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Bhaskar Chakravorty,
Apurav Yash Bhatiya,
Clement Imbert,
Maximilian Lohnert,
Poonam Panda &
Roland Rathelot

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Bhaskar Chakravorty

Apurav Yash Bhatiya

Clément Imbert

Maximilian Lohnert

Poonam Panda

Roland Rathelot*

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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 labor 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 a 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 labor markets requires more active and targeted policy interventions, especially for female workers.

Key words: Youth unemployment, gender, vocational training, public policy.

JEL Codes: J2, J3, J6, J7, M5.

*Chakravorty: University of Warwick and GLO. Bhatiya: University of Birmingham and CAGE. Imbert: BREAD, CEPR, EUDN, JPAL and Warwick. Lohnert, Panda: JPAL SA. Rathelot: CEPR and Institut Polytechnique de Paris.

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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 (Dasgupta and Robinson, 2021; Kansiime et al., 2021; Amare et al., 2021; APU, 2021; Deshpande, 2022; Abraham et al., 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. 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 to 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 four 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.

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 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 labor market, we find that the job application rate was much lower than the

[1] `http://ddugky.gov.in/` accessed on 6 July 2022.

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. One year later, training graduates were still twice as likely to hold a salaried job as the drop-outs (26% against 13%). 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 labor 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 mobile app used by several state governments in India to help trainees search for and apply to jobs. 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 encouragement design to evaluate the impact of using YuvaSampark on job search and job finding. We randomly allocated youth 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 the 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 labor 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 March 2020 (Egger et al., 2021). In India specifically, the COVID-19 had a stronger impact on the employment of women and younger workers (APU, 2021; Deshpande, 2022; Abraham et al., 2022). The economic impact of the pandemic on urban informal sectors has been largely spread across India: in the Delhi National Capital Region (Afridi et al., 2021a), in Bihar, Jharkhand and Uttar Pradesh (Dhingra and Machin, 2020) as well as for slum communities in Patna and Bangalore (Downs-Tepper et al., 2022). At the same time as economic and labor-market shocks, food insecurity increased (Amare et al., 2021; Dasgupta and Robinson, 2021) and well-being declined (Afridi et al., 2021a). Other country-specific studies reported similar findings (Mahmud and Riley, 2021; Kansiime et al., 2021; Janssens et al., 2021; Aggarwal et al., 2020). A longitudinal household survey study from Ethiopia, Malawi, Nigeria and Uganda estimates that 77% of the population live 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 and Trinh, 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.[2] 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 information and to 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. (2021) finds that training South African job seekers to use LinkedIn improves durably their labor-market outcomes. Kelley et al. (2020) 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 et al. (2022) documents that the usage of digital job platforms

[2]Our surveys maintained an overall attrition rate between 10% and 15%.

is not associated with better labor market outcomes for job seekers in Mozambique. In the context of France, Dhia et al. (2022) finds using an online platform designed to provide tips to broaden 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 labor-market impacts, governments should dedicate time and energy to design online tools, to improve both their user-friendliness and their coverage of labor 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 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 31th. 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: The second phase of lockdown was approximately from April 5–15 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, many 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 on the labor market, i.e. female, less educated and SC/ST, 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 equally split between male and female. 66% respondents are from Bihar and 34% 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 7% are from General Caste, which shows that DDU-GKY successfully targets disadvantaged youth. A very high fraction (79%) of respondents are from households below the poverty line, which reflects the pro-poor targeting of DDU-GKY. Around 86% 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 of placement (52%) than men (Figure A1).

The findings presented in this study are based on three survey rounds (Figure 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 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 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.

3 Descriptive findings

Employment. Figure 2 shows respondents' employment status for four time periods: (1) before the first lockdown, (2) shortly after the first lockdown, (3) one year after the first lockdown and shortly before the second, (4) 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 lockdown to shortly after the 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 the lockdown (Appendix Table A2).[3] While this loss of salaried work led to an increase in the non-earning category (from 50% 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 continued in the first year after the lockdown, and then stabilizes: 20 months after the first lockdown 26% of youth in the sample were in the informal sector and 26% in the formal sector.

Employment trajectories by gender. Women are at a disadvantage on the labor market in India, with lower labor force participation and higher unemployment than men (Afridi et al., 2021b). 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 trajec-

[3] Holi is an annual two-day festival and was on 9th of March in 2020.

tories for men and women and present them in Figure 3. While both men and women started with an equal employment rate of around 40% in salaried jobs pre-lockdown, around 28% men continued being in salaried jobs one year after the lockdown, as compared to 20% in women. These proportions seemed to stabilize afterward: 31% of men and 20% of women in salaried job 20 months after the first lockdown. 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. As a result, the proportion of men and women in wage employment were starkly different: in November-December 2021 two third of men but only one third of women were employed in salaried or informal work.

Figure A2 takes a closer look at the type of employment trajectories for male 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.[4] More than a third (37%) lost and could not recover their work,[5] while only 11% could recover their employment.[6] 16% moved from formal to informal work, with only 3% moving 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 was a fallback option: while 20% of men moved into informal work, only 11% of women did. The formalisation rate was also higher among men.

Employment trajectories 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. Figure 4 compares employment trajectories of trained youth and dropouts. We find that the trainees have a much higher rate of

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

[5] *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.

[6] *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 had transitioned back into the same type of work (salaried or informal) later.

employment to start with, especially in salaried jobs (44%) compared to the training dropouts (15%). One year down the line, 26% of the trained individuals retained their salaried employment and 21% resorted to informal work. By contrast, those who had dropped out of training had a much higher rate of employment in the informal sector (32%).

The findings for the trained men and women remain consistent with the finding from the overall sample, with 60% men engaged in earning activities in March−April 2021, against 33% of women. However, trained women have a slightly higher rate of salaried employment in the pre-lockdown period (Appendix Figure 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 for male dropouts is around 60%, against 20% for female dropouts (Appendix Figure 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.

Job search. Given that one year 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. Figure 5 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 indicating that respondents did not know where or how to apply for jobs, or that 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: 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 (Figure 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 training organisation (PIA),[7] and 35% individuals took a more formal approach to job search using various online job portals.[8]

Location and migration. Since the COVID-19 crisis led many migrants workers to return to their home states (Imbert, 2020), we tracked the location of our respon-

[7]Project Implementing Agencies (PIAs) are private training organisations that provide training and placements under the DDU-GKY scheme.

[8]This was a multiple answer question, so the percentages won't add up to 100%.

dents across the three time periods (Figure 6). The proportion of young people in our sample who worked outside of state decreased by half, from 32% before the lockdown to 16% one year later. 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 migration' that followed the announcement of the national lockdown in March 2021, where migrant workers that lost their job returned to their homes. Half of those still outside the state shortly after the lockdown had returned to their home state one year later. However, in the same time period, there was also some movement in the opposite direction: 11% of those at home and 8% of those within their home state had migrated outside of state one year after the lockdown. Of those that were outside of state before the lockdown but had returned to their home state shortly after the lockdown, only 23% had re-migrated out of state one year later.

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 (Figure 7). Among the men in our sample, the willingness to migrate out of state remain unchanged over the past one year (36% shortly after the lockdown and 37% one year after the lockdown). However, for women, it decreased from 26% shortly after the lockdown to 17% one year after the lockdown. This suggests that not only did women's employment suffer more from COVID-19, but that their prospects of reintegrating the labor market are also worse than men.

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 with no plans to migrate again, in stark contrast to their male counterparts. To investigate the reasons behind this gender differences, we consider separately men and women who got married since the first lockdown. As Figure 8 shows, women who did not get married have employment level 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 and Jayachandran, 2016). The differences are even more stark when we focus only on men and women who were employed in the same sector (services) before lockdown: 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.

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 of 0 to 100 per cent.[9] Figure 9 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 indicates a lasting negative impact of the COVID-19 crisis on youth well-being, especially for men.

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

[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 in December 2019 to March 2020, i.e. prior to Round 1 (Chakravorty et al., 2021).

search, and (iii) job application. A preview for all three steps are shown in the Appendix Figures. The main method of registration on the app is by entering the unique registration number that trainees are allotted in the DDU-GKY program. The benefit from using the training registration number is that the app fetches all the trainee details from the portal of the training scheme (Appendix Figure 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 job posting and sector of a job (Appendix Figure A7). A typical job posting looks as shown in Appendix Figure 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. Figure 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 1 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 J-PAL South Asia surveyor in the following week to help them register. All candidates who registered received another call to assist them in applying to jobs through the app. The full sample was called in the Round 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:

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

β is the intention-to-treat effect, the parameter of interest in our setting. We use post-double selection lasso as in Belloni et al. (2014) 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 2 and Figure 10 present the results for our main outcomes in Columns numbered [1]-[3]. Panel A shows the outcomes in the survey round 2 (March - April 2021) and Panel B shows the outcomes from the 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 have applied to salaried jobs in Round 2, which is not different from the treatment group respondents (Figure 10). Towards the end of 2021, 12.5% of the control group respondents have applied for a salaried job, and again it was not different compared to the treatment group (Figure 10). Table 2 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 the Appendix Table A3 show that the null effects are robust to selection on attrition.

Table A4 and A5 reports 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 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 15% among the less educated ones. However, we find no differential impact of the treatment based on these dimensions of heterogeneity.

Table A7 and A8 shows the results for the take-up and utilisation for the mobile application of YuvaSampark during the survey rounds 2 and 3 respectively. We examine the effect of the intervention on the rate of registration and utilisation of the YuvaSampark app. We first asked the respondents if they were aware about 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% 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 to 32% in the treated group. Towards the end of 2021, though registration on YuvaSampark app increased among both the groups, treatment group respondents were more likely to have registered on the app (21% in the control group as against to 52% 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. 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 government, for instance to help job seekers find jobs (Kelley et al., 2020; Wheeler et al., 2021). 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 labor 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 policy-making 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 on labor 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 to 2500 vacancies from 1-6 employers concentrated on a few job postings. 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 use the tool. From a visual and user-friendliness point of view, YuvaSampark also looks sub-par compared to industry standards. Also, a smart phone and internet are a prerequisite to use the app: they are not universally available to rural youth, which were 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 labor 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, (ii) easy to use even from the devices available among the population of interest.

5 Conclusion

This report presents evidence on 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 a year later. Job loss was often accompanied with return migration: many 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 labor 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 labor 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 access 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 Yuva Sampark. We find that few young people in the treatment group actually used the platform, and that they did not apply to more jobs or found employment more quickly than the control group. Our take-away from the experiment is that bridging the gap between rural young workers and urban formal labor 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.

References

Abraham, R., A. Basole, and S. Kesar (2022): "Down and out? The gendered impact of the Covid-19 pandemic on India's labour market," *Economia Politica*, 39, 101–128.

Afridi, F., A. Dhillon, and S. Roy (2021a): "The gendered crisis: Livelihoods and mental well-being in India during COVID-19," Tech. rep., WIDER Working Paper.

