Informing the Job Search: A Field Experiment in an Urban Labor Market *

Farzana Afridi[†] Soubhagya Sahoo[‡] Nikita Sangwan[§]

August 4, 2026

Abstract

We examine the impact of labor market information on beliefs, job search and employment outcomes of job seekers in urban India. Through a cluster-randomized intervention in Delhi, over 3000 men and women are randomized into a treatment group in which they are informed and assisted in accessing a job matching platform, supplemented by phone messages that deliver either non-personalized or personalized labor market information; or a control group in which neither assistance with the matching platform nor any phone messages is given. A year after intervention, men reduce overall job search while women's search shifts to online modes in both treatment groups. Although there is no impact on overall employment, we find evidence of a marginal shift in occupational structure – away from casual jobs towards salaried work – along with higher earnings, for women in later months. These employment impacts are relatively stronger in the personalized messaging group. We highlight the role of (mis-)beliefs about the labor market and gendered information frictions in explaining our findings.

JEL classification: J21, J28, J62, 015
Keywords: job search, digital platforms, employment, expectations, gender, youth

*This study is registered at AEA RCT Registry, ID 0012778. The paper has benefited from feedback from conference and seminar participants at AFE (University of Chicago), ACEGD (ISI Delhi), Trinity College Dublin-CEPH Seminar, IEA Conference (Belfast), SEED Development Workshop (University of Bath), and QUB Economics Seminar. We thank Gaurav Chiplunkar and Yogita Shamdasani for helpful discussions on study design; Stefano Caria, Sanchari Roy and Niharika Singh for thoughtful feedback. Vikas Lilhare, Anant Singh, Rohan Regi Varghese and Shubham Singh provided excellent research assistance. The authors acknowledge financial support from the Digital Platforms and WEE grant by the Bill and Melinda Gates Foundation. The usual disclaimers apply.

†Indian Statistical Institute (Delhi) and IZA. Email: fafridi@isid.ac.in
‡Higher School of Economics University, Moscow, Russia. Email: ssahoo@hse.ru
§Queen's University Belfast, UK. Email: n.sangwan@qub.ac.uk

1 Introduction

Job seekers often lack full information about job opportunities due to informational frictions (Conlon *et al.*, 2018), which may engender mis-perceptions and mis-beliefs about labor market opportunities. Furthermore, limited networks and access to information sources can exacerbate informational frictions for some job seekers, affecting their job search and labor market outcomes (Cortés *et al.*, 2023). However, there exists little research on what types of information on the labor market can reduce these frictions and for whom. In this paper, we conduct a novel study on the nature of labor market information that can be effective in addressing informational asymmetries and how they impact job seekers' expectations, search and subsequent employment outcomes.

We study job seekers in an urban labor market with high levels of unemployment to address information frictions on the supply side. Specifically, we design a cluster-randomized intervention that provides information on digital job matching platforms, along with assisting them in registering on a specific nation-wide grey collar job matching platform. The in-person information and assistance is followed by phone messages to job seekers to further increase take-up and usage of digital job search platforms. Phone messages are designed in two ways – either general, non-personalized messages or personalized messages that were tailored to labor market preferences.

Our field-experiment is implemented in Delhi, India with more than 3000 young men and women residing in 130 clusters of urban residential neighborhoods between May 2023 and December 2024. We randomly vary the nature of labor market information provided by assigning a cluster to either in-person information and assistance on registering on our partner platform plus up to 6 non-personalized phone messages to increase usage of digital platforms (Non-Personalized or Non-P); or same in-person information and assistance (as in Non-P) plus up to 6 personalized phone messages based on job preferences at baseline (Personalized or P); and a control group, that neither receives the in-person information and assistance nor the phone messages (C). We utilize both survey data and administrative data from the platform to study the impact of the information intervention on the job search behavior, employment status, and the nature of work undertaken up to 12 months post intervention.

At baseline, job seekers exhibited high expectations and misperceived beliefs about the labor market. Specifically, an overwhelming majority believed they were on their ideal career path. Respondents' aspirations centered on securing salaried positions with expectation of significant growth in earnings in their ideal jobs. They quoted higher expected salaries than actual for most jobs. Interestingly, men were significantly more likely to have high aspirations and expectations of the labor market, than women. Furthermore, of those who had ever looked for work at baseline, we find significant gender differences in job search behavior at baseline. While men are more likely to depend on their "weak ties" such as friends and family for job information and referrals, women are more likely to depend on formal channels for job search and application, such as their educational institutions.

At intervention, almost 65% of participants in the treatment groups expressed interest in registering on the partner platform but women's interest in the platform was almost 10 percentage points (pp) higher in both treatment arms. Registration rates were, therefore, high at 65% – almost all who were interested in the platform registered, with more women (70%) registering than men (60%). Following the in-person intervention, 6 phone messages with labor market information (personalized or non-personalized) were sent to individuals assigned to treatment, irrespective of whether they registered on our partner platform or not.

Six to twelve months post intervention, we find that the personalized messages significantly dampened job seekers' labor market expectations. Men in the P treatment group, in particular, were 8.4 pp less likely to report being on their ideal career path. While women's expectations also fall, there is insignificant impact on their beliefs in both groups. The fall in labor market expectations is accompanied by a decline in men's job search intensity in both groups, but significantly by 5 pp in the P group, 12 months post intervention. In contrast, women's job search intensity did not decline. Instead, there is a persistent increase in women's usage of online platforms and other digital modes for job search by 6 pp up to a year after intervention in both treatment groups. This is attributable to substitution of search from offline, particularly friends and family, to online modes of search by women.

While we do not find employment impacts on the extensive margin, women's labor market earnings in the P group were significantly higher than their counterparts in the Non-P group, from the ninth month post intervention. P women also earned (marginally) significantly more than the Non-P women in the months following the intervention. In contrast, we find no such impact on men. This increase in earnings of women is accompanied by women in the P group transitioning out of casual work in early months and into salaried work in later months, post intervention. We do not find similar, systematic occupational shifts for men. Overall, these results point towards marginally better labor market outcomes in P relative to Non-P, and particularly for women in the P group.

Our findings can be explained by the intervention aligning prior mis-beliefs and mis-matched expectations with the realities of the labor market, particularly through personalized information. Men, with upward-biased expectations of labor earnings at baseline, lower their job market expectations at endline. Specifically, men who reported being on track to their ideal job at baseline lower expectations of ideal job attainment by 7.5 pp after 12 months in the treatment group. In addition, the P treatment generates a significant downward revision in perceived salary gains a year later, for men with upward-biased beliefs. Consistent with belief correction, P men defer labor force entry by remaining enrolled in educational institutions (if enrolled at baseline) and report higher satisfaction with their current jobs (if working). Women in both treatment groups also lowered their beliefs about perceived earnings gains. But in contrast to men, women in both treatment groups were more likely to enroll in an educational institution to upgrade their skills, if not enrolled at baseline.

On similar lines, men whose earnings expectations were higher than in reality reduced job search, while those with downward-biased salary expectations increased job search due to the intervention. In contrast, the impact on women's job search behavior is driven by the over-optimistic sub-sample of women who increase the usage of digital modes of search in both treatment groups, with no such effect on women with downward-biased expectations. This suggests that by providing credible information on the labor market, the intervention instead reduced women's perceived cost of searching for jobs. Women entered our study with lower exposure to the labor market, reflected in lower employment rates and lower likelihood of applying for jobs even when seeking work (69% compared to 74% for men). Consequently, women were almost 10 pp more likely to register on the platform. Thus, while men's belief adjustments led to lower intensity of job search, the information intervention encouraged women to search for jobs using non-traditional modes.

Women were less exposed to the labor market and had lower access to traditional modes of job search relative to men at baseline. Therefore, more women took up the intervention and experienced occupational mobility and earnings gains due to their relatively lower earnings expectations. These effects are driven by the P group in which we sent personalized nudges to all respondents, irrespective of whether they were registered on the collaborating platform or not. Hence, tailoring messages by individuals' job preferences may have ensured that respondents aspiring to specific types of jobs were guided toward relevant vacancies and immediate openings. Indeed, job applications on the portal increased by almost 10% following the first message and rose cumulatively to 86% fourteen weeks after the in-person intervention. Although the search behavior on the collaborating platform is not significantly different between the treatment arms, the P group responded earlier through significant increase in job applications in the week following the first message. Further, self-reported viewing of job vacancies on government job portals, which were more likely to provide information on women's preferred public sector jobs, are higher for women in the personalized group. This again, suggests that the personalized nature of the phone messages, relative to non-personalized messages, may have lead to more focused and efficient search.

Our paper speaks to emerging concerns about employment opportunities in low-income settings – populations with low rates of labor force participation and high levels of precarious, informal work (Bandiera *et al.*, 2025). Youth unemployment in low- and middleincome countries (LMICs) remains persistently high inspite of supply side interventions, viz. vocational skilling (McKenzie, 2017; Carranza & McKenzie, 2024). Meta-analyses of these programs in LMICs reveal modest employment gains (∼5 percentage points) and highlight systemic mismatches between the supply and demand for labor (Agarwal & Mani, 2024). But while it is well-acknowledged that labor market frictions often lead to inefficient allocation of workers to jobs in low-income settings (Caria *et al.*, 2024), there is limited evidence on the impact of addressing informational frictions through information and job matching interventions. Findings from experiments in high-income settings with white-collar workers indicate mixed results – while Dhia *et al.* (2022) provide personalized information on jobs in France to find no labor market impacts, Belot *et al.* (2026) conduct a similar experiment providing personalized information to around 1500 long-term job-seekers (most unemployed for more than a year, many with a disability) in the UK to find improvements in earnings.[1]

New technologies, such as digital labor platforms, have the potential to improve labor market outcomes by addressing labor market information asymmetries, and enabling more efficient matching of workers and jobs at scale. The existing evidence on the impact of job matching platforms, however, is also mixed. For instance, Kelley *et al.* (2022); Dhia *et al.* (2022); and (Jones & Sen, 2024) find minimal or negative effects on labor market outcomes, whereas Wheeler *et al.* (2022) finds large positive effects but for white-collar job seekers on LinkedIn. Recent reviews underscore the challenges of government-led digital job platforms in LMICs, where low take-up by job-seekers and employers often limits impacts (McKenzie, 2017; Carranza & McKenzie, 2024). Experimental studies, such as those conducted in sub-Saharan Africa and India, demonstrate negligible aggregate employment gains from these online platforms, driven by job-seekers' overly optimistic wage expectations (Fernando & Singh, 2026). However, unlike our field experiment, much of this research focuses on a select sample of job seekers registered on platforms. Hence there is limited insight into the contexts and reasons for why these digital technologies do or do not impact labor market outcomes and whether the estimated effects are generalizable.

Existing research based on field experiments suggests that as good job offers fail to materialize, some job seekers adjust their expectations downwards and may remain in the same jobs or drop out of the labor market. These findings indicate that job seekers' beliefs about the arrival rate of jobs mediate the effectiveness of matching interventions. This is consistent with Bandiera *et al.* (2025), who show that job seekers revise their beliefs

[1] Altmann *et al.* (2018) provide general information on job search strategies to job seekers through a brochure in Germany to find positive effects amongst long-term job seekers only. Field *et al.* (2022) randomize whether users of a platform in Pakistan receive information about potential job matches through variation in mode of information - only text messages or both text messages and phone calls. Calling users raises their job application rate by 1.5 percentage points or 750% of the control group mean, relative to only texting them. They do not follow up to estimate labor market effects.

downwards in response to negative signals about their labor market prospects (when call back rates from employers are lower than they anticipated) in a vocational training program in Uganda. Fernando & Singh (2026), in an informational intervention amongst job seekers on a platform in India, also find employment gains amongst those with downward-biased beliefs and possible persistence in employment of those who were already employed at baseline.

While several papers studying labor market policies find that job seekers expectations about their job prospects are too high (Abebe *et al.* (2020); Banerjee & Chiplunkar (2024); Banerjee & Sequeira (2023)), the evidence on demographic differences - gender or age - in labor market expectations is limited. Cortés *et al.* (2023) are among the few papers that highlight the role of beliefs in explaining gender differences in job-finding behavior, and consequently, early-career wage gaps among the highly-skilled men and women, in a developed country setting. Lee (2022) finds similar results in South Korea, where sector-specific informational intervention reduces gender-based occupational segregation.

Our study contributes to the literature on the role and nature of labor market information in three key ways. First, we evaluate what types of information are likely to be most effective in making job search more efficient and improving labor market outcomes and for whom in a field experiment. Our hybrid intervention combines in-person assistance with personalized digital nudges, addressing the 'intention-behavior gap' noted in the job search literature (Abel *et al.*, 2019). This allows us to better understand the nature of information outreach that may be effective at the margin of take-up of new job search technologies and how that may differ by gender and age groups. Specifically, we find that personalizing information can lead to improved labor market outcomes for individuals who experience greater informational frictions.

Second, and more importantly, we extend the emerging literature on the pathways through which information affects behavior and labor market outcomes of job seekers, by deep-diving into individuals' beliefs, aspirations and expectations. Specifically, we are able to assess how informational interventions can affect search behavior and employment outcomes via their impact on beliefs and expectations of job seekers. Given our large study sample, we analyze impacts on multiple demographics groups - by gender and age. We disentangle the effect of beliefs on job search behavior and outcomes of women, men and the youth – primarily single and relatively educated populations in the growing urban areas of LMICs. We find that new technologies can reduce labor market frictions differentially for women who are looking for work, but face greater informational frictions and lower access to traditional sources of labor market information in low-income settings. Finally, while most labor market studies in LMICs analyze one-time impacts, the high-frequency panel structure of our study allows us to assess monthly labor market behavior to evaluate whether usage and effects vary over time, while accounting for the seasonality of employment and occupations in low-income settings.

In the following section we elaborate on the experiment design and the intervention. Section 3 discusses the data and methodology. The results are outlined in Section 4. We discuss mechanisms in Section 5 and conclude in Section 6.

2 Experiment Design

We conduct our study in the state of Delhi, India. Drawing on data from the State Election Commission, we sample 15 assembly constituencies (ACs) across six districts of Delhi. 130 randomly selected polling stations (PS) within the sampled ACs form our primary sampling units or clusters. From each of these polling stations, 25-28 households are selected randomly for a baseline survey. Households with a member aged between 18-40 years, currently looking for work or planning to work in the near future, with atleast high school level of education, and with access to a smartphone are considered eligible for the survey. Our baseline data, thus, consist of a sample of over 3000 male and female current or prospective *job seekers*, surveyed between May and August 2023. Appendix Figure A.1 shows the map of Delhi with the districts in the study shaded in and the sampled polling stations by treatment groups.

2.1 The Intervention

Following the baseline survey, our intervention, conducted between September 2023 and February 2024, consisted of two components: (1) in-person information on and assistance with registering on a Mobile App & Web based job aggregation platform that advertises job openings, matches job seekers with employers and (2) phone messages with job market information, to bolster the in-person intervention through higher take-up of digital platforms at both the extensive and intensive margins. Below we discuss the interventions in detail.

2.1.1 Job matching platform

We partnered with a digital job search platform, powered by one of India's leading business services provider and with the second largest subscriber base (6.5 million) of job matching platforms in India. The platform primarily focuses on connecting blue and grey-collar workers with employers across various sectors in India, offering a streamlined and accessible job search experience through its mobile application.

The platform operates through a mobile app that is available for download. The app is lightweight and easy to navigate, making it accessible even to those who may not be tech-savvy. Once a user downloads the app, they create a profile by entering personal details, work experience, and educational qualifications. The platform allows users to upload their resumes, which are then used to apply for jobs directly through the app. Once the profile is set up, users can begin searching for jobs. The search functionality is quite advanced, allowing users to filter jobs by location, job type, and even specific employers. The hyperlocal feature is particularly useful as it lets users search for jobs in very specific localities within a city, which is a significant advantage for those who prefer or need to work close to home.

The platform offers a diverse range of job opportunities and vacancies, catering primarily to blue and grey-collar but also some white-collar segments of the labor market:
(1) Blue-Collar Jobs: These include roles in sectors such as logistics, retail, delivery, and security. Positions such as delivery drivers, warehouse workers, and security guards are commonly listed. The platform is particularly focused on these roles, which are in high demand across many cities in India.
(2) Grey-Collar Jobs: Opportunities in sectors such as IT, finance, and administration, such as accounts keeper, data entry. These jobs might require higher education levels or specialized skills, and the platform provides relevant assessments to ensure candidates meet the required standards.
(3) Flexible Jobs: The platform also provided flexible, remote and part-time work opportunities like digital marketing, graphic design, and creative content production. These roles often require specific skills, which can be validated through the platform app's skill-testing feature.
(4) Work-from-Home Opportunities: Recognizing the growing demand for remote work, the platform includes work-from-home job listings across various sectors, from customer service to content creation.

Registered workers can either submit their applications to job postings using the 'Apply' button on the app or directly contact the HR representative of employers via the 'Call HR' button. This feature eliminates intermediaries, potentially allowing job seekers to get quicker response to applications and direct interaction with potential employer. The platform also includes a variety of skill tests that can be taken directly within the app. These tests are often linked to specific job postings, ensuring that candidates meet the necessary qualifications before applying. For example, a candidate applying for a customer service job might need to pass a basic communication skills test. In addition, the platform offers micro-learning modules and certifications that help job seekers enhance their skills, making them more attractive to potential employers. In order to enhance trust, the employers are verified by the platform. Employers can also highlight their legitimacy by earning a 'Verified Employer' tag on their postings.

Once a worker registers, the platform employs an AI-assisted algorithm to match job seekers and employers. The platform pre-screens candidates, verifying their identities and ensuring that their profiles meet the job requirements before they are matched with employers. This pre-screening includes role-based assessments and the verification of personal details such as address and contact information. Employers can also post job requirements, which include specific skill tests that candidates should pass. The shortlisted candidates either receive callbacks from the employer or the HR department. Note that the platform does not record data on the final job offer, the nature of the contract offered, or whether the offer was accepted.

2.1.2 Phone messages

To address the issue of potential low-take up and usage of the digital platform (Carranza & McKenzie (2024)), the second component of our intervention consisted of a series of phone messages delivered sequentially via both WhatsApp and text messages to all individuals, irrespective of platform registration status, in both treatment groups. Our objective was to encourage platform registration by those who did not register during the in-person visit, as well as regular and more efficient usage of job search platforms. The messages were, therefore, designed to enhance respondents' awareness of job opportunities on digital platforms, and reduce informational frictions that may constrain effective job search behavior.

All respondents assigned to treatment (and irrespective of platform registration) were sent six WhatsApp and text messages sequentially, after the in-person intervention session in their PS, over (almost) three months:

- Message 1: Guidance on how to search for a job effectively on the partner platform.
- Message 2: Information on the number of jobs currently available in Delhi on our partner platform using platform data.
- Message 3: Details of the top three jobs, most in-demand, on the platform, to provide information about the competitiveness of specific vacancies, using data from our partner platform.
- Message 4: Information on the importance and requirement of English-speaking skills for available jobs on the platform.
- Message 5: Details about subsidized government skilling programs and initiatives to improve employability.
- Message 6: Information on accessing and using a government job portal with information on public sector jobs.

For each of these six general messages we created personalized versions. To do so, we first analyzed job aspirations and preferences, reported at baseline, by respondent characteristics. Specifically, we accounted for preferences related to:
(i) workplace characteristics (e.g. preferences by work facilities, gender composition of co-workers and immediate supervisor, and workplace safety);
(ii) job characteristics (e.g. preferred work timings, hours of work, work location, benefits, salary, non-monetary compensation, work environment and flexibility of work hours or location);
(iii) occupational aspirations (public or private sector, self-employment, salaried/professional, home-maker or pursue higher education).

We also compared job market expectations by education (high school completed vs. above high school education), marital status (married vs not married), age group (below vs. above 24 years), gender (male vs female), and job seeking status (current vs. prospective job seeker). Following this exercise, three dimensions emerged as the strongest predictors of systematic differences in job market expectations and aspirations - (1) gender, (2) current job-seeking status and (3) aspiration for jobs listed on the partner platform. Based on these, respondents were categorized into seven distinct groups, with each group receiving a customized stream of messages.[2]

Personalized messages, therefore, mapped job information to the recipient's gender, job-seeking status, and sectoral preferences. For instance, messages to the category of men who are prospective job seekers aspiring for the non-public sector jobs on our partner platform covered information about part-time and work-from-home opportunities, along with details on skill investment returns and available vacancies in Delhi. Similarly, prospective job seeking women with preference for public-sector jobs, received messages highlighting part-time vacancies in government positions and openings specifically targeted at female candidates. This customization ensured that the information provided was relevant, actionable, and resonated with respondents' preferences, to improve the efficiency of their job search. Note that job platforms too send personalized messages to registered job seekers that match their registered profile to job vacancies advertised on the platform.[3] Our personalized intervention, in contrast, was sent to all individuals assigned to P treatment, irrespective of platform registration status; included aggregate platform-level information on preferred jobs; and

[2]These groups are: 4 groups of male, current/prospective job seeker and don't aspire/aspire to jobs on our partner platform. Similar 4 groupings for female respondents were created. As the women pursuing education and preferring platform jobs had similar labor market engagement and usage of online platforms at baseline as those who did not prefer such jobs, we club these two categories together. Thus, we use seven of the eight possible categories for personalized messaging.

[3]The partner platform also sends reminders for jobs applied to and push notifications for exploring the platform's features to all the registered job seekers.

provided information on non-partner platforms such as government portals. Hence our personalized messaging intervention was not selective and addressed comprehensive labor market preferences of the job seeker.

