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Short communication

Can information about jobs improve the effectiveness of vocational training? Experimental evidence from India[☆,☆☆]

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ABSTRACT

We use a randomized experiment to evaluate the impact of providing richer information about prospective jobs to vocational trainees on their employment outcomes. The setting of the study is the vocational training program DDU-GKY in India. We find that including in the training two information sessions about placement opportunities make trainees 18% more likely to stay in the jobs in which they are placed. We provide suggestive evidence that the effect is driven by improved selection into training: as a result of the intervention, trainees that are over-optimistic about placement jobs are more likely to drop out before placement.

1. Introduction

Youth unemployment and underemployment are major issues for developing countries. Although vocational training programs have been found to be generally effective in promoting employment in some contexts (Alfonsi et al., 2020; Maitra and Mani, 2017), evidence is mixed (Betcherman, 2004; Blattman and Ralston, 2017; McKenzie, 2017). In many instances, high attrition from programs limit their impact on employment outcomes. For example, Heckman et al. (2000) report dropout as high as 79% in U.S. training programs. Developing-country examples include Hirshleifer et al. (2016) for Turkey, Card et al. (2011) for Dominican republic, and Cho et al. (2013) for Malawi. One potential reason for this attrition is the mismatch between youth expectations and the jobs available to them. In training programs that also do placement, this mismatch is potentially easy to address by better information about placement opportunities.

We examine this question in the context of the vocational training program DDU-GKY (Deen Dayal Upadhyay Grameen Kaushalya Yojana), one of the largest vocational training programs in the world, launched in 2014 by the Indian government for the rural youth. The scheme is implemented in a public–private partnership mode, whereby registered private sector partners or project implementation agencies

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(PIA) plan and implement skills training and place program participants. Although the program guarantees placement to every trainee, only about 60% of the 1.3 million DDU-GKY trainees have been placed so far.[1] We build on three years of collaboration with the agencies in charge of DDU-GKY in two of the poorest states of India (Bihar and Jharkhand). We developed two short information sessions that provided details of the placement opportunities (e.g. job title, company name, location, compensation) which were known to the training provider but not the trainees. We report on a randomized experiment that evaluates the effect of these sessions on training completion and job placement.[2]

A simple conceptual framework suggests that providing information about prospective jobs can improve placement outcomes of vocational trainees in two ways. First, some trainees may be over-optimistic about placement prospects, and participate in the training even though their outside options are better than the placement jobs provided by the scheme, while others may be over-pessimistic, and drop out too early. Better information will lead the over-optimistic trainees to leave the training and the over-pessimistic to stay. This *selection* channel implies that the intervention could increase the probability of staying in the job conditional on placement but have an ambiguous effect on average training completion and placement. Second, knowing about the details of the placement jobs may make it easier for trainees to transition into employment. This *job readiness* channel implies that the intervention increases the value of the job, decreases dropout, and increases placement.

We find that trainees in the treatment group were on average 18% more likely to stay in the jobs in which they were placed, but we do not find a significant effect on dropout or placement on average. These findings tend to support the selection rather than the job-readiness channel. A direct way to test for the mechanisms is to estimate the effect of information on trainees' expectations about the placement jobs. We leverage post-intervention data on trainees expectations, and find some evidence that trainees in the treatment group are on average less optimistic about their likelihood of taking-up and staying in placement jobs. However, these results are not fully conclusive because the data were collected a few months after the first information session, and we were unable to measure expectations for trainees who had updated their expectations negatively and dropped out.

To provide more evidence on the mechanisms, we test for heterogeneous effects of our treatment along three dimensions: gender, education, and caste. In terms of gender, we find the treatment effects to be entirely concentrated on men, for whom the treatment increased the probability of staying for at least five months in the placement job by 55%. In contrast, there was no effect on women, who in the control group were much more likely to complete the training and take up placement jobs than men. This is consistent with a selection channel, because women in this context have far worse labor market opportunities than men outside of the program, so mismatched expectations are likely to be a bigger issue for men. Turning to heterogeneity by education levels, we find the intervention to have opposite effects on less educated trainees relative to more educated ones. For the less educated trainees, who in the absence of the intervention had a higher dropout relative to more educated ones, the intervention reduced dropout by 35%. For more educated trainees, however, the treatment increased dropout by 50%. These results are again in line with the selection channel since more educated trainees have better outside options and are less likely to value the placement jobs than the others. Finally, we do not find any significant effect of our treatment across different caste groups.

[1] Official statistics from http://ddugky.gov.in/ accessed on 31st March 2023.

[2] The information intervention was based on the extensive discussions with the training providers. They were unable to conduct such information sessions as these were not a part of the training curriculum.

Our paper contributes to the relatively thin literature on the effectiveness of vocational training programs in developing countries. The two review papers by Blattman and Ralston (2017) and McKenzie (2017) suggest that vocational training often has limited effect on employment outcomes, although experiments in India by Maitra and Mani (2017) and in Uganda by Alfonsi et al. (2020) show that vocational training can have large positive long-term effects on employment and earnings. A recent follow-up paper by Bandiera et al. (2023) on the Ugandan experiment highlights the importance of trainees' expectations for the effectiveness of vocational training. Other evidence from India suggests that vocational training provided by Industrial Training Institutes is usually of poor quality (Gasskov et al., 2003; Bertrand and Crepon, 2015). On the DDU-GKY program itself, Chakravorty and Bedi (2019) find that 2–6 months after training completion, the employment rates are not significantly different between DDU-GKY participants and non-participants. Prillaman et al. (2017) also document low rates of employment among DDU-GKY trainees nine months after training. Our contribution is to show that a simple information intervention can make vocational training programs more effective.