——— (2021b): "Livelihoods and mental well-being during COVID-19: A study using matched husband-wide-friend data in urban India," Tech. rep., IGC reference number: COVID-19-20093-IND-1.

Aggarwal, S., D. Jeong, N. Kumar, D. S. Park, J. Robinson, and A. Spearot (2020): "Did COVID-19 market disruptions disrupt food security? Evidence from households in rural Liberia and Malawi," Tech. rep., National Bureau of Economic Research.

Amare, M., K. A. Abay, L. Tiberti, and J. Chamberlin (2021): "COVID-19 and food security: Panel data evidence from Nigeria," *Food Policy*, 101, 102099.

APU (2021): "State of Working India 2021: One year of Covid-19, Centre for Sustainable Employment," Tech. rep.

Belloni, A., V. Chernozhukov, and C. Hansen (2014): "Inference on treatment effects after selection among high-dimensional controls," *The Review of Economic Studies*, 81, 608–650.

Benjamini, Y. and Y. Hochberg (1995): "Controlling the false discovery rate: a practical and powerful approach to multiple testing," *Journal of the Royal statistical society: series B (Methodological)*, 57, 289–300.

Chakravorty, B., W. Arulampalam, C. Imbert, and R. Rathelot (2021): "Can Information about Jobs Improve the Effectiveness of Vocational Training? Experimental Evidence from India," *IZA DP No. 14427*.

Dasgupta, S. and E. J. Robinson (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, 9997.

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, 75–100.

Dhia, A. B., B. Crépon, E. Mbih, L. Paul-Delvaux, B. Picard, and V. Pons (2022): "Can a Website Bring Unemployment Down? Experimental Evidence from France," Tech. rep., National Bureau of Economic Research.

Dhingra, S. and S. Machin (2020): "The Crisis and Job Guarantees in Urban India," *IZA DP No. 13760*.

Downs-Tepper, H., A. Krishna, and E. Rains (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, 190–208.

Egger, D., E. Miguel, S. S. Warren, A. Shenoy, E. Collins, D. Karlan, D. Parkerson, A. M. Mobarak, G. Fink, C. Udry, et al. (2021): "Falling living standards during the COVID-19 crisis: Quantitative evidence from nine developing countries," *Science advances*, 7, eabe0997.

Heath, R. and S. Jayachandran (2016): "The Causes and Consequences of Increased Female Education and Labor Force Participation in Developing Countries," Working Papers id:11434, eSocialSciences.

Imbert, C. (2020): "Expected migrant movement as lockdown eases," *Ideas for India*.

Janssens, W., M. Pradhan, R. de Groot, E. Sidze, H. P. P. Donfouet, and A. Abajobir (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, 105280.

Jones, S., K. Sen, et al. (2022): "Labour market effects of digital matching platforms: Experimental evidence from sub-Saharan Africa," Tech. rep., World Institute for Development Economic Research (UNU-WIDER).

Josephson, A., T. Kilic, and J. D. Michler (2021): "Socioeconomic impacts of COVID-19 in low-income countries," *Nature Human Behaviour*, 5, 557–565.

Kansiime, M. K., J. A. Tambo, I. Mugambi, M. Bundi, A. Kara, and C. Owuor (2021): "COVID-19 implications on household income and food security in Kenya and Uganda: Findings from a rapid assessment," *World development*, 137, 105199.

Kelley, E. M., C. Ksoll, and J. Magruder (2020): "How do Online Job Portals affect Employment and Job Search? Evidence from India," Tech. rep., Working Paper.

Lee, D. S. (2009): "Training, wages, and sample selection: Estimating sharp bounds on treatment effects," *The Review of Economic Studies*, 76, 1071–1102.

Mahmud, M. and E. Riley (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, 105318.

Morgan, P. and L. Q. Trinh (2021): "Impacts of COVID-19 on households in ASEAN countries and their implications for human capital development," .

Wheeler, L., R. Garlick, E. Johnson, P. Shaw, and M. Gargano (2021): "LinkedIn (to) Job Opportunities: Experimental Evidence from Job Readiness Training," *American Economic Journal: Applied Economics*.

Figures

Figure 1—Time periods

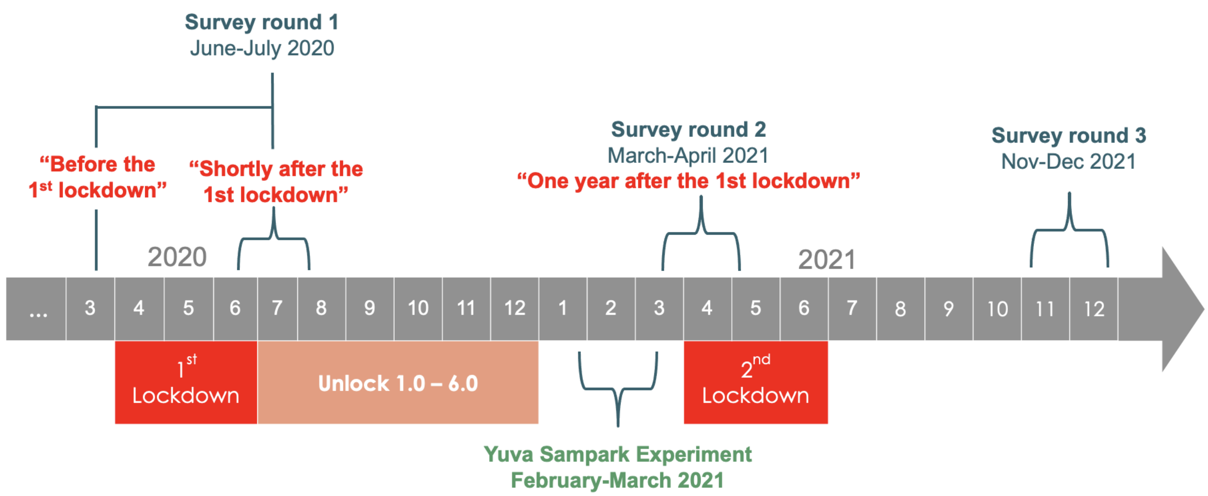


Figure 2—Employment change

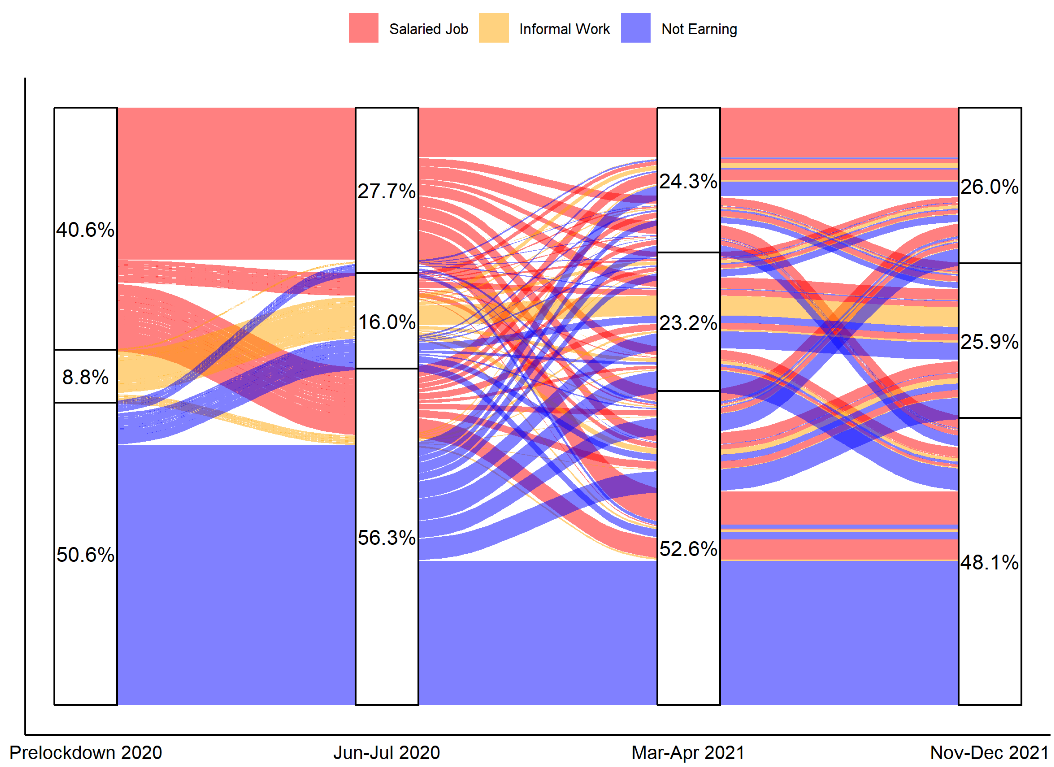
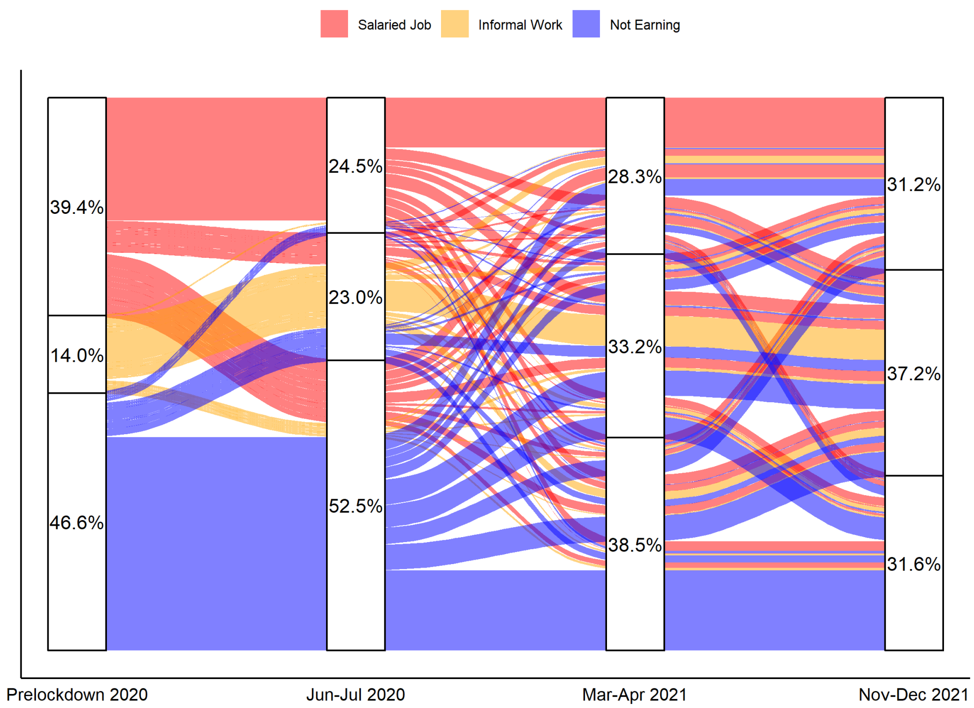
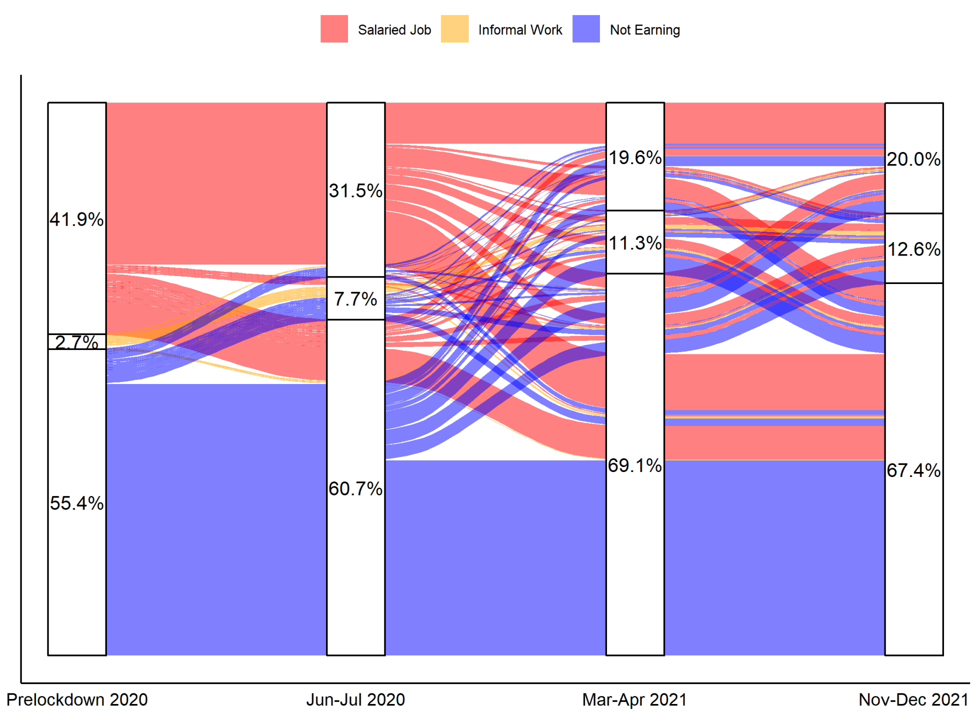