In contrast, the non-personalized messages contained the same general labor market information for all respondents, without accounting for their individual characteristics or preferences. These messages provided broad guidance on job search strategies, the number and types of jobs available, English language requirements, and information on both government and private sector opportunities. The full message content for both personalized and non-personalized treatments for each of these categories is provided in Appendix Table A.1.

2.2 Randomization

We implemented a cluster-level randomization of the intervention. The 130 clusters, i.e. the PS, sampled at baseline were randomized into three groups:

Non-P (Non-Personalized treatment) in which we offered in-person information on job search/skilling via digital resources and assistance with registering on the collaborating platform plus 6 non-personalized phone messages to increase usage of digital platforms (44 clusters);

P (Personalized treatment) wherein we provided the same in-person information and assistance (as in Non-P above) plus 6 personalized phone messages based on job preferences, education and other characteristics measured at baseline (44 clusters);

C (Control group), that neither receives the in-person information and assistance nor the phone messages (42 clusters).

Respondents in both the Non-P and P groups were administered the interventions in the following order:

(1) An in-person information session conducted at the individual level in each PS, which consisted of an explanation of the benefits of digital job search platforms in obtaining information for preferred job vacancies and reducing search costs. This was followed by information on a specific job search platform that we collaborated with and an offer to assist them in registering on the platform. We also provided individual-level assistance on how to register and develop a profile, opportunities for up-skilling, and how to search for preferred jobs on our collaborating platform;

(2) The in-person session was followed by 6 phone messages sent at intervals of about 15 days each (beginning with approximately 10 days after the in-person intervention session), over two months. Phone messages were sent to all respondents in a PS on the same date. These messages aimed to nudge individuals who were unregistered towards registration on our collaborating digital portal, and/or ensure regular and efficient usage of search platforms.

In the P group, the phone messages were personalized to the labor market preferences of the individual, which we had elicited at baseline, as discussed above.

Following the intervention we conducted two surveys – first, at approximately 6 months (Endline 1 during April-June 2024) and second, about 12 months (Endline 2 during September-December 2024) after the in-person information session. At both endline surveys we collect data on the entire work history of the individual since the previous survey round, which allows us to obtain high-frequency, monthly information on labor market outcomes. The timeline of the study is provided in Appendix Figure A.2.

3 Data and Methodology

3.1 Data

3.1.1 Baseline survey data

Our sample consists of a relatively young population with an average age of about 24 years, as shown in Appendix Table A.2. 52% of our sample is female, and only 28% are married. 61% have completed high school or higher level of education. 77% of the sample is either currently looking or planning to look for work in the near future.[4] About 34% had previously used digital/online modes to search for jobs, with insignificant gender difference. But the probability of a woman being employed is half of that of men (25% vs 50%). Amongst those currently looking for work, an average of over 8 hours per day are spent on job search, majority of which (89%) is offline. Appendix Table A.3 shows that the sample is balanced across the three treatment arms for both the household and individual characteristics, overall (columns 1 – 6) as well as separately for females (columns 7 – 12) and males (columns 13 – 18).

Note that there is a high and significant correlation (0.58, $p< 0.01$) between belonging to the younger age group (18 - 24 years) and the probability of being currently enrolled in an educational institution (at baseline), for both men and women. Furthermore, younger age groups, but women only, are also less likely to be actively looking for work (0.03, $p< 0.01$). However, male youth are looking for work or actively searching for jobs (at baseline), irrespective of their enrollment status.

Next, we summarize the expectations, beliefs and perceptions about the labor market and the job search behavior of our sample at baseline:

[4]The intention to search for jobs in the future is evidenced by the fact that while over 46% of individuals were enrolled in an education institution at baseline, only 3% were enrolled after 12 months at endline.

Job market expectations: At baseline respondents were asked whether they believed they were on their ideal career path, and to select the category of occupation they aspired to, shown in Table 1, Panel A.[5] Approximately 69% of respondents, but more men than women (Panel A, column 3), reported being on their ideal career path or 'Ideal job'. Respondents were also ambitious – the predominant occupation preference was salaried positions, more so for women job seekers. Women job seekers exhibited higher aspirations for salaried positions (0.80 compared to 0.67 for men, $p = 0.00$) but lower interest in self-employment (0.14 vs 0.31, $p = 0.00$). Women were also more likely to prefer public sector or government salaried jobs (45%) than men (36%). Thus women's aspirations appear more aligned with formal, stable jobs. Youth (18 - 24 years) in our sample, exhibit similar high expectations and aspirations, particularly, for salaried work relative to the 25 and above age group (0.77 vs 0.69, $p = 0.00$).

These are in sharp contrast to the labor market realities in India. According to the nationally representative Periodic Labor Force Survey (PLFS, 2022-23), only 27.8% of individuals, in the 18-40 age group with at least high school education, in urban India are engaged in salaried jobs. This figure drops to 13.7% for those aged 18-24. Gender differences further highlight the gap, with only 15.1% of women in salaried roles compared to 39.4% of men in this demographic group. This indicates that the job seekers in our study were aspirational.

Labor market beliefs: At baseline, we asked respondents about salary expectations from a range of jobs on the partner platform. We estimate the deviation of these salary expectations from the actual salaries offered for these jobs in urban India using the nationally representative Periodic Labor Force Survey (PLFS, 2022-23).[6] We report the deviations by gender in columns 1 - 3 and age group in columns 4 - 6 in Panel B of Table 1. Job seekers reported higher expected salary than actual on average for jobs that are typically either salaried or casual. However, these deviations are smaller for the blue collar jobs, i.e. casual work. Participants, therefore, exhibited over-optimistic expectations about earnings, particularly in their preferred occupation, i.e. salaried jobs. Interestingly, men showed greater overoptimism in salary expectations relative to women (column 3), with higher deviations from actual average salary, for all jobs (INR 7878.43 vs INR 6714.31, $p = 0.00$) and for salaried jobs (INR 8608.42 vs. INR 7488.73, $p = 0.00$). This suggests men's baseline mis-perceptions were more

[5] The respondents aspirations are measured using two variables: (1) 'Ideal Job' derived from the binary response (Yes=1, No=0) to "Is the type of job you have now or the job opportunity you are looking for now aligned with your ideal career path?" and (2) Occupation type from the question "What is the career goal that you envisage for yourself?"

[6] Since individuals are likely to form expectations based on prior information or experience, we use data on occupational earnings of the urban population of India in the 2022-23 PLFS survey round (which covers the period July 2022 to June 2023), to benchmark actual labor market earnings. Our results are unchanged if we use salaries for these jobs posted on our partner platform.

pronounced (41% deviation from actual average salary vs 35% for women), particularly for preferred jobs. The gender difference in upward-biased beliefs in expected earnings is evident from Figure 1, which shows that the distribution of women's expected earnings deviated significantly less from actual earnings than men's.

While both the young (18 - 24 age group) and the older job seekers show upward-biased beliefs about occupational earnings (columns 4 and 5), the difference in deviations between the two groups (column 6) is only marginally significant overall and insignificant for salaried jobs.

Job search and application behavior: The summary statistics at baseline indicate that 41% of our sample was actively looking for work, while 34% had used online platforms for job search (Appendix Table A.2). Table 2, Panel A shows job search activity by gender, at baseline. Men are significantly more likely to have ever searched for jobs, and applied for jobs (both unconditional and conditional on having ever searched). We do not find any gender differences in the number of jobs applied for, although women search insignificantly more intensively (i.e. apply for more jobs, if ever applied) than men. We do not find significant gender differences in usage of online platforms for job search, although smartphone usage is about 30 minutes lower per day for women than men (Appendix Table A.3).

Our data suggest that women faced greater constraints in accessing job market information through traditional network of family and friends. At baseline, more women than men report that not having friends or family to discuss job opportunities with negatively affected their job search (49% vs 41%, $p<0.01$). This is corroborated by data on job search methods at baseline. In Panel B, Table 2, we condition the sample on those who have ever applied for a job to analyze the modes of job application. Both genders use family, friends and peers most for job applications or referrals (54.9%). But men are almost 9 pp more likely to utilize "weak ties", i.e. family, friends and neighbors, to search for jobs (p-value= 0.01), while women are more dependent on formal educational institutions or digital platforms (p-value= 0.05). Men also have significantly higher probability of accepting jobs that come through their weak ties, while women do not show higher acceptance rate than men in any job search mode, except (insignificantly) via educational institutions. This suggests that job offers coming to women may be less aligned with their preferences. Usage of offline modes of search, overall, dominates with 61.6% of respondents who ever applied for jobs reporting this mode of usage as against 34.5% using online or digital modes.

Overall, while the entire sample exhibited high job market aspirations and expectations, mis-beliefs (viz. earnings mis-perceptions) are higher amongst male jobseekers. Furthermore, women job seekers have lower access to traditional sources of job information and are less likely to search and apply for jobs than men. This suggests that women may experience greater informational frictions in their job search if their social networks are less amenable to providing job information or referrals.

3.1.2 Intervention take-up

We use several sources of data to assess intervention take-up: (1) survey data; (2) phone messaging data; and (3) partner platform data.

Survey data: Self-reported interest in the platform was quite high - almost 65% of participants in the treatment groups (both arms) expressed interest in registering on the platform as shown in Panel A of Appendix Table A.4. Women's interest in the platform (columns 2 - 3) was almost 10 pp higher than men's (columns 5 - 6) in both treatment arms (columns 8 and 9).[7] Of those interested in the platform, almost all registered. Unconditional on interest, registration rate was 65% overall (of those in the treatment groups), as shown in Panel A, column 1.[8] Registration rate (unconditional) for women was significantly higher than men's by 8 to 11 pp across Non-P and P groups, as shown in Panel A (columns 8 and 9). We do not find any significant difference in registration rates between and P and Non-P group (columns 4 and 7).

Phone messaging data: Appendix Table A.5 shows the delivery and receipt of phone messages by treatment group and gender. We define "delivery" as dispatch of a message either through SMS (did not bounce back) or WhatsApp (single tick) or both; "receipt" by either SMS (did not bounce back) or WhatsApp (double tick) or both and "seen" as a change of color of a double ticked WhatsApp message. Note that since recipients could have turned-off "message seen" notifications on WhatsApp, the reported average number of recipients who saw a message is a lower bound on the actual proportion of recipients who would have seen the message.

Appendix Table A.5 shows that message delivery rates did not differ between the two treatment groups (column 3 across all panels). Earlier messages were more likely to be received and seen in both groups and by gender. However, personalized messages were more likely to be received and seen than non-personalized messages (columns 6 and 9). This difference is driven primarily by male message recipients in the personalized intervention group, as shown in Panel C. It suggests that the take-up of the intervention was higher if the phone messages were personalized, particularly for men.

[7]Younger individuals, those with lower levels of education, currently not employed and those with lower levels of income also showed more interest in registering on the platform.

[8]Both interest and (unconditional) registration rates were higher for the youth (18 - 24 age group) than for the full sample – more younger women than younger men registered (higher by almost 10 pp), with insignificantly higher registration in P relative to Non-P for both genders.

Platform data: In addition to the platform registration data mentioned above, we collected detailed platform usage data from September 2023 to May 2024 (which spans the start of the intervention at Month 0 to just before Endline 1 survey in Month 6) for all the respondents who registered on the platform in both treatment groups. These data are reported in Panel B of Appendix Table A.4.[9] The data cover job seekers' activity on the platform, including whether they undertook any online skill training. Job applications could be made either through submitting an application online or via direct calls to the HR. We also observe the callbacks received by the applicants from HR of the companies they applied to.

39% of those who registered on the portal were active users (Panel B, column 1), i.e. submitted at least one job application. On average, a job seeker submitted more than 4.7 applications, mostly online. 13.7% of calls to HR were returned.[10] We do not find any significant differences in platform engagement between treatment groups (columns 4 and 7) or by gender within groups (columns 8 and 9), except that more non-P women undertook skill training, while P men (relative to P women) submitted more online job applications.

Using the platform administrative data, we assess whether phone messages influenced job seekers' engagement on the platform after each message in the week immediately following that message, over 14 weeks post the in-person intervention. Following Freyaldenhoven *et al.* (2024)'s event study framework, we analyze the effect of messages on job applications submitted online (other than direct calls to HR to apply for a job), the main mode of applying, in a specification that includes individual and week fixed effects (see details in Appendix Section B). We plot the event study estimates for each of the six messages for the pooled sample of both treatment groups in a single plot in Appendix Figure B.1 (a) for ease of visual comparison.[11] We find that the first message generated a significant effect of 0.152 ($p < 0.05$) additional applications a week later, i.e., a 9.8% increase in job applications from an average of 1.552 job applications on the platform prior to first message, for the pooled sample of both treatment groups.[12] This effect size increased with subsequent messages – for the second

[9]The platform data are available from the date of registration of the individual on the platform (or date of intervention if already registered on the platform) till May 30, 2024.

[10]Less than 10% of our sample self-reported usage of our partner platform at baseline, comparable between control and treatment groups. At Endline 1 (Endline 2), however, self-reported usage jumped to 54.4% (46%) for Non-P and 46.5% (49.3%) for P groups but remained at 1.8% (5%) for the control group. This aligns with awareness about the platform's activities – 73.5% of Non-P and 76.5% of P respondents compared to 20.2% for the control group were aware of the platform at Endline 2. Across all groups, women reported significantly higher awareness relative to men (p<0.1) at Endline 2.

[11]Each of the six messages is treated as a separate event and is shown in a distinct color in Appendix Figure B.1. The dots represent the average treatment effect over time. The coefficient for week t-1 (the week before the message) is normalized to zero to allow for estimating the marginal effect of having received the message. Note, however, that the timing of each message differs by PS and individuals therein. Hence, we present the average estimated effect for each message and do not compare the estimated effects between the P and non-P groups.

[12]After the in-person intervention and before Message 1 was sent to each respondent, on average, 1.552

message the marginal effect is 0.21 more applications ($p < 0.01$), 0.218 ($p < 0.01$) for Message 3, and remains significant at 0.176 additional job applications ($p < 0.01$) for Message 4. The marginal effect is no longer significant after Message 5 and turns significantly negative for Message 6 (-0.1, $p < 0.01$), consistent with diminishing returns to repeated nudges. Further, recall that the last two messages were specific to the government skilling program and job portal and thereby may direct respondents away from our partner platform, accounting for the decline in their activity on the platform.

Since the six messages were sent at fortnightly intervals, the weekly event study estimate of the kth message (starting from one week after the receipt of the message) captures the cumulative effects of all the prior messages.[13] The cumulative effect (as shown by the blue point estimates) grew steadily over time, as shown in Appendix Figure B.1 (a). By Week 3 the effect was significant at 0.305 (p<0.01), covering upto Message 2 and further compounds over subsequent messages to 0.467 by Week 5 (p<0.01), covering up to Message 3), 0.638 by week 7 (p<0.01), covering upto Message 4), 0.803 by Week 9 (p<0.01), covering up to Message 5), and increases to 0.882 by Week 10 (p<0.01), covering up to Message 6. The cumulative effect continues to show an upward trend – increasing to 1.335 (p<0.01) more online applications by Week 14, an 86% increment in the number of online job applications since the first message.

We find similar trends within Non-P and P groups in Appendix Figure B.1 (b) and (c), respectively. However, the P group responds earlier to the messages, with significantly higher job applications starting from the first week (Week 0, p<0.1), while the effect on Non-P group was lagged and significant only from Week 2 (p<0.1). By Week 14, the cumulative effect of the nudges was 103.6% (1.608, p<0.01) in Non-P group and 69.8% (1.084, p<0.01) in P group. The Non-P group, thus, applied to more jobs on the portal than the P group. This is consistent with the personalized messages accelerating engagement by directing respondents immediately toward relevant vacancies, whereas generic messages in the Non-P group generated a slower but larger increase in platform activity as the respondents explored the platform more broadly.[14]

job applications were made on the platform by 1,608 respondents — Non-P averaging 1.374 job applications (772 respondents) and P averaging 1.717 job applications (836 respondents).

[13]For instance, by the second week from the receipt of the first message, the second message was timed and so on. Therefore, the coefficients for Week 3 of the event study analysis of Message 1 capture the cumulative effect of these two messages.

[14]Splitting the data by gender, we find that both Non-P and P women follow a similar trajectory. By Week 14, the cumulative effect of the nudges was 132% (2.049, p<0.01) in Non-P group and 57.5% (0.892, p<0.01) in the P group. We find similar overall trends for Non-P and P group men, but with a smaller impact on job applications in the Non-P group (see Appendix Figure B.2 for details). The effects are qualitatively the same, but lower in magnitude, for job applications through calls to HR. While the number of callbacks received by respondents from HR were significantly higher from Week 2 (Week 6) onwards for the Non-P (P)

Overall, our results suggest that phone messages had an immediate and cumulative impact on job search volume in both treatment groups in the initial weeks post the in-person intervention, although the marginal effect of each subsequent message decreased.

3.1.3 Endline and attrition

Overall attrition in our sample was low at 5.49% at Endline 1 and 14.95% at Endline 2. Attrition across treatment arms was also comparable at both endlines - 5.4%, 6.1% and 4.9% at Endline 1 and 13.5%, 16.9% and 14.3% at Endline 2 in the control, Non-P and P groups, respectively. We discuss and check robustness of the results to attrition later.

3.2 Estimation strategy

We estimate the impact of the intervention on multiple outcomes, following our pre-registered analysis plan. Our main estimating equation first clubs both treatments into a single indicator of treatment status (T_v) that takes value 1 if the PS belongs to either treatment group, and 0 otherwise. The specification, therefore, is:

$$Y_{iv} = \alpha + \beta T_v + \varphi Y_{iv}^0 + \gamma' X_{iv}^0 + \epsilon_{iv} \tag{1}$$

The second specification distinguishes between the two types of treatments (Non-P and P), as follows:

$$Y_{iv} = \alpha + \beta_1 NonP_v + \beta_2 P_v + \varphi Y_{iv}^0 + \gamma' X_{iv}^0 + \epsilon_{iv} \tag{2}$$

where $NonP_v$ (P_v) is a dummy variable that takes value 1 if the PS is assigned to the in-person information session and non-personalized (personalized) phone messages and 0 otherwise. The outcome variable Y_{iv} represents multiple outcomes for individual i in cluster v post intervention. We focus on three sets of outcomes: (1) labor market beliefs and expectations; (2) job search; and (3) labor market outcomes (employment, earnings and occupational choice). Individuals' labor market beliefs and expectations are measured at the endlines while their job search behavior are recorded since the baseline survey. Employment, occupation and earnings are measured at monthly frequency, post intervention, to assess trends in impacts over time. β_1 and β_2 capture the treatment effects for $NonP_v$ and P_v, respectively, φ represents the effect of the baseline outcome Y_{iv}^0, X_{iv}^0 are the baseline individual characteristics, ϵ_{iv} is the error term.

group, we do not find any significant effect of the messages on the proportion of callbacks received from HR for either treatment.

The baseline control variables in the vector X_{iv} include the pre-specified variables – (1) household characteristics, such as asset index[15], number of young children, household size, caste, religion, and years living in current location; (2) individual characteristics, such as gender, age, marital status, whether currently looking for work, completed education of individual, smartphone usage, employment status, uses/used online job platforms for job search, and whether skill trained. Throughout the ANCOVA estimation models outlined above, the standard errors are clustered at the polling station (PS) level.

In order to address any potential employment trends in the labor market we compare the outcomes of the treatment and control groups for the same reference period (relative to the intervention timing) for the employment outcomes. We utilize the actual dates of intervention to track employment outcomes for the treatment groups over the subsequent months. We create the counterfactual period by assigning a hypothetical intervention date to each participant in the control group, (which did not receive any intervention) by analyzing the control group's outcomes starting with approximately 120 days or 4 months after the baseline survey date, i.e. the intervention time period. This allows us to compare employment outcomes at similar post-intervention time intervals for the control and treatment groups for each month post intervention and until endline, for up to 12 months. We also utilize the sequence of month-specific coefficient estimates as raw data and fit least-squares, smooth quadratic curve through the monthly estimates, using the time index and its square as predictors to capture the trend in the impact of the intervention (Abebe *et al.*, 2020).[16]

4 Main results

4.1 Expectations, beliefs and aspirations

Table 3 reports the intent-to-treat (ITT) estimates of the impact of the intervention on labor market expectations 6 months (Endline 1) and 12 months (Endline 2) post intervention using equations (1) and (2) described above. Panel A reports the results for the full sample, while Panels B and C provide the results for female and male sub-samples, respectively. The first row under 'Treatment' in each panel presents the pooled treatment effects combining both treatment groups as specified in equation (1). The subsequent rows for Non-P and P provide

[15] Using principal components analysis we create an index of household assets, such as house/land ownership, and a list of consumer durables as per the registered pre-analysis plan.

[16] Using the estimated monthly coefficients β^m for month, $m = 0, \ldots, 12$ as data points, we estimate the quadratic specification:

$$\beta^m = \theta_0 + \theta_1 m + \theta_2 m^2 + u_m, \quad m = 0, \ldots, 12 \tag{3}$$

separate estimates for the two treatment groups using equation (2). Panel D reports the gender differences in estimated effects within each group for each outcome.

The provision of job market information led to a significant downward adjustment in individuals' expectation of being on their ideal career path, as shown by the coefficient on overall treatment in columns 1 and 2 of Panel A. Respondents in the P group were significantly less likely to report 'working in or towards their ideal job' by 6.2 pp (i.e., 9.19%, $p<0.05$) at Endline 1 and 5 pp (i.e., 7.41%, $p<0.05$) at Endline 2 (Panel A, columns 1 - 2).[17] The coefficients for Non-P point in the same direction but are statistically insignificant at either endline. While there was no significant overall treatment effect on optimism about finding an ideal job (column 3), P respondents revised their perceived salary in their ideal job downwards (-0.398, $p<0.05$, column 4). The coefficients on Non-P group are insignificant. Moreover, these changes in expectations and beliefs are significant for men (Panel C, columns 1 and 4), whose beliefs and expectations were more mis-aligned than that of women at baseline (Table 1). In particular, men in the P group reduce their job market expectations significantly more than those in the Non-P group, as per the p values for the Wald Test shown in columns 1 and 4 in Panel C. Although women's expectations also fell there was no significant impact on them in both treatment groups (Panel B). In line with these results, we observe no change in investment in skill training or willingness to invest in skilling (results available on request). Note that we did not ask respondents about expected earnings in these occupations at endline.

