



Impact of the COVID-19 crisis on India's rural youth: Evidence from a panel survey and an experiment



Bhaskar Chakravorty^{a,*}, Apurav Yash Bhatiya^b, Clément Imbert^a, Maximilian Lohnert^c, Poonam Panda^c, Roland Rathelot^d

^a Department of Economics, University of Warwick, Coventry CV4 7AL, United Kingdom

^b Department of Economics, University of Birmingham, Edgbaston, Birmingham B15 2TT, United Kingdom

^c Abdul Latif Jameel Poverty Action Lab (J-PAL), South Asia, AADI, 02 Balbir Saxena Marg, Hauz Khas, New Delhi 110016, India

^d Department of Economics, Institut Polytechnique de Paris (ENSAE), 5 avenue Le Chatelier 92100 Palaiseau, France

ARTICLE INFO

Article history:

Accepted 13 March 2023

Available online 23 March 2023

JEL Codes:

J2

J3

J6

J7

M5

Keywords:

Youth unemployment

Gender

Vocational training

Public policy

ABSTRACT

This paper presents evidence on the short and long-term impact of the COVID-19 crisis on India's rural youth. We interviewed about 2,000 vocational trainees from Bihar and Jharkhand three times after the first national lockdown in 2020, between June 2020 and December 2021. We find that a third of respondents who were in salaried jobs pre-lockdown lost their jobs, and half of those who worked out of state returned home shortly after the lockdown. We report a stark difference between men and women: while many male workers took up informal employment, most female workers dropped out of the labour force. In the second part of the paper, we use a randomised experiment to document the effects of a government-supported digital platform designed to provide jobs to low-skilled workers. The platform turned out to be difficult to use and publicised only few job ads. We find no effect on job search intensity or employment. Our findings suggest that bridging the gap between rural young workers and urban formal labour markets requires more active and targeted policy interventions, especially for female workers.

© 2023 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

1. Introduction

About 100 million Indian workers lost their jobs during the nationwide lockdown in April–May 2020 (APU, 2021), with women, less formally educated, and lower-income households being disproportionately affected (Agarwal, 2021; Amare et al., 2021; APU, 2021; Dasgupta & Robinson, 2021; Kansime et al., 2021; Mamgain, 2021; Abraham et al., 2022; Bundervoet et al., 2022; Deshpande, 2022). Data from the Periodic Labour Force Survey in India suggests that young workers were hit the hardest and their unemployment rate increased from 21% to 36% in April–June 2020 as compared to the same quarter in 2019. Among them, migrant workers were the most vulnerable: the most defining

images of the first COVID-19 wave were of migrant workers who lost their jobs and livelihood in cities, walking back hundreds of kilometres to their rural hometowns. Imbert (2020) estimates that across India, around 11 million inter-state migrant workers returned home after the first lockdown.

In this paper, we provide new evidence on the effect of the pandemic on young migrant workers using novel longitudinal data and provide experimental evidence on re-connecting them with the labour market. We followed a cohort of 2,260 young workers from rural areas within Bihar and Jharkhand between 2019 and 2021. The respondents were recent participants in a large-scale national vocational training scheme called Deen Dayal Upadhyay Grameen Kaushal (DDU-GKY, henceforth). DDU-GKY provides trade-specific training for a duration of 3–12 months and places disadvantaged rural youth into formal salaried jobs, often located in other states.¹ In addition to the survey rounds used by Chakravorty et al. (2021), we surveyed the same individuals three times after the national lockdown in 2020, in June 2020, April 2021, and December 2021.

* Corresponding author.

E-mail address: bhaskar.chakravorty.1@warwick.ac.uk (B. Chakravorty).

URLs: <https://warwick.ac.uk/fac/soc/economics/> (B. Chakravorty), <https://www.birmingham.ac.uk/schools/business/departments/economics> (A.Y. Bhatiya), <https://warwick.ac.uk/fac/soc/economics/> (C. Imbert), <https://www.povertyactionlab.org/south-asia> (M. Lohnert), <https://www.povertyactionlab.org/south-asia> (P. Panda), <https://eco.crest.science/> (R. Rathelot).

¹ <https://ddugky.gov.in/> (last accessed on 10th November 2022).

We first document the devastating immediate effects of the COVID crisis. Nearly half of the respondents who worked outside of their home states before the lockdown had returned to their native states shortly after the lockdown. Nearly a third of respondents (32%) that had a salaried job in the pre-lockdown period had lost their job. Anxiety was higher and life satisfaction was lower as compared to the pre-lockdown period. Only half of the migrants who had returned home were willing to migrate again, most of them men. On re-connecting respondents with the labour market, we find that the job application rate was much lower than the job search rate, possibly indicating either unavailability of jobs or unawareness on where or how to apply for jobs. 87% of the respondents of our sample completed the DDU-GKY training. We find stark differences between them and the remaining 13% who dropped out of the training. Pre-lockdown, 44% of training graduates had a salaried job, against 15% among training drop-out. By November–December 2021, training graduates were still twice as likely to hold a salaried job as the dropouts (28% against 14%). These results suggest that while employment opportunities worsened for all the youth in the sample, those who completed the DDU-GKY program did comparatively better.

Given the policy challenge of (re)integrating youth into the labour market, the local government planned to ramp up the use of an app-based job platform (Yuvasampark) to encourage job search and application in the population. Yuvasampark is a privately owned and managed mobile app that was used by several state governments in India especially during the Covid-19 pandemic to help trainees search for and apply for jobs.² It offers information on available jobs, including salary and location, and enables candidates to maintain a professional profile and apply for available vacancies.

We carried out a randomised controlled trial with an encouragement design to evaluate the impact of using Yuvasampark on job search and job finding. We randomly allocated youth from our sample into a control and treatment group. The Jharkhand State Livelihood Promotion Society (JSLPS) called the treatment group to inform them about the Yuvasampark app and to encourage and help them register. Those who registered were also helped to apply for jobs on the app.

We find that using Yuvasampark had no impact on job search or job-finding outcomes. We try to understand the reasons for the lack of effect: the most likely explanation is that Yuvasampark, at least during the period of the experiment, displayed very few vacancies and was difficult to use. Our results illustrate the fact that not all low-cost digital interventions are effective in bridging the gap between rural youth and formal jobs. The fact that many of the same respondents had been successfully placed into salaried jobs by the training program DDU-GKY in the past suggests that more heavy-handed interventions are needed.

Our paper contributes to the literature that documents the economic impact of COVID-19 on workers in developing countries. The economic impact of the first wave was devastating to labour markets throughout the globe. A study across nine countries in Africa, Asia, and Latin America reported a stark decline in employment and income in all settings beginning in March 2020 (Egger et al., 2021). Based on data from 31 developing countries, one of the initial studies to estimate the short-term impacts of the pandemic reports that 36% of respondents stopped working in the immediate aftermath of the pandemic, and 65% of households reported a decrease in income (Bundervoet et al., 2022). In India specifically, COVID-19 had a stronger impact on the employment of women and younger workers (Agarwal, 2021; APU, 2021; Abraham et al., 2022; Deshpande, 2022). The economic impact of

the pandemic on urban informal sectors has been documented across India: in the Delhi National Capital Region (Afridi et al., 2021), in Bihar, Jharkhand and Uttar Pradesh (Dhingra & Machin, 2020) as well as for slum communities in Patna and Bangalore (Downs-Tepper et al., 2022). At the same time as economic and labour-market shocks, food insecurity increased (Amare et al., 2021; Dasgupta & Robinson, 2021; Kesar et al., 2021) and well-being declined (Afridi et al., 2021; Fenn et al., 2021).

Other country-specific studies reported similar findings (Janssens et al., 2021; Kansime et al., 2021; Mahmud & Riley, 2021; Aggarwal et al., 2022; Dang et al., 2023). Using panel datasets from Bangladesh and Nepal, Barker et al. (2020) find a 15–25% decline in earnings and a fourfold greater prevalence of food insecurity among migrant households in the first few months of the pandemic. A longitudinal household survey study from Ethiopia, Malawi, Nigeria, and Uganda estimates that 77% of the population lives in households that have lost income during the pandemic (Josephson et al., 2021). Most households in Cambodia, the Lao People's Democratic Republic, Indonesia, Malaysia, Myanmar, the Philippines, Thailand, and Vietnam experienced significant declines in income and employment and having at least one person who lost their job or had reduced working time increased the likelihood of experiencing financial difficulties by 17 percentage points (Morgan & Trinh, 2021). The impacts are no different in the context of developed countries. A study conducted across six countries (China, South Korea, Japan, Italy, the United Kingdom, and the four largest states in the United States) reports that women are 24% more likely to permanently lose their job than men because of the pandemic and are 50% more likely to expect a fall in their labour income (Dang & Viet Nguyen, 2021). Our contribution is to rely on long-term panel data of our study sample, which we have collected over several survey rounds from 2019–2021.³ This allows us to analyse their employment and location trajectories before, during and after the first and the second COVID-19 waves.

We also contribute to the relatively thin literature on how online platforms can help job seekers. Governments increasingly look to digital tools as low-cost interventions to overcome information friction and engage job seekers. The interest in digital tools has increased further as the COVID-19 pandemic made in-person interventions more difficult and costly. Wheeler et al. (2022) find that training South African job seekers to use LinkedIn improves durably their labour-market outcomes. Kelley et al. (2021) connect graduates from another Indian vocational training (Pradhan Mantri Kaushal Vikas Yojana or PMKVY) to a private job platform (Job-Shikari) and find negative effects on employment initially and no effect in the long run. Jones and Sen (2022) document that the usage of digital job platforms is not associated with better labour market outcomes for job seekers in Mozambique. In the context of France, Dhia et al. (2022) find that using an online platform designed to provide tips to broaden their job search does not help unemployed job seekers to find more or better jobs. We contribute to this literature by providing additional well-powered experimental evidence on a failed attempt to help job seekers using a digital job platform in India. We argue that in order to achieve positive labour market impacts, governments should dedicate time and energy to developing online tools, improving both their user-friendliness and their coverage of labour demand.