Our paper is one of few papers that evaluate information interventions in vocational training programs. Hicks et al. (2011) inform prospective vocational trainees about returns to vocational training, with little effect on enrollment, apart from more females enrolling into male-dominated courses. Jensen (2012) finds that providing information about new work opportunities in call centers to female youth in India increases their demand for vocational training and employment. In a very similar context to ours, Banerjee and Chiplunkar (2018) study the mismatch between DDU-GKY preferences of the trainees and the jobs they are placed in. They find that an intervention which informs placement officers about trainee preferences improves the match between trainees and jobs, and that trainees who were matched with their preferred job stay longer in that job. Our contribution is to show that informing vocational trainees about placement opportunities can improve their placement outcomes in another way: by inducing self-selection of trainees who are a better fit for the available jobs.

We also contribute to the literature on barriers to youth employment in developing countries. The literature emphasizes search costs (Franklin, 2018; Abebe et al., 2021b), skills signaling (Carranza et al., 2022; Abebe et al., 2021a; Bassi and Nansamba, 2022; Abel et al., 2020; Groh et al., 2015), or the mismatch between employers' and workers' expectations (Abebe et al., 2017). Our contribution is to show that providing more accurate information about the characteristics of the jobs available to young workers may help them to successfully complete their training and transition to employment.

The paper is structured as follows: Section 2 describes our experimental design and data, Section 3 provides a theoretical framework to interpret the effects of the intervention, Section 4 presents the empirical results and Section 5 concludes.

2. The training program and the experimental design

2.1. The vocational training program

India's DDU-GKY is one of the largest government-sponsored vocational training and placement program in the world, with 1.3 million trainees since its inception in 2014. It targets unemployed rural youth aged 15–35 years from poor families with some secondary education (10th or 12th grade). There are quotas for female and low caste (Scheduled Tribes and Scheduled Castes) trainees.

DDU-GKY relies on a complex institutional set-up. The Ministry of Rural Development (MoRD) and the National Mission Management Unit (NMMU) are responsible for framing policy, and monitoring the scheme. The bulk of the funding, about 75% comes from the central government through the MoRD and the remainder from state governments. DDU-GKY courses are offered based on skills gap assessment studies carried out by the National Skill Development Corporation

(NSDC). State Management Missions (SMM) also called State Rural Livelihood Missions (SRLM) are responsible for planning and implementing the program. They invite tenders from private Project Implementing Agencies (PIA), which are then responsible for identifying prospective applicants, providing information on the training courses, delivering training and placing the trained graduates.

The program is mainly residential, and provides a mix of classroom and on-the-job training. Each course consists of two broad components. The first component includes training on soft skills, English and information technology and the second component deals with sector specific training. Depending on the course, the duration of training may be for 3 (576 h), 6 (1152 h), 9 (1578 h) or 12 months (2304 h). The scheme provides for on-the-job training (OJT) for a maximum duration which ranges from 30 days for a 3-month course to 120 days for a 1-year course. The training courses offered by the PIA have to be approved by the National Council for Vocational Training (NCVT) or Sector Skill Councils (SSCs). These Technical Support Agencies (TSA) also provide support in terms of designing the curriculum and certifying the trained graduates.

After the training, PIAs are required to place a minimum of 70% of trainees in jobs which offer regular monthly wages at or above a minimum monthly wage of Rs. 6000.[3] Trainees are offered semi-skilled blue collar jobs mostly located in urban sectors. To encourage them to take up and stay in the placement jobs, the scheme has provisions for post-placement financial support.[4] Proof of employment is to be regularly submitted by the PIA to the DDU-GKY administration to avail the post placement financial support. A trained candidate is considered 'employed' only if he/she continues in a PIA job for at least three months. To enhance employment sustainability, PIA are mandated to track all trained/placed candidates for 1 year. During this year, they are also entitled to counseling and guidance.[5]

The study is located in the states of Bihar and Jharkhand, two of the poorest states of India, where job opportunities are scarce, so that most DDU-GKY placement jobs are located in other states (Online Appendix Table B.1.1).

2.2. Intervention

This particular intervention was designed based on extensive face-to-face and virtual meetings we had with Project Implementation Agencies (PIAs) and government agencies (Ministry of Rural Development and State Rural-Livelihood Mission) on the issues they faced regarding training and job dropout, and their possible causes. Based on these discussions, we hypothesized together that a lack of information about the placement jobs was one of the reasons for training and job dropout. Precise information about placement opportunities was neither part of the recruitment process, which was led by mobilizers who had incentives to attract as many trainees as possible, nor of the curriculum, which was set nationally and strictly followed. Our experiment focuses on this aspect and examines the impact of information about placement jobs on training completion and job retention.

The sample includes 86 batches from training centers located in Bihar and Jharkhand. A batch is a group of students who enroll, have classes, and graduate together. There were 2,488 trainees in total or an average of 30 trainees per batch. The randomization was carried out at the training batch level, stratified by state and sector of training, forming 13 randomization strata. 42 batches were treated (Online Appendix Table B.2.1). All sampled batches were residential programs consisting of 107 days of classroom training on average (between 58 and 205 days) and 17 days of on-the-job-training (between 0 and 60 days).

The intervention was delivered in two classroom sessions (A and B):

- Session A took place in the first two weeks after batch start, before "batch freezing', the time after which no new trainees can be enrolled. Treatment batches were provided with a list of detailed characteristics of *potentially* available placement jobs. Each list was specific to a training-center and trade, and included: job title, company name, location (city and state), and compensation package (net monthly wage and in-kind benefits). The session ends by a Q&A with placement officers.
- Session B took place approximately 10 days before the completion of the classroom training. Trainees from the treatment batches were provided with a detailed list of positions that were *actually* available to them, with job title, company name, location, and compensation package. Trainees were warned about the need to prepare to take up a for possible migration. The session ends by a Q&A with placement officers.[6]

2.3. Data

Our research is based on primary data collected from four rounds of surveys of trainees: the baseline and the midline surveys were conducted face-to-face, and the two endline surveys on the phone (Online Appendix Figure B.2.1). Trainees who were not surveyed at baseline (either because they were absent on the day of the baseline survey, or due to some other reason), were not surveyed in the followup rounds.