Thus, the intervention dampened individuals' optimism about attaining ideal jobs, particularly among men in the P group, whose baseline earnings expectations were farthest from actual market wages. Men, in particular, revised salary expectations downward, while women showed an imprecise reduction. This is consistent with personalized messages leading to belief updation that could occur through Non-P messaging as well, albeit more slowly.[18]

[17] Treatment effects expressed in percentage terms are calculated as $(\frac{\hat{\beta}}{\bar{Y}_{\text{control}}} \times 100)$, where $\hat{\beta}$ is the regression coefficient from the intent-to-treat estimate and $\bar{Y}_{\text{control}}$ is the mean of the outcome variable for the control group at baseline. Refer to Supplementary Results (Table S3.1) for baseline mean values of outcomes for the control group.

[18] We do not find any effects of the intervention on occupational aspirations at Endline 2, as shown in Appendix Table A.6 and in the transition matrices shown in Appendix Figure A.3, although there is an insignificant fall in aspiration for salaried work and a move toward self-employment at Endline 2. Since occupational aspirations reflect longer-term targets, they may not respond to short-run information about the labor market, especially for the relatively young cohort in our study. Relatedly, the intervention did not yield significant aggregate effects on skilling enrollment in the full sample. For general skilling programs, neither Non-P nor P showed significant impacts. Similarly, online skilling enrollment exhibited insignificant pooled effects across all months.

4.2 Job search behavior

Table 4 presents the intent-to-treat (ITT) estimates of the treatment effect on job search behavior 6 months (Endline 1) and 12 months (Endline 2) post the intervention, for the full sample (Panel A), disaggregated by gender (Panels B and C), and estimated using equations (1) and (2) described above. The first row under 'Treatment' in each panel presents the pooled treatment effects combining both groups as specified in equation (1). The subsequent rows provide separate estimates for the two treatment groups using Equation (2). The two outcomes of interest are 'ever searched using any mode' and 'ever searched using any digital/online mode' to look for work during the previous three months from the date of the survey. Any mode of job search includes offline modes (e.g. social networks and as mentioned in Panel B of Table 2) and digital or online modes (e.g. search platforms).

The intervention reduced the likelihood of individuals reporting having 'ever searched using any mode' in the full sample, by 1.9 pp (i.e., 3.31%, $p>0.1$), relative to the baseline mean, at Endline 1 and 3.5 pp (i.e., 6.1%, $p<0.05$) at Endline 2 (Table 4, Panel A, columns 1 and 2). However, no significant overall effects were observed on the use of digital or online modes (columns 3 - 4). While the decline in offline modes of search is due to the P treatment at both endlines (3.6 pp, i.e., 8.28% $p<0.05$ at Endline 1 & 6.6 pp, i.e., 15.17% $p<0.01$ at Endline 2, we find no significant difference in impact on search by any (or online) mode between the treatment groups, as shown by the p-values of the Wald Test (WT) in last row of Panel A.[19]

While we do not find a significant impact on ever looking for work using any mode for women, both by overall treatment or by treatment group (Panel B, columns 1 - 2), we find a persistent increase in women's usage of online platforms and other digital modes for job search – by 4.3 pp (i.e., 13.07%, $p<0.05$) at Endline 1 and 6 pp (i.e., 18.24%, $p<0.01$) at Endline 2. This is attributable to the Non-P intervention at Endline 1 but P women also show a similar significant increase in online search by Endline 2, as shown by the p-values of the Wald Test (WT) in the last row of Panel B. This suggests substitution of modes of search from offline to online, by women – usage of any offline mode declined by 5.0 pp (i.e., 13.02%, $p<0.05$) overall and 7.1 pp (i.e., 18.49%) in P ($p<0.01$) at Endline 2, primarily due to reduced use of friends and family for job search in P treatment at Endline 2 (6.5 pp i.e., 19.46% , $p<0.05$).

In contrast, men exhibited a significant decline in overall job search behavior, with reductions in any mode for job search that intensified over time to 4.2 pp (i.e., 6.81%, $p<0.05$) at Endline 2, as shown in Panel C (columns 1 - 2, Table 4). This is primarily attributable

[19] Refer to Supplementary Results (Figure S1.1) for ITT estimates of the treatment effect on offline job search behavior.

to P men reducing any search by 5 pp at Endline 2. Any offline search declined by 5.9 pp (i.e., 11.97%, p<0.05) in P at Endline 2, driven by offline applications directly to employers (1.4 pp, i.e., 14.14%, p<0.1) and via their social network (4.6 pp,i.e., 10.31% p<0.1). Online platform usage for search also declined over time by 4.1 pp (i.e., 11.68%, p<0.1) at Endline 2. Again, there is no significant difference in impacts by treatment group.

These results are supported by an increase in the proportion of time spent on online job search by women in the P group – insignificantly at Endline 1 (4.01 pp, i.e., 9.11%, p>0.1) but significantly at Endline 2 by 7.66 pp (17.40%, p<0.1) – significantly different impact from the Non-P group (p<0.1). This is accompanied by reduced expenditure on offline job search – at Endline 1 and Endline 2 women in P-treatment spent about INR 58.99 (35.89%, p<0.1) and INR 37.55 (22.85%, p<0.1) less, respectively, while the estimate for Non-P women at Endline 1 is imprecise, it becomes weakly significant with a reduction of INR 45.49 (27.68%, p<0.1) at Endline 2. For men on the other hand, days per week spent on all modes of job search has a negative coefficient for both treatment groups with a magnitude of 0.232 (9.78%, p<0.1) for Non-P and 0.203 (8.56%, p<0.1) for P group at Endline 2. In line with the reduced search intensity, men significantly reduced money spent on online as well as offline job search. The observed gender differences in online job search persist and become more significant between Endline 1 and Endline 2 (Panel D, columns 3 - 4 of Table 4).[20] These gender differences in take-up of digital modes of job search are significant in both treatment groups at Endline 2, as shown in Panel D (column 4).

Consistent with the above results, estimating equations (1) and (2), we find that the overall treatment reduced total jobs applications at Endline 2 while increasing job offers received in the full sample, particularly in the P group. These effects were driven by a significant decline in applications among men and an increase in job offers for women, especially under personalized messaging but with insignificant differences between treatment arms.[21]

4.3 Labor market outcomes

4.3.1 Employment and earnings

In this section, we discuss the impact of the intervention on employment and labor market earnings across months, beginning with the month of intervention (Month 0) and 30 (x N) days after intervention for each subsequent (N*th*) month.

[20] Refer to Figure S1.2 and S1.3 of Supplementary Results.
[21] Refer to Figure S1.4 of Supplementary Results

Extensive margin: We assess the intent-to-treat (ITT) estimates of the treatment effects on current employment status over a 12-month post-intervention period, disaggregated by gender. The pooled treatment effects (combining both treatment groups) for the full sample were statistically insignificant across all months, as shown in Panel A of Figure 2. Similarly, neither Non-P nor P yielded significant effects in the full sample, although the point estimates turn positive for P women in later months. We find insignificant gender differences in this outcome.[22]

Intensive margin: We examine the impact of treatment on work intensity, measured by hours worked per day and days worked per month, over 12-months post-intervention. For the full sample, the treatment effect on both these margins (days and hours worked) was insignificant. However, we find a significant gender differential for the first two months of the intervention in the Non-P group, with men exhibiting a decline in work hours relative to women. In these same initial two months, men in the P group had significantly higher working hours relative to the Non-P group ($p<0.05$).[23]

Earnings: Panel B of Figure 2 shows the intent-to-treat (ITT) estimates of the treatment effects on monthly labor earnings (in INR) over 12 months post-intervention, disaggregated by gender. In the full sample, the intervention had mixed effects on monthly income. While the pooled treatment effect was negative in later months, primarily due to negative coefficients on men, women's earnings in P were significantly higher than women's in Non-P group in Months 9, 10 and 11 (INR 922.54, 1084.16, and 986.74, or 29.94%, 35.18%, and 32.02%, respectively, in P; P women > Non-P women ($p<0.1$)). Women in the P group also showed an increase in earnings relative to men in Month 10 after the intervention ($p = 0.076$).

Overall, these results point towards marginally better labor market outcomes in P relative to Non-P, and particularly for women in the P group.

4.3.2 Occupational choice

We assess the impact of the intervention on occupation - salaried work, casual work and self-employment. As shown in Panel A of Figure 3, the pooled treatment effects on salaried employment were positive but insignificant for the full sample and Wald tests indicate insignificant differences between Non-P and P impacts. On the other hand, we find negative

[22]We find that from Month 6 onward, men in the treatment group were more likely to have sourced information on their current job through offline channels and less through online channels, but with a modest increase through our partner platform in early months. Refer to Figure S1.5 of Supplementary Results.

[23]Refer to Figure S2.1 of Supplementary Results. This initial (significant) decline in Non-P men's intensity of work is driven by the relatively older sample (aged 25 and above) and remains significantly different from the men in the P group for six months post intervention (refer to Figure S2.2 of Supplementary Results).

treatment effects on casual labor. P group showed statistically significant decline in casual labor in Month 0 (0.8 pp, i.e., 80%, $p < 0.1$), Month 1 (0.8 pp, i.e., 80%, $p < 0.1$), and Month 4 (0.7 pp, i.e., 70%, $p < 0.1$). The Wald tests do not indicate differential impacts between Non-P and P. On the likelihood of being self-employed for the full sample, the pooled treatment effect was small and statistically insignificant across all 12 months.

Across all occupation categories, the null hypothesis of equal treatment effects for males (Panel C) and females (Panel B) is rarely rejected. However, personalized nudges (P) show marginally positive effects on women's salaried employment in later months – Month 4 (4.4 pp, i.e., 29.14%, $p < 0.1$), Month 5 (4.7 pp, i.e., 31.13%, $p < 0.1$), Month 9 (4.8 pp, i.e., 31.79%, $p < 0.1$), Month 10 (5.4 pp, i.e., 35.76%, $p < 0.1$), and Month 11 (5.3 pp, i.e., 35.10%, $p < 0.1$). However, for men the effects were insignificant throughout the 12 months post intervention. In contrast, the treatment effects were negative on women's probability of being in casual labor in both treatment groups – about 1 pp (i.e., 145.86%, $p < 0.1$) – in the early months (Months 0, 1, 2 & 4), before petering out in later months. We do not find any impacts on self-employment, by gender.

Overall, the results suggest that women in the P group exit casual work in the months immediately following the intervention (Months 0-4) and subsequently transition into salaried work (Months 4-11). This two-stage pattern suggests that the intervention first loosened women's attachment to casual work by raising the perceived return to search, then enabled upward occupational mobility as search translated into better matches. Non-P women exited casual work at similar rates without a transition to salaried work, pointing to the marginal contribution of personalization in converting improved search into occupational gains. Other than a somewhat marginal decline in P men's casual labor, we do not find evidence of any occupational transition by them.

4.4 Heterogeneity

In this section, we report impacts on our main outcomes of interest for the youth in our sample, i.e. individuals in the age group of 18 - 24 years.

A. Expectations, beliefs and aspirations

For the younger respondents in our sample, the intervention reduced the likelihood of reporting ideal jobs for P group men at both endlines while for women there is an imprecise negative effect (columns 1 - 2, Appendix Table A.7). However, there was no change in the optimism of finding the ideal job or the perceived gain in earnings in ideal jobs for either gender (columns 3 - 4). As with the overall sample, we do not find any significant impacts on occupational aspirations of youth of either gender.

These findings suggest that among the youth, the P intervention reduced reported ideal job attainment more quickly for men (at Endline 1), without altering their expectations of earnings in their ideal job.

B. Job search

The observed overall reduction in job search is driven by the youth (Panel A, columns 1 - 2, Appendix Table A.8). Younger individuals experienced pronounced and persistent negative effects on job search, which strengthened over time – 3.4 pp (i.e., 6.45%, $p < 0.1$) at Endline 1 to 4 pp (i.e., 7.59%, $p < 0.05$) decline in 'ever searched using any mode' at Endline 2. This was driven entirely by young men (-6.4 pp, i.e., 11.49%, $p < 0.01$ at Endline 2 in Panel C). Younger men also reduced online platform usage (-5.4 pp, i.e., 15.52%, $p < 0.01$) at Endline 2. In contrast, young women did not exhibit any differential effects by age (Panel B). The difference in young men and young women's response to online search was significant.

Overall, the heterogeneity analysis indicates that male youth, including those who were planning to take up employment in the near future (i.e. they were in educational institutions and not actively looking for work at baseline), experienced an adverse effect on their search behavior. These negative impacts were more pronounced 12 months after the intervention. There were, however, no significant differences in heterogeneous effects on job search by treatment group.

C. Employment, earnings and occupational choice

Employment and earnings: Younger individuals showed insignificant employment effects (Panel A of Appendix Figure A.4) in contrast to older males (25+ years) who experienced an increase in employment in the P group by 6.2 pp (i.e., 8.68%, $p < 0.1$) in Month 6 and 8.1 pp (i.e., 11.34%, $p < 0.1$) in Month 12, though the gender gap remained insignificant.[24] The positive treatment effect on monthly earning of younger individuals in P by Rs. 1010.62 (i.e., 26.67%, $p < 0.1$) in Month 2 to Rs. 1072.49 (i.e., 28.30%, $p < 0.1$) in Month 6, petered out in later months (Panel B of Appendix Figure A.4). Further, we find positive treatment effect for younger females in Month 8 to 11 (Figure (b) in Panel B) and for males in Month 4 & 6 driven by P treatment (Figure (c) in Panel B).

Occupational choice: Individuals in the 18 - 24 age groups showed no effect on the likelihood of being salaried, as shown in Panel A of Appendix Figure A.5. Young women did not show treatment effects on salaried work (Panel B). Hence the overall impact on women's salaried work mentioned above is due to the older women (25+) who exhibit positive effects

[24]Results on the 25+ age group are available on request.

on salaried work in later months in the P group – Month 5 (7.6 pp, i.e., 50%, $p < 0.05$), Month 6 (7.4 pp, i.e., 48.68%, $p < 0.05$), Month 8 (5.9 pp, i.e., 38.82%, $p < 0.1$), Month 9 (5.8 pp, i.e., 38.16%, $p < 0.1$), Month 10 (5.9 pp, i.e., 38.82%, $p < 0.1$), and Month 11 (6.6 pp, i.e., 43.42%, $p < 0.1$). On the other hand, younger women exhibit a persistent decline in casual labor due to overall treatment. For younger males, too, overall treatment (largely due to P treatment) reduced participation in casual labor (1.4 - 1.8 pp, i.e., 233.33% - 300%, $p < 0.05$) in Months 8–11 (Panel C). At the same time, we observe significant differences between Non-P and P male youth in transition towards self-employment - the latter show positive effects compared to negative coefficients on the former (both insignificant) - in later months.

Overall, younger women showed some increase in probability of being employed, which petered out. Younger women also exhibit an increase in earnings in later months. Both these effects are driven by the P group. We find some evidence of shift away from casual work by both young women and men.[25]

4.5 Robustness

In this section we conduct several robustness checks of our main results for the full sample.

Impact of treatment-on-the-treated (ToT): In addition to the intention-to-treat (ITT) estimates, we also estimate the treatment-on-the-treated (ToT) effects. For this we instrument the proportion of the six target messages delivered to respondents via WhatsApp or text with dummy variables indicating random assignment to treatment. For the joint treatment specification, we use a single indicator for assignment to either the non-personalized (Non-P) or personalized (P) message treatments.[26] For the treatment-wise specification, we include separate indicators for assignment to the NP and P treatment groups, estimating both specifications using a two-stage least squares (2SLS) framework. The first-stage F-statistics are very high, indicating strong predictive power of treatment assignment. The ToT results are qualitatively similar to the ITT estimates but with larger effect sizes, as shown in Appendix Tables A.9 and A.10. This is on expected lines as the ToT estimates capture the impact of

[25]While we find a significant decline in salary expectations and an increase in the probability of being employed amongst those who were employed at baseline; amongst those who were *not* employed at baseline – men reduced their job search, while women switched to online/digital modes of search. These results are available on request.

[26]We also generate an alternative set of ToT estimates using a stricter definition of treatment take-up – the proportion of the six target WhatsApp messages that were seen by respondents. We are able to track message views for those who enabled 'read' receipts on their mobile phones. This measure, of course, is a lower bound on the actual number of respondents who viewed the messages. Our results are consistent and larger in magnitude when we instrument for this strictest definition of compliance to message treatment.

the intervention among those who actually received the information via the messages rather than the average effect across all individuals assigned to treatment.

Attrition: The overall attrition in our sample was low and balanced across the treatment arms at both endlines - 5.4%, 6.1% and 4.9% at Endline 1 and 13.5%, 16.9% and 14.3% at Endline 2 in the control, Non-P and P groups, respectively. We test for selective attrition by comparing baseline characteristics of individuals who remained in the sample at Endline 2 with those that dropped out across treatment groups in Appendix Table A.11. While a few baseline characteristics significantly predict attrition, we find no significant differential attrition by treatment when comparing the Control group with either the Non-P or P treatments. However, we observe a significant difference ($p<0.05$) between the the Non-P and P treatments, driven by men in the sample: P-treated men are marginally more likely to be from larger household sizes ($p<0.1$) relative to those in the Non-P group.

To address any potential concerns about selective attrition, we conduct two robustness checks: (1) Lee bounds estimation and (2) Inverse Probability Weighting (IPW). The estimated lower and upper Lee bounds for treatment impacts are presented in Appendix Tables A.12 and A.13. In Panel B of Appendix Table A.12, the lower and upper bounds for use of digital platforms for search by women are significantly positive (column 3). And for men the lower (upper) bounds at Endline 2 for use of digital platforms are significantly (insignificantly) negative (column 4). If we look at the younger male sample, their job search using any or digital modes, both have a significant lower and upper bound (columns 5-7). To further address potential concerns of selective attrition, we employ Inverse Probability Weighting (IPW). We first estimate the propensity scores for being observed at Endline 2, i.e. the likelihood of remaining in the sample at the second endline, and then use these scores to weight the observations in our regressions. The IPW-adjusted estimates, presented in Appendix Tables A.14 and A.15, are qualitatively comparable to those reported in our main results. These findings rule out any selective attrition and reinforce the robustness of our main findings.

Multiple Hypothesis Testing: Since we examine the impact of the intervention on several job search and labor market expectations outcomes, we compute the Michael Anderson's False Discovery Rate (FDR) q-values to allay any concerns of false rejections. In Appendix Tables A.16 and A.17 we report the original p-values in parentheses and the FDR adjusted p-values of our main estimates in square brackets. The results for job search outcomes remain robust after applying the FDR correction, indicating a stronger reliance of women on digital platforms, whereas men appear to reduce their job search. The negative effects on ideal job expectations of men in P group are now marginally significant in Panel C of Appendix Table A.17.

Sample Selection: In the monthly analysis of the labor market outcomes, we do not observe the full sample of individuals throughout the 12 months. In particular, our sample size is smaller in later months. To address potential sample selection concerns, we re-estimate the main specification using Inverse Probability Weighting (IPW) where the monthly propensity scores, i.e., the likelihood of the respondents being present in each month, are used as weights. Our previous results are qualitatively unchanged as shown by the IPW ITT estimates for earnings (Panel A) and occupational outcomes of women (Panel B) in Appendix Figure A.6. In Panel A, the weighted earnings of women in the P group remain significantly higher than women in the Non-P group for Months 9, 10, and 11, consistent with the findings reported in Section 4.2. In Panel B, we continue to find significant treatment effect on salaried employment for women in the P group and a reduction in casual labor, with no impact on self-employment. Treatment impacts on men's occupation (and other labor market outcomes) remain statistically insignificant throughout, and are not shown here for brevity.

5 Discussion and mechanisms

In this section we summarize the key take-ways from our analysis and the mechanisms that potentially explain our results.

1. Informational interventions affect individuals' priors on labor market opportunities

Recall that at baseline, respondents' job market expectations were significantly misaligned with the realities of the labor market. Men, in particular, entered the study with significantly greater job market optimism relative to women, as discussed previously in Table 1 and Figure 1. More men believed they were already in, or on track toward their ideal job and expected earnings that were substantially higher than the market wages for comparable jobs. On being exposed to the informational intervention, we observe a significant recalibration of the ideal job expectations, particularly among men, as shown in Table 3.

Assessing heterogeneity in treatment impact on ideal job expectations by baseline expectations, we find that individuals who believed they were already in, or on track towards their ideal job at baseline, were more likely to lower their expectations at Endline 2 – whether they were working in or looking for their ideal job and perceived gain in earnings in their ideal job (columns 2 and 4, respectively, in Panel A of Table 5) – significantly in the P group. While those who reported not being on track also lowered expectations at Endline 1 in the P group, they recovered by Endline 2 (columns 5 and 6, respectively).