Figure 3—Employment change by gender. Males (a) and Females (b)

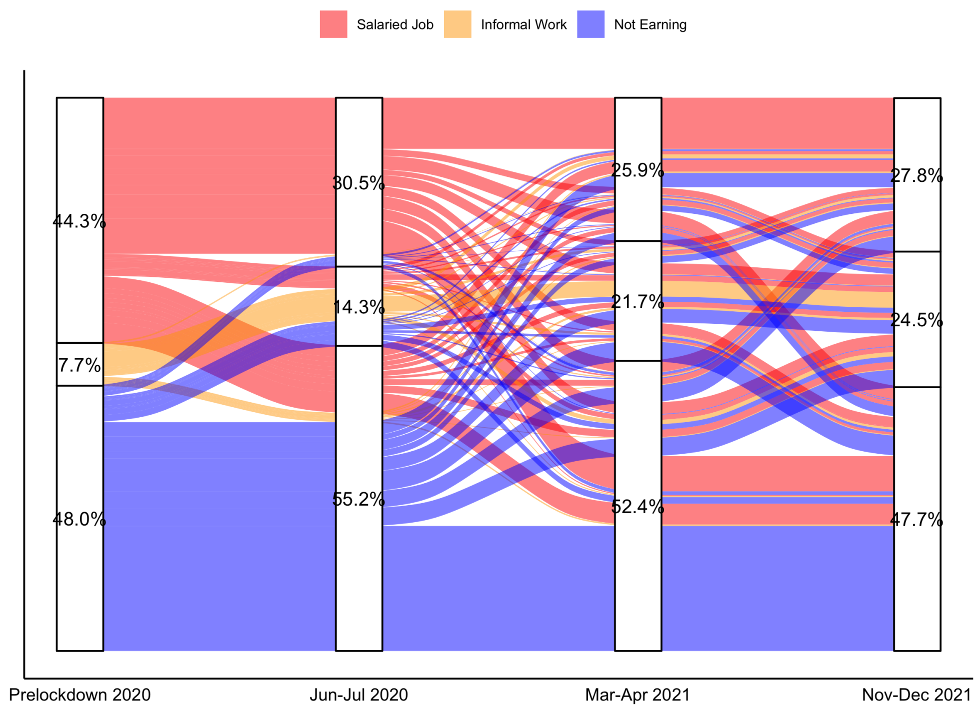


(a) Males

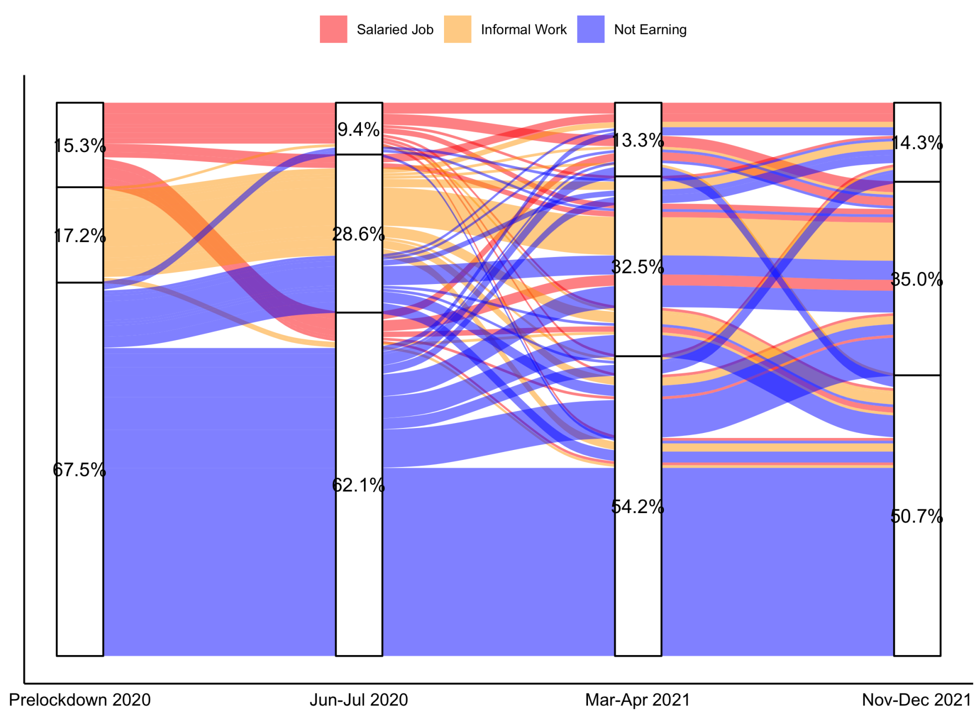


(b) Females

Figure 4—Employment change by training status. Trained individuals (a) and training dropouts (b)