- The baseline survey was administered from December 2018 to October 2019, to all (2,488) participants present before batch freezing. We collected information on a wide range of socioeconomic characteristics of the trainee and household, a range of psychometric tests (GRIT, BIG 5, Attitude and self-esteem, life goals, risk preference), expectations, preferences, opportunity cost, and program awareness (Online Appendix Table B.3.1).
- The midline survey was conducted at the end of the classroom training but before the trainees left for their placement jobs. This survey mainly captured the change in expectations of the trainees. Interviews were carried out from March 2019 to January 2020 and covered 1,812 trainees who were present in the training center on the day of the survey (Panel B and C of Online Appendix Table B.3.3).
- The first endline survey was conducted approximately two months after the end of the training, and the second endline five months after the end of the training. We collected information on post-training outcomes focusing on training completion, job placement, and job tenure. The first one took place from May 2019 to April 2020 and cover 2,389 respondents. The second one from August 2019 to May 2020 and covered 2,367 trainees (Panel A of Online Appendix Table B.3.3).

[3] Prior to project approval, PIA are required to submit a tentative list of employers to the DDU-GKY administration. This list is part of the PIA's proposal, but the jobs actually provided to candidates may or may not be the same as those on the proposed list. In practice, the placement officer of the PIA liaises with potential employers using all possible networks on a continuous basis. Post-placement, proof of regular wage has to be demonstrated either by a salary slip from the human resource department of the organization or in the absence of a human resource department, a certificate issued by the employer indicating wages paid and counter signed by the employee along with a bank statement.

[4] An amount of Rs. 1000 per month is available for 2 months in case the placement is within the district of residence; Rs. 1000 per month for 3 months if placement is outside the district but within the state of residence; and Rs. 1000 per month for 6 months if placement is outside the state of residence.

[5] The Standard Operating Guidelines and Procedures last accessed on 8th Jan 2024, available at https://ddugkysop.in/mod/page/view.php?id=725http.

[6] A sample intervention session is provided in the Appendix B.6.

Sample restrictions. The Covid-19 pandemic and the lockdown that started on March 24 2020 caused severe disruption to the collection of our endline surveys. To accommodate the disruption, we amended the original focus of the second-endline questionnaire regarding respondents' current status, to ask about status at the time of the 2020 Holi festival (which started on March 9 2020) in order to better anchor the recollection of their activities. Online Appendix Table B.2.2 shows the number of individuals surveyed during the three sub-periods: (i) pre-Holi (before March 9), (ii) between Holi and March 25 2020, and (iii) after March 25 2020. We restrict our analysis to the 2,163 individuals who had their first endline survey before Holi.[7]

Attrition. The attrition rate for each wave of the surveys, and the *p*-values associated with the test of no difference across the treated and the control groups, are provided in Online Appendix Table B.2.3. Attrition is very low for the two endline surveys: 4% for the first endline and 5% for the second endline. Attrition in the midline survey is higher (27%) as the survey was only administered to trainees who were present at the time of the interview. Importantly, attrition rates in all survey rounds are similar across the treatment and control groups. The COVID-related sample restrictions is also uncorrelated with treatment assignment (Row 4 of Table B.2.3).

2.4. Summary statistics and balance tests

The full set of variables and their definitions are provided in Online Appendix Tables B.3.1 and B.3.3. Summary statistics of our baseline variables, and the results of the balance tests for randomization, are provided in Online Appendix Table B.4.1.

The average age in our sample is 20, and most trainees have some secondary education. There are more female than male trainees, which is a remarkable achievement given the low labor force participation of women in this context generally. In terms of caste, 15% of the trainees are Scheduled Tribes, and 30% Scheduled Castes, which shows that DDU-GKY successfully targets disadvantaged youth.[8] Another evidence of the pro-poor targeting of DDU-GKY is the very high fraction (79%) of trainees from households below the poverty line. Median household earnings are about 9,000 INR (122 USD) a month.

We conducted balancing tests for 77 covariates individually across five domains, and out of these, seven covariates were found to have statistically significant imbalances at 5% level (Table B.4.1). Domain-wise test of joint significance shows that one domain (Panel D) has a significant imbalance at 5% level with the most concerning difference in the household earnings variable. The joint test for balance across all covariates across all domains is also significant at 5% level.

Baseline data also includes information about trainees' expectations. We asked trainees what they thought they would earn currently if they were not doing the training, and how much they expected to earn after a year. We also asked them about their expectation regarding training completion, the likelihood of a placement offer, the wage they would be offered, the location of the job (in or outside of state) and their likelihood of accepting that offer. All these variables are balanced between treatment and controls (see Table B.4.1). Appendix Figure B.4.1 compares trainees' baseline expectations about the wage offered at the end of the training with the median wage actually earned by trainees placed from their batch. There is wide variation in expectations, and a majority of trainees are over-optimistic. This is the key information friction that our intervention aim to address, and in the following section, we present a brief conceptual model to think about its effect on placement and retention.

3. Model

We provide a simple theoretical framework to guide the interpretation of our results. It illustrates two potential effects of information on employment and training outcomes: a selection effect, and a job readiness effect. The proofs of the propositions listed below are in Appendix A.1–Appendix A.4.

Setup and propositions. At the time trainees enter the placement job, they compare their reservation utility to the actual utility they derive from the job. R denotes the difference between the reservation utility and the actual value of the job and is assumed to be uniformly distributed. If $R > 0$, youths leave the job. If $R < 0$ they stay in the job. At the time trainees join the program, they form an expectation about the utility of the job they will be offered at the end of the training. Let V_0 denote the difference between the expected value of the job at the time of joining the program and the actual value of the job. At the time trainees finish the training and before they start in the job, they refine their expectations. Let V_1 denote the difference between the expected value of the job at the time of completing the training and the actual value of the job.