The remainder of the paper is structured as follows. Section 2 describes the data. Section 3 presents the descriptive findings. Section 4 provides the randomised experiment on Yuvasampark and its results. Section 5 concludes.

² https://hstpl.com/?page_id=327 (last accessed, 10th November 2022).

³ Our surveys maintained an overall attrition rate between 10% and 15%.

2. Context and data

2.1. COVID-19 lockdown in India

First lockdown: The Government of India ordered a nationwide lockdown for 21 days on the 24th of March 2020, restricting the movement of the entire population of India as a preventive measure to check the spread of the Covid-19 pandemic. By the end of this period, state governments and other advisory committees recommended extending the lockdown. On April 14th, Prime Minister Narendra Modi extended the nationwide lockdown until May 3rd. On May 1st, the nationwide lockdown was extended by two weeks until May 17th. All districts were divided into three zones based on the spread of the virus—green, red, and orange—with relaxations applied accordingly. On May 17th, the lockdown was further extended until May 31st. On May 30th, it was announced that lockdown restrictions were to be lifted from then onwards, while the ongoing lockdown would be further extended until June 30th for only the containment zones. Services would be resumed in a phased manner starting from 8 June. It was termed “Unlock 1.0”.

Second lockdown: There was no second national lockdown but a wave of State lockdowns between 8 April and 15 June 2021. When cases rapidly increased in Maharashtra, the Chief Minister announced a complete lockdown and night curfews in the state from 4 April until 30 April. Most States and Union Territories imposed complete or partial lockdown and major mobility restrictions. From 15 June 2021, States started lifting lockdowns in a phased manner.

2.2. Data

The sample for the study includes 2,260 young adults from Bihar and Jharkhand who entered the DDU-DKY program. The survey has an overall survey attrition rate of 15%: we report results on 1,924 respondents. We find that the categories of workers that are disadvantaged in the labour market, i.e., female, less educated and scheduled tribes, were less likely to respond to the survey (Appendix Table A1), which suggests that if anything we may underestimate the negative effects of the pandemic. Among the respondents, the sample is almost equally split between males and females, 64% of respondents are from Bihar and 36% are from Jharkhand. The average age is 19–20 years, and most trainees have some secondary education. Half of the sample respondents are from Other Backward Class (OBC), around a quarter from Scheduled Caste, 18% are Scheduled Tribe, and the rest 6.7% are from General Caste, which shows that DDU-GKY successfully targets disadvantaged youth. A very high fraction (79%) of respondents is from households below the poverty line, which reflects the pro-poor targeting of DDU-GKY. Around 87% of the sample completed the training, and about 44% were placed in salaried jobs, mostly outside their home states (Chakravorty et al., 2021). DDU-GKY has specific targets for women, and our study suggests that there is high take-up of the program among women, with higher likelihoods of training completion (89%) and placement (52%) than men (Fig. A1).

The findings presented in this study are based on three survey rounds (Fig. 1):

- Round 1 - was conducted shortly after the first lockdown in June-July 2020. We collected information on employment, location, willingness to migrate and well-being indicators for both current as well as the pre-lockdown situation.
- Round 2 - was carried out one year after the first lockdown in March-April 2021, just after the Yuva Sampark experiment (see below) and just before the second lockdown. In addition

to the above variables, we also collected information on job search intensity and mechanisms in this round. We asked: “Are you currently searching for a job?”, “How have you been searching for a job?”, “Have you applied for any jobs in the past 2 months?”.

- Round 3 - took place in November-December 2021, 20 months after the first lockdown and eight months after the second lockdown. We repeated our survey questions from round 2.

3. Panel survey findings

In this section, we report descriptive findings on the employment and location trajectory of DDU-GKY candidates using survey rounds 1 and 3 (mostly for ease of interpretation with the flow diagrams). We discuss evidence on job search, migration intentions, marriage, life satisfaction and anxiety using all survey rounds. We also present regression estimates on salaried employment by sub-groups defined by gender, training completion status, and caste. This exercise aims to see how the unconditional estimate for the gap in salaried employment changes for the subgroups after controlling for the sector of training, individual characteristics, and household characteristics. In the estimation model below, y_i denotes the outcome for individual i . T_i is an indicator variable equal to one if i is a part of a sub-group and zero otherwise. X_i is a vector of baseline characteristics which we use as control variables.

$$y_i = \beta T_i + X_i' \alpha + \varepsilon_i$$

3.1. Employment and migration

Employment. Fig. 2 shows respondents’ employment status for three time periods: (1) before the first lockdown, (2) shortly after the first lockdown, and (3) 20 months after the first and eight months after the second lockdown. We can assess the immediate impact of the COVID-19 crisis on youth employment in the transition from before the first lockdown to shortly after the first lockdown. The proportion of respondents in salaried jobs declined from 41% to 28%, i.e., nearly a third (32%) of the respondents who were in salaried jobs before the lockdown had lost their job. For those that lost their salaried work, nearly half (47%) reported that they had left their jobs voluntarily, 23% said that they had lost their jobs as offices were closed because of the lockdown, and 9% because they had come home for Holi and could not go back to work due to the lockdown (Appendix Table A2).⁴ While this loss of salaried work led to an increase in the non-earning category (from 51% to 56%), it also led to informalization, as the proportion of those working in the informal sectors increased from 9% before the lockdown to 16% shortly after the lockdown. This trend of informalization increased to about 26% after 20 months of the first lockdown with many individuals moving from both salaried jobs and non-earning category to informal work. Similarly, while the proportion of salaried employment stayed at almost similar levels between June-July 2020 and November-December 2021, there has been a movement of individuals from non-earning and informal work to salaried job and vice versa.

Location and migration. Since the COVID-19 crisis led many migrant workers to return to their home states (Imbert, 2020), we tracked the location of our respondents over time (Fig. 3). Nearly half of youth who before the lockdown were residing outside their home state (45%) or within another district in their home state (44%) had already returned to their homes shortly after the lockdown. These results are indicative of the great ‘reverse migra-

⁴ Holi is an annual two-day festival and was on the 9th of March in 2020.

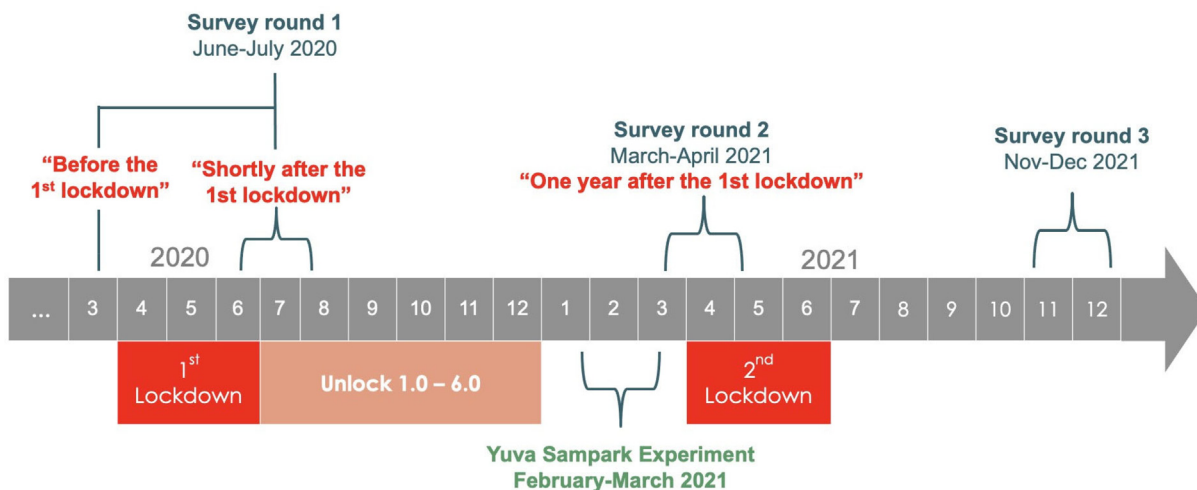


Fig. 1. Data collection timeline.

