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ABSTRACT

What If It Never Happened? Subjective Treatment Effects of a Negative Shock on Youth Labour Market Outcomes in Developing Countries*

This paper examines the subjective treatment effects of a negative shock created by the COVID-19 pandemic on the labour market outcomes of young adults in India, Peru, and Vietnam. We leverage subjective counterfactual outcomes at the individual-level that were purposely collected from over 7,000 individuals to this aim. Our findings suggest that the shock denied employment opportunities and reduced earnings. On average, the pandemic reduced monthly earnings by 19.4% and employment levels by 17.5% in our three-country-sample. Country-specific magnitudes are lowest for India and highest for Vietnam. However, these average effects belie that a substantial proportion of individuals, particularly those from disadvantaged backgrounds, are pushed into employment by the pandemic. This frequently comes at the expense of their education, hinting at youth labour acting as a buffer against transitory shocks. According to our findings, the perceived effects of the pandemic on labour market outcomes carry important implications for young people's well-being and behaviour. Individuals who are denied employment display significantly higher rates of anxiety, lower rates of COVID-19 vaccination, and lower desired fertility.

JEL Classification: J21, J11, C21, C83, D84

Keywords: subjective treatment effects, labour market, COVID-19, youth, developing countries

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1. Introduction

How does a negative macroeconomic shock affect individual labour market outcomes? On the one hand, macroeconomic hardship might decrease labour demand through a negative *income effect*, thereby denying employment to job seekers and reducing earnings for the employed (Fornaro and Wolf, 2020; Guerrieri et al., 2022). This is particularly true for young workers, who have little job-specific human capital and thus may be relatively less valuable to their firms (Forsythe, 2022; Glewwe and Hall, 1998). On the other hand, however, worsening conditions at the household level can lead to a *positive substitution effect* (increasing labour supply), pushing otherwise economically inactive individuals into employment. Previous research has shown that, as family income declines during temporary household income shocks, adolescents - particularly from poor households - may enter the labour market to boost household incomes (Bandara et al., 2015; Jacoby and Skoufias, 1997; Beegle et al., 2006). Thus, the average effect depends on the relative strengths of the income and substitution effects.

Against this backdrop, this paper investigates the impact of the negative shock created by the COVID-19 pandemic on the labour market outcomes of young adults in India, Peru, and Vietnam as perceived by them.[2] In a non-experimental setting, the absence of an appropriate counterfactual (in this case, a scenario in which the pandemic never occurred) creates challenges for inferring causal effects. We circumvent this problem by using purposely collected data on young people's subjective expectations as part of Young Lives, a 20-year longitudinal cohort study.

In 2021, the Young Lives survey was explicitly designed to not only collect young adults' outcomes after the onset of the pandemic, but also to recover subjective counterfactual outcomes in the absence of the COVID-19 outbreak. Specifically, the survey asked respondents about their current experiences in the labour market and what those experiences would have

[2] Our focus on young adults speaks to the impressionable years hypothesis, which suggests that events during young adulthood shape individuals' perspectives and behaviour. Further, this population group is of interest due to the particularly detrimental effects of employment disruptions for labour market entrants (von Wachter and Bender, 2006; Arellano-Bover, 2020). In line with this, pandemic-induced earnings and job losses are more pronounced among this group. Globally, the youth unemployment rate was estimated at 15.6% in 2021, up more than 15% relative to 2019, and more than three times the adult rate (ILO, 2022).

been in the absence of the pandemic. This information, conditional on both states of the world, allows us to directly estimate subjective treatment effects at the individual level.

This approach brings the advantage of exploring individuals' beliefs, which have been shown to play a key role in individuals' decision-making and behaviour (e.g., Arteaga et al., 2022; Attanasio and Kaufmann, 2014). We exploit this feature of our measures to evaluate whether subjective treatment effects influence the well-being and behaviour of those affected. More specifically, we use value-added models and COVID-19 related information to investigate the association between the subjective treatment effects and changes in mental health (i.e., increase in reported symptoms of anxiety), fertility preferences (i.e., changes in the desired number of children), and health investments (i.e., COVID-19 vaccination compliance).

Overall, our findings indicate that the shock induced by the COVID-19 pandemic has denied employment opportunities and reduced earnings for young people in our study countries. On average, the pandemic reduced monthly earnings by 19.4% and employment levels by 17.5% in our three-country-sample. Country-specific magnitudes of these effects are lowest for India and highest for Vietnam. We further investigated whether the effects were stronger among disadvantaged individuals as per their maternal education and pre-pandemic wealth. Our results show that some of the negative effects are systematically attenuated for individuals with disadvantaged backgrounds, which hints at youth labour being used as a buffer against transitory shocks and flexible labour markets among the most disadvantaged.

We then exploit the availability of individual-level counterfactuals to examine the possibility of positive employment effects in detail. Our analysis suggests that a non-negligible share of young adults have been pushed into employment in India and Peru. In the case of the latter, labour may be acting as a buffer against the shock at the expense of educational investments. In accordance with Klasen and Pieters (2015), the "pushed-into-employment" phenomenon in India is pronounced among the disadvantaged, in particular among women living in the poorest households who were not in education before the pandemic.

Finally, in relation to the implications of subjective treatment effects on young people's well-being and future behaviours and decision-making, we find that individuals who have been denied employment by the pandemic display significantly higher increases in anxiety and, for the case of India, a decrease in the desired number of children. Furthermore, being denied employment is associated with lower rates of COVID-19 vaccination in both India and Vietnam. Altogether, our analysis suggests that irrespective of the real effects of negative economic shocks, the perceived effects carry important, and arguably long-term, implications for key choices in the lives of young individuals.

This paper contributes to the growing literature on subjective treatment effects and their relevance for welfare and behaviour (Delavande, 2014). These studies are characterised by having a counterfactual space tied to a counterfactual outcome. Recent articles investigate subjective treatment effects of college completion (Wiswall and Zafar, 2021), college major (Arcidiacono et al., 2020), university choice (Delavande and Zafar, 2019) and the COVID-19 pandemic (Rodriguez-Planas, 2022; Aucejo et al., 2020) on the experiences and expectations of college students.[3] Given our focus on subjective treatment effects of the pandemic, our analysis is closest to Rodriguez-Planas (2022) and Aucejo et al. (2020).[4] We expand this literature in three ways: first, by investigating labour market outcomes for a sample of young individuals that goes beyond investigated student samples, both in terms of the profile of respondents and sample size; second, by examining, for the first time, subjective effects on labour market outcomes across three developing countries, as most of this research has been conducted with samples of students enrolled in the United States.

A third contribution to this field relates to the implications of the subjective effects on well-being and behaviour. The literature on subjective treatment effects indicates that quantifying perceived effects are key for understanding human behaviour and corresponding outcomes, given that they are fundamental to informing people's current and future choices.[5] The few available examples connect a realised behaviour with the treatment effect within the same domain. For instance, Wiswall and Zafar (2021) link subjective returns to university majors with sorting into university majors. However, this nascent literature has not addressed the implications of the treatment effects for people's behaviour and well-being indicators in domains other than the subjective treatment effect itself. This paper contributes to this literature

[3] Other studies investigate the effects of hypothetical health scenarios on employment (Giustinelli and Shapiro, 2019) and individual-level income shocks on consumption patterns (Fuster et al. 2021; Christelis et al., 2019).
[4] A second similarity to these studies consists of our focus on ex-post treatment effects. Taking the perspective of the respondent, ex-post effects are measured after the effects take place, as opposed to ex-ante effects, which are estimated before the outcome materializes.
[5] For instance, several studies suggest that perceptions and beliefs about returns to education and admission chances drive important educational choices (e.g., Arteaga et al., 2022; Perez-Alvarez and Strulik, 2021; Attanasio and Kaufmann, 2014; Jensen, 2010).

by linking, for the first time, treatment effects (on labour market outcomes) with well-being and behaviour in other domains (mental health, health behaviour, and desired fertility). In this respect, the longitudinal nature of the data allows us to estimate value-added models, strengthening the implications of our analysis significantly.

The second strand of literature we contribute to investigates labour supply responses to income and wealth changes. While labour responses are usually studied in the context of positive income changes, this paper explores the opposite direction by investigating them at the onset of global macroeconomic hardship.[6] Relatedly, we contribute to the literature on shocks and their distributional impacts. It has long been recognised that income shocks do not affect all equally (Glewwe and Hall, 1998; World Bank, 1990). A great advantage of our setup relies on the observation of individual-level counterfactuals instead of group-level ones. Thus, we can examine the distribution of effects and estimate the prevalence of the subgroups' outcome type without imposing further assumptions. The income shock engendered by the COVID-19 pandemic appears to be no different, as it has been documented that less wealthy population groups and women suffered disproportionate job losses during the pandemic (Adams-Prassl et al., 2020; Dang and Nguyen, 2021; Scott et al., 2021). In our case, we focus on the subjective effects of the pandemic-induced negative income shock, investigating whether individuals from different groups perceive the severity of the shock differently.

We also add to the nascent economic literature on the impressionable years. This field investigates to what extent events during young adulthood play a formative role in shaping preferences and behaviour. For example, events during young adulthood have been shown to influence long-term preferences for job attributes (Cotofan et al., 2023), redistribution (Carreri and Teso, 2023; Roth and Wohlfart, 2018; Giuliano and Spilimbergo, 2014), risk (Shigeoka, 2019) and even compliance with health-related policies (Eichengreen et al., 2021). This literature typically leverages data from developed countries with long time frames to compare cohorts that were impacted by the event with cohorts that were not, thereby exploring the extensive margin of the event. We contribute to this by exploring the intensive margin of the impressionable years hypothesis (i.e., the perceived intensity of exposure to the COVID-19 shock) in the aftermath of the event with data from developing countries.

[6] See for instance studies investigating the labour response to income increases resulting from cash transfer programs (Baird et al., 2018; Handa et al., 2018; Salehi-Isfahani and Mostafavi-Dehzooei, 2018), housing programs (Jacob and Ludwig, 2012), inheritances (Bø et al., 2019) or lotteries (Cesarini et al., 2017).

The rest of the paper is organised as follows: Section 2 describes our data and discusses the different country contexts during the pandemic. Section 3 describes our analytical framework, while Section 4 presents the empirical strategy used to estimate the subjective treatment effects. Our main results are reported in Section 5, while Sections 6 and 7 explore heterogeneous treatment effects. Section 8 tests whether the treatment effects are associated with other health and well-being realised behaviours. Section 9 concludes.