We assume that the learning process is such that $V_1 = \lambda V_0 + \varepsilon$, where ε is a noise parameter centered around zero that affects the value update during the training, and $\lambda \in [0, 1]$ is the stickiness parameter. Let λ_T denote the parameter for the treated group, and λ_C for the control group. We assume $\lambda_T \leq \lambda_C$: treated individuals learn faster than control ones. Let Z be a binary treatment assignment indicator, which is randomized. Let D be a binary indicator for training completion and placement. Let S be a binary indicator for the individual staying in the DDU-GKY job for at least 5 months.

To sum up, the timing is as follows:

- $t = 0$: individual enters the program if and only if $V_0 > R$.
- $t = 1$: individual completes the training and takes up the job ($D = 1$) iff $V_1 > R$.
- $t = 2$: individual in placement job learns about its true value and decide to stay in the job for at least five months ($S = 1$) iff $R < 0$.

Proposition 1. *The treatment effect on training completion depends on youth expectations:*

$$P(D = 1|Z = 1, V_0 > 0) - P(D = 1|Z = 0, V_0 > 0) < 0,$$
$$P(D = 1|Z = 1, V_0 < 0) - P(D = 1|Z = 0, V_0 < 0) > 0.$$

The information session brings trainees' expectations closer to the true value of the job for them. Hence the treatment discourages over-optimistic ($V_0 > 0$) trainees, who become more likely to drop out of the training and refuse placement, and encourages over-pessimistic ($V_0 < 0$) ones, who become more likely to complete training and accept placement. Online Appendix A.5 Figure Appendix A1 illustrates this proposition using a numerical simulation.

Proposition 2. *The treatment effect on the probability to stay in job conditional on placement (Selection effect) depends on candidates expectations but is positive overall:*

$$P(S = 1|\lambda_T V_0 + \varepsilon > R, V_0 > 0) - P(S = 1|\lambda_C V_0 + \varepsilon > R, V_0 > 0) > 0,$$
$$P(S = 1|\lambda_T V_0 + \varepsilon > R, V_0 < 0) - P(S = 1|\lambda_C V_0 + \varepsilon > R, V_0 < 0) < 0.$$

Among the over-optimistic trainees ($V_0 > 0$), who overall are less likely to stay in the training, those who do decide to complete the training have a higher value of the placement job relative to their outside option. By contrast, among over-pessimistic trainees ($V_0 < 0$) who adjust their expectations upward and are more likely to complete

[7] We were not able to match 9 observations — see Row 1 Column 4 of online Appendix Table B.2.2.

[8] Scheduled Castes (SCs) and Scheduled Tribes (STs) are various officially designated groups of historically disadvantaged people in India. Other Backward Class (OBC) includes groups/communities that are eligible for affirmative action but not SC or ST, and the rest of the population is classified as general caste. As per Census 2011, the national average of SC population is 16.6% and that of ST population is 8.6%.

Table 1
Results: Main outcomes.

	In Placement Job after 5 m (unconditional)	Training Dropout	Job Placement (conditional)	In Placement Job after 5m (conditional)
	[1]	[2]	[3]	[4]
Treatment	0.028	0.008	0.012	0.109
	(0.043)	(0.019)	(0.053)	(0.051)
p-value	0.515	0.692	0.817	0.032
q-value (MHT)	0.817	0.817	0.817	0.126
Observations	2,070	2,089	1,799	890
Control Mean	0.330	0.136	0.493	0.624
Sample	All	All	Trained	Placed

Notes: See Appendix Table B.3.3 for variable definitions. The dependent variables are all binary indicators taking the value of 1 as follows. Column [1]: The trainee was still in a DDU-GKY job after five months (unconditional); Column [2]: The trainee dropped out of training; Column [3]: The trainee was placed in DDU-GKY job conditional on training completion; Column [4]: The trainee was still in a DDU-GKY job after five months conditional on training completion and placement. All regressions control for baseline characteristics chosen by a random forest approach (Wright and Ziegler, 2017) as well as strata fixed effects. See Appendix Table B.3.2 for the list of selected baseline characteristics. Standard errors reported in parenthesis account for clustering at the batch level. 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). Panel A of Appendix Table B.5.4 reports the treatment and control mean differences without controlling for any baseline characteristics.

the training in response to the information intervention, candidates who stay on may have relatively lower values of the placement job relative to their reservation utility. But at the placement stage there are more over-optimistic than over-pessimistic candidates, so that the overall selection effect is positive.

Proposition 3. *The treatment has an ambiguous effect on the (unconditional) probability of being in the job five months after training:*

- *For trainees for whom the job has a lower value than the outside option ($R > 0$), the treatment does not affect the probability to be in the job five months after training.*
- *For trainees for whom the job has a higher value than the outside option ($R < 0$) and who are over-optimistic ($V_0 > 0$), the treatment decreases the probability to be in the job five months after training by decreasing their probability to be placed.*
- *For trainees for whom the job has a higher value than the outside option ($R < 0$) and who are over-pessimistic ($V_0 < 0$), the treatment increases the probability to be in the job five months after training by increasing their probability to be placed.*

Finally, by increasing awareness about the jobs early on in the training, the intervention may help trainees prepare themselves to the transition to employment. We model this as an increase in the true value of the job by τ, leaving the outside option unchanged.

Proposition 4. *For all trainees, an increase in τ will increase training completion, placement, and the probability of being in the job unconditionally and conditional on being placed.*

Propositions 3 and 4 offer contrasted predictions, which suggest an empirical test of the mechanisms through which the intervention might affect placement. If we observe better retention conditional on placement but not higher training completion, higher placement or even higher (unconditional) retention on average, this would suggest that the intervention is to improve selection, rather than through better job readiness.