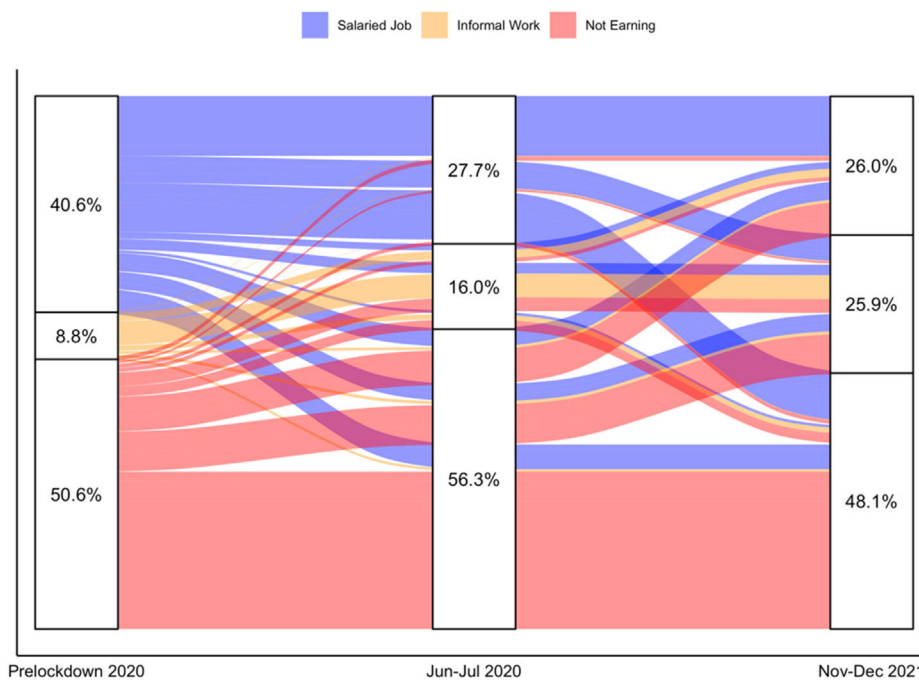


Fig. 2. Panel survey findings: employment transitions. Notes: The figure shows employment transitions between salaried job, informal work and not earning categories for a sample of 2260 DDU-GKY training participants over the panel survey rounds.

tion' that followed the announcement of the national lockdown in March 2021, where migrant workers that lost their job returned to their homes. However, there was also some movement in the opposite direction: nearly half of the individuals who were outside the state in November-December 2021 came from the sample that was within the state or at home pre-lockdown, and a majority of individuals who were living somewhere else within the state in the last survey round were at home pre-lockdown.

3.2. Effects by gender

Employment trajectories by gender. Women are at a disadvantage in the labour market in India, with lower labour force participation and higher unemployment than men. The DDU-GKY program gave the young women in our sample a somewhat unique opportunity to migrate and be formally employed. It is hence

important to assess whether women in our sample were differently affected by the COVID-19 crisis. We consider separately the employment trajectories for men and women and present them in Fig. 4. While both men and women started with an equal employment rate of around 40% in salaried jobs pre-lockdown, men were less likely to be in a salaried job immediately after the first lockdown as compared to women (25% vs 32%). These proportions switched 20 months after the first lockdown where men were more likely to be in a salaried job as compared to women (31% vs 20%). The striking difference is in the importance of informal jobs in male workers' trajectory: after 20 months, 37% of men were engaged in informal jobs as opposed to merely 13% of women. We find men moving across employment categories a lot more as compared to women who are unable to recover employment in a similar way. As a result, the proportion of men and women in wage employment was starkly different: in November-

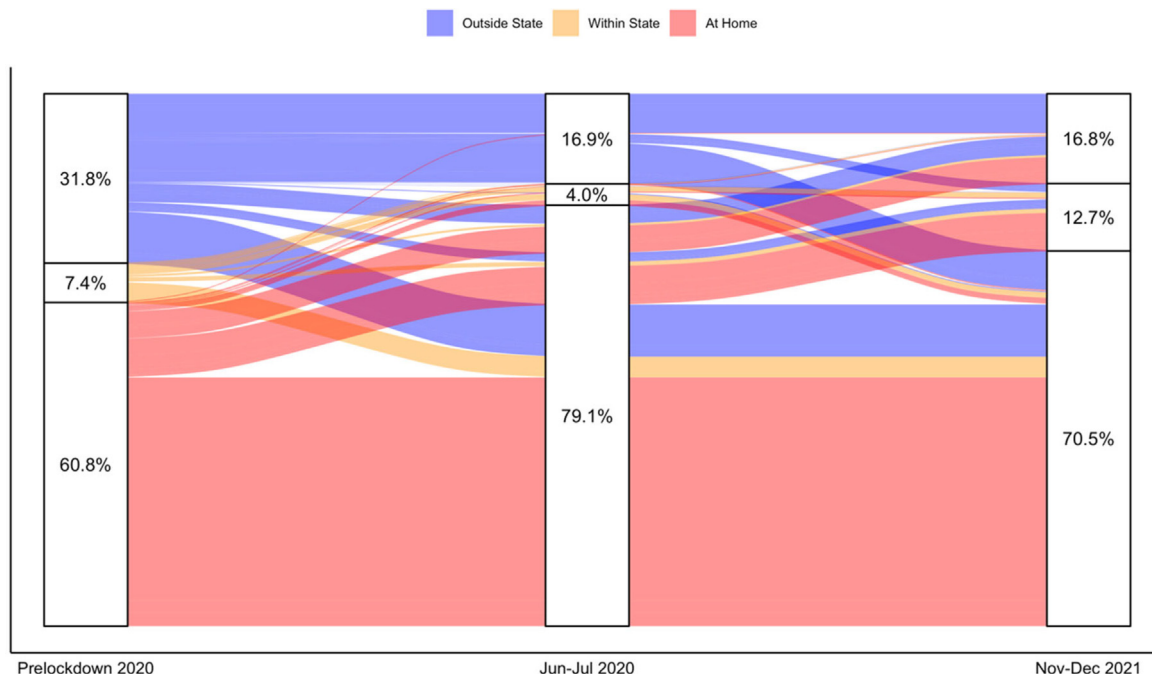


Fig. 3. Panel survey findings: location transitions. Notes: The figure shows location transitions between outside state, within state and at home categories for a sample of 2,260 DDU-GKY training participants over the panel survey rounds.

December 2021, two-third of men but only one-third of women were employed in salaried or informal work.

Fig. A2 takes a closer look at the type of employment trajectories for males and females that were working (in salaried or informal jobs) before the lockdown. Across the whole sample that was in work (salaried or informal) before the lockdown, only a third (33%) was not affected in terms of their work throughout the period studied in this project.⁵ More than a third (37%) lost and could not recover their work,⁶ while only 11% could recover their employment.⁷ 16% moved from formal to informal work, with only 3% moved in the opposite direction from informal to formal work. Importantly, however, these employment trajectories differed by gender: the “no recovery” trajectory was much higher among women as compared to men (53% vs 25%). A reason for this may be that men are more likely to have informal work as a fallback option: while 20% of men moved into informal work, only 11% of women did. The formalisation rate was also higher among men.

In Table 1, we present regression estimates on the dummy variable for females on the probability of being in salaried employment across different periods and progressively including control variables for the sector of training, individual and household characteristics. Broadly, we find the females were 8.4 p.p. significantly more likely to be employed in a salaried job immediately before and after the first lockdown (survey round 1) and significantly less likely to be employed in a salaried job during the survey rounds 2 and 3 as compared to males. The difference between male and female employment remains significant in survey round 1 despite adding a plethora of control variables. However, in the survey

⁵ No effect means that the respondent was in the same employment category before the lockdown and the subsequent survey rounds until 20 months after the first lockdown.

⁶ No recovery means that the respondent was either in salaried or informal work before the lockdown but was not earning even 20 months after the first lockdown.

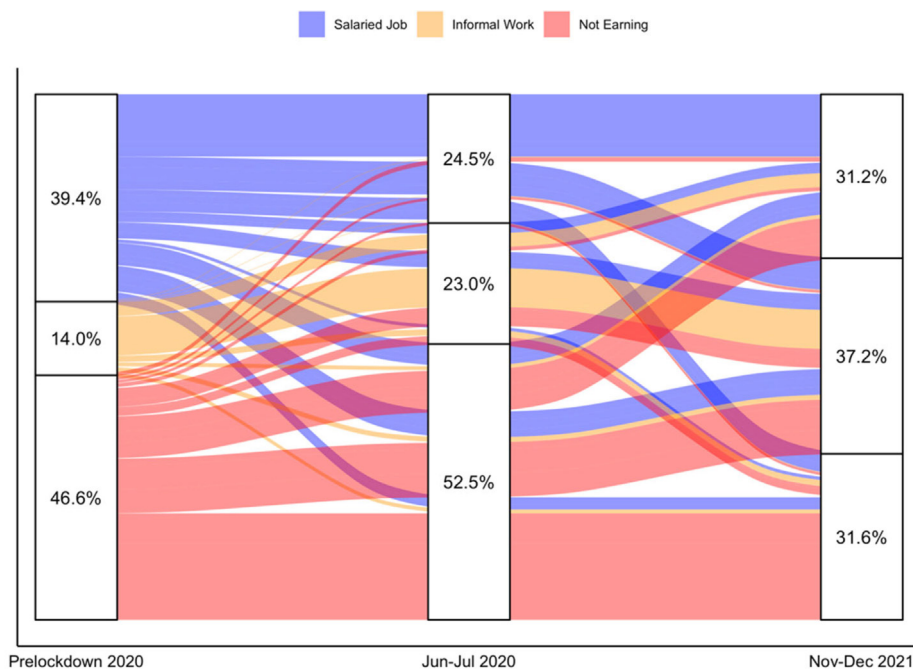
⁷ Recovery means that the respondent was engaged in an earning activity (salaried or informal) before the lockdown, not earning shortly after the first lockdown, but then transitioned back into the same type of work (salaried or informal) later.

rounds 2 and 3, most of the differences in employment by gender can be accounted for by including controls for the sector of training, individual and household characteristics.⁸

