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How did the COVID-19 crisis affect different types of workers in the developing world?

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ABSTRACT

This paper examines how the COVID-19 pandemic affected the employment of different groups of workers across 40 mostly low and middle-income countries. Employment outcomes during the crisis are tracked through high-frequency phone surveys conducted by the World Bank and national statistics offices. Our results show that larger shares of female, young, less educated, and urban workers stopped working at the beginning of the pandemic. Gender gaps in work stoppage stemmed mainly from gender differences within sectors rather than differential employment patterns of men and women across sectors. Differences in work stoppage between urban and rural workers were markedly smaller than those across gender, age, and education groups. Preliminary results from 10 countries suggest that following the initial shock at the start of the pandemic, employment rates partially recovered between April and August 2020, with greater gains for those groups that had borne the brunt of the early jobs losses. Although the high-frequency phone surveys over-represent household heads and therefore overestimate employment rates, a validation exercise for five countries suggests that they provide a reasonably accurate measure of disparities in employment levels by gender, education, and urban/rural location following the onset of the crisis, although they perform less well in capturing disparities between age groups. These results shed new light on the distributional labor market consequences of the COVID-19 crisis in developing countries, and suggest that real-time phone surveys, despite their lack of representativeness, are a valuable source of information to measure differential employment impacts across groups during an unfolding crisis.

1. Introduction

The COVID-19 pandemic led to an unprecedented and massive shock to labor markets worldwide. Yet there is very little systematic evidence about the crisis's impact on different groups of workers in developing countries. Empirical evidence from developed countries suggests that traditionally disadvantaged workers in the labor market were disproportionately affected by the pandemic (Lee et al., 2021; Couch et al., 2020; Bluedorn et al., 2022). These studies utilize a variety of data sources, such as government administrative data, real-time surveys, and information from social media, to explore the labor market impacts of the pandemic and document that inequality has been exacerbated. Much less is known about what happened to workers in developing countries, since the pandemic disrupted traditional data collection systems in many of these countries and alternative data sources are rarely available.[1]

This study draws on information from High Frequency Phone Surveys (HFPS), collected by national statistical offices and the World Bank, and harmonized by the World Bank for 40 countries, to explore which types of workers in developing countries were hit hardest by the COVID-19 shock. A companion paper to the current

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[1] An exception is the study by Dang et al. (2023), who leverage nationally representative labor force survey data for the period 2015–2020 to analyze the labor market impacts of the COVID-19 pandemic in Vietnam.

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analysis by Khamis et al. (2021) already quantifies the massive early adverse labor market impacts of COVID-19 in developing countries using the HFPS data. This paper focuses on the distributional implications of the crisis, in order to shed light on the extent to which the crisis is exacerbating traditional disparities and the potential need for policy interventions.

The HFPS have the virtue of collecting data widely and fast. However, they are potentially subject to sampling and selection biases that are crucial to consider carefully. The HFPS may provide a biased picture of employment changes during the COVID-19 pandemic for two reasons. First, only households where at least one member had a phone and that had access to electricity and were willing to participate in the survey were interviewed. This will lead to bias if individuals residing in households not represented in the sample experienced systematically different labor market outcomes from those that were represented. Second, in many countries the samples overrepresent household heads and underrepresent children and other household members that are neither the head nor the spouse, affecting the representativeness of the survey at the individual level and potentially providing a biased picture of labor market outcomes. Among the set of HFPS at our disposal, the phone surveys that were drawn from an existing sample were more likely to overrepresent the household head than the phone surveys that used a different sampling approach (mostly Random Digit Dialing). This is because, in the case of the former, the recontact information was captured only or mainly for the head of household. In addition, the household head was also interviewed in contexts where it was difficult to contact other household members without the head's authorization, in order to reduce non-response. Finally, some surveys elected to collect information on the head under the assumption that they are the main income earner in the household. This choice may have been accurate in some cases, but the definition of headship can vary across countries and households.[2]

In 19 of the 40 countries included in this study, the sample was drawn from a previous survey. In these cases, household weights were constructed by World Bank country teams in conjunction with national statistics offices, often by using information from prior surveys on phone ownership and other household characteristics. Evidence from four African countries suggests that this reweighting procedure was highly effective at reducing the first source of bias, i.e., the potential underrepresentation of certain types of households (Ambel et al., 2021). In contrast, the second source of bias, individual sampling bias, was not addressed by the teams producing the data. Evidence from the same four African countries indicates that this leads to overrepresentation of heads, as well as respondents who were older, more educated, and own a household enterprise. Furthermore, there is evidence that reweighting using an individual-level model is only partially able to address the sample selection bias that arises from the non-random selection of individuals (Brubaker et al., 2021).

While the main objective of the paper is to document differential employment impacts of the COVID-19 pandemic across groups, it is important to test the extent to which sample selection bias may affect comparisons of individual labor market outcomes to be confident in the results. We examine the role of sample selection bias in two ways. First, in an exercise similar to that carried out by Brubaker et al. (2021), we reweight observations in the HFPS based on individual characteristics to match nationally representative microdata collected prior to the pandemic. Second, we evaluate the performance of standard estimates that use the household weights calculated by the World Bank teams, as well as the reweighted estimates based on individual characteristics, in five countries. These five countries are unusual because they collected survey data during the pandemic that contains information on the labor market outcomes of all household members, which provides a natural benchmark for evaluating the extent of the individual sampling bias in the HFPS data.

This paper has five key findings:

1. Female workers were substantially more likely than men to stop working in the initial phase of the pandemic, i.e., between April and June 2020. When taking a simple average across countries, women were 8 percentage points more likely than men to stop working during this time period, and gender disparities were larger than those by age (with a 4 percentage point gap between youth and older workers), education (with a 4 percentage point gap between workers with low and high levels of education), and locality (with a 3 percentage point gap between urban and rural workers).
2. For those who remained employed, changes in sectoral employment and employment type were generally similar for all groups except for age. Wage employment fell 8 percent for youth as opposed to 2 percent for adults. Besides that, there were no marked differentials in either the change in wage employment or sectoral employment patterns.
3. Between April and August, employment increased in the 10 countries for which repeated surveys are available but remained moderately below pre-crisis levels. Employment gains during this time were larger for the groups that experienced the greatest initial job losses, meaning that female, less educated, young, and to a lesser extent urban workers experienced disproportionate employment gains. As a result, between the pre-crisis period and August, net falls in employment were larger for adults than youth and in five countries, similar for better-educated and less well-educated workers. Female and urban residents, however, still experienced larger overall net employment reductions than their male and rural counterparts. Because of limitations in the data, it is difficult to know if the jobs gained were of similar quality to those lost.
4. The phone surveys have proven to be a quick and efficient source of data over the course of the pandemic. They suffer from different types of bias, which leads them to overestimate employment rates relative to the full population.[3] However, evidence from five countries suggests that this bias is of similar magnitude across gender, education, and urban/rural groups, meaning that the phone surveys give an accurate picture of group disparities in employment rates following the onset of the crisis though they may be less reliable capturing differences between age groups. Furthermore, for two countries in which data are available both directly before and after the onset of the pandemic, the phone surveys generally provide accurate measures of group disparities in employment changes measured in absolute terms.

[2] Even though the household head is normally associated with the main decision-maker and/or main income earner in the household, it is possible that this may not be the case and the head of household may be the eldest member of the household, a status position not associated with income, ownership or decision-making. Additionally, survey-reported headship status may not be consistently defined across or even within countries since it is at the discretion of survey respondents (Brown and van de Walle, 2020). The fact that the definition of headship varies across countries, makes cross-country comparisons difficult (Grown, 2014). Additionally, Brown and van de Walle (2020) highlight that "survey-reported headship status .... is at the discretion of survey respondents. However, this is equally true of many routinely collected variables such as labor status, years of education, age, household size, religion, marital status, etc., that nonetheless prove to be useful in analysis. What is important is that household members themselves judge an individual to be the agreed head."

[3] Throughout the paper, the term "employment rate" refers to the employment to population ratio.

Overall, the results highlight the vulnerability of female and less educated workers to the crisis.[4] They also show that HFPS, despite their skewed composition and potential biases, are a useful tool for monitoring disparities across gender, education, and urban/rural location during an unfolding crisis. Disparities between youth and adult employment rates from these phone surveys, however, are less likely to be accurate and should be interpreted with a degree of caution.