Discussion. The model simplifies the decision-making process in two important ways. First, the number of periods and hence the possibilities to drop out is kept to a minimum in the model. In reality, trainees can drop out any time during training and employment spells (e.g., after batch freezing but before midline, after placement but before training completion, after placement but before three months). We refrain from exploiting this variation for simplicity and to preserve statistical power.

Second, in our framework, training completion and job placement are a single decision. This is because the information intervention focuses on placement jobs, hence if it changes the decision to complete the training, we assume that it is in relation to the value of the placement job. We rules out other potential mechanisms: for example, the intervention could lead candidates to update their beliefs about their outside option, which may be better if they complete the training.

4. Results

4.1. Empirical framework

We restrict our estimation sample to trainees present at baseline. A batch b is in the treatment group if $Z_b = 1$, in the control group if $Z_b = 0$. An individual i in batch $b(i)$, assigned to a randomization stratum $s(i)$, has a vector of baseline characteristics $\mathbf{X_i}$ (control variables). We assume the following partially linear model:

$$y_i = \beta Z_{b(i)} + f(\mathbf{X_i}, s(i)) + \varepsilon_i, \quad \mathbb{E}(\varepsilon|Z, X, s) = 0$$
$$Z_{b(i)} = g(\mathbf{X_i}, s(i)) + u_i, \quad \mathbb{E}(u|X, s) = 0$$

β is the intention-to-treat effect, the parameter of interest in our setting, and $f(.)$ and $g(.)$ are unknown flexible functions. We estimate β using the DoubleML procedure (Chernozhukov et al., 2018; Bach et al., 2021), using random forests to approach $f(.)$ and $g(.)$ (Wright and Ziegler, 2017). A naive estimator that compares the treatment-control means can be contaminated by small-sample imbalances in the other determinants of the outcomes, even in the case of an RCT. In the pre-analysis plan, we had committed to use Double/Debiased Machine Learning to tie our hands in the way we control for the influence of covariates. We use all default parameters of the *ranger* package, except for the number of folds, set to 10 instead of 5 to allow for better resampling.[9] We cluster standard errors at the batch level, and compute q-value following the False Discovery Rate method by Benjamini and Hochberg (1995) to handle multiple hypothesis testing.

4.2. Main outcomes

Table 1 presents the results for our main outcomes in columns numbered [1]-[4]. We first consider the probability that the trainee is in the DDU-GKY job five months after training completion (column [1]). This is the unconditional probability based on the full sample: the dependent variable takes the value of 0 for trainees who did not complete the training and those who completed the training but were not placed. In the control group, 33% of all trainees who started the training are in a placement job. This probability is 2.8 percentage points (ppt) (8%) higher in the treatment group. However, the difference is not statistically significant.

The probability of dropping out of the program is 14% in the control group, and not significantly different in the treatment group (column [2]). The probability of being placed among those who completed the training is 50% and is not different in the two groups (column [3]). Column [4] presents the treatment effect on the conditional probability of being in the job for at least 5 months conditional on placement. This probability is estimated to be 11 ppt higher in the treatment group compared to 62% in the control group, a 17% increase. The effect is positive and significant at the 5% level, but the q-value is 12% after adjusting for multiple hypothesis testing.

[9] Appendix Table B.3.2 lists control variables selected by the random forest algorithm. We note that household earnings are included for all outcomes for the main sample.

Table 2
Results: Short-Term and Long-Term Outcomes.

	Formal Job	Outside State	Use Skills from Training	Life Satisfaction
	[1]	[2]	[3]	[4]
Panel A: Two Months after Training				
Treatment	−0.001	0.035	−0.105	−0.945
	(0.046)	(0.061)	(0.075)	(2.205)
p-value	0.989	0.560	0.161	0.668
q-value (MHT)	0.989	0.764	0.645	0.764
Observations	2,089	2,088	961	2,089
Control Mean	0.461	0.431	0.804	72.811
Panel B: Five Months after Training				
Treatment	0.027	0.037	−0.031	7.705
	(0.040)	(0.047)	(0.070)	(3.782)
p-value	0.498	0.440	0.655	0.042
q-value (MHT)	0.764	0.764	0.764	0.333
Observations	2,070	2,070	864	1,222
Control Mean	0.400	0.344	0.687	70.952

Notes: See Appendix Table B.3.3 for variable definitions. The dependent variables [1], [2] and [3] are binary indicators taking the value of 1, and [4] is a continuous variable ranging from 0% to 100%. Column [1]: The trainee was in formal wage employment; Column [2]: The trainee lived outside their home state; Column [3]: The trainee used the skills learned in training in their current occupation; Column [4]: Life satisfaction of the trainees. The sample in Column 4 of Panel B is smaller as this question was added later to the questionnaire for this survey round. All regressions control for baseline characteristics chosen by a random forest approach (Wright and Ziegler, 2017) as well as strata fixed effects. See Appendix Table B.3.2 for the list of selected baseline characteristics. Standard errors reported in parenthesis account for clustering at the batch level. 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). Panels B and C of Appendix Table B.5.4 report the treatment and control mean differences without controlling for any baseline characteristics.

In summary, the intervention did not affect the dropout probability or the probability of placement conditional on dropout, but we find suggestive evidence that it improved the conditional probability of staying in the DDU-GKY job. Within the framework of our theoretical model, these findings are consistent with selection effects canceling out on average. For example, the increase in dropout among trainees who are a poor fit for the job and a decrease in dropout among trainees who are a good fit for the job, canceling out.

Table 2 reports the results for the additional outcomes collected from the endline surveys (Panel A & B): whether trainees work in the formal sector (column [1]), whether they live outside of their state of origin (column [2]), whether they use skills from training in their current employment (if they are employed; column [3]), and their life satisfaction (column [4]). We do not find any evidence in support that the intervention increased formal employment among trainees: although the estimated treatment effect is about 7% of the control mean (Panel B), it is insignificant. This suggests that some of the positive treatment effects on the probability of being in the placement job after five months were compensated by trainees in the control finding other jobs in the formal sector. We find no significant difference between the two groups, except for an 11% increase in life satisfaction five months after training, which is not robust to adjustments for multiple hypothesis testing.

