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IZA DP No. 14829

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ABSTRACT

Unpacking the Post-lockdown Employment Recovery of Young Women in the Global South

This paper analyses the difference in short-term employment recovery between young men and women in India, Peru and Vietnam following the national lockdowns imposed in all three countries during 2020. We employ a mediation model to establish whether - and to what extent – commonly suggested mechanisms are responsible for a relatively slower recovery among young women and an increase in the gender employment gap. In line with the literature, we find evidence that the unequal distribution of caring responsibilities explains a meaningful proportion of the disparity in Peru and Vietnam, but a smaller share of the change in the employment gap in India. Contrary to the previous literature, however, we find little evidence that the work activity performed before the pandemic explains the slower female recovery in any of the three study countries.

JEL Classification: J21, J16, J6

Keywords: COVID-19, job loss, work resilience, gender gap

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1. Introduction

The Covid-19 pandemic, and the associated lockdown measures adopted to contain the spread of the virus, plunged the global economy into the deepest economic recession since the Great Depression (International Monetary Fund, 2020). As more data emerges on the labour market impacts of the pandemic, there is mounting evidence that women's employment outcomes have been disproportionately affected (International Labour Organization, 2021). Suggested explanations for differential job losses, adjustment, and recovery between genders commonly cite the uneven allocation of childcare and household responsibilities or the characteristic of the economic activity performed pre-pandemic as likely mechanisms (Alon *et al*., 2020a; Adams-Prassl *et al*., 2020; Albanesi and Kim, 2021). To date, however, little empirical evidence exists on the relative contribution of these channels to unequal employment recovery, especially in low- and middle-income countries (LMICs). This paper aims to fill this gap and improve our understanding of precisely how the pandemic may have worsened employment prospects for young women. To do this, we use directly comparable longitudinal data on a sample of young adults from India (Andhra Pradesh and Telangana states), Peru and Vietnam, three countries with very different experiences of the health crisis.

We make two key contributions. First, we document the magnitude and persistence of the change in the gender employment gap among working young people (aged 18-26) in our three study countries, during the latter half of 2020. Second, we quantify and compare the extent to which the two most commonly cited mechanisms - unequal caring responsibilities and pre-pandemic employment - play a role in explaining differential employment impacts. To isolate the effect of the pandemic through these potential channels we employ a mediation model, whereby we estimate the *Average controlled direct effect* (ACDE), a measure of the effect of gender on employment status, under the condition that gender is unable (by construction) to influence the outcome variable through our potential mediators. This approach

provides us with a means of identifying the effect of gender through our hypothesised channels, absent potential bias derived from intermediate covariates that may be correlated with both employment status (our outcome) and the mediators (Acharya *et al.,* 2016).

Between March and June 2020, national lockdowns or stay-at-home requirements were imposed in India, Peru, and Vietnam, although the nature of these restrictive measures varied in both severity and duration. Our main findings suggest that, in all three countries, previously employed young women were relatively more likely than young men to be out of employment (unemployed or inactive) in the two post-lockdown periods for which we have data (August-October 2020, and November-December 2020). In Peru and Vietnam, while women appear to have experienced similar initial employment losses to men, female employment recovered more slowly, resulting in a 19 percentage point change in the gender employment gap in Peru and an 8 percentage point change in Vietnam by November-December of 2020. In India, young women were relatively *less* likely to lose their jobs during the 2020 lockdown than men, but (having lost work) were also significantly less likely to regain employment. This led to a 19 percentage point change in the employment gap by the end of the year.

In accordance with the channels suggested in the previous literature, we find that unequal household caring responsibilities explain a meaningful proportion of the gender-specific employment impact in two of our study countries, accounting for between 5% (August-October) and 11% (November-December) of the change in the employment gap in Peru, and between 12% (August-October) and 27% (November-December) of the relatively smaller change in the gender gap in Vietnam. (In India, this channel explains no more than 6% of the change, based on our main results). Overall, we find that previously working in a vulnerable job, defined here as an economic activity where employment was especially impacted by the pandemic, fails to provide a satisfying explanation for asymmetric recovery between males and

females.[1] Instead, in our sample, we find that the additional risk of being out of work, associated with these economic activities, is at least as likely to affect young men as young women.

The paper is organised as follows: the remainder of this section provides an overview of the experiences of the Covid-19 pandemic in the three countries. Section 2 briefly reviews some of the related literature on the outbreak and the subsequent gender gap in employment. Section 3 describes the approach to mediation and defines the *Average controlled direct effect* and *Eliminated effect* of gender on employment status. Section 4 describes the data used in our analysis, while Section 5 presents the empirical strategy used to estimate the change in the employment gap, and isolate to what extent this change is attributable to our potential mediators. The main results are reported in Section 6, with issues of robustness addressed in Section 7. Section 8 concludes.

1.1 Country context

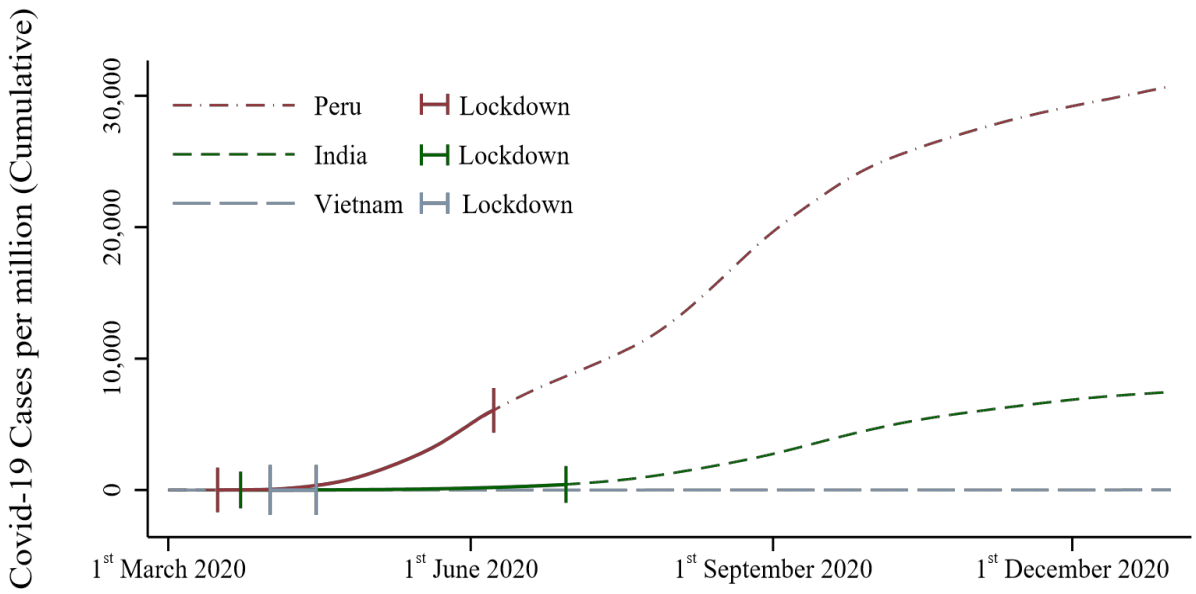
Prior to the pandemic, the three study countries differed notably in terms of the extent of young women's involvement in the labour market. According to the International Labour Organization, 61.8% of the 20 to 24-year-old female population in Peru were in employment in 2019 (compared to 73.8% of the male population of a similar age), while 66.5% of 20 to 24-year-old women (and 74.5% of young men) were working in the year before the health crisis in Vietnam. The share of working Indian women in this age range was only 11.7%, however (compared to 53.9% of 20 to 24-year-old men), with 68.6% not in education, employment or training.[2]

[1] We also consider alternative definitions of what constitutes a vulnerable (pre-lockdown) work activity in Section 7.2. We find this result is robust to defining a vulnerable job as i) a job in services or ii) a job that cannot easily be performed from home (Dingel and Neiman, 2020; Gottlieb *et al*., 2021).

[2] All labour market figures are sourced from the ILOSTAT database https://ilostat.ilo.org. Data retrieved on October 5th, 2021. As the two age cohorts in the Young Lives data are between 18-19 and 25-26, we acknowledge that the ILO figures reported do not exactly reflect the same ages as those in our sample. Our final sample averages between 21-23 years old (across countries).

During 2020, the three countries were subjected to very different experiences of the pandemic, both with regard to the number of Covid-19 cases and in their respective government's policy responses. Figure 1 illustrates the cumulative cases per million in Peru, India, and Vietnam throughout 2020.

Figure 1. Timeline of Covid-19 cases in India, Peru and Vietnam



Source: Authors' calculations using data from https://ourworldindata.org.

Peru experienced the highest number of cases per capita among the three countries and occupied the highest position in the global rankings of Covid-19 cases and deaths per capita during most of 2020. As of 31st December 2020, the number of deaths (per million) was more than 26 times higher in Peru than in India, and more than 7,000 times higher in Peru than in Vietnam. In terms of policy to control the spread of the virus, the vertical bars in Figure 1 indicate the start and end dates of periods where national lockdowns were imposed, with both India and Peru implementing strict and lengthy lockdowns during the early part of the year.

India began a nationwide lockdown in response to the pandemic from the 23rd of March 2020. Only essential services were permitted to continue, educational institutions were closed and large gatherings outlawed. The national lockdown lasted for 75 days, before a phased relaxation of restrictions began on the 8th of June (Favara *et al*., 2020). By October, subsequent relaxations gave state-level administrations flexibility to declare virus containment zones, and reopen schools (Ellanki *et al*., 2021). In spite of this, educational institutions at all levels remained closed in Telangana throughout 2020, including government-sponsored *anganwadi* (child-care) centres. In Andhra Pradesh, secondary schools began re-opening from November the 2nd (on a stagged and half-day basis), while pre-primary and primary schools remained closed throughout 2020.

In Peru, the government declared a state of national emergency, closed borders, and implemented mandatory social isolation from March 16th of 2020. Movement was limited to essential activities and excluded physical attendance at schools, universities and other educational institutions. The lockdown was extended on five consecutive occasions until the 30th of June (a total of 107 days), although a series of regional- and provincial-level lockdowns continued through July, August and September. Some restrictions remained in place throughout 2020, including the physical closure of educational and childcare institutions (at all levels), with the exception of some rural schools in areas where cases were low (Sánchez *et al*., 2021). The national childcare programme (*Cuna Más*) remained active throughout 2020, but operated remotely.

In contrast to Peru and India, Vietnam implemented a relatively short 15-day national lockdown from the 1st of April 2020, extended to 21 days in some provinces, including Lao Cai and Da Nang city (covered by the data used in this analysis). Even before the lockdown, however, in response to the first Covid-19 cases, the government had already implemented a series of early measures, including the closure of nonessential businesses, a ban on large

gatherings, and extensive contact tracing (Scott *et al*., 2020). All educational institutions were closed from the 3rd of February to the 4th of May, with primary and pre-primary schools remaining closed for a further week.

In Peru and India, the strict and prolonged national lockdowns contributed to a fall in real GDP of 11.1% and 8.0% in 2020, respectively (compared to an average decline among LMICs of 1.9%). In Vietnam, due largely to the country's relative success in curbing the spread of the virus, real GDP growth was recorded at 2.9% in 2020 (The World Bank, n.d.).