2. Young Lives survey

2.1 Data

Our data comes from the Young Lives, a unique longitudinal cohort study following two cohorts of children since 2002 in India (states of Andhra Pradesh and Telangana), Peru and Vietnam.[7] In each country, the initial sample included about 2,000 Younger Cohort children, aged approximately 1-year-old, and around 1,000 Older Cohort children who were 7–8 years old.[8] From its inception, the study was not intended to be nationally representative, but rather the original sample design oversampled children living in poor families and communities. Despite this, studies by Escobal and Flores (2008), Nguyen (2008), and Kumra (2008) showed that the Young Lives data still cover a broad range of characteristics and attributes of each national population. Prior to the global pandemic, the two 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 five-part phone survey was conducted over the course of 2020/21, aimed at measuring the short-term impacts of the pandemic (Favara et al., 2021a). At the time, the two cohorts were aged between 18-19-years-old (Younger Cohort) and 25-26-years-old (Older Cohort). An initial contact phone call with respondents took place in June-July 2020, while the second and third calls took place in August-October and November-December of 2020, respectively. In 2021, two more phone surveys were implemented - a short

[7] Young Lives also collected data in Ethiopia. In this paper, we chose to exclude Ethiopia, as concerns about the COVID-19 pandemic have been greatly overshadowed by the recent civil conflict.
[8] In Peru, the Older Cohort comprised 714 children in 2002.

fourth phone call in August 2021, and a more comprehensive follow-up fifth call in November-December 2021.

Attrition rates observed in the Young Lives sample have been relatively low compared to similar long-running studies. In 2016 (the last in-person survey round), the attrition rate was 5.1%, 6.5% and 10.8% in Vietnam, India, and Peru, respectively (Sánchez and Escobal, 2020). Furthermore, given the long-standing relationship with the participants, the Young Lives COVID-19 phone survey had a higher response rate than most phone surveys during the pandemic. In total, 97%, 91%, and 85% of the 2016 samples in India, Peru, and Vietnam participated in the fifth phone survey - a very low rate of attrition compared to similar follow-up COVID-19 phone surveys on longitudinal studies.[9]

In the Young Lives COVID-19 phone surveys, we gathered employment information and asked participants whether, in the week before the survey (from Monday through Sunday), they had worked for at least one hour in their own business, for a household member or for someone else. The 2021 phone survey was also explicitly designed to not only collect participants' employment outcomes after the onset of the pandemic, but also to recover subjective counterfactual outcomes in the absence of the outbreak. Specifically, the phone survey asked respondents whether, *if the pandemic had not occurred*, they would have worked for at least one hour in the week before the survey in their own business, for a household member or for someone else in the week before the survey. Those who reported that they had worked, or would have worked if not for the pandemic, were asked what their current earnings are, or would have been.[10]

Table 1 presents an overview of the characteristics of our samples. Across the countries, the samples are broadly balanced across age and gender; on average, participants are between 21-22 years old (in 2021), with a minimum age of 19 and a maximum age of 29. However, a larger proportion of the samples in India and Vietnam live in rural areas, compared to the Peruvian

[9] For example, the UK Millennium Cohort study began at a similar time to Young Lives with 18,818 participants, though only 24% participated in their third COVID-19 survey in February-March 2021 (see https://cls.ucl.ac.uk/covid-19-survey/content-and-data-wave-3/).

[10] We ensured that participants were reporting their net earnings (the sum of all wages/salaries, tips, gratuities, bonuses, and the value of any in-kind payment after deducting taxes and any other work-related payment). If the participant worked in their own business, they were reminded to capture the sum of profits and self-determined wage from this activity, net of production costs.

sample (by sample design), and a relatively larger proportion of the Indian and Peruvian samples were still in education in 2020, compared to the Vietnamese sample. Additionally, Table 1 suggests that the average household in Vietnam is relatively wealthier than the average household in India and Peru, as households in the Vietnamese sample scored higher on the Young Lives wealth index and were less likely to worry about running out of food in 2021, on average.

Table 1. Descriptive statistics of the Young Lives samples

	India	Peru	Vietnam
Age (Nov-Dec 2021)	21.79	21.22	21.91
	(3.31)	(3.04)	(3.35)
Female	0.48	0.49	0.51
	(0.50)	(0.50)	(0.50)
Urban (Nov-Dec 2021)	0.28	0.85	0.37
	(0.45)	(0.36)	(0.38)
Wealth index (2016)	0.64	0.65	0.71
	(0.15)	(0.17)	(0.13)
Mother's education grade (2002)	2.60	7.18	5.54
	(2.98)	(4.28)	(4.11)
Vulnerable group	0.33	0.11	0.13
	(0.47)	(0.32)	(0.34)
Worried about running out of food in 2021	0.44	0.62	0.29
	(0.50)	(0.49)	(0.45)
Enrolled in education (2020)	0.47	0.35	0.36
	(0.50)	(0.48)	(0.48)
Number of individuals	2,667	2,163	2,419

Notes: All variables are dichotomous except for age and the wealth index score. Standard deviations are reported in parentheses. The YL wealth index takes values between zero and one, such that a larger value reflects a wealthier household. It is the simple average of a housing-quality index, an access-to-services index, and a consumer-durables index (Briones, 2017). 'Vulnerable group' takes the value of one if a participant is from a Scheduled Caste or Tribe in India, is a non-native Spanish speaker in Peru, and is from a minority ethnic group in Vietnam. 'Enrolled in education (2020)' takes the value of one if the participant reported being enrolled in full-time education in the second phone survey (August-October 2020).

2.2 Country contexts

Prior to the pandemic, our three study countries differed notably in terms of the extent of young people's labour market participation. According to the International Labour Organization, 75% of the 20 to 24-year-old population in Vietnam were in employment in 2019, compared to 68% in Peru, and just 34% in India. The countries also differed greatly in terms of young women's labour force participation rates; 62% of the 20 to 24-year-old female population in Peru were in employment in 2019 (compared to 74% of the male population of a similar age), while 67% of 20 to 24-year-old women (and 75% 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 12%, however (compared to 54% of 20 to 24-year-old men), with 67% not in education, employment, or training (NEET).[11]

During the first two years of the pandemic, the three study countries were subjected to very different experiences, both with regard to the number of COVID-19 infections (and deaths) and in their government's policy responses. Figure 1 reports the cumulative cases per million in India, Peru, and Vietnam until the end of 2021.

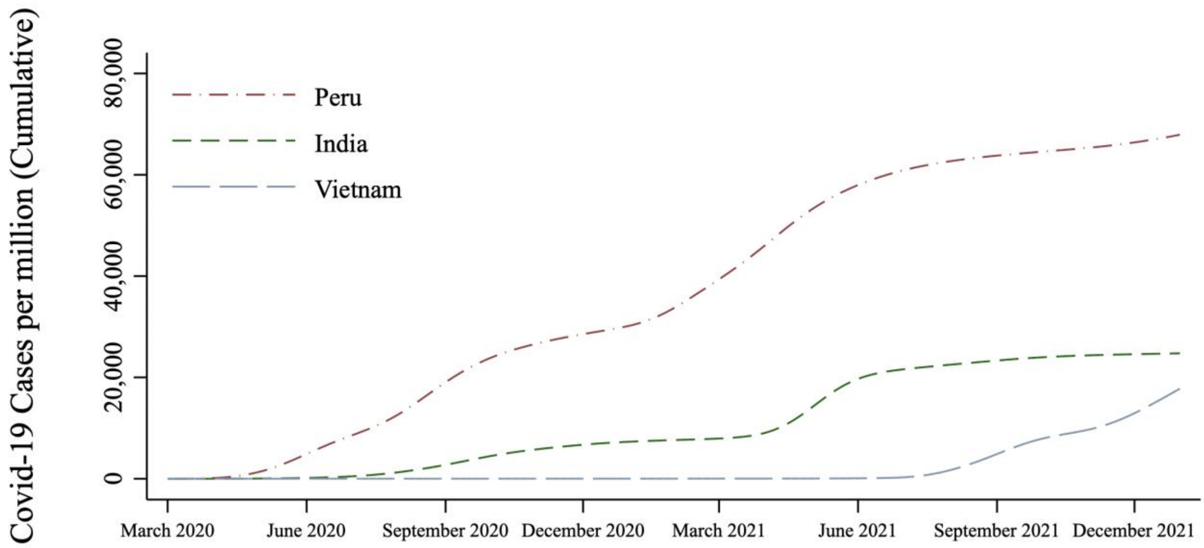

Figure 1. Timeline of COVID-19 cases during 2020 and 2021. Generated using locally weighted-regression scatter-plot smoothing (LOWESS), using data from https://ourworldindata.org.

In the first year of the pandemic, Peru experienced the greatest direct health impacts of the virus, occupying the highest position in the global rankings of COVID-19 cases and deaths (per capita). In contrast, during 2020, Vietnam had been remarkably successful at limiting infections. Figure 1 highlights that, during 2020, confirmed cases in both India and Vietnam fell far below those recorded in Peru. As of 31st December 2020, cases in India and Vietnam stood at 7,454 and 15, respectively, compared to 30,788 in Peru (per million).

Following a second wave of the pandemic between January and July, Peru continued to have the highest rate of death from COVID-19 in 2021. While India and (particularly) Vietnam were successful at containing the spread of the virus in 2020, subsequent waves of infections in 2021

[11] All labour market figures are sourced from the ILOSTAT database https://ilostat.ilo.org. Data retrieved on October 10th, 2022. As the two age cohorts in the Young Lives data are between 19-20 and 26-27, we acknowledge that the ILO figures reported do not exactly reflect the same ages as those in our sample. The average age in our samples is between 21-22 years old in all countries.

put an end to this narrative. Following the first wave in 2020, India experienced a devastating second wave of COVID-19 cases in April and May 2021. Similarly, a fourth COVID-19 wave in Vietnam (which started in April 2021) seriously affected the health and lives of millions of people, disrupting business operations in many provinces - particularly in those with key economic zones. By the end of December 2021, cases in India and Vietnam stood at 24,767 and 17,762, respectively, compared to 68,124 in Peru (per million).