(a) Trained individuals



(b) Training dropouts

Figure 5—Job search

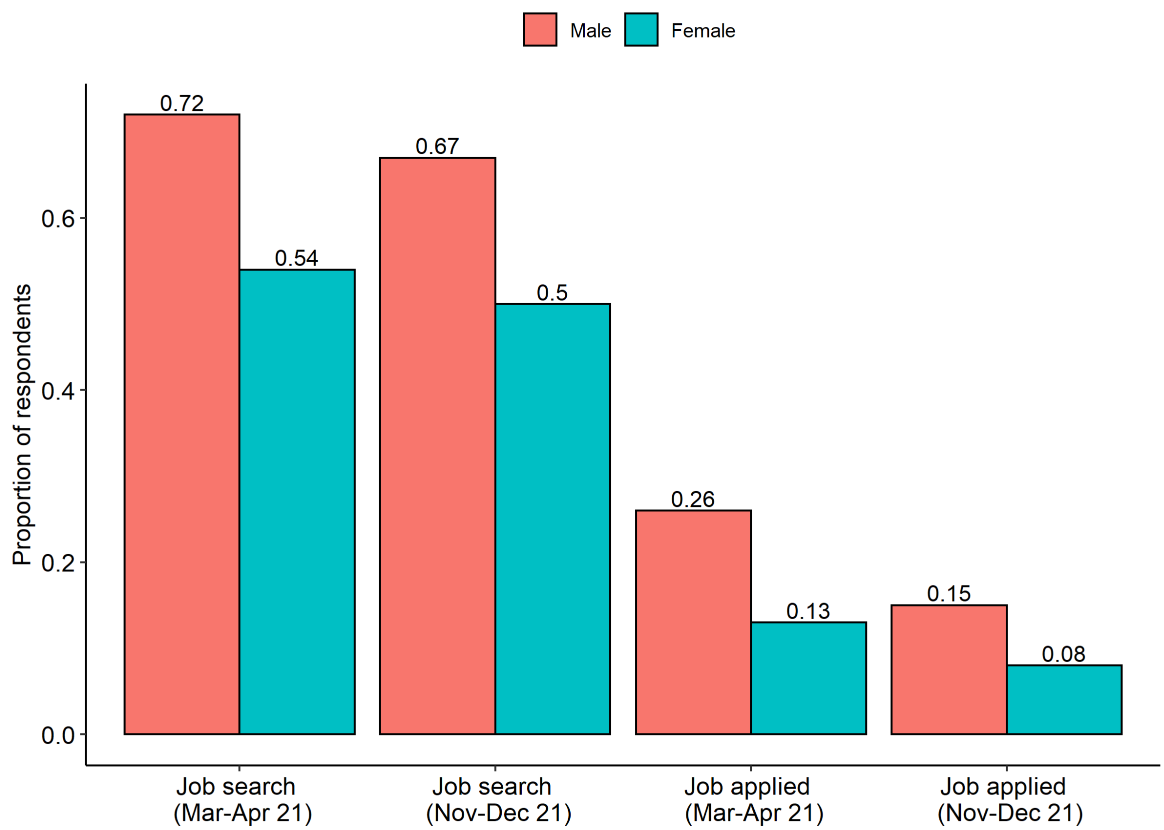


Figure 6—Location change

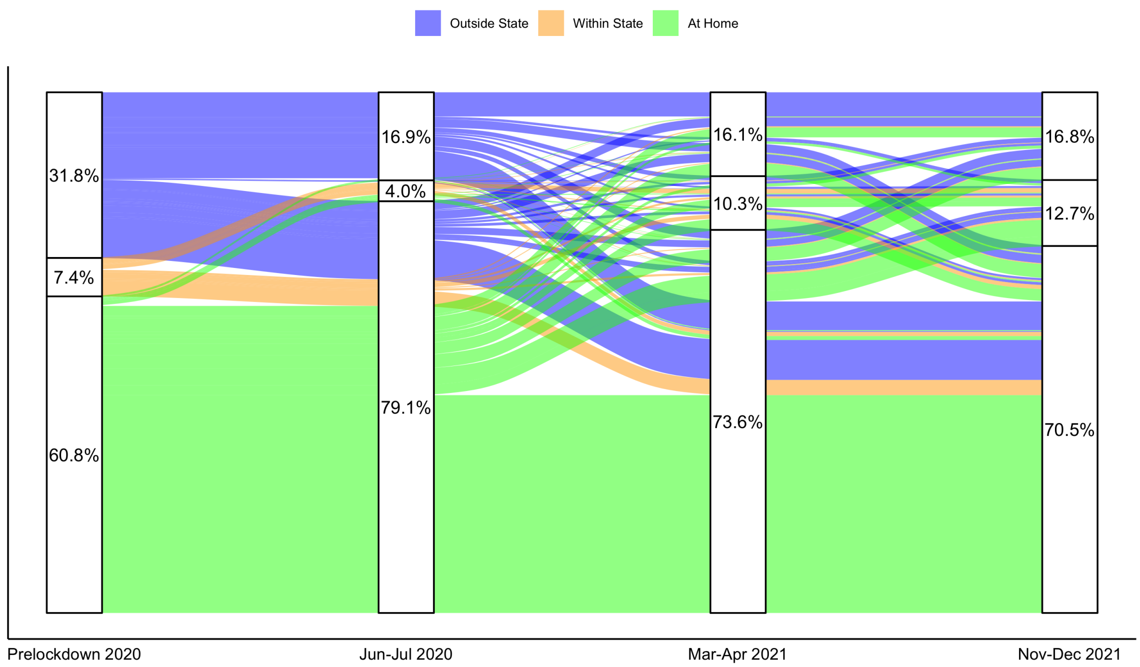


Figure 7—Willingness to migrate

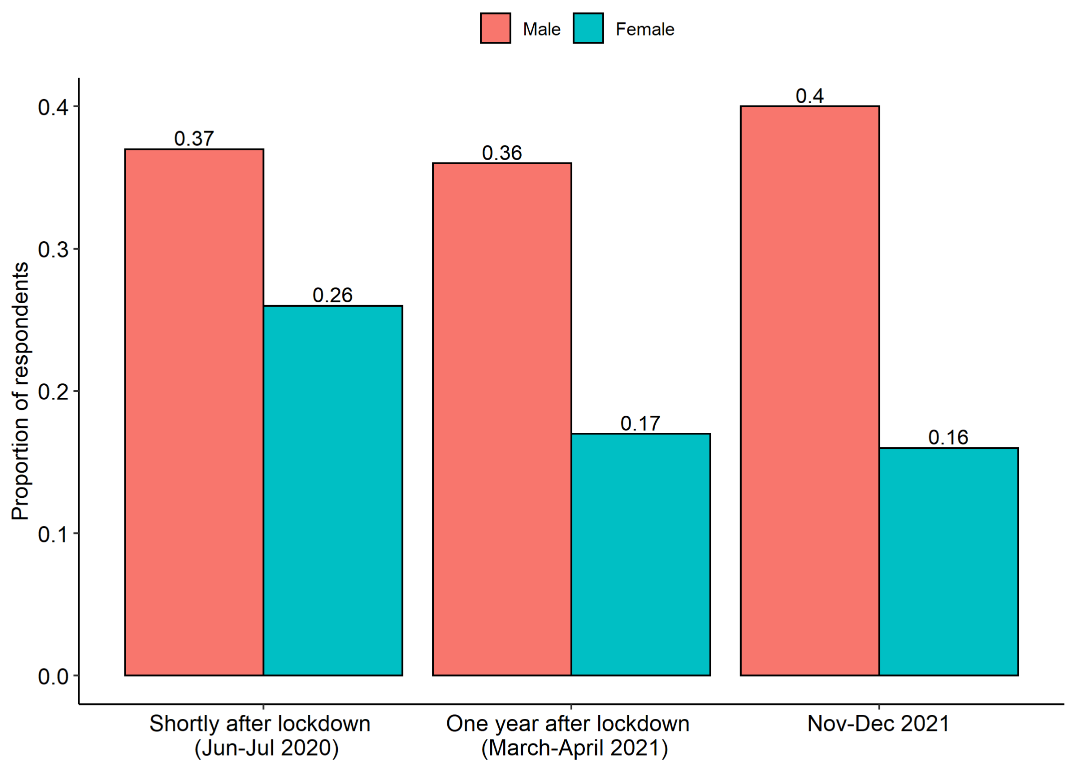
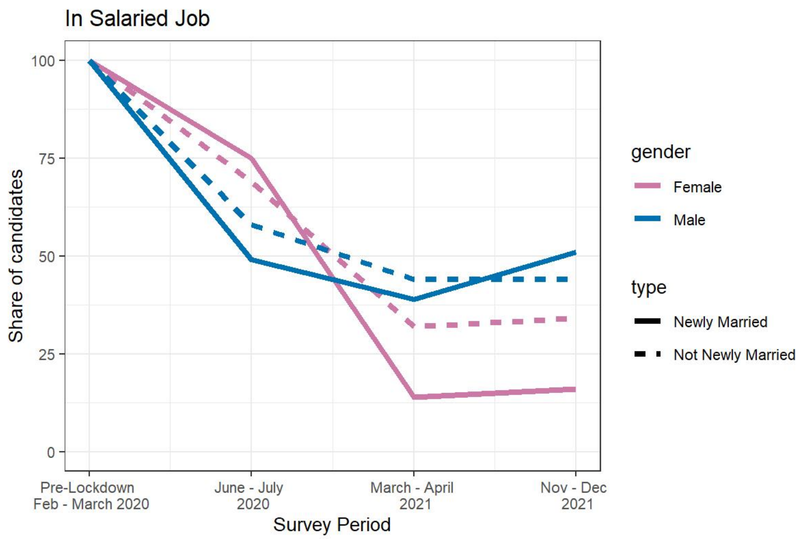
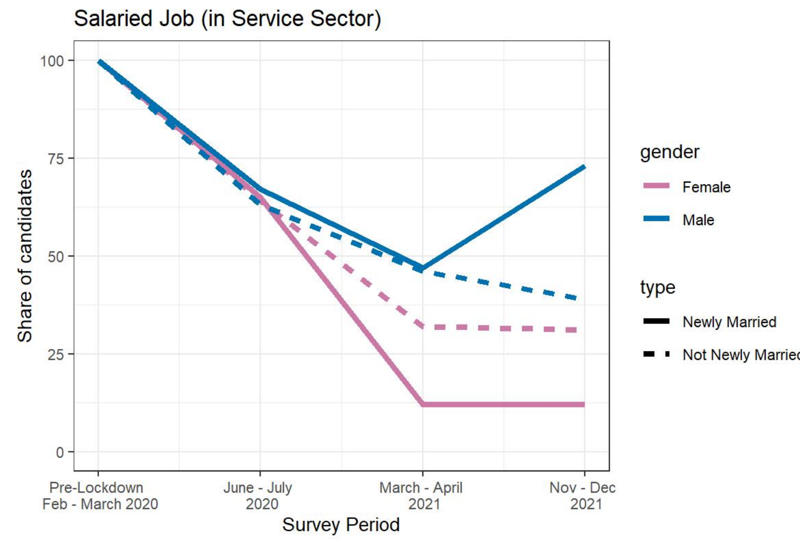


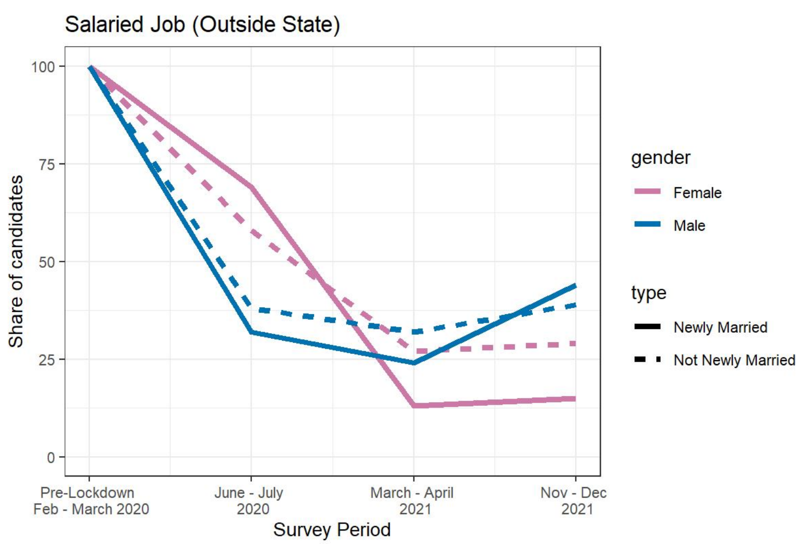
Figure 8—Changes in employment by gender and marriage



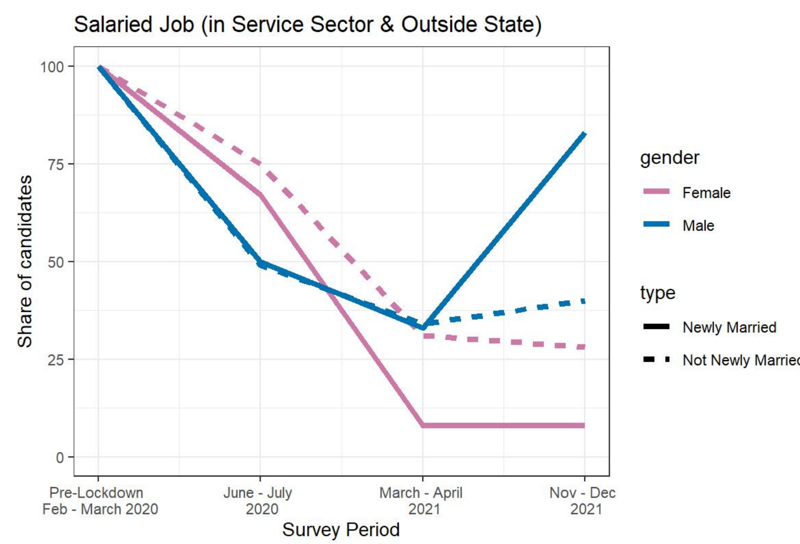
(a) Salaried Job



(b) Salaried Job (in Service Sector)



(c) Salaried Job (Outside State)



(d) Salaried Job (in Service Sector & Outside State)