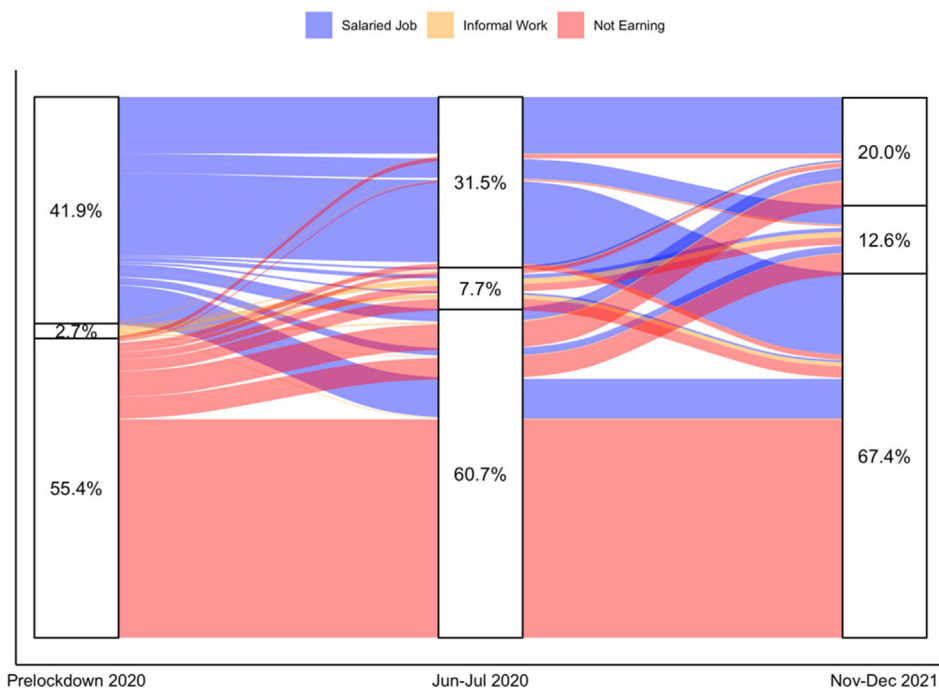
Marriage. Our results suggest that many young women who took up salaried jobs in other states thanks to DDU-GKY came home and dropped out of wage employment, in stark contrast to their male counterparts. To investigate the reasons behind these gender differences, we consider separately men and women who got married since the first lockdown. As Fig. 5 Panel [a] shows, women who did not get married have employment levels similar to men who did not get married. However, newly married women were much less likely to work in a salaried job, which is likely due to social norms which prevent married women from working in rural India (Heath & Jayachandran, 2017). The differences are even starker when we focus only on men and women who were employed in the same sector (services) before the lockdown (Panel [b]): they experienced the same employment shock immediately after the first lockdown, but their paths diverged radically in the year that followed. In the last period, there is even evidence that newly married men were more likely to take up salaried work than unmarried men, the opposite picture as compared to women. We find similar patterns when looking at the sample of trainees who were outside the state and employed in the service sector outside the state in the pre-lockdown period (Panel [c] and [d]): newly married women have the lowest probability to be in a salaried job and newly married men have the highest probability.

Life satisfaction and anxiety. One would expect the COVID-19 crisis, with the loss of employment and the threat on livelihoods to have profound negative effects on wellbeing. We asked respondents to score their level of life satisfaction and anxiety on a scale

⁸ In Table A11, we present similar estimates for a sub-group defined by social category- SC/ST vs others. While unconditionally, SC/ST trainees are more likely to be in salaried employment (this is expected because they have a worse outside option). Conditional on the sector of training, individual and household characteristics, we do not find any significant differences in salaried employment in any survey round for this sub-group.



(a) Males



(b) Females

Fig. 4. Panel survey findings: employment transitions by gender. Males (a) and Females (b).

of 0 to 100 per cent.⁹ Fig. 6 presents the results. Life satisfaction rates fell shortly after the first lockdown and did not reach pre-lockdown levels even one year after. Similarly, anxiety rose shortly

after the first lockdown and was still higher one year after. In the longer run, after the second wave had passed, life satisfaction was still lower, and anxiety still higher but only among men.¹⁰ This indi-

⁹ Life satisfaction: 0 is "not at all satisfied" and 100 is "completely satisfied", Anxiety: 0 is "not at all anxious" and 100 is "completely anxious".

¹⁰ Pre-lockdown well-being levels are obtained from surveys implemented from December 2019 to March 2020, i.e., before Round 1 (Chakravorty et al., 2021).

Table 1
Panel survey findings: effect of gender on salaried employment.

	Salaried Employment			
	[1]	[2]	[3]	[4]
Panel A: Survey Round 1 (Pre-lockdown 2020)				
Female	0.033 (0.021)	0.065** (0.029)	0.090*** (0.029)	0.085*** (0.031)
Observations	2259	2259	2259	2259
Male Mean	0.395	0.395	0.395	0.395
Panel B: Survey Round 1 (Jun-Jul 2020)				
Female	0.078*** (0.019)	0.066** (0.027)	0.084*** (0.027)	0.084*** (0.029)
Observations	2259	2259	2259	2259
Male Mean	0.242	0.242	0.242	0.242
Panel C: Survey Round 2 (Mar-Apr 2021)				
Female	-0.084*** (0.019)	-0.082*** (0.029)	-0.058** (0.029)	-0.041 (0.031)
Observations	1924	1924	1924	1924
Male Mean	0.281	0.281	0.281	0.281
Panel D: Survey Round 3 (Nov-Dec 2021)				
Female	-0.102*** (0.020)	-0.089*** (0.028)	-0.067** (0.029)	-0.053* (0.031)
Observations	1955	1955	1955	1955
Male Mean	0.302	0.302	0.302	0.302
Sector Controls		Yes	Yes	Yes
Individual Controls			Yes	Yes
Household Characteristics				Yes

Notes: This table shows the effect of gender on salaried employment. Each panel refers to each survey round. Columns [1]: Shows the regression results on the salaried employment dummy without any control variables. Column [2] & [3]: Shows the regression results progressively adding sector of training and baseline individual characteristics (such as caste, religion, age, marital status, education, and migration experience). Column [4] controls for household characteristics, such as household earnings, agricultural land, if the household belongs to the Below-poverty line (BPL) category or if any member of the household is a Self-help group (SHG) member or if any member has worked in National Rural Employment Guarantee Act (NREGA) or the household is enrolled in government health insurance (Rashtriya Swasthya Bima Yojna/RSBY). The specification also controls for migration history in the family. * p < 0.10, ** p < 0.05, *** p < 0.01.

cates a lasting negative impact of the COVID-19 crisis on youth well-being, especially for men.

3.3. Effects by training status

Our sample consists of youth who were enrolled in the DDU-GKY training scheme in 2019–2020, but not all of them completed their training: out of the 1924 respondents, 238 respondents (13%) dropped out before training completion, and the remaining 1652 (87%) trainees completed the full training course. Fig. 7 compares employment trajectories of trained youth and dropouts. We find that the trainees have a much higher rate of employment to start with, especially in salaried jobs (44%) compared to the training dropouts (15%). By November–December 2021, 28% of the trained individuals retained their salaried employment and 25% resorted to informal work. By contrast, those who had dropped out of training had a much higher rate of employment in the informal sector (35% vs 17% in the pre-lockdown period) and had a lower proportion of the non-earning category (51% vs 68% in the pre-lockdown). In Table 2, we provide regression estimates on the differences in salaried employment using the dummy variable- Trained. A large and significant gap exists in the probability of salaried employment across all periods (31% in pre-lockdown to 14–16% in November–December 2021). Importantly, these differences remain unaffected with the inclusion of control variables for the sector of training, individual and household characteristics. In Table A12, we examine the differences closely by sector of training, and we do not find any significant effect of training in any sector on coping with the employment shock after the lockdown.

The findings for the trained men and women remain consistent with the finding from the overall sample, with 70% men engaged in earning activities in November–December 2021, against 34% of women. However, trained women have a slightly higher rate of salaried employment in the pre-lockdown period (Appendix Fig. A3). The differential impact of COVID-19 on the employment of men and women is more striking in the training dropout cohort. The employment rate at the end of survey period for male dropouts is around 63%, against 19% for female dropouts (Appendix Fig. A4). This confirms that apart from vocational training schemes like DDU-GKY young rural women in Bihar and Jharkhand have few employment opportunities in the formal sector.

3.4. Going forward

Willingness to migrate. Migrant workers were among the worst affected by the national lockdown: many lost their jobs, and since they were outside of their home state, they could access little support. While migration used to be an attractive pathway for entering the workforce for rural youth from Bihar and Jharkhand, we assessed whether the COVID-19 crisis had affected youth’s willingness to migrate (Fig. 8). Among the men in our sample, the willingness to migrate out of state remains unchanged over the past one year (37% shortly after the first lockdown and 36% one year after the first lockdown). However, for women, it decreased from 26% shortly after the first lockdown to about 17% one year after the first lockdown and 16% 20 months after the first lockdown. This suggests that not only did women’s employment suffer more from COVID-19 but that their prospects of reintegrating into the labour market were also worse than men’s.