The COVID-19 waves and associated economic restrictions led to severe disruptions and significant economic impacts in all three countries. In Peru and India, the strict and prolonged national lockdowns contributed to a fall in GDP of 11.0% and 6.6% in 2020, respectively (compared to an average decline among low- and middle-income countries of 1.3%). During this time, youth unemployment increased by 71% in Peru, and 9.6% in India (relative to 2019) - reaching 13.0% and 24.9%, respectively. In Vietnam, due largely to the country's relative success in curbing the spread of the virus, positive GDP growth was recorded at 2.9% in 2020. However, youth unemployment still increased by around 8.9% in the year, reaching 7.3% in 2020.

In 2021, decentralised policy decisions and relaxation of economic and social restrictions led to a subsequent economic recovery in Peru and India, as they recorded GDP growth of 13.3% and 8.9%, respectively. Despite this, youth unemployment continued to rise in India, reaching a record 28.3%, and failed to revert to pre-pandemic levels in Peru (11.2%). In Vietnam, GDP growth was recorded at 2.6% in 2021 – the lowest growth rate since records began – and youth unemployment in the country remained relatively high, at 7.2% (compared to a total unemployment rate of 2.2%).

3. Analytic framework

In this section, we briefly outline a simple analytic framework that guides the empirical analysis.[12] Following the notation of the Rubin Causal Model, let $Y_i(COVID)$ be the potential outcome of individual i associated with COVID-19 treatment. We are interested in the perceived effect of COVID-19 on individuals' labour market outcomes:

[12] Our framework closely follows the implementation of Aucejo et al. (2020).

$$\Delta_i Y = Y_i(COVID = 1) - Y_i(COVID = 0) \quad (1)$$

Recovering the subjective treatment effect at the individual-level entails the comparison of the individual's outcomes in two alternate states of the world. The approach we use in this paper is to directly ask individuals for their expected outcomes in both states of the world along the counterfactual space, which, in this case, is the existence of the pandemic. This allows us to calculate the individual-level *subjective* treatment effects, following a growing literature that leverages subjective counterfactuals to study consumption (Fuster et al., 2021; Christelis et al., 2019), university student outcomes (Rodriguez-Planas, 2022; Wiswall and Zafar, 2021; Arcidiacono et al., 2020; Aucejo et al., 2020; Delavande and Zafar, 2019) and labour supply (Giustinelli and Shapiro, 2019). For the unbiased estimation of these subjective treatment effects, we require that respondents report their beliefs without systematic biases, which is a standard assumption in survey data collection. A great advantage of this approach is that by keeping the individual constant across the counterfactual space, the estimation is not prone to biases that arise from respondents interpreting the survey questions differently.

As an example, consider beliefs about employment in the week before the phone survey. The survey asked individuals the following: "*During the last week (from Monday through Sunday), did you work for at least 1 hour, in your own business, for a household member or for someone else?*" This is the first term on the right-hand side of Equation (1). The counterfactual outcome was elicited as follows: "*If COVID had not happened would you have worked for at least 1 hour, in your own business, for a household member or for someone else during the last week?*". This is the second term on the right-hand side of Equation (1). The difference in the responses to these two questions gives us the subjective expected treatment effect of COVID-19 on employment status in the week before the survey. The within-person variation that we leverage allows us to eliminate unobserved factors confounding the estimation of interest.

Following Aucejo et al. (2020) and Rodriguez-Planas (2022), our estimates can also be interpreted as objective treatment effects that are measured after the effect took place. This would rely on the assumption that young individuals have well-formed expectations for outcomes in both the realised state and the counterfactual state. Although there has historically been concern about the plausibility of this assumption (Diamond and Hausman, 1994; Harrison, 2014), there is growing evidence that the two approaches of using stated choices or actual choices yield similar preference estimates (Mas and Pallais, 2017; Wiswall and Zafar,

2018) and that the stated approach yields meaningful responses when the counterfactual scenarios presented to respondents are realistic and relevant for them.[13]

A further benefit of our framework on subjective treatment effects arises from its unique focus on observing counterfactual outcomes at the individual-level, as opposed to obtaining group-level counterfactuals. This allows us to estimate the entire distribution of treatment effects rather than the group-level average effects. Further, instead of predicting with error the outcome differences in both scenarios for each individual, our approach grants us with the flexibility of directly observing these differences. For this reason, disaggregating the sample by those with positive, null, and negative effects to observe the prevalence of each of these groups does not require additional assumptions.

4. Empirical Strategy

Our empirical strategy is based on an individual fixed-effects model (Equation 2):

$$Y_{is} = \alpha_i + \beta COVID_{is} + \varepsilon_{is.} \qquad (2)$$

Y_{is} is a generic term for the employment outcome of individual i in scenario s. In the next section, Y_{is} either refers to a binary indicator of employment status or total earnings in the month before the phone survey. We winsorise monthly earnings at the ninety-ninth percentile, though this does not change results.[14] $COVID_{is}$ is an indicator variable taking the value of one in the realised scenario with COVID-19, and zero in the hypothetical scenario if COVID-19 had not happened. α_i is an individual fixed-effect intended to capture any fixed or prior characteristics of the individual or environment which influence the probability of employment in either scenario.[15] The parameter of interest is β, which captures the subjective treatment

[13] Previous evidence using Young Lives data (Favara et al., 2021b) shows that young people have well-informed expectations of their local labour markets, as subjective earnings expectations at 14-15-years-old closely match the average earnings of 25-year-olds from the same area with the same level of education. Therefore, while we cannot guarantee that the counterfactual outcome for each individual is correct, we believe that their ability to have well-informed expectations for employment outcomes in the counterfactual state is a credible assumption.

[14] Unfortunately, we did not ask participants about the frequency of their work in the hypothetical state without COVID-19. Consequently, for both states of the world, we constructed monthly earnings under the assumption of full-time work. Full-time work here refers to working 8 hours a day, 5 days a week, 4 weeks a month, and 12 months a year. While this is clearly a stringent assumption, it would imply that we would be likely to *understate* the magnitude of the pandemic's earnings effect if it also led to declines in working hours.

[15] Note that differencing or using fixed effects is algebraically equivalent with two scenarios.

effect of the COVID-19 pandemic on the labour market outcomes. Standard errors are clustered at the individual-level.

We extend Equation (2) to identify heterogeneous treatment effects:

$$Y_{is} = \alpha_i + \beta COVID_{is} + \delta X_{ih} + \gamma COVID_{is} * X_{ih} + \varepsilon_{ihs,} \quad (3)$$

where X represents a participant's individual or household characteristic of interest. In particular, we are interested in whether the subjective treatment effects differ by educational enrolment, gender, and socio-economic background.

5. Main results

5.1 Average subjective effects

We start with the analysis of the average effects, which are presented in Table 2. Panel A reports the results for monthly earnings among the full sample, Panel B reports the results for employment status, and Panel C shows the results for monthly earnings among individuals who reported being employed in both scenarios. In all countries, monthly earnings are first transformed to constant 2020 PPP USD to facilitate cross-country comparisons. The first two columns of the table show the average values in both states of the world. The average treatment effects are shown in column (3).

Table 2. Subjective treatment effects

	With COVID-19 (1)	Without COVID-19 (2)	$\hat{\beta}$ (3)	Number of individuals (4)
Panel A: Monthly earnings (2020 US$)				
All countries	321.87	407.64	-79.28***	7,049
	(478.29)	(562.77)	(3.66)	
India	162.22	183.65	-21.435***	2,613
	(292.09)	(340.42)	(3.510)	
Peru	351.56	428.57	-77.011***	2,118
	(426.99)	(491.00)	(7.600)	
Vietnam	475.27	621.81	-146.545***	2,318
	(610.94)	(672.05)	(7.638)	
Panel B: Employment status				
All countries	0.57	0.69	-0.121***	7,249
	(0.49)	(0.46)	(0.005)	

India	0.47	0.48	-0.013*	2,667
	(0.50)	(0.50)	(0.008)	
Peru	0.67	0.77	-0.103***	2,163
	(0.47)	(0.42)	(0.011)	
Vietnam	0.59	0.85	-0.255***	2,419
	(0.49)	(0.36)	(0.010)	
Panel C: Monthly earnings (intensive margin, 2020 US$)				
All countries	595.62	713.80	-109.459***	3,573
	(520.91)	(595.80)	(4.515)	
India	375.04	454.32	-80.773***	1,011
	(354.15)	(415.83)	(5.590)	
Peru	540.35	673.78	-126.920***	1,213
	(424.11)	(489.39)	(8.167)	
Vietnam	811.17	943.03	-115.256***	1,349
	(615.01)	(700.34)	(8.224)	

Notes: Panels A and B are calculated using the full sample. Panel C is calculated only using those individuals who reported that they would be employed in both scenarios. Monthly earnings are transformed to constant 2020 US Dollars. Column 3 shows the estimated $\hat{\beta}$ coefficient estimated using Equation (2), with standard errors clustered at the individual level. ***p < 0.01, **p < 0.05, *p < 0.10.

The table shows that the shock induced by the COVID-19 pandemic has significantly reduced earnings and denied employment opportunities for young people in our study countries. On average, the pandemic reduced monthly earnings by 19.4%, employment levels by 17.5% and monthly earnings among the employed by 15.3% in our three-country-sample.

Our country-specific estimates suggest that the average treatment effects are negative and statistically significant in all three countries. However, the magnitude of these effects varies substantially. On average, respondents experienced a decrease in monthly earnings of 11.7%, 18.0% and 23.6% in India, Peru, and Vietnam, respectively (Panel A). The full distribution of this effect among those who reported a non-zero treatment effect is depicted in Figure A.1 in the Appendix.[16] In all three countries, the treatment effect distribution is skewed to the left. However, note that a hump appears in all countries to the right of the zero value, more pronounced in India and Peru.

The impact on monthly earnings conflates changes in the extensive margin (i.e., changes in the employment status) and changes in the intensive margin (i.e., changes in earnings for those who remain employed). Analysing the effect of the pandemic on employment (Panel B), we find that average treatment effects are negative in all three countries, suggesting that, on

[16] We also report the full distribution of the subjective treatment effects for monthly earnings when they are not winsorised in Figure A.2.

average, young adults perceive that their employment has been disrupted by the COVID-19 pandemic. However, the magnitude of the effect is small in the Indian sample. On average, the pandemic reduced employment levels by 2.7%, 13.4%, and 30.0% in India, Peru, and Vietnam, respectively.