2. Literature

There exists a rapidly growing literature on the labour market impacts of the Covid-19 pandemic, often arguing that women's employment outcomes have been disproportionately affected by the outbreak (Adams-Prassl *et al*., 2020; Albanesi and Kim, 2021; Alon *et al*., 2020a; Alon *et al*., 2021; Dang and Nguyen, 2021; Farré *et al*., 2020, among others). To date, however, investigations into the widening gender gap in employment have predominantly focussed on high-income economies (The US, Germany and the UK, in particular). Among the relatively few studies that have addressed this topic in a low- or middle-income setting, Deshpande (2021) finds that, conditional on previous employment, Indian women were 9.5 percentage points less likely to be employed than men in August 2020, compared to the pre-pandemic period, while Levya and Urrutia (2020) find that labour recovery, in late 2020, was faster for males than for females in Brazil, Chile, Colombia, Mexico, and Peru.

Even among the more abundant literature related to the increasing gender gap in advanced economies, clear evidence on the underlying mechanisms is scarce. Nonetheless, two explanations are commonly advanced: The first is that women are relatively more likely to be employed in contact-intensive sectors, such as hospitality, which have been more severely

affected by the Covid-19 pandemic and subsequent restrictions (Adams-Prassl *et al*., 2020; Alon *et al*., 2020b; Cortes and Forsythe, 2020; Alon *et al*., 2021; Albanesi and Kim, 2021; Graeber *et al*., 2021). The second is that women tend to have a higher responsibility for domestic work and childcare, and that time dedicated to these activities has increased since the outbreak, due to restrictions such as school closures (Alon *et al*., 2020b; Hupkau and Petrongolo 2020; Russell and Sun, 2020; Alon *et al*., 2020b; Albanesi and Kim, 2021; Montenovo, 2021). While often suggested as the link between the pandemic and differential labour outcomes, little formal analysis exists on the relative contribution of these two channels to the gender employment gap.[3]

3. Mediation Analysis

In this section, we motivate the approach used to identify a causal pathway, between an individual's gender and their employment status, operating through one of our potential mediators. The empirical approach in Section 5 is directly translatable to more than one mediator, however, and in Section 6, we also report the share of the total effect explained by both channels.

We rely on a methodology initially developed in the biostatistics literature (see Joffe and Greene, 2009; Vansteelandt, 2009) and estimate the *Average controlled direct effect* (ACDE), a measure of the effect of gender on post-lockdown employment status, purged of any effects operating through a mediator variable (or group of mediators). In doing so, we are able to isolate the *Eliminated effect*, representing the causal effect of gender through our two potential channels (Acharya *et al.,* 2018). One advantage of this approach is the avoidance of

[3] One exception is Alon *et al*. (2021), who use data from the United States to provide a decomposition analysis of the relative importance of childcare and occupation. The authors find that approximately 14% of the US gender gap can be attributed to childcare and 12% to occupational channels.

intermediate variable bias, whereby a covariate in our estimations, which is (in part) a function of an individual's gender, is also correlated with both the mediator and outcome. In contrast to other methods, the ACDE is identified irrespective of such confounders (Acharya *et al.,* 2016).

As we will clearly only observe the employment status of an individual if they are either male or female, we motivate our approach via Rubin's (1974) potential outcomes framework. We define the sample average treatment effect of being female (relative to male) on the probability of employment in a given time period as follows:

$$\mathbb{E}\,[W_i(f) - W_i(m)] = \mathbb{E}\,[W_i(f, Y(f)) - W_i(m, Y(m))] \quad (1)$$

In equation (1), we assume the existence of a single, binary mediator variable Y, such that the expected change in the probability of an individual being in work W_i, were they female (noted as f) as opposed to male (noted as m), is a function of the direct effect of their gender, the effect the mediator Y has on employment status, and also the effect gender has on the value of the mediator. Based on Acharya *et al*. (2016), it is possible to decompose this total effect into three components:

$$\begin{aligned}&\mathbb{E}\,[W_i(f, Y(f)) - W_i(m, Y(m))]\\ &= \mathbb{E}\,[W_i(f,0) - W_i(m,0)] + \mathbb{E}\,[W_i(f, Y(f)) - W_i(f, Y(m))] + \mathbb{E}\,[I(Y,m,f)] \quad (2)\end{aligned}$$

The first term on the right-hand side is the *Average controlled direct effect* (ACDE), representing the average effect an individual's gender would have on the probability of retaining work, were the value of the mediator fixed at 0. The second term on the right-hand side represents the *Average natural indirect effect* of being female on the outcome W_i, operating through the mediator Y. This captures the change in the outcome, holding the direct

effect of gender fixed, but permitting gender to influence W_i through a change in the value of the mediator. The magnitude of this term will depend on both the effect the mediator has on the outcome and the effect of gender on the value of Y. The final term in (2) represents an *Interaction effect* (formally defined in VanderWeele, 2014). This final term captures the average extent to which the direct effect of gender (at the individual level) changes as the value of the mediator changes from 0 to 1.

From (2), it is possible to isolate the effect of gender on employment operating through Y as the total effect, less the ACDE. If we are willing to assume that the direct effect of gender on employment status is independent of the value of Y, then the total effect less the ACDE represent the *Average natural indirect effect* only (the final term in (2) will equal zero). This assumption may be unrealistic in most settings, however (Petersen *et al*., 2006). Instead, we refer to the estimated effect of gender operating through our mediators as the *Eliminated effect*, representing the full causal channel, through both the *Average natural indirect effect* and the causal *Interaction effect* of the mediator with the direct effect of gender (Acharya *et al*., 2018).

4. Data

Our data comes from the Young Lives study in India (Telangana and Andhra Pradesh), Peru and Vietnam.[4] The variables employed are directly comparable across the three countries. Prior to the global pandemic, two age-cohorts of children had been visited in-person on five occasions since 2002, approximately once every three years, and most recently in 2016. Following the Covid-19 outbreak, a three-part phone survey was conducted over the course of 2020, aimed at measuring the short-term impacts of the health crisis: the 'Listening to Young

[4] Young Lives also collected similar data for Ethiopia. However, the Ethiopia sample is omitted from the analysis as no national lockdown was imposed in this country. We do, however, provide a basic estimation of the post-Covid-19 gender employment gap for young people in Ethiopia in Appendix A, which suggests an overall fall in employment of between 10-13 percentage points, but little evidence of heterogeneity in post-lockdown recovery by gender.

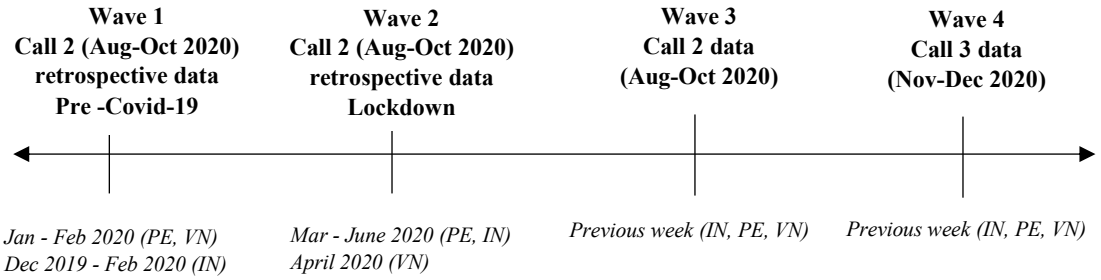
Lives at Work: Covid-19 Phone Survey' (Favara *et al.,* 2021). At that time, the two age cohorts were between 18-19 and 25-26 years old: Henceforth, the Younger and Older Cohorts. Unlike many surveys during the pandemic, the 2020 phone survey was able to reach the rural poor, including those without access to the internet or mobile phones. For example, in India, this was achieved via local guides living in respondents' villages.

The 2002 Indian survey included 3,019 participants from the state of Andhra Pradesh (later Andhra Pradesh and Telangana). Although poorer areas were intentionally oversampled, the sample included a range of living standards akin to the variability found in the two states and covering the full diversity of households within the region (Kumra, 2009). In Peru, the initial 2002 survey round collected information on 2,766 participants, randomly selected from the universe of districts in the country (excluding the wealthiest 5%). While, again, not intended to be nationally representative, comparison with the Peruvian Demographic and Health Surveys indicates that the original sample contained households across the entire wealth spectrum (Escobal and Flores, 2008). In Vietnam, the last of our three study countries, the 2002 sample comprised of 3,000 participants from the provinces of Lao Cai (North-East region), Hung Yen (Red River Delta), Da Nang city and Phu Yen (South Central Coast), and Ben Tre (Mekong River Delta). Comparison to national statistics data indicates that the Vietnamese sample can be considered representative at the regional level (Nguyen, 2008).

An initial contact phone call with respondents took place in June-July 2020, a few months after the Covid-19 outbreak. The second and third calls took place in August-October and November-December of 2020. During calls two and three, detailed information was collected on the participant's employment status in the week before they were interviewed. Retrospective information about employment before the pandemic (defined here as January-February in Peru and Vietnam, and December-February in India), and employment during the first national lockdowns in 2020 (between March-June in India and Peru, and during April only

in Vietnam) was also collected during the second survey call.[5] We use this information to create a four-wave panel of observations in each country, consisting of the pre-pandemic wave (Wave 1), the lockdown wave (Wave 2), and two post-lockdown waves: August-October 2020 (Wave 3) and November-December 2020 (Wave 4). The data available for each respondent is summarized in Figure 2 below.

Figure 2: Timeline of employment information in the Young Lives Covid-19 Phone Survey



Our outcome variable is a dichotomous indicator of work status, defined as working (paid or unpaid) for at least an hour in one's own business, for a household member, or for someone else (during the given reference period). In India, 31% of females and 53% of males who were contacted during the phone survey were working prior to the outbreak. This proportion stood at 56% and 71% of females and males in Peru, and 65% and 75% in Vietnam. As with the ILO figures in Section 1.1, we see a higher probability of pre-pandemic employment for young men, relative to young women in all three countries (especially in India). We restrict the sample to those whose primary activity before the outbreak was working,

[5] Information on employment status during lockdowns is only used in our motivating analysis of general trends in Figure 3. In section 6, this wave (Wave 2) is omitted from the sample used to estimate the change in the gender gap and study the channels through which the pandemic impacted post-lockdown recovery. Given the unprecedented nature and, therefore, salience of the events taking place at the time, one would expect any recall error in our binary outcome variable of (work status) to be negligible.

here defined as those who were: i) working before the pandemic (based on the definition above), and ii) not enrolled in full-time education at any point during 2020. Subsequently, our dependent variable will equal 1 for all observations in the first wave of the panel.

While the Younger Cohort represents the largest share of the original 2020 phone survey sample, 68% in India, 77% in Peru, and 67% in Vietnam, this proportion drops notably in the final analysis, primarily due to excluding those in full-time education. Only 19% (India), 27% (Peru), and 35% (Vietnam) of the Younger Cohort who were surveyed were both working prior to the pandemic and not in full-time education. Among the Older Cohort, 61% (India), 57% (Peru), and 87% (Vietnam) met the two sample inclusion conditions. Furthermore, with the relatively lower probability of pre-pandemic employment among females, women are also relatively under-represented in our final sample. We present a comparison of the mean characteristics of included and omitted females in Appendix C, and a general discussion of selection effects in Section 7.1.