Women, who believed they were on-track to their ideal job, significantly lowered their perceived earnings gains at Endline 2 (Panel B, column 4) in both P and Non-P groups. On the other hand, women who believed they were 'not on track' raised their perceived earnings in their ideal job in the Non-P group (Panel B, column 8). For men, however, the P treatment reduced the likelihood of reporting ideal job attainment by 8.0 pp ($p<0.05$) at Endline 1 and 8.2 pp ($p<0.05$) at Endline 2, as shown in Panel C of Table 5. The Non-P treatment also shows a marginally significant negative effect of 6.9 pp ($p<0.1$) for men, but only at Endline 2. Moreover, P men who reported not being on track at baseline, also reduce their perception of earnings gains at Endline 2 ($p<0.01$), as shown in Panel C, column 8. The overall treatment impact on the perceived earnings gain by those who report being 'not on track' at baseline is significantly different for men and women (Panel D, column 8). Hence, men's expectations fell persistently and irrespective of whether they believed they were on track or not at baseline.

We further explore heterogeneity of treatment impacts on the perceived earnings gain in the ideal job by classifying our sample into two groups – (1) 'Upward biased', i.e whose average expected salary was *higher* than the actual average salary across occupations at baseline and (2) 'Downward biased', i.e. whose average expected salary was *lower* than the actual average salary across occupations at baseline, as discussed previously in Table 1. Panel C in Table 6 shows that the P treatment generated a significant downward revision in perceived salary gains in the ideal job for men with upward-biased expectations (-0.426, $p<0.05$) at Endline 2, though insignificantly different from men in the Non-P group ($p=0.123$). This effect is insignificant among women (Panel B) with upward-biased expectations. These findings reinforce the mechanism of personalized information being effective at correcting beliefs among those whose priors were biased upwards relative to market realities. Men entered the study with greater overoptimism in salary expectations relative to women. Accordingly, men, particularly those in the P group, exhibit significant corrections in the expected gain in earnings in their ideal job.

Consistent with belief correction, we show two pieces of supporting evidence. First, we find a 2.2 pp ($p<0.1$) higher probability of men in the P group being enrolled in an educational institution Endline 2, as shown in Panel C, column 2 of Table 7. This effect is strongly driven by P men who are 5.4 pp ($p<0.05$) more likely to remain enrolled in education, if they were enrolled at baseline (Panel C, column 4).[27] On the other hand, women in both groups responded to the intervention by enrolling into education, if not enrolled at baseline (Panel B, column 6), suggesting that the intervention encouraged women to invest in their labor market skills.[28] These enrollment effects are significantly different by gender, particularly in

[27]In particular, younger men were more likely to be enrolled in education at Endline 2. They deferred entry into the labor force and chose to (remain) enrolled in education following the intervention (Appendix Table A.18).

[28]Indeed, individuals (irrespective of gender) who were enrolled at baseline were 18.75 pp more likely to

the P group (Panel D, columns 4 and 6).

Second, we find suggestive evidence of an increase in P individuals' self-reported satisfaction with their current employment at Endline 2. Respondents who were employed at Endline 2 report higher satisfaction with their current job on multiple dimensions (Panel A, Appendix Table A.19).[29] The P group reported higher satisfaction with monetary, non-monetary compensation and other work characteristics by 0.143 to 0.275 standard deviations (Panel A, columns 1 - 6). Women in both treatment arms report an increase in overall, monetary, and non-monetary satisfaction of similar magnitude (Panel B, columns 1-3). For men, however, this effect was significantly more pronounced in the P group, with satisfaction improving by 0.187 - 0.244 standard deviations across all dimensions (Panel C, columns 1 - 6). These results provide suggestive evidence that individuals, particularly men in the P group, update their beliefs following the intervention and consequently reconcile with the job at hand.

In summary, while both men and women, with upward-biased beliefs, lower their labor market expectations, there is a strong gender difference. First, men, who had significantly higher expectations at baseline, show more significant corrections of their beliefs than women. Second, women appear less disheartened by the new information. They respond to the new information by enrolling in educational institutions to upgrade their skills, while men respond by maintaining status quo.

2. Informational interventions affect job search behavior by updating prior beliefs and labor market expectations

The intervention generated opposing job search responses in men and women. While men reduced job search, women shifted to using digital modes of search without a change in job search intensity as shown previously in Table 4.

Table 8 shows the heterogeneity of the job search effects at endline by baseline earnings mis-match, i.e. upward or downward biased. Those whose earnings expectations were biased upwards (columns 1 - 4), show a decline in ever searching for a job by 3.7 pp in column (2) of Panel A. This decline is stronger for the P group (column 2 of Panel A). In contrast, those with downward biased salary expectations (columns 5 - 8), show no significant effect on job search in Panel A. Consistent with this, we indeed find that the decline in job search

report 'will look for work in the future' at Endline 2 than those not enrolled, suggesting deferment of labor market entry and upskilling to improve employment outcomes. On the other hand, we find a significant increase in the probability that men, who were not enrolled at baseline, were employed at endline due to either treatment from Month 6, and sustained through Month 12, peaking at 10.6 pp. Results available on request.

[29]This question was asked only to respondents who were employed, at Endline 2. We, therefore, do not claim causal effects of treatment on reported job satisfaction.

is driven entirely by the over-optimistic sub-sample of men ($p<0.05$, column 2 of Panel C in Table 8).[30] Conversely, Non-P men with downward-biased beliefs increase job search at Endline 2 by 25.4 pp ($p<0.05$, column 6 of Panel C in Table 8). Interestingly, the impact on women's job search behavior is driven by the over-optimistic sub-sample of women who increased usage of digital modes of search by Endline 2 in both treatment groups, as shown in Panel B (column 4 of Table 8). But there is no impact on job search by women with downward-biased expectations (Panel B, columns 5 - 8).

Thus, for men the mechanism that explains the decline in their job search intensity runs through the correction of their over-optimistic labor market expectations at baseline. The information intervention primarily served to correct high expectations, resulting in reduced search effort. As one would expect, when the anticipated returns to search are lower than expected, the marginal return from costly job search effort falls. This is corroborated by men's reduced expenditure on any mode of job search, discussed previously in Section 4.2. On the other hand, we hypothesize that the impact on women can be explained by the fact that their beliefs were less mis-aligned with reality, and that they faced higher information frictions in job search at baseline.

In urban India, where overall female labor force participation is low, women often lack reliable information on job opportunities through their networks (Caria *et al.*, 2024). The limited information they do receive is typically generic and shared through working men in their social network (Afridi *et al.*, 2023), effectively reflecting the preferences and experiences of male contacts rather than women's own aspirations. Women entered our study with lower exposure to the labor market, reflected in lower employment rates and lower likelihood of applying for jobs even when seeking work (69% compared to 74% for men, Table 2). In addition, significantly more women in our sample were married and had children (relative to men), possibly constraining the time allocated to job search. Indeed, only 57% of women reported actively searching relative to 61% of men, despite women expressing a 6 pp higher desire to find work (Table 2).

By providing credible information on job availability on the platform, the intervention may have reduced women's perceived cost of searching for jobs, regardless of the type of messages. This is reflected in greater take-up of the intervention – women were 10 pp more likely to express interest in registering on the platform and almost 10 pp more likely to register than men (Appendix Table A.4). Consequently, women switch to more efficient modes of job search with no change in their overall search intensity – they increase the time spent on online search and reduce expenditure on offline search, as discussed in Section 4.2

[30] This effect is concentrated among younger men with upward biased expectations, who reduced their job search due to the overall treatment by 4.3 pp ($p<0.1$) at Endline 1 and by 8 pp ($p<0.01$) at Endline 2 (Appendix Table A.20).

above. Furthermore, treated women report 7.4 pp ($p<0.01$) higher awareness of and 0.39 ($p<0.1$) more job viewings on the government job portal (on which the last two messages provided information) at Endline 1 (refer to Appendix Table A.21). This pattern aligns with women's baseline aspirations for public sector (salaried) work — the type of jobs most accessible on government (digital) platforms.

Thus, while men's belief adjustments may have fed into lower intensity of job search due to the information intervention, it simultaneously encouraged women to search for jobs using non-traditional modes by reducing their information frictions and providing access to job openings that aligned with their preferences.

3. Personalized information may be more effective at improving labor market outcomes of individuals with job search frictions

As discussed previously, women exhibit lower access to traditional networks of family, friends and neighbors for job search and information at baseline. Consequently, we find that women, who applied for more jobs through traditional networks (at baseline), were less likely to shift to online modes of job search due to treatment (see Supplementary Results Table S1.1). Thus, due to the intervention, online modes of search substituted for traditional networks in job search assistance for women who had lower network support. Moreover, this substitution is driven by women who received personalized labor market information.

Recall that it is the women in the personalized group who transition out of casual work and into salaried work in later months of our study. At the same time, their labor earnings are marginally higher. We do not find such impact for men in either group or women in the Non-P group. In line with the marginally significant improvement in P women's labor market outcomes, we find that women in this group viewed 0.76 more jobs on the government portal at Endline 1, significantly different from the Non-P women (see Appendix Table A.21).

Thus, tailoring messages by women's job preferences may have ensured that respondents aspiring to specific types of jobs were guided towards relevant vacancies and job openings. Therefore, personalization of information may have improved search efficiency by directing women job seekers, who face greater informational frictions, toward vacancies aligned with their specific preferences. This is reflected in their search behavior and labor market outcomes. In contrast, the increased digital search effort observed among Non-P women did not translate into occupational transitions or earnings gains comparable to those in the P group.

6 Conclusion

This study examines the nature of information provision – combining in-person information sessions with personalized and non-personalized nudges – in improving the efficiency of job search, employment outcomes, and occupational choice among job seekers in Delhi, India. The intervention sought to mitigate labor market frictions by leveraging a digital job-matching platform and addressing information gaps. Our field-based randomized controlled trial (RCT) reveals nuanced, heterogeneous effects, highlighting both the potential and limitations of such interventions in a low-income, urban context.

The intervention reduced the overall likelihood of individuals reporting having ever looked for work, driven primarily by men, particularly younger men. Conversely, women increased their engagement with online job platforms, narrowing the gender gap in digital job search. Aggregate employment effects were muted, but personalized nudges marginally increased the earnings of women in the P group in later months as the personalized intervention facilitated their transition to salaried employment. Our results can be explained by individuals' prior (mis-)beliefs and high labor market expectations, and their interactions with pre-existing information frictions. Those individuals who were overly optimistic were more likely to revise their labor market expectations downwards and consequently reduce job search. On the other hand, individuals' with relatively more realistic beliefs, such as women, correct their labor market expectations but do not reduce job search intensity. Instead, women leveraged digital modes of job search and the personalized information to marginally improve their labor market outcomes due to greater frictions they face in accessing labor market information.

Our study contributes to the emerging literature on the role of informational frictions in labor market outcomes. It allows us to understand the types of outreach that may lead to more efficient job search. Specifically, we highlight the gendered impact of providing job market information, as well as the nature and mode of information in addressing labor market frictions in low-income, high unemployment settings.

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Table 1: Job expectations and labor market beliefs (at baseline)

Variable	Gender			Age		
	Female	Male	Diff [*p*-value]	18 to 24	25 & above	Diff [*p*-value]
	Panel A: Job Expectations					
	(1)	(2)	(3)	(4)	(5)	(6)
Ideal job	0.68	0.71	[0.058]	0.70	0.68	[0.133]
Salaried work	0.80	0.67	[0.000]	0.77	0.69	[0.000]
Public sector	0.45	0.36	[0.000]	0.46	0.32	[0.000]
Non-public sector	0.35	0.31	[0.012]	0.31	0.37	[0.001]
Self-employed work	0.14	0.31	[0.000]	0.18	0.28	[0.000]
Not in labor force	0.05	0.02	[0.000]	0.04	0.03	[0.035]
Panel B: Deviation of Expected Monthly Salary from Actual (INR)						
	(1)	(2)	(3)	(4)	(5)	(6)
All	6714.31	7878.43	[0.000]	7069.34	7580.50	[0.082]
Salaried	7488.73	8608.42	[0.000]	7848.52	8293.87	[0.225]
Accounts keeper	5847.50	7958.07	[0.000]	7237.87	6276.44	[0.114]
Teacher in primary school	8384.65	10685.18	[0.003]	9010.73	10211.87	[0.123]
Data entry operator	6946.52	7785.82	[0.111]	7060.26	7788.43	[0.176]
Hospital attendant/nurse	8776.24	8004.62	[0.139]	8085.22	8898.72	[0.127]
Casual	5165.46	6418.45	[0.000]	5510.97	6153.75	[0.055]
Worker in garment factory	5980.91	6748.36	[0.006]	6148.37	6653.75	[0.075]
Electrician/Fitter	4350.01	6088.53	[0.002]	4873.56	5653.76	[0.169]
Obs	1768	1623		2050	1341	

Note: **Panel A** shows the proportion of respondents selecting an employment category, *Self-employed* or *Salaried (Public sector or Non-public sector)* or to *Not in labor force* at baseline, disaggregated by gender (columns 1 - 2) and age (columns 4 - 5). Proportions are based on responses to the question: "What is the career goal that you envisage for yourself?" with original response options recoded into two categories: *Self-employed* includes options 1 (Start your own business), 6 (Work for own or family farm) and 8 (Work for family business); *Salaried* includes options 2 (Work for government or public sector), 3 (Work for an MNC), 4 (Work for a private company), 5 (Work for nonprofit organization), 7 (Work on someone else's farm), and 9 (Professional doctor, lawyer, certified public accountant, etc.)); *Not be in labor force* includes options 10 (Be a housewife) and 11 (Pursue higher education). The *Ideal Job* variable is derived from the binary response (Yes=1, No=0) to "Is the type of job you have now or the job opportunity you are looking for now aligned with your ideal career path?" **Panel B** shows the deviation of respondents' expected monthly salary elicited at baseline from the average weighted monthly earnings for each job category/type in the urban sample of the PLFS (2022-23). *All* represents the aggregate across all job types; *Salaried* includes accounts keeper, teacher in primary school, data entry operator, and hospital attendant/nurse; *Casual* worker in garment factory and electrician/fitter. *p*-values of gender (age group) difference reported in column 3 (6).

Table 2: Job search and application behavior (at baseline)

Panel A: Full Sample				
	All (N=3,391) (1)	**Female** (N=1,768) (2)	**Male** (N=1,623) (3)	**Female - Male** (4)
Prop. ever searched for job	0.585	0.565	0.606	-0.041**
Prop. ever applied for job (full sample)	0.420	0.392	0.450	-0.058***
Prop. ever applied for job (if ever searched)	0.718	0.694	0.743	-0.049**
No. of jobs applied (full sample)	2.747	2.972	2.503	0.469
No. of jobs applied (if ever searched)	4.698	5.259	4.128	1.131
No. of jobs applied (if ever searched and applied)	6.542	7.582	5.557	2.025
Panel B: If Ever Applied for a Job				
Application Mode	**All** (N=1,424) (1)	**Female** (N=693) (2)	**Male** (N=731) (3)	**Female - Male** (4)
All offline modes				
Prop. applied using this mode	0.616	0.583	0.647	-0.064***
No. of jobs applied	2.256	2.15	2.356	-0.206
No. of calls to HR	1.590	1.479	1.695	-0.216
Prop. of interviews received	0.711	0.666	0.751	-0.085*
Prop. of job offers received	0.576	0.554	0.596	-0.042
Prop. of offers accepted	0.614	0.572	0.648	-0.076**
Family, neighbors and peers				
Prop. applied using this mode	0.549	0.504	0.592	-0.089***
No. of jobs applied	1.871	1.654	2.078	-0.424***
No. of calls to HR	1.346	1.193	1.490	-0.296**
Prop. of interviews received	0.705	0.669	0.736	-0.067
Prop. of job offers received	0.577	0.561	0.590	-0.029
Prop. of offers accepted	0.617	0.562	0.659	-0.097**
Offline job ads				
Prop. applied using this mode	0.029	0.033	0.025	0.008
No. of jobs applied	0.178	0.250	0.111	0.139
No. of calls to HR	0.072	0.095	0.049	0.046
Prop. of interviews received	0.546	0.550	0.541	0.010
Prop. of job offers received	0.320	0.327	0.311	0.017
Prop. of offers accepted	0.500	0.367	0.654	-0.287
Educational institutions				
Prop. applied using this mode	0.064	0.077	0.052	0.025**
No. of jobs applied	0.206	0.247	0.167	0.080*
No. of calls to HR	0.173	0.190	0.156	0.035
Prop. of interviews received	0.738	0.657	0.855	-0.197
Prop. of job offers received	0.599	0.560	0.654	-0.094
Prop. of offers accepted	0.571	0.624	0.504	0.120
All online modes				
Prop. applied using this mode	0.345	0.373	0.319	0.054**
No. of jobs applied	4.257	5.411	3.163	2.248
No. of calls to HR	1.756	1.781	1.732	0.049
Prop. of interviews received	0.550	0.524	0.577	-0.053
Prop. of job offers received	0.393	0.411	0.375	0.036
Prop. of offers accepted	0.502	0.228	0.781	-0.553

Note: The table shows self-reported survey data on respondents' job search behavior and modes of search at baseline. **Panel A** shows the average response for the full sample. In **Panel B** the sample is conditional on respondents who report having ever searched for work and applied for work, at baseline. Proportion of interviews received, job offers received (accepted) are conditional on having applied (received offer) to at least one job in that mode. 'All offline modes' includes: (1) Family, neighbors and peers; (2) Offline job ads and (3) Educational institutions. Column (4) shows the female vs. male differences. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table 3: Impact of information on ideal job expectations

	Working in an ideal job/ working towards it		Optimism for getting ideal job (if applied)	Perceived earnings gain in ideal job
	Endline 1	Endline 2	Endline 2	Endline 2
	(1)	(2)	(3)	(4)
Panel A - Full Sample				
Treatment	-0.039*	-0.039*	0.001	-0.268
	(0.023)	(0.022)	(0.041)	(0.165)
Non-P	-0.016	-0.028	0.027	-0.130
	(0.026)	(0.025)	(0.048)	(0.199)
P	-0.062**	-0.050**	-0.024	-0.398**
	(0.029)	(0.024)	(0.047)	(0.200)
WT	[0.121]	[0.329]	[0.304]	[0.235]
Obs.	3162	2845	2672	2305
Panel B - Female				
Treatment	-0.029	-0.036	-0.011	-0.256
	(0.030)	(0.027)	(0.044)	(0.200)
Non-P	-0.020	-0.029	0.023	-0.162
	(0.033)	(0.033)	(0.051)	(0.226)
P	-0.037	-0.043	-0.043	-0.345
	(0.037)	(0.029)	(0.051)	(0.249)
WT	[0.649]	[0.663]	[0.206]	[0.479]
Obs.	1675	1512	1405	1222
Panel C - Male				
Treatment	-0.049*	-0.042	0.009	-0.262
	(0.027)	(0.030)	(0.058)	(0.177)
Non-P	-0.014	-0.027	0.026	-0.053
	(0.032)	(0.034)	(0.069)	(0.218)
P	-0.084***	-0.056	-0.007	-0.458**
	(0.032)	(0.034)	(0.067)	(0.205)
WT	[0.043]	[0.347]	[0.649]	[0.087]
Obs.	1487	1333	1267	1083
Panel D - $H_0 : \beta(M) = \beta(F)$				
Treatment	[0.542]	[0.871]	[0.748]	[0.977]
Non-P	[0.859]	[0.970]	[0.970]	[0.589]
P	[0.253]	[0.738]	[0.618]	[0.618]

Note: In columns (1) - (2) the dependent variable is an indicator that takes a value of one if the respondent reports working in their ideal job or looking for a job aligned with their ideal career path, and zero otherwise; in column (3) the dependent variable takes value 1 if the respondent is very pessimistic, 2 if pessimistic, 3 if optimistic, 4 if very optimistic about getting their ideal job, and 5 if they are already in their ideal job. In column (4), the dependent variable is the range of monthly salary they expect to gain from their ideal/aspiring job, which ranges from 1 if No change, 2 if Less than 1000 INR, 3 if 1000-5000 INR, 4 if 5001-7500 INR, 5 if 7501-10000 INR, 6 if 10001-20000 INR, 7 if 20001-50000 INR, 8 if 50001-100000 INR, and 9 if more than 100,000 INR expected change. **Panel A** includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel D** reports p-values for tests of equality of treatment effects between males and females within each group. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table 4: Impact of information on job search

	Ever searched using any mode		Ever searched using any digital/online mode	
	Endline 1	Endline 2	Endline 1	Endline 2
	(1)	(2)	(3)	(4)
Panel A - Full Sample				
Treatment	-0.019	-0.035**	0.016	0.012
	(0.015)	(0.013)	(0.015)	(0.015)
Non-P	-0.015	-0.029*	0.027	0.017
	(0.017)	(0.015)	(0.018)	(0.018)
P	-0.024	-0.040**	0.006	0.007
	(0.017)	(0.016)	(0.018)	(0.018)
WT	[0.555]	[0.472]	[0.262]	[0.629]
Obs	3162	2845	3162	2845
Panel B - Female				
Treatment	-0.021	-0.027	0.043**	0.060***
	(0.020)	(0.019)	(0.018)	(0.020)
Non-P	-0.017	-0.024	0.068***	0.069***
	(0.023)	(0.022)	(0.021)	(0.025)
P	-0.024	-0.030	0.019	0.052**
	(0.023)	(0.022)	(0.021)	(0.025)
WT	[0.730]	[0.806]	[0.029]	[0.589]
Obs	1675	1512	1675	1512
Panel C - Male				
Treatment	-0.016	-0.042**	-0.012	-0.041*
	(0.019)	(0.018)	(0.024)	(0.024)
Non-P	-0.011	-0.034	-0.015	-0.039
	(0.022)	(0.022)	(0.028)	(0.028)
P	-0.020	-0.050**	-0.010	-0.043
	(0.020)	(0.020)	(0.026)	(0.027)
Wald Test	[0.640]	[0.475]	[0.852]	[0.868]
Obs	1487	1333	1487	1333
Panel D - $H_0 : \beta(M) = \beta(F)$				
Treatment	[0.839]	[0.542]	[0.047]	[0.001]
Non-P	[0.840]	[0.763]	[0.012]	[0.004]
P	[0.881]	[0.471]	[0.320]	[0.007]