This paper is organized as follows. Section 2 describes the structure of the data. Section 3 presents the initial impacts of the pandemic shock on different types of workers. Section 4 documents how different types of workers fared after the initial phase of the COVID-19 pandemic. Section 5 details several robustness checks, including distinguishing results by the type of sampling frame, reweighting the HFPS, corroborating the key HFPS results with International Labour Organization (ILO) data, and the exercise to compare the HFPS data with household surveys in five countries that collected employment data for all household members. Section 6 offers concluding remarks.

2. Data

The main data source for this paper is the March 2021 vintage of the harmonized HFPS data.[5] The data cover 40 countries in 5 regions. Specifically, the HFPS cover 13 countries in the Sub-Saharan Africa region (SSA), 12 countries in the Latin American and Caribbean region (LAC), 9 countries in the East Asia and Pacific (EAP) region, 5 countries in the Europe and Central Asia region (ECA), and one country in the Middle East and North Africa (MNA) region.[6] We use the first wave of the data (collected between April and August 2020) to study the initial impacts of the crisis and subsequent waves to explore its evolution by comparing data collected in April or May 2020 with information gathered in August 2020.[7]

To measure the initial impacts of the COVID-19 pandemic, we rely on the following questions in the harmonized HFPS data. First, we explore whether workers stopped working since the start of the pandemic using information on pre-pandemic employment ("Was the respondent working before the pandemic?") and current employment ("Did the respondent work in the last week?"). Outside LAC, the HFPS did not ask about pre-pandemic employment for people employed at the time of the survey. We therefore cannot observe those who only started working since the onset of the pandemic. We deal with this data limitation by assuming that nobody entered work since the crisis and dividing the number of persons who stopped working by the sum of the number of persons who stopped working and the number of persons employed at the moment of the survey. Data from LAC show that this assumption has a minor effect on the estimated share that stopped working, because few people began working after the pandemic (Khamis et al., 2021). Second, we use information on pre-pandemic and current sector of employment to analyze patterns of sectoral changes after the onset of the pandemic. We classify sectors into four groups: 1) agriculture and mining, 2) industry, 3) public administration, and 4) other services.[8] Third, we examine changes in the type of employment, using information on whether workers were in self- or wage-employment both before and after the beginning of the pandemic based on workers' recall of their employment type before the pandemic.[9] Finally, we analyze a variable that asked whether total household income increased, stayed the same, declined or whether no household income was received since the start of the pandemic. To measure the evolution of employment during the pandemic, we rely mainly on whether respondents reported that they are currently working.

The data include people 18 years of age and older. We group them according to sex (women and men), age (young workers defined as those between 18 and 24 years old), level of education (low level of education defined as primary education or less), and location (urban and rural areas).

The HFPS used three different sampling strategies, which has important implications for the surveys' representativeness of the countries' population. (a) Random Digit Dialing (RDD), (b) sampling phone numbers based on a pre-existing list, and (c) interviewing a subset of respondents (mostly heads) from a previous in-person survey. A pure RDD strategy, where phone numbers were dialed at random, was applied in 16 of the 40 countries, mostly in the LAC region. The process ensured coverage of all landline and cell phone numbers active at the time of the survey, meaning that the RDD survey estimates are solely taking into account persons 18 years of age or above who have an active cell phone number or a landline at home. For these RDD surveys, household and individual weights were constructed, separately for the landline and cell-phone samples, based on inclusion probabilities.[10] Eight other countries randomly sampled phone numbers from a non-survey list.[11] Meanwhile, 16 other countries used a sampling frame based on a previous survey.[12] Among them, most surveys sought to interview household heads.

For all sampling strategies, population groups with more limited mobile phone coverage are underrepresented. In addition, for those surveys that sampled from a previous survey and intentionally prioritized household heads, there is the additional issue of oversampling household heads and spouses, which makes the surveys highly non-representative at the individual level. The results in this paper, presented in section 5, show that collecting data mainly from household heads produces greater bias for age comparisons of employment trends than for comparisons by gender, education level or urban vs. rural (see Section 1 of the Supplementary material).

To address the first issue (i.e., the non-random selection of households) country teams that fielded the HFPS generated household sampling weights that seek to correct for the non-random selection of households. We use these weights in all our analyses. The second issue (i.e., the non-random selection of individuals within households) poses a more difficult challenge. Sections 5 and 6 utilize a range of different reweighting and validation

[4] This mirrors the results in Bundervoet et al. (2022), who also document heterogeneity in the labor market impacts of COVID-19, but for a smaller sample of HFPS and without further exploration of possible sample selection bias.

[5] Except for section 4, where we use the April 2021 vintage.

[6] Microdata from the MNA region are generally not available for analysis by World Bank staff, due to agreements the country teams made with respective National Statistics Offices over data access.

[7] There is a lag of six to nine months between when the data are collected and when they are available for analysis. This accounts for the time needed to process the data, obtain clearance for its release, harmonize the data to a common format, and check its quality. Different countries obtain data in different months. We selected August as a cut-off month for the analysis to balance the competing desires for greater country coverage and more recent data.

[8] Primary sector includes agriculture, hunting, fishing, and mining. Industry includes manufacturing and construction. Other services include public utility services, commerce, transport and communication, financial and businesses services and other services.

[9] Wage employment includes employees and seasonal/temporary workers. Self-employment includes self-employed workers and family business.

[10] Additionally, different strategies were followed to minimize nonresponse and base weights of individuals and households were adjusted to compensate for nonresponse and reduce potential bias. Further information is available in the technical note at the World Bank COVID-19 high frequency survey dashboard.

[11] These eight countries are: Croatia, Papua New Guinea, Myanmar, Romania, Solomon Islands, St. Lucia, Sudan, and Zambia.

[12] These 16 countries are: Burkina Faso, Cambodia, Djibouti, Ethiopia, Ghana, Indonesia, Kenya, Madagascar, Malawi, Mali, Mongolia, Nigeria, Uganda, Uzbekistan, Vietnam, and Zimbabwe.

approaches to deal with this second possible source of sampling bias.

3. Initial impacts of the pandemic shock by worker type

To better understand which types of workers in developing countries were hit hardest by the labor market impacts of COVID-19, this section explores three questions: 1) How did the COVID-19 pandemic affect different segments of the labor force (in terms of employment and other labor outcomes), 2) what was the magnitude of these differences by gender relative to age, education, and location, and 3) what were the drivers of heterogenous impacts between men and women?

The first wave of the HFPS data contains information on initial impacts, from April to August 2020, of the crisis on employment for different socio-demographic groups defined by gender, age, education level, and location. In particular, the first wave collected retrospective information on the fraction of persons who stopped working since the start of the pandemic, and the share of workers who changed their employment type (wage employee versus self-employed) or sector of employment. This information sheds light on which groups were hit hardest by the COVID-19 pandemic, in terms of work stoppage, employment type or employment sector changes, by making comparisons within groups (e.g., men vs. women) and across groups (e.g., groups defined by sex vs. groups defined by education).

3.1. Employment indicators

The HFPS data show that women, youth, less educated, and urban workers bore the brunt of the burden from work stoppage, but with the urban vs. rural differences being smaller than the other disparities. As shown in Table 1, women were 8 percentage points more likely than men to stop working in the initial phase of the crisis, and gender disparities were larger than those by age (with a 4 percentage point gap between young workers and other adult workers), education (with a 4 percentage point gap between low and high educated workers), and locality (with a 3 percentage point gap between urban and rural workers). Table 2 further disaggregates the large gaps across gender and age groups, to explore the possible intersectionality of multiple labor market disadvantages.[13] In absolute terms, the gender gap was similar for youth and older workers, less and better educated workers, and urban and rural workers. The age gap, however, was larger among the highly educated and in rural areas. Overall, these results do not suggest significant intersectionality, if anything young workers (who suffered disproportionate job losses during the initial phase of the crisis) fared relatively better when they had less education and lived in urban areas, despite the fact that less educated workers were more adversely affected and that urban areas in general were hit harder than rural areas.

The overall average effects across the countries in the sample reported above are revealing in themselves. Yet, the dispersion across these countries is also of potential interest. There are informative insights from the variation across countries by geographic region and by country income level group. We first discuss the regional patterns and then turn to the results by income level group. Finally, we consider the dispersion in employment indicators at the country level.

First, disaggregating the results above by region shows that the largest gender gaps in work stoppage were observed in LAC, with a whopping 16 percentage point gap in the rates at which male and female workers stopped working (Table 3). In the other regions, gender gaps are much smaller, but still to the disadvantage of women. Further country level disaggregation shows that out of the 24 countries in our sample for whom the gender gap is statistically significant, all but two have higher rates of work stoppage for women than for men, which confirms the notion that gender gaps are not just driven by a few countries or confined to any one region (Fig. A1 in Section 2 of the Supplementary material). Conversely, the most pronounced age and education gaps were observed in ECA followed by LAC, and the disparity in work stoppage between urban and rural areas was greater in SSA, followed by LAC, than in other regions.