4.3. Heterogeneity

Tables 3 and 4 report results for the main outcomes by sub-samples defined by gender (women vs. men), caste (Schedules Caste/Scheduled Tribe vs. OBC/General Caste), education (below 12th grade vs. 12th grade and above), and expected salary in the placement job at baseline (distinguished by whether the expected salary is above or below the median of the realized placement salary).[10] Caste and gender

Table 3
Heterogeneity of treatment effects by gender & caste.

	In Placement Job after 5 m (unconditional)	Training Dropout	Job Placement (conditional)	In Placement Job after 5m (conditional)
	[1]	[2]	[3]	[4]
Panel A: Female				
Treatment	0.017	−0.017	−0.031	0.047
	(0.061)	(0.025)	(0.062)	(0.042)
p-value	0.783	0.500	0.618	0.263
q-value (MHT)	0.783	0.678	0.706	0.527
Observations	1,081	1,097	974	547
Control Mean	0.460	0.116	0.602	0.744
Panel B: Male				
Treatment	0.076	0.021	0.110	0.282
	(0.066)	(0.032)	(0.092)	(0.089)
p-value	0.252	0.509	0.231	0.001
q-value (MHT)	0.527	0.678	0.527	0.012
Observations	989	992	825	343
Control Mean	0.185	0.158	0.365	0.390
Panel C: Lower Caste				
Treatment	0.045	−0.008	0.019	0.133
	(0.070)	(0.034)	(0.077)	(0.062)
p-value	0.519	0.822	0.802	0.031
q-value (MHT)	0.822	0.822	0.822	0.251
Observations	888	891	770	432
Control Mean	0.380	0.137	0.567	0.669
Panel B: Higher Caste				
Treatment	0.030	0.014	0.025	0.064
	(0.042)	(0.024)	(0.053)	(0.064)
p-value	0.474	0.574	0.637	0.320
q-value (MHT)	0.822	0.822	0.822	0.822
Observations	1,182	1,198	1,029	458
Control Mean	0.291	0.136	0.437	0.579

Notes: The dependent variables are all binary indicators taking the value of 1 as follows. Column [1]: The trainee was in the DDU-GKY job five months after the end of training; Column [2]: The trainee dropped out of training; Column [3]: The trainee was placed in the DDU-GKY job conditional on training completion; Column [4]: The trainee was still in a DDU-GKY job after five months conditional on training completion and placement. "Lower Caste" is a dummy variable equal to one for Scheduled Tribes and Scheduled Caste, and "Higher Caste" a dummy variable for Other Backward Class and General Castes. All regressions control for baseline characteristics chosen by a random forest approach (Wright and Ziegler, 2017) as well as strata fixed effects. See Appendix Table B.3.2 for the list of selected baseline characteristics. Standard errors reported in parenthesis account for clustering at the batch level. The p-values corresponding to the equality of treatment effects between women and men for all four outcomes are: 0.51, 0.35, 0.20, 0.02. For the equality between castes, p-values are: 0.85, 0.60, 0.95, 0.44.

correspond to two dimensions of interest for the DDU-GKY program. Education and expectations are natural dimensions of heterogeneity according to our conceptual framework: more educated trainees may be less likely to join the placement job as they have higher outside options, and trainees who expect the placement jobs to pay more than it does may be more likely to be disappointed when they are placed.

We first consider the treatment effects for women and men separately — Table 3 Panels A-B. In the absence of any intervention, women are more likely to be placed in DDU-GKY jobs (60% vs. 37%) and to be working in that job five months after training (74% vs. 39%). This may be due to the fact that DDU-GKY offers rare work opportunities for rural women, whose labor force participation is low (Chatterjee et al., 2015). The intervention has differential effects by gender: small and insignificant for women, much stronger among men. The effects for men are significant at conventional significance levels and are very large in economic terms: the intervention increases the probability of staying in DDU-GKY jobs conditional on placement by 71%, from 39% to 67%, closing 80% of the gender gap. A possible explanation is that the mismatch between trainees' expectations and the placement job is more of an issue for men because they have a broader range of outside options than women.

[10] The median is computed within strata defined by state × trade.

Table 4
Heterogeneity of treatment effects by education & baseline expectations.

	In Placement Job after 5 m (unconditional)	Training Dropout	Job Placement (conditional)	In Placement Job after 5m (conditional)
	[1]	[2]	[3]	[4]
Panel A: Less educated				
Treatment	0.039	−0.039	0.025	0.138
	(0.051)	(0.030)	(0.062)	(0.060)
p-value	0.448	0.199	0.692	0.021
q-value (MHT)	0.716	0.397	0.791	0.168
Observations	890	896	755	428
Control Mean	0.379	0.183	0.573	0.664
Panel B: More educated				
Treatment	0.023	0.045	0.007	0.090
	(0.043)	(0.023)	(0.062)	(0.057)
p-value	0.603	0.052	0.915	0.114
q-value (MHT)	0.791	0.207	0.915	0.303
Observations	1,180	1,193	1,044	462
Control Mean	0.293	0.101	0.437	0.587
Panel C: Lower Salary Expectations				
Treatment	0.014	0.014	−0.008	0.145
	(0.046)	(0.022)	(0.057)	(0.061)
p-value	0.762	0.505	0.885	0.018
q-value (MHT)	0.871	0.808	0.885	0.140
Observations	1,205	1,214	1,055	516
Control Mean	0.333	0.127	0.489	0.601
Panel B: Higher Salary Expectations				
Treatment	0.048	−0.010	0.047	0.096
	(0.050)	(0.027)	(0.062)	(0.061)
p-value	0.341	0.728	0.451	0.115
q-value (MHT)	0.808	0.871	0.808	0.460
Observations	865	875	744	374
Control Mean	0.325	0.149	0.499	0.655