Table 1 reports descriptive statistics from our final analytical sample. Panel A reports sample characteristics separately for males and females (Older and Younger Cohort pooled). In each country, the sample of males and females are broadly balanced by age, across cohorts, and by household wealth. Young women have, on average, completed relatively fewer years of education in India, but slightly more than their male counterparts in the other two countries. In the Indian sample, the self-employed are more likely to be female (50% of females are self-employed, yet only 27% of males), but more likely to be male in Vietnam (26%, relative to 19% of females). In the Indian case, self-employment may be linked to the difference between male's and female's location (urban or rural), with a higher proportion of females living in the more agriculture-dependent rural areas.[6]

[6] As the most recent pre-pandemic measure of urban/rural location comes from 2016, we use the urban/rural status recorded in the first interview call of the phone survey (June-July 2020). While this will represent the pre-

TABLE 1. *Descriptive statistics*

	India		*Peru*		*Vietnam*	
	Males (mean)	*Females* (mean)	*Males* (mean)	*Females* (mean)	*Males* (mean)	*Females* (mean)
Panel A: Sample characteristics						
Individual characteristics						
Age (in years)	22.58	22.64	21.04	21.59*	22.36	22.60
Younger Cohort	0.40	0.39	0.62	0.55	0.45	0.41
Completed years of education	10.83	9.89***	11.11	11.50**	10.31	11.19***
Self-employed (pre-pandemic)	0.27	0.50***	0.28	0.31	0.26	0.19***
Household characteristics						
Wealth index tercile 1 (poorest)	0.45	0.49	0.37	0.30	0.41	0.40
Wealth index tercile 2	0.34	0.30	0.37	0.42	0.34	0.35
Wealth index tercile 3	0.21	0.21	0.26	0.28	0.25	0.24
Urban household	0.26	0.14***	0.75	0.79	0.28	0.32
Mother's years of education	1.94	1.73	6.35	6.46	5.19	5.71*
Panel B: Potential mediators						
Cares for others (pre-pandemic)	0.07	0.38***	0.03	0.15***	0.04	0.25***
Vulnerable job (pre-pandemic)	0.23	0.14***	0.25	0.14***	0.26	0.23
Number of participants	517	250	274	188	527	443
Sample proportion (%)	67.4	32.6	58.5	41.5	54.4	45.6
Observations (all waves)	2,068	1,000	1,082	742	2,102	1,770

Notes: All variables presented in Table 1 are dichotomous, with the exception of *Age* and those relating to years of education. Wealth terciles are based on the Young Lives Round 5 (2016) wealth index (Briones, 2017). The variable *Cares for others* captures whether the participant took care of children, old people, ill, disabled or other household members that required special care, before the pandemic. The variable *Vulnerable job* records if (before the pandemic) a respondent was working in an economic activity where employment was especially badly impacted. Results of *t*-tests of the equality of means between males and females are reported. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

Table 1, Panel B, reports two potential mediating variables, intended to isolate the most commonly suggested mechanisms underlying changes in the gender employment gap. The first is *Cares for others*: An indicator variable that takes the value 1 if, before the pandemic, the individual took care of children, old people, ill, disabled, or other household members who required special care. The second is *Vulnerable job*: An indicator equal to 1 if the participant was working in one of the three economic activities (before the outbreak) that were worst affected by job losses during the national lockdowns. This variable is based on Wave 1 and 2

pandemic location for the majority of respondents, we acknowledge the potential for induced migration with robustness checks on our key results, using only non-migrating respondents, in Section 7.3.

information, considering only activities that employed 5% or more of our sample in Wave 1 (pre-lockdown).[7] Alternative definitions of vulnerable economic activities are considered in Section 7.2.

Table 1 reports that the provision of care is heavily weighted towards young women in all countries, most notably (but not exclusively) in India, where 38% of sampled females report caring responsibilities prior to the pandemic (as opposed to 7% of males). Perhaps surprisingly, given the suggested importance of pre-pandemic employment activity in the literature (see Section 2), it is young *men* who are, on average, more likely to have been working in jobs that were most severely impacted by the pandemic, in all countries. We also consider alternative definitions of *vulnerable job* in Section 7.2.

4.1 Change in the average probability of being employed during 2020

Figure 3 shows the change in the (linear) probability of being employed for males and females in Waves 2, 3 and 4, relative to Wave 1 (where the probability of Wave 1 employment = 1). We report 95% confidence intervals around each estimation point, while the dashed lines suggest what the relative employment adjustment paths would be (based on the data points observed).[8]

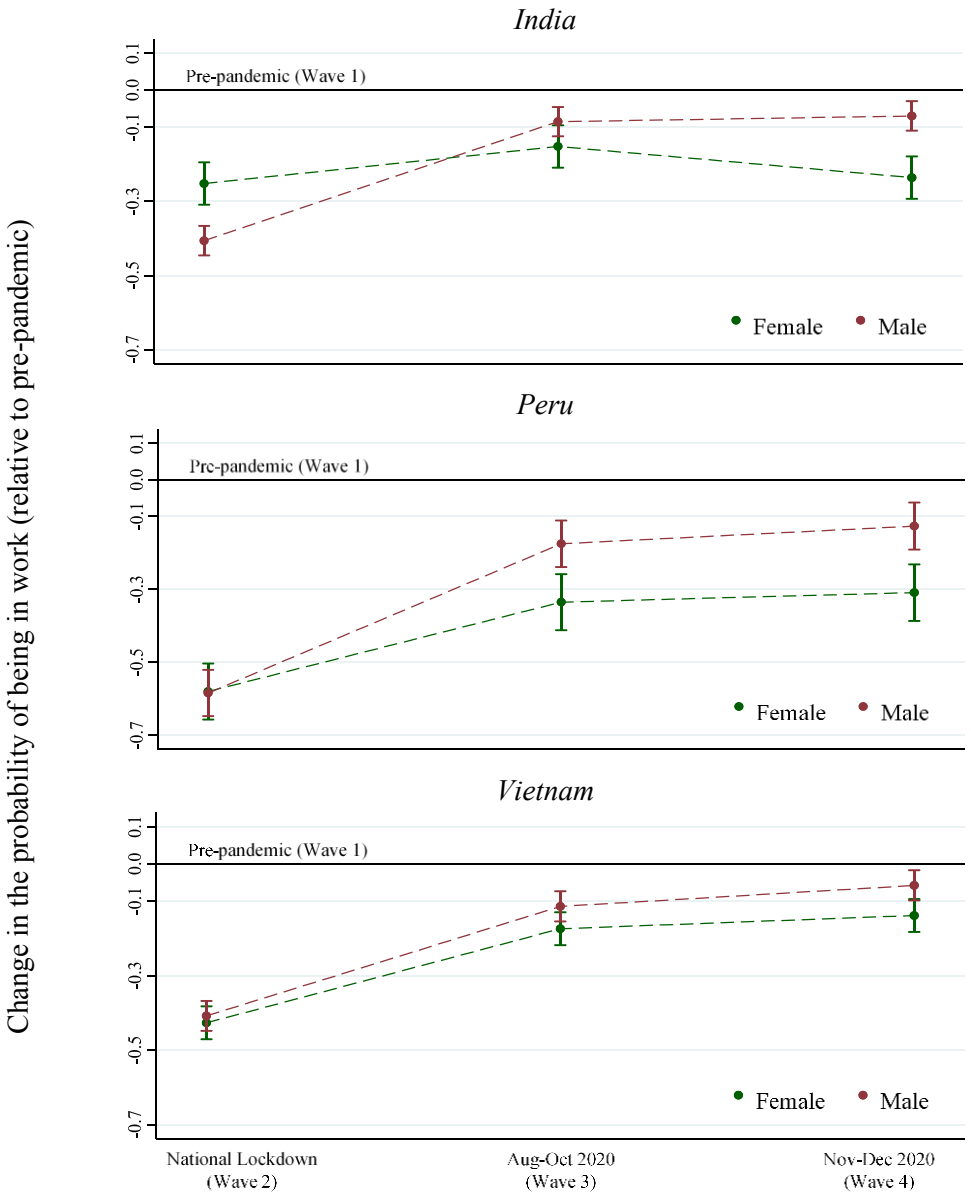
In India, Figure 3 suggests that, although females were relatively more likely to be working during the national lockdown (Wave 2), the gender employment gap reverses towards

[7] Economic activities are categorised according to the definition of 'Section' in the International Standard Industrial Classification (ISIC). In India, vulnerable economic activities were: i) Wholesale/retail trade and repair of motor vehicles; ii) Accommodation and food services, and iii) Other services (employing 9%, 5.5% and 5.8% of the Indian sample, respectively). In Peru, these activities were: i) Construction; ii) Accommodation and food services, and iii) Transportation and storage (employing 6.5%, 6.7% and 5.9% of the Peru sample). In Vietnam, vulnerable jobs were: i) Wholesale/retail trade and repair of motor vehicles; ii) Accommodation and food services, and iii) Construction (employing 10.4%, 9.7% and 5.5% of the Vietnamese sample).

[8] We estimate Figure 3 using the equation: $Work_{it} = \beta_0 + \sum_{t=2}^{4} \omega_t Wave_t + \sum_{t=2}^{4} \xi_t (Wave_t * female_i) + \varepsilon_{it}$, where $Work_{it}$ is a binary outcome variable, indicating whether participant i in country c is working in Wave t. We treat pre-pandemic labour status (Wave 1) as the base category, while $\sum_{t=2}^{4} Wave_t$ contains indicator variables for the three later waves. The estimation results underlying Figure 3 are reported in Appendix A.

the end of the year, with young females being nearly 17 percentage points less likely than men to be in work in Wave 4 (November-December). In Peru and Vietnam, Figure 3 suggests little differential employment loss by gender during the national lockdown. However, in Peru, men were relatively more likely to have re-joined the labour market by Wave 3, and by November-December, were roughly 18 percentage points more likely than women to be in work. There also appears to be a slower recovery by females in Vietnam, leading to an estimated 8 percentage point employment gap by the end of the year (although not different from zero at

Figure 3: Labour market recovery towards pre-pandemic levels



5. Empirical Strategy

In this section, we describe the empirical approach used to estimate the gender gap in employment recovery. We then describe the methods used to measure the extent to which commonly suggested mediators explain the difference in recovery between males and females in our three study countries.