Second, grouping countries by income level, the largest gender gap in work stoppage was observed in upper-middle income countries. Also, age and education gaps were larger in high-income countries, and then upper middle-income countries. At the same time, the disparity between urban and rural workers was greater in low-income countries and low middle-income countries (Table 4). The overall country average masks a large degree of variation in the group gaps across individual countries as is evident when looking at the shares of work stoppage for the different groups at the country level (Figs. A1 to A4 of the Supplementary material).

Now, we explore this variation across individual countries in further detail (Table A1 Section 2 of the Supplementary material). In terms of work stoppages, the countries with the highest registered shares of the workforce experiencing work stoppage, comparing pre-and post-pandemic, are clustered in South America (Bolivia, 69%; Peru, 59%; Colombia, 52%: Ecuador, 51%) and Central America (El Salvador, 56%; Honduras, 52%) with the exception of Myanmar (58%) in EAP and the Dominican Republic (52%), which like the other countries is also in LAC. The countries in South America are all Andean countries and share a common border with at least one of the others (Bolivia) or two of the others (Colombia and Ecuador), with Peru sharing a common border with all of the others. The countries in Central America also share a common long border. This is strongly suggestive of neighbor effects across countries in the severity of COVID-19 contagion making it necessary to have strict and prolonged lockdowns that induced widespread work stoppages.

The countries with the lowest rates of work stoppage are clustered in Sub-Saharan Africa (Kenya, 8%; Madagascar, 10%; Burkina Faso, 11%; Malawi, 13%; Ethiopia, 17%; Uganda, 17%) and East Asia (Vietnam, 3%; Lao PDR, 10%; Cambodia, 14%). Most of these SSA countries are not sharing any borders but Ethiopia, Kenya and Uganda all share common borders while the EAP countries all share common borders. This suggests that neighbor effects across countries can cut both ways, in limiting as well as exacerbating contagion. At the same time, the prevalence of low work-stoppage rate in all these countries reflects that they are all low-income countries or low middle-income countries and workers living there do not have access to social safety nets, formal or informal, that make unemployment spells possible. The absence of unemployment insurance induces workers to accept jobs even if they are precarious and informal with low remuneration as labor is essentially their only source of income to cover the basic necessities for their households.

The gender gap in work stoppage is largest in LAC countries (Costa Rica, Paraguay, Honduras, Colombia, Dominican Republic, Guatemala, and Saint Lucia), illustrating the very adverse labor market conditions for women in this region (Fig. A1). The gender gap is smallest in countries mainly located in SSA and EAP (Nigeria, Philippines, Central African Republic, Ethiopia, Indonesia, Madagascar, Romania and Solomon Islands). In SSA, many women are employed on family farms. In EAP, there has been

[13] Other studies have shown that the intersection of gender with other characteristics of disadvantageous status can confer cumulative disadvantages (e.g., Taş et al., 2014).

Table 1
Net employment changes and gross flows by groups, simple averages.

	Pre-pandemic employment (40 countries)	Current employment (40 countries)	% change in employed people (40 countries)	Rate of work stoppage (40 countries)	Rate of work starting (17 countries)
Women	71%	48%	−34%	36%	8%
Men	85%	62%	−27%	28%	21%
Young	71%	48%	−33%	35%	15%
Adults	80%	56%	−30%	31%	11%
Low educated	76%	49%	−36%	37%	10%
High educated	81%	56%	−31%	33%	13%
Urban	80%	56%	−30%	31%	9%
Rural	78%	58%	−26%	28%	16%

Source: Authors' calculations based on the HFPS.
Note: The table presents statistics using Wave 1 of the HFPS. Employment defined as the share of all respondents aged 18 or above that report the results of a retrospective question on working either before the pandemic (pre-pandemic employment) or during the first wave of the survey (current employment). Work stoppage defined as the share of those working before the pandemic that were not working during the survey. Work starting defined as those not working before the pandemic that were working during the survey. Results are simple averages across available countries.

Table 2
Rate of work stoppage by interactions between groups.

	Women	Men	Young	Adult	Low-eductaed	High-educated	Urban	Rural
Women	.	.	0.39	0.35	0.42	0.37	0.35	0.32
Men	.	.	0.32	0.28	0.33	0.29	0.28	0.26
Young	0.39	0.32	.	.	0.36	0.38	0.33	0.35
Adult	0.35	0.28	.	.	0.39	0.33	0.31	0.28

Source: Authors' calculations based on the HFPS.
Note: The table presents statistics using Wave 1 of the HFPS.

Table 3
Rate of work stoppage by groups and regions.

	All	EAP	ECA	LAC	MNA	SSA
Women	0.36	0.23	0.31	0.58	0.27	0.26
Men	0.28	0.21	0.27	0.42	0.25	0.23
Young	0.35	0.22	0.43	0.53	0.20	0.26
Adult	0.31	0.21	0.28	0.48	0.27	0.23
Low educated	0.37	0.25	0.38	0.56	.	0.22
High educated	0.33	0.25	0.23	0.47	.	0.24
Urban	0.31	0.22	0.29	0.48	.	0.25
Rural	0.28	0.20	0.29	0.47	.	0.20
Average	**0.32**	**0.22**	**0.31**	**0.50**	**0.25**	**0.24**

Source: Authors' calculations based on the HFPS.
Note: The table presents statistics using Wave 1 of the HFPS.

Table 4
Rate of work stoppage by groups and income level.

	Low income	Lower-middle income	Upper-middle income	High income
Women	0.26	0.33	0.53	0.30
Men	0.20	0.29	0.37	0.23
Young	0.23	0.32	0.50	0.40
Adult	0.22	0.30	0.43	0.26
Low educated	0.23	0.33	0.53	0.38
High educated	0.25	0.32	0.42	0.26
Urban	0.22	0.30	0.44	0.27
Rural	0.16	0.26	0.45	0.26
Average	**0.22**	**0.31**	**0.46**	**0.29**

Source: Authors' calculations based on the HFPS.
Note: The table presents statistics using Wave 1 of the HFPS.

progress in leveling the playing field for women in the labor market.

The age gap is significantly different from zero mainly in EAP (Fig. A2), pointing to youth being adversely affected by seniority norms (Croatia, Solomon Islands, Paraguay, Ecuador, Lao PDR, Papua New Guinea and Vietnam).

The education gap is highest mainly in LAC countries (Fig. A3), where the digital divide affecting low skill workers is very severe (Peru, Chile, Costa Rica, Ecuador, Guatemala, El Salvador and Philippines). The education gap is lowest mainly in SSA, where workers across the board are forced to work due to the absence of safety nets (Uganda, Mongolia, Kenya, Madagascar, Kenya and Malawi).

Finally, the urban–rural gap is significantly different from zero mainly in SSA (Ethiopia, Uganda, Nigeria, Indonesia, Madagascar, Zimbabwe, Bolivia, Burkina Faso and Kenya). City dwellers were hardest hit in these primarily low-income and low middle-income countries, with the exception of Indonesia (Fig. A4).

The evidence shows that the most vulnerable groups to the pandemic macroeconomic shock in the labor markets were primarily women, youth, the less educated, and urban workers. These workers were the most disadvantaged from the point of view of being exposed to work stoppage due to the COVID-19 lockdowns and other measures that induced turbulence in economics activity leading many businesses to shrink or shutdown and therefore reduce employment.

Overall, these results are consistent with other studies showing that the groups traditionally disadvantaged in the labor market were hit hardest by the crisis, at least during its initial phase.[14] Lee et al. (2021) show that in the United States, the initial negative impacts of the pandemic were larger for women, minorities, less educated and young workers. Similarly, the COVID-19 crisis disproportionately affected women, young and contingent workers in Japan (Kikuchi et al. 2021). Dang and Nguyen (2021) use data from China and five OECD countries to show that women were significantly more likely to lose their jobs than men and suffered larger income losses.

