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Impact of COVID-19 Crisis on Rural Youth: Evidence from a Panel Survey and an Experiment

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Impact of COVID-19 Crisis on Rural Youth: Evidence from a Panel Survey and an Experiment

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Abstract

This paper presents evidence on the short and long-term impact of the first COVID-19 wave on India's rural youth. We interviewed about 2,000 vocational trainees from Bihar and Jharkhand between March 2020 and March 2021. 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. Using a randomised experiment, we find that a government supported digital job platform does not increase job search or employment. Our findings suggest that bridging the gap between rural youths and urban formal labour markets requires much 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.

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1 Introduction

In March 2020, when the Indian government imposed a national lockdown in response to the first COVID-19 wave, it became clear that the health emergency would also lead to an economic crisis. As India is now grappling with a devastating second wave, it is more urgent than ever to learn about the economic and social fallout of the first. The shock of the first wave on labor markets was devastating: a study done by Azim Premji University (APU) estimates that about 100 million workers lost their jobs during the nationwide lockdown in April-May 2020 (APU, 2021). Young workers were hit the hardest: data from the Periodic Labor Force Survey suggests that the unemployment rate has increased from 21% to 36% in April-June 2020 as compared to the same quarter in 2019. Among them, young 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 kilometers to their rural hometowns. Imbert (2020) estimates that in total 11 million inter-state migrant workers returned home after the first lockdown.

This study draws on a long-term panel data of a sample of youth from Bihar and Jharkhand. The sample was part of a randomized controlled trial (RCT) who were surveyed four times between 2019 and 2020 (Chakravorty et al., 2021). The respondents are recent graduates from 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]

We followed a cohort of 2,260 young rural workers from Bihar and Jharkhand, through the COVID-19 crisis. In addition to the four survey rounds used by Chakravorty et al. (2021), we conducted two telephonic surveys with this sample post the national lockdown in 2020: one was conducted shortly after the first lockdown from June to July 2020 (round 1)[2], and the next one year after the lockdown from March to April 2021 (round 2). The first survey round assessed the immediate impact of the COVID-19 lockdown (Chakravorty et al., 2020) on India's

[1] http://ddugky.gov.in/ accessed on 10 June 2021.

[2] The first survey round conducted in June-July 2020 captured the pre-lockdown status and the current status during the survey.

rural youth.

The findings from this survey round showed that 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, and nearly a third of interstate migrants (31%) did not receive any support from any source (that is, the government, employer, or community organisations) during the lockdown. To cope with the distress, 31% of the interstate migrants reported that they had to reduce their daily food intake, indicating rising levels of food insecurity among the migrant population. 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.

Given the employment losses among our sample seen in the first survey round and the policy challenge of (re)integrating youth into the labour market, we enrolled our sample in an experiment to evaluate the effectiveness of an app-based job platform (YuvaSampark) that matches job seekers with employers, using an encouragement design. YuvaSampark is a mobile app used by numerous state governments in India to help trainees 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. We randomly allocated half of the sample to treatment and control. The Jharkhand State Livelihood Promotion Society (JSLPS) called the treatment respondents to inform them about the YuvaSampark app, and to encourage and help them register. Those who registered were also supported to apply for jobs on the app. We then surveyed the entire sample to evaluate the effectiveness of the intervention. In this paper, we report the long-term effects of the COVID-19 crisis drawing on the panel survey as well as the results of a policy experiment that was carried out in February-March 2021.

Our study contributes to the existing literature in two ways. First, we contribute to the literature that documents the economic impact of COVID-19 in India with a sample of young rural labour market entrants from Bihar and Jharkhand. We have long-term panel data of our study sample, which we followed over several survey rounds from 2019−2021. This allows us to analyse their employment and location trajectories before, during and after the first COVID-19 wave.

The study by APU (2021) quantifies job loss, and argues that the poorest households suffered the greatest income losses. It also emphasizes that COVID-19 had a stronger impact on female and younger workers: they find that 47% of women (against 7% of men) and 33% of the 15–24-year-olds (against 6% of the 25- to 44-year-olds) who lost their job did not find their way back into employment (APU, 2021). Deshpande (2020) report that six months after the first COVID-19 wave in March 2020, the likelihood of women being employed in August 2020 was 9.5 percentage points lower than that for men, compared to the pre-pandemic period. Other COVID-19 impact surveys across India corroborate the detrimental economic impact of the pandemic for urban informal sectors in the Delhi National Capital Region (Afridi et al., 2021), in Bihar, Jharkhand and Uttar Pradesh (Dhingra and Machin, 2020) as well as for slum communities in Patna and Bangalore (Krishna et al., 2020). In addition to economic shocks, several surveys documented the detrimental impact of the COVID-19 crisis on food security (APU, 2021) and wellbeing (Afridi et al., 2021).

Second, we experimentally evaluate the effectiveness of a government-sponsored app-based platform to help rural youth from Bihar and Jharkhand go back to formal sector jobs and employment in other states. Governments increasingly look to digital tools as low-cost interventions for overcoming information asymmetries and supporting labour market integration. The interest in digital tools has increased further as the COVID-19 pandemic made in-person interventions impractical. The evidence from the economic literature on the effectiveness of job platforms to promote job search in developing countries is mixed. Wheeler et al. (2021) experimentally evaluate the effect of training South African job seekers to use LinkedIn and find sustained positive effects. Kelley et al. (2020) connect randomly chosen 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.

The paper is structured as follows. Section 2 provides an overview of the mobile application and our experimental design, Section 3 describes the data and the balancing tests, Section 4 presents the descriptive findings, Section 5 presents the empirical results , and Section 6 concludes.

2 The mobile application and the experimental design

2.1 YuvaSampark app

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.[3] 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. In the current COVID-19 situation, job search through personal networks or direct contact with employers is less feasible.

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 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 of using the training registration number is that the app fetches all the trainee details from the portal of the training scheme (Appendix Figure A1). 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 A2). A typical job posting looks as shown in Appendix Figure A3. 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 1 shows that the number of advertised vacancies during the intervention period ranged from 1500 to 2500. Table 1 shows the sectoral bifurcation of job postings during the intervention, along with the number of employers and the

[3] https://www.yuvasampark.com/

location of the job. The jobs were almost all located outside of Jharkhand and Bihar, and the number of job advertisements ranged from 1-6.

2.2 Intervention

We randomly allocated half of the sample to treatment (1122) and control arm (1138). The randomization was stratified over state, sector of training, treatment status in the previous experiment, and gender. The intervention was carried out over the phone 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 an interest to register but could not register on the JSLPS call, received a second call from the J-PAL South Asia survey team in the following week to help them register on the app. All candidates who registered on the app received another call to assist them on the job application process on the app.

3 Data

The sample for the study is 2,260 and with an overall survey attrition rate of 15%, this paper reports the findings from 1,924 respondents. We find that categories of workers who 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 is from households below the poverty line, which is another evidence of 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 2).

The findings are drawn from two surveys (Figure 3):

- Round 1 - This survey round was conducted shortly after the 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 - This was carried out one year after the lockdown in March-April 2021. 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*".

3.1 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 A2. 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 A3. 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.

4 Descriptive findings

Employment. The COVID-19 crisis and the nationwide lockdown led to a widely documented employment crisis, affecting workers in both salaried and informal jobs. Figure 4 shows respondents' employment status at the three time periods described in the previous section: before the lockdown, shortly after the lockdown, one year after the 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 A4). While this loss of salaried work led to an increase in the non-earning category (from 50% to 56%), it also led to informalisation, 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 informalisation continued until one year after the lockdown, at which point it increased to 23%.