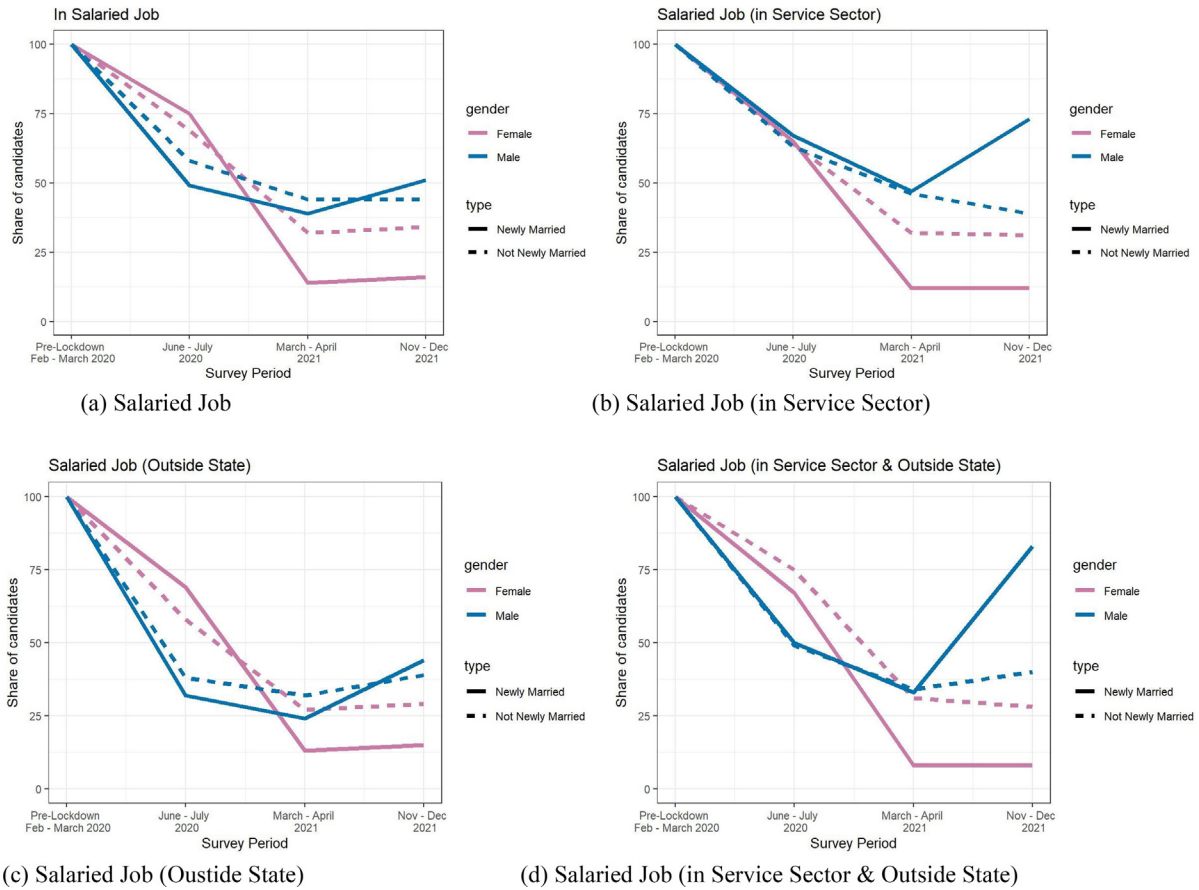


Fig. 5. Panel survey findings: changes in salaried employment by gender and marriage.

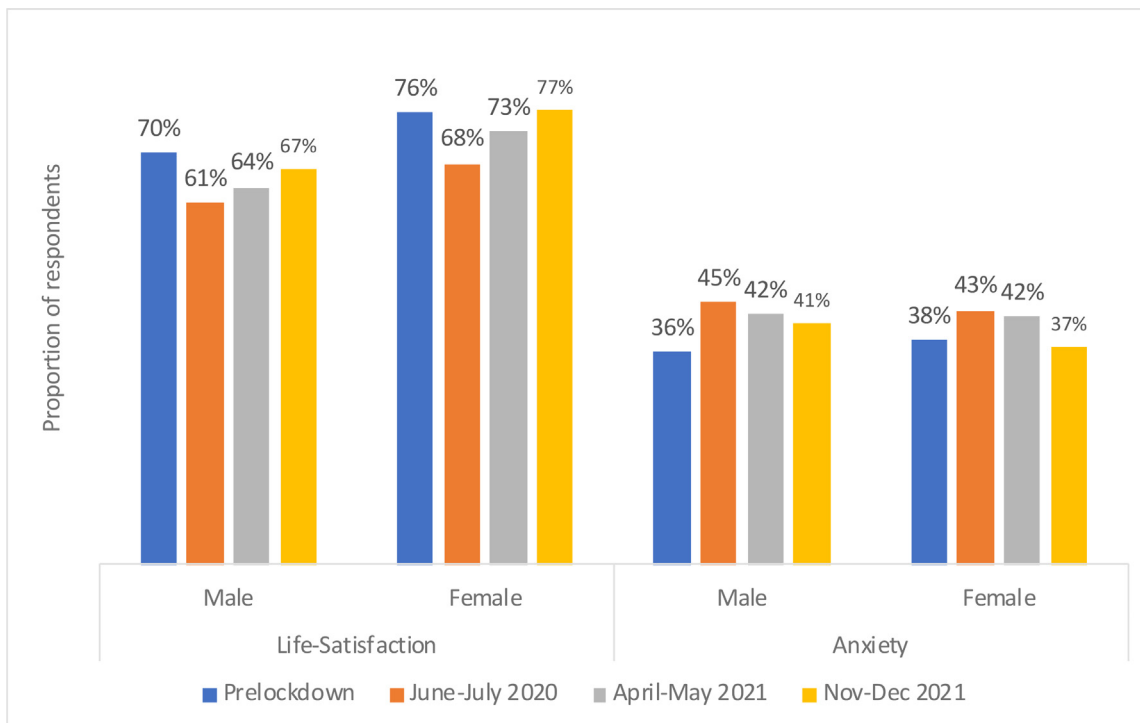
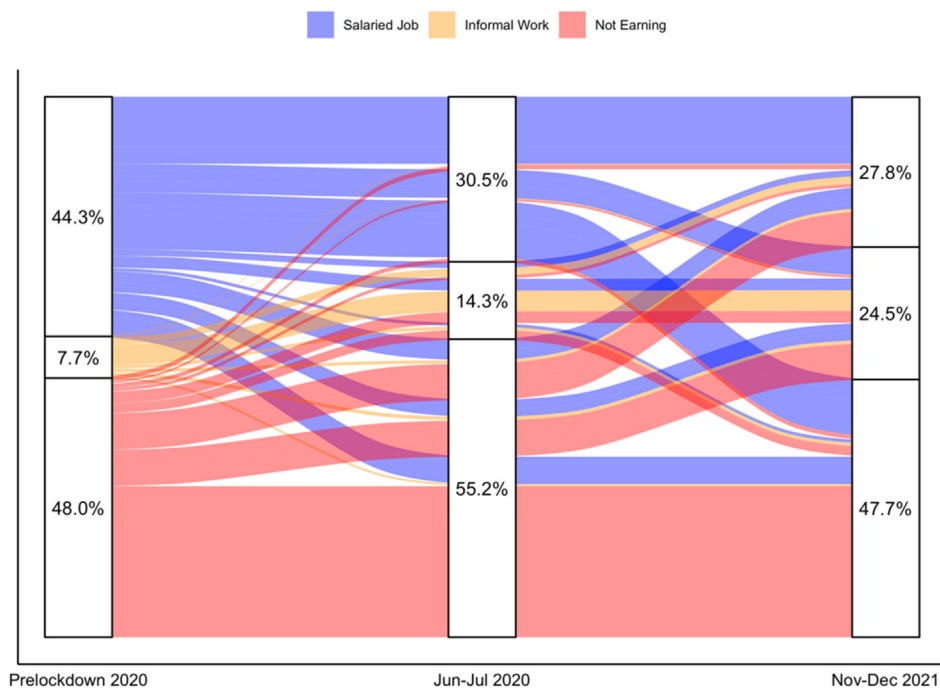
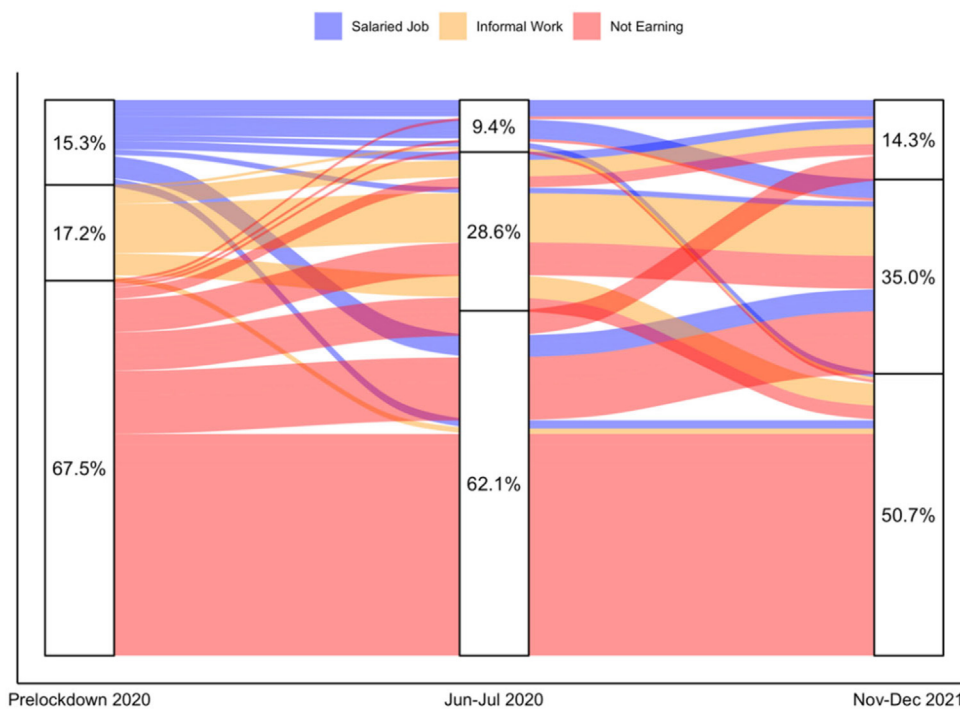


Fig. 6. Panel survey findings: well-being indicators: life satisfaction and anxiety. Notes: The figure shows well-being indicators for life satisfaction and anxiety for a sample of 2,260 DDU-GKY training participants over the panel survey rounds.



