response rates of at least 50 percent for the two variables included in the bivariate regression. Regressions control for country fixed effects. Sampling weights are used to weight observations within countries. Countries are weighted equally. Sample size ranges from 22,026 respondents in 24 countries (employment type transitions) to 162,885 respondents in 49 countries (stopped working). Standard errors are robust. 95% confidence intervals shown.

Figure A6.5. Within country correlates of food insecurity from bivariate regressions, by period



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.19. Characteristics associated with income loss relative to prepandemic, and income gain or recovery during the pandemic

	Income decreased since prepandemic				**Income increased since previous HFPS wave (panel)**			
	Full sample		Panel households		If reported		If income loss reported in any previous HFPS wave	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Urban	0.008	0.006	0.004	−0.003	0.014***	0.025***	0.017**	0.025***
	(0.007)	(0.014)	(0.012)	(0.015)	(0.005)	(0.006)	(0.007)	(0.009)
Larger household	0.038***	0.035***	0.039***	0.022*	0.004	0.002	0.004	−0.002
	(0.006)	(0.012)	(0.011)	(0.013)	(0.005)	(0.006)	(0.008)	(0.009)
Low education	0.059***	0.082***	0.052***	0.070***	−0.021***	−0.016***	−0.016*	−0.015*
	(0.006)	(0.012)	(0.012)	(0.014)	(0.005)	(0.006)	(0.008)	(0.009)
Stopped working	0.138***	0.113***	0.094***	0.116***				
	(0.007)	(0.013)	(0.013)	(0.015)				
Stringency index (std.)	0.057***	0.075***	0.075***	0.080***	−0.024***	−0.045***	−0.048***	−0.061***
	(0.004)	(0.008)	(0.007)	(0.016)	(0.004)	(0.005)	(0.006)	(0.009)
HH member owns business		0.179***		0.191***		0.010*		0.004
		(0.012)		(0.013)		(0.006)		(0.008)
HH member worked on farm		−0.012		−0.010		0.010		−0.008
		(0.017)		(0.019)		(0.010)		(0.013)
Back working					0.039***	0.032***	0.046***	0.042***
					(0.008)	(0.008)	(0.010)	(0.011)
Did not stop working					0.034***	0.034***	0.038***	0.037***
					(0.006)	(0.006)	(0.008)	(0.009)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.13	0.14	0.12	0.13	0.05	0.05	0.03	0.04
N	71,954	22,825	21,174	12,361	44,459	21,889	19,119	8,518
Countries	41	22	19	18	22	22	17	17

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: Regression results from a linear probability model. Household sample weights are used within countries and countries are weighted equally. OxCGRT stringency index is matched to surveys at month level and standardized within countries across the period April 2020 to December 2021. The baseline employment status (not shown) indicates respondents that have stopped working and not started back at work. Standard errors are robust. 95% confidence intervals shown. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6.20. Effect of policy stringency on income loss and recovery by population group

	Income decreased since pandemic		Income increased since previous HFPS wave (panel)			
			If reported		If income loss reported in any previous HFPS wave	
	(1)	(2)	(3)	(4)	(5)	(6)
Stringency index (std.)	0.036***	0.043***	−0.013***	−0.035***	−0.017***	−0.032***
	(0.002)	(0.006)	(0.002)	(0.005)	(0.003)	(0.009)
Urban × Stringency index (std.)		0.009		0.025***		0.015
		(0.006)		(0.006)		(0.010)
Female × Stringency index (std.)		0.003		0.011*		−0.009
		(0.006)		(0.006)		(0.010)
Low education × Stringency index (std.)		0.006		0.011*		0.011
		(0.006)		(0.006)		(0.009)
Household FE	✓	✓	✓	✓	✓	✓
R^2	0.58	0.59	0.39	0.43	0.38	0.45
N	153,414	99,646	77,774	41,711	45,518	18,095
Countries	31	27	9	7	7	5