Employment trajectories by gender. Women are at a disadvantage on the labour market in India, with lower labour force participation and higher unemployment than men. The DDU-GKY program gave to the young women in our sample a somewhat unique opportunity to migrate and be formally employed. It is hence important to assess whether women were differently affected by the COVID-19 crisis. We consider separately the employment trajectories for men and women and present them in Figure 5. 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. Also, around 33% of men were engaged in informal jobs as opposed to merely 12% of women. Overall, 61% of men and 32% of women were found to be engaged in earning activities (either in salaried or informal work) in the last survey round (March−April 2021).

Figure 6 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 (5%) than women (0.5%).

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 1924 respondents, 238 respondents (13%) dropped

[4] *No effect* means that the respondent was in the same employment category before, shortly after and one year after the lockdown.

[5] *No recovery* means that the respondent was either in salaried or informal work before the lockdown but was not earning one year after the lockdown.

[6] *Recovery* means that the respondent was engaged in an earning activity (salaried or informal) before the lockdown, not earning shortly after the lockdown, but then had transitioned back into the same type of work (salaried or informal) one year after the lockdown.

out before training completion, and the remaining 1652 (87%) trainees completed the full training course. Figure 7 compares employment trajectories of trained youth and dropouts. We find that the trained youths have a much higher rate of 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. It is not surprising that those who had dropped out of training had a much higher rate of employment in the informal sector (32%). However, the unemployment rate is almost the same among the trained and dropouts.

The findings for the trained men and women remain consistent with the finding from the overall sample, with 60% men engaged in earning activities (30% in salaried jobs and 30% in informal works) in March−April 2021 as against 33% of women. However, trained women have a slightly higher rate of salaried employment in the pre-lockdown period (Appendix Figure A4). The differential impact of COVID-19 on the employment of men and women is more striking in the training dropout cohort. The employment rate among the dropout males is around 60% (20% in salaried jobs and 40% in informal work) but is merely 20% (2% in salaried jobs and 17% in informal work) among dropout females (Appendix Figure A5). This indicates that outside of vocational training schemes like DDU-GKY young rural females from Bihar and Jharkhand have few opportunities to gain employment in the formal sector.

Job search. Given that one year after the first lockdown many youths in our sample have 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. The results are presented in Figure 8. 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 9). 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. As the employment losses because of COVID-19 led many migrants workers to return to their home states (Imbert, 2020), we tracked the location of our respondents across the three time periods (Figure 10). 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 11). 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 labour market are also worse than men.

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

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

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] Life satisfaction rates fell shortly after the lockdown, and did not reach pre-lockdown levels even one year after the lockdown. Anxiety levels rose shortly after the lockdown, and even one year after the lockdown, were still higher than the pre-lockdown levels (Figure 12). This indicates a lasting negative impact of the COVID-19 crisis on the well-being of our sample.

5 Results

5.1 Empirical framework

We consider the outcome y_i. An individual i is in treatment group then $T = 1$ and 0 otherwise. An individual i, assigned to a randomisation stratum $s_{(i)}$, has a vector of baseline characteristics X_i (control variables). Our main estimation model will be:

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

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 the regressions control for strata fixed effects (δ_s).

5.2 Main outcomes

Table 2 and Figure 13 present the results for our main outcomes in Columns numbered [1]-[3]. 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

[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”.

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, which is not different to the treatment group respondents (Figure 13). Table 2 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 in the Appendix Table A5 show that the null effects are robust to selection on attrition.

5.3 Secondary outcomes

Table 3 reports the results for the additional outcomes collected from the latest follow-up survey: 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. If anything, treated individuals are less likely to say they are job seekers (Column [4]). 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 (Columns [6] and [10]).

5.4 Heterogeneity

Table 4 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 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.

5.5 Take-up and utilisation of the app

Table 5 shows the results for the take-up and utilisation for the mobile application of YuvaSampark. 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 are aware about the app. As expected, 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 experiment was to inform the treatment group respondents about the app, and supported them with the registration and application process. In the control group, the registration rate was 5% as against to 32% in the treated group. The treatment effect on both these indicators 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, we asked about the number of jobs they were interested in on this online job portal. About 25% of the control group respondents said that none of the advertised jobs interested them, and the treatment group was not significantly different than the control group. Also, practically no one applied to any job on the YuvaSampark application, at least until this survey round.

5.6 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 labour market.

One limitation of this study is that the respondents were surveyed within two-three weeks of the intervention. It could be the case that respondents took more time to get accustomed with the app, and to jobs after our survey. With this caveat, we provide the following discussion. 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 a 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 a few aspects to consider:

- *What is the goal of the tool?* The objective of online job boards is to solve the information asymmetry on the labour market. 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 vacancies. In our study period, YuvaSampark had between 1500 to 2500 vacancies from 1-6 employers, depending on the sector of job. The limited number of employers severely restricts the options available to the job seekers. A low number of vacancies may produce two kinds of effects: (i) direct effect: it will not help the job seekers that register on the portal, (ii) it reduces the credibility and the incentive to use the tool.

- *Is the tool 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. A smart phone and internet are a prerequisite to use the app, which of course is not universally available for the rural population, to whom this platform is mainly targeted. Also, all the modules in the mobile application are in English, which could be another hindrance for the rural population to use this app.

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, (ii) is easy to interact with, and to use even from the devices available among the population of interest.

6 Conclusion

This report presents evidence on the dramatic short and long-term impact of the first COVID-19 wave 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 a year since the first national lockdown in March 2020. We show that most youths 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 youths 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.

Overall, these 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 youths 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 youths and urban formal labour markets requires much more targeted, active interventions from the government, such as expanding the training and placement program DDU-GKY which got these youths (many women among them) into jobs pre-lockdown.

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Figures

Figure 1—Number of advertised vacancies

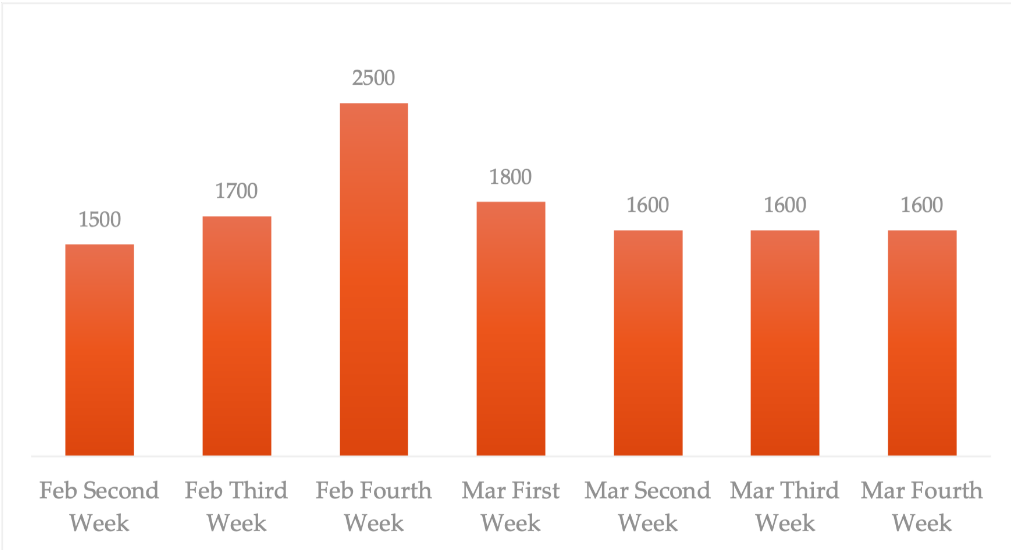


Figure 2—Training Completion and Job Placement Status

Figure 3—Time periods

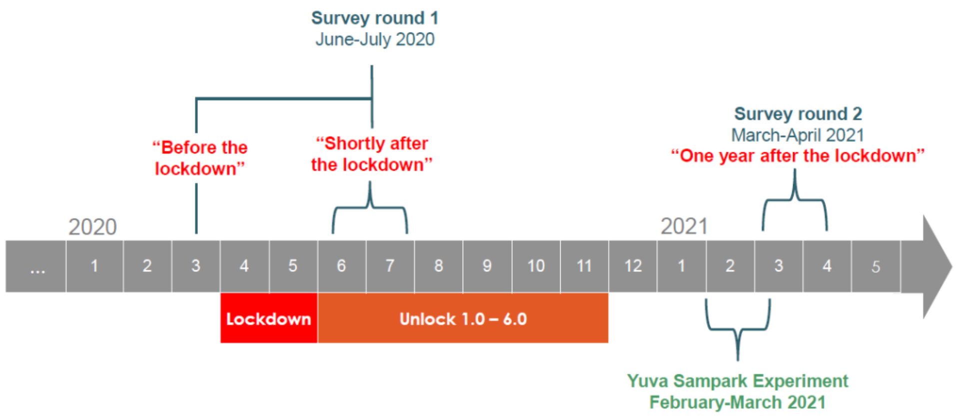


Figure 4—Employment change pre-lockdown, shortly after lockdown and one year after lockdown