Lastly, to isolate the subjective treatment effects on earnings at the intensive margin, we re-estimate Equation (2) on the sample of employed individuals who report no change in their employment status due to the pandemic (i.e., those who are working and reported that they would have worked in the absence of the pandemic).[17] We find that, on average, these respondents experienced a decline in monthly earnings of 17.8%, 18.8% and 12.2% in India, Peru, and Vietnam, respectively (Panel C).

When comparing the results for India and Vietnam, we observe an inverse relationship between the effect sizes at the extensive and intensive margin. That is, while a smaller (bigger) proportion of young people perceived that the pandemic decreased their employment opportunities in India (Vietnam), those employed perceived larger (smaller) reductions in their earnings. This hints at a potential trade-off between shock absorption at the extensive and intensive margin. A potential explanation for this lies in the formality degree of labour markets. Among the three country samples, India has the highest level of informal employment, whereas Vietnam has the lowest one.[18] While the higher levels of formality may be advantageous in 'normal' circumstances, workers may suffer a 'reversal of fortune' during negative income shocks as the formality might bring with it inflexibility to adjust earnings accordingly, thereby forcing a shock absorption at the extensive margin.

6. Heterogeneity analysis of treatment effects

To understand the distributional impact of the pandemic, we investigate next whether disadvantaged individuals are more or less strongly affected by the pandemic. More specifically, we explore heterogeneous effects by socioeconomic status and gender. Further, we test whether those that were in education near the onset of the pandemic were affected differently than the rest. This variable is used as a proxy for the school-to-work transition

[17] This represents 40% of the sample in India, and 58% in both Peru and Vietnam.

[18] The Indian economy is estimated to have the largest proportion of total employment in the informal sector, namely 89%. Vietnam on the other hand shows the lowest value of 71%. These cross-country differences are resembled in the Young Lives samples (Elgin et al., 2021). In 2016, 37% of the Older Cohort participants who were working in Vietnam had a written job contract - compared to 27% in Peru, and just 4% in India.

period. This stage may play an important role in how the negative shock affects the labour market outcomes of the youth. A large literature has investigated the impact of graduating during recessions on unemployment rates, finding that, relative to prior cohorts, those entering the labour market in a recession face large losses in employment (e.g., Rothstein, 2021; Oreopoulos et al., 2012; Fernández-Kranz and Rodríguez-Planas, 2018).

Figure 2 plots the differences in treatment effects by gender, education enrolment, and socio-economic status. For the latter, we use as a proxy low maternal education and whether participants belong to a historically vulnerable ethnic group.[19] The coefficient estimates are interpreted as the differences in the subjective treatment effects relative to the baseline categories.[20]

We find that the most disadvantaged participants reported weaker employment effects in all three countries, and weaker earnings effects among those who remained employed in India and Vietnam, whereas no differential pattern is observed for monthly earnings. Indeed, those with low maternal education in India and non-native Speakers in Peru show statistically insignificant employment effects (see Table A.6 in the Appendix). This result may, at least partially, relate to disadvantaged individuals being pushed into employment by the pandemic, which we investigate in Section 7. Another explanation may be due to the flexibility of the informal sector. In all three countries, the less wealthy were significantly more likely to be working in flexible, informal sectors (i.e., as self-employed in agriculture) just before the pandemic, compared to their wealthier counterparts who were more likely to be operating in a stickier, formal sector.[21]

Looking at the differences by gender, two findings emerge. First, in all three countries, females experienced larger negative effects on employment compared to males, as shown in the centre

[19] Given the differences in development between the three countries, mothers median education is defined separately for each country. In India, the median education in 2002 was 0 years of schooling, while in Peru and Vietnam, it was 7 and 6 years, respectively. The vulnerable group variable takes the value of one if a participant belongs to a Scheduled Caste/Tribe in India, is a non-native Spanish-speaker in Peru, or belongs to a minority ethnic group in Vietnam.

[20] Figure 2 thus shows the estimated $\hat{\gamma}$ coefficients from Equation (3). Full regression results are shown in Appendix tables A.2-A.10. In the Appendix, we also show coefficients for an additional proxy of socioeconomic status, namely whether participants were in the lowest tercile in the wealth index distribution in 2016. The wealth index takes values between zero and one, such that a larger value reflects a wealthier household. It is the simple average of a housing-quality index, an access-to-services index, and a consumer-durables index (Briones, 2017). The latter takes the value of one if a participant belongs to a Scheduled Caste/Tribe (India); is a non-native Spanish-speaker (Peru); or belongs to a minority ethnic group (Vietnam).

[21] Table A.11 in the Appendix presents a comparison of the self-employment rates in agriculture before the pandemic according to maternal education.

panel. This is in line with growing international evidence, which documents that women's employment has been disproportionately affected by the COVID-19 pandemic (Scott et al., 2021; Adams-Prassl et al., 2020; Alon et al., 2020; Albanesi and Kim, 2021). Second, in India and Vietnam, male earnings are more affected than female earnings, although this only holds in Vietnam when conditioning on maintaining employment in both scenarios. This combination of results resembles the absorption trade-off previously observed across countries. This time, women absorb the shock more at the extensive margin, whereas men absorb it more at the intensive margin instead. Possible explanations for this pattern consist of gender norms on employment normalizing the labour market withdrawal of women, as well as to the male earnings premium making a larger reduction in earnings possible during crises.[22]

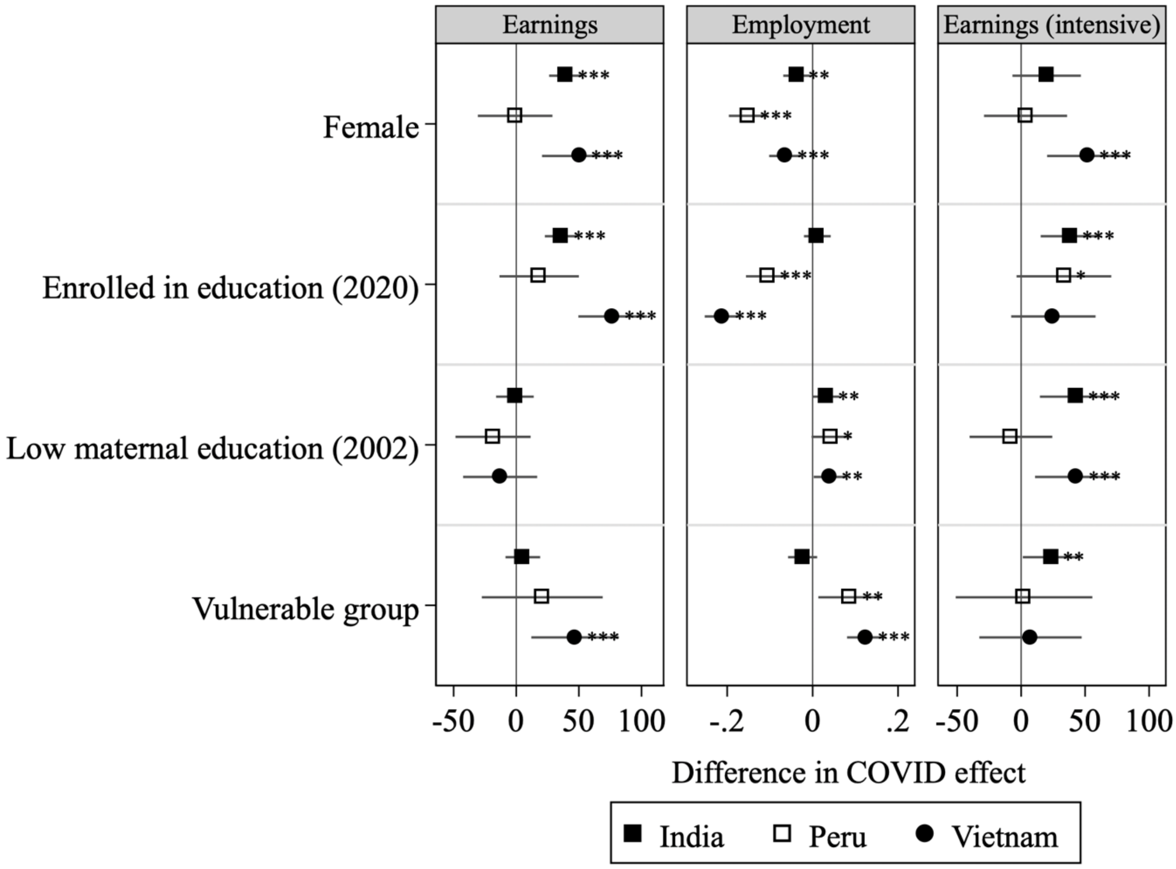

Figure 2. Differences in subjective treatment effects by demographic group and socioeconomic status.

Notes: Figure shows estimated $\hat{\gamma}$ from separate regressions of Equation (3). Low maternal education takes the value of one if a participants' mother had below median education in 2002, and zero otherwise. In India, mothers' median education in 2002 was 0 years of schooling, while in Peru and Vietnam, it was 7 and 6 years, respectively. Vulnerable group refers to whether the participant belongs to a Scheduled Caste/Tribe (India), is a non-native Spanish speaker (Peru), and belongs to a minority ethnic group (Vietnam). 'Enrolled in education (2020)' takes

[22] In India, Peru, and Vietnam, before the pandemic, men were earning roughly 2.60, 1.39 and 1.13 times more than women on average. This difference is significant at the 1% level in all three countries.

the value of one if the participant reported being enrolled in full-time education in the second phone survey (August-October 2020). Baseline categories refer to males, not enrolled in education in 2020, high maternal education, and non-vulnerable group, respectively. Earnings and Employment regressions are estimated on the full sample, while the Earnings (intensive) regressions are only estimated on those who remain employed in both scenarios. Vertical bars indicate a 95% confidence interval around predictions. ***p < 0.01, **p < 0.05, *p < 0.10.

We next analyse differences according to education enrolment near the onset of the pandemic (i.e., August-October 2020). We observe that, in Peru and Vietnam, those enrolled in education perceived more pronounced declines in employment compared to those who were not in education. In fact, those who were not in education reported no significant effect on earnings or employment in India. In each country, over 90% of respondents enrolled in education in 2020 are from the Younger Cohort, who were, on average, 18.5 years old in 2020.[23] Our results therefore suggest that the COVID-19 pandemic may have denied a substantial proportion of secondary school graduates entry into the labour market.