The analysis of the driving forces behind the larger rates of work stoppage for women than men has been extensively covered by the COVID-19 related literature.[15] The two mechanisms that are most prominently mentioned are gender differences in care and domestic responsibilities as well as occupational and sectoral gender segregation. The closing of schools and nurseries implied an increase in the time allocated to housework and childcare. The evidence so far shows that, in general, both women and men increased the amount of time allocated to these activities, but the extra time was not equally distributed between them and was larger for women.[16] On the occupational and sectoral gender segregation side, the pandemic recession differs from previous ones in that contact-intensive sectors, such as travel, restaurant, and other services, were more affected due to social distancing measures. These sectors tend to employ larger shares of women which helps explain the gender gaps in employment losses.[17] Given the lack of information on the distribution of care activities within households and the absence of granular data on the economic sector of employment for persons who were employed before the pandemic and other potential drivers of gender gaps, such as discrimination, we refrain from analyzing the possible causes of the larger rates of work stoppage for women in comparison to men using the HFPS.

3.2. Disparities in employment type and sector

As shown in Table 5, the changes in the shares of wage employment are largest for young workers with an 8 percentage points drop, followed by women and less educated workers, who experienced a 3 percentage points fall. The disproportionate fall in wage employment, and equivalent increase in the share of self-employment, among younger workers could reflect lower levels of job security related to tenure among such workers.

Table 5
Average changes in the share of wage employees by group (percentage points).

Women	−0.03
Men	−0.02
Young	−0.08
Adult	−0.02
Low educated	−0.03
High educated	−0.03
Urban	−0.02
Rural	−0.03

Source: Authors' calculations based on the HFPS.
Notes: The table presents statistics using Wave 1 of the HFPS. Calculations use HFPS retrospective data as pre-COVID information. The table shows the average change in the share of wage employment, which includes seasonal/temporary employment, in total employment by group.

Table 6
Average changes in employment sector by group (percentage points).

Panel A: Primary		**Panel C: Services**	
Women	0.006	Women	0.005
Men	0.009	Men	−0.010
Young	0.018	Young	0.000
Adult	0.006	Adult	−0.005
Low educated	0.007	Low educated	−0.007
High educated	0.008	High educated	−0.005
Urban	0.003	Urban	0.004
Rural	0.012	Rural	−0.009
Panel B: Industry		**Panel D: Public Administration**	
Women	−0.010	Women	−0.001
Men	0.002	Men	−0.001
Young	−0.021	Young	0.003
Adult	0.001	Adult	−0.001
Low educated	−0.007	Low educated	0.001
High educated	−0.002	High educated	−0.001
Urban	−0.006	Urban	−0.001
Rural	0.002	Rural	−0.005

Source: Authors' calculations based on the HFPS.
Notes: The table presents statistics using Wave 1 of the HFPS. Calculations use HFPS retrospective data as pre-COVID information. The table shows the average change in the share of employment in the primary sector/industry/services (other than public administration)/public administration in total employment by group.

The average changes in employment sector do not display any substantive differences between groups (Table 6). Employment fell slightly more for youth than adults in the industrial sector, but overall, we find no marked differentials.

3.3. Household income from farm income, non-farm income, and wage work

Household income change provides another useful indicator of economic well-being. However, because it is a household rather than individual outcome, it is difficult to interpret differences by individual characteristics such as gender, education, and age of the respondent. When looking at the changes in the distribution of household income by urban and rural location, the most salient pattern is the self-reported decline in household non-farming income (affecting 66 percent of households in rural areas and 70 percent of households in urban areas) and wage income (46 percent of households in both urban and rural areas), as illustrated in Table 7. As expected, the declines in income from farming activities affected rural more than urban households (60 percent in rural locations and 55 percent in urban locations). Overall, this indicates widespread income losses in both urban and rural areas, resulting from the labor market turbulence and employment disruptions triggered by the COVID-19 pandemic.

Finally, we examine whether income declines in the household are associated with the entrance of women into employment, sim-

[14] An exception is the higher rates of work stoppage among urban workers, which can, however, be linked to the fact that densely populated areas were disproportionately affected by the lockdown and social distancing measures.
[15] See Alon et al. (2022), Lee et al. (2021), Albanesi and Kim (2021), and Montenovo et al. (2020) for the U.S., Kikuchi et al. (2021) for Japan, Dang and Nguyen (2021) for China and five OECD countries, Qian and Fuller (2021) for Canada, Farré et al. (2022) for Spain, Del Boca et al. (2020) for Italy, Andrew et al. (2020) for England, Adams-Prassl et al. (2020) for U.K., U.S. and Germany, and World Bank (2021a, 2021b) for countries in the LAC and EAP regions.
[16] Adams-Prassl et al. (2020); Del Boca et al. (2020); Sevilla and Smith (2020).
[17] Mongey et al. (2021), Alon et al. (2020, 2022), Hupkau and Petrongolo (2020), Queisser et al. (2020), Torres et al. (2023).

Table 7
Distribution of household income changes by type of income and location.

	Increased	Stayed the same	Decreased	Stopped receiving
Panel A: Urban				
Family farming	6%	29%	55%	10%
Non-farming	5%	16%	70%	10%
Wage employment	4%	44%	46%	7%
Panel B: Rural				
Family farming	6%	28%	60%	7%
Non-farming	5%	17%	66%	11%
Wage employment	5%	41%	46%	7%

Source: Authors' calculations based on the HFPS.
Note: The table present statistics using Wave 1 of the HFPS.

Table 8
Average rate and change in employment between April and August.

	Pre-pandemic	April/May	August	Diff. Agust vs. April/May	Diff. August vs. Pre-pandemic	Number of countries
Women	0.55	0.36	0.50	38%	−9%	10
Men	0.75	0.58	0.71	23%	−5%	10
Young	0.59	0.43	0.58	34%	−3%	10
Adult	0.66	0.48	0.62	29%	−7%	10
Low educated	0.68	0.35	0.51	44%	−25%	5
High educated	0.77	0.46	0.59	28%	−23%	5
Urban	0.65	0.47	0.60	30%	−7%	9
Rural	0.62	0.48	0.62	28%	0%	9

Source: Authors' calculations based on the HFPS.
Notes: The table presents the employment rate by group in April/May and August. Countries with available information in April/May and August: Chile, Costa Rica, Dominican Rep., Ethiopia, Guatemala, Cambodia, St. Lucia, Myanmar, Nigeria and Uzbekistan. Education level n.a. in Ethiopia, Cambodia, St. Lucia, Nigeria and Uzbekistan. Urban/rural location n.a. in Guatemala.

ilar to an "added worker" effect.[18] A total of 8 percent of women started working following the crisis in the 13 countries where income change and work stoppage are both measured. Of these, about 61 percent of women lived in households that reported an income decline while 39 percent lived in households where total household income increased, did not change or was not received. Of the women that did not enter employment, 58 percent lived in households that reported an income decline while 42 lived in households where total household income increased, did not change, or was not received. We speculate this evidence could be suggestive of a small added worker effect for women.

4. Evolution of the employment impact by worker type

4.1. Employment indicators

Table 8 shows the evolution of employment after the initial shock due to the pandemic, for a subset of 10 countries for which information is available for both April and August of 2020.[19] Employment rates increased for all groups between April and August. In absolute terms, growth ranged from 13 percentage points for male, urban, and high educated workers, to 16 percentage points for less educated workers. In percentage terms, less educated, female, and younger workers experienced disproportionately large gains between April and August. The right column of Table 8 shows that, except for rural workers, this was not enough to return to pre-crisis levels of employment. Furthermore, net job losses from before the crisis to August remained moderately higher for women than for men (9 percent vs. 5 percent), and for urban than rural residents (7 percent vs no change). On the other hand, the disproportionate gains for young workers erased the penalty that youth faced, relative to adults, in the first stage of the crisis. It is important to note that we can only assess whether workers were able to regain employment between April and August but are unable to gauge to what extent they experienced a deterioration in the wage or some other measure of employment quality.

Fig. 1 shows the relationship between workplace mobility, taken from Google community mobility reports, and employment change by gender, for the seven countries for which both are available. In general, increases in mobility are correlated with employment growth, although the sample is very limited. Meanwhile, in five of the seven countries, mobility increased between April and August, providing further indication that the initial phase of the crisis in April and May was the most constrictive in terms of mobility. Overall, this suggests the comparison in this section, of April/May to August 2020, is indicative of the short-term labor market recovery during a period in which the brunt of the initial phase of the pandemic and associated lockdowns started to subside and mobility started to normalize. This is notwithstanding the fact that the pandemic, obviously, continued and that many countries experienced additional, severe waves of infections and mobility restrictions in the latter part of 2020 and early 2021.

Table 9 shows that the share of women in wage employment fell moderately more than the comparable share for men. This indicates that the disproportionate recovery in overall employment for female workers in these 10 countries did not fully extend to wage employment, where the recovery was slower than for self-employment.