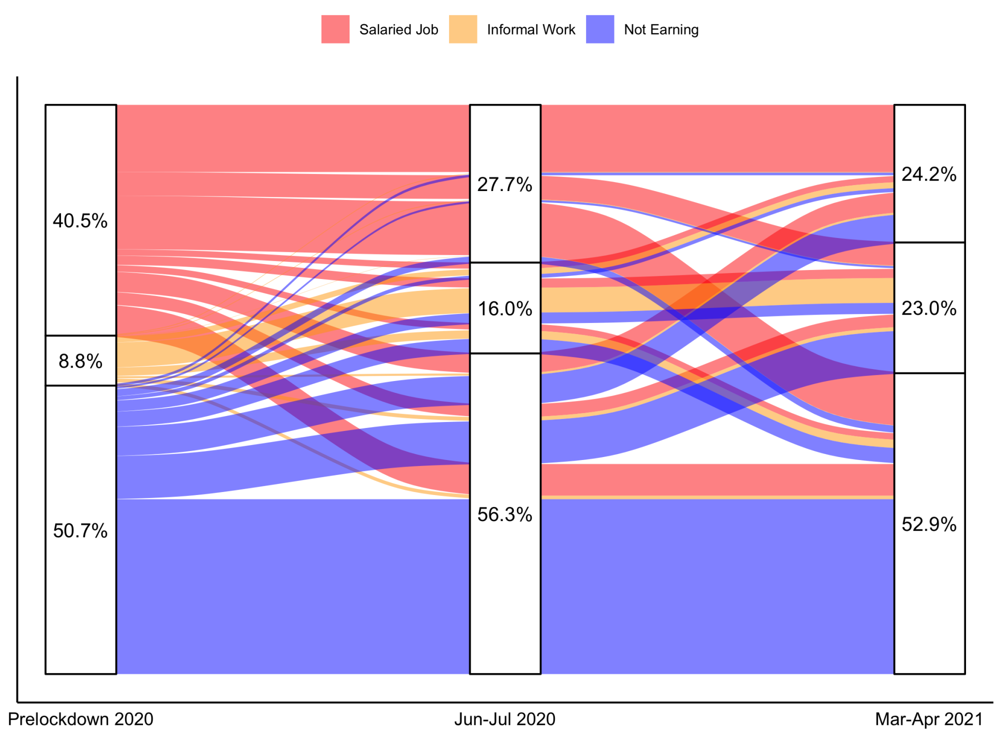
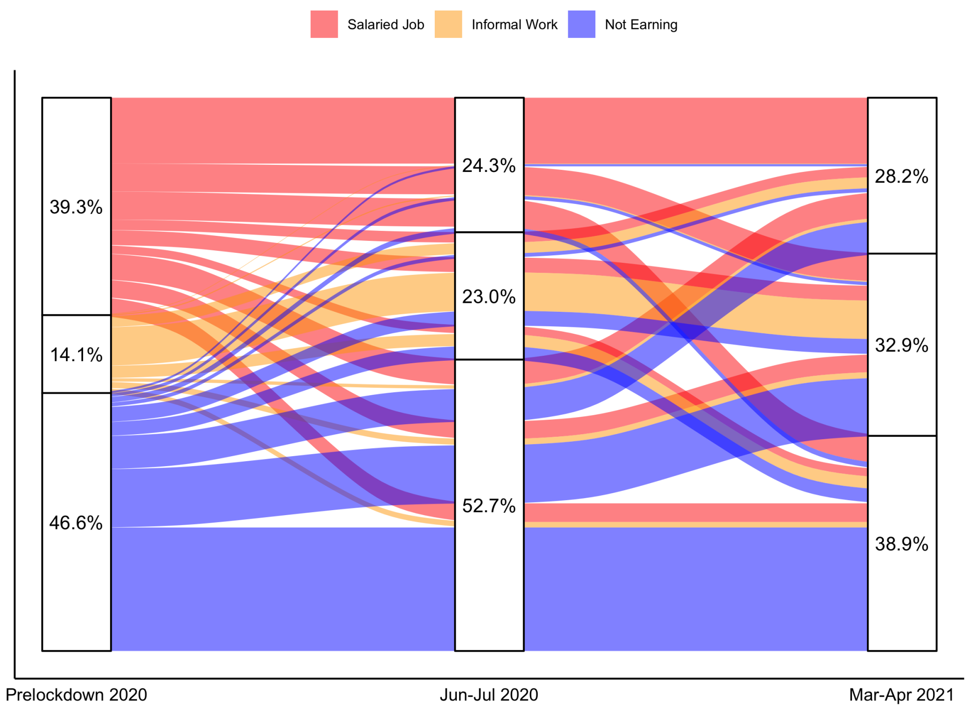
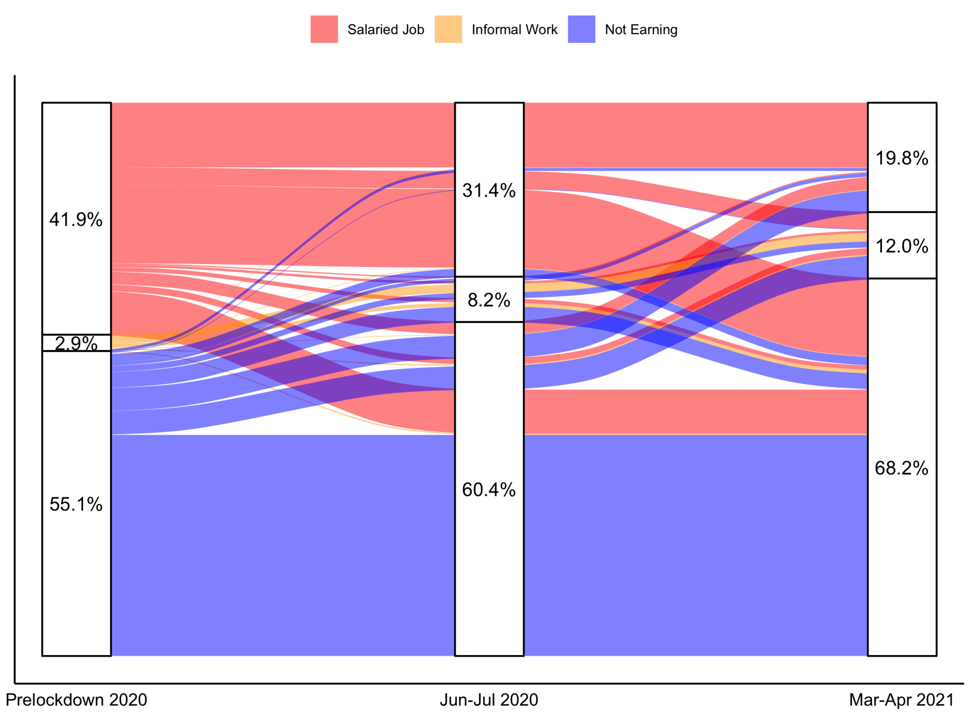