7. Different employment strokes for different folks

The analysis in Table 2 and Figure 2 does not tell the full story of subjective treatment effects. Due to its opposing income and substitution effects, the shock might have resulted in negative changes for some and positive changes for others. Our methodology permits us to explore this issue in depth. This is because we observe counterfactual outcomes for each individual, rather than for a group of individuals, which allows us to gauge effects at the individual level.

Since the dichotomy of opposing effects is most traceable for the extensive margin of labour market outcomes, we focus on employment effects in this subsection. That is, we investigate the extent to which individuals have been pushed into work or been denied employment instead. Along this line, Table 3 provides a sample breakdown by the type of outcome differences across scenarios.

Table 3. Sample breakdown by outcome type

	India	**Peru**	**Vietnam**
Panel A: No change in employment	2,226	1,544	1,728
	(83.5)	(71.4)	(71.4)
Employed in both scenarios	*1,054*	*1,254*	*1,395*
	(39.5)	*(58.0)*	*(57.67)*
Inactive in both scenarios	*1,172*	*290*	*333*
	(43.9)	*(13.4)*	*(13.8)*

[23] This percentage was 96% in India, 91% in Peru, and 97% in Vietnam.

Panel B: Change in employment	441	619	691
	(16.5)	(28.6)	(28.6)
Denied employment	*238*	*421*	*654*
	(8.9)	*(19.4)*	*(27.0)*
Pushed into employment	*203*	*198*	*37*
	(7.6)	*(9.2)*	*(1.6)*
Total number of individuals	2,667	2,163	2,419
	(100)	(100)	(100)

Notes: Number of individuals in each subgroup. Percentage of full sample reported in parentheses. 'No change in employment' takes the value of one if a participant's employment status is the same in the realised scenario and the hypothetical scenario in which COVID-19 had not happened. 'Denied employment' takes the value of one if a participant reported not working in the week before call 5 but reported that they would have worked in the week if COVID-19 had not happened. 'Pushed into employment' takes the value of one if a participant reported working in the week before call 5 but reported that they would not have worked in the week if COVID-19 had not happened.

Panel A of the table shows that, in all three countries, the majority of young adults perceived that the COVID-19 pandemic did not alter their employment status (83.5% in India and 71.4% in Peru and Vietnam). We can further disaggregate this category into those that either work in both scenarios or remain inactive. In Peru and Vietnam, most of these individuals report working in both scenarios, while, in India, there is roughly an even split between those who report working in both scenarios and those who are inactive in both scenarios. The high level of inactivity in India reflects the country's low female labour force participation rates, as 68% of the inactive are females.

Among those who felt that the pandemic led to a change in their labour market status (Panel B), relatively more respondents believe that the pandemic has denied them employment rather than pushed them into employment. Note that the differences between being pushed and denied employment is larger for Vietnam and smallest for India, which is in line with the pattern we observe in the estimates of the previous section.

Out of the total sample, we find that 9% in India, 19% in Peru, and 27% in Vietnam perceive being denied employment by the macroeconomic shock. Importantly, a nontrivial proportion of respondents perceive that the pandemic has pushed them into employment in the Indian (7.6%) and Peruvian (9.2%) samples. In Vietnam, this "pushed into employment" phenomenon is much lower, at only 1.6%. This lack of a (positive) substitution effect provides an explanation as to why the magnitude of the negative earnings effect is largest in Vietnam, as described in Section 5.

7.1 Who gets pushed into employment?

In the previous section, we uncovered that a non-trivial proportion of respondents in India and Peru have been pushed into the labour market by the negative shock. One of the primary mechanisms posited for this phenomenon is that youth labour acts as a buffer against transitory shocks, suggesting that the effect might be more pronounced among relatively poorer and vulnerable households (Beegle et al., 2006). To assess this, we generate a binary variable which takes the value of one if a participant believes that the pandemic has pushed them into employment, and regress this on gender, education enrolment, the interaction of these two, and proxies for socio-economic status. Table 4 reports the results.

Table 4. Differences in being pushed into employment by demographic group and socioeconomic status.

	India	**Peru**
Female	0.023	-0.030
	(0.021)	(0.025)
Enrolled in education (2020)	0.057***	-0.036
	(0.020)	(0.025)
Female*Enrolled in education (2020)	-0.074***	0.013
	(0.026)	(0.034)
Low median maternal education (2002)	0.039***	-0.026
	(0.013)	(0.017)
Vulnerable group	0.003	0.072**
	(0.014)	(0.030)
Mean pushed into employment	0.076	0.092

Notes: Regressions are on the full samples. Standard errors are clustered at the individual level. Low maternal education takes the value of one if a participants' mother had below median education in 2002, and zero otherwise. In India, mothers' median education in 2002 was 0 years of schooling, while in Peru and Vietnam, it was 7 and 6 years, respectively. Vulnerable group refers to whether the participant belongs to a Scheduled Caste/Tribe (India), is a non-native Spanish speaker (Peru), and belongs to a minority ethnic group (Vietnam). Enrolled in education (2020) takes the value of one if the participant reported being enrolled in full-time education in the second phone survey (August-October 2020). ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

In both India and Peru, we find that those who have been pushed into employment are significantly more likely to come from disadvantaged households (low maternal education in India and vulnerable ethnic group in Peru). This is in line with the weaker employment effects observed among disadvantaged groups in Figure 2.

In Peru, we observe no systematic differences for those in the school-to-work transition, as proxied by educational enrolment during August-October 2020. Given that we explicitly asked about the perceived reasons for being pushed into employment, we can explore the role of education further. It turns out that 81% of participants who have been pushed into employment said that they would be studying instead of working had the pandemic never happened.[24] Thus, the COVID-19 shock has forced them into the labour market at the detriment of their potential education. This is consistent with previous literature analysing the effect of transitory income shocks on child labour in low- and middle-income countries (e.g., Bandara et al., 2015 Beegle et al., 2006).

In India, we also find no average differences according to education enrolment. However, females who were in education are less likely to have been pushed into employment by the pandemic, compared to their male counterparts. This might be due to women having a harder time finding a job during the school-to-work transition than men. An alternative explanation relates to the fact that females not in education are more likely to be pushed into employment than their male counterparts.[25] On average, these females are relatively older than the rest of the sample (24.0 years vs 21.7), come from the poorest households (45% in lowest 2016 wealth tercile vs 33%), and have completed fewer years of schooling (6.3 years of schooling vs 10.10) (Table A.11 in the Appendix). Therefore, although, on average, females in India experienced larger negative employment treatment effects, female respondents from the poorest households are more likely to be pushed into employment than their male counterparts.

Against this backdrop, Klasen and Pieters (2015) argue that there is a negative income effect among women from poor households with low education such that, as household incomes decline to very low levels or are insecure, these women are forced to work in low-skilled jobs to survive. However, as household incomes rise, women face barriers to labour force participation related to both the absence of an urgent need to work, and the presence of social stigmas associated with female employment in menial jobs. Indeed, 73% of the women in India who have been pushed into employment said that they would not be working in the absence of the pandemic as there would be fewer job offers that were relevant for them. Our findings are also consistent with Berniell et al. (2023), who find that women in Latin America act as secondary workers in economic downturns.

[24] In combination with Table 4, this suggests that in Peru, which was heavily affected by the pandemic in early 2020, some individuals who were in education before the pandemic had already dropped out by August-October 2020 (see Figure 1).

[25] Nearly 10% of females who were not in education in 2020 have been pushed into employment, compared to just 4% of males not in education (difference significant at the 1% level).

8. Impact of subjective treatment effects on health and fertility

In this section, we investigate whether the labour market subjective treatment effects are associated with a change in the well-being and behaviour of those affected. More specifically, we examine whether young people who believe the COVID-19 pandemic has impacted their employment experience a larger deterioration in their mental health (specifically an increase in self-reported anxiety symptoms), compared to those who perceive no labour market effect. A growing body of literature finds that job losses during the pandemic have led to a deterioration in mental health in low- and middle-income countries (e.g., Freund et al., 2022; Baranov et al., 2022). Therefore, we might expect that the perceived impact of the pandemic on employment may be reflected on their mental health, particularly of those who feel that the pandemic has denied them employment.

Furthermore, we investigate the impact of the subjective treatment effects on fertility preferences, specifically, a change in the number of desired children. There is a vast literature on the link between household income (shocks) and fertility decisions. A negative income shock might decrease the demand for children if they are perceived as ‘normal goods’, or it might increase the demand for children if they are seen as substitutes for missing institutions and markets (Becker, 1960). Thus, the net effect is theoretically ambiguous and depends on which force is stronger in our contexts.

Lastly, individuals who feel particularly affected by the negative income shock may be less likely to have been vaccinated against COVID-19, compared to those who feel their employment is not affected. The assumption behind is that affected individuals might experience a reduction in their trust in the government, and its measures to deal with the pandemic, and so we may expect to see an association between the treatment effects and vaccination compliance (Bollyky et al., 2022; Lazarus et al., 2021; Soares et al., 2021).[26]

In August-October 2020 (call 2), November-December 2020 (call 3) and November-December 2021 (call 5), symptoms of anxiety were measured using the Generalized Anxiety Disorder-7 (GAD-7) scale, which assesses the frequency of seven symptoms of anxiety over the past 14 days.[27] The GAD-7 has been validated, and previously been used in all three of our study

[26] Alternatively, employers and co-workers could promote vaccination among employees, resulting in higher compliance among the employed.

[27] The full list of statements is reported in Figure A.2 in the Appendix.

countries (Zhong et al., 2015; Hakim et al., 2017; Collier et al., 2020; Pham Tien, 2020). From this information, we generated a binary variable where 0 indicates no/minimal anxiety and 1 indicates the presence of symptoms consistent with at least mild anxiety.[28] The August 2021 survey (call 4) asked participants what they thought their ideal number of children would be (independent of the number of children they may have already had). Importantly, a similar question was asked in a previous in-person survey round in 2016. This allows us to run a value-added specification for this particular outcome, thereby easing endogeneity concerns. Lastly, in November-December 2021 (call 5) participants were also asked whether they had been infected with COVID-19 (or suspected to be), had access to a COVID-19 vaccination, and whether they had been vaccinated.