5.1 Estimating the post-lockdown gender gap in employment

To gauge the magnitude of the change in the employment gender gap, we first estimate the baseline model (3). Our outcome variable of interest $Work_{it}$ is an indicator of whether individual *i* is working in Wave *t*. Here, however, we omit the second wave of the panel (National Lockdown) [9] and consider employment status only in the post-lockdown recovery period (Wave 3 and 4), relative to Wave 1 (pre-pandemic). As all respondents in our sample were employed in Wave 1, this implies our dependent variable equals 1 for all observations in the first wave. In our baseline model, we include no additional controls other than the wave indicators and an individual fixed effect α_i, intended to capture any fixed or prior characteristics of the individual or environment which influence the probability of working post-lockdown. The key coefficients of interest are the δ_t parameters. These provide an estimate of the percentage point disparity between females and males in the probability of being in work during either wave 3 or wave 4.

$$Work_{it} = \alpha_i + \sum_{t=3}^{4} \omega_t Wave_t + \sum_{t=3}^{4} \delta_t (Wave_t * female_i) + \varepsilon_{it} \quad (3)$$

[9] While it would clearly be possible to include the second wave of the panel, the recall period used to define if a respondent has or has not worked is both imprecisely defined for this wave and will vary greatly between countries (and in some cases between individuals within countries). Therefore, we focus only on post-lockdown recovery.

In model (4) we add a vector of individual and household-level controls ***X***, including completed grades of education (measured in the August-October interview),[10] cohort (representing age), pre-lockdown self-employment status (recalled from the August-October interview), and the location of the household (urban/rural). These covariates are interacted with the wave 3 and 4 indicators, under the assumption that the importance of these characteristics as a predictor of employment may vary at different stages of the pandemic.

$$Work_{it} = \alpha_i + \sum_{t=3}^{4} \omega_t Wave_t + \sum_{t=3}^{4} \delta_t (Wave_t * female_i) + \sum_{t=3}^{4} \boldsymbol{\gamma_t} (Wave_t * \boldsymbol{X_i}) + \varepsilon_{it} \quad (4)$$

5.2 Estimating the Average Controlled Direct Effect

In models (5) and (6), we present our approach to estimating the ACDE, by fixing the value of potential mediators at zero. This serves to (artificially) eliminate the 2nd and 3rd terms on the right-hand side of equation (2), leaving only the ACDE. We estimate the ACDE individually for each of our mediating variables, *Cares for others* and *Vulnerable job*, following the two-step approach of Acharya *et al.* (2016).

First, equation (5) augments the previous model with a single mediator variable, interacted with the wave indicator.

$$Work_{it} = \alpha_i + \sum_{t=3}^{4} \omega_t Wave_t + \sum_{t=3}^{4} \delta_t (Wave_t * female_i) + \sum_{t=3}^{4} \varphi_t (Wave_t * mediator_i) + \sum_{t=3}^{4} \boldsymbol{\gamma_t} (Wave_t * \boldsymbol{X_i}) + \varepsilon_{it} \quad (5)$$

[10] Completed grades of education is recorded in the second call of the phone survey (August-October 2020). As our sample did not attend full-time education during 2020, however, this will also represent pre-pandemic education levels.

We then generate a de-mediated measure of our outcome variable, as the fitted value of the dependent variable obtained from (5), after setting the mediator variable equal to zero for all observations. This predicted value $\widetilde{Work}_{it}$ reflects the variation in the dependent variable which *cannot* be explained by the mediator. Re-estimating equation (4), having replaced the dependent variable with the newly derived (de-mediated) outcome, yields the ACDE. This controlled effect is measured by the $\tilde{\delta}$ coefficients in equation (6).

$$\widetilde{Work}_{it} = \alpha_i + \sum_{t=3}^{4} \omega_t Wave_t + \sum_{t=3}^{4} \tilde{\delta}_t (Wave_t * female_i) + \sum_{t=3}^{4} \boldsymbol{\gamma_t} (Wave_t * \boldsymbol{X_i}) + \varepsilon_{it} \quad (6)$$

By construction, the $\tilde{\delta}$ coefficients measure the effect of being female, while partialling out any effect of an individual's gender operating through the mediator. To gauge the importance of our mediators in explaining the total change in the gender employment gap, however, we compare the total effect δ with the corresponding ACDE coefficients $\tilde{\delta}$. The difference between the two measures provides our estimate of the *Eliminated effect*. In Section 6, we present the percentage of the total effect which can be attributed to our mediator variables.

6. Results

6.1 The post-lockdown change in the gender employment gap

We first present our estimates of the change in the total gender gap in employment, derived from models (3) and (4). Table 2, column 1, 3 and 5, reports the δ coefficients, without the inclusion of the pre-pandemic controls. These controls are included in columns 2, 4 and 6.

TABLE 2. *The gender gap in post-lockdown employment*

	India	*India*	*Peru*	*Peru*	*Vietnam*	*Vietnam*
	(1)	(2)	(3)	(4)	(5)	(6)
Female*Aug-Oct (Wave 3)	-0.067***	-0.096***	-0.160***	-0.164***	-0.060***	-0.057**
	(0.026)	(0.027)	(0.041)	(0.040)	(0.023)	(0.023)
Female*Nov-Dec (Wave 4)	-0.166***	-0.191***	-0.179***	-0.186***	-0.080***	-0.083***
	(0.029)	(0.030)	(0.040)	(0.040)	(0.019)	(0.020)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls*Wave	No	Yes	No	Yes	No	Yes
Observations	2,301	2,301	1,362	1,362	2,902	2,902

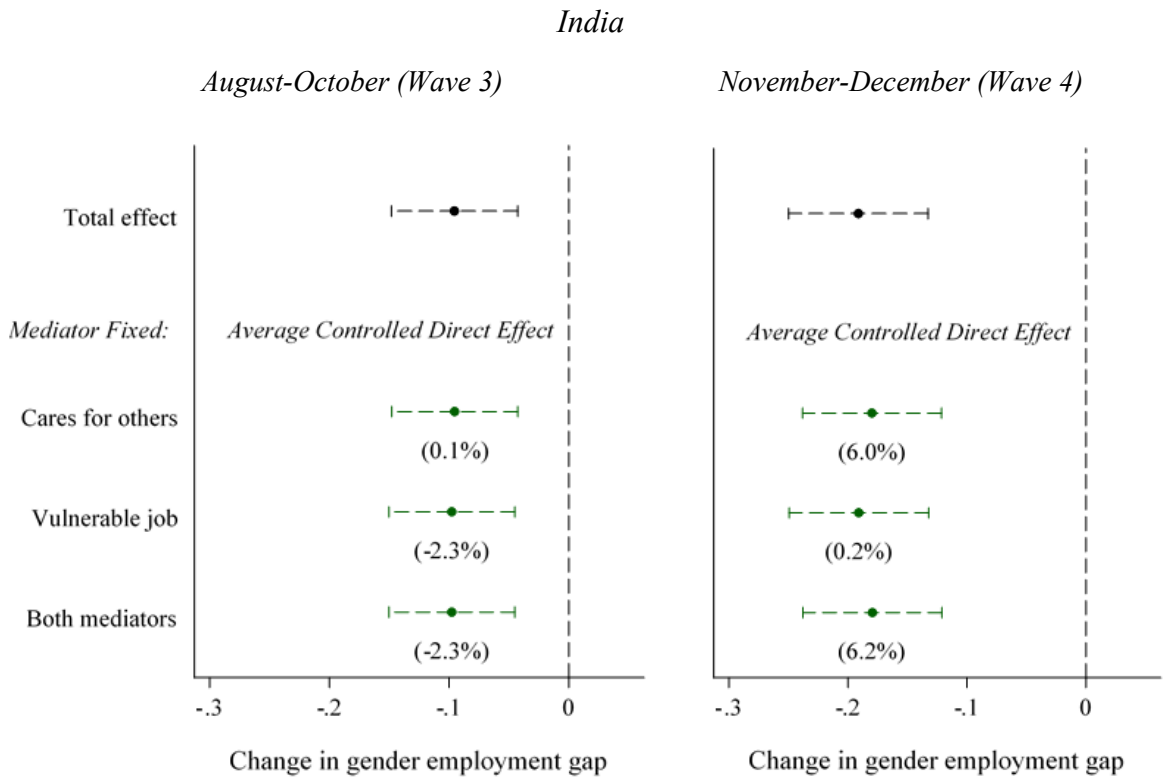
Notes: All control variables are interacted with the wave indicators. These include: Completed grades of education, Cohort (age), Self-employed (in Wave 1), Urban/rural household. The full estimation results can be found in columns 1 and 2 of Appendix tables B1, B2 and B3. Standard errors are clustered at the individual-level and reported in parentheses. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

Results from the Indian sample imply a 7-10 percentage point relative difference in the probability of young women being out of work in August-October of 2020 (compared to young men). This is a similar estimate to Deshpande (2021). This gender gap increases, however, to 17-19 percentage points towards the end of the year (November-December). In Peru, we observe the largest disparity among the three countries during August-October (in-line with Figure 3). This 16 percentage point deficit in the probability of being in work for females in Wave 3, increases further to approximately 18-19 percentage points in Wave 4. In Vietnam, although the change in the gender gap is far less pronounced, there is still evidence of a disadvantage for young women. An approximate 6 and 8 percentage points lower probability of employment is observed in Waves 3 and 4, respectively. The inclusion of the interaction of pre-pandemic controls with the wave indicators clearly influences the magnitude of the coefficients (particularly in India). Therefore, we treat model (4) as our preferred specification in the remainder of the analysis.

6.2 Accounting for the post-lockdown employment gap in India

We now present the results of the mediation analysis for the Indian sample. Figure 4 reports the total effect (see Table 2, column 2) alongside the ACDE for the two potential channels and the two post-lockdown time periods. The full results of the mediation analysis for all countries can be found in Appendix B. The horizontal bars indicate 95% confidence intervals around the estimated coefficients. Following Abebe *et al*. (2021), in the case of each mediator, the percentage in brackets represents the proportion of the total effect which can be attributed to that mediator: 1 - $\tilde{\delta}/\delta$.

Figure 4: The change in the gender gap explained by the mediators in the Indian sample



The left-hand side of Figure 4 reports the change in the total employment gap for the Indian sample in August-October (9.6 percentage points in Table 2, column 2). Estimations of the ACDE, holding *Care for others* fixed, suggests little of the total effect in Wave 3 (0.1%) can be explained by the higher probability of young women having responsibility for the care

of others (relative to men). Fixing the *Vulnerable job* mediator yields an ACDE larger than the total effect, implying that (if at all) working in these economic activities is a stronger mediating factor for the poor employment recovery of *males* than females. This result can be explained by noting that it was young men who were more likely to be employed in vulnerable activities in the pre-pandemic period in all three countries (see Table 1). This result carries over to the share of the effect which can be explained when holding both of our potential mediators fixed in Wave 3.