Notes: The dependent variables are all binary indicators taking the value of 1 as follows. Column [1]: The trainee was in the DDU-GKY job five months after the end of training; Column [2]: The trainee dropped out of training; Column [3]: The trainee was placed in the DDU-GKY job conditional on training completion; Column [4]: The trainee was still in a DDU-GKY job after five months conditional on training completion and placement. "Less Educated" denotes trainees with less than 12th grade and "More Educated" trainees with 12th grade and above. "Low Expectations" denotes trainees with baseline salary expectations below the median wage earned by trainees of the same batch after placement. "High Expectations" denotes trainees with expectations above the median wage. All regressions control for baseline characteristics chosen by a random forest approach (Wright and Ziegler, 2017) as well as strata fixed effects. See Appendix Table B.3.2 for the list of selected baseline characteristics. Standard errors reported in parenthesis account for clustering at the batch level. The p-values corresponding to the equality of treatment effects between more and less educated for all four outcomes are: 0.81, 0.03, 0.84, 0.56. For the equality between salary expectations, p-values are: 0.61, 0.49, 0.51, 0.57.

We next explore heterogeneity in treatment effects along the caste dimension. On average, trainees from disadvantaged background (SC/ST) are more likely to be placed (57% vs. 44%) and to stay in the placement job (67% vs. 58%) after five months compared to those from OBC/General castes (Table 3 Panels C-D). We find that the treatment effects on the probability of staying in the placement job conditional on being placed is strong for SC/ST trainees (13pp increase, p-value of 0.03, q-value of 0.25) but smaller in magnitude and insignificant for higher-caste ones. This suggests that SC/ST trainees may have been less well informed overall than higher caste ones, which left more scope for improved selection among them.

In Panels A-B of Table 4, we study treatment heterogeneity by educational attainment, whether trainees have completed 12th grade or higher or not. As expected, in the control group, conditional on training completion, less educated trainees were more likely to be placed and stay in the job than more educated ones, which is consistent with the fact that the placement jobs were only semi-skilled. At the same time, however, less educated trainees drop out twice as often as more educated ones (18% vs. 10%), which may be due to learning difficulties in the training program. Interestingly, the intervention reduces dropout for the less educated by 35% (p-value 0.20) and increases dropout for the more educated trainees by 50% (p-value 0.052). Since placement jobs are more valuable for less educated trainees, these results suggest that the intervention improved selection of trainees. The effect seems to be entirely driven by differential training drop-out: we find no effect on placement conditional on completing training for either group.

Finally, Panels C-D of Table 4 display the heterogeneity in terms of expected placement salary at baseline. The intervention has a strong and significant positive impact on the probability of staying in placement jobs, conditional on being placed, for trainees with initially low salary expectations. By contrast, the effect for trainees with initially high salary expectations is smaller and insignificant. However, we do not find that the intervention led to higher dropout among high-expectations trainees or lower dropout among low-expectations trainees. This lack of impact is not consistent with our framework: we believe it has to do with the fact that our survey may have failed to extract credible information about expectations.[11] In Appendix Table B.5.1, we present the results of a horse-race between the two variables (education and salary expectation) used in the heterogeneity analysis, and show that education is significantly correlated with future wages and formal employment, while our measure of expectations is not.[12]

4.4. Mechanisms

Following our theoretical framework, our intervention can affect the outcomes via two distinct channels: increasing job readiness and improving selection to remain in training. The selection channel comes from the intervention delivering information about jobs. Better-informed trainees make more time-consistent decisions about completing the training and accepting the placement job; those who get placed are a better fit for the jobs available. The job readiness channel comes from the fact that the intervention prepares trainees better for the transition to employment so that they are more likely to stay in the job once placed.

The heterogeneity results point to an increase in the probability of dropping out of training among more educated trainees and an (insignificant) decrease in dropout among the less educated. At the same time, less educated trainees are more likely to stay in the DDU-GKY job once placed following the intervention. This is consistent with the selection mechanism: more educated trainees have better outside options than the jobs offered to DDU-GKY trainees and would be less likely to stay in the DDU-GKY job anyway. If all results were driven by job readiness, we would not have expected an increase in dropout among the more educated. As discussed above, we would have expected the same heterogeneity to occur depending on to baseline salary expectations, which is not the case, and could be due to the imperfection of our expectation measure.

We can also explore the effect of the intervention on trainees' expectations about their labor market prospects, using information collected in the midline survey, which was carried out right before the second part of the intervention, before the end of the training. An important caveat is that 27% of trainees were absent at the time of the

[11] In the survey, we asked: "if you are offered a job after training then what will be the minimum, maximum, and average salary of the job then (1) What will be the minimum salary of the job? (2) What will be the maximum salary of the job? (3) What will be the average salary of the job?". We suspect a lack of clarity in the question on whether we are asking about the gross salary (without any deductions) or the take-home salary (the salary received in the bank account after deductions of health insurance, pension contributions, and in some cases, cost of accommodation and travel) is a possible reason for the lack of estimated impact.

[12] The correlation between the two measures in our sample is an insignificant 0.008. We still show the results because we committed to in the pre-analysis plan.

midline survey, including those who dropped out following the first intervention. This implies that the information collected in this survey is unlikely to capture the mechanisms highlighted in the model. In particular, if the intervention lowered expectations of over-optimistic trainees and induced them to drop out or increased expectations of over-pessimistic trainees and made them stay, average expectations in the trainees still enrolled may not change. With this caveat in mind, Table 5 presents the estimated treatment effects on the expectations of the trainees. In Panel A of Table 5, we do not find any significant effect on: (i) the perceived probability of getting a job; (ii) the average wage they expected from this offer; (iii) the range in which they expected this offer to be; (iv) the location of the job. Panel B of Table 5 presents some evidence that trainees in the treatment group revised downwards their willingness to accept a job inside of their state of residence (p-value 0.089) and the likelihood that they would stay 12 months in the state (p-value 0.087). While these effects are small and borderline significant, given the actual placement rates, which are much lower (50% conditional on training completion), they suggest that on average trainees became more realistic about their placement outcomes.