Figure 5—Employment change by gender. Males (a) and Females (b)



(a) Males



(b) Females

Figure 6—Employment trajectories by gender

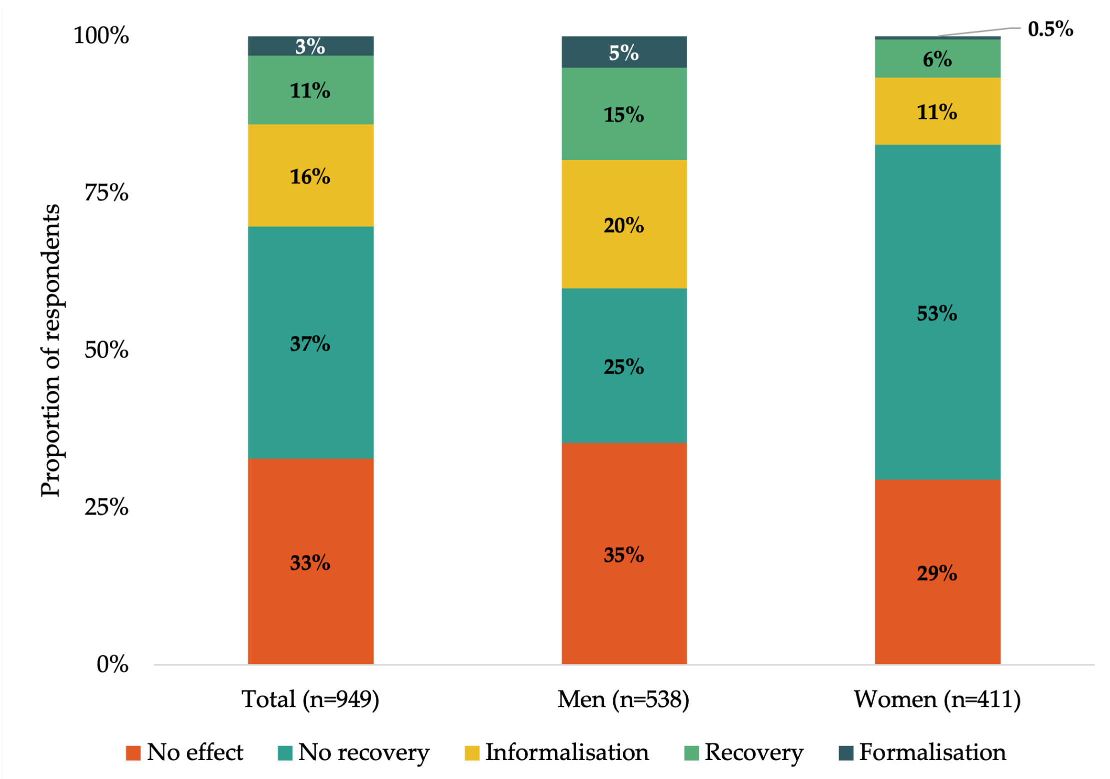
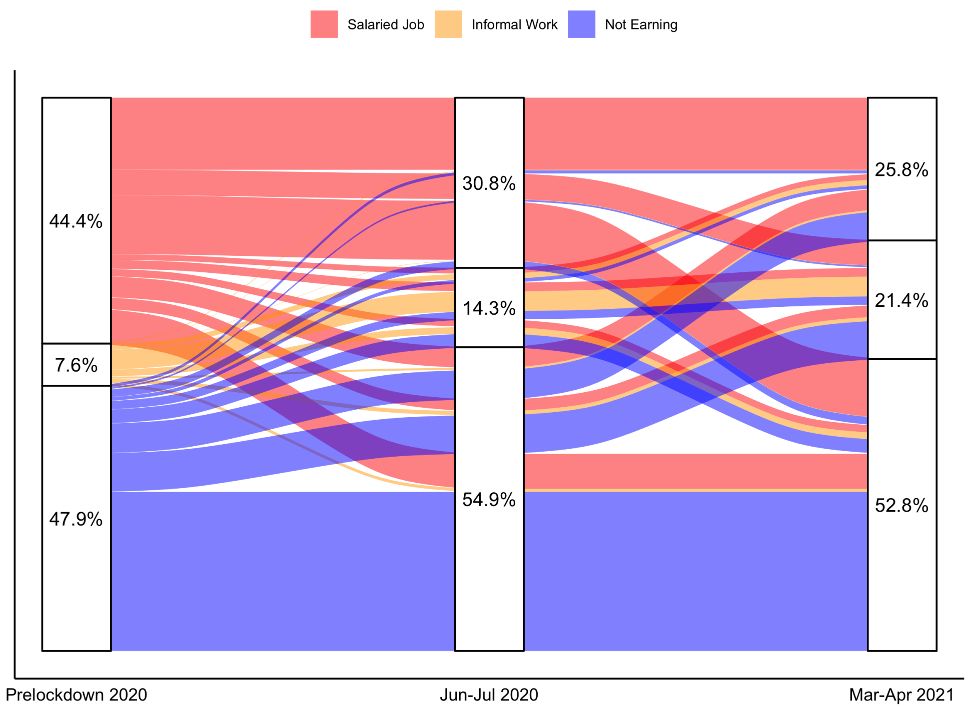
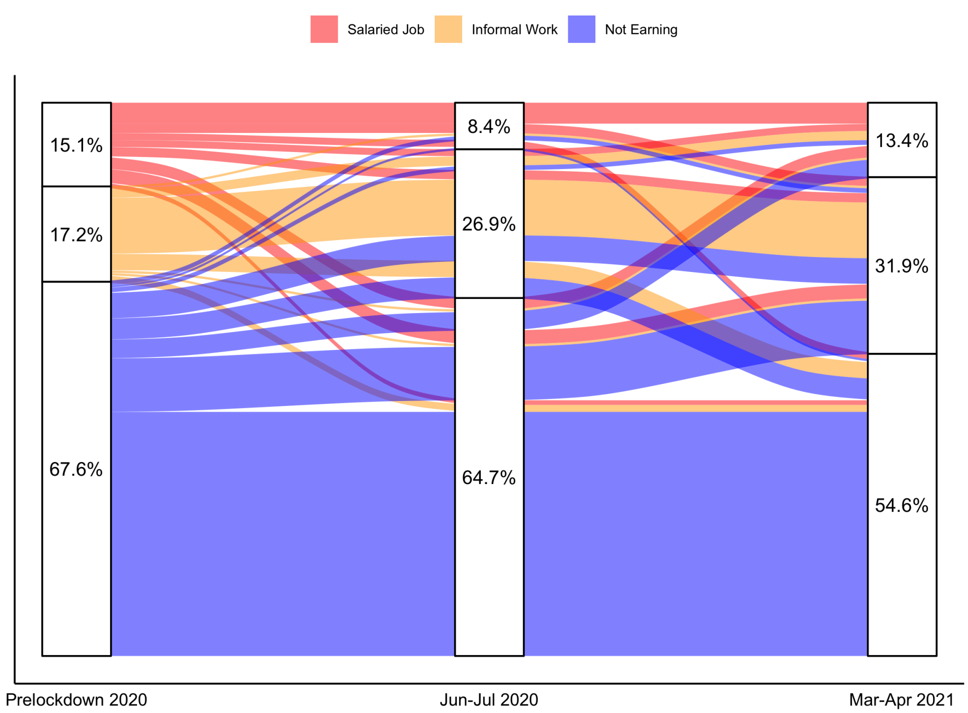