Figure 9—Well-being indicators. Life Satisfaction and Anxiety

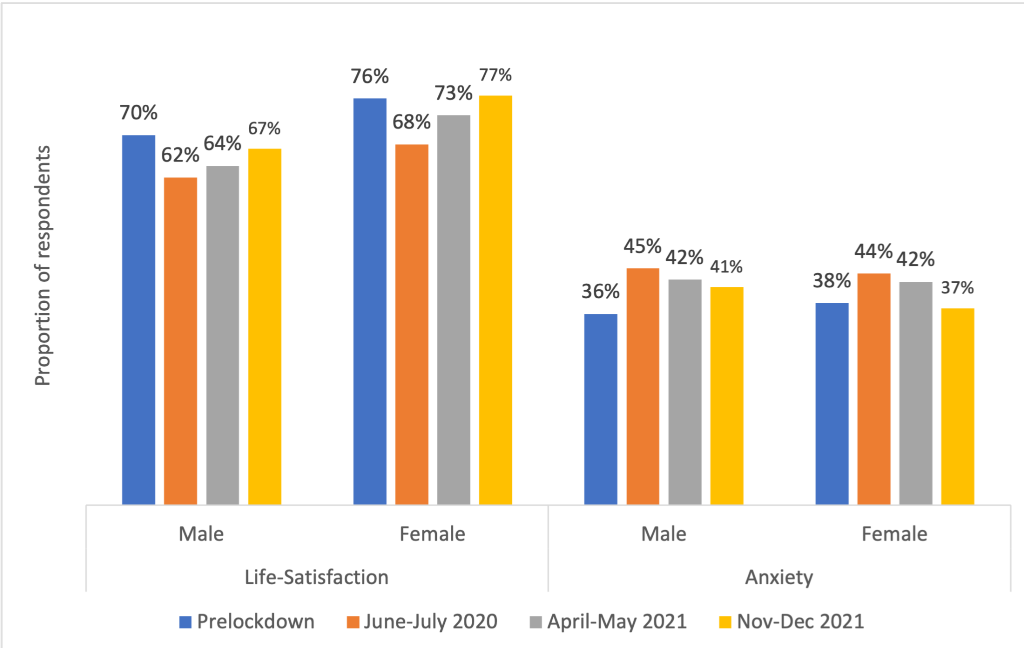
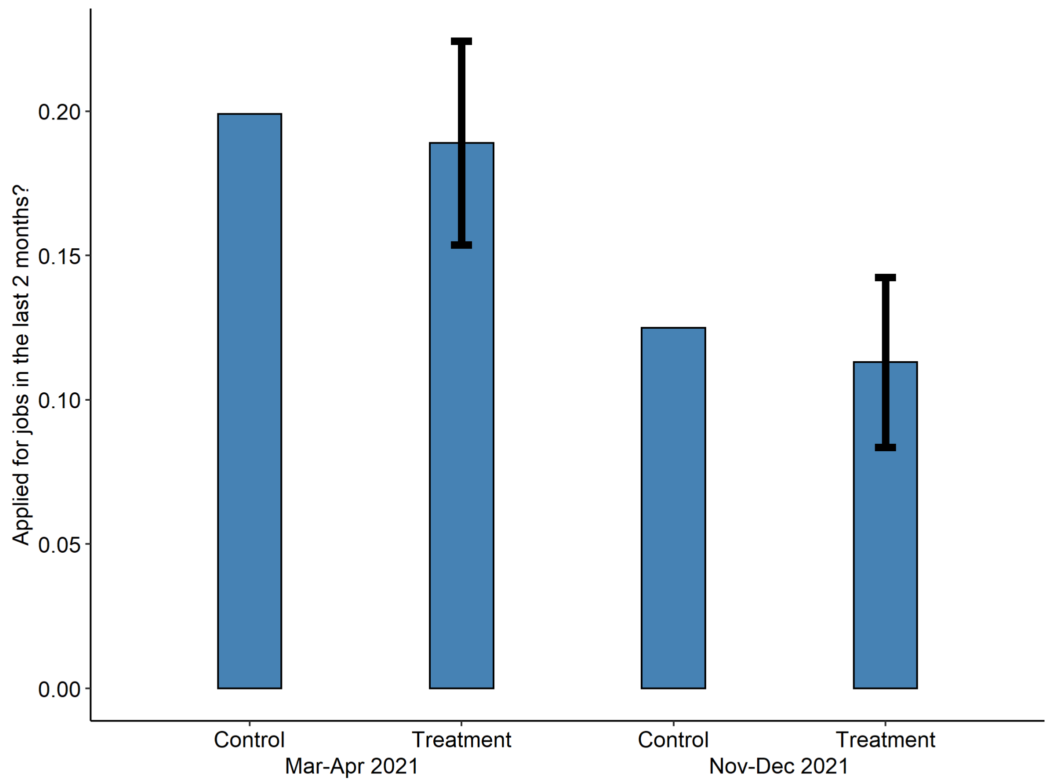


Figure 10—Treatment effects on job applications



Tables

Table 1—Sectoral bifurcation of the job postings on Yuvasampark app

Sector	Vacancies	Employers	States
	[1]	[2]	[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		

Table 2—Results: Main Outcomes

	Applied for jobs in the last 2 months?	Number of job applications (1-2)	Number of job applications (3 or more)
	[1]	[2]	[3]
Panel A: Survey Round 2 (Mar-Apr 2021)			
Treatment	-0.010	-0.011	0.003
	(0.018)	(0.016)	(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	-0.011	-0.004
	(0.015)	(0.013)	(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

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., 2014) 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 and Hochberg (1995).

Online Appendix

Table A1—Summary statistics (averages) of the survey respondents and non-respondents

	Respondents Group	Non-respondents Group	Diff [2-1]	p-value
	[1]	[2]	[3]	[4]
Female	0.476	0.645	0.169	0.000
Older (More than 20)	0.279	0.257	-0.022	0.408
Caste: ST	0.168	0.284	0.116	0.000
Caste: OBC	0.495	0.385	-0.110	0.000
Caste: General	0.065	0.081	0.015	0.310
Middle school (6-8 class)	0.041	0.096	0.055	0.000
Lower secondary (9-10 class)	0.345	0.403	0.058	0.039
Tertiary education	0.091	0.063	-0.028	0.090
BPL card	0.793	0.767	-0.025	0.292
Number of observation	1924	336		

Notes: Columns [1] and [2] report the mean value in the survey respondent group and survey attrition group respectively. Attrition dummy coefficient estimates in the regression of the variable, controlling for the strata fixed effects are in Column [3]. The p-value associated with the test of no difference between the groups is in Column [4]. Total number of observation is 2,260.

Table A2—Reason for job loss

Reason for job loss	Proportion of respondents
Company shut down	5.57
Asked not to come now	8.08
Terminated contract	4.74
Voluntary	47.08
Shutdown	23.4
Couldn't go back to work from home due to lockdown	8.64
Others	2.51

Notes: Reasons mentioned by respondents for loosing jobs during the survey conducted in June-July 2020.

Table A3—Results: Main Outcomes (Lee Bounds)

	Applied for jobs in the last 2 months?
	[1]
Treatment (lower bound)	-0.012
	(0.036)
p-value	0.519
Treatment (upper bound)	0.036
	(0.023)
p-value	0.130
Control Mean	0.199
Trimming proportion	0.0459
Observations	1924

Notes: This table report Lee bounds (Lee, 2009) for the main outcome variable to understand if selection on attrition biases the results.

Table A4—Results: Secondary Outcomes (Mar-Apr 2021)

	Treatment	Standard Error	p-value	q-value	Control Mean
	[1]	[2]	[3]	[4]	[5]
Salaried job	-0.010	0.018	0.563	0.614	0.255
Casual work	-0.017	0.018	0.350	0.428	0.240
Not earning	0.027	0.020	0.187	0.313	0.505
Seek job	-0.051	0.021	0.016	0.116	0.656
Job preference-inside state	-0.015	0.016	0.356	0.428	0.841
Job preference-outside state	0.032	0.019	0.095	0.285	0.257
Job search-help of PIA	-0.009	0.018	0.613	0.701	0.189
Job search-help of relatives/friends	-0.030	0.021	0.157	0.340	0.349
Job search-online	0.017	0.019	0.364	0.486	0.214
Applied job in sector of training	0.016	0.010	0.105	0.340	0.040

Notes: This table shows the effect of the intervention on additional outcomes. The dependent variables are all binary indicators. Salaried job, casual job and not earning are current employment status of the respondents as captured in the last survey round (March-April 2021). Seek job is 1 if the respondent was searching for jobs. Their job preference is captured as withing native state or in any other state. Job search mechanism is captured in terms of- help from their training institute (PIA) relatives/friends/acquaintances, or through online job portals. The last variable shows if the respondents have applied in jobs (in the last 2 months) within the sector in which they received training. All regressions control for baseline characteristics chosen by lasso selection (Belloni et al., 2014) 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 and Hochberg (1995). The total number of observation is 1924 respondents.

Table A5—Results: Secondary Outcomes (Nov-Dec 2021)

	Treatment	Standard Error	p-value	q-value	Control Mean
	[1]	[2]	[3]	[4]	[5]
Salaried job	-0.039	0.019	0.041	0.242	0.275
Casual work	0.018	0.019	0.334	0.402	0.250
Not earning	0.025	0.021	0.230	0.345	0.474
Seek job	0.005	0.021	0.800	0.800	0.592
Job preference-inside state	0.029	0.016	0.080	0.242	0.817
Job preference-outside state	-0.027	0.019	0.158	0.316	0.300
Job search-help of PIA	0.025	0.015	0.081	0.245	0.106
Job search-help of relatives/friends	-0.006	0.022	0.770	0.771	0.387
Job search-online	0.012	0.018	0.498	0.747	0.196

Notes: This table shows the effect of the intervention on additional outcomes. The dependent variables are all binary indicators. Salaried job, casual job and not earning are current employment status of the respondents as captured in the last survey round (Nov-Dec 2021). Seek job is 1 if the respondent was searching for jobs. Their job preference is captured as withing native state or in any other state. Job search mechanism is captured in terms of- help from their training institute (PIA) relatives/friends/acquaintances, or through online job portals. The last variable shows if the respondents have applied in jobs (in the last 2 months) within the sector in which they received training. All regressions control for baseline characteristics chosen by lasso selection (Belloni et al., 2014) 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 and Hochberg (1995). The total number of observation is 1955 respondents.

Table A6—Heterogeneity of treatment effects by gender and education

	Respondent applied for any jobs in the past 2 months?	Job preference outside state	Applied job in the sector of training
	[1]	[2]	[3]
Panel A: Gender			
Treatment * Female	0.010	0.009	0.015
	(0.022)	(0.024)	(0.013)
Treatment * Male	-0.021	0.042	0.017
	(0.027)	(0.030)	(0.014)
p-value Treatment Female	0.663	0.725	0.270
p-value Treatment Male	0.435	0.158	0.253
p-value Difference	0.378	0.383	0.923
Control Mean Female	0.125	0.166	0.034
Control Mean Male	0.265	0.340	0.046
Observations	1924	1924	1924
Panel B: Education			
Treatment * Less Educated	-0.023	0.032	0.014
	(0.025)	(0.030)	(0.016)
Treatment * More Educated	0.005	0.025	0.013
	(0.024)	(0.026)	(0.012)
p-value Treatment Less Educated	0.352	0.291	0.396
p-value Treatment More Educated	0.839	0.340	0.272
p-value Difference	0.420	0.854	0.976
Control Mean Less Educated	0.156	0.224	0.045
Control Mean More Educated	0.227	0.279	0.037
Observations	1924	1924	1924

Notes: This table shows the effect of the intervention on the outcomes by sub-samples defined by gender (women vs. men), and education (below 12th grade vs. 12th grade and above). 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]: Their preference for employment is outside of their native state; Column [3]: They applied jobs in their sector of training. All regressions control for baseline characteristics chosen by lasso selection (Belloni et al., 2014) 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 and Hochberg (1995).