An alternative explanation for our findings, not included in our model, is that the intervention improved the match between trainees' preferences and the jobs offered to them. For example, a better awareness of job available after DDU-GKY may lead trainees to express their preferences to placement officers and choose their preferred options. Banerjee and Chiplunkar (2018) show that providing information to placement officers about trainees' preferences leads to more durable matches. In our context, there is little scope for better matching: the median batch was offered three placement jobs which were all similar in terms of job description and sector of employment. Still, we investigate the treatment effects in two ways. First, we estimate treatment effects on three separate steps of the placement process: job offer, offer acceptance, and job placement for the sample of trainees who completed the training. Appendix Table B.5.2 presents the results. There is no evidence that the treatment increases the likelihood of a job offer (column [1]) or the likelihood that the offer is accepted conditional on having been made (column [2]). In contrast, there is a positive but insignificant effect on trainees' likelihood of staying on the job for two months (p-value 0.145). Conditional on staying for two months, they stay for at least five months (p-value 0.033). Second, we estimate the correlation between candidates' wage expectations at baseline and the actual wage they received once placed (for the subsample of candidates who were actually placed). Appendix Table B.5.3 shows that there is a positive and significant correlation between expectations and wage received (column [1]). It is not however very large, due to the wide variation in expectations we documented in Appendix Figure B.4.1. The correlation disappears once we control for trainee and batch characteristics (column [2]) and when we add batch fixed effects (column [3]). When we include an interaction term between baseline expectations and a treatment dummy, the coefficient is also small and insignificant. Hence there is no evidence that candidates with higher wage expectations work in better-paying jobs in treatment or control batches. These results confirm that the treatment improved the fit between trainees and jobs by changing the pool of trainees, not by changing the offers made to them.

Table 5
Results: Additional outcomes.

	Treatment Effect	Standard Error [1]	p-value [2]	q-value (MHT) [3]	Control Mean [4]
Panel A: Intermediary Outcomes					
Expected proba of job offer	0.028	(0.091)	0.761	0.915	9.410
Average expected salary	32	(304)	0.915	0.915	11,334
Expected Max - Min salary	−41	(251)	0.869	0.915	3,693
Expected job out of state	0.041	(0.148)	0.780	0.915	8.857
Panel B: Secondary Outcomes					
Expected earnings (in 12 mths)	365	(558)	0.513	0.836	14,616
Preferred earnings (in 12 mths)	903	(678)	0.183	0.475	18,184
Proba training completion	0.056	(0.038)	0.137	0.475	9.800
Training useful	0.043	(0.076)	0.569	0.836	9.452
Training satisfaction	0.095	(0.068)	0.161	0.475	9.507
Proba accept job in state	−0.359	(0.212)	0.089	0.475	8.548
Proba stay 12 mths in state	−0.362	(0.212)	0.087	0.475	8.501
Proba accept job out of state	0.086	(0.154)	0.579	0.836	8.730
Proba stay 12 mths out of state	−0.098	(0.164)	0.550	0.836	8.618

Notes: The total number of observations used is 1613. The dependent variables are measured at the midline survey. See Appendix Table B.3.3 for variable definitions. Likelihood variables range from 0% to 100%. Panel A comprises of Likelihood of getting a job at the end of the training; the Expected average salary on the job offered at the end of the training (in rupees); The difference between the maximum and the minimum expected salary on the job offered at the end of the training (in rupees); Likelihood of getting a job outside of the state at the end of the training. Panel B shows the treatment effects on Expected earnings after 12 months; Desired earnings after 12 months; Likelihood of completing the training; The degree to which the training is useful; The degree to which the trainees are satisfied with the training; Likelihood of accepting a job in the state; Likelihood of staying 12 months in a job in the state after accepting it; Likelihood of accepting a job outside the state; Likelihood of staying 12 months in a job outside the state after accepting it. All regressions control for baseline characteristics chosen by a random forest approach (Wright and Ziegler, 2017) as well as strata fixed effects. See Appendix Table B.3.2 for the list of selected baseline characteristics. Standard errors reported in parenthesis account for clustering at the batch level. 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). Panels D and E of Appendix Table B.5.4 report the treatment and control mean differences without controlling for any baseline characteristics.

5. Conclusion

We conducted a randomized experiment to evaluate an intervention that provided detailed information about placement jobs to trainees of the Indian vocational training program DDU-GKY. We find that better informed trainees were 18% more likely to stay in the jobs they were placed in, with higher effects for lower-caste, less-educated, low-expectations male trainees. We analyze our results through the lens of a conceptual model in which two channels could drive the results: (i) the intervention prepares trainees for DDU-GKY jobs, (ii) the intervention allows trainees with better outside options to drop out earlier from the training. While we cannot rule out that job readiness does not play a role in this setting, we find suggestive evidence in favor of the self-selection channel.

Our results suggest that providing detailed information about post-training job opportunities can help trainees form more accurate expectations, improve self-selection into training, and improve placement outcomes. Given the low cost and the simplicity of the information sessions, the intervention can easily be scaled up to help the program meet its objectives. Importantly, this kind of intervention should take place early enough in the training spell (or even right before it starts) to minimize costs for trainees and training institutions.

CRediT authorship contribution statement

Bhaskar Chakravorty: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Wiji Arulampalam:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Apurav Yash Bhatiya:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Clément Imbert:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Roland Rathelot:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2024.103273.

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