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.
Notes: Linear probability model with household fixed effects, controlling for differential effects of policy stringency by education level and location. Household sample weights are used within countries and countries are weighted equally. OxCGRT stringency index is matched to surveys at month level and standardized within countries across the period April 2020 to December 2021. Standard errors are robust. 95% confidence intervals shown. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6.21. Received public assistance since pandemic (share of households)

	Received public assistance (% of households)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	17.2	27.3	40.2	68	214,643
Country panel	22.2	27.7	40.2	23	105,432
High income	5.9	12.4	34.6	7	19,020
	5.9	12.4	24.5	4	16,599
Upper-middle income	27.6	35	51.6	25	73,137
	27.7	32.9	49.3	10	38,248
Lower-middle income	18.1	36.4	32.8	21	76,691
	32.8	40.2	52.2	6	32,859
Low income	5.7	13.6	18.7	15	45,795
	4.7	6.1	6.5	3	17,726
East Asia and Pacific	43.4	86.4	58	8	30,630
	69.7	82.3	85.6	2	15,188
Europe and Central Asia	4.9	22.1	20	9	37,094
	4.9	6.9	6.5	5	22,101
Latin America and Caribbean	26.2	32.4	47.7	24	50,317
	25.7	32.4	53.8	13	36,491
Middle East and North Africa	6.6	35.9	78.3	6	20,383
	.	.	.	0	0
Sub-Saharan Africa	8.2	12.4	17.4	21	76,219
	4.6	5.6	7	3	31,652
Non-urban/Rural	18.3	29.6	43.6	63	80,916
	22.6	27.4	38.8	20	39,688
Urban	15.8	26.5	38.6	64	118,387
	20.8	24.9	35.6	20	58,441
Low education	19.1	33.7	45.5	54	85,207
	23.8	30.2	45.2	20	49,442
High education	14.4	29.9	36	54	82,399
	19.2	25.3	36.2	20	45,215

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.22. Adults went a day without food in past 30 days (share of households)

	Adults went a day without food in past 30 days (% of households)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	16.9	12.6	14.1	60	192,952
Country panel	13.4	8.7	11.8	20	79,735
High income	5.3	1.8	8.4	4	5,317
	5.3	1.8	3.6	1	2,896
Upper-middle income	12.4	7.7	13.6	16	40,683
	12.4	7.9	12.2	10	30,687
Lower-middle income	16.2	12.2	13.5	23	82,792
	13	8.3	9.2	3	8,978
Low income	22.9	17.4	17.9	17	64,160
	16.6	11.5	13.9	6	37,174
East Asia and Pacific	21.1	9.7	9.5	8	31,749
	5.1	5.8	2.7	1	3,571
Europe and Central Asia	1.9	3.5	3.5	2	8,115
	1.9	1.8	3.5	1	3,575
Latin America and Caribbean	12.3	7.7	13.9	24	52,133
	12.5	7.7	11.5	13	38,990
Middle East and North Africa	3.5	3.5	.	3	11,134
	.	.	.	0	0
Sub-Saharan Africa	22.8	18.4	17.9	23	89,821
	19.6	13.5	15.9	5	33,599
Non-urban/Rural	17.4	13.5	15.4	56	72,817
	15.1	10	13.4	18	26,532
Urban	15.7	11.2	13.2	58	111,653
	10.9	7.2	10.8	18	48,183
Low education	20.1	15.3	16.6	47	63,139
	16.1	10.2	12.9	17	32,227
High education	11.8	8.7	9.3	47	75,169
	7.6	4.2	6.4	17	36,058

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.23. Reduced consumption during the pandemic (share of households)