Note: The dependent variables is an indicator that takes a value of one if the respondent reports having ever searched for a job using any mode at Endline 1 (column 1) or at Endline 2 (column 2); ever searched for a job using any digital or online mode in the reference period at Endline 1 (column 3) or Endline 2 (column 4). **Panel A** includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel D** reports p-values for tests of equality of treatment effects between males and females within each group. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table 5: Impact of information on ideal job expectations (by on-track to ideal job at baseline)

	On track to ideal job (at baseline)				Not on track to ideal job (at baseline)			
	Working in an ideal job/ working towards it		Optimism for getting ideal job (if applied)	Perceived earnings gain in ideal job	Working in an ideal job/ working towards it		Optimism for getting ideal job (if applied)	Perceived earnings gain in ideal job
	Endline 1	Endline 2	Endline 2	Endline 2	Endline 1	Endline 2	Endline 2	Endline 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Full Sample								
Treatment	-0.038	-0.050*	0.011	-0.348*	-0.036	-0.015	-0.026	-0.124
	(0.025)	(0.027)	(0.048)	(0.188)	(0.036)	(0.036)	(0.056)	(0.209)
Non-P	-0.028	-0.040	0.050	-0.285	0.019	0.001	-0.032	0.187
	(0.028)	(0.030)	(0.058)	(0.222)	(0.040)	(0.043)	(0.070)	(0.242)
P	-0.048	-0.061**	-0.025	-0.409*	-0.086**	-0.030	-0.020	-0.402
	(0.031)	(0.029)	(0.053)	(0.226)	(0.042)	(0.042)	(0.066)	(0.263)
WT	[0.534]	[0.391]	[0.185]	[0.614]	[0.009]	[0.489]	[0.874]	[0.050]
Obs.	2195	1972	1848	1586	967	873	824	719
Panel B - Female								
Treatment	-0.025	-0.026	0.040	-0.498**	-0.041	-0.052	-0.108	0.163
	(0.032)	(0.034)	(0.059)	(0.223)	(0.048)	(0.047)	(0.066)	(0.260)
Non-P	-0.035	-0.011	0.096	-0.518**	0.011	-0.058	-0.126*	0.500*
	(0.037)	(0.039)	(0.066)	(0.256)	(0.053)	(0.063)	(0.074)	(0.281)
P	-0.015	-0.040	-0.012	-0.480*	-0.092	-0.046	-0.091	-0.167
	(0.040)	(0.037)	(0.065)	(0.266)	(0.057)	(0.050)	(0.081)	(0.342)
WT	[0.631]	[0.376]	[0.071]	[0.890]	[0.057]	[0.858]	[0.674]	[0.067]
Obs.	1139	1028	956	835	536	484	449	387
Panel C - Male								
Treatment	-0.053*	-0.075**	-0.018	-0.168	-0.040	0.021	0.075	-0.459**
	(0.031)	(0.032)	(0.065)	(0.228)	(0.050)	(0.054)	(0.082)	(0.230)
Non-P	-0.028	-0.069*	-0.001	-0.013	0.016	0.065	0.075	-0.088
	(0.034)	(0.036)	(0.079)	(0.258)	(0.061)	(0.060)	(0.117)	(0.304)
P	-0.080**	-0.082**	-0.034	-0.324	-0.085	-0.015	0.075	-0.742***
	(0.037)	(0.036)	(0.075)	(0.272)	(0.053)	(0.065)	(0.087)	(0.280)
WT	[0.160]	[0.683]	[0.701]	[0.251]	[0.074]	[0.202]	[0.995]	[0.074]
Obs.	1056	944	892	751	431	389	375	332
Panel D - $H_0 : \beta(M) = \beta(F)$								
Treatment	[0.463]	[0.208]	[0.440]	[0.181]	[0.992]	[0.286]	[0.051]	[0.026]
Non-P	[0.861]	[0.214]	[0.257]	[0.051]	[0.953]	[0.166]	[0.106]	[0.085]
P	[0.161]	[0.340]	[0.806]	[0.588]	[0.923]	[0.684]	[0.124]	[0.101]

Note: In columns (1) - (2) and (5) - (6) the dependent variable is an indicator that takes a value of one if the respondent reports having their ideal job or looking for a job opportunity aligned with their ideal career path career path now, and zero otherwise; in column (3) and (7) the dependent variable takes value 1 if the respondent is very pessimistic, 2 if pessimistic, 3 if optimistic, 4 if very optimistic about getting their ideal job, and 5 if they are already in their ideal job. In column (4) and (8), the respondents choose from a range of monthly salary they expect to gain from ideal/aspiring job, which ranges from 1 if No change, 2 if Less than 1000 INR, 3 if 1000-5000 INR, 4 if 5001-7500 INR, 5 if 7501-10000 INR, 6 if 10001-20000 INR, 7 if 20001-50000 INR, 8 if 50001-100000 INR, and 9 if more than 100,000 INR expected change. **Panel A** includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel D** reports p-values for tests of equality of treatment effects between males and females within each group. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table 6: Impact of information on perceived earnings gain in ideal job (by earnings mis-match at baseline)

	Upward biased expectations (at baseline)	Downward biased expectations (at baseline)
	(1)	(2)
Panel A - Full Sample		
Treatment	-0.267	-0.205
	(0.165)	(0.366)
Non-P	-0.152	0.097
	(0.203)	(0.403)
P	-0.378*	-0.416
	(0.200)	(0.399)
WT	[0.334]	[0.130]
Obs.	2042	263
Panel B - Female		
Treatment	-0.279	-0.177
	(0.203)	(0.428)
Non-P	-0.215	0.089
	(0.229)	(0.470)
P	-0.341	-0.372
	(0.257)	(0.477)
WT	[0.642]	[0.280]
Obs.	1050	172
Panel C - Male		
Treatment	-0.240	-0.204
	(0.182)	(0.547)
Non-P	-0.048	0.262
	(0.228)	(0.660)
P	-0.426**	-0.472
	(0.209)	(0.593)
WT	[0.123]	[0.156]
Obs.	992	91
Panel D - $H_0 : \beta(M) = \beta(F)$		
Treatment	[0.847]	[0.965]
Non-P	[0.432]	[0.807]
P	[0.732]	[0.876]

Note: An individual is classified as having 'Upward biased' ('Downward biased') expectations if their average expected salary was more (less) than the average weighted monthly earnings from PLFS 2022-23 urban sample, at baseline. The respondents choose from a range of monthly salary they expect to gain from ideal/aspiring job, which ranges from 1 if No change, 2 if Less than 1000 INR, 3 if 1000-5000 INR, 4 if 5001-7500 INR, 5 if 7501-10000 INR, 6 if 10001-20000 INR, 7 if 20001-50000 INR, 8 if 50001-100000 INR, and 9 if more than 100,000 INR expected change. **Panel A** includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel D** reports p-values for tests of equality of treatment effects between males and females within each group. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table 7: Impact of information on enrollment in educational institution

	Enrolled		If enrolled (at baseline)		If not enrolled (at baseline)	
	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Full Sample						
Treatment	0.017	0.009	0.030	0.013	0.002	0.007
	(0.019)	(0.007)	(0.034)	(0.013)	(0.014)	(0.005)
Non-P	0.004	0.005	0.023	0.004	-0.015	0.008
	(0.022)	(0.008)	(0.041)	(0.015)	(0.015)	(0.006)
P	0.030	0.013	0.038	0.022	0.017	0.007
	(0.021)	(0.008)	(0.037)	(0.016)	(0.016)	(0.006)
WT	[0.202]	[0.335]	[0.690]	[0.275]	[0.035]	[0.827]
Obs	3162	2845	1478	1323	1684	1522
Panel B - Female						
Treatment	0.028	0.003	0.036	-0.012	0.022	0.015***
	(0.023)	(0.008)	(0.047)	(0.018)	(0.017)	(0.006)
Non-P	0.010	0.001	0.015	-0.014	0.003	0.014**
	(0.027)	(0.010)	(0.057)	(0.020)	(0.018)	(0.007)
P	0.045*	0.005	0.058	-0.010	0.039*	0.017**
	(0.024)	(0.010)	(0.049)	(0.021)	(0.020)	(0.008)
WT	[0.133]	[0.694]	[0.410]	[0.808]	[0.057]	[0.805]
Obs	1675	1512	716	648	959	864
Panel C - Male						
Treatment	0.005	0.015	0.022	0.038**	-0.019	-0.004
	(0.025)	(0.010)	(0.043)	(0.018)	(0.022)	(0.008)
Non-P	-0.001	0.008	0.025	0.021	-0.031	-0.002
	(0.029)	(0.011)	(0.049)	(0.020)	(0.024)	(0.010)
P	0.010	0.022*	0.019	0.054**	-0.009	-0.006
	(0.029)	(0.013)	(0.050)	(0.023)	(0.025)	(0.008)
WT	[0.679]	[0.288]	[0.906]	[0.179]	[0.293]	[0.574]
Obs	1487	1333	762	675	725	658
Panel D - $H_0 : \beta(M) = \beta(F)$						
Treatment	[0.445]	[0.364]	[0.807]	[0.047]	[0.114]	[0.039]
Non-P	[0.757]	[0.637]	[0.890]	[0.171]	[0.251]	[0.180]
P	[0.308]	[0.300]	[0.550]	[0.042]	[0.105]	[0.041]

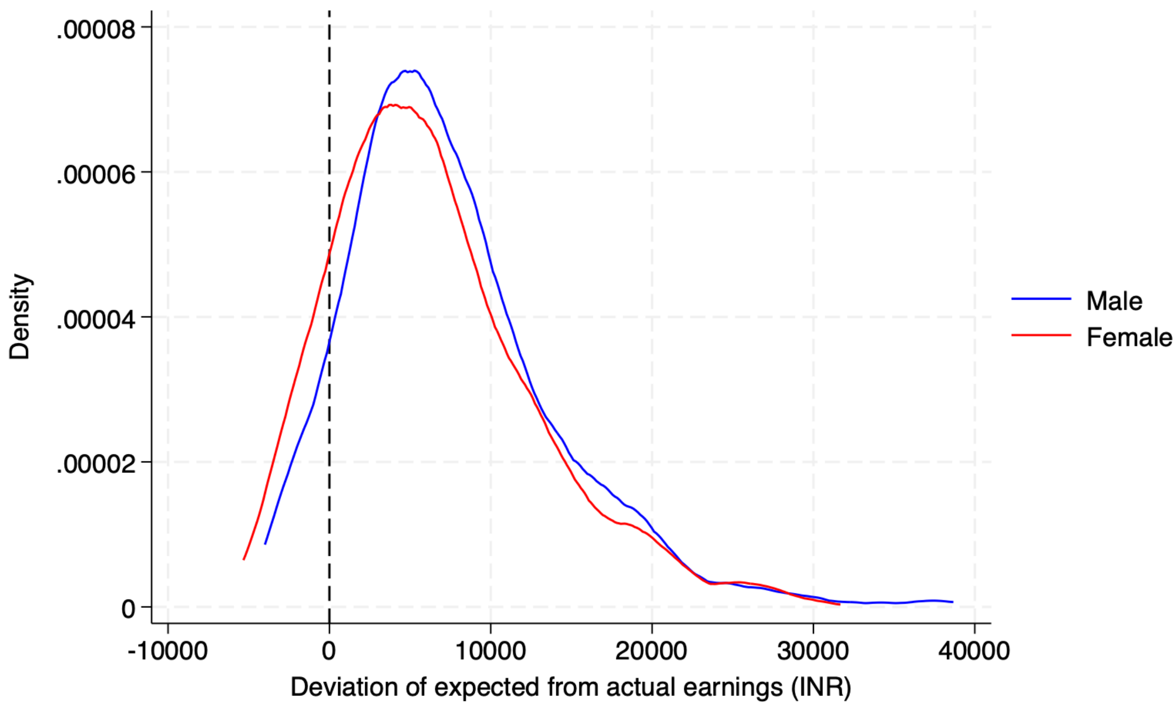
Note: The dependent variables are indicators of whether the respondent was enrolled in any educational institution between baseline and Endline 1 or between Endline 1 and Endline 2 in columns (1) and (2), respectively. Columns (3) and (4) restrict the sample to those who were enrolled at baseline and columns (5) and (6) includes those not enrolled at baseline. **Panel A** includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel D** reports p-values for tests of equality of treatment effects between males and females within each group. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table 8: Impact of information on job search (by earnings mis-match at baseline)

	Upward biased expectations (at baseline)				Downward biased expectations (at baseline)			
	Ever searched using any mode		Ever searched using any digital/online mode		Ever searched using any mode		Ever searched using any digital/online mode	
	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Full Sample								
Treatment	-0.019	-0.037***	0.020	0.017	-0.017	0.007	-0.006	-0.014
	(0.016)	(0.014)	(0.016)	(0.016)	(0.039)	(0.036)	(0.040)	(0.043)
Non-P	-0.015	-0.031*	0.029	0.022	0.000	0.025	0.014	0.000
	(0.017)	(0.016)	(0.019)	(0.019)	(0.043)	(0.039)	(0.047)	(0.052)
P	-0.023	-0.042**	0.010	0.013	-0.031	-0.009	-0.024	-0.027
	(0.018)	(0.016)	(0.020)	(0.019)	(0.043)	(0.041)	(0.043)	(0.048)
WT	[0.642]	[0.495]	[0.334]	[0.682]	[0.372]	[0.317]	[0.347]	[0.582]
Obs.	2782	2503	2782	2503	380	342	380	342
Panel B - Female								
Treatment	-0.019	-0.022	0.048**	0.074***	-0.027	-0.040	0.030	-0.000
	(0.022)	(0.020)	(0.019)	(0.022)	(0.043)	(0.039)	(0.047)	(0.056)
Non-P	-0.012	-0.014	0.077***	0.084***	-0.041	-0.065	0.028	-0.003
	(0.025)	(0.024)	(0.022)	(0.027)	(0.049)	(0.046)	(0.055)	(0.066)
P	-0.027	-0.031	0.021	0.065**	-0.014	-0.017	0.031	0.002
	(0.024)	(0.023)	(0.022)	(0.027)	(0.049)	(0.042)	(0.056)	(0.063)
WT	[0.488]	[0.482]	[0.015]	[0.569]	[0.565]	[0.252]	[0.948]	[0.937]
Obs.	1436	1287	1436	1287	239	225	239	225
Panel C - Male								
Treatment	-0.018	-0.053***	-0.011	-0.043	0.039	0.156**	-0.038	-0.017
	(0.019)	(0.018)	(0.025)	(0.026)	(0.060)	(0.065)	(0.058)	(0.075)
Non-P	-0.019	-0.050**	-0.018	-0.043	0.100	0.254***	-0.001	0.020
	(0.022)	(0.022)	(0.029)	(0.029)	(0.069)	(0.070)	(0.070)	(0.087)
P	-0.017	-0.055***	-0.003	-0.043	-0.006	0.093	-0.065	-0.041
	(0.022)	(0.021)	(0.028)	(0.029)	(0.064)	(0.068)	(0.060)	(0.082)
WT	[0.923]	[0.817]	[0.570]	[0.992]	[0.065]	[0.009]	[0.263]	[0.431]
Obs.	1346	1216	1346	1216	141	117	141	117
Panel D - $H_0 : \beta(M) = \beta(F)$								
Treatment	[0.949]	[0.252]	[0.043]	[0.001]	[0.298]	[0.006]	[0.326]	[0.853]
Non-P	[0.822]	[0.270]	[0.006]	[0.002]	[0.062]	[0.000]	[0.723]	[0.825]
P	[0.715]	[0.417]	[0.432]	[0.006]	[0.911]	[0.114]	[0.218]	[0.672]

Note: The dependent variables is an indicator that takes a value of one if the respondent reports having ever searched for a job using any mode at Endline 1 (columns (1) and (5)) or at Endline 2 (columns (2) and (6)); ever searched for a job using any digital or online mode at Endline 1 (columns (3) and (7)) or Endline 2 (columns (4) and (8)). An individual is classified as having 'Upward biased' ('Downward biased') expectations if their average expected salary was more (less) than the average weighted monthly earnings from PLFS 2022-23 urban sample, at baseline. **Panel A** includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel D** reports p-values for tests of equality of treatment effects between males and females within each group. $***p < 0.01, **p < 0.05, *p < 0.10$.
$***p < 0.01, **p < 0.05, *p < 0.10$.

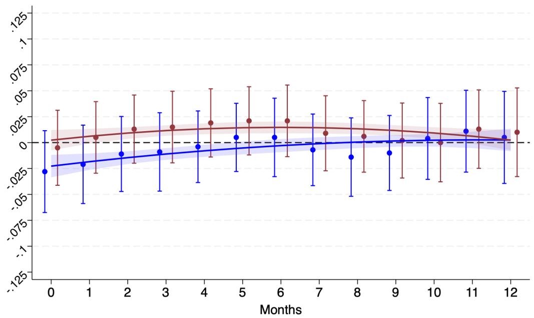
Figure 1: Kernel density of mismatch between expected and actual earnings (at baseline)



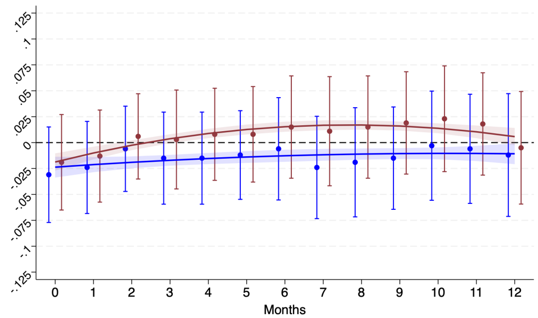
Note: The X-axis shows the mismatch between the average expected salary of each respondent and the average weighted monthly earnings from PLFS 2022-23 urban sample (in INR). We drop the top and bottom 1% of observed mismatches. The p-value of the Kolmogorov-Smirnov test of whether the women's and men's density functions differ is 0.000.

Figure 2: Impact of information on current employment and monthly earnings

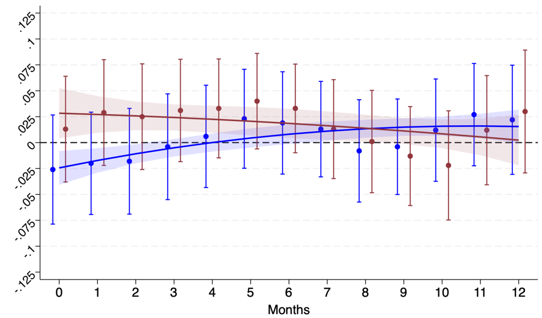
Panel A: Current employment



(a) Overall

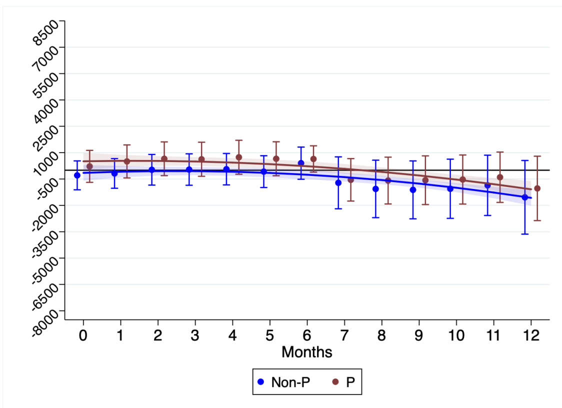


(b) Female

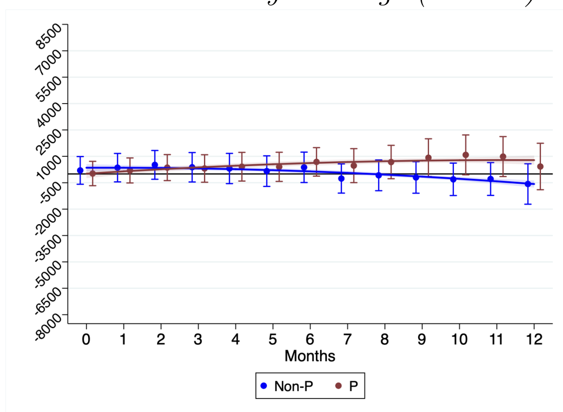


(c) Male

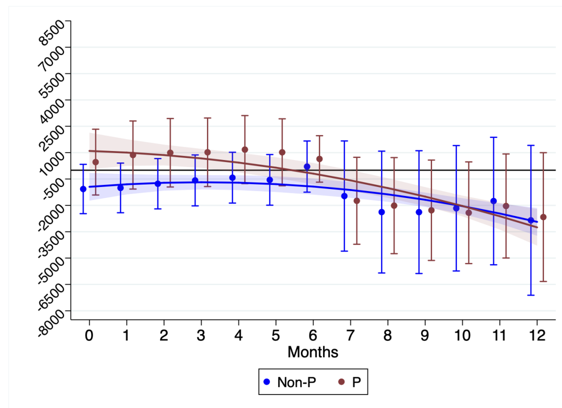
Panel B: Monthly earnings (in INR)



(a) Overall



(b) Female

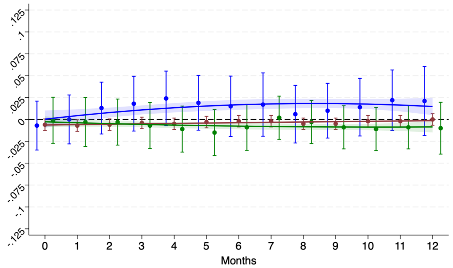


(c) Male

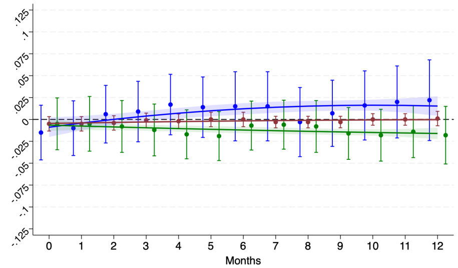
Note: 90% confidence bands are plotted around the regression coefficients and the smooth fitted quadratic trend of the estimated coefficients for the two color-coded treatment groups. Standard errors are clustered at the PS level.