Figure 7—Employment change by training status. Trained individuals (a) and training dropouts (b)



(a) Trained individuals



(b) Training dropouts

Figure 8—Job search

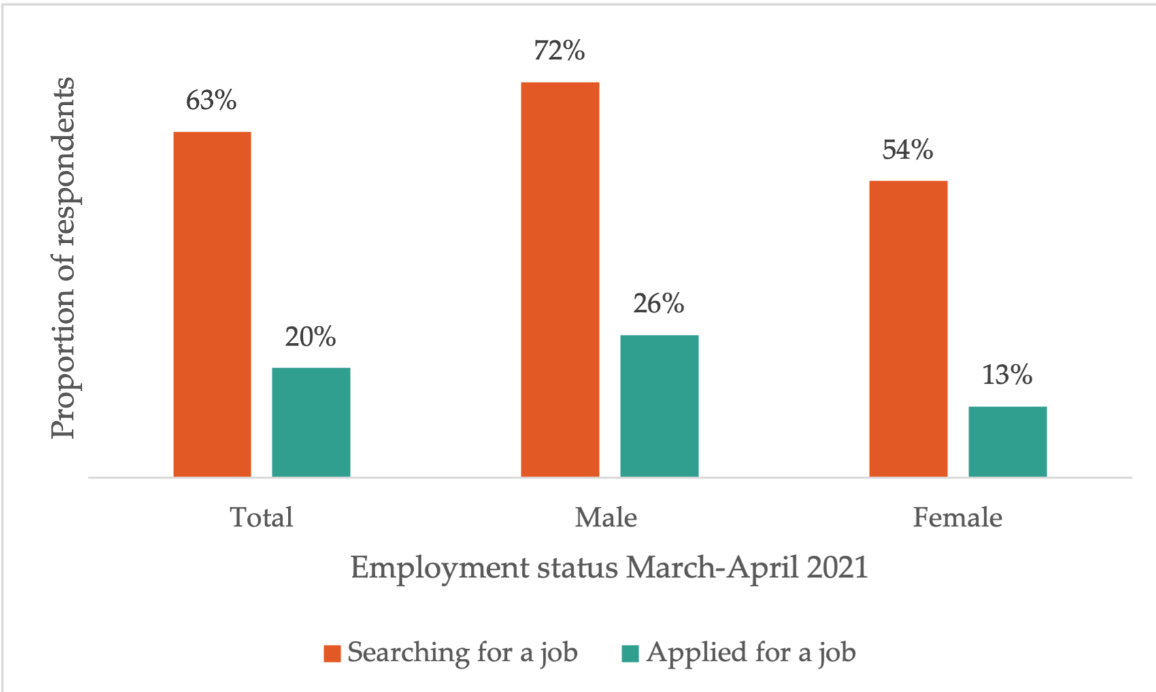


Figure 9—Job search mechanisms

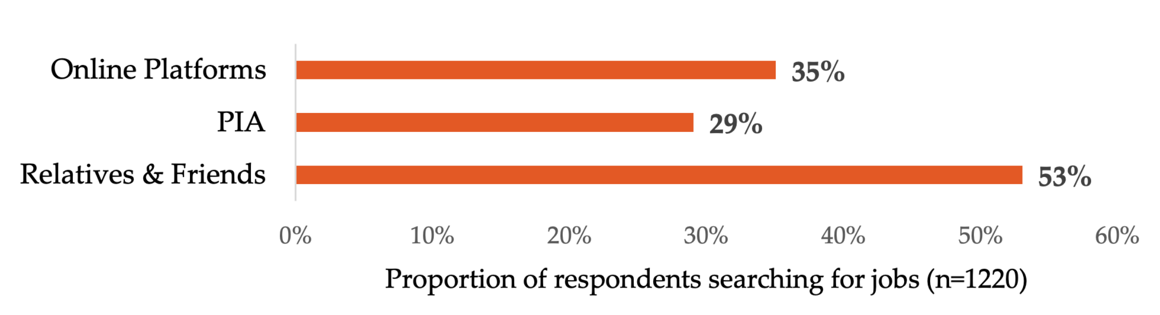


Figure 10—Location change pre-lockdown, shortly after lockdown and one year after lockdown