Differences also emerge between groups when looking at the sectoral composition of employment between April and August (Table 10). Men were disproportionately more likely to shift out of services into agriculture (a 4 percentage points shift), while the share of women employed in different sectors changed very lit-

[18] The added worker effect refers to a temporary increase in married women's labor supply due to their husband's job or income loss (e.g., Lundberg, 1985; Skoufias and Parker, 2006).
[19] For urban and rural indicators, only 9 countries are available, while for education only five are.

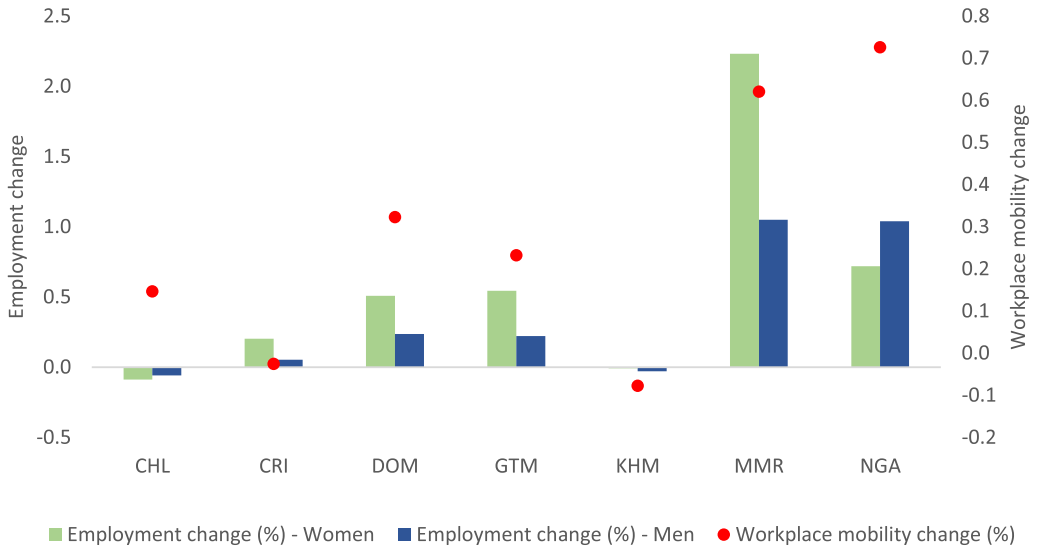

Fig. 1. Relationship between employment change by gender and workplace mobility change between April and August. Source: Authors' calculations based on the HFPS and OurWorldInData. Notes: The workplace mobility measure captures the change in number of visitors workplaces compared to baseline days (the median value for the 5 week period from January 3 to February 6, 2020). Measure not available for Ethiopia, St. Lucia and Uzbekistan.

Table 9
Average rate and change in wage employment share between April and August.

	April/May	August	Difference
Women	0.57	0.52	−9%
Men	0.55	0.52	−5%
Young	0.60	0.56	−6%
Adult	0.55	0.52	−7%
Low educated	0.55	0.53	−4%
High educated	0.68	0.65	−5%
Urban	0.60	0.58	−4%
Rural	0.50	0.47	−6%

Source: Authors' calculations based on the HFPS.
Note: The table shows the share of wage employment, which includes seasonal/temporary employment, in total employment by group in April/May and August. Countries with available information in April and August: Chile, Costa Rica, Dominican Rep., Ethiopia, Guatemala, Cambodia, St. Lucia, Nigeria, and Uzbekistan.

tle. Young workers shifted out of industry and public administration and into services and agriculture, whereas adults were more likely to shift out of services and into agriculture. The share of less educated workers in the industrial sector increased, while the sectoral shares of more educated workers remained relatively constant. Finally, the share of rural workers in agriculture increased by 3 percentage points. In general, the sectoral picture suggests that men, younger workers, and rural workers may have had less favorable sectoral shifts than other groups during the period from April to August.[20]

4.2. Household income from farm income, non-farm income, and wage work

The evolution in the share of households self-reporting an increase in income is also consistent with improvements in labor market conditions between April and August 2020 (Table 11). For urban households, the share of households reporting a rise or no change in non-farm enterprise income increased from 17 to 31 percent, while the share reporting a higher or constant wage income rose from 40 to 62 percent. Rural areas saw similar improvements,

[20] It is important to emphasize that we treat the data as repeated cross-sections and do not follow individuals over time. The 'shifts' described in this paragraph should therefore be viewed as aggregate changes in the sectoral composition of employment and do not necessarily correspond to individual transitions across sectors.

Table 10
Average change in employment sector between April and August.

	April/May	August	Difference
Panel A: Primary			
Women	0.19	0.20	6%
Men	0.27	0.31	14%
Young	0.19	0.23	17%
Adult	0.25	0.28	11%
Low educated	0.25	0.24	−2%
High educated	0.09	0.09	0%
Urban	0.14	0.16	18%
Rural	0.41	0.44	7%
Panel B: Industry			
Women	0.05	0.05	−5%
Men	0.13	0.13	5%
Young	0.12	0.09	−26%
Adult	0.10	0.10	6%
Low educated	0.08	0.11	49%
High educated	0.09	0.10	10%
Urban	0.10	0.10	−4%
Rural	0.11	0.11	2%
Panel C: Services			
Women	0.68	0.69	0%
Men	0.54	0.50	−7%
Young	0.63	0.66	4%
Adult	0.58	0.56	−4%
Low educated	0.65	0.63	−3%
High educated	0.76	0.77	0%
Urban	0.68	0.67	−1%
Rural	0.43	0.41	−5%
Panel D: Public administration			
Women	0.07	0.06	−17%
Men	0.06	0.05	−12%
Young	0.05	0.03	−48%
Adult	0.07	0.06	−12%
Low educated	0.02	0.01	−40%
High educated	0.05	0.04	−19%
Urban	0.08	0.07	−14%
Rural	0.05	0.04	−17%

Source: Authors' calculations based on the HFPS.
Notes: The table shows the share of employment in the primary sector/industry/services (other than public administration)/public administration in total employment by group in April/May and August. Countries with available information in April/May and August (Chile, Costa Rica, Dominican Rep., Ethiopia, Guatemala, Cambodia, St. Lucia, Nigeria).

as the share of households reporting higher or constant non-farm enterprise income increased from 17 to 29 percent, and from 39 to 59 percent for wage income. These figures suggest that urban and rural areas were both benefiting from improved labor market conditions during this time. In the case of rural regions, it may well be the case that seasonal harvests were a factor behind this evolution in labor incomes, especially with respect to income from farming.

5. Robustness checks

5.1. Sampling frame

We start by confirming the disproportionate declines in employment and higher rates of work stoppage for women, young and low educated workers in countries with RDD sampling frame (Table 12). The RDD samples are less skewed towards household heads and therefore would be expected to provide more accurate information on employment disparities between types of workers. The gender and education differences are larger in RDD countries than in countries with a sampling frame based on previous surveys. Fig. 2 shows country level calculations for the gender gap. It is impossible to distinguish, however, how much of this is due to absence of selection bias, as opposed to systematic differences between RDD countries, which are mainly in LAC, and the countries that implemented other types of sampling frames. Nonetheless, it is reassuring that the substantial gender and education differences observed in the full sample are also observed in the RDD samples.

5.2. Reweighting of HFPS

The reweighting approach in this section seeks to correct for biases introduced by the under-sampling of some population groups in the HFPS. Given that the source of the sample selection is related to, besides having a phone, position in the household and gender, we use a reweighting scheme based on observables reflecting these characteristics. We merged the HFPS (selected sample) to nationally representative microdata collected before the pandemic (representative sample) and estimated a Probit model for the probability of being selected into the HFPS-Wave 1 sample. Depending on availability, the independent variables included sex, age, educational level, and urban/rural area. The reweighting factor is defined as the inverse of the propensity score.

Table 12
Net employment changes and gross flows by sampling frame and groups, simple averages, wave 1 of survey.

	% change in employed people	Rate of work stoppage	Rate of work starting
Panel A: RDD			
Women	−49%	50%	8%
Men	−35%	37%	23%
Young	−44%	47%	16%
Adults	−41%	42%	10%
Low educated	−48%	50%	9%
Higheducated	−39%	41%	12%
Urban	−39%	40%	11%
Rural	−39%	41%	13%
Panel B: Based on previous surveys			
Women	−25%	26%	10%
Men	−22%	23%	18%
Young	−25%	27%	13%
Adults	−23%	24%	14%
Low educated	−23%	25%	13%
High educated	−23%	24%	14%
Urban	−25%	25%	7%
Rural	−19%	21%	21%

Source: Authors' calculations based on the HFPS.