	Reduced consumption during the pandemic (% of households)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	44.1	36.6	32.4	49	161,494
Country panel	45.7	39.7	37.1	4	43,773
High income	39.1	33.3	17.9	3	6,410
	.	.	.	0	0
Upper-middle income	51	39.8	55.7	16	44,936
	79.8	59.1	50.6	1	11,540
Lower-middle income	42.6	40.1	34.1	18	72,648
	29.2	33.6	37.7	2	22,549
Low income	38.5	27.5	9.2	12	37,500
	44.5	32.6	22.5	1	9,684
East Asia and Pacific	49.8	44.3	50.1	11	45,984
	49.5	38.3	40.4	2	15,066
Europe and Central Asia	.	23.9	17.7	4	13,096
	.	.	.	0	0
Latin America and Caribbean	47	46	.	13	20,979
	.	.	.	0	0
Middle East and North Africa	.	0	59.4	1	5,479
	.	.	.	0	0
Sub-Saharan Africa	37.9	30.2	17.1	20	75,956
	41.8	41.1	33.9	2	28,707
Non-urban/Rural	41.8	34.1	30.6	42	63,170
	44.8	38.3	35.3	4	18,501
Urban	44.7	36.9	31.7	43	84,781
	46.6	41.1	37.7	4	25,250
Low education	41.8	38.1	38.4	39	62,873
	43.5	40.2	38.3	4	21,091
High education	41.4	34.5	35.5	39	67,274
	43.4	38.8	32.8	4	22,568

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.24. Used savings to cover basic living expenses (share of households)

	Used savings to cover basic living expenses (% of households)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	21.5	15.6	20.8	52	167,504
Country panel	21.7	15.8	16.8	6	51,946
High income	15.7	8.4	8.9	3	6,410
	.	.	.	0	0
Upper-middle income	19.8	16.5	36.3	17	43,141
	31.6	25.1	22.2	1	11,540
Lower-middle income	23.2	14.8	16.8	19	75,700
	19.1	13.2	16.4	3	27,147
Low income	22.4	17.6	16.6	13	42,253
	20.6	15.1	14.8	2	13,259
East Asia and Pacific	24.3	20.8	24.9	11	45,984
	18.5	15.5	13.2	2	15,066
Europe and Central Asia	17.6	22	14.8	7	24,174
	17.6	18.9	15.4	2	8,173
Latin America and Caribbean	14.9	7.2	.	13	20,979
	.	.	.	0	0
Middle East and North Africa	28	30.2	.	2	2,330
	.	.	.	0	0
Sub-Saharan Africa	27.2	15.4	20.6	19	74,037
	29	13.1	21.9	2	28,707
Non-urban/Rural	19.8	13.9	20.2	45	70,713
	21.4	15.5	17.3	6	24,744
Urban	23.3	15.8	21.5	46	87,939
	21.6	15.4	14.9	6	27,178
Low education	18.3	14.9	22.1	41	63,336
	18.1	13.6	18.3	5	21,496
High education	23.4	16.9	25	41	68,815
	28.2	19	19.3	5	24,635

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.25. Sold assets to pay for basic living expenses (share of households)

	Sold assets to pay for basic living expenses (% of households)			Sample	
	Apr-Jun20	**Jul-Dec20**	**2021**	**Countries**	**N**
All countries	6.7	5.4	7.2	51	168,775
Country panel	4.9	4.3	8.7	7	59,871
High income	1.1	0.4	.	2	3,411
	.	.	.	0	0
Upper-middle income	5.1	5.4	12.2	17	49,489
	7.4	6.4	19.2	2	19,354
Lower-middle income	6.5	4.3	6.3	19	72,409
	4.9	3.7	3.7	3	27,258
Low income	10.6	8	4.3	13	43,466
	2.3	3.1	5.7	2	13,259
East Asia and Pacific	9.9	7	8.5	10	40,322
	8.8	7.2	5.5	2	15,066
Europe and Central Asia	2.2	6.2	4.3	5	19,820
	2.2	3.5	5.1	2	8,284
Latin America and Caribbean	3.6	2.1	.	13	20,979
	.	.	.	0	0
Middle East and North Africa	4.3	7.8	28.2	3	9,307
	0	0	28.2	1	7,814
Sub-Saharan Africa	9.4	6.8	5.5	20	78,347
	6	4.3	5.8	2	28,707
Non-urban/Rural	7.3	5.3	6.8	43	65,961
	7.1	6.5	6.1	6	24,828
Urban	6	4.3	5.4	44	86,148
	4.3	3.6	4.5	6	27,205
Low education	6.5	5.3	8.3	41	66,765
	6.2	4.8	9.9	6	26,557
High education	5.2	4.4	7.3	41	72,766
	4.4	4.1	10.1	6	26,820