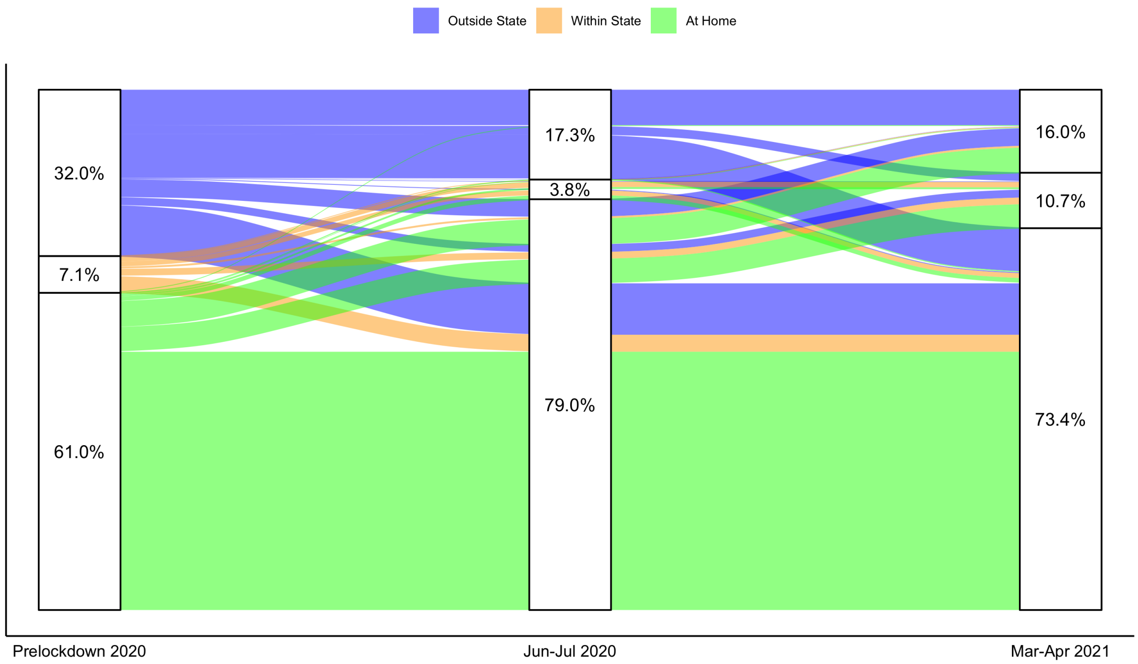


Figure 11—Willingness to migrate

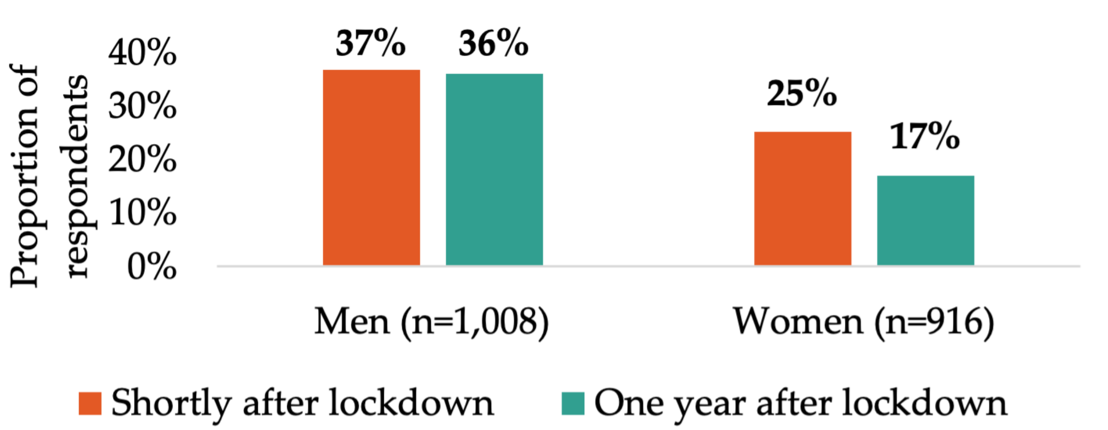


Figure 12—Well-being indicators. Life Satisfaction and Anxiety

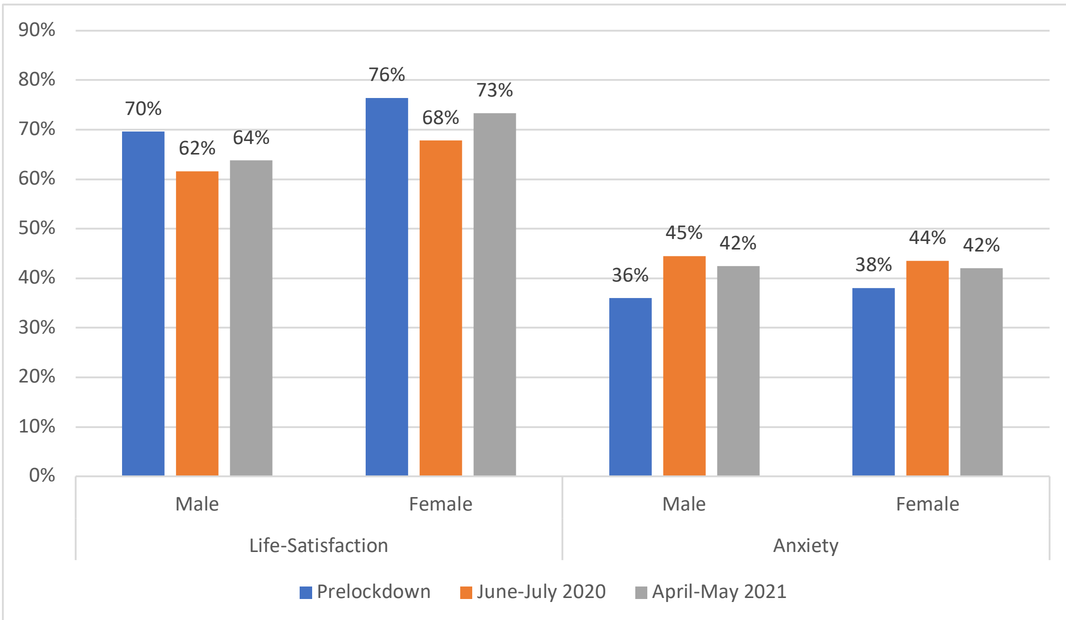
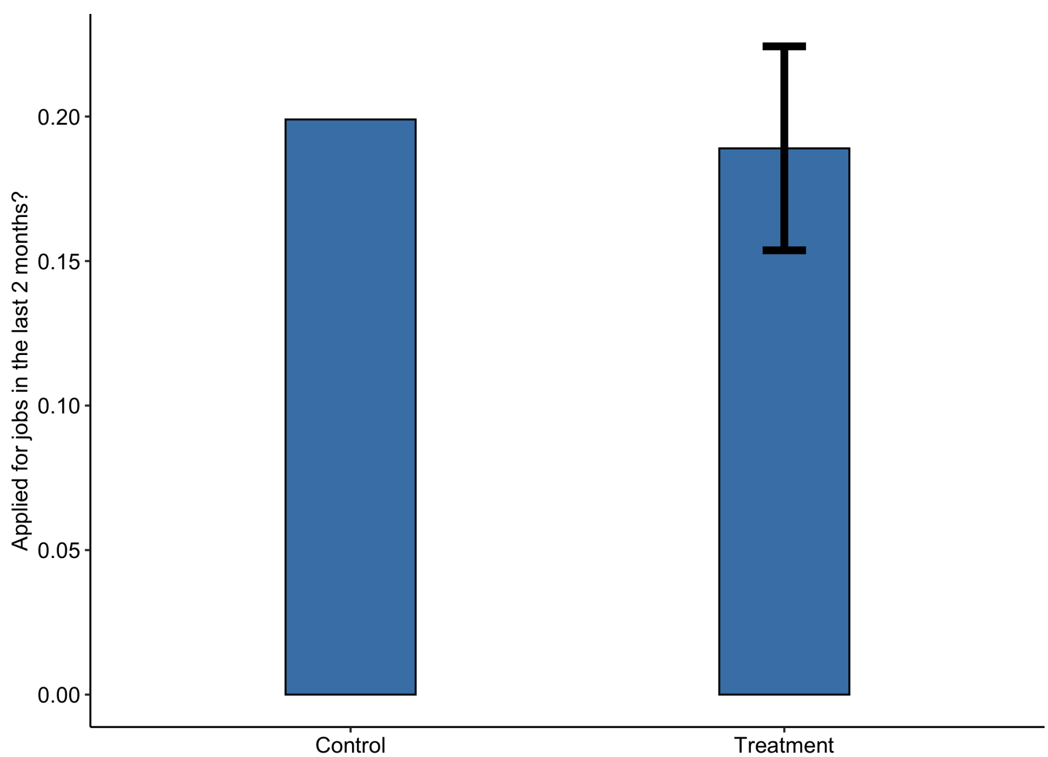


Figure 13—Treatment effects on job applications



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]
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

Notes: This table shows the effect of the intervention on the main outcomes of the study. 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).

Table 3—Results: Secondary Outcomes

	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 4—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 5—Yuvasampark mobile application take-up and utilisation

	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.

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—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 A2—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 A2—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].

Table A3—Survey attrition rates

	Survey attrition
	[1]
Treatment	0.041
	(0.015)
Observations	2260
p-value	0.006
Control Mean	0.128

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. The number of observations is 2,260.

Table A4—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

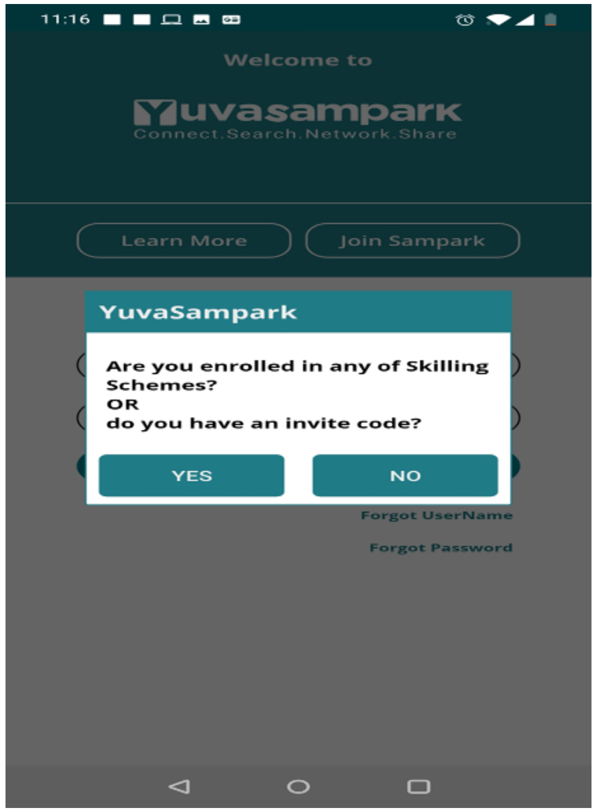
Notes: Reasons mentioned by respondents for loosing jobs during the survey conducted in June-July 2020.