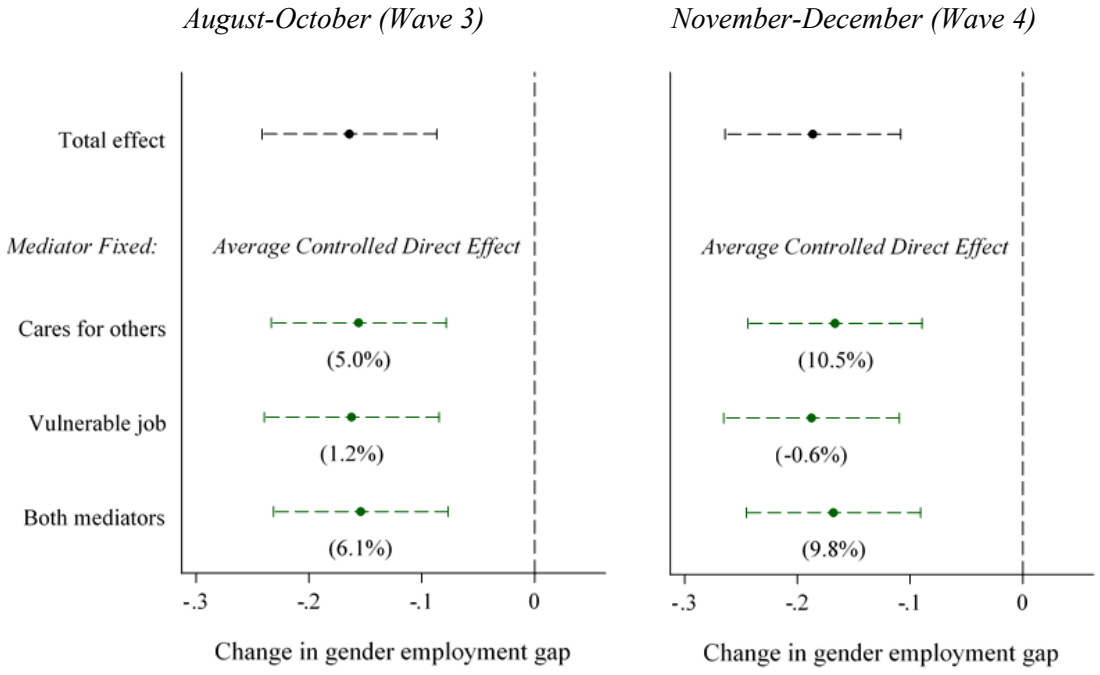
The right-hand side of Figure 4 shows the proportion of the Wave 4 (November-December) gender gap (19.1 percentage points) explained by the two mediator variables. Additional caring responsibilities are able to explain a relatively larger proportion of the continued poor female recovery (around 6%) and, overall, in Wave 4, we are able to explain around 6.3% of the gender employment gap in November-December of 2020. The analysis presented below, for Peru and Vietnam, will demonstrate that the two mediators provide the least insight into changes in the gender gap in the Indian sample.

6.3 Accounting for the post-lockdown employment gap in Peru

We now turn to the results for the Peruvian sample. Figure 5 presents the total effect (Table 2, column 4) alongside the ACDE for each mediator. We find that, in August-October 2020 (Wave 3), pre-pandemic employment and caring responsibilities account for 6.1% of the overall gender gap (16.4 percentage points). Figure 5 indicates that the majority of this is owed to the relatively higher probability of young women (compared to young men) being responsible for the care of others, while pre-Covid employment explains relatively little of the total effect.

Figure 5: The change in the gender gap explained by the mediators in the Peruvian sample

Peru



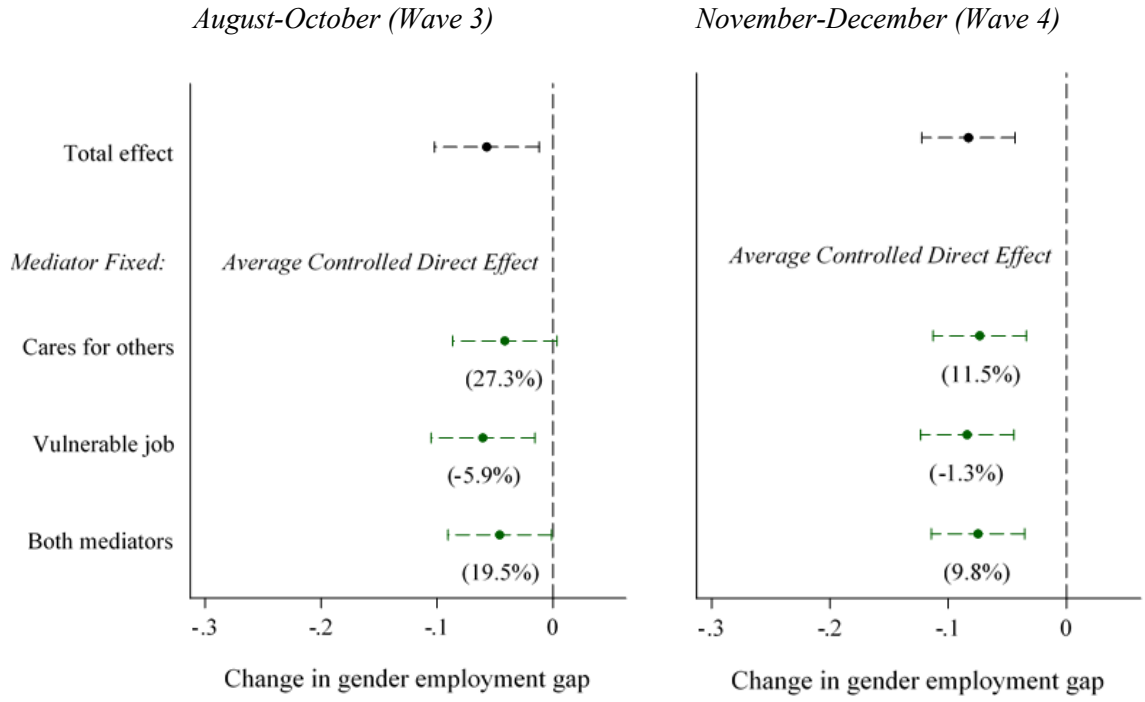
Considering the right-hand side panel of Figure 5, again, employment in a vulnerable economic activity prior to the pandemic is not a key driver of the (18.6 percentage point) gender gap in November-December, but caring responsibilities still are (and alone account for 10.5% of the total effect). This likely follows from the continued closure of almost all childcare facilities in Peru throughout November-December of 2020. As in India, it is young males who were more likely to be employed in vulnerable activities in the pre-pandemic period (see Table 1), again implying (if anything) a stronger mediating effect for young men. Overall, our two proposed channels explain 9.8% of the total, wave 4 change in the gender employment gap.

6.4 Accounting for the post-lockdown employment gap in Vietnam

Lastly, we present the results for the Vietnamese sample. Figure 6 highlights that Vietnam has seen the smallest increase in the gender gap in the initial post-lockdown period, at 5.7

percentage points. This increases to around 8 percentage points by Wave 4 (still less than half the November-December gap in India and Peru).

Figure 6: The change in the gender gap explained by the mediators in the Vietnamese sample



The right-hand side of figure 6 suggests that 27.3% of the (relatively small) total effect in Wave 3 can be explained by the higher probability of young women being responsible for the care of others. Again, fixing the *Vulnerable job* mediator yields an ACDE larger than the total effect, indicating that pre-pandemic work activity is a stronger mediating factor in job losses for males than females. Holding both mediators fixed, we are able to explain approximately 19.5% of the gender employment gap in Wave 3.

Similar to the initial post-lockdown period, the Wave 4 results suggest that caring responsibilities continue to explain a meaningful proportion of the poor recovery of young females (approximately 11.5%), while pre-pandemic employment does not. Overall, in Wave

4, we are able to explain around 10% of the change in the gender employment gap present in November-December of 2020.

7. Robustness

7.1 Sample selection

In the analysis above, we focus on the population of young people for whom work was the main activity prior to the pandemic. Our final analytical sample, therefore, represents only 28%, 22% and 39% of young people who responded to the 2020 phone survey in India, Peru and Vietnam, respectively.

In the original phone survey, in all three countries, the proportion of females among those not working before the pandemic is relatively large (58% in India, 57% in Peru, and 58% in Vietnam). In Peru and Vietnam (not India), there also exists a larger proportion of females than males among those who were in full-time education in the original 2020 phone survey (52% in Peru and 53% in Vietnam were female). These figures may be found in Appendix Table C.1. Subsequently, the overall share of females in our final sample is 32.6% (India), 40.7% (Peru), and 45.7% (Vietnam), whereas the original phone survey was split more equally by gender.

It follows, that the characteristics of those women included in our sample may differ substantially from those who are not. A comparison of variable means between included and omitted females is reported in Appendix Table C.2. Compared to the phone survey, we find that women in our final sample are more likely to come from rural areas and the poorest wealth tercile in India and Vietnam (not Peru), and relatively less likely to come from the highest wealth tercile in all countries. Our final sample are also less formally educated (on average)

and more likely to have caring responsibilities, reflecting the higher average age of our final sample (due to many in the Younger Cohort still being in full-time education - see Section 4).

If both the probability of being in full-time education and the probability of working prior to the pandemic were not correlated with gender, we would observe that the gender split in our sample exactly reflected that in the 2020 phone survey. Instead, we find a selection process, whereby males are more likely to be in employment pre-lockdown, and (to some extent) less likely to be in full-time education. As a result of our sample restrictions and this selection process, our final analytical sample contains what could be considered an *excess* number of young males. If these additional males represent a group with fundamentally different labour market outcomes than the typical male respondent, our estimates of the gender employment gap in Table 2 will be biased, as will our estimates of the ACDE.

In Appendix Table C.3, we summarise the results of a bounding exercise, whereby we trim the sample of males such that the proportion of males and females corresponds (as closely as possible) to that in the 2020 phone survey sample (see Lee, 2009). We rely on a randomization approach, whereby we draw (with replacement) repeated, random samples of p males from those in our data, where p is the number of observations required to equate the gender split in each sample to the gender split in the original phone survey. We add each random draw to the (full) sample of females, before re-estimating the total effect and the ACDE. The highest and lowest estimates of the change in the gender gap from repeated samples should yield a credible approximation of the upper and lower bounds of our results, under the most extreme possible assumptions regarding selection bias.

Based on 1,000 random samples, we estimate that the relatively lower probability of employment for young women in India is bounded between 5.4 and 14.3 percentage points in August-October, and between 15.5 and 23.4 percentage points in November-December.

Notably, in the case of the August-October results, we are unable to reject the hypothesis that $\delta = 0$ in the smallest (absolute) estimate of the change in the gender gap (at any common level). Based on the same estimations, in November-December, the proportion of the total effect explained by the mediator *Cares for others* lies between 7.0% and 14.8%, while the proportion attributable to the mediator *Vulnerable job* lies between -0.4% and 0.4%.

In Peru, we are able to bound the relative change in the probability of employment for young women as a negative effect between 7.6 and 24.5 percentage points in August-October (relative to men), and between 9.4 and 36.8 percentage points in November-December. As in the Indian sample, however, it is not possible to distinguish the most conservative estimate of the August-October gender gap from zero. In November-December, this gap is still significant (although, only at a 10% level). From these November-December estimates, the proportion of the total effect attributable to unequal caring responsibilities lies between 7.1% and 23.4%, and the effect of gender through the mediator *Vulnerable job* accounts for between -1.9% and 0.3% of the total effect.