(a) Trained Individuals



(b) Training Dropouts

Fig. 7. Panel survey findings: employment transitions by training status. Trained Individuals (a) and Training Dropouts (b).

Job search. Given that immediately after the first lockdown many young people in our sample had lost formal jobs and are either unemployed or in informal work, we asked all respondents whether they were currently searching for a job or had applied

for a job in the past two months (in survey rounds 2 and 3). Fig. 9 presents the result. Irrespective of their current employment status (salaried work, informal work, not earning), the job application rate was much lower than the job search rate, possibly indicat-

Table 2
Panel survey findings: effect of training on salaried employment.

	Salaried Employment			
	[1]	[2]	[3]	[4]
Panel A: Survey Round 1 (Pre-lockdown 2020)				
Trained	0.309*** (0.031)	0.332*** (0.029)	0.322*** (0.029)	0.318*** (0.029)
Observations	2204	2204	2204	2204
Dropout Mean	0.147	0.147	0.147	0.147
Panel B: Survey Round 1 (Jun-Jul 2020)				
Trained	0.235*** (0.028)	0.249*** (0.027)	0.242*** (0.027)	0.237*** (0.027)
Observations	2204	2204	2204	2204
Dropout Mean	0.080	0.080	0.080	0.080
Panel C: Survey Round 2 (Mar-Apr 2021)				
Trained	0.123*** (0.030)	0.139*** (0.030)	0.132*** (0.030)	0.135*** (0.030)
Observations	1890	1890	1890	1890
Dropout Mean	0.134	0.134	0.134	0.134
Panel D: Survey Round 3 (Nov-Dec 2021)				
Trained	0.139*** (0.030)	0.157*** (0.030)	0.161*** (0.031)	0.162*** (0.031)
Observations	1916	1916	1916	1916
Dropout Mean	0.133	0.133	0.133	0.133
Sector Controls		Yes	Yes	Yes
Individual Controls			Yes	Yes
Household Characteristics				Yes

Notes: This table shows the effect of training completion on salaried employment. Each panel refers to each survey round. Columns [1]: Shows the regression results on the salaried employment dummy without any control variables. Column [2] & [3]: Shows the regression results progressively adding sector of training and baseline individual characteristics (such as caste, religion, age, marital status, education, and migration experience). Column [4] controls for household characteristics, such as household earnings, agricultural land, if the household belongs to the Below-poverty line (BPL) category or if any member of the household is a Self-help group (SHG) member or if any member has worked in National Rural Employment Guarantee Act (NREGA) or the household is enrolled in government health insurance (Rashtriya Swasthya Bima Yojna/RSBY). The specification also controls for migration history in the family. * p < 0.10, ** p < 0.05, *** p < 0.01.

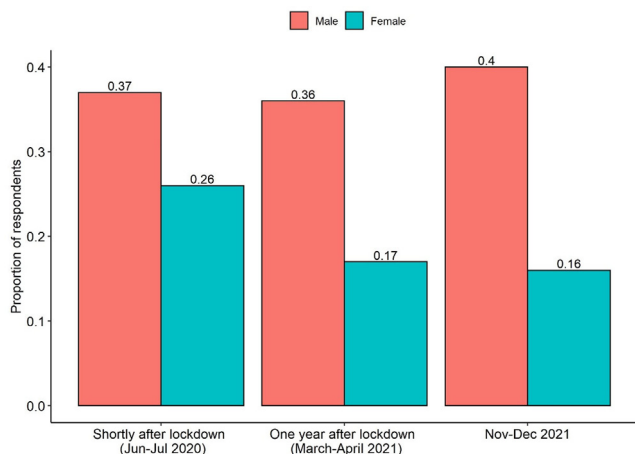


Fig. 8. Panel survey findings: willingness to migrate. Notes: The figure shows willingness to migrate by gender for a sample of 2,260 DDU-GKY training participants over the panel survey rounds.

ing that respondents did not know where or how to apply for jobs, or that there were no jobs available in the first place. Both the job search rate and the application rate were substantially lower for female than male and became worse over time. In March-April 2021, half of the women said they were looking for jobs (three quarters of men), and only 13% had actually applied to a job in the last two months. We also collected information about the method of job search (Fig. A5). About half of the youth who searched for jobs relied on informal channels, such as friends, relatives, and acquaintances, 30% respondents had support of the

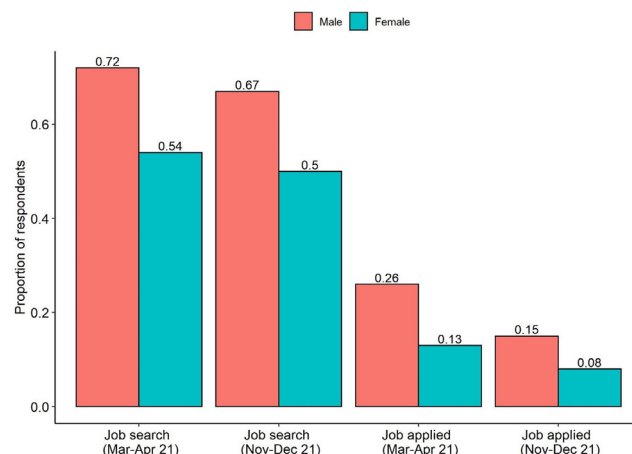


Fig. 9. Panel survey findings: job search and job application rate. Notes: The figure shows job search and job application rate by gender for a sample of 2,260 DDU-GKY training participants over the panel survey rounds.

training organisation (PIA),¹¹ and 35% individuals took a more formal approach to job search using various online job portals.¹² In the next section we evaluate the effect of connecting young people in our sample to one government-sponsored job portal, Yuva Sampark.

¹¹ Project Implementing Agencies (PIAs) are private training organisations that provide training and placements under the DDU-GKY scheme.
¹² This was a multiple-answer question, so the percentages won't add up to 100%.

4. The Yuvasampark experiment

4.1. The Yuvasampark app and the intervention

Yuvasampark is a mobile app used by numerous state governments in India to help trainees search for and apply for jobs. It offers information on available jobs, including salary and location, and enables candidates to maintain a professional profile and apply for available vacancies. Jobs are often located in urban areas or manufacturing hubs in richer states (Delhi, Gujarat, Maharashtra, Tamil Nadu), and job seekers from rural areas of poorer states have limited opportunities to find out about and apply for jobs outside of their state. Due to the pandemic, job search through personal networks or direct contact with employers is more challenging.

There are three steps to apply for jobs in Yuvasampark: (i) registration (ii) job search, and (iii) job application. A preview for all three steps is shown in the Appendix Figures. The main method of registration on the app is by entering the unique registration number those trainees are allotted in the DDU-GKY program. The benefit of using the training registration number is that the app fetches all the trainee details from the portal of the training scheme (Appendix Fig. A6). In case the candidate does not remember the registration number, they can register afresh using their mobile number, and once registered they can update their training registration number at a later stage. The next step is to search for job vacancies, which are bifurcated in the app based on the state of the job posting and the sector of a job (Appendix Fig. A7). A typical job posting looks as shown in Appendix Fig. A8. The advertisements show the application deadline, details of the contact person, eligibility criteria, gross and take-home salary, and other benefits (accommodation, transport facilities, incentives, bonus etc).

The number of job advertisements and vacancies (i.e., one job advertisement could have several hundred vacancies) kept changing over the time of the intervention. Fig. A9 shows that the number of job postings during the intervention period (February–March 2021) ranged from 1500 to 2500, lumped in a limited number of job ads. Table 3 shows the sectoral bifurcation of job postings during the intervention, along with the number of employers and the location of the job. The jobs were almost all located outside of Jharkhand and Bihar, and the number of job advertisements ranged from one to six.

We randomly allocated half of the sample to treatment (1122) and control arm (1138). The randomisation was stratified by state, sector of training, treatment status in the previous experiment (Chakravorty et al., 2021), and gender. The intervention was implemented between February 2021 and March 2021. The Jharkhand State Livelihood Promotion Society (JSLPS), the nodal government department for implementation of DDU-GKY in Jharkhand, called the treatment sample to inform them about the Yuvasampark app and supported the interested candidates to register on the app. The candidates who expressed their interest in registering but could not register on the call with JLSPS received a second call from the J-PAL South Asia surveyors the following week to help them register. All candidates who registered received another call to assist them in applying for jobs through the app. The full sample was called in Rounds 2 and 3 of the surveys to understand the effectiveness of the app.

4.2. Empirical framework

Let y_i denote the outcome for individual i . T_i is a dummy variable equal to one if i is in the treatment group and zero otherwise. $s_{(i)}$ denotes the randomisation stratum and X_i a vector of baseline characteristics which we use as control variables. Our main estimation model will be:

Table 3

Yuvasampark experiment: sectoral bifurcation of job postings on app.

Sector	Vacancies [1]	Employers [2]	States [3]
Automotive/ Construction	1300	6	Haryana, Rajasthan
Apparel	500	1	Tamil Nadu
Banking/Financial Service	300	1	Uttarakhand
HealthCare	200	1	Bangalore, Hyderabad
Retail	200	1	Uttar Pradesh, New Delhi
Total	2500		

Notes: This table shows the sectoral bifurcation of the job posting (vacancies and employers) on the Yuvasampark app for the different states.

$$y_i = \beta T_i + X_i' \alpha + \delta_{s(i)} + \varepsilon_i$$

β is the intention-to-treat effect, the parameter of interest in our setting. We use a post-double selection lasso as in Belloni et al. (2013) to select the control variables in X_i . We compute q-value following the False Discovery Rate method by Benjamini and Hochberg (1995) to handle multiple hypothesis testing. All regressions control for strata fixed effects (δ_s).