Figure 3: Impact of information on occupational choice

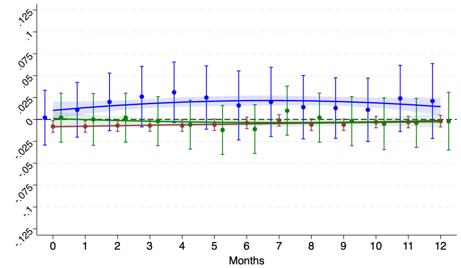
Panel A: Overall



(a) Treatment

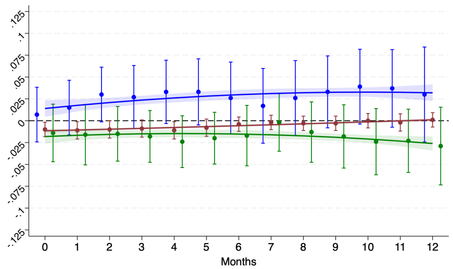


(b) Non-P

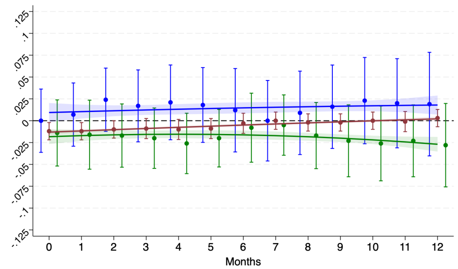


(c) P

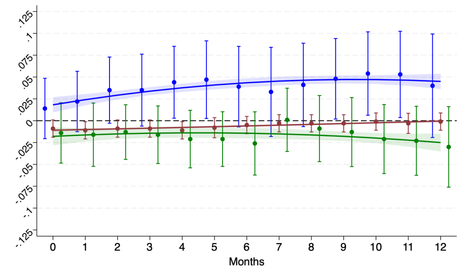
Panel B: Female



(a) Treatment

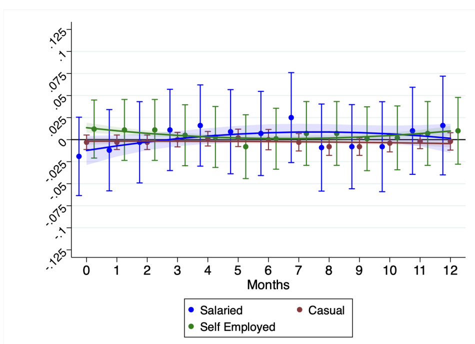


(b) Non-P

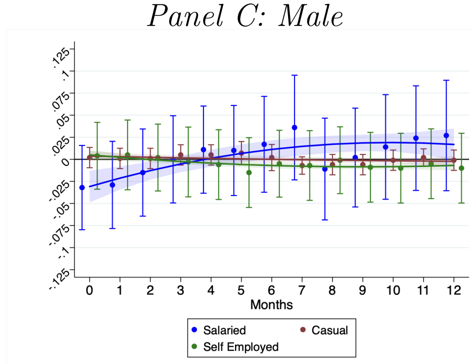


(c) P

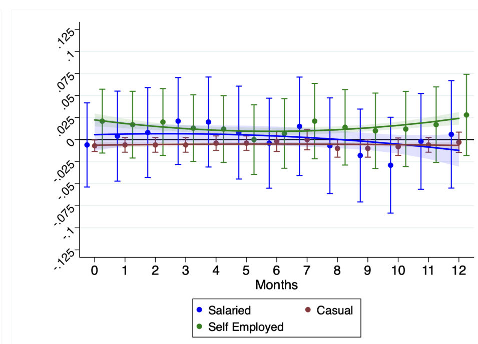
Panel C: Male



(a) Treatment



(b) Non-P



(c) P

Note: 90% confidence bands are plotted around the regression coefficients and the smooth fitted quadratic trend of the estimated coefficients for the three color-coded occupational choices. Standard errors are clustered at the PS level.

ONLINE APPENDIX

Contents

A Additional Analysis

Figure A.1: Sampled districts and polling stations of Delhi (by treatment)

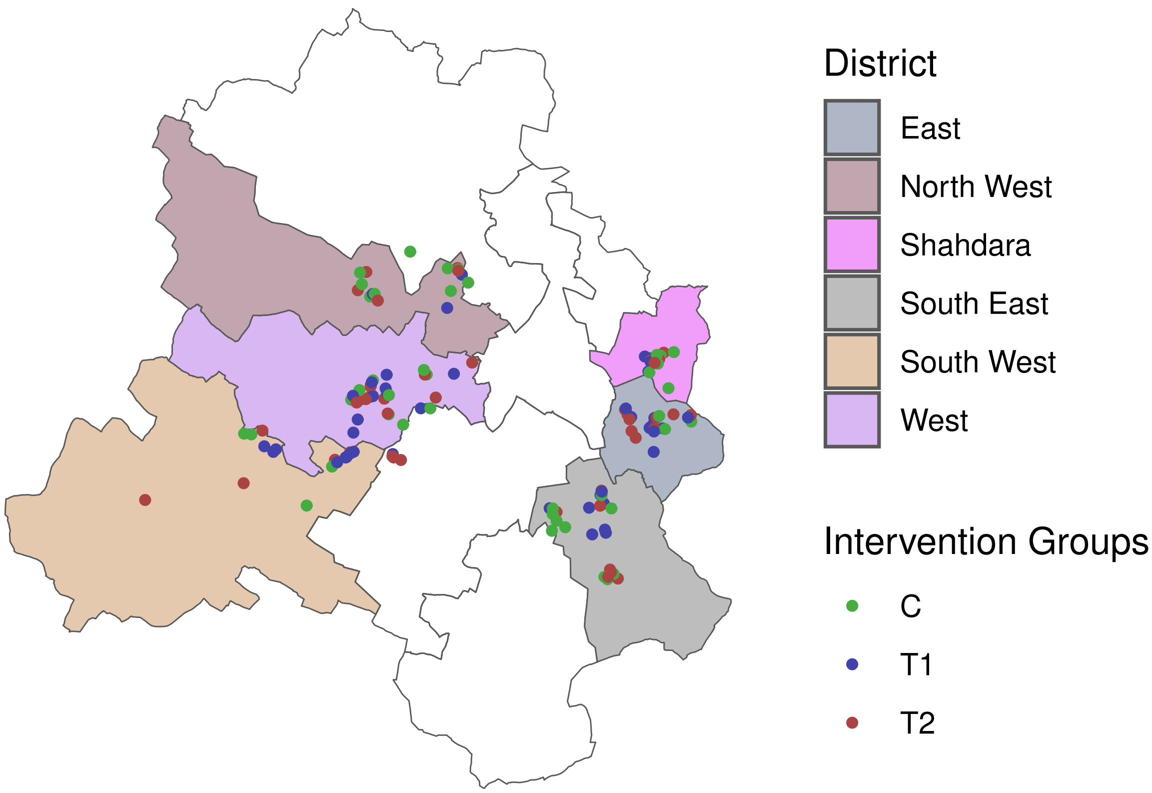
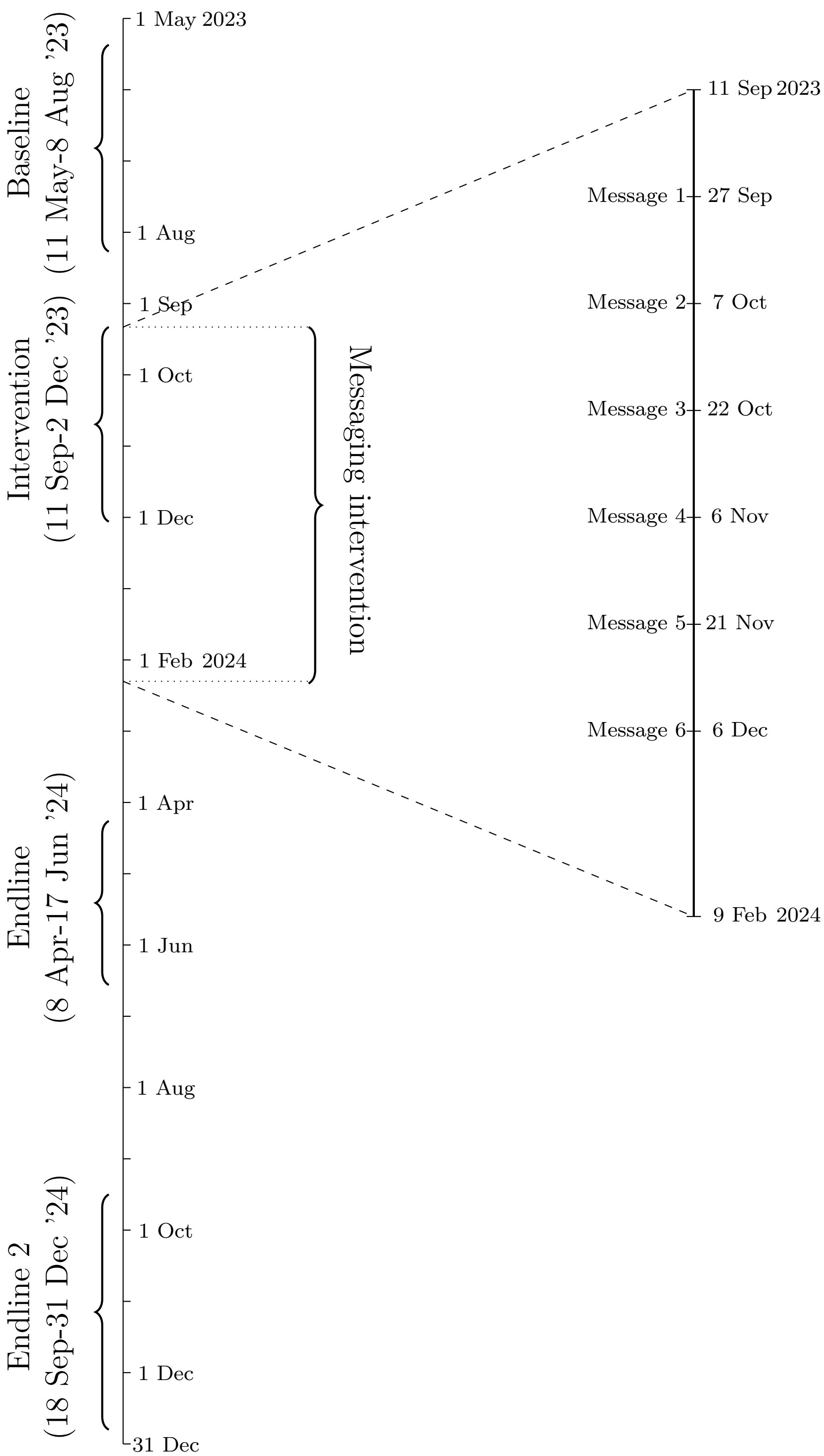


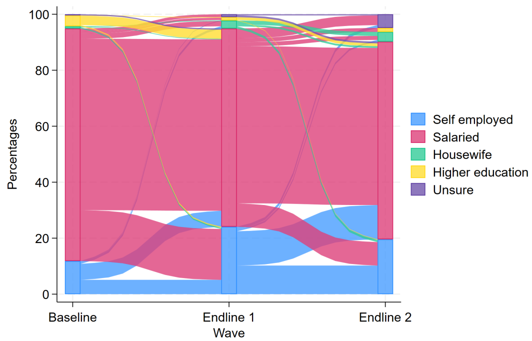
Figure A.2: Timeline of study



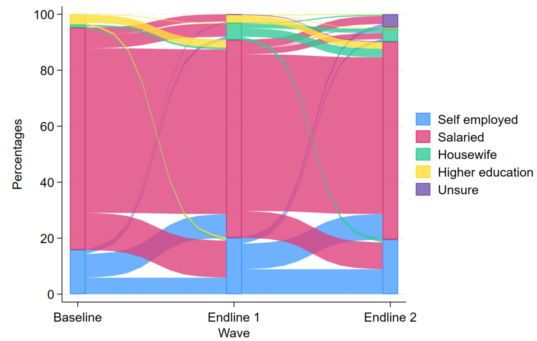
Note: The *intervention* began on September 11, 2023, and concluded on December 2, 2023. The *messaging intervention* was conducted from September 27, 2023 to February 9, 2024. A total of six messages (via SMS and WhatsApp) were sent to the participants' mobile phones at equal intervals of 15 days. The first message to all the treated individuals in a cluster was initiated 10 days after 90% of the respondents in that cluster received the intervention. Endline 1 survey was conducted about six months after the intervention between April 8 and June 17, 2024. A second endline survey (Endline 2) was conducted after twelve months of the intervention from September 18 to December 31, 2024.

Figure A.3: Transitions in labor market aspirations (by gender and treatment)

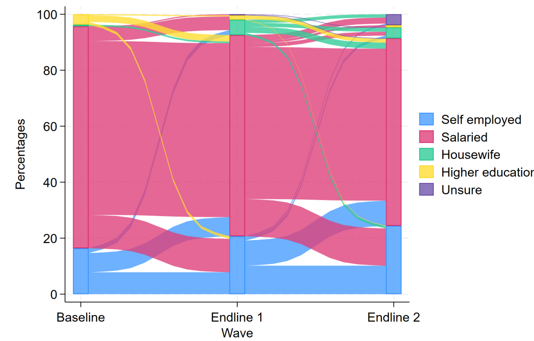
Panel A: Female



(a) Control

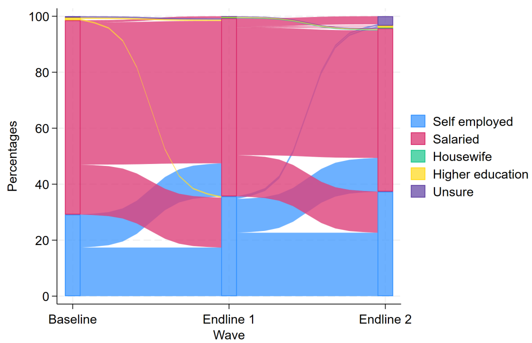


(b) Non-P

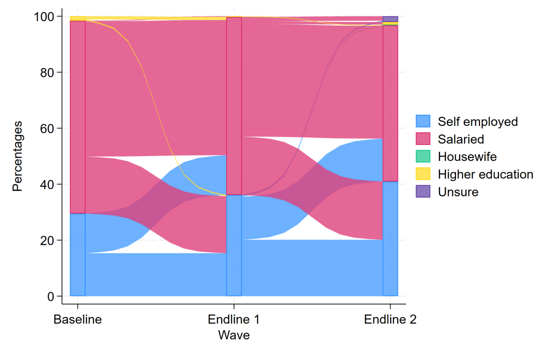


(c) P

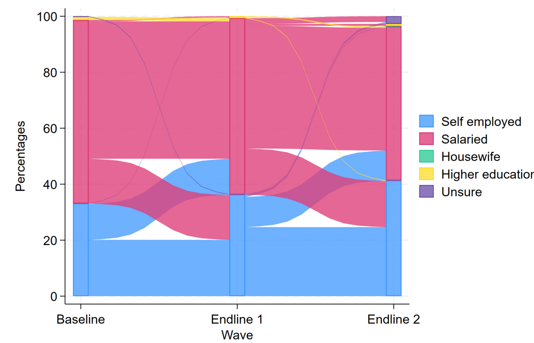
Panel B: Male



(a) Control



(b) Non-P

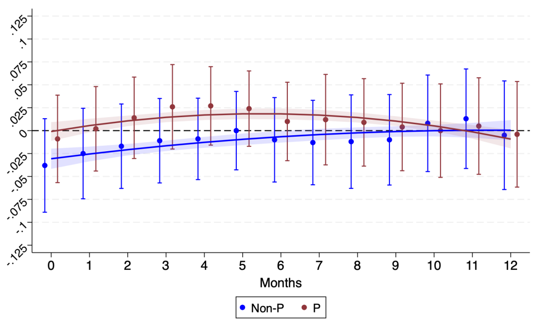


(c) P

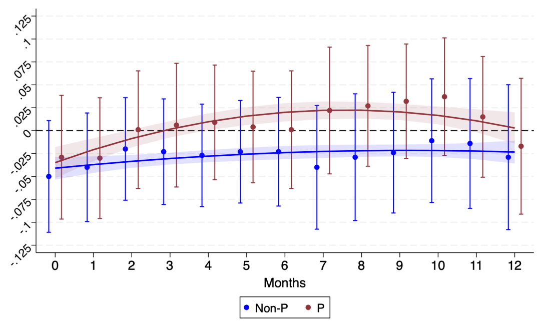
Note: The Y-axis plots the response to the question 'What is the career goal that you envisage for yourself?' at different surveys- Baseline, Endline 1 and 2. An individual can respond as follows: *Salaried*: 'Work for the government or public sector, multinational corporation, private company, Non-Profit organization, someone else's farm, or Professional work (doctor, lawyer, certified public accountant, etc.); *Self-employed*: Start own business, Work for own or family farm, or Work for family business; *Not in labor force*: Housewife/Housemaker, or Pursuing education; *Unsure*: Unsure or Don't know/Can't say; and zero otherwise.

Figure A.4: Impact of information on current employment and monthly earnings (Youth)

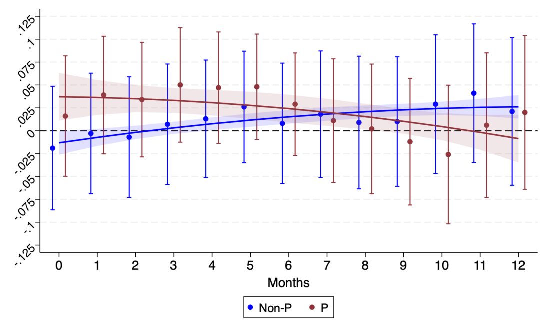
Panel A: Current employment



(a) Overall

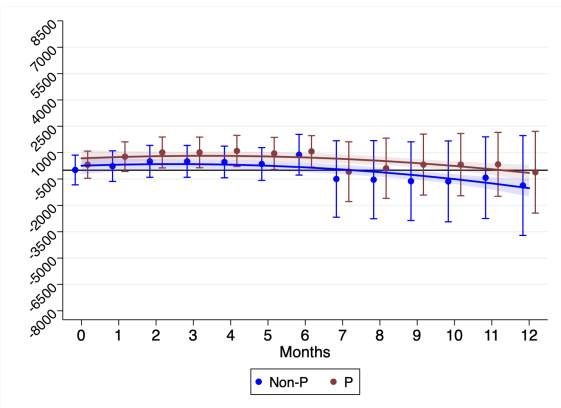


(b) Female

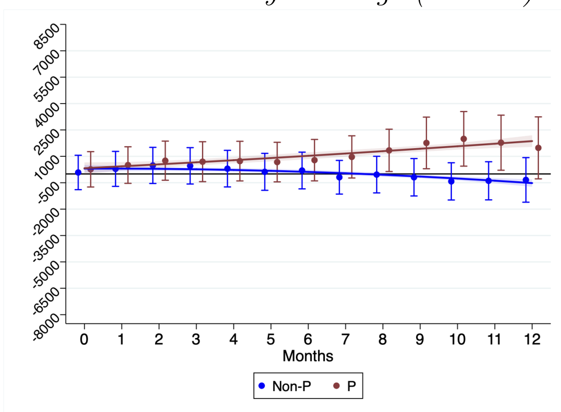


(c) Male

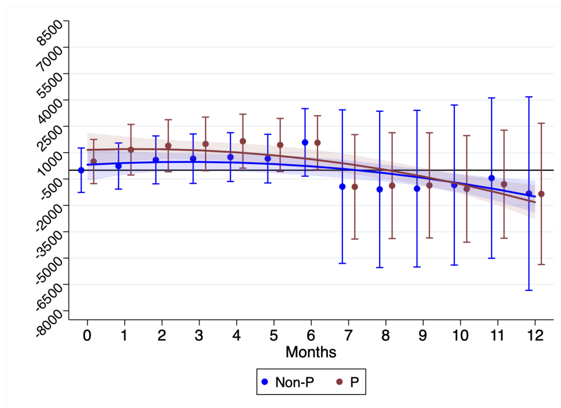
Panel B: Monthly earnings (in INR)



(a) Overall



(b) Female

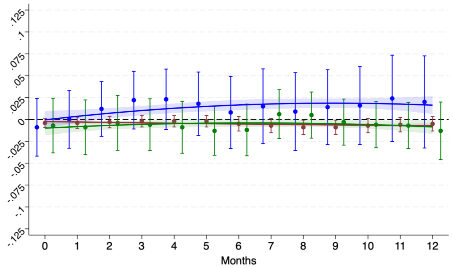


(c) Male

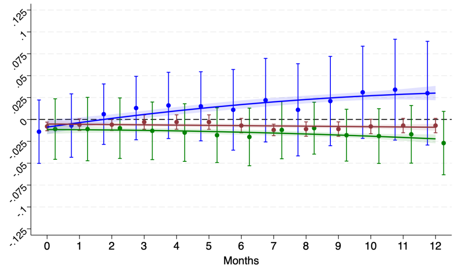
Note: The classification of youth is based on the baseline age of 18-24 years. 90% confidence bands are plotted around the regression coefficients for the two color-coded treatment groups. Standard errors clustered at the PS level.