Finally, in Vietnam, our estimated bounds on the change in the gender gap in employment in August-October of 2020 are 0.7 and 10.1 percentage points, while we estimate the effect in November-December lies between 4.1 and 11.9 percentage points. In both post-lockdown periods, our most conservative estimate of the gender gap does not allow for a rejection of the hypothesis that $\delta = 0$ (i.e., no differential employment effect between males and females). Notwithstanding this result, we again see a similar pattern in the mediation results, with *Vulnerable job* acting as a mediator on male (not female) employment.

7.2 Alternative definitions of vulnerable work activities

In Section 6, we find that working in a vulnerable economic activity before the pandemic fails to provide a satisfying explanation for differential employment recovery in any of the three countries. To ensure that this result is not overly sensitive to our definition of vulnerable jobs, we re-estimate our results based on two alternative definitions of which pre-pandemic work activities should lead to a lower probability of post-lockdown employment.

Our first alternative definition classifies all pre-lockdown work activities which are classed as *services*, under ISIC Rev. 4 (UN, 2008), as vulnerable (and only these). This would reflect a view that the relatively higher probability of women working in high-contact, service roles led to an increase in the gender employment gap during the pandemic (Albanesi and Kim, 2021; Graeber *et al*., 2021). Re-defining the vulnerable jobs mediator in this manner, we find that we are able to explain -3.7% (India), -2.4% (Peru) and 2.4% (Vietnam) of the total change in the gender employment gap in August-October. Similarly, we are only able to explain -0.2% (India), 0.2% (Peru) and 0.3% (Vietnam) of the total effect in November-December. Again, this implies the widening gender gap cannot easily be linked to differences in pre-pandemic employment. These results can be found in Appendix Table D.1.

Our second alternative definition is based on the ability of individuals to work from home (Dingel and Neiman, 2020; Mongey and Weinberg, 2020). Gottlieb *et al*. (2021) use worker-level data on task content from the Skills Toward Employability and Productivity (STEP) survey, covering 17,000 urban workers across ten low- and middle-income countries, to determine which jobs cannot easily be performed at home.[11] We follow this methodology in classifying workers in the STEP data as unable to work from home if they i) do not use a

[11] Gottlieb *et al.* (2021) show that a higher *work from home* score was strongly associated with the likelihood of remaining employed through 2020 in Peru. We use the STEP survey data on urban workers, with the caveat that our three-country sample contains both urban and rural households.

computer at work, ii) lift heavy objects, iii) repair electronic equipment, iv) operate heavy machinery or *v*) report that customer interaction is very important. We estimate the proportion of workers that can work from home in each economic activity as the (equally weighted) average share of home workers across the ten STEP countries,[12] and define a vulnerable job as working in one of the three economic activities with the lowest average share of individuals able to work from home. These activities are: i) Households as employers, ii) Water supply, sewerage and waste management, and iii) Accommodation and food services.[13]

Based on this definition, the *Eliminated effect* attributable to pre-pandemic employment represents -2.9% (India), -2.8% (Peru) and 0.5% (Vietnam) of the total change in the gender gap in August-October, and 0.3% (India), -0.4% (Peru) and 0.2% (Vietnam) of the total effect in November-December. Therefore, defining the mediator in this way clearly does not provide any further evidence that this channel explains the observed gender disparity. These results can be found in Appendix Table D.2.

As task content and employment structures may differ by region, we also conduct a further robustness check using low ability to work from home to define vulnerable work activities. In Table D.2, we report mediation results for Vietnam (which was part of the STEP survey), based on the STEP worker information from Vietnam only.[14] Again, however, the results are similar to our main estimations, with the mediator *Vulnerable job* only explaining between 0.2% and 0.5% of the change in the total gender gap.

[12] This first requires grouping the 2-digit occupations in the STEP data into the economic activities in the Young Lives data, where both are defined in ISIC Rev. 4 (UN, 2008).
[13] A job that cannot easily be done from home does not necessarily imply that all work of that type ceased during the pandemic, however. Water supply and sewerage, for example, would certainly be considered an essential activity during the lockdowns.
[14] In Peru, we also create a measure based on the (equally weighted) mean of the two Latin American countries (LAC) sampled in the STEP surveys: Bolivia and Colombia. This approach does not change the classification of economic sectors used to generate Table D.2 (and so results remain unchanged).

7.3 Migration

The onset of the Covid-19 pandemic was clearly a highly unanticipated event. As such, no Young Lives survey was conducted just prior to the outbreak. Instead, the most recent pre-pandemic information in this data was often sourced from the 2016 (round 5) survey. One exception to this is the urban/rural location variable, which is taken from the first phone interview of the survey in June-July 2020. As this information post-dates the outbreak, this variable may (in some cases) be a function of an individual's experiences of the pandemic. More generally, as we employ individual-level fixed effects to control for any time-invariant household or location characteristics, if individuals moved away from the location where their household was initially based (to find work, for example), we cannot be sure that these individual effects capture the unobserved characteristic we intend. To ensure that our results are not unduly affected by differential migration following the outbreak, we re-estimate our main specifications on a sample of individuals who did not move locations during our timeline. Overall, we conclude that the interpretation of our findings is robust to this sample limitation. These results are presented in Appendix Table E.1.

7.4 Interview timing

The data defining the panel used in all estimations is based on the second and third phone interviews of the Young Lives phone survey (August-October and November-December of 2020). As can be seen in Figure 1, economic and health-related conditions may have changed substantially within the timeframe of each data collection – particularly in Peru and India.

To ensure that any bias generated by the differential timing of the specific interviews is minimal, we re-estimate our results using only information collected during the most common survey month. In the second call (Waves 1, 2 and 3), the majority of interviews in all

countries were conducted in September (51% in India, 56% in Peru and 59% in Vietnam). Similarly, in the third survey call (Wave 4) the vast majority of calls took place in the month of November (99% in India, 90% in Peru and 98% in Vietnam). Re-estimating the key results from Section 5 using only data from interviews conducted in these months, we find that restricting our sample in this way does little to alter their interpretation. These results may be found in Appendix Table F.1.

8. Conclusion

We analyse the employment recovery of young men and women, following the 2020 Covid-19 national lockdowns in three LMICs: India, Peru and Vietnam. We highlight four key findings. First, we conclude that, while young women's employment appears not to have been disproportionately affected by the national lockdowns in 2020, those who lost their jobs were significantly less likely to re-join the labour market after the lockdowns in all three countries.[15] Second, considering the two most common explanations for the gendered employment impact of the pandemic, we find that unequal caring responsibilities are an important mediator of the gender-specific employment impact in Peru and Vietnam. This channel explains less of the overall effect in India.[16] This result broadly corresponds to the suggested mechanism in the literature relating to high income economies (Alon *et al.*, 2020b; Alon *et al.*, 2021; Hupkau and Petrongolo, 2020). Third, and contrary to this literature (Alon *et al*., 2021 on the US, for example), in all three of our study countries, previously working in an economic activity where employment was badly impacted by the pandemic fails to explain a substantial portion of the asymmetric post-lockdown recovery. Furthermore, this result appears robust to alternative

[15] Based on the bounding exercise presented in section 7.1, only the gender gap for Wave 4 (November-December) is significantly different from zero, under the most extreme assumptions on selection bias, and only in India ($p < 0.01$) and Peru ($p < 0.1$). We acknowledge this as a caveat to our results.

[16] One explanation of this finding may come from the relatively low numbers of young Indian women in work prior to the pandemic (see Section 1.1), suggesting these women may be a somewhat select group of individuals within our sample.

definitions of vulnerable jobs (see Section 7.2). Fourth, and perhaps most importantly, the majority of the increase in the gender employment gap (nearly 95% of the gap in November-December 2020 in India) still remains unaccounted for by the two commonly cited mechanisms.

The existence of a large post-lockdown change in the employment gap, which cannot be attributed to either of the commonly suggested channels, poses the question of what other mechanisms may be in play? Comparing our male sample with females who i) did not have caring responsibilities and ii) did not previously work in a vulnerable job, we find that a significantly larger proportion of young men had switched to a new work activity or employer in both Peru (50%, compared to 30% of females) and Vietnam (27%, compared to 18%). Therefore, a higher flexibility for males to switch activity or employer may also explain some of the remaining heterogeneity in post-lockdown employment outcomes.

The results presented here are, by definition, short-term. However, if the gender imbalance in employment persists, it may have important long-term consequences. If women remain outside of the labour market, a potential rise in fertility rates, resulting from a decline in the opportunity cost of marriage and childbearing (Mammen and Paxson, 2000), may result in women finding it even harder to re-enter employment, or facing an earnings penalty if they do (Agüero *et al*., 2020; Berniell *et al*., 2021). A substantial literature also finds a stronger correlation between female (as opposed to male) household earnings and expenditure on children and nutrition (Hoddinott and Haddad, 1995; Attanasio and Lechene, 2002; Duflo, 2003), potentially extending the impact of increasing inequality in employment beyond the current generation.

From a policy perspective, our findings suggest a need to support adversely impacted female workers in labour market re-entry. In 2020, the near-complete shut-down of the face-to-face care and teaching provided by schools and childcare facilities in India and Peru (and

similar closures in Vietnam at the beginning of the year) will inevitably have left many women facing responsibilities that cannot easily be balanced with work. Even before the Covid-19 pandemic, evidence suggests that women's employment may be especially sensitive to measures that help alleviate caring responsibilities (Baker *et al*., 2008; Martínez and Perticará, 2017). Based on our findings, such policies may be of particular value in Peru and Vietnam, where we demonstrate a clear link between caring responsibilities and slower employment recovery for young women. This result mirrors similar findings in more developed economies.

As all three countries continue to struggle with the health impacts of the Covid-19 pandemic, and vaccination rates continue to lag behind those of high-income countries, it is possible that there may be the need for further lockdowns or economic restrictions in the future. If such restrictions are required, the evidence presented here suggests this can only lead to a further widening of the gender employment gap if practical and effective policy responses are not put in place to support young women in re-entering the labour force.

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Appendices

Appendix A

Table A.1 reports the OLS regression used to generate Figure 3. In column 4, we also report the gender difference in the probability of being in work for Ethiopia, the fourth of the Young Lives study countries. Although measures such as school closures and a ban on public meetings were put in place, the Ethiopian government did not impose an official national lockdown in 2020. We, therefore, exclude Ethiopia from our main analysis. The table suggests that - relative to pre-pandemic levels - any gender gap that may have existed in Ethiopia in Wave 3 or 4 is minimal.

TABLE A.1

Employment trajectories during 2020 relative to pre-pandemic employment

	India	*Peru*	*Vietnam*	†*Ethiopia*
	(1)	(2)	(3)	(4)
National lockdown (Wave 2)	-0.406***	-0.584***	-0.408***	*n/a*
	(0.020)	(0.032)	(0.021)	
August-October (Wave 3)	-0.085***	-0.175***	-0.114***	-0.099***
	(0.020)	(0.032)	(0.021)	(0.020)
November-December (Wave 4)	-0.070***	-0.127***	-0.058***	-0.131***
	(0.020)	(0.033)	(0.021)	(0.023)
National lockdown * Female	0.154***	0.004	-0.019	*n/a*
	(0.035)	(0.051)	(0.031)	
August-October * Female	-0.067*	-0.160***	-0.060**	-0.064*
	(0.035)	(0.051)	(0.031)	(0.038)
November-December * Female	-0.166***	-0.182***	-0.081***	-0.047
	(0.035)	(0.051)	(0.031)	(0.043)
Observations	3,068	1,824	3,872	1,232

Notes: †Ethiopia is one of the four Young Lives study countries. As no lockdown was imposed here, we omit this country from our main analysis. Standard errors are clustered at the individual-level and reported in parentheses. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

Appendix B

Tables B.1 to B.3 report the full estimation results, inclusive of control variable coefficients, used to generate Figures 4 to 6 and the estimates of the change in the gender employment gap reported in Table 2.