Table A7—Yuvasampark mobile application take-up and utilisation (Mar-Apr 2021)

	Treatment	Standard Error	p-value	Control Mean	Observations
	[1]	[2]	[3]	[4]	[5]
Panel A: Awareness about app					
Knows about Yuvasampark mobile app	0.418	0.020	0.000	0.219	1924
Registered on the app	0.270	0.017	0.000	0.050	1924
Panel B: Use frequency					
Almost everyday	0.043	0.052	0.407	0.120	343
At least once a week	0.092	0.079	0.245	0.320	343
Less than once a week	0.021	0.052	0.684	0.120	343
Not at all	-0.132	0.075	0.082	0.440	343
Panel C: Interested in jobs					
None	0.151	0.095	0.114	0.250	218
1-3 jobs	0.022	0.110	0.839	0.393	218
More than 3 jobs	-0.173	0.097	0.077	0.357	218
Panel D: Job application					
Applied jobs on the app	0.017	0.004	0.000	0.001	1924

Notes: This table shows the effect of the intervention on the knowledge and utilisation of the Yuvasampark mobile app. The dependent variables are all binary indicators. Panel A captures the awareness about the app in terms of whether respondents knew about Yuvasampark, and if they are registered on the app. Conditional on registration, Panel B shows the frequency of app utilisation. In case the respondents confirmed ever using the app, they were asked about the number of jobs they were interested in, and this is shown in panel C. Panel D shows the number of respondents who applied for jobs on the Yuvasampark mobile app. All regressions control for baseline characteristics chosen by lasso selection (Belloni et al., 2014) as well as strata fixed effects. The reported p-value is for the test of no treatment effect.

Table A8—Yuvasampark mobile application take-up and utilisation (Nov-Dec 2021)

	Treatment	Standard Error	p-value	Control Mean	Observations
	[1]	[2]	[3]	[4]	[5]
Panel A: Awareness about app					
Knows about Yuvasampark mobile app	0.299	0.021	0.000	0.285	1955
Registered on the app	0.311	0.033	0.000	0.214	847
Panel B: Use frequency					
Almost everyday	-0.064	0.040	0.110	0.117	352
At least once a week	-0.031	0.055	0.568	0.167	352
Less than once a week	-0.039	0.047	0.409	0.133	352
Not at all	0.134	0.072	0.065	0.583	352

Notes: This table shows the effect of the intervention on the knowledge and utilisation of the Yuvasampark mobile app. The dependent variables are all binary indicators. Panel A captures the awareness about the app in terms of whether respondents knew about Yuvasampark, and if they are registered on the app. Conditional on registration, Panel B shows the frequency of app utilisation. All regressions control for baseline characteristics chosen by lasso selection (Belloni et al., 2014) as well as strata fixed effects. The reported p-value is for the test of no treatment effect.

Figure A1—Training Completion and Job Placement Status

Figure A2—Employment trajectories by gender

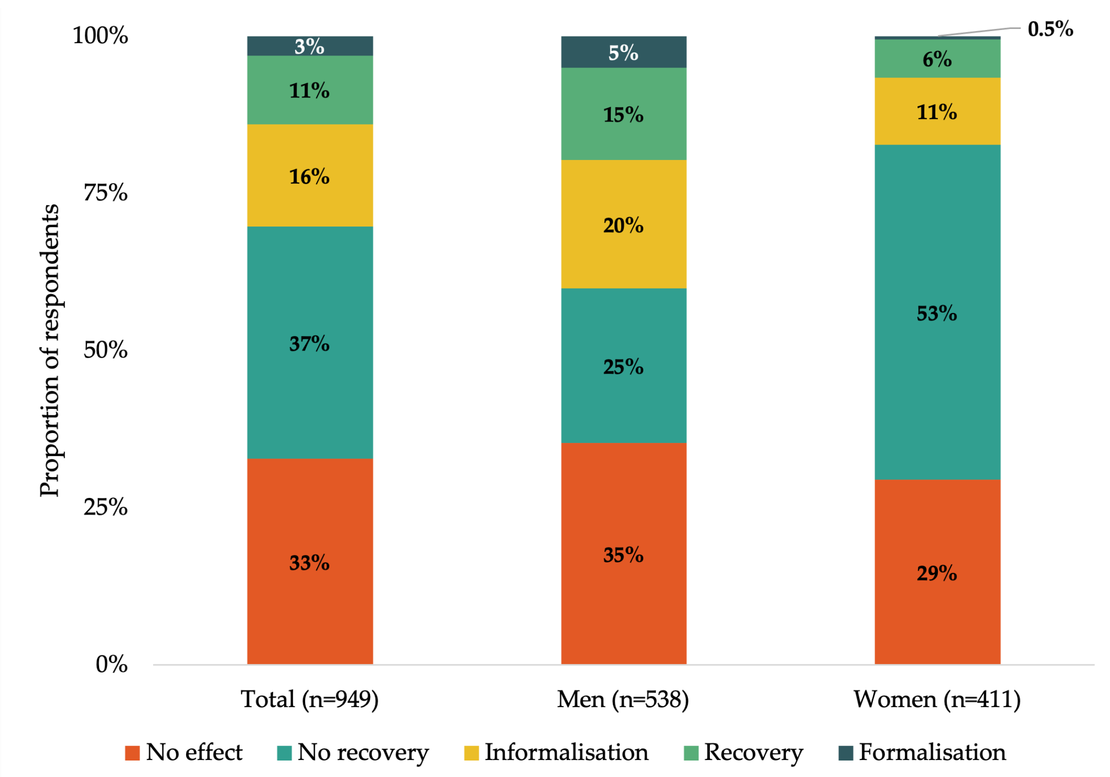
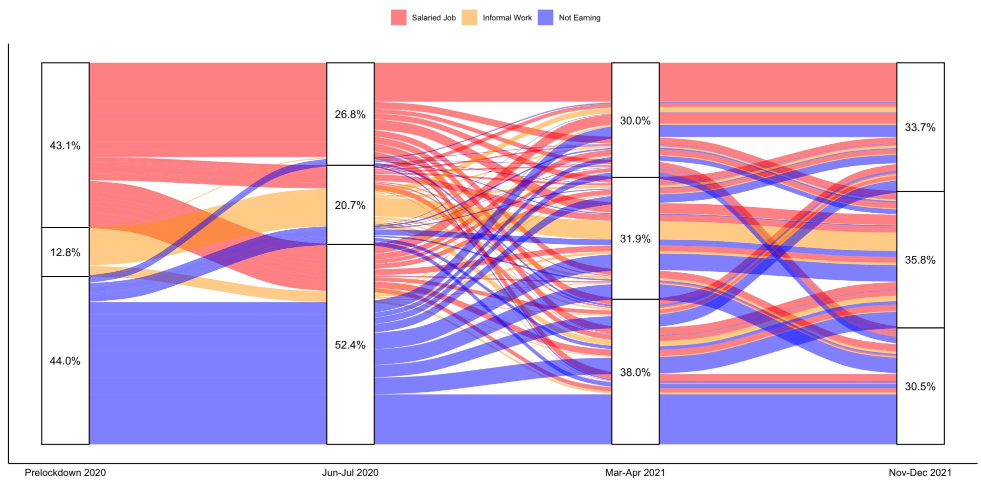
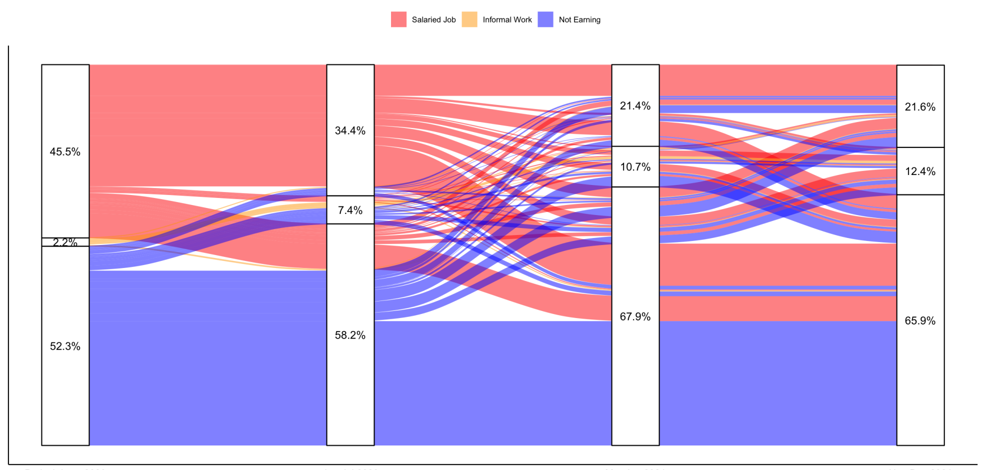


Figure A3—Employment change among trained youth by gender. Male (a) Female (b)