This gives greater weight to observations that are in fact present in the phone survey despite having a low predicted probability of being sampled by the phone survey.

The comparison of results with and without reweighting reveals that the differences that stem from the adjustment are not substantive (see Fig. 3, focusing on gender differences). In other words, reweighting based on observables does not materially alter the main results reported in this paper.

5.3. Comparison with ILO data

As an additional robustness check, we examine ILO data on employment rates by groups for a small set of 14 developing and transition countries (mostly middle income) with available information from 2019Q2 to 2020Q2 (Table 13). The ILO data come from nationally representative labor force surveys that cover all workers and were able to continue data collection activities during the pandemic, but cover fewer countries, and particularly no low-income countries. Analyzing the ILO data largely corroborates HFPS findings of larger employment declines for women, young and low-

Table 11
Change in share of households reporting income changes since the start of the pandemic between April/May and August by direction of income change and location.

	April/May	August	Difference	April/May	August	Difference
Panel A: Farm income						
Increased	0.04	0.06	0.02	0.03	0.09	0.06
Stayed the same	0.23	0.30	0.07	0.20	0.33	0.13
Decreased	0.53	0.50	−0.03	0.69	0.48	−0.21
Not received	0.20	0.15	−0.05	0.08	0.10	0.02
Panel B: Non-farm income						
Increased	0.02	0.08	0.05	0.04	0.07	0.03
Stayed the same	0.15	0.23	0.08	0.13	0.22	0.09
Decreased	0.72	0.44	−0.28	0.67	0.43	−0.24
Not received	0.10	0.25	0.14	0.16	0.28	0.12
Panel C: Wage income						
Increased	0.05	0.09	0.04	0.06	0.11	0.05
Stayed the same	0.35	0.53	0.18	0.33	0.48	0.15
Decreased	0.52	0.36	−0.16	0.52	0.37	−0.16
Not received	0.08	0.02	−0.06	0.08	0.04	−0.04

Source: Authors' calculations based on the HFPS.
Notes: The table presents the share of household reporting income changes by type of income, direction of change, and location in April/May and August. Statistics include information on Chile, Costa Rica, Dominican Rep., Ethiopia, Cambodia, St. Lucia, Myanmar and Uzbekistan. For April we use a question capturing income changes since the start of the pandemic; in August, the question refers to income changes since the last wave of the survey.

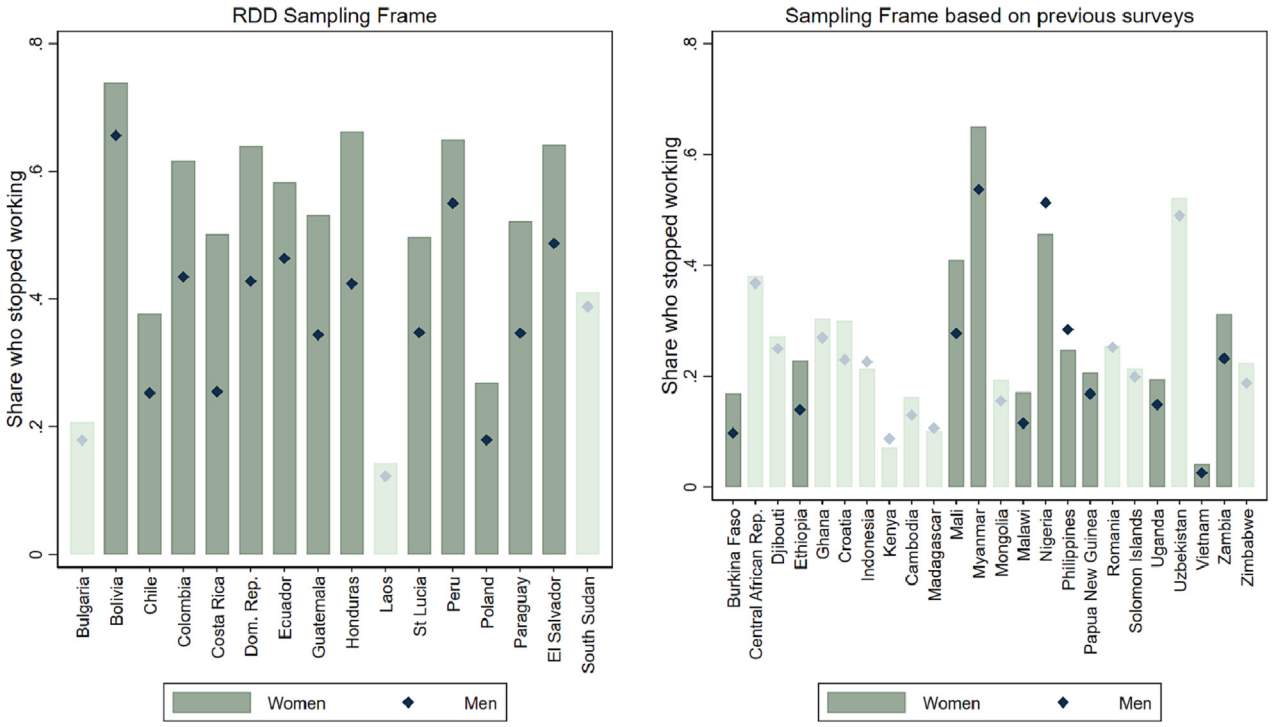

Fig. 2. Gender gaps in rate of work stoppage by sampling frame and country. Source: Authors' calculations based on the HFPS. Notes: Dark (light) colors indicate that the difference between groups is (not) statistically significant at 5% level or less.

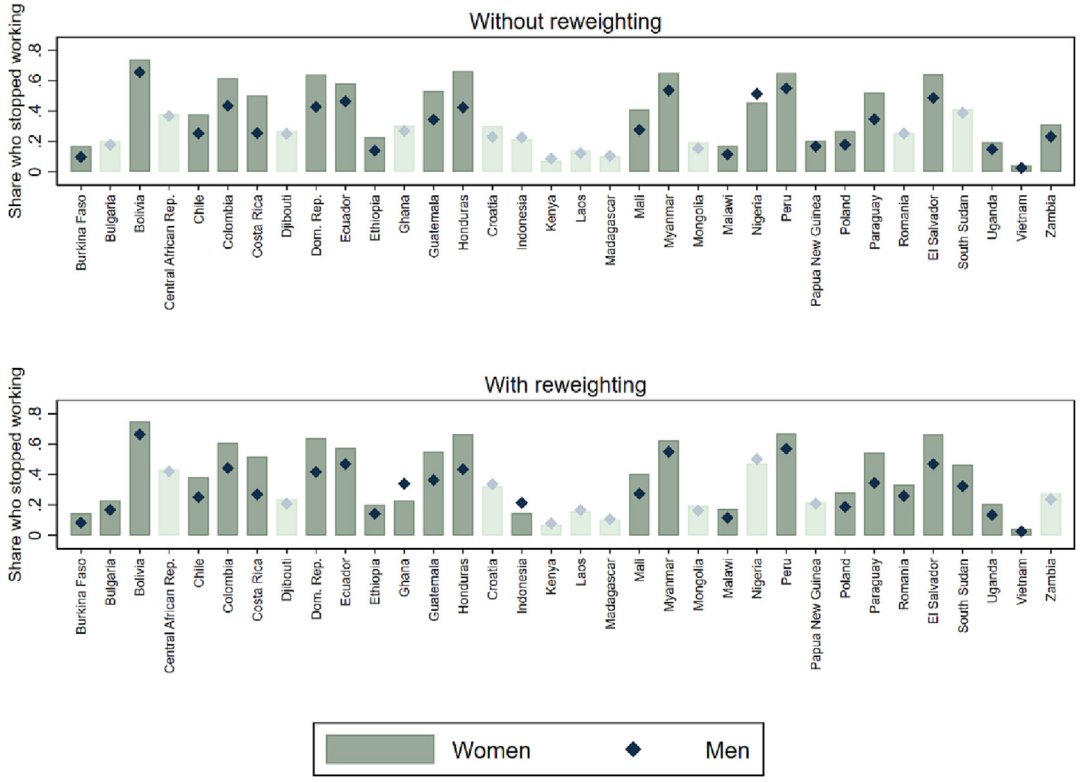

Fig. 3. Gender gaps in rate of work stoppage by country without and with reweighting. Source: Authors' calculations based on the HFPS. Notes: Dark (light) colors indicate that the difference between groups is (not) statistically significant at 5% level or less.