TABLE B.1

India: Full results

	(1)	(2)	(3)	(4)	(5)
			Mediator fixed (ACDE)		
	Total effect	*Total effect*	*Cares for others*	*Vulnerable job*	*Both*
Female*Aug-Oct	-0.067***	-0.096***	-0.095***	-0.098***	-0.098***
	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
Female*Nov-Dec	-0.166***	-0.191***	-0.180***	-0.191***	-0.179***
	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)
Urban*Aug-Oct		-0.031	-0.031	-0.025	-0.025
		(0.031)	(0.031)	(0.031)	(0.031)
Urban*Nov-Dec		-0.073**	-0.073**	-0.074**	-0.075**
		(0.031)	(0.031)	(0.031)	(0.031)
Younger Cohort*Aug-Oct		-0.031	-0.031	-0.030	-0.030
		(0.024)	(0.024)	(0.024)	(0.024)
Younger Cohort*Nov-Dec		-0.038	-0.048*	-0.038	-0.048*
		(0.025)	(0.025)	(0.025)	(0.025)
Self-employed*Aug-Oct		0.079***	0.079***	0.078***	0.078***
		(0.022)	(0.022)	(0.022)	(0.022)
Self-employed*Nov-Dec		0.046*	0.047*	0.046*	0.047*
		(0.024)	(0.024)	(0.024)	(0.024)
Years of education*Aug-Oct		-0.007*	-0.007*	-0.006*	-0.006*
		(0.003)	(0.003)	(0.003)	(0.003)
Years of education*Nov-Dec		-0.005	-0.006*	-0.005	-0.006*
		(0.004)	(0.004)	(0.004)	(0.004)
August-October (Wave 3)	-0.085***	-0.013	-0.013	-0.010	-0.010
	(0.012)	(0.042)	(0.042)	(0.042)	(0.042)
October-November (Wave 4)	-0.070***	0.011	0.029	0.010	0.028
	(0.011)	(0.045)	(0.045)	(0.045)	(0.045)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	2,301	2,301	2,301	2,301	2,301

Notes: Standard errors are clustered at the individual-level and reported in parentheses. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

TABLE B.2

Peru: Full results

	(1)	(2)	(3)	(4)	(5)
			Mediator fixed (ACDE)		
	Total effect	*Total effect*	*Cares for others*	*Vulnerable job*	*Both*
Female*Aug-Oct	-0.160***	-0.164***	-0.156***	-0.162***	-0.154***
	(0.041)	(0.040)	(0.040)	(0.040)	(0.040)
Female*Nov-Dec	-0.179***	-0.186***	-0.167***	-0.187***	-0.168***
	(0.040)	(0.040)	(0.039)	(0.040)	(0.039)
Urban*Aug-Oct		-0.239***	-0.238***	-0.240***	-0.240***
		(0.034)	(0.034)	(0.034)	(0.034)
Urban*Nov-Dec		-0.107***	-0.107**	-0.106***	-0.106**
		(0.041)	(0.041)	(0.041)	(0.041)
Younger Cohort*Aug-Oct		-0.146***	-0.152***	-0.146***	-0.151***
		(0.040)	(0.040)	(0.040)	(0.040)
Younger Cohort*Nov-Dec		-0.015	-0.026	-0.015	-0.026
		(0.044)	(0.044)	(0.044)	(0.044)
Self-employed*Aug-Oct		0.103***	0.102**	0.102***	0.102**
		(0.040)	(0.040)	(0.040)	(0.040)
Self-employed*Nov-Dec		0.026	0.024	0.026	0.024
		(0.040)	(0.041)	(0.040)	(0.041)
Years of education*Aug-Oct		-0.004	-0.004	-0.004	-0.004
		(0.010)	(0.010)	(0.010)	(0.010)
Years of education*Nov-Dec		0.027**	0.025**	0.027**	0.025**
		(0.012)	(0.013)	(0.012)	(0.012)
August-October (Wave 3)	-0.175***	0.108	0.121	0.103	0.116
	(0.023)	(0.118)	(0.119)	(0.119)	(0.119)
October-November (Wave 4)	-0.126***	-0.345**	-0.317*	-0.342**	-0.312*
	(0.021)	(0.159)	(0.161)	(0.158)	(0.161)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,362	1,362	1,362	1,362	1,362

Notes: Standard errors are clustered at the individual-level and reported in parentheses. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

TABLE B.3

Vietnam: Full results

	(1)	(2)	(3)	(4)	(5)
			Mediator fixed (ACDE)		
	Total effect	*Total effect*	*Cares for others*	*Vulnerable job*	*Both*
Female*Aug-Oct	-0.060***	-0.057**	-0.042*	-0.061***	-0.046**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Female*Nov-Dec	-0.080***	-0.083***	-0.073***	-0.084***	-0.075***
	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)
Urban*Aug-Oct		-0.143***	-0.154***	-0.132***	-0.142***
		(0.029)	(0.029)	(0.029)	(0.029)
Urban*Nov-Dec		-0.043*	-0.049**	-0.039*	-0.046*
		(0.023)	(0.023)	(0.023)	(0.023)
Younger Cohort*Aug-Oct		-0.046**	-0.059**	-0.040*	-0.051**
		(0.023)	(0.023)	(0.023)	(0.023)
Younger Cohort*Nov-Dec		0.002	-0.005	0.005	-0.003
		(0.020)	(0.020)	(0.020)	(0.020)
Self-employed*Aug-Oct		0.036	0.039	0.038	0.041*
		(0.025)	(0.025)	(0.025)	(0.025)
Self-employed*Nov-Dec		0.000	0.002	0.001	0.003
		(0.023)	(0.023)	(0.023)	(0.023)
Years of education*Aug-Oct		0.004	0.004	0.004	0.004
		(0.004)	(0.004)	(0.004)	(0.004)
Years of education*Nov-Dec		0.005	0.005	0.005	0.005
		(0.004)	(0.004)	(0.004)	(0.004)
August-October (Wave 3)	-0.114***	-0.103**	-0.089*	-0.092*	-0.079
	(0.014)	(0.049)	(0.049)	(0.049)	(0.049)
October-November (Wave 4)	-0.059***	-0.101**	-0.092*	-0.097**	-0.089*
	(0.010)	(0.047)	(0.047)	(0.047)	(0.047)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	2,902	2,902	2,902	2,902	2,902

Notes: Standard errors are clustered at the individual-level and reported in parentheses. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

Appendix C

Table C.1 presents the female proportion of the following groups in each country: i) The final analytical sample, ii) those in the 2020 Young Lives phone survey sample, who were in full-time education (at any point in 2020) and iii) those in the phone survey sample who were not working (paid or unpaid) for at least one hour in their own business, for a household member or for someone else, in the Wave 1 reference period (see Section 4).

TABLE C.1

The correlation of gender with reasons for omission from the analytical sample

	India			*Peru*			*Vietnam*		
	Final sample	*In FTE*	*Not working*	*Final sample*	*In FTE*	*Not working*	*Final sample*	*In FTE*	*Not working*
Female share	0.33	0.43***	0.58***	0.41	0.52***	0.57***	0.46	0.53***	0.58***
Total Observations	767	1,368	1,587	462	850	884	970	997	761

Notes: FTE refers to being in full-time education during 2020. *In FTE* and *Not working* are not mutually exclusive. Results from *t*-tests of equality of the female share between *Final sample* and *In F*TE, and *Final sample* and *Not working* are reported. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

Table C.2 records the mean values of the variables reported in Table 1 for females in the 2020 phone survey sample, separated by whether they were included in the final sample (Included) or not (Omitted). The results of *t*-test of the equality of means between these two groups are reported in the Included column in each case.

TABLE C.2

Characteristics of included and omitted females

	India (females)		*Peru (females)*		*Vietnam (females)*	
	Omitted	*Included*	*Omitted*	*Included*	*Omitted*	*Included*
Panel A: Sample characteristics						
Individual characteristics						
Age (in years)	20.36	22.68***	19.55	21.57***	19.77	22.59***
Younger Cohort	0.72	0.39***	0.84	0.55***	0.81	0.41***
Completed years of education	12.57	9.89***	12.27	11.50***	12.68	11.19***
Self-employed (pre-pandemic)	0.57	0.50	0.36	0.31	0.26	0.19**
Household characteristics						
Wealth index tercile 1 (poorest)	0.31	0.49***	0.34	0.30	0.30	0.40***
Wealth index tercile 2	0.33	0.30	0.28	0.42***	0.35	0.35
Wealth index tercile 3	0.37	0.21***	0.39	0.28**	0.35	0.24***
Urban household	0.31	0.14***	0.81	0.79	0.60	0.32***
Mother's years of education	3.57	1.67***	7.39	6.30**	6.69	5.70***
Panel B: Potential mediators						
Cares for others (pre-pandemic)	0.22	0.38***	0.08	0.15***	0.11	0.25***
Vulnerable job (pre-pandemic)	0.18	0.14	0.12	0.14	0.40	0.23***
Number of participants	1,072	250	831	188	833	443
% Working pre-pandemic	11	100	39	100	45	100

Notes: All variables follow the same definitions as Table 1. Results from *t*-tests of equality of means between females *Omitted* and *Included* are reported. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

Table C.3 reports an estimated upper and lower bound on the change in the gender employment gap. These values come from the most extreme coefficient estimates obtained from 1,000 bootstrapped samples. Each sample drops a random group of size *p* male observation, where *p* is a number sufficient to equate (as closely as possible) the gender split in each random sample to the split in the 2020 Young Lives phone survey. Based on these extreme measures of the

change in the gender gap, we also report the corresponding ACDE and the proportion of the total effect explained by the *Eliminated effect*.