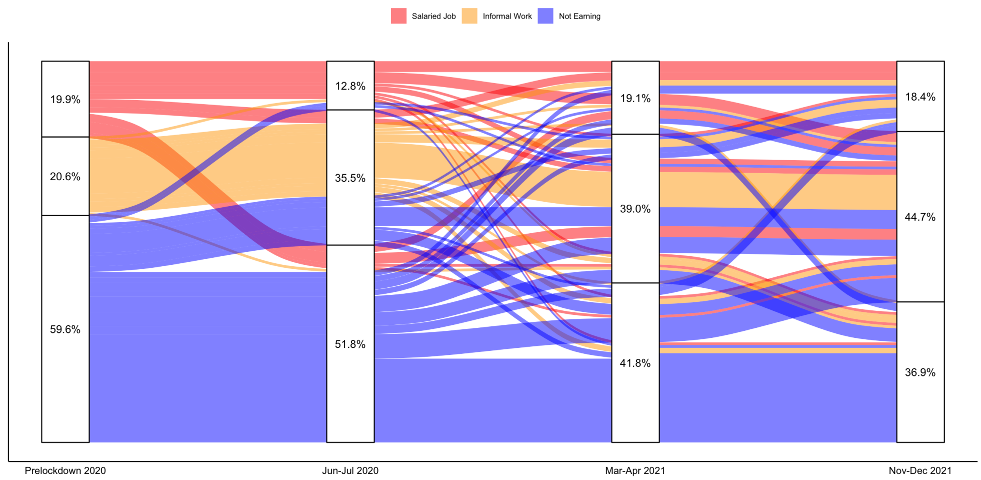


(a) Males

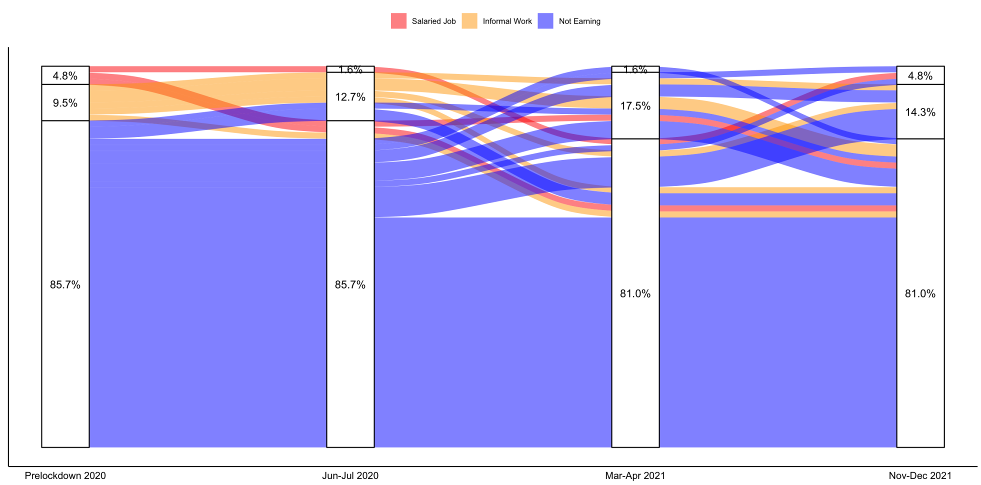


(b) Females

Figure A4—Employment change among dropouts by gender. Male (a) Female (b)



(a) Males



(b) Females

Figure A5—Job search mechanisms

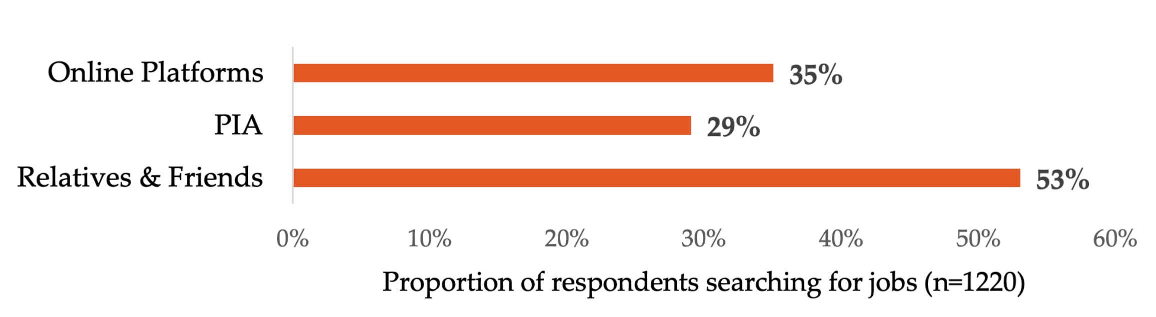
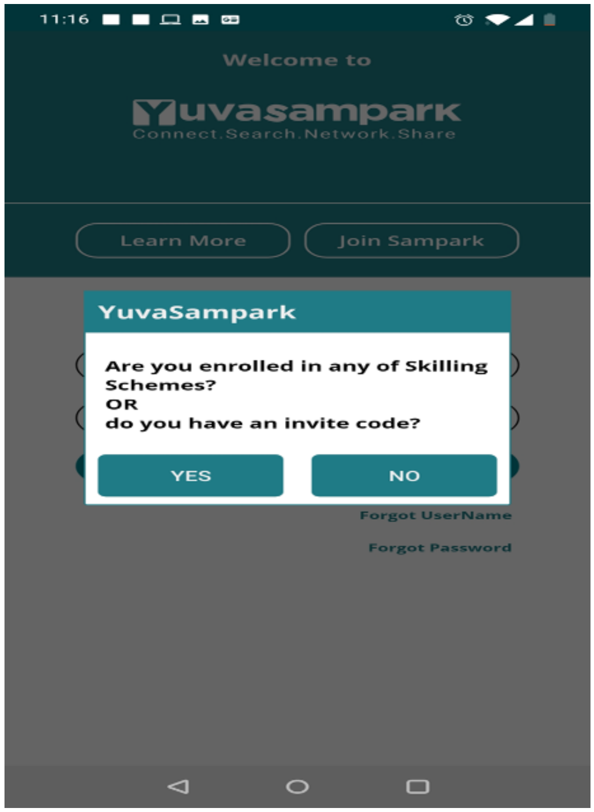
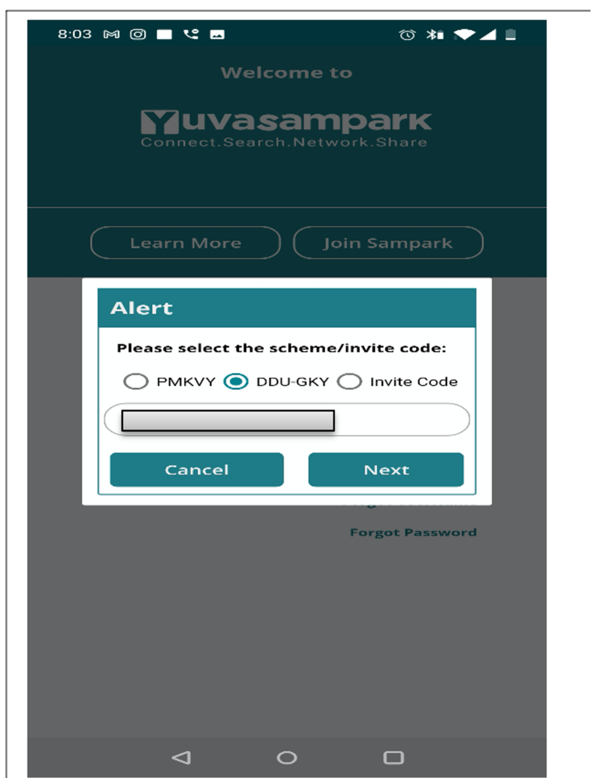


Figure A6—Candidate registration on Yuvasampark mobile app



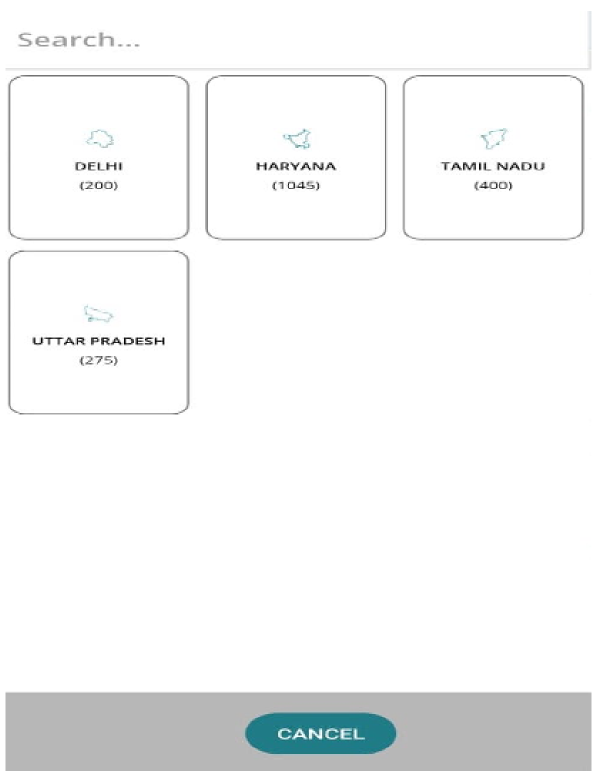
(a) Step 1



(b) Step 2

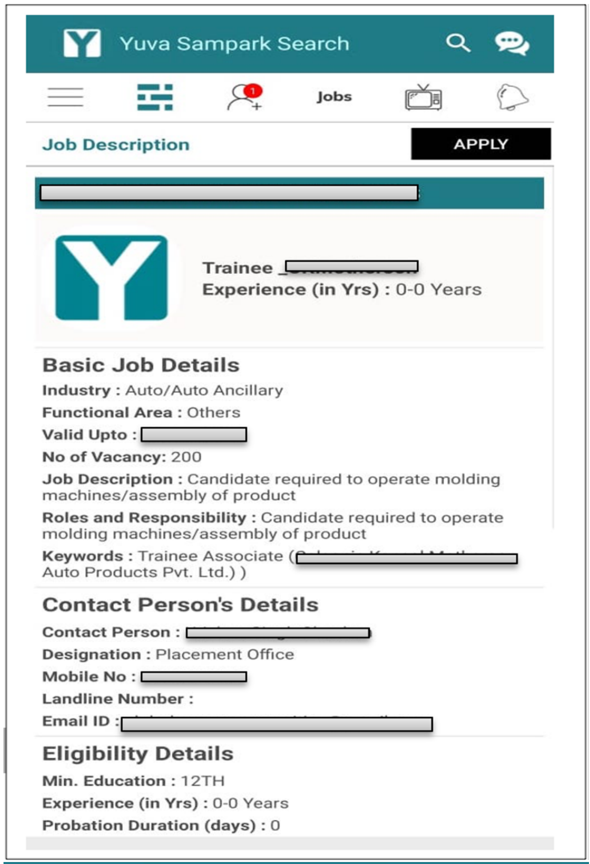
Figure A7—Job search on Yuvasampark mobile app

(a) by sector



(b) by location

Figure A8—Job advertisement on Yuvasampark mobile app



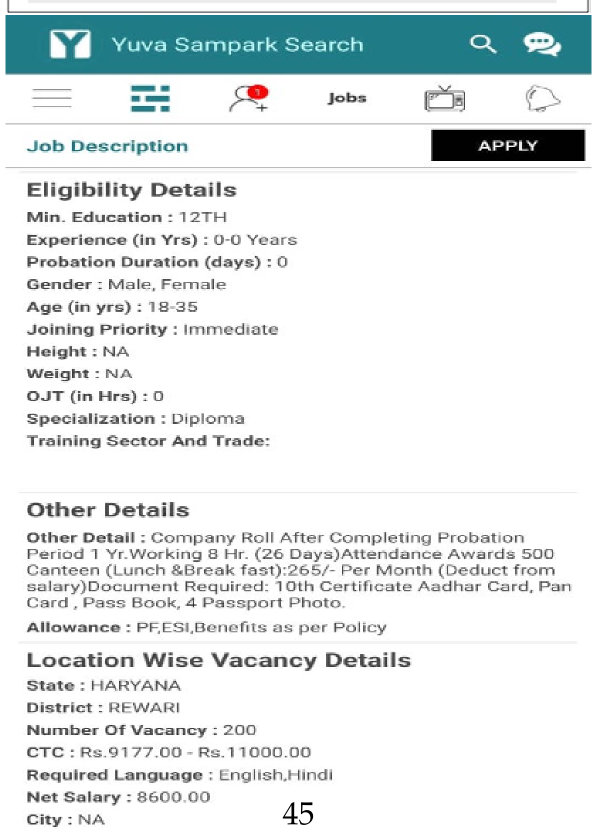


Table A9—Baseline summary statistics (averages) and balance tests - [Part 1 of 3]