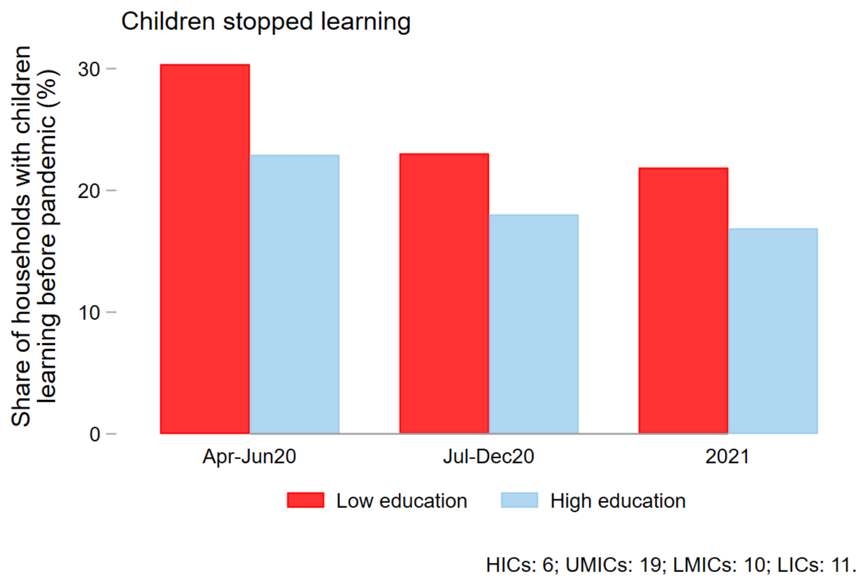
Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Table A6.26. Children stopped learning after school closures (share of households with children enrolled prepandemic)

	Children stopped learning (% of households with children learning prepandemic)			Sample	
	Apr-Jun20	Jul-Dec20	2021	Countries	N
All countries	28.5	22.2	19.4	59	97,115
Country panel	15.6	14	19.4	16	37,764
High income	10.2	4.2	5.4	6	2,800
	4.1	4.2	2.9	1	1,168
Upper-middle income	4.1	6.4	17.3	19	21,966
	4.4	6.6	12.5	6	7,441
Lower-middle income	29.8	22.8	22.8	20	44,035
	15.9	15.6	17.6	6	18,095
Low income	56.5	44.1	29.4	14	28,314
	41.1	28.6	42.4	3	11,060
East Asia and Pacific	21.1	22.7	27.4	7	15,917
	37.5	20.3	23.3	1	875
Europe and Central Asia	24.7	7.7	25.1	5	5,739
	36.1	11.6	37.7	2	4,581
Latin America and Caribbean	5.2	8.4	12	24	22,702
	5.6	8.4	10.6	10	13,047
Middle East and North Africa	49	12.5	94.2	3	6,948
	.	.	.	0	0
Sub-Saharan Africa	52	40.3	28.4	20	45,809
	28	31.9	35.2	3	19,261
Non-urban/Rural	32.5	23.7	20.7	55	41,389
	18.7	16.1	20.4	13	17,664
Urban	26.9	21.2	18.4	57	50,723
	16.8	14.4	19.5	13	15,970
Low education	30.4	23	21.9	46	34,282
	20.7	14.4	26.7	11	14,378
High education	22.9	18	16.9	46	31,658
	14.6	10.3	20.8	11	12,914

Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.

Figure A6.6. Share of households in which children stopped learning since school closure, by respondent education



Source: World Bank estimates based on COVID-19 High-Frequency Phone Surveys.