TABLE C.3

Approximated upper and lower bound of the change in the gender employment gap

	(2)	(3)		(4)		(5)	
		Mediator fixed (ACDE)					
	Total effect	*Cares for others*	†*Mediator attributed*	*Vulnerable job*	*Mediator attributed*	*Both mediators*	*Mediator attributed*
				India			
Female*Aug-Oct (upper)	-0.054	-0.059	-9.1%	-0.055	-1.5%	-0.060*	-10.8%
	(0.036)	(0.036)		(0.036)		(0.036)	
Female*Aug-Oct (lower)	-0.143***	-0.140***	1.8%	-0.145***	-0.8%	-0.141***	1.0%
	(0.030)	(0.030)		(0.030)		(0.030)	
Female*Nov-Dec (upper	-0.155***	-0.132***	14.8%	-0.154***	0.4%	-0.132***	15.1%
	(0.036)	(0.035)		(0.036)		(0.035)	
Female*Nov-Dec (lower)	-0.234***	-0.218***	7.0%	-0.235***	-0.4%	-0.219***	6.6%
	(0.031)	(0.030)		(0.031)		(0.030)	
				Peru			
Female*Aug-Oct (upper)	-0.076	-0.066	14.0%	-0.068	10.6%	-0.057	25.1%
	(0.051)	(0.051)		(0.051)		(0.051)	
Female*Aug-Oct (lower)	-0.245***	-0.243***	0.9%	-0.240***	1.9%	-0.239***	2.8%
	(0.042)	(0.042)		(0.042)		(0.042)	
Female*Nov-Dec (upper	-0.094*	-0.073	23.4%	-0.093*	0.3%	-0.072	23.8%
	(0.054)	(0.054)		(0.054)		(0.054)	
Female*Nov-Dec (lower)	-0.268***	-0.249***	7.1%	-0.272***	-1.9%	-0.254***	5.2%
	(0.038)	(0.038)		(0.038)		(0.038)	
				Vietnam			
Female*Aug-Oct (upper)	-0.007	0.011	254.7%	-0.010	-41.3%	0.005	180.0%
	(0.031)	(0.031)		(0.031)		(0.031)	
Female*Aug-Oct (lower)	-0.101***	-0.088***	13.2%	-0.103***	-1.6%	-0.091***	10.5%
	(0.024)	(0.024)		(0.023)		(0.023)	
Female*Nov-Dec (upper	-0.041	-0.028	32.9%	-0.043	-5.9%	-0.030	26.7%
	(0.028)	(0.028)		(0.028)		(0.028)	
Female*Nov-Dec (lower)	-0.119***	-0.111***	6.9%	-0.120***	-0.9%	-0.112***	5.9%
	(0.019)	(0.019)		(0.019)		(0.019)	

Notes: †Mediator attributed measures the proportion (%) of the total gender gap attributable to each mediator variable. All estimations are estimated with individual fixed effects. All controls in Table 2 included but not reported. Observations for India = 1,563 (47.98% female); Peru = 1,123 (49.33% female); Vietnam = 2,626 (50.53% female). Standard errors are clustered at the individual-level and reported in parentheses. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

Appendix D

Table D.1 reports the coefficients of interest, generated under the first alternative definition of the mediator *Vulnerable job*. Here, we define a job type, where employment is more likely to be impacted by the pandemic and lockdown condition, as any work activity classified as *services* in the ISIC, Rev. 4.

TABLE D.1

Services as an alternative definition of vulnerable job

	(2)	(3)		(4)		(5)	
		Mediator fixed (ACDE)					
	Total effect	*Cares for others*	†*Mediator attributed*	*Vulnerable job*	*Mediator attributed*	*Both mediators*	*Mediator attributed*
				India			
Female*Aug-Oct	-0.096***	-0.095***	0.1%	-0.099***	-3.7%	-0.099***	-3.4%
	(0.027)	(0.027)		(0.027)		(0.027)	
Female*Nov-Dec	-0.191***	-0.180***	6.0%	-0.192***	-0.2%	-0.180***	5.7%
	(0.030)	(0.030)		(0.030)		(0.030)	
				Peru			
Female*Aug-Oct	-0.164***	-0.156***	5.0%	-0.168***	-2.4%	-0.160***	2.7%
	(0.040)	(0.040)		(0.039)		(0.039)	
Female*Nov-Dec	-0.186***	-0.167***	10.5%	-0.186***	0.2%	-0.167***	10.4%
	(0.040)	(0.039)		(0.040)		(0.039)	
				Vietnam			
Female*Aug-Oct	-0.057**	-0.042*	27.3%	-0.056**	2.4%	-0.040*	29.3%
	(0.023)	(0.023)		(0.023)		(0.023)	
Female*Nov-Dec	-0.083***	-0.073***	11.5%	-0.083***	0.3%	-0.073***	11.9%
	(0.020)	(0.020)		(0.020)		(0.020)	

Notes: †Mediator attributed measures the proportion (%) of the total gender gap attributable to each mediator variable. All estimations are estimated with individual fixed effects. All controls in Table 2 included but not reported. Observations for India = 2,301; Peru = 1,362; Vietnam = 2,902.Standard errors are clustered at the individual-level and reported in parentheses. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

Table D.2 reports the coefficients of interest, generated under the second alternative definition of the mediator *Vulnerable job*. Here, we define a job type, where employment is more likely to be impacted by the pandemic and lockdown condition, according to the proportion of workers in that work activity who can work from home. We define a vulnerable job as one of

three economic activities with the lowest share of home-workers. In the first three panels of Table D.2, these are: i) Activities of households as employers, ii) Water supply; sewerage, waste management and remediation activities, and iii) Accommodation and food service activities. In the final panel of Table D.2, based on the Vietnam STEP data only, ii) Water supply; sewerage, waste management and remediation activities, is replaced with ii) Other services.

TABLE D.2

Low ability to work from home as an alternative definition of vulnerable job

	(2)	(3)		(4)		(5)	
		Mediator fixed (ACDE)					
	Total effect	*Cares for others*	†*Mediator attributed*	*Vulnerable job*	*Mediator attributed*	*Both mediators*	*Mediator attributed*
			India (all STEP countries)				
Female*Aug-Oct	-0.096***	-0.095***	0.1%	-0.098***	-2.9%	-0.098***	-2.5%
	(0.027)	(0.027)		(0.027)		(0.027)	
Female*Nov-Dec	-0.191***	-0.180***	6.0%	-0.191***	0.3%	-0.179***	6.2%
	(0.030)	(0.030)		(0.030)		(0.030)	
			Peru (all STEP countries/LAC)				
Female*Aug-Oct	-0.164***	-0.156***	5.0%	-0.169***	-2.8%	-0.161***	2.2%
	(0.040)	(0.040)		(0.040)		(0.040)	
Female*Nov-Dec	-0.186***	-0.167***	10.5%	-0.187***	-0.4%	-0.167***	10.5%
	(0.040)	(0.039)		(0.040)		(0.039)	
			Vietnam (all STEP countries)				
Female*Aug-Oct	-0.057**	-0.042*	27.3%	-0.057**	0.5%	-0.039*	31.2%
	(0.023)	(0.023)		(0.023)		(0.023)	
Female*Nov-Dec	-0.083***	-0.073***	11.5%	-0.083***	0.2%	-0.072***	13.1%
	(0.020)	(0.020)		(0.020)		(0.020)	
			Vietnam (Vietnam STEP data only)				
Female*Aug-Oct	-0.057**	-0.042*	27.3%	-0.055**	3.1%	-0.037	34.7%
	(0.023)	(0.023)		(0.023)		(0.023)	
Female*Nov-Dec	-0.083***	-0.073***	11.5%	-0.082***	1.6%	-0.070***	15.4%
	(0.020)	(0.020)		(0.020)		(0.020)	

Notes: †Mediator attributed measures the proportion (%) of the total gender gap attributable to each mediator variable. All estimations are estimated with individual fixed effects. All controls in Table 2 included but not reported. Observations for India = 2,301; Peru = 1,362; Vietnam = 2,902. Standard errors are clustered at the individual-level and reported in parentheses. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

Appendix E

In Table E.1, we restrict our sample to those individuals who did not move location at any point after the Covid-19 outbreak in their respective countries and the final survey interview in November-December of 2020.

TABLE E.1

Omitting individuals who migrated after the outbreak

	(2)	(3)		(4)		(5)	
		Mediator fixed (ACDE)					
	Total effect	*Cares for others*	†*Mediator attributed*	*Vulnerable job*	*Mediator attributed*	*Both mediators*	*Mediator attributed*
			India				
Female*Aug-Oct	-0.093***	-0.089***	4.3%	-0.094***	-1.1%	-0.090***	-3.4%
	(0.028)	(0.028)		(0.028)		(0.028)	
Female*Nov-Dec	-0.191***	-0.183***	4.2%	-0.190***	0.2%	-0.182***	5.7%
	(0.031)	(0.031)		(0.031)		(0.031)	
			Peru				
Female*Aug-Oct	-0.155***	-0.147***	4.7%	-0.154***	0.2%	-0.147***	4.8%
	(0.042)	(0.042)		(0.042)		(0.042)	
Female*Nov-Dec	-0.195***	-0.178***	9.0%	-0.195***	0.2%	-0.177***	9.1%
	(0.042)	(0.042)		(0.042)		(0.042)	
			Vietnam				
Female*Aug-Oct	-0.051**	-0.032	37.3%	-0.053**	-4.9%	-0.035	30.6%
	(0.023)	(0.023)		(0.023)		(0.023)	
Female*Nov-Dec	-0.078***	-0.067***	14.0%	-0.079***	-1.2%	-0.069***	12.5%
	(0.020)	(0.020)		(0.020)		(0.020)	

Notes: †Mediator attributed measures the proportion (%) of the total gender gap attributable to each mediator variable. All estimations are estimated with individual fixed effects. All controls in Table 2 included but not reported. Observations for India = 1,965; Peru = 1,249; Vietnam = 2,833. Standard errors are clustered at the individual-level and reported in parentheses. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

Appendix F

Given that the phone survey interviews took place over a number of months, in Table F.1 we restrict our sample to those surveyed only in September for the first survey interview and only those interviewed in November for the second survey interview.

TABLE F1

The most common interview month only

	(2)	(3)		(4)		(5)	
		Mediator fixed (ACDE)					
	Total effect	*Cares for others*	†*Mediator attributed*	*Vulnerable job*	*Mediator attributed*	*Both mediators*	*Mediator attributed*
			India				
Female*Aug-Oct	-0.078**	-0.084**	-8.5%	-0.079**	-2.2%	-0.087**	-11.3%
	(0.039)	(0.039)		(0.039)		(0.039)	
Female*Nov-Dec	-0.191***	-0.181***	5.4%	-0.191***	0.2%	-0.180***	5.6%
	(0.030)	(0.030)		(0.030)		(0.030)	
			Peru				
Female*Aug-Oct	-0.153***	-0.139***	9.1%	-0.150***	2.0%	-0.136***	11.0%
	(0.045)	(0.045)		(0.045)		(0.045)	
Female*Nov-Dec	-0.179***	-0.159***	11.1%	-0.182***	-1.7%	-0.163***	9.3%
	(0.041)	(0.041)		(0.041)		(0.041)	
			Vietnam				
Female*Aug-Oct	-0.085***	-0.070***	18.3%	-0.086***	-1.0%	-0.071***	17.0%
	(0.024)	(0.024)		(0.024)		(0.024)	
Female*Nov-Dec	-0.082***	-0.072***	12.3%	-0.083***	-1.3%	-0.073***	10.6%
	(0.020)	(0.020)		(0.020)		(0.020)	

Notes: †Mediator attributed measures the proportion (%) of the total gender gap attributable to each mediator variable. All estimations are estimated with individual fixed effects. All controls in Table 2 included but not reported. Observations for India = 1,887; Peru = 1,173; Vietnam = 2,629. Standard errors are clustered at the individual-level and reported in parentheses. * denotes significance at 10%, ** significance at 5% and *** significance at 1%.