Figure A.5: Impact of information on occupational choice (Youth, by treatment)

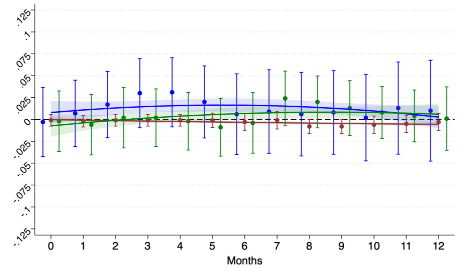
Panel A: Overall



(a) Treatment

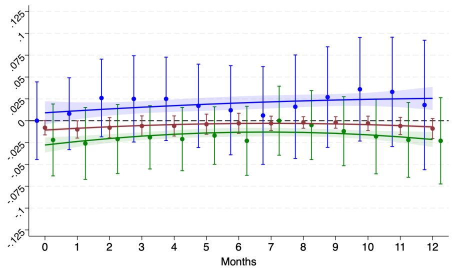


(b) Non-P

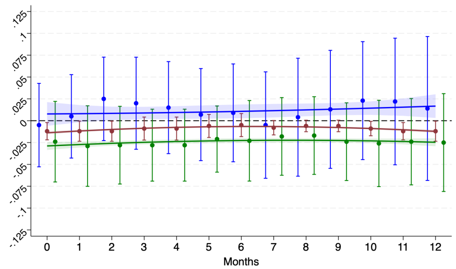


(c) P

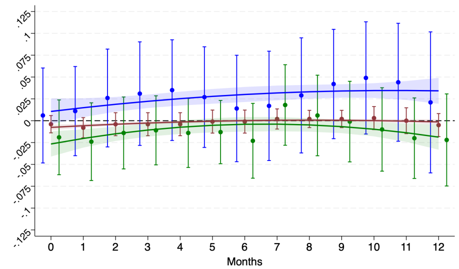
Panel B: Female



(a) Treatment

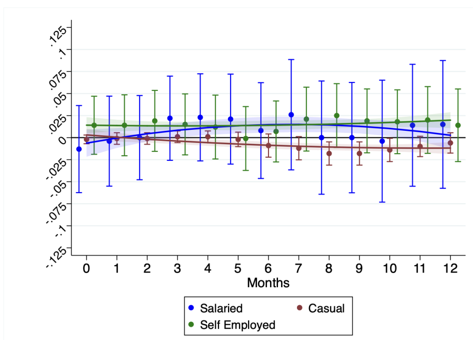


(b) Non-P

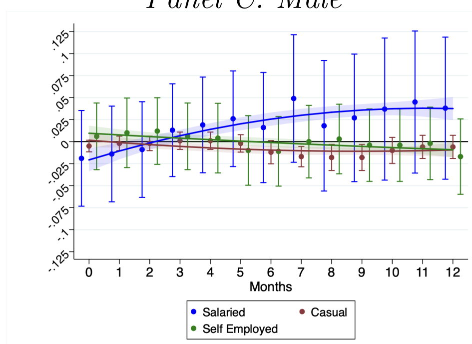


(c) P

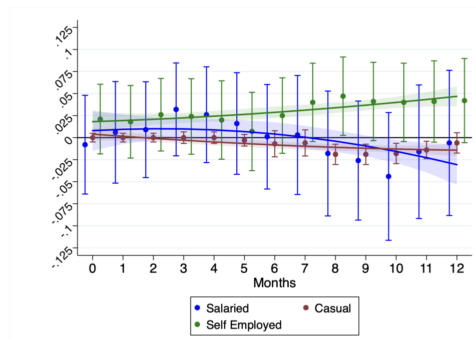
Panel C: Male



(a) Treatment



(b) Non-P

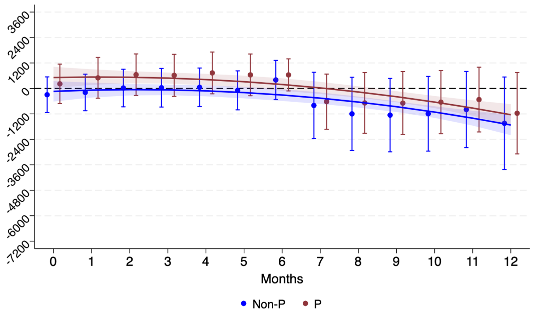


(c) P

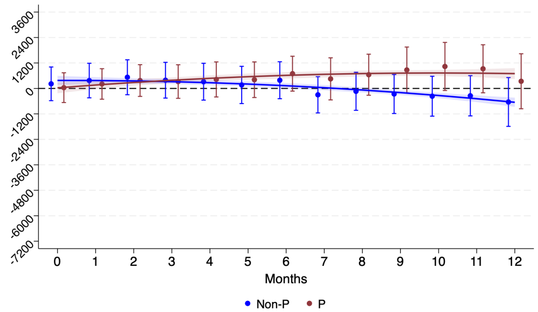
Note: The classification of youth is based on the baseline age of 18-24 years. 90% confidence bands are plotted around the regression coefficients and the smooth fitted quadratic trend of the estimated coefficients for the three color-coded occupational choices. Standard errors are clustered at the PS level.

Figure A.6: Robustness (IPW Weights): Impact of information on monthly earnings and occupational choice

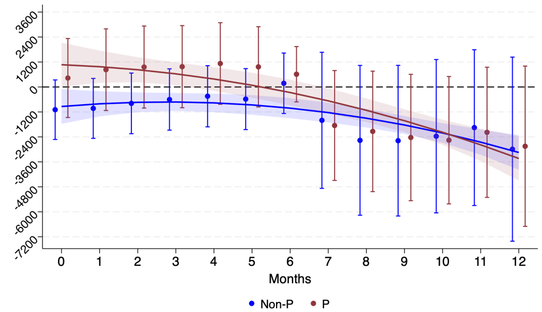
Panel A: Monthly earnings (in INR)



(a) Overall

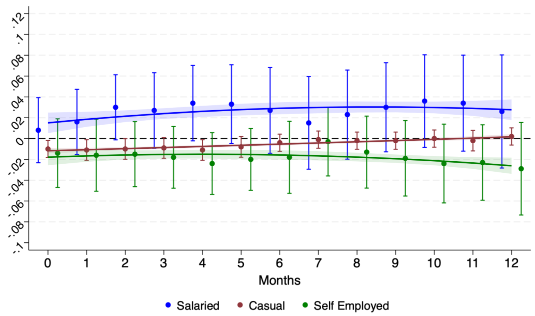


(b) Female

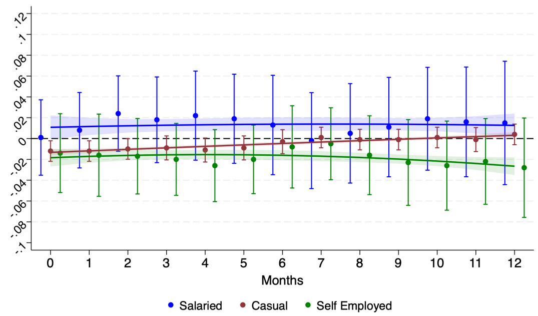


(c) Male

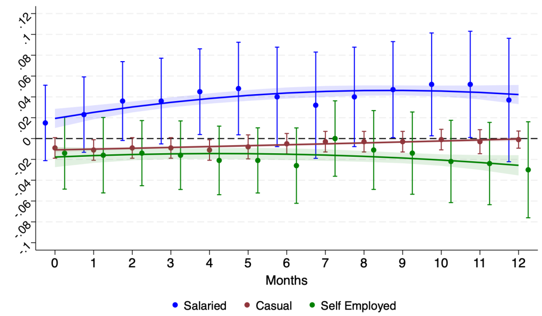
Panel B: Female Occupational Choice



(a) Treatment



(b) Non-P



(c) P

Note: We re-estimate monthly earnings and occupational choice using the propensity scores generated using the controls to model the likelihood of being present at each month as weights. 90% confidence bands are plotted around the regression coefficients and the smooth fitted quadratic trend of the estimated coefficients for the two color-coded treatment groups in Panel A and for the three color-coded occupational choices in Panel B. Standard errors are clustered at the PS level.

Table A.1: Content of phone messages

Group	Message 1 How to search for a job	Message 2 Number of jobs available in Delhi	Message 3 Top 3 jobs on the platform	Message 4 Requirement of english speaking skills	Message 5 Government skilling programs	Message 6 Informtaion on Government job portals
Non−P	To find the job of your choice, watch this video and visit the App https://youtu.be/TXsjsi_4L2I	Last 6 months, there were over 2700+ jobs available in Delhi on the platform. Find your dream job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Top 3 Jobs in Delhi (as per the last 6 months): 1. Document Verification (Office), 2. Field Sales Executive, 3. Real Estate Sales. To find the job of your choice, watch this video and visit the App https://youtu.be/TXsjsi_4L2I	Last week 50% Jobs in Delhi required English Skills. To enhance your job options watch this Video and access the Skills Option on the App https://youtu.be/TXsjsi_4L2I	Skills Training increases jobs by 2.5 times. Watch the Video today and access the Skills option on the App https://youtu.be/TXsjsi_4L2I and for Government Skilling Programs use the link −https://youtu.be/WwrNt0VY51A	In the last 6 months, Delhi Government Job Portal had 290+ Permanent jobs and 300+ Contract jobs. Over 16 lakhs+ people benefitting from this portal. Find your dream job today by going to the App (https://youtu.be/TXsjsi_4L2I) and Government Job Portal (https://www.ncs.gov.in/)
P — Cat1 Male, prospective job seeker and aspire private job	Find your dream Part−time/Work from home by watching this video and visiting the App https://youtu.be/TXsjsi_4L2I	Last 6 months, there were 1100+ part time/work from home job openings in Delhi on the platform. Find your dream job today by watching this Video https://youtu.be/TXsjsi_4L2I	Top 3 Jobs for you in Delhi (as per the last 6 months): 1. Real Estate Sales, 2. Field Sales Executive, 3. Business Development Executive. Find your dream job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last week 25% part time/Work from home Jobs in Delhi required English Skills. To enhance your Part−time/Work from home job options watch this Video and access the Skills Option on the App https://youtu.be/TXsjsi_4L2I	Skills Training increases Part−time/Work from home job opportunities by 1.5 times. Watch the Video today and access the Skills option on the App − https://youtu.be/TXsjsi_4L2I and for Government Skilling Programs use the link −https://youtu.be/WwrNt0VY51A	In the last 6 months, Delhi Government Job Portal had 290+ Permanent jobs and 300+ Contract jobs (Monthly Salary Rs. 30,000/−). 300+ Freshers, 400+ 12th Pass Jobs. Over 16 lakhs+ people benefitting from this portal. Find your dream job today by going to the App (https://youtu.be/TXsjsi_4L2I) and Government Job Portal (https://www.ncs.gov.in/)
P — Cat2 Male, prospective job seeker and don't aspire private job	Find your dream Government/Part−time/Work from home job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last 6 months, there were over 1100+ Part−time/Work from home and 164+ Government jobs available in Delhi on the platform. Find your dream job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I, Government Job Portal पर जाएं https://www.ncs.gov.in/	Top 3 Jobs for you in Delhi (as per the last 6 months): 1. Real Estate Sales, 2. Field Sales Executive, 3. Business Development Executive. Find your dream Government/Part−time/Work from home job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last week 25% part time/Work from home Jobs in Delhi required English Skills. To enhance your Government/Part−time/Work from home job options watch this Video and access the Skills Option on the App https://youtu.be/TXsjsi_4L2I	Skills Training increases Part−time/Work from home job opportunities by 1.5x times. Watch the Video today and access the Skills option on the App − https://youtu.be/TXsjsi_4L2I and for Government Skilling Programs use the link −https://youtu.be/WwrNt0VY51A	In the last 6 months, Delhi Government Job Portal had 290+ Permanent jobs and 300+ Contract jobs (Monthly Salary Rs. 30,000/−). 300+ Freshers, 400+ 12th Pass Jobs. Over 16 lakhs+ people benefitting from this portal. Find your dream job today by going to the App (https://youtu.be/TXsjsi_4L2I) and Government Job Portal (https://www.ncs.gov.in/)
P — Cat3 Male, current job seeker and aspire private job	Find your dream Private job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last 6 months, there were over 2700+ Private jobs available in Delhi on the platform. Find your dream job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Top 3 Jobs for you in Delhi (as per the last 6 months): 1. Real Estate Sales, 2. Telesales, 3. Corporate Sales Executive. Find your dream job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last week 50% Private jobs in Delhi required English Skills. To enhance your Private job options watch this Video and access the Skills Option on the App https://youtu.be/TXsjsi_4L2I	Skills Training increases Private job opportunities by 3x times. Watch the Video today and access the Skills option on the App − https://youtu.be/TXsjsi_4L2I and for Government Skilling Programs use the link −https://youtu.be/WwrNt0VY51A	In the last 6 months, Delhi Government Job Portal had 290+ Permanent jobs and 300+ Contract jobs (Monthly Salary Rs. 30,000/−). 300+ Freshers Jobs. Over 16 lakhs+ people benefitting from this portal. Find your dream job today by going to the App (https://youtu.be/TXsjsi_4L2I) and Government Job Portal (https://www.ncs.gov.in/)
P — Cat4 Male, current job seeker and don't aspire private job	Find your dream Government job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last 6 months, there were over 164+ Government jobs available in Delhi on the Government platform. Find your dream job today by watching this Video and going to the App https://www.ncs.gov.in/	Top 3 Jobs for you in Delhi (as per the last 6 months): 1. Real Estate Sales, 2. Telesales, 3. Corporate Sales Executive. Find your dream job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last week 50% Jobs in Delhi required English Skills. To enhance your Government job options watch this Video and access the Skills Option on the Apphttps://youtu.be/TXsjsi_4L2I	Skills Training increases Government job opportunities by 3x times. Watch the Video today and access the Skills option on the App − https://youtu.be/TXsjsi_4L2I and for Government Skilling Programs use the link−https://youtu.be/WwrNt0VY51A	In the last 6 months, Delhi Government Job Portal had 290+ Permanent jobs and 300+ Contract jobs (Monthly Salary Rs. 30,000/−). 300+ Freshers Jobs. Over 16 lakhs+ people benefitting from this portal. Find your dream job today by going to the App (https://youtu.be/TXsjsi_4L2I) and Government Job Portal (https://www.ncs.gov.in/)
P — Cat5 Female, prospective job seeker and both (aspire private job or don't aspire private job)	Find your dream Government/Part−time/Work from home/Female job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last 6 months, there were over 1100+ Part−time/Work from home, 400+ female, and 164+ Government jobs available in Delhi on the platform. Find your dream job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I, Government Job Portal पर जाएं https://www.ncs.gov.in/	Top 3 Jobs for you in Delhi (as per the last 6 months): 1. Document Verification (Office), 2. Back Office Coordinator, 3. Back Office Operations. Find your dream job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I.	Last week 35% part time/work from home/Female Jobs in Delhi required English Skills. To enhance your Government/Part−time/Work from home/Female job options watch this Video and access the Skills Option on the Apphttps://youtu.be/TXsjsi_4L2I	Skills Training increases Government/Part−time/Work from home/Female job opportunities by 3x times. Watch the Video today and access the Skills option on the App − https://youtu.be/TXsjsi_4L2I and for Government Skilling Programs use the link −https://youtu.be/WwrNt0VY51A	In the last 6 months, Delhi Government Job Portal had 290+ Permanent jobs and 300+ Contract jobs (Monthly Salary Rs. 30,000/−). 300+ Freshers, 400+ 12th Pass and 200+ Female Jobs. Over 16 lakhs+ people benefitting from this portal. Find your dream job today by going to the App (https://youtu.be/TXsjsi_4L2I) and Government Job Portal (https://www.ncs.gov.in/)
P — Cat6 Female, current job seeker and aspire private job	Find your dream Private/Female job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last 6 months, there were over 2700+ Private and 400+ female jobs available in Delhi on the platform. Find your dream job today by watching this Video and going to the Apphttps://youtu.be/TXsjsi_4L2I, Government Job Portal पर जाएं https://www.ncs.gov.in/	Top 3 Jobs for you in Delhi (as per the last 6 months): 1. Document Verification (Office), 2. Data Entry Operator, 3. Back Office Coordinator. Find your dream job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last week 50% Private/Female Jobs in Delhi required English Skills. To enhance your Private/Female job options watch this Video and access the Skills Option on the App https://youtu.be/TXsjsi_4L2I	Skills Training increases Private/Female job job opportunities by 5.5x times. Watch the Video today and access the Skills option on the App − https://youtu.be/TXsjsi_4L2I and for Government Skilling Programs use the link −https://youtu.be/WwrNt0VY51A	In the last 6 months, Delhi Government Job Portal had 290+ Permanent jobs and 300+ Contract jobs (Monthly Salary Rs. 30,000/−) . Over 16 lakhs+ people benefitting from this portal. Find your dream job today by going to the App (https://youtu.be/TXsjsi_4L2I) and Government Job Portal (https://www.ncs.gov.in/)
P — Cat7 Female, current job seeker and don't aspire private job	Find your dream Government/Private/Female job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last 6 months, there were over 2700+ Private, 400+ female, and 164+ Government jobs available in Delhi on the platform. Find your dream job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I and Government Job Portal https://www.ncs.gov.in/	Top 3 Jobs for you in Delhi (as per the last 6 months): 1. Back Office Coordinator, 2. MIS Executive, 3. Back Office Operations. Find your dream job today by watching this Video and going to the App https://youtu.be/TXsjsi_4L2I	Last week 50% Private/Female Jobs in Delhi required English Skills. To enhance your Private/Female job options watch this Video and access the Skills Option on the App https://youtu.be/TXsjsi_4L2I	Skills Training increases Government/Private/Female job opportunities by 5.5x times. Watch the Video today and access the Skills option on the App − https://youtu.be/TXsjsi_4L2I and for Government Skilling Programs use the link −https://youtu.be/WwrNt0VY51A	In the last 6 months, Delhi Government Job Portal had 290+ Permanent jobs and 300+ Freshers Jobs (Monthly Salary Rs. 30,000/−). Over 16 lakhs+ people benefitting from this portal. Find your dream job today by going to the App (https://youtu.be/TXsjsi_4L2I) and Government Job Portal (https://www.ncs.gov.in/)

Table A.2: Summary statistics (at baseline)

Variable	N	Mean	S.D.	Definitions
Panel A: Household Characteristics				
Household Size	3391	4.84	1.68	number of household members
Young Children	3391	0.47	0.81	number of children below 10 years of age
SC/ST	3349	0.29	0.45	=1 if the household belongs to scheduled tribe or caste, 0 otherwise
Hindu	3391	0.87	0.33	=1 if household identifies as Hindu, 0 otherwise
Asset Index	3391	0.00	1.00	PCA of assets
Panel B: Individual Characteristics				
Age	3391	24.07	5.37	years
Female	3391	0.52	0.50	=1 for females, 0 otherwise
Married	3391	0.28	0.45	=1 if married, 0 otherwise
Education	3391	0.61	0.49	=1 if education is above 12th standard, 0 otherwise
Smartphone usage	3391	3.72	2.06	in hours per day
Employed	3391	0.37	0.48	=1 if currently employed, 0 otherwise
Currently looking for work	3391	0.41	0.49	=1 if currently looking for work, 0 otherwise
Uses/used online job platforms	3391	0.34	0.47	=1 if uses/used online job platforms for job search, 0 otherwise
Skill trained	3387	0.32	0.47	=1 if previously acquired skill training, 0 otherwise
Native of Delhi	3389	0.70	0.46	=1 if native of Delhi, 0 otherwise
Years in Delhi	3391	20.46	8.96	number of years lived in Delhi
Hours worked per day	3391	2.79	4.06	hours per day worked
Days worked per month	3391	9.42	12.64	days per month worked
Monthly earnings (INR)	3391	6157.20	11755.81	monthly income

Note: The *Asset Index* is constructed using principal components analysis (PCA) on the households' ownership of assets (LCD TV, fridge, generator, stove, mixer, sewing machine, washing machine, bike, car, AC, credit card, smartphone, computer, internet, flat, agricultural land, residential land, and commercial land). **Panel A** shows the average household-level characteristics of individuals in our sample, while **Panel B** shows their individual characteristics.