4.3. Results

Table 4 and Fig. 10 present the results for our main outcomes in Columns numbered [1]–[3]. Panel A shows the outcomes of survey round 2 (March – April 2021) and Panel B shows the outcomes from survey round 3 (November – December 2021). We first consider the probability that the respondent has applied to any salaried jobs in the last two months (Column [1]). The dependent variable is binary, which takes the value 1 if the respondents have applied to jobs and 0 otherwise.

In the control group, 20% of all respondents applied to salaried jobs in round 2, which is not different from the treatment group respondents (Fig. 10). Towards the end of 2021, 12.5% of the control group respondents applied for a salaried job, and again it was not different compared to the treatment group (Fig. 10). Table 4 Panel A also shows that out of those who applied, around 16% of the respondents applied for one to two jobs and the remaining applied to three or more jobs (Columns [2] and [3]). Lee bounds for the main outcomes of Panel A in Appendix Table A3 show that the null effects are robust to selection on attrition.

Tables A4 and A5 report the results for the additional outcomes collected in the survey rounds 2 and 3: respondents' employment status, whether they seek jobs, their preference for inside state or outstation jobs, job search mechanisms, and if they have applied for any jobs in their sector of training in the past two months. We do not find any difference in the employment status or in the job search intensity and mechanism between the treated and control group trainees during both the survey rounds. If anything, treated individuals are less likely to say they are job seekers (Table A4, Row [4]) and less likely to be in a salaried job (Table A5, Row [1]). At the same time, however, treated individuals are more prepared to migrate outside of their native states, and 40% more likely to apply for jobs for which they have been trained (Table A4, Row [6] and [10]).

Table A6 reports results for the main outcomes by sub-samples defined by gender (women vs. men), and education (below 12th grade vs. 12th grade and above) in the survey round 2. In the absence of the intervention, in the control group, male respondents are more than twice as likely as female respondents to apply to salaried jobs in the past two months. As expected, 22% of more educated respondents have applied to salaried jobs as compared to

Table 4
Yuvasampark experiment: effect of treatment on main outcomes.

	Applied for jobs in the last 2 months? [1]	Number of job applications (1-2) [2]	Number of job applications (3 or more) [3]
Panel A: Survey Round 2 (Mar-Apr 2021)			
Treatment	-0.010 (0.018)	-0.011 (0.016)	0.003 (0.009)
p-value	0.573	0.512	0.727
q-value	0.727	0.727	0.727
Control Mean	0.199	0.162	0.036
Observations	1924	1924	1924
Panel B: Survey Round 3 (Nov-Dec 2021)			
Treatment	-0.012 (0.015)	-0.011 (0.013)	-0.004 (0.007)
p-value	0.416	0.388	0.573
q-value	0.574	0.574	0.574
Control Mean	0.125	0.097	0.024
Observations	1955	1955	1955
Controls	Yes	Yes	Yes

Notes: This table shows the effect of the intervention on the main outcomes of the study during the survey round 2 (Panel A) and survey round 3 (Panel B). The dependent variables are all binary indicators taking the value of 1 as follows. Column [1]: The respondents applied for salaried jobs in the last two months from the date of survey.; Column [2] and Column [3]: Respondents applied to either 1-2 jobs or 3 and more jobs. All regressions control for baseline characteristics chosen by lasso selection (Belloni et al., 2013) as well as strata fixed effects. The reported p-value is for the test of no treatment effect and the q-value is the p-value of the same test accounting for multiple hypothesis testing (MHT) following the False Discovery Rate method by Benjamini & Hochberg (1995).

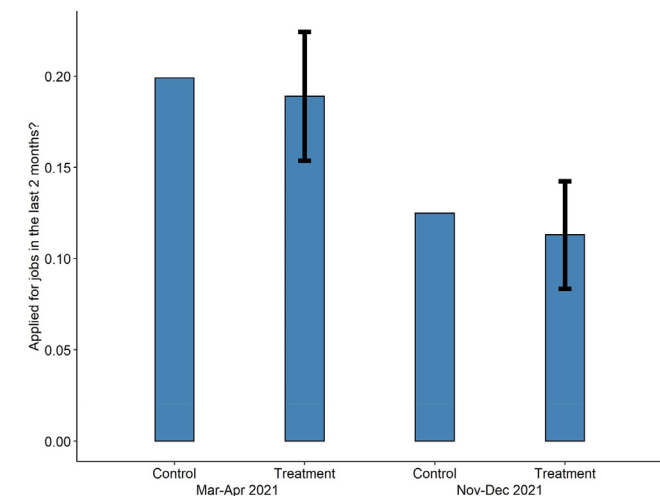


Fig. 10. Yuvasampark Experiment: Treatment Effects on Job Applications. Notes: The figure shows the effect of Yuvasampark app treatment for randomized sample of 2,260 DDU-GKY training participants over the last two panel survey rounds on the outcome variable- “applied for jobs in the last two months?”.

15% among the less educated ones. However, we find no differential impact of the treatment based on these dimensions of heterogeneity.

Tables A7 and A8 shows the results for the rate of registration and utilisation for the mobile application of Yuvasampark during the survey rounds 2 and 3 respectively. We first asked the respondents if they were aware of the app. As expected, during the survey round 2 (March - April 2021) only 22% of the control group respondents knew about the app as compared to 64% of respondents from the treatment group. It is worthwhile to reiterate that the intervention informed treatment group respondents about the app and

supported them with the registration and application process. In the control group, after the intervention in round 2 the registration rate was 5% as against 32% in the treated group. Towards the end of 2021, the registration on the Yuvasampark app remained almost the same for both groups, treatment group respondents were more likely to have registered on the app (6% in the control group as against 30% in the treated group) (Table A8). The treatment effect on both awareness about the app and registration is strongly significant.

Conditional on registration, we then enquired about the utilisation frequency of the app and find no difference in the utilisation rate between the treatment and control group trainees. For those who reported having used the app, in the survey round 2 we asked about the number of jobs they were interested in on this online job portal. About 25% of candidates who registered to the app in the control group said that none of the advertised jobs interested them. If anything, this fraction was higher in the treatment group (40% but the difference is not statistically significant). In the end, no one in the control, and only 1.7% of the treatment group had applied to any job through Yuvasampark by the time of the survey round 2 (Table A7).

4.4. Discussion

There is a growing literature (mostly in developed countries) about how digital tools may complement traditional policies implemented by the government, for instance, to help job seekers find jobs (Kelley et al., 2021; Wheeler et al., 2022). Digital tools are cheap and even if their benefits were to be small, it might not be difficult to design cost-effective digital tools. This is what motivated the government’s decision to support the use of Yuvasampark, and our decision to evaluate it as a promising digital tool for integrating youth into the labour market.

In this setting, we found that Yuvasampark did not motivate job seekers to increase their search intensity and it did not help them get jobs. While this may seem disappointing, there are several lessons to take away from academic and policymaking points of view. Digital tools can give zero effect, or even backfire. The fact that they help should not be taken for granted, and it is better to test their effectiveness before scaling them up. There are at least two aspects to consider.

The first question is what the goal of the tool is. The objective of online job boards is to remedy information imperfections in labour markets. Employers would like to advertise their vacancies, and job seekers to be informed about job opportunities at the lowest possible cost. Online job boards are effective when they manage to attract a very large number of vacancies, and most of the online platforms typically gather hundreds of thousands of job postings. In our study period, Yuvasampark had between 1500 and 2500 vacancies from 1 to 6 employers concentrated on a few job postings. Most of these jobs were not DDU-GKY placement jobs but other job openings that were seeking applications during the study period. The limited number of jobs and employers restricts the options available to job seekers. First, it may deter job seekers from registering to the portal. Second, it reduces the credibility of the tool, and hence the incentives to use it.

The second is whether the tool is easy to use. Contrary to most online job boards, Yuvasampark requires logging in to search for jobs. During our experiment, we identified the registration and log-in process as one of the potential barriers to the use of the tool. From a visual and user-friendliness point of view, Yuvasampark also looks sub-par compared to industry standards. Also, a smartphone and the internet are a prerequisite to use the app: they are not universally available to rural youth, which was the main target of the platform. Finally, all the modules in the mobile application are in English, another hindrance for the rural youth.

While the Indian labour market suffers from several information imperfections, especially for the unskilled workforce, there is room for well-designed digital tools to guide job seekers in their search. However, not all tools will help them. Governments should invest in a tool that is (i) able to attract the attention of employers, and (ii) easy to use even from the devices available among the population of interest.

5. Conclusion

This report presents evidence of the dramatic short and long-term impact of the COVID-19 crisis on India's rural youth and on potential policy solutions that could be implemented to help them recover from this unprecedented shock. We followed a cohort of 2,260 young rural workers from Bihar and Jharkhand who had enrolled into the training and placement program DDU-GKY in the year prior to the pandemic and surveyed them for 20 months since the first national lockdown in March 2020. We show that most young women and men who had a formal salaried job pre-lockdown lost it in the pandemic and had not gotten back into formal employment until almost two years later. Job loss was often accompanied by return migration: many of those who were working in other states went back home and had not migrated again a year later. We also document starkly different patterns for men and women. While many male workers took up informal employment and kept looking for jobs, most female workers simply dropped out of the labour force to do domestic work. Similarly, while many young men were still willing to migrate out of state most women expected to stay home. The divergence in labour market trajectories between men and women was especially marked among those who got married in the interval.