To assess whether the employment subjective treatment effects are associated with symptoms of anxiety, the ideal number of children, and vaccination status, we estimate linear probability models. We regress each outcome on two dummy variables for whether the participant believes that the COVID-19 pandemic has denied them, or pushed them into, employment.[29] We control for individual (time-invariant) characteristics (sex, age, main language, ethnicity/caste, and highest schooling grade) as well as (pre-pandemic) household-level characteristics (wealth score in 2016 and whether any parent has completed primary schooling).

For the anxiety regressions, we estimate value-added models by controlling for anxiety symptoms from November-December 2020. Although this was during the COVID-19 pandemic, most of the pandemic-induced job losses in India and Vietnam occurred in 2021, motivating us to explore the value-added specification. We also estimate value-added specifications for the ideal number of children to account for decisions made in the participants' lives before the pandemic; we do so by controlling for the lagged ideal number of children measured in 2016.

Lastly, for the vaccination regressions, while we are not able to estimate value-added regressions (due to data availability), we include controls on whether the participant has

[28] For each item in the scale, we asked participants whether the symptom had been experienced (Yes/No), and, if 'Yes', we then asked about the frequency. The frequency was reported using a 3-item Likert scale ranging from 1 'Less than half the days' to 3 'nearly every day'. We summed up all symptoms by multiplying the binary Yes (1)/No (0) by the frequency of symptoms. A cut-off of ≥5 on the raw score was used to represent the presence of symptoms of "at least mild symptoms" of anxiety (Spitzer et al., 2006).

[29] The omitted baseline category is thus individuals who do not feel that the pandemic has affected their employment status. This represents 84% of the sample in India, and 71% in both Peru and Vietnam (Table 3).

previously been infected with COVID-19 (or suspected) and the participant's subjective risk of COVID-19 infection (ranging from 0 'No Risk' to 3 'High Risk'), as COVID-19 risk perceptions have been found to be strongly associated with vaccination uptake (Lazarus et al., 2021 Caserotti et al., 2021). Additionally, we control for whether the participant would be able to get a COVID-19 test, if required, as a proxy for vaccination availability. Table 5 reports the results.

Table 5. Associations between subjective treatment effects and change in anxiety, ideal number of children, and COVID-19 vaccination

	At least mild anxiety	Ideal number of children	COVID-19 vaccination
Panel A: India			
Denied	0.059**	-0.184***	-0.078**
	(0.023)	(0.048)	(0.033)
Pushed	-0.008	0.028	-0.003
	(0.021)	(0.033)	(0.025)
Number of observations	2,633	2,412	2,628
Panel B: Peru			
Denied	0.025	0.055	-0.029
	(0.029)	(0.052)	(0.029)
Pushed	-0.019	0.026	0.026
	(0.037)	(0.075)	(0.040)
Number of observations	1,852	1,532	1,842
Panel C: Vietnam			
Denied	0.038**	0.007	-0.044*
	(0.015)	(0.024)	(0.026)
Pushed	0.017	-0.079	0.034
	(0.047)	(0.088)	(0.085)
Number of observations	2,272	2,140	2,225
Mean at least mild anxiety (Nov-Dec 2021)	0.098	0.327	0.082
Mean ideal number of children (August 2021)	1.927	1.864	1.981
Mean COVID-19 vaccination	0.652	0.648	0.582

Notes: Calculated using the full phone survey sample. All regressions control for the participant's sex, age, main language, ethnicity/caste, highest schooling grade, household wealth score (measured in 2016), and whether any parent has completed primary schooling. COVID-19 vaccination regressions also include whether the participant has been infected with COVID-19 (or suspected), the subjective risk of COVID-19 infection, and whether the participant would be able to get a COVID-19 test if required. Ideal number of children regressions also include the ideal number of children measured in 2016. Robust standard errors reported in parentheses. 'Denied' takes the value of one if the participant believes that the COVID-19 pandemic has denied them employment, while 'Pushed' takes the value of one if the participant believes that the COVID-19 pandemic has pushed them into employment. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

According to our findings, subjective treatment effects are associated with a lower probability of getting vaccinated against COVID-19 and increased anxiety in India and Vietnam, and with a change in fertility preference (i.e., a decrease in the ideal number of children) in India. No significant association is found in Peru. These associations are driven by those who have been denied employment (as no significant association is found for those who have been pushed into work). In fact, those denied employment are 7.8 and 4.4 percentage points (ppts) less likely to have been vaccinated, compared to those who do not believe that the pandemic has altered their employment. Similarly, those denied employment are 5.9 and 3.8 ppts, respectively, more likely to have symptoms consistent with at least mild anxiety, compared to those who do not believe that the pandemic has altered their employment status.

9. Conclusion

In this paper, we estimate the subjective treatment effects of the negative income shock created by the COVID-19 pandemic on the labour market outcomes of young adults in three developing countries. To study these effects, we surveyed over 7,000 young adults in India, Peru, and Vietnam as part of the Young Lives study, and asked them about their current labour market experiences and what those experiences would have been had it not been for the pandemic. We present evidence showing that, on average, young adults believe that the COVID-19 pandemic has denied them employment opportunities and reduced their earnings, but with important differences in magnitude between the three study countries.

Looking beyond the average treatment effects, we find that the pandemic has affected the labour market outcomes of young adults in low- and middle-income countries in a number of different ways. We find evidence that, in India and Peru, the pandemic has pushed a nontrivial proportion of participants into employment, frequently at the detriment of their education. These participants tend to come from poorer and more vulnerable households, suggesting that their labour may be acting as a buffer against the negative pandemic shock. In India, we also find evidence that the pandemic may have led to an increase in labour force participation among older females in poor households who were not in education before the pandemic.

We also observe that many young adults believe that the pandemic has denied them entry into the labour market. This effect is stronger among 18-19-year-old participants in Peru and Vietnam during their school-to-work transition. This has important implications, as there is an increasing literature showing that graduating during an economic downturn not only has temporary negative effects but can also leave lasting scars on workers' professional careers and earnings (Escalonilla et al., 2021; Oreopoulos et al., 2012, for example). Moreover, our findings have relevance for comprehending the true labour market ramifications of adverse income shocks among young adults. Neglecting to consider individuals who have been barred from entering the job market, as well as those that have been pushed into employment, and solely concentrating on job losses, may result in an underestimation of the negative employment effects of the shock.

Finally, we evaluate to what extent these subjective treatment effects are associated with higher anxiety, changes in fertility preferences, and COVID-19 vaccination. We find evidence that individuals who have been denied employment by the pandemic display significantly higher increases in rates of anxiety, and lower rates of COVID-19 vaccination in both India and Vietnam. In India, being denied employment is also associated with a reduction in the ideal number of children. This suggests that, irrespective of the real effects that a negative economic shock might have on individuals, the perceived effects carry important implications in the lives of young individuals. While these associations are short-term, they occur during the so-called impressionable years, thereby increasing the likelihood of long-term implications. For instance, the detrimental effects of being denied employment on mental health could persist and leave enduring scars, as has been well-documented among young workers in high-income countries (e.g., Eberl et al., 2022; Clark et al., 2001; Lucas et al., 2004; Mousteri et al., 2018; Strandh et al., 2014). We conclude that uncovering the nature of subjective treatment effects from economic shocks is at the core of understanding the choices and changes in well-being linked to these shocks. This understanding may thus inform public policies on economic shocks aiming at improving the livelihoods of workers in developing countries.

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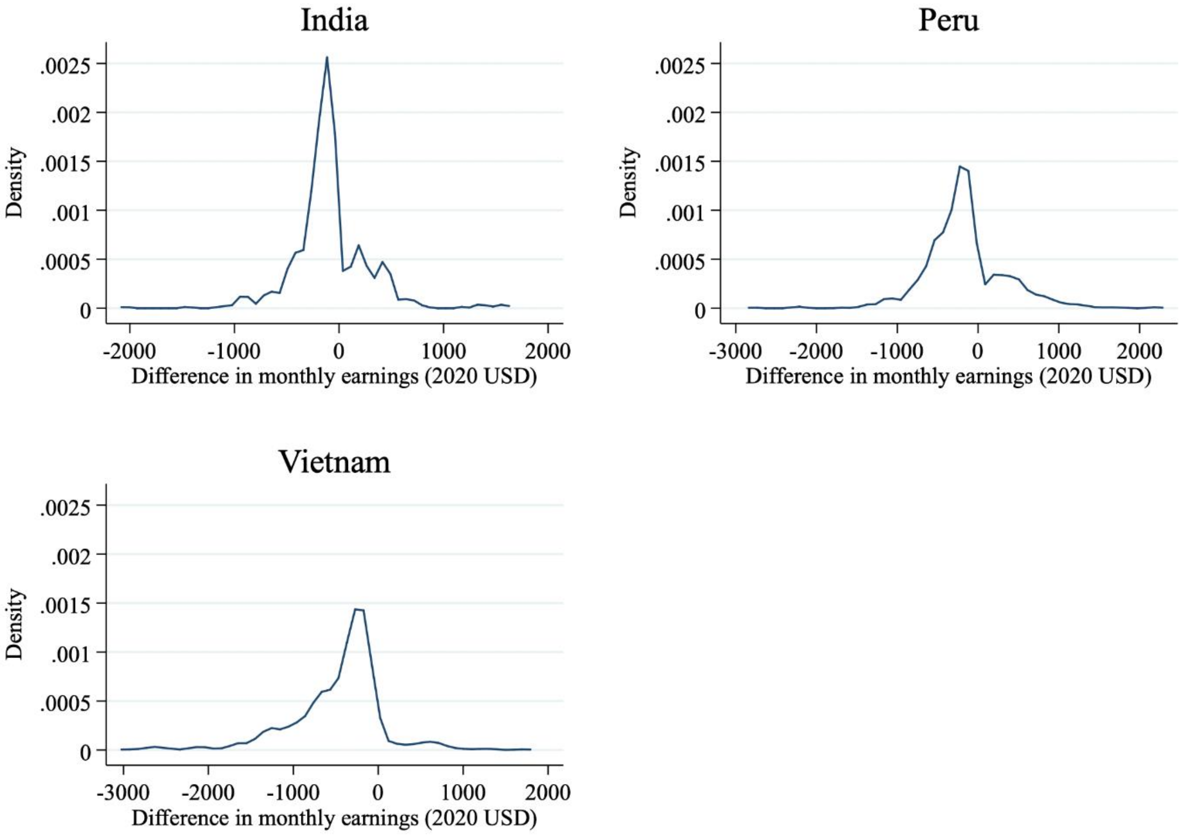
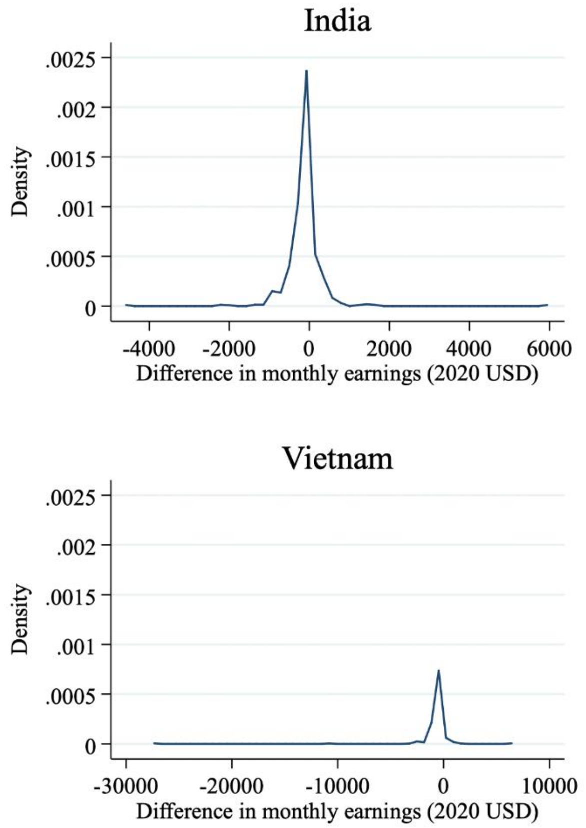
Appendix