	Control Group	Treatment Group	Diff [2-1]	p-value
	[1]	[2]	[3]	[4]
Panel A: Demographics and Caste				
Older (More than 20)	0.281	0.270	-0.010	0.578
Married	0.094	0.091	-0.004	0.756
Caste: ST	0.186	0.184	0.000	0.978
Caste: OBC	0.481	0.477	-0.005	0.790
Caste: General	0.073	0.062	-0.011	0.296
Religion: Muslim	0.062	0.057	-0.005	0.618
Religion: Christian	0.048	0.049	0.002	0.829
Panel B: Education				
Middle school (6-8 class)	0.045	0.053	0.008	0.336
Secondary level (9-10 class)	0.357	0.349	-0.009	0.662
Tertiary education (Graduate & above)	0.088	0.086	-0.002	0.841
Matric exam	0.933	0.936	0.002	0.819
More than 50%	0.523	0.480	-0.044	0.032
Inter exam	0.583	0.585	0.002	0.922
Less than 50%	0.237	0.230	-0.006	0.723
Panel C: Skills				
Big 5 Extraversion Test (1 to 5)	3.298	3.282	-0.016	0.474
Big 5 Agreeableness Test (1 to 5)	3.757	3.768	0.011	0.621
Big 5 Conscientiousness Test (1 to 5)	3.855	3.852	-0.003	0.917
Big 5 Neuroticism Test (1 to 5)	2.437	2.409	-0.028	0.330
Big 5 Openness Test (1 to 5)	3.945	3.923	-0.022	0.471
Grit Test (1 to 5)	3.408	3.429	0.021	0.409
ASE Test (1 to 4)	2.092	2.101	0.009	0.542
Life goal Test(1 to 4)	2.136	2.151	0.015	0.274
Duration of baseline survey (above median)	0.505	0.496	-0.008	0.677
Number of observation	1138	1122		

Notes: Columns [1] and [2] report the mean value in the control group and treatment group respectively. Treatment dummy coefficient estimates in the regression of the variable, controlling for the strata fixed effects are in Column [3]. The p-value associated with the test of no treatment effect is in Column [4]. Total number of observations is 2,260.

Table A9—Baseline summary statistics (averages) and balance test [Part 2 of 3]

	Control Group	Treatment Group	Diff [2-1]	p-value
	[1]	[2]	[3]	[4]
Panel D: Socioeconomic background				
Household head relationship (mother)	0.069	0.086	0.017	0.134
Household head relationship (others)	0.097	0.083	-0.014	0.233
Immediate difficulty to family	0.101	0.105	0.004	0.607
Future difficulty to family	0.140	0.150	0.010	0.324
Earning members (3 or more)	0.085	0.110	0.024	0.051
Household earning (15000 or more)	0.164	0.182	0.018	0.264
Household earning (5000 or less)	0.284	0.269	-0.014	0.436
Household earning (5001-9000)	0.230	0.226	-0.003	0.858
Agriculture land	0.660	0.651	-0.008	0.647
BPL card	0.797	0.781	-0.016	0.355
RSBY card	0.381	0.403	0.022	0.272
MNREGA	0.248	0.259	0.012	0.515
SHG member	0.739	0.737	-0.002	0.933
Semi pucca house	0.214	0.189	-0.025	0.132
Pucca house(IAY)	0.093	0.098	0.005	0.695
Pucca house(Non IAY)	0.191	0.214	0.023	0.174
Own house	0.996	0.993	-0.003	0.397
Internet use	0.518	0.529	0.010	0.546
Joint household	0.058	0.078	0.020	0.062
Household members (2 or less)	0.059	0.054	-0.005	0.633
Household members (6 or more)	0.376	0.372	-0.005	0.817
Ever migrated out of state (self)	0.120	0.139	0.020	0.149
Ever migrated out of state (relatives)	0.478	0.504	0.026	0.190
Relatives migrated (one)	0.325	0.369	0.044	0.027
Relatives migrated (2 or more)	0.152	0.135	-0.018	0.217
Number of observation	1138	1122		

Notes: Difficulty variables are expressed as a fraction between zero and one. Also see notes provided with the first part of this Table [Part 1 of 3].

Table A9—Baseline summary statistics (averages) and balance test [Part 3 of 3]

	Control Group	Treatment Group	Diff [2-1]	p-value
	[1]	[2]	[3]	[4]
Panel E: Expectations				
Previous earning	0.118	0.119	0.001	0.918
Hypothetical earning (immediate)	0.158	0.140	-0.019	0.197
Hypothetical earning (in one year)	0.232	0.225	-0.007	0.682
Expected earning (in one year)	0.406	0.386	-0.020	0.320
Preferred earning (in one year)	0.467	0.422	-0.045	0.028
Training awareness	0.532	0.542	0.010	0.401
Training usefulness	0.934	0.935	0.001	0.841
Training satisfaction	0.944	0.949	0.004	0.383
Likelihood of training completion	0.945	0.949	0.004	0.466
Likelihood of job offer	0.900	0.902	0.002	0.812
Expected minimum salary (immediate)	0.396	0.384	-0.013	0.502
Expected maximum salary (immediate)	0.409	0.408	-0.001	0.966
Expected average salary (immediate)	0.478	0.446	-0.033	0.110
Likelihood of job offer outside state	0.786	0.798	0.011	0.224
Likelihood of accepting job inside state	0.841	0.836	-0.006	0.568
Likelihood of retention in job inside state	0.836	0.825	-0.011	0.265
Likelihood of accepting job outside state	0.824	0.829	0.005	0.587
Likelihood of retention in job outside state	0.818	0.818	0.001	0.949
Internet use	0.865	0.853	-0.012	0.395
Panel F: Prelockdown status				
Post-lockdown location: At Home	0.769	0.798	0.029	0.084
Post-lockdown location: Within State	0.040	0.037	-0.003	0.729
Post-lockdown location: Outside State	0.192	0.166	-0.027	0.090
Pre-lockdown location: At Home	0.600	0.610	0.011	0.590
Pre-lockdown location: Within State	0.065	0.070	0.006	0.599
Pre-lockdown location: Outside State	0.335	0.320	-0.016	0.389
Post-lockdown employment: Salaried Job	0.300	0.262	-0.038	0.032
Post-lockdown employment: Casual Work	0.164	0.149	-0.013	0.355
Post-lockdown employment: Not Earning	0.536	0.589	0.052	0.009
Pre-lockdown employment: Salaried Job	0.426	0.398	-0.028	0.147
Pre-lockdown employment: Casual Work	0.094	0.077	-0.017	0.133
Pre-lockdown employment: Not Earning	0.480	0.525	0.045	0.021
Number of observation	1138	1122		

Notes: Earning variables are dummy variables equal to one if the survey response is above the median in state$x$trade strata. Likelihood variables are expressed as a fraction between zero and one. Pre-lockdown refers to the period immediately after Holi (10th March) until the announcement of the nationwide lockdown on 25th March 2020, and post-lockdown refers to the period of June and July 2020. Also see notes provided with the first part of this Table [Part 1 of 3].

Figure A9—Number of advertised vacancies

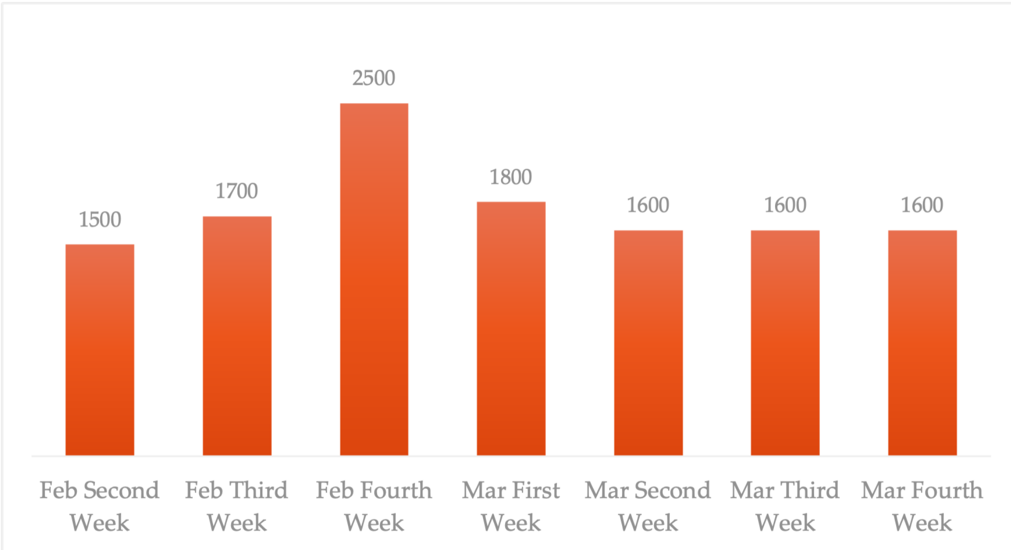


Table A10—Survey attrition rates

	Survey Attrition	
	Round 2	Round 3
	[1]	[2]
Treatment	0.041	0.003
	(0.015)	(0.013)
Observations	2260	2259
p-value	0.006	0.847
Control Mean	0.128	0.123

Notes: This table is obtained from the regression of attrition dummy on an intercept and the treatment indicator, controlling for strata fixed effects. The p-values is associated with the test of no effect of treatment.

Balancing tests and survey attrition

To check that our randomisation achieved balance between treatment and control groups, we estimate for each control variable X_i:

$$X_i = \beta T_{(i)} + \delta_{s(i)} + \epsilon_i$$

where $T = 1$ if an individual i is in treatment group and $T = 0$ if in control group. δ_s denote the fixed effects for strata. We then test the null of no difference between the treatment and control groups ($\beta = 0$).

Summary statistics of our baseline variables, and the results of the balance tests for randomisation, are provided in Appendix Table A9. Balancing tests suggest that there are no issues with most of the baseline characteristics, such as demographic, education, socio-economic, skills, and expectations of the treatment and control group trainees. However, there are some differences in the pre-and post-lockdown employment status.

We also test for differential attrition by treatment group. The attrition rate for the survey round and the p-values associated with the test of no difference across the treated and the control groups, are provided in Appendix Table A10. The survey attrition rate is around 15% and is around 4 percentage points more in the treatment sample. Additional phone calls to the treatment group individuals, for the intervention, might be the reason for the differential response rates. We also report Lee bounds (Lee, 2009) for the main outcome variable to understand how selection on attrition biases the results. The method involves trimming the distribution of the control group so that the share of observed individuals is equal for both groups. It assumes that assignment to treatment can only affect attrition in one direction, i.e., no heterogeneous effect of treatment on selection.