Overall, our results suggest that the barriers to accessing formal jobs that rural youth face, especially women, have been reinforced by the pandemic. We experimentally evaluate a low-cost intervention by the government to match these rural workers with jobs through an app-based digital platform called Yuvasampark. We find that few young people in the treatment group used the platform and that they did not apply to more jobs or found employment more quickly than the control group. Our takeaway from the experiment is that bridging the gap between rural young workers and urban formal labour markets requires either better-designed tools or more targeted, active interventions from the government, such as expanding the training and placement program DDU-GKY which got the young people of our sample (many women among them) into jobs pre-lockdown. The panel survey suggests that young people who completed the training were more likely to be in a salaried job not only pre-lockdown but also 20 months after the COVID-19 shock.

Data availability

Data will be made available on request.

Declaration of Competing Interest

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

Acknowledgements

We thank Wiji Arulampalam, Gaurav Chiplunkar, Santhosh Mathew, Rohini Pande, Simon Quinn, Chris Woodruff for useful comments at many stages of the projects. This project has been funded by International Growth Centre, EQUIP-ESRC, CAGE Univer-

sity of Warwick, and British Academy. This project would not have been possible without the amazing collaboration of Mr Sanjay Kumar (BRLPS), Mr Abhinav Bakshi (JSLPS) and the Ministry of Rural Development. Chakravorty is affiliated with GLO, Bhatiya with CAGE, Imbert with BREAD, CEPR, EUDN, and J-PAL, Rathelot with CREST, CEPR, and J-PAL.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.worlddev.2023.106242>.

References

- Abraham, R., Basole, A., & Kesar, S. (2022). Down and out? The gendered impact of the Covid-19 pandemic on India's labour market. *Economia Politica*, 39(1), 101–128. <https://doi.org/10.1007/s40888-021-00234-8>.
- Afridi, F., Dhillon, A., Roy, & Sanchari. (2021). The gendered crisis: livelihoods and mental well-being in India during COVID-19. *WIDER Working Paper*. 10.35188/UNU-WIDER/2021/003-0.
- Agarwal, B. (2021). Livelihoods in COVID times: Gendered perils and new pathways in India. In *World Development* (Vol. 139). Elsevier Ltd. 10.1016/j.worlddev.2020.105312.
- Aggarwal, S., Jeong, D., Kumar, N., Park, D. S., Robinson, J., & Spearot, A. (2022). COVID-19 market disruptions and food security: Evidence from households in rural Liberia and Malawi. *PLoS ONE*, 17(8 August). 10.1371/journal.pone.0271488.
- Amare, M., Abay, K. A., Tiberti, L., & Chamberlin, J. (2021). COVID-19 and food security: Panel data evidence from Nigeria. *Food Policy*, 101. <https://doi.org/10.1016/j.foodpol.2021.102099>.
- APU. (2021). *STATE OF WORKING INDIA 2021 Centre for Sustainable Employment*. <https://cse.azimpremjiuniversity.edu.in/state-of-working-india/>.
- Barker, N., Davis, C. A., López-Peña, P., Mitchell, H., Mobarak, A. M., Naguib, K., Reimão, M. E., Shenoy, A., & Vernot, C. (2020). *Migration and the labour market impacts of COVID-19* (Vol. 2020). UNU-WIDER. 10.35188/UNU-WIDER/2020/896-2.
- Belloni, A., Chernozhukov, V., & Hansen, C. (2013). Inference on treatment effects after selection among high-dimensional controls. *Review of Economic Studies*, 81(2), 608–650. <https://doi.org/10.1093/restud/rdt044>.
- Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate - a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society Series B-Methodological* 1995.pdf. In *Journal of the Royal Statistical Society Series B (Methodological)* (Vol. 57, Issue 1).
- Bundervoet, T., Dávalos, M. E., & Garcia, N. (2022). The short-term impacts of COVID-19 on households in developing countries: An overview based on a harmonized dataset of high-frequency surveys. *World Development*, 153. <https://doi.org/10.1016/j.worlddev.2022.105844>.
- Chakravorty, B., Arulampalam, W., Bhatiya, A. Y., Imbert, C., & Rathelot, R. (2021). Can information about jobs improve the effectiveness of vocational training? Experimental evidence from India. *SSRN Electronic Journal*. 10.2139/ssrn.3865452.
- Dang, H. A. H., & Viet Nguyen, C. (2021). Gender inequality during the COVID-19 pandemic: Income, expenditure, savings, and job loss. *World Development*, 140. <https://doi.org/10.1016/j.worlddev.2020.105296>.
- Dang, H.-A.-H., Nguyen, C. V., & Carletto, C. (2023). Did a successful fight against COVID-19 come at a cost? Impacts of the pandemic on employment outcomes in Vietnam. *World Development*, 161. <https://doi.org/10.1016/j.worlddev.2022.106129>.
- Dasgupta, S., & Robinson, E. J. Z. (2021). Food insecurity, safety nets, and coping strategies during the COVID-19 pandemic: Multi-country evidence from sub-Saharan Africa. *International Journal of Environmental Research and Public Health*, 18(19). <https://doi.org/10.3390/ijerph18199997>.
- Deshpande, A. (2022). The Covid-19 pandemic and gendered division of paid work, domestic chores and leisure: Evidence from India's first wave. *Economia Politica*, 39(1), 75–100. <https://doi.org/10.1007/s40888-021-00235-7>.
- Dhia, A. ben, Crépon, B., Mbih, E., Paul-Delvaux, L., Picard, B., & Pons, V. (2022). *Can a website bring unemployment down? Experimental evidence from France*. <http://www.nber.org/papers/w29914.ack>.
- Dhingra, S., & Machin, S. (2020). *The crisis and job guarantees in urban India*. IZA DP No. 13760.
- Downs-Tepper, H., Krishna, A., & Rains, E. (2022). A threat to life and livelihoods: Examining the effects of the first wave of COVID-19 on health and wellbeing in Bengaluru and Patna slums. *Environment and Urbanization*, 34(1). <https://doi.org/10.1177/09562478211048778>.
- Egger, D., Miguel, E., Warren, S. S., Shenoy, A., Collins, E., Karlan, D., ... Vernot, C. (2021). Falling living standards during the COVID-19 crisis: Quantitative evidence from nine developing countries. *Science Advances*, 7(6). <https://doi.org/10.1126/sciadv.abe0997>.
- Fenn, Chacko, N., Thomas, T., Varghese, V. K., & George, S. (2021). Stress, sources of stress and coping during the Covid-19 lockdown: A population study from India. *Indian Journal of Social Psychiatry*, 37(1).

- Heath, R., & Jayachandran, S. (2017). The causes and consequences of increased female education and labor force participation in developing countries. *The Oxford Handbook of Women and the Economy*. <https://doi.org/10.1093/oxfordhb/9780190628963.013.10>.
- Imbert, C. (2020). *Covid-19: Expected migrant movement as lockdown eases*. <https://www.ideasforindia.in/topics/governance/covid-19-expected-migrant-movement-as-lockdown-eases.html>.
- Janssens, W., Pradhan, M., de Groot, R., Sidze, E., Donfouet, H. P. P., & Abajobir, A. (2021). The short-term economic effects of COVID-19 on low-income households in rural Kenya: An analysis using weekly financial household data. *World Development*, 138. <https://doi.org/10.1016/j.worlddev.2020.105280>.
- Jones, S., & Sen, K. (2022). *Labour market effects of digital matching platforms: Experimental evidence from Sub-Saharan Africa*. <https://ssrn.com/abstract=4154052>.
- Josephson, A., Kilic, T., & Michler, J. D. (2021). Socioeconomic impacts of COVID-19 in low-income countries. *Nature Human Behaviour*, 5(5), 557–565. <https://doi.org/10.1038/s41562-021-01096-7>.
- Kansiime, M. K., Tambo, J. A., Mugambi, I., Bundi, M., Kara, A., & Owuor, C. (2021). COVID-19 implications on household income and food security in Kenya and Uganda: Findings from a rapid assessment. *World Development*, 137. <https://doi.org/10.1016/j.worlddev.2020.105199>.
- Kelley, E. M., Ksoll, C., & Magruder, J. (2021). *How do online job portals affect employment and job search? Evidence from India*. Working Paper.
- Kesar, S., Abraham, R., Lahoti, R., Nath, P., & Basole, A. (2021). Pandemic, informality, and vulnerability: Impact of COVID-19 on livelihoods in India. *Canadian Journal of Development Studies*, 42(1–2), 145–164. <https://doi.org/10.1080/02255189.2021.1890003>.
- Lee, D. S. (2009). Training, wages, and sample selection: Estimating sharp bounds on treatment effects. *Review of Economic Studies*, 76(3). <https://doi.org/10.1111/j.1467-937X.2009.00536.x>.
- Mahmud, M., & Riley, E. (2021). Household response to an extreme shock: Evidence on the immediate impact of the Covid-19 lockdown on economic outcomes and well-being in rural Uganda. *World Development*, 140. <https://doi.org/10.1016/j.worlddev.2020.105318>.
- Mamgain, R. P. (2021). Understanding labour market disruptions and job losses amidst COVID-19. *Journal of Social and Economic Development*, 23(S2), 301–319. <https://doi.org/10.1007/s40847-020-00125-x>.
- Morgan, P. J., & Trinh, L. Q. (2021). *Impacts of COVID-19 on households in Asian countries and their implications for human capital development*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3870909.
- Wheeler, L., Garlick, R., Johnson, E., Shaw, P., & Gargano, M. (2022). LinkedIn(to) job opportunities: Experimental evidence from job readiness training. *American Economic Journal Applied Economics*, 14(2). <https://doi.org/10.1257/APP.20200025>.