Table A5—Results: Main Outcomes (Lee Bounds)

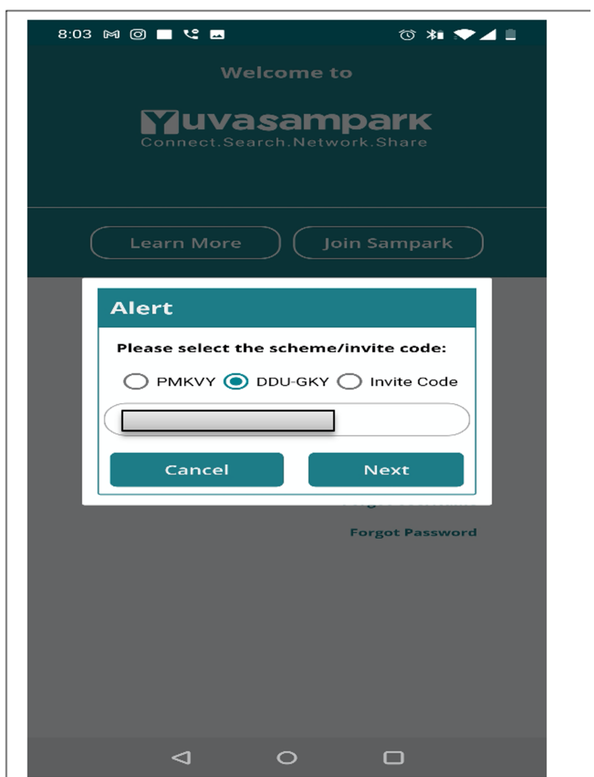
	Applied for jobs in the last 2 months?
	[1]
Treatment (lower bound)	-0.012
	(0.036)
p-value	0.519
Treatment (upper bound)	0.036
	(0.023)
p-value	0.130
Control Mean	0.199
Trimming proportion	0.0459
Observations	1924

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

Figure A1—Candidate registration on Yuvasampark mobile app



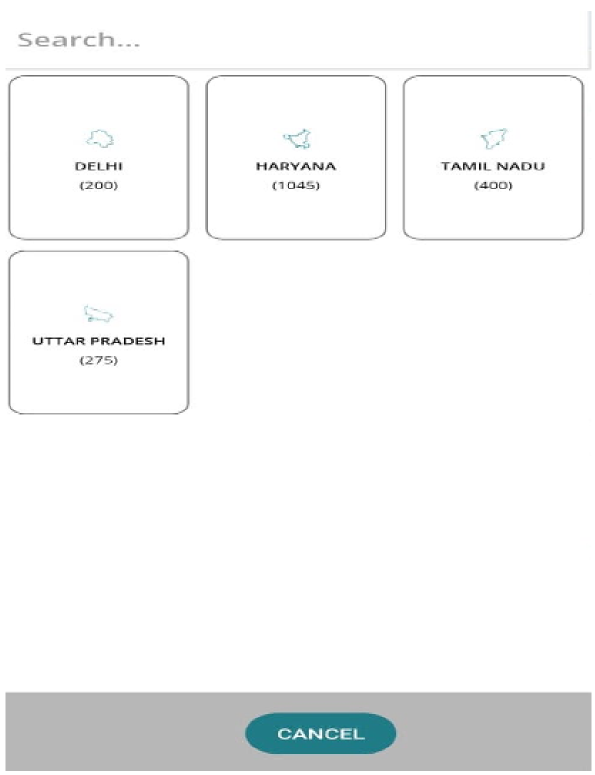
(a) Step 1



(b) Step 2

Figure A2—Job search on Yuvasampark mobile app

(a) by sector



(b) by location

Figure A3—Job advertisement on Yuvasampark mobile app

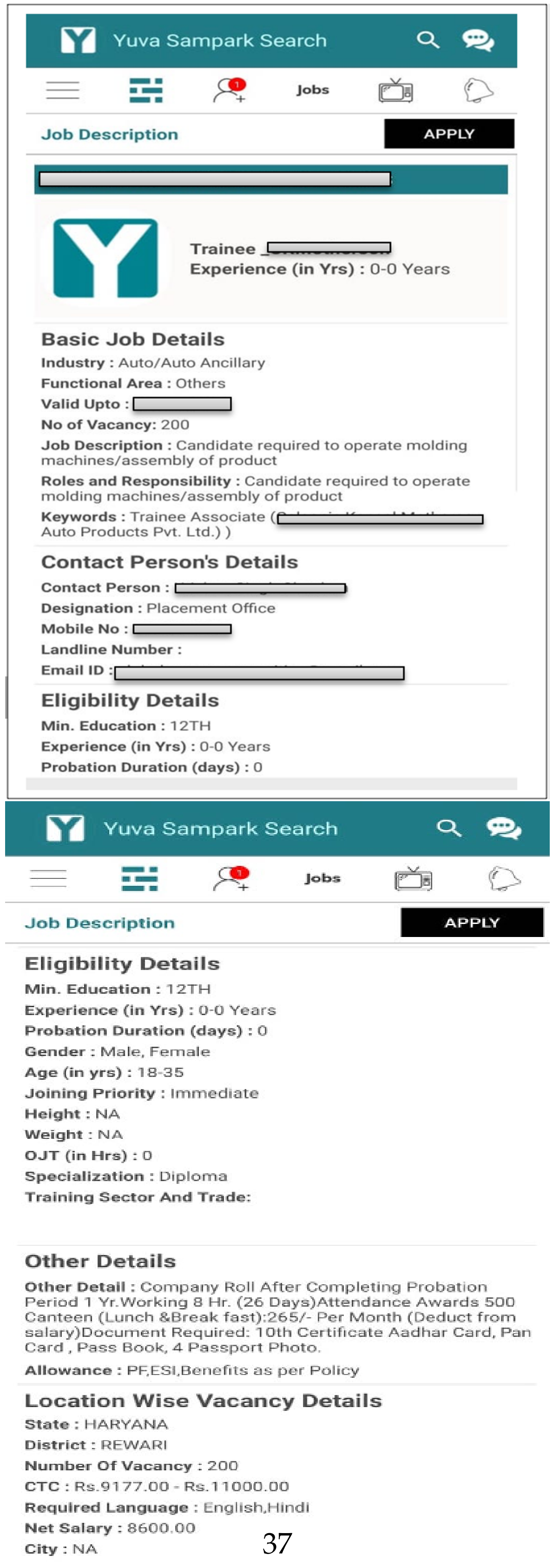
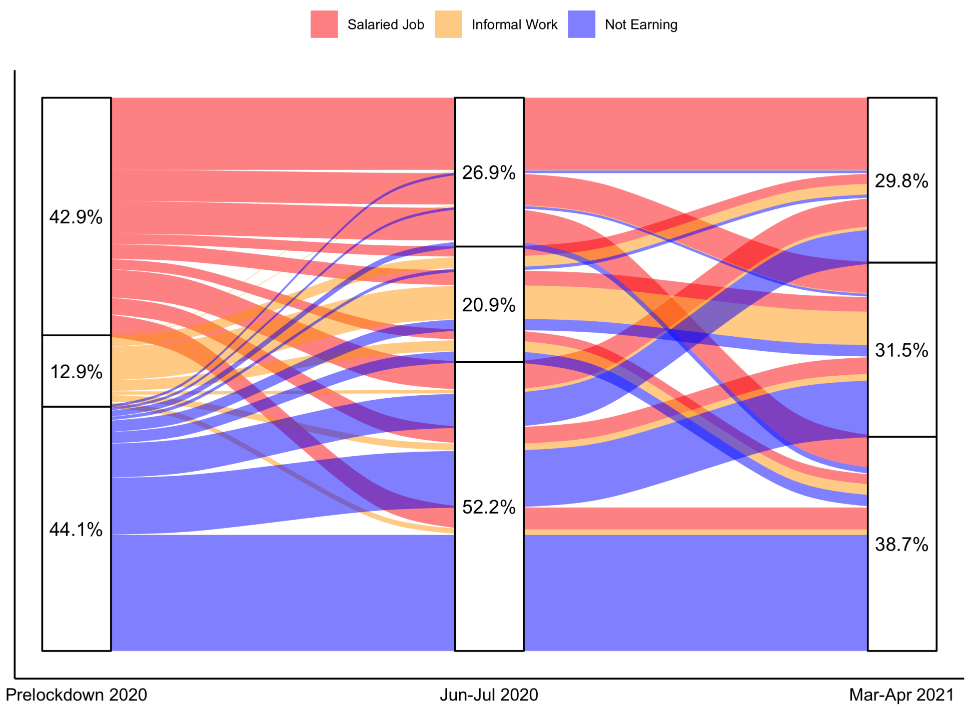
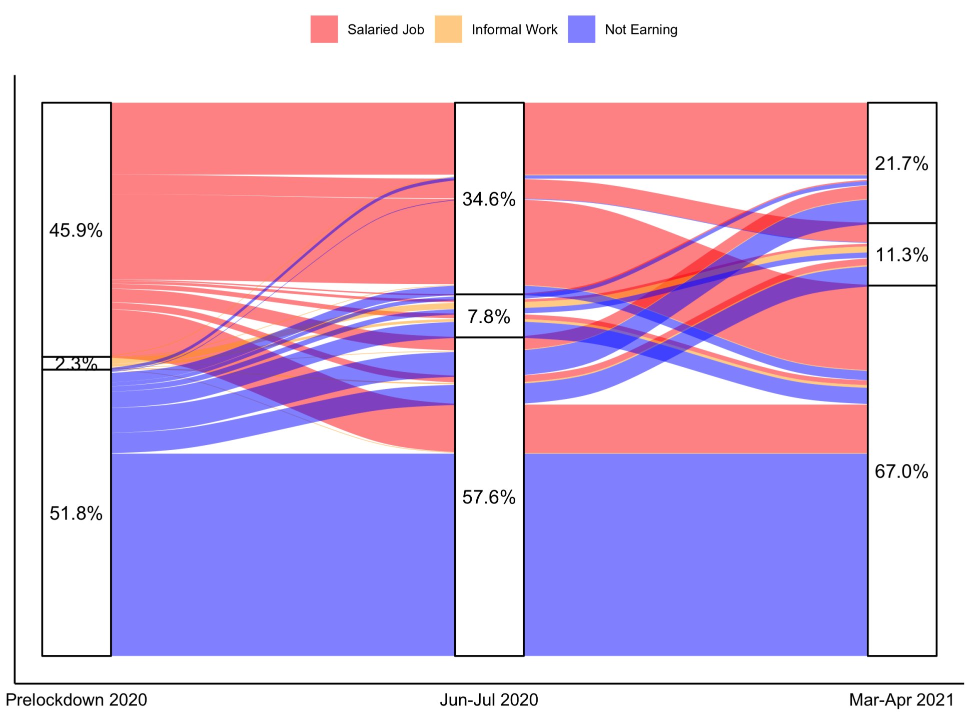