Table 13
Average employment change between 2019Q2 and 2020Q2 (in percentages).

Women	−17.6
Men	−12.4
Young	−21.7
Adult	−14.3
Low educated	−16.9
High educated	−14.2
Urban	−15.8
Rural	−11.0

Source: Authors' calculations based on data from ILO Stat.
Notes: The sample includes 14 countries (Argentina, Brazil, Chile, Colombia, Costa Rica, Ecuador, St. Lucia, Mexico, Mongolia, Peru, Paraguay, Thailand, Vietnam, and South Africa).

educated, and urban workers. However, the differences by education are less pronounced than those in the HFPS data.

5.4. Validation of HFPS sampling methodology and reweighting

5.4.1. Method and descriptive statistics

The robustness checks above, while encouraging, only partially address a key question that arises when analyzing phone surveys: Does the skewed selection of household respondents bias the assessment of which types of workers experienced the largest declines in employment? As noted above, the HFPS sampling strategy leads to bias because it only samples one member per household, which tends to be the head in most countries that drew the sample from a previous survey. Moreover, unlike traditional household surveys that often use proxy respondents to provide information on behalf of other household members not available to be interviewed, the HFPS (due to the time constraints induced by the phone survey setting) typically only ask about the employment situation of the respondent. To better understand how this source of bias affects comparisons between types of workers and the effectiveness of reweighting strategies, we use data from five countries which collected household surveys containing labor market information for all household members during the COVID-19 pandemic. These five countries are Brazil, Colombia, Kenya, Malawi, and Nigeria. Using this information, we compare employment statistics of all working-age household members, defined as 18 years old and above, with those from a subsample comprising only one person per household without and with reweighting. For Nigeria, we use the Wave 5 of the National Longitudinal Phone Survey collected in September 2020. For Kenya, we use the World Bank Covid-19 Rapid Response Phone Survey collected between May and June of 2020, while for Malawi, we use information from the Wave 5 of the HFPS.[21] For these three countries, we can identify the respondent of the survey who provided information of all household members. Because the data was collected after the pandemic started, and there is no comparable data from 2019 or 2020, we compare between-group differences in employment *levels* during the pandemic for all working-age household members versus the subsample of respondents.

It is important to clarify that for Brazil and Colombia, we do not use the HFPS data to validate the HFPS sampling methodology.[22] Instead, we use household phone survey data collected by national statistics offices using pre-existing sampling frames. This means that, for both Brazil and Colombia, we have information from before and directly after the pandemic. For Brazil, we use the Pesquisa Nacional por Amostra de Domicilios Continua (PNAD-C) and compare the second quarter of 2019 (pre-pandemic period) with the second quarter of 2020 (during-pandemic period). For Colombia, we use data from January to June 2020 from the Gran Encuesta Integrada de Hogares (GEIH). We consider the first quarter of 2020 as a pre-pandemic period and the second quarter as a during-pandemic period. For these two countries, we cannot identify a respondent of the survey. Therefore, we simulate a phone survey following the composition of HFPS by selecting only one person per household. We randomly draw individuals in a way that the resulting sample consists of 66 percent of household heads, 20 percent of spouses, 11 percent of children, and 3 percent of other members, to match the pooled composition of HFPS surveys (in countries that collected relationship to head).

We use four candidate reweighting methods. First, similarly to the reweighting of the HFPS presented in previous section, we calculate an inverse propensity score from a Probit model where the dependent variable takes the value one when the observation belongs to the subsample of respondents or to the simulated phone survey, depending on the country considered. For Brazil and Colombia, we run the model combining data from the pre-COVID complete sample (including all household members) and during-COVID simulated phone survey, while for Nigeria, Kenya and Malawi we combine the during-COVID full household data and during-COVID respondent subsample. Depending on availability, controls include age, gender, education, location, and region. In this method, weights are defined as the original household weights times the inverse of the propensity score.[23]

Second, relying on the propensity score obtained previously, we calculate the average value by deciles and define weights as the original household weights times the inverse of the average propensity score by deciles, as is common in the epidemiological literature.[24]

Third, we adjust weights using raking applied to the simulated phone survey sample in Colombia and Brazil or respondents' sample in Nigeria, Kenya, and Malawi. This method adjusts the original weights allowing them to represent the total number of women, men, young, adult, low-educated, high–educated, urban and rural people in the pre-COVID full household data in Colombia and Brazil, or during-COVID complete sample in Nigeria, Kenya and Malawi.[25]

Finally, we combine the raking and inverse probability score methods. In this case, the weights obtained applying raking are multiplied by the inverse probability.

In the next subsection we present results comparing employment levels between the complete household data, the sample of respondents or simulated phone survey, and sample of respondents or simulated phone survey using the inverse propensity score reweighting method. Results using the other methods are shown in Section 3 of the Supplementary material and are generally similar. The same section presents the results obtained when comparing employment changes.

Below, we provide descriptive statistics comparing characteristics between the complete household data and the samples of respondents or simulated phone survey data, depending on the country. As expected, the simulated phone survey samples (Table 14) and respondent samples (Table 15) are, on average, older, and contain a higher share of household heads, compared to the samples of all household members. This shows that the reweighting approach successfully improves the balance of characteristics that were used to estimate the propensity score.

[21] For some specific waves and countries, the HFPS collected information of all household members.
[22] No HFPS data was collected in Brazil.
[23] Following Horvitz and Thompson (1952), Robins et al. (1995), Wooldridge (2002), and many others.
[24] Kurth et al. (2006), Schneeweiss et al. (2009), and others.
[25] See Kalton and Flores-Cervantes (2003) for more information on raking.

Table 14
Surveys with simulated phone survey.

	Colombia		Brazil	
	Pre-COVID 2020Q1	During-COVID 2020Q2	Pre-COVID 2019Q2	During-COVID 2020Q2
Panel A: Complete sample				
Female	0.54	0.55	0.52	0.52
Young	0.16	0.16	0.24	0.23
Low educated	0.27	0.27	0.88	0.89
Urban	0.88	0.88	0.88	0.85
Share heads	0.42	0.42	0.34	0.35
Share spouses	0.23	0.23	0.22	0.21
Share children	0.21	0.22	0.39	0.39
Share other members	0.14	0.14	0.06	0.05
N	94,506	99,700	82,175	81,248
Panel B: Simulated phone survey				
Female	0.55	0.55	0.54	0.55
Young	0.11	0.10	0.14	0.13
Low educated	0.29	0.29	0.85	0.86
Urban	0.87	0.87	0.88	0.86
Share heads	0.66	0.66	0.66	0.66
Share spouses	0.20	0.20	0.19	0.19
Share children	0.11	0.11	0.11	0.11
Share other members	0.03	0.03	0.04	0.04
N	40,110	41,422	27,840	27,840

Source: Authors' calculations based on the GEIH 2020 (Colombia) and PNAD-C 2019 and 2020 (Brazil).
Notes: The table shows basic descriptive statistics of samples in Colombia and Brazil. These surveys obtained labor market information for all household members.

Table 15
Surveys with observed respondent.

	Nigeria		Kenya		Malawi	
	Respondent	All hhld members	Respondent	All hhld members	Respondent	All hhld members
Share heads	0.82	0.33	0.65	n.a.	0.75	0.40
Share spouses	0.10	0.31	0.22	n.a.	0.20	0.30
Share children	0.07	0.24	0.06	n.a.	0.04	0.19
Share other members	0.02	0.13	0.06	n.a.	0.01	0.12
Female	0.25	0.51	0.52	0.52	0.40	0.51
Young	0.05	0.26	0.10	0.26	0.10	0.29
Low-educated	n.a.	n.a.	0.47	n.a.	n.a.	n.a.
Urban	0.39	0.37	0.55	0.54	0.37	0.39
N	1,527	4,454	4,057	10,268	1,570	3,868

Source: Authors' calculations based on NLPS-Wave 5 (Nigeria), World Bank Covid-19 Rapid Response Phone Survey (Kenya), and HFPS-Wave 5 (Malawi).
Notes: The table shows basic descriptive statistics of samples in Nigeria, Kenya, and Malawi. These surveys obtained labor market information for all household members. Data on all respondents is not available for certain characteristics in Kenya and Malawi.