Figure A.1. Distribution of monthly earnings subjective treatment effects, winsorised



Notes: Figure shows the kernel densities of the subjective treatment effects for monthly earnings, among those who reported a non-zero subjective treatment effect. Subjective treatment effects are defined as realised monthly earnings minus hypothetical monthly earnings had the COVID-19 pandemic never happened. Earnings are transformed to constant 2020 US Dollars and are winsorised at the ninety-ninth percentile.

Figure A.2. Distribution of monthly earnings subjective treatment effects, not winsorised



Notes: Figure shows the kernel densities of the subjective treatment effects for monthly earnings, among those who reported a non-zero subjective treatment effect. Subjective treatment effects are defined as realised monthly earnings minus hypothetical monthly earnings had the COVID-19 pandemic never happened. Earnings are transformed to constant 2020 US Dollars.

Table A.2. Heterogenous subjective treatment effects on earnings, by education enrolment and gender

	India		Peru		Vietnam	
	Female	Enrolled in education (2020)	Female	Enrolled in education (2020)	Female	Enrolled in education (2020)
COVID	-40.54***	-38.56***	-76.55***	-80.13***	-172.14***	-174.54***
	(5.51)	(5.67)	(11.51)	(10.50)	(11.73)	(11.11)
X_i	-231.44***	-217.86***	-228.42***	-207.53***	-160.53***	-606.57***
	(12.24)	(12.23)	(20.73)	(20.80)	(27.77)	(23.33)
COVID*X_i	39.74***	36.23***	-0.93	18.29	50.49***	77.02***
	(6.90)	(6.84)	(15.19)	(16.17)	(15.28)	(13.99)
COVID effect	-0.80	-2.33	-77.48***	-61.84***	-121.65***	-97.52***
among X_i	(4.16)	(3.84)	(9.91)	(12.30)	(9.79)	(8.50)
Observations	5,226	5,220	4,236	3,796	4,636	4,636

Notes: Results estimated using Equation (2). Enrolled in education (2020) takes the value of one if a participant was enrolled in education in August-October 2020. 'COVID effect among X_i' reflects the average subjective treatment effect on monthly among the X_i group. It is calculated as the linear combination of the COVID and COVID*X_i regression coefficients. Standard errors are clustered at the individual level. * : p<0.1, ** : p<0.05, *** : p<0.01.

Table A.3. Heterogenous subjective treatment effects on earnings by maternal education, and vulnerable group

	India		Peru		Vietnam	
	Low maternal education	Vulnerable group	Low maternal education	Vulnerable group	Low maternal education	Vulnerable group
COVID	-20.65***	-23.18***	-67.79***	-80.17***	-138.64***	-152.62***
	(6.43)	(4.51)	(10.92)	(8.09)	(10.53)	(8.45)
X_i	55.14***	8.58	50.08**	-65.41**	23.77	-152.52***
	(14.18)	(13.62)	(21.47)	(32.47)	(28.22)	(33.98)
COVID*X_i	-1.09	5.22	-18.56	20.75	-12.89	46.95***
	(7.67)	(7.06)	(15.30)	(24.61)	(15.09)	(17.83)
COVID effect among X_i	-21.74***	-17.96***	-86.35***	-59.43**	-151.52***	-105.67***
	(4.17)	(5.43)	(10.72)	(23.25)	(10.80)	(15.70)
Observations	5,201	5,226	4,196	4,196	4,600	4,636

Notes: Results estimated using Equation (2). Low maternal education takes the value of one if a participants' mother had below median education in 2002, and zero otherwise. In India, mothers' median education in 2002 was 0 years of schooling, while in Peru and Vietnam, it was 7 and 6 years, respectively. Vulnerable group refers to whether the participant belongs to a Scheduled Caste/Tribe (India), is a non-native Spanish speaker (Peru), and belongs to a minority ethnic group (Vietnam). 'COVID effect among X_i' reflects the average subjective treatment effect on monthly among the X_i group. It is calculated as the linear combination of the COVID and COVID*X_i regression coefficients. Standard errors are clustered at the individual level. * : p<0.1, ** : p<0.05, *** : p<0.01.

Table A.4. Heterogenous subjective treatment effects on earnings by wealth tercile

	India	Peru	Vietnam
	Lowest wealth tercile (2016)	Lowest wealth tercile (2016)	Lowest wealth tercile (2016)
COVID	-25.58***	-83.46***	-148.11***
	(4.53)	(9.85)	(9.55)
X_i	8.27	-54.87**	3.63
	(13.29)	(21.80)	(28.54)
COVID*X_i	11.65	12.77	7.87
	(7.09)	(15.34)	(15.96)
COVID effect among X_i	-13.93**	-70.69***	-140.24***
	(5.45)	(11.76)	(12.79)
Observations	5,198	4,196	4,594

Notes: Results estimated using Equation (2). Lowest wealth tercile takes the value of one if a participant's household was in the lowest tercile of the wealth index in 2016. The wealth index takes values between zero and one, such that a larger value reflects a wealthier household. It is the simple average of a housing-quality index, an access-to-services index, and a consumer-durables index (Briones, 2017). 'COVID effect among X_i' reflects the average subjective treatment effect on monthly among the X_i group. It is calculated as the linear combination of the COVID and COVID*X_i regression coefficients. Standard errors are clustered at the individual level. * : p<0.1, ** : p<0.05, *** : p<0.01.

Table A.5. Heterogenous subjective treatment effects on employment by education enrolment, and sex

	India		Peru		Vietnam	
	Female	Enrolled in education (2020)	Female	Enrolled in education (2020)	Female	Enrolled in education (2020)
COVID	0.01	-0.02	-0.03**	-0.06***	-0.21***	-0.17***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
X_i	-0.35***	-0.29***	-0.06***	-0.06***	-0.06***	-0.19***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
COVID*X_i	-0.04**	0.01	-0.15***	-0.11***	-0.06***	-0.21***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
COVID effect among X_i	-0.03**	-0.00	-0.18***	-0.17***	-0.27***	-0.38***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Observations	5,226	5,220	4,236	3,796	4,636	4,514

Notes: Results estimated using Equation (2). Enrolled in education (2020) takes the value of one if a participant was enrolled in education in August-October 2020. 'COVID effect among X_i' reflects the average subjective treatment effect on monthly among the X_i group. It is calculated as the linear combination of the COVID and COVID*X_i regression coefficients. Standard errors are clustered at the individual level. * : p<0.1, ** : p<0.05, *** : p<0.01.

Table A.6. Heterogenous subjective treatment effects on employment by maternal education, and vulnerable group

	India		Peru		Vietnam	
	Low maternal education	Vulnerable group	Low maternal education	Vulnerable group	Low maternal education	Vulnerable group
COVID	-0.03**	-0.00	-0.13***	-0.12***	-0.26***	-0.26***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
X_i	0.21***	0.11	0.05***	-0.03	0.03**	0.01
	(0.02)	(0.20)	(0.02)	(0.03)	(0.02)	(0.02)
COVID*X_i	0.03**	-0.02	0.04*	0.09**	0.04**	0.13***
	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)
COVID effect	0.00	-0.03*	-0.08***	-0.03	-0.22***	-0.13***
among X_i	(0.01)	(0.01)	(0.02)	(0.04)	(0.01)	(0.02)
Observations	5,210	5,226	4,196	4,196	4,600	4,636

Notes: Results estimated using Equation (2). Low maternal education takes the value of one if a participants' mother had below median education in 2002, and zero otherwise. In India, mothers' median education in 2002 was 0 years of schooling, while in Peru and Vietnam, it was 7 and 6 years, respectively. Vulnerable group refers to whether the participant belongs to a Scheduled Caste/Tribe (India), is a non-native Spanish speaker (Peru), and belongs to a minority ethnic group (Vietnam). 'COVID effect among X_i' reflects the average subjective treatment effect on monthly among the X_i group. It is calculated as the linear combination of the COVID and COVID*X_i regression coefficients. Standard errors are clustered at the individual level. * : p<0.1, ** : p<0.05, *** : p<0.01.