Figure A4—Employment change among trained youth by gender. Male (a) Female (b)

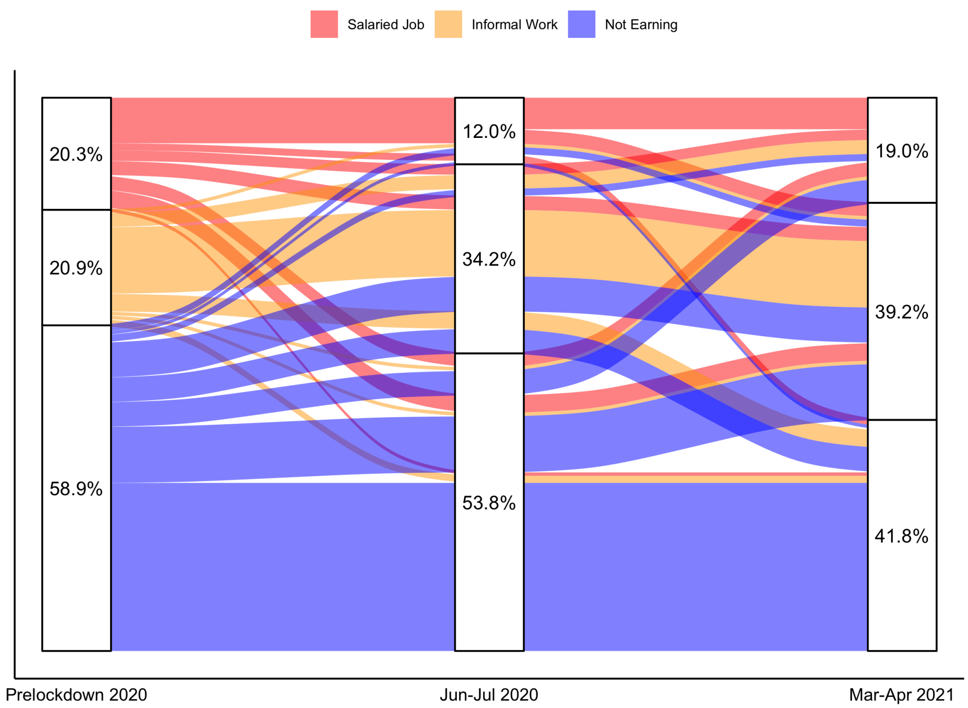


(a) Males

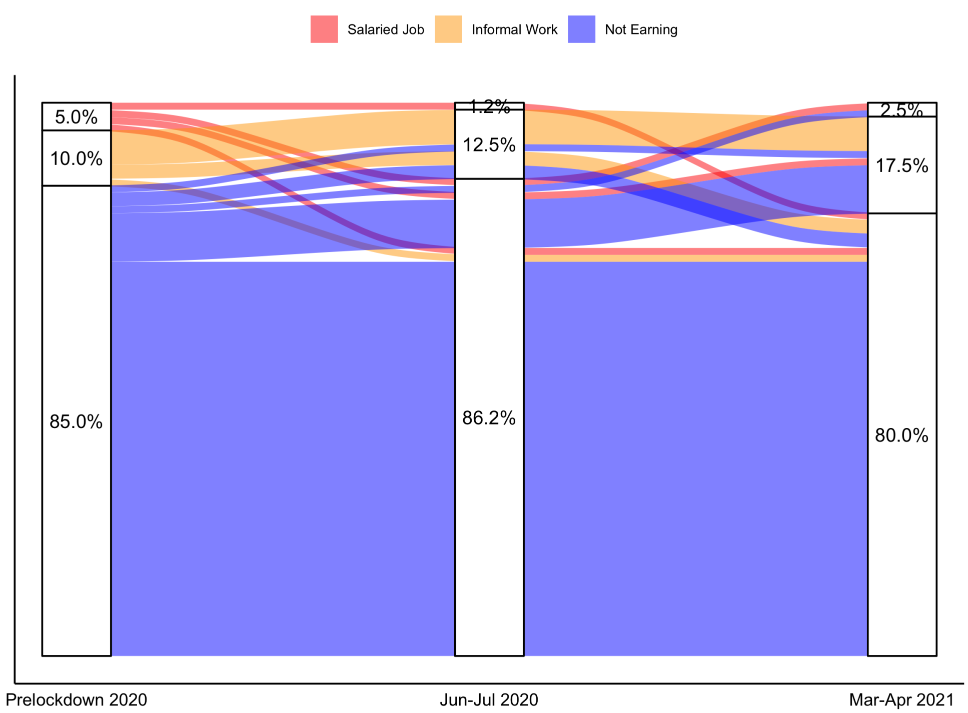


(b) Females

Figure A5—Employment change among dropouts by gender. Male (a) Female (b)



(a) Males



(b) Females