5.4.2. Validation of differences in employment levels

Table 16 compares between group differences in employment levels for the samples of all household members and the samples that mimic the phone survey, i.e., the simulated phone survey samples in Brazil and Colombia and the respondent samples in Kenya, Malawi, and Nigeria. The table shows that the simulated phone surveys and respondent samples, because they are skewed towards household heads, consistently overestimate employment rates. The amount of the bias ranges from about 2 percentage points in Brazil to about 12 percentage points in Malawi.

For Brazil and Colombia, the simulated phone survey provides reasonably good estimates – i.e., close to the values observed in the sample of all household members—of between-groups differences in employment levels. There are exceptions when the grouping variable is very unbalanced between samples, such as age in Brazil. For Kenya, Malawi and Nigeria, the sample of respondents provides a close estimation of differences in employment levels observed in the complete sample when grouping by gender and location but underestimates the difference by age groups. A possible explanation is that in the three countries, age is the variable for which the samples of all household members and respondents differ the most.

In Brazil and Colombia, the inverse propensity score reweighting method provides results that are close to those obtained using the simulated phone surveys. Thus, the reweighting method is close to the between-group differences in employment levels observed in the sample of all household members, except when the grouping variable is unbalanced between samples. In Kenya, Malawi and Nigeria, the inverse propensity score reweighting method tends to overestimate differences in employment between groups in Nigeria and provides mixed results – i.e., overestimation or underestimation—depending on the grouping variable in Kenya and Malawi.

To summarize, the simulated phone survey and respondents' samples provide good estimates of between-group differences in employment levels when the grouping variable is balanced between samples, suggesting that the specific selection approach of household members in the phone surveys does not have a strong effect on measured employment gaps between groups. All things considered, the reweighting methods do not improve the accuracy of the estimated disparities across groups.

Table 16
Between-group differences in employment levels during-COVID.

	All hhld members	Simulated PS/ Respondents	Simulated PS/Respondents Reweighted
Panel A: Colombia			
Women	0.37	0.41	0.41
Men	0.66	0.70	0.71
	−43%	−42%	−42%
Young	0.38	0.44	0.44
Adults	0.54	0.56	0.57
	−28%	−21%	−22%
Low-educated	0.45	0.50	0.51
High-educated	0.54	0.58	0.58
	−16%	−14%	−12%
Urban	0.50	0.54	0.54
Rural	0.54	0.59	0.59
	−8%	−9%	−8%
All people	0.51	0.55	0.55
Panel B: Brazil			
Women	0.40	0.40	0.42
Men	0.58	0.62	0.63
	−31%	−35%	−34%
Young	0.29	0.37	0.37
Adults	0.53	0.51	0.54
	−45%	−28%	−32%
Low-educated	0.44	0.46	0.48
High-educated	0.74	0.73	0.75
	−40%	−38%	−37%
Urban	0.49	0.51	0.52
Rural	0.42	0.44	0.46
	18%	15%	14%
All people	0.48	0.50	0.52
Panel C: Nigeria			
Women	0.67	0.75	0.69
Men	0.80	0.88	0.88
	−16%	−15%	−21%
Young	0.62	0.73	0.57
Adults	0.77	0.86	0.82
	−19%	−15%	−31%
Urban	0.68	0.79	0.67
Rural	0.76	0.88	0.82
	−10%	−10%	−19%
All people	0.74	0.85	0.77
Panel D: Kenya			
Women	0.47	0.53	0.53
Men	0.55	0.62	0.62
	−14%	−15%	−14%
Young	0.40	0.50	0.50
Adults	0.55	0.59	0.60
	−27%	−15%	−15%
Urban	0.39	0.45	0.44
Rural	0.57	0.64	0.64
	−31%	−31%	−32%
All people	0.51	0.57	0.58
Panel E: Malawi			
Women	0.59	0.71	0.70
Men	0.73	0.89	0.88
	−19%	−20%	−21%
Young	0.43	0.78	0.73
Adults	0.74	0.82	0.79
	−42%	−5%	−8%
Urban	0.57	0.74	0.69
Rural	0.68	0.84	0.82
	−17%	−13%	−16%
All people	0.66	0.82	0.79

Source: Authors' calculations based on GEIH (Colombia), PNAD-C (Brazil), NLPS-Wave 5 (Nigeria), World Bank Covid-19 Rapid Response Phone Survey (Kenya), and HFPS-Wave 5 (Malawi). Propensity score reweighting approach shown. Notes: The reweighting method presented in the last column is the inverse propensity score.

6. Conclusion

The primary objective of this research was to identify which groups, defined by gender, age, education, and urban/rural location, were hit hardest by the labor market impacts of COVID-19 in developing countries. The analysis is based on combined information from high-frequency phone surveys in 40 countries. The results indicate that the brunt of the burden from the pandemic, in terms of employment losses, were borne by women, young, less educated, and urban segments of the workforce.

Between April and August, employment increased moderately in the 10 countries for which data are available, and gains were more pronounced for the groups that experienced the largest initial job losses. In other words, female, less educated, and to a lesser extent, young and urban workers experienced disproportionate employment gains. However, these were not sufficient to offset the size of the initial losses and we cannot gauge if the new employment opportunities offer wages or conditions similar to the jobs lost. Thus, there are relative improvements compared to the early stage of the crisis, but these may reflect an evolution towards a lower-level equilibrium. Our results may also reflect a 'trampoline' effect, with some groups having a stronger rebound given their relatively lower baseline, due to the employment losses they experienced in the early stages of the pandemic.

In order to be confident in the differences we observe in employment impacts from the pandemic across different groups of workers, we needed to carefully examine the role of bias in the phone surveys. The HFPS could provide a biased picture of labor market conditions because (i) people lacking access to phones experienced systematically different labor market outcomes than people included in the sample, and (ii) samples that used previous surveys as sample frames overrepresented household heads and underrepresented members who are neither heads nor spouses. To address these sources of bias, we further reweighted observations in the HFPS based on individual characteristics, and tested the performance of the reweighting methods. To assess the extent of bias in the sample and the reweighted estimates, we compared post-COVID-19 levels and, when possible, trends in employment from the HFPS with those from household surveys for a selected group of five countries: Brazil, Colombia, Kenya, Malawi, and Nigeria.[26] These five countries were selected because they collected employment data, since the beginning of the pandemic, on all household members and not only the single member who responded to the phone survey.

Because of its skewed composition, the evidence from the five countries indicates that the HFPS surveys overstate employment rates for the full population. However, the phone surveys did reasonably well at tracking overall disparities in employment rates across gender, education, and urban/rural groups. Furthermore, evidence from two of these countries suggests that, in general, the HFPS accurately tracked the pattern of changes between these groups.[27] In other words, gender, education, and urban/rural gaps in employment were generally similar for heads, who were overrepresented in the HFPS, and members that were not heads or spouses who were underrepresented. Thus, the non-representative nature of the surveys (i.e., oversampling household heads) did not seriously affect estimates of group differences in employment outcomes and trends and could provide meaningful guidance to policymakers.

The conclusion that the biased nature of the sample did not seriously affect estimates of group differences is based on evidence for five countries, since these countries were the only ones with individually representative data to serve as a benchmark. We therefore assume that sample selection bias, which in this context is largely due to differences in employment gaps between heads and non-heads, in these five countries is similar to the other countries included in the analysis. While this is a strong assumption, there is no plausible reason to believe that employment gaps between heads and non-heads are systematically different in these five countries than in others.

[26] In Brazil and Colombia, it was possible to compare trends in employment from directly before and after the crisis from a simulated phone survey with a phone survey that interviewed all household members (see Section 4 of the Supplementary material).

[27] Results are presented and discussed in Section 4 of the Supplementary material.

The analysis of the distributional impacts of the COVID-19 crisis presented in this paper provides important information to policy makers and development practitioners on how to target post-COVID-19 recovery efforts. For example, in light of recent analytic work on the gendered labor market impacts of the pandemic (including the analysis presented in this paper), several recent World Bank Group operations seek to help women to return to economic activity, through cash-for-work programs, investments in childcare services, and improved access to liquidity for women-led firms.[28] Likewise, the 20th replenishment round of the International Development Association (IDA), which includes a number of commitments to raise ambition in areas where gender gaps widened during the COVID-19 pandemic, has been informed by this analysis (IDA, 2022). More generally, cross-country analyses such as this one, while inevitably lacking granularity and country-level specificity, can shine a spotlight on common patterns across countries and galvanize the attention of policymakers and the broader public. In this case, the findings supported actions to prevent the immediate distributional consequences of the pandemic from solidifying into longer-term disadvantages for those groups that bore the brunt of the pandemic early on.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2023.106331.

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[28] https://www.worldbank.org/en/topic/gender/overview#1.

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