Table A.7. Heterogenous subjective treatment effects on employment by wealth tercile

	India	Peru	Vietnam
	Lowest wealth tercile (2016)	Lowest wealth tercile (2016)	Lowest wealth tercile (2016)
COVID	-0.03***	-0.13***	-0.27***
	(0.01)	(0.01)	(0.01)
X_i	0.14***	0.03	0.02
	(0.02)	(0.02)	(0.02)
COVID*X_i	0.04**	0.05**	0.08***
	(0.02)	(0.02)	(0.02)
COVID effect among X_i	0.02	-0.07***	-0.19***
	(0.01)	(0.02)	(0.01)
Observations	5,198	4,196	4,594

Notes: Results estimated using Equation (2). Lowest wealth tercile takes the value of one if a participant's household was in the lowest tercile of the wealth index in 2016. The wealth index takes values between zero and one, such that a larger value reflects a wealthier household. It is the simple average of a housing-quality index, an access-to-services index, and a consumer-durables index (Briones, 2017). 'COVID effect among X_i' reflects the average subjective treatment effect on monthly among the X_i group. It is calculated as the linear combination of the COVID and COVID*X_i regression coefficients. Standard errors are clustered at the individual level. * : p<0.1, ** : p<0.05, *** : p<0.01.

Table A.8. Heterogenous subjective treatment effects on earnings (intensive margin) by education enrolment, and gender

	India		Peru		Vietnam	
	Female	Enrolled in education (2020)	Female	Enrolled in education (2020)	Female	Enrolled in education (2020)
COVID	-85.33***	-91.49***	-128.34***	-136.91***	-138.85***	-120.76***
	(6.29)	(6.76)	(10.73)	(10.51)	(12.33)	(9.90)

X_i	-182.36***	-247.00***	-191.92***	-220.27***	-76.58**	-497.29***
	(26.83)	(25.03)	(27.01)	(28.36)	(35.62)	(39.15)
COVID*X_i	19.95	38.41***	3.43	33.43*	51.85***	25.18
	(13.63)	(11.79)	(16.55)	(18.86)	(16.08)	(16.80)
COVID effect	-65.38***	-53.08***	-124.90***	-103.48***	-87.01***	-95.59***
among X_i	(12.09)	(9.66)	(12.61)	(15.66)	(10.32)	(13.58)
Observations	2,022	2,022	2,426	2,150	2,698	2,624

Notes: Regressions estimated only on sample who reported being employed in both scenarios. Results estimated using Equation (2). Enrolled in education (2020) takes the value of one if a participant was enrolled in education in August-October 2020. 'COVID effect among X_i' reflects the average subjective treatment effect on monthly among the X_i group. It is calculated as the linear combination of the COVID and COVID*X_i regression coefficients. Standard errors are clustered at the individual level. * : p<0.1, ** : p<0.05, *** : p<0.01.

Table A.9. Heterogenous subjective treatment effects on earnings (intensive margin), by maternal education and vulnerable group

	India		Peru		Vietnam	
	Low maternal education	Vulnerable group	Low maternal education	Vulnerable group	Low maternal education	Vulnerable group
COVID	-114.23***	-89.71***	-122.80***	-127.49***	-138.80***	-116.43***
	(12.99)	(7.27)	(11.95)	(8.64)	(13.38)	(9.16)
X_i	-113.33***	-63.05***	-19.85	-107.65**	-130.52***	-331.62***
	(34.97)	(25.38)	(27.70)	(45.06)	(36.50)	(40.50)
COVID*X_i	42.89***	23.48**	-7.98	2.23	43.36***	7.34
	(14.37)	(11.31)	(16.48)	(27.21)	(16.56)	(20.39)
COVID effect	-71.34***	-66.24***	-130.78***	-125.26***	-95.44***	-109.09***
among X_i	(6.13)	(8.66)	(11.35)	(25.80)	(9.77)	(18.22)
Observations	2,014	2,022	2,406	2,404	2,674	2,698

Notes: Regressions estimated only on sample who reported being employed in both scenarios. Results estimated using Equation (2). Low maternal education takes the value of one if a participants' mother had below median education in 2002, and zero otherwise. In India, mothers' median education in 2002 was 0 years of schooling, while in Peru and Vietnam, it was 7 and 6 years, respectively. Vulnerable group refers to whether the participant belongs to a Scheduled Caste/Tribe (India), is a non-native Spanish speaker (Peru), and belongs to a minority ethnic group (Vietnam). 'COVID effect among X_i' reflects the average subjective treatment effect on monthly among the X_i group. It is calculated as the linear combination of the COVID and COVID*X_i regression coefficients. Standard errors are clustered at the individual level. * : p<0.1, ** : p<0.05, *** : p<0.01.

Table A.10. Heterogenous subjective treatment effects on earnings (intensive margin), by wealth tercile

	India	Peru	Vietnam
	Lowest wealth tercile (2016)	Lowest wealth tercile (2016)	Lowest wealth tercile (2016)
COVID	-97.69***	-138.38***	-122.82***
	(8.23)	(10.93)	(10.89)
X_i	-136.86***	-151.77***	-140.90***
	(24.77)	(27.64)	(35.61)
COVID*X_i	38.78***	29.41*	21.92
	(10.85)	(16.31)	(16.55)
COVID effect among	-58.91**	-108.97***	-100.90***
X_i	(7.08)	(12.10)	(12.47)
Observations	2,008	2,362	2,666

Notes: Regressions estimated only on sample who reported being employed in both scenarios. Results estimated using Equation (2). Lowest wealth tercile takes the value of one if a participant's household was in the lowest tercile of the wealth index in 2016. The wealth index takes values between zero and one, such that a larger value reflects a wealthier household. It is the simple average of a housing-quality index, an access-to-services index, and a consumer-durables index (Briones, 2017). 'COVID effect among X_i' reflects the average subjective treatment effect on monthly among the X_i group. It is calculated as the linear combination of the COVID and COVID*X_i regression coefficients. Standard errors are clustered at the individual level. * : p<0.1, ** : p<0.05, *** : p<0.01.

Table A.11 Percent working as self-employed in agriculture, by mother's education (2002)

	India		Peru		Vietnam	
	Low maternal education	High maternal education	Low maternal education	High maternal education	Low maternal education	High maternal education
Self-employed in agriculture before the pandemic	16.58	4.58***	5.88	2.42***	14.01	3.77***
Observations	1,689	895	935	988	1,249	1,086

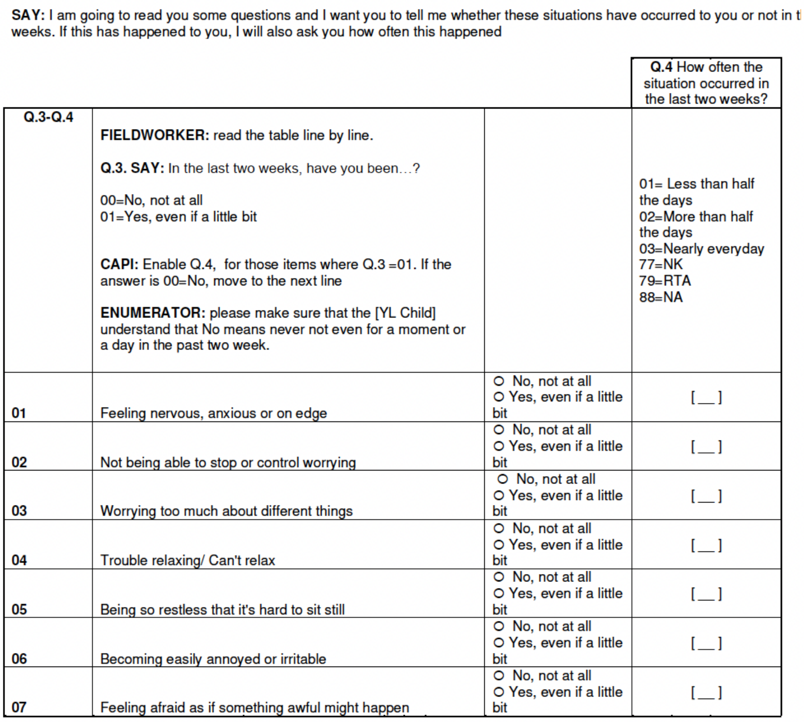
Notes: Percentage of each group working as self-employed in agriculture is shown. The period 'before the pandemic' is defined here as January-February 2021 in Peru and Vietnam, and December-February 2021 in India. Results of t-tests for differences in means between the those whose mothers had below median education in 2002 and those whose mothers had above median education in 2002 is shown. * : p<0.1, ** : p<0.05, *** : p<0.01.

Table A.12. Characteristics of females out of education pushed into employment

	Pushed into employment (females not in education in 2020)	Rest of sample
Age in years (2021)	24.04	21.73
Top wealth tercile (2016)	0.28	0.33
Middle wealth tercile (2016)	0.27	0.34
Bottom wealth tercile (2016)	0.45	0.33**
Low maternal education (2002)	0.81	0.65**
Highest schooling grade (Nov-Dec 2021)	6.33	10.10***
Number of individuals	67	2,600

Notes: Wealth terciles are based on the Young Lives wealth index (Briones, 2017). Low maternal education takes the value of one if a participants' mother had below median education in 2002, and zero otherwise. Mothers' median education in 2002 was 0 years of schooling. * : p<0.1, ** : p<0.05, *** : p<0.01.

Figure A.3. GAD-7 questionnaire in the Young Lives survey


SAY: I am going to read you some questions and I want you to tell me whether these situations have occurred to you or not in t weeks. If this has happened to you, I will also ask you how often this happened

Q.3-Q.4	**FIELDWORKER:** read the table line by line. **Q.3. SAY:** In the last two weeks, have you been…? 00=No, not at all 01=Yes, even if a little bit **CAPI:** Enable Q.4, for those items where Q.3 =01. If the answer is 00=No, move to the next line **ENUMERATOR:** please make sure that the [YL Child] understand that No means never not even for a moment or a day in the past two week.		**Q.4** How often the situation occurred in the last two weeks? 01= Less than half the days 02=More than half the days 03=Nearly everyday 77=NK 79=RTA 88=NA
01	Feeling nervous, anxious or on edge	O No, not at all O Yes, even if a little bit	[__]
02	Not being able to stop or control worrying	O No, not at all O Yes, even if a little bit	[__]
03	Worrying too much about different things	O No, not at all O Yes, even if a little bit	[__]
04	Trouble relaxing/ Can't relax	O No, not at all O Yes, even if a little bit	[__]
05	Being so restless that it's hard to sit still	O No, not at all O Yes, even if a little bit	[__]
06	Becoming easily annoyed or irritable	O No, not at all O Yes, even if a little bit	[__]
07	Feeling afraid as if something awful might happen	O No, not at all O Yes, even if a little bit	[__]