Table A.3: Balance of individual and household characteristics (at baseline)

	Overall						Female						Male					
	Control	Treatment		Difference			Control	Treatment		Difference			Control	Treatment		Difference		
	C (N=1,088)	Non-P (N=1,146)	P (N=1,157)	C-Non-P	C-P	Non-P-P	C (N=581)	Non-P (N=589)	P (N=598)	C-Non-P	C-P	Non-P-P	C (N=507)	Non-P (N=557)	P (N=559)	C-Non-P	C-P	Non-P-P
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Currently looking for work	0.422	0.409	0.398	0.883	0.557	0.609	0.415	0.469	0.432	0.181	0.674	0.319	0.429	0.345	0.363	0.072	0.104	0.786
	(0.494)	(0.492)	(0.490)				(0.493)	(0.499)	(0.496)				(0.495)	(0.476)	(0.481)			
Education level above 12th standard	0.410	0.375	0.398	0.298	0.789	0.462	0.438	0.416	0.438	0.666	0.859	0.578	0.377	0.330	0.354	0.259	0.593	0.516
	(0.492)	(0.484)	(0.490)				(0.497)	(0.493)	(0.497)				(0.485)	(0.471)	(0.479)			
Married	0.286	0.260	0.289	0.244	0.771	0.200	0.363	0.344	0.381	0.647	0.482	0.270	0.198	0.169	0.191	0.307	0.856	0.476
	(0.452)	(0.439)	(0.454)				(0.481)	(0.476)	(0.486)				(0.399)	(0.375)	(0.394)			
Age (in years)	23.966	24.031	24.235	0.813	0.330	0.469	24.331	24.373	24.841	0.901	0.243	0.292	23.546	23.664	23.587	0.736	0.737	0.990
	(5.338)	(5.247)	(5.531)				(5.645)	(5.439)	(5.682)				(4.935)	(5.011)	(5.293)			
Female	0.535	0.517	0.517	0.199	0.273	0.848	-	-	-	-	-	-	-	-	-	-	-	-
	(0.499)	(0.500)	(0.500)				.	.	.	.	.	.	.	.	.	.	.	.
Smartphone usage in a day (in hours)	3.779	3.621	3.759	0.279	0.966	0.325	3.517	3.336	3.556	0.246	0.744	0.195	4.082	3.926	3.977	0.372	0.563	0.737
	(2.050)	(2.058)	(2.088)				(1.927)	(1.929)	(2.158)				(2.145)	(2.148)	(1.988)			
Employed	0.370	0.360	0.375	0.788	0.867	0.662	0.261	0.241	0.272	0.489	0.807	0.368	0.496	0.486	0.486	0.935	0.861	0.922
	(0.483)	(0.480)	(0.484)				(0.440)	(0.428)	(0.445)				(0.500)	(0.500)	(0.500)			
Uses/used online job platforms for job search	0.342	0.332	0.336	0.854	0.870	0.991	0.331	0.341	0.336	0.697	0.865	0.837	0.355	0.323	0.366	0.447	0.626	0.795
	(0.475)	(0.471)	(0.472)				(0.471)	(0.474)	(0.473)				(0.479)	(0.468)	(0.473)			
Skill trained	0.336	0.319	0.323	0.632	0.727	0.877	0.345	0.344	0.344	0.954	0.995	0.943	0.325	0.292	0.301	0.353	0.573	0.717
	(0.472)	(0.466)	(0.468)				(0.476)	(0.476)	(0.475)				(0.469)	(0.455)	(0.459)			
Asset Index	0.036	0.027	-0.046	0.964	0.372	0.425	0.058	-0.037	-0.093	0.416	0.151	0.598	0.010	0.095	0.003	0.365	0.958	0.344
	(1.022)	(1.017)	(0.969)				(1.036)	(0.976)	(0.934)				(1.007)	(1.056)	(1.003)			
Number of children below 10 years of age	0.477	0.442	0.505	0.391	0.411	0.084	0.573	0.589	0.663	0.694	0.089	0.152	0.367	0.284	0.336	0.090	0.617	0.250
	(0.802)	(0.795)	(0.836)				(0.858)	(0.882)	(0.890)				(0.718)	(0.654)	(0.738)			
Number of household members	4.807	4.808	4.922	0.968	0.234	0.196	4.937	5.009	5.115	0.590	0.159	0.351	4.657	4.593	4.717	0.578	0.588	0.228
	(1.723)	(1.641)	(1.703)				(1.726)	(1.772)	(1.771)				(1.709)	(1.459)	(1.603)			
SC/ST	0.268	0.278	0.316	0.769	0.305	0.441	0.280	0.286	0.319	0.855	0.419	0.518	0.254	0.270	0.312	0.714	0.257	0.426
	(0.443)	(0.448)	(0.465)				(0.449)	(0.452)	(0.466)				(0.436)	(0.444)	(0.464)			
Hindu	0.873	0.888	0.865	0.668	0.847	0.597	0.874	0.896	0.847	0.512	0.460	0.227	0.871	0.879	0.884	0.860	0.674	0.796
	(0.334)	(0.316)	(0.342)				(0.332)	(0.306)	(0.361)				(0.336)	(0.327)	(0.320)			
Years in Delhi	20.147	20.840	20.441	0.261	0.498	0.610	19.532	20.374	20.025	0.260	0.411	0.710	20.855	21.340	20.887	0.479	0.791	0.598
	(9.120)	(8.788)	(8.995)				(9.094)	(9.043)	(9.663)				(9.108)	(8.486)	(8.206)			
Native of Delhi	0.681	0.709	0.698	0.327	0.584	0.702	0.680	0.688	0.676	0.744	0.982	0.737	0.683	0.730	0.722	0.180	0.328	0.760
	(0.466)	(0.455)	(0.459)				(0.467)	(0.464)	(0.468)				(0.466)	(0.444)	(0.448)			
Test of joint significance	-	-	-	[0.377]	[0.600]	[0.487]	-	-	-	[0.469]	[0.571]	[0.130]	-	-	-	[0.349]	[0.570]	[0.984]

Note: Non-P denotes treatment where the in-person information session and general phone messages was provided; P represents treatment in which the in-person information session as well as tailored phone messages were provided and C denotes the control group where no such service was offered. t-test p-values are derived from linear regression, with the variable of interest as the dependent variable and the treatment indicator as an independent variable with standard errors clustered at the PS level (Control group is base for column (4), (5), (10), (11), (16) & (17) and Non-P is base for column (6), (12) & (18)) reported in parenthesis. The p-values of joint significance reported in the last row of the table correspond to F-test of joint significance of individual characteristics in determining the treatment status in a linear probability model.

Table A.4: Summary of platform registration and engagement

Variable	All	Female			Male			Female - Male	
		Non-P	P	Non-P vs. P	Non-P	P	Non-P vs. P	Non-P	P
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Registration rate - Survey Data									
Interested	64.52	68.59	69.73	[0.885]	57.27	61.90	[0.289]	[0.002]	[0.057]
	(1,486)	(404)	(417)		(319)	(346)			
Registered	99.80	99.75	99.52	[0.582]	100	100	[1.000]	[0.375]	[0.198]
(Conditional)	(1,483)	(403)	(415)		(319)	(346)			
Registered	65.00	68.76	70.57	[0.897]	57.99	62.08	[0.395]	[0.004]	[0.030]
(Unconditional)	(1,497)	(405)	(422)		(323)	(347)			
Panel B: Engagement - Platform Data									
Prop. of active users	0.390	0.404	0.373	[0.375]	0.377	0.403	[0.496]	[0.473]	[0.400]
	(1,460)	(396)	(407)		(310)	(347)			
Prop. of skill takers	0.215	0.265	0.194	[0.017]	0.200	0.196	[0.897]	[0.043]	[0.949]
	(1,460)	(396)	(407)		(310)	(347)			
Total job applications	4.746	5.194	4.017	[0.255]	4.248	5.533	[0.251]	[0.392]	[0.151]
	(1460)	(396)	(407)		(310)	(347)			
Applications submitted online	4.007	4.359	3.224	[0.213]	3.571	4.914	[0.204]	[0.422]	[0.085]
	(1,460)	(396)	(407)		(310)	(347)			
Applications through calls to HR	0.739	0.836	0.794	[0.857]	0.677	0.620	[0.748]	[0.520]	[0.351]
	(1,460)	(396)	(407)		(310)	(347)			
Callbacks from HR	0.482	0.614	0.504	[0.403]	0.406	0.372	[0.765]	[0.150]	[0.231]
	(1,460)	(396)	(407)		(310)	(347)			
Prop. of callbacks from HR	0.137	0.138	0.160	[0.580]	0.134	0.113	[0.458]	[0.868]	[0.259]
	(569)	(160)	(152)		(117)	(140)			

Note: **Panel A** shows individuals in the treatment group (N=2,303) who were offered the opportunity to register on the platform. The first row reports the *Interest rate* of the respondents to join the platform. The second and third row report the Conditional and Unconditional *Registration rates*, respectively. The former conditions registration (including already registered before treatment) on being interested in on-boarding the platform while the latter is unconditional. The registration rates (unconditional) are slightly greater than the interest rates due to 14 individuals (Non-P: 6 & P: 8) who expressed no interest in registering but registered on the platform anyway. Columns (1)-(9) list the sign-up rates for the respondents who were treated-overall (column (1)), for the treated women (columns (2)-(4)) and treated men (columns (5)-(7)). Columns (4) and (7) report Non-P vs. P p-values within gender groups. Columns (8)-(9) report Female-Male p-values for Non-P and P, respectively. **Panel B** summarizes the platform engagement outcomes as of May 30, 2024 (Endline 1) for individuals who registered on the platform (N=1,460). Prop. of active users refers to the proportion of participants who are actively engaging on the platform by either submitting applications or making calls to HR. Prop. of skill takers refers to the proportion of respondents who are taking skills tests on the platform. Number of applications submitted refers to the total job applications either via submission on platform or through calls made to HR. Prop. of applications shortlisted is calculated as the ratio of the number of applications shortlisted by employer to the number of applications. Prop. of callbacks from HR is calculated as the ratio of the number of HR callbacks to the number of applications. Columns (1) lists the overall (column (1)), for women (columns (2)-(4)) and men (columns (5)-(7)). Columns (4) and (7) report Non-P vs. P p-values within gender groups. Columns (8)-(9) report Female-Male p-values for Non-P and P respectively. The number of participants per category is in parentheses. p-values are shown in square brackets.

Table A.5: Delivery and receipt of phone messages by treatment group

	Message Delivered			Message Received			Whatsapp Message Seen		
	Non-P	P	Diff [p-value]	Non-P	P	Diff [p-value]	Non-P	P	Diff [p-value]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A - Full Sample									
Message 1	0.997	0.999	[0.176]	0.941	0.949	[0.381]	0.722	0.736	[0.454]
Message 2	0.997	0.999	[0.176]	0.873	0.919	[0.000]	0.636	0.672	[0.074]
Message 3	0.997	0.999	[0.176]	0.854	0.879	[0.081]	0.549	0.565	[0.429]
Message 4	0.997	0.999	[0.176]	0.815	0.858	[0.005]	0.424	0.483	[0.004]
Message 5	0.997	0.999	[0.176]	0.801	0.837	[0.027]	0.36	0.402	[0.040]
Message 6	0.997	0.999	[0.176]	0.792	0.830	[0.022]	0.238	0.278	[0.028]
Total (M1-M6)	5.979	5.995	[0.176]	5.076	5.271	[0.006]	2.929	3.136	[0.013]
N	1,146	1,157		1,146	1,157		1,146	1,157	
Panel B - Female									
Message 1	0.997	1.000	[0.154]	0.947	0.950	[0.848]	0.756	0.744	[0.651]
Message 2	0.997	1.000	[0.154]	0.879	0.923	[0.012]	0.664	0.711	[0.082]
Message 3	0.997	1.000	[0.154]	0.862	0.878	[0.429]	0.594	0.582	[0.667]
Message 4	0.997	1.000	[0.154]	0.815	0.861	[0.030]	0.457	0.510	[0.066]
Message 5	0.997	1.000	[0.154]	0.815	0.838	[0.299]	0.399	0.443	[0.124]
Message 6	0.997	1.000	[0.154]	0.801	0.824	[0.309]	0.267	0.279	[0.623]
Total (M1-M6)	5.980	6.000	[0.154]	5.121	5.274	[0.111]	3.136	3.269	[0.244]
N	589	598		589	598		589	598	
Panel C - Male									
Message 1	0.996	0.998	[0.561]	0.934	0.948	[0.303]	0.686	0.726	[0.138]
Message 2	0.996	0.998	[0.561]	0.865	0.914	[0.009]	0.607	0.630	[0.432]
Message 3	0.996	0.998	[0.561]	0.846	0.880	[0.094]	0.501	0.547	[0.120]
Message 4	0.996	0.998	[0.561]	0.815	0.855	[0.072]	0.390	0.454	[0.028]
Message 5	0.996	0.998	[0.561]	0.786	0.835	[0.036]	0.320	0.358	[0.178]
Message 6	0.996	0.998	[0.561]	0.783	0.835	[0.025]	0.208	0.277	[0.007]
Total (M1-M6)	5.978	5.989	[0.561]	5.029	5.268	[0.024]	2.711	2.993	[0.018]
N	557	559		557	559		557	559	

Note: Proportion of phone messages delivered and received (either text or WhatsApp) and seen by treatment group. 'Message Delivered' refers to messages dispatched to participants through either SMS or WhatsApp; 'Message Received' refers to messages received by participants through either mode; and 'WhatsApp Message Seen' refers to WhatsApp messages viewed (color of tick changed to blue or green) by participants. Difference (Non-P vs. P) p-value reported in columns (3), (6) and (9).

Table A.6: Impact of information on labor market aspirations

	Salaried		Self-employed		Not in labor force		Unsure	
	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Full Sample								
Treatment	0.003	-0.017	-0.025	0.014	0.014	0.001	-0.003	-0.009
	(0.018)	(0.017)	(0.017)	(0.014)	(0.008)	(0.008)	(0.003)	(0.011)
Non-P	-0.001	-0.007	-0.021	-0.001	0.017*	0.000	-0.004	-0.008
	(0.022)	(0.021)	(0.020)	(0.018)	(0.010)	(0.009)	(0.003)	(0.012)
P	0.008	-0.026	-0.028	0.027	0.010	0.001	-0.002	-0.010
	(0.020)	(0.021)	(0.019)	(0.017)	(0.009)	(0.009)	(0.003)	(0.013)
WT	[0.687]	[0.446]	[0.754]	[0.151]	[0.498]	[0.888]	[0.362]	[0.859]
Obs.	3162	2845	3162	2845	3162	2845	3162	2845
Panel B - Female								
Treatment	0.012	-0.016	-0.047**	0.009	0.024	0.002	-0.005	-0.008
	(0.028)	(0.024)	(0.023)	(0.021)	(0.015)	(0.014)	(0.005)	(0.015)
Non-P	-0.001	-0.006	-0.041	-0.017	0.033*	0.002	-0.007	-0.001
	(0.033)	(0.028)	(0.027)	(0.024)	(0.019)	(0.016)	(0.005)	(0.017)
P	0.024	-0.026	-0.052**	0.034	0.015	0.001	-0.004	-0.015
	(0.030)	(0.029)	(0.025)	(0.023)	(0.016)	(0.016)	(0.006)	(0.017)
WT	[0.396]	[0.514]	[0.657]	[0.035]	[0.369]	[0.937]	[0.307]	[0.422]
Obs.	1675	1512	1675	1512	1675	1512	1675	1512
Panel C - Male								
Treatment	-0.009	-0.016	0.004	0.017	0.002	0.000	-0.000	-0.009
	(0.026)	(0.029)	(0.026)	(0.026)	(0.004)	(0.006)	(0.003)	(0.012)
Non-P	-0.005	-0.009	0.004	0.017	0.001	0.000	0.000	-0.014
	(0.029)	(0.035)	(0.028)	(0.031)	(0.004)	(0.007)	(0.003)	(0.013)
P	-0.014	-0.023	0.003	0.018	0.003	0.000	-0.000	-0.004
	(0.030)	(0.033)	(0.030)	(0.029)	(0.006)	(0.007)	(0.003)	(0.014)
WT	[0.759]	[0.699]	[0.989]	[0.965]	[0.759]	[0.979]	[0.980]	[0.422]
Obs.	1487	1333	1487	1333	1487	1333	1487	1333
Panel D - $H_0 : \beta(M) = \beta(F)$								
Treatment	[0.591]	[0.994]	[0.157]	[0.812]	[0.122]	[0.924]	[0.347]	0.970
Non-P	[0.931]	[0.955]	[0.240]	[0.410]	[0.082]	[0.900]	[0.238]	[0.478]
P	[0.392]	[0.944]	[0.173]	[0.695]	[0.441]	[0.962]	[0.562]	[0.554]

Note: The dependent variables are indicators of responses to the question 'What is the career goal that you envisage for yourself?'. It takes a value of 1 if the responses are: column (1)-(2) *Salaried*: 'Work for the government or public sector, multinational corporation, private company, noNon-Profit organization, someone else's farm, or Professional work (doctor, lawyer, certified public accountant, etc.); column (3)-(4) *Self-employed*: Start own business, Work for own or family farm, or Work for family business; column (5)-(6) *Not in labor force*: Housewife/Housemaker, or Pursuing education; column (7)-(8) *Unsure*: Unsure or Don't know/Can't say; and zero otherwise. **Panel A** includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel D** reports p-values for tests of equality of treatment effects between males and females within each group. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.7: Impact of information on ideal job expectations (Youth)

	Working in an ideal job/ working towards it		Optimism for getting ideal job (if applied)	Perceived earnings in ideal job
	Endline 1	Endline 2	Endline 2	Endline 2
	(1)	(2)	(3)	(4)
Panel A - Full Sample				
Treatment	-0.032	-0.052**	-0.019	-0.218
	(0.027)	(0.026)	(0.046)	(0.200)
Non-P	-0.013	-0.030	0.013	-0.109
	(0.030)	(0.030)	(0.052)	(0.235)
P	-0.050	-0.073**	-0.050	-0.325
	(0.033)	(0.029)	(0.054)	(0.247)
WT	[0.260]	[0.136]	[0.241]	[0.428]
Obs.	1932	1727	1657	1448
Panel B - Female				
Treatment	-0.010	-0.048	0.018	-0.142
	(0.033)	(0.033)	(0.054)	(0.231)
Non-P	-0.019	-0.032	0.048	-0.076
	(0.036)	(0.039)	(0.061)	(0.257)
P	-0.001	-0.064	-0.011	-0.211
	(0.041)	(0.039)	(0.064)	(0.295)
WT	[0.641]	[0.447]	[0.352]	[0.656]
Obs.	966	875	834	740
Panel C - Male				
Treatment	-0.053	-0.052	-0.055	-0.254
	(0.037)	(0.039)	(0.069)	(0.223)
Non-P	-0.008	-0.023	-0.022	-0.086
	(0.044)	(0.043)	(0.079)	(0.272)
P	-0.096**	-0.081*	-0.086	-0.417
	(0.043)	(0.043)	(0.079)	(0.255)
WT	[0.056]	[0.118]	[0.401]	[0.247]
Obs.	966	852	823	708
Panel D - $H_0 : \beta(M) = \beta(F)$				
Treatment	[0.334]	[0.930]	[0.364]	[0.624]
Non-P	[0.836]	[0.875]	[0.444]	[0.969]
P	[0.070]	[0.760]	[0.415]	[0.443]

Note: Sample is restricted to the respondents aged 18-24 years at baseline. In columns (1) - (2) the dependent variable is an indicator that takes a value of one if the respondent is working in their ideal job or looking for a job aligned with their ideal career path, and zero otherwise; in column (3) the dependent variable takes value 1 if very pessimistic, 2 if pessimistic, 3 if optimistic, 4 if very optimistic, and 5 if they are already in their ideal job. In column (4), the respondents choose from a range of monthly salary they expect to gain from ideal/aspiring job, which ranges from 1 if No change, 2 if Less than 1000 INR, 3 if 1000-5000 INR, 4 if 5001-7500 INR, 5 if 7501-10000 INR, 6 if 10001-20000 INR, 7 if 20001-50000 INR, 8 if 50001-100000 INR, and 9 if more than 100,000 INR. **Panel A** includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel D** reports p-values for tests of equality of treatment effects between males and females within each group. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.8: Impact of information on job search (Youth)

	Ever searched using any mode		Ever searched using any digital/online mode	
	Endline 1	Endline 2	Endline 1	Endline 2
	(1)	(2)	(3)	(4)
Panel A - Full Sample				
Treatment	-0.034*	-0.040**	-0.006	-0.014
	(0.019)	(0.017)	(0.019)	(0.018)
Non-P	-0.025	-0.032	0.001	-0.010
	(0.022)	(0.020)	(0.022)	(0.023)
P	-0.043**	-0.047**	-0.014	-0.017
	(0.021)	(0.018)	(0.022)	(0.021)
WT	[0.371]	[0.438]	[0.496]	[0.766]
Obs	1932	1727	1932	1727
Panel B - Female				
Treatment	-0.025	-0.017	0.032	0.025
	(0.025)	(0.023)	(0.024)	(0.026)
Non-P	-0.017	-0.004	0.056*	0.040
	(0.031)	(0.029)	(0.032)	(0.037)
P	-0.033	-0.030	0.009	0.011
	(0.027)	(0.027)	(0.027)	(0.030)
WT	[0.556]	[0.401]	[0.152]	[0.498]
Obs	966	875	966	875
Panel C - Male				
Treatment	-0.038	-0.064***	-0.039	-0.054*
	(0.025)	(0.022)	(0.028)	(0.028)
Non-P	-0.031	-0.063**	-0.048	-0.060*
	(0.030)	(0.028)	(0.032)	(0.031)
P	-0.044*	-0.065***	-0.031	-0.048
	(0.026)	(0.024)	(0.032)	(0.032)
Wald Test	[0.630]	[0.943]	[0.566]	[0.690]
Obs	966	852	966	852
Panel D - $H_0 : \beta(M) = \beta(F)$				
Treatment	[0.684]	[0.119]	[0.044]	[0.033]
Non-P	[0.712]	[0.136]	[0.020]	[0.039]
P	[0.746]	[0.315]	[0.293]	[0.179]

Note: Sample is restricted to the young respondents aged 18-24 years at baseline. The dependent variables are indicator for job search that take a value of one if: ever searched using any mode at Endline 1 (columns 1 and 5), or Endline 2 (columns 2 and 6), ever searched using digital or online mode at Endline 1 (columns 3 and 7), or Endline 2 (columns 4 and 8). **Panel A** includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel D** reports p-values for tests of equality of treatment effects between males and females within each group. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.9: Impact of information on job search (2SLS)

	Ever searched using any mode		Ever searched using any digital/online mode	
	Endline 1	Endline 2	Endline 1	Endline 2
	(1)	(2)	(3)	(4)
Panel A - Full Sample				
Prop. delivered	-0.022	-0.040***	0.019	0.013
	(0.017)	(0.015)	(0.017)	(0.017)
First stage F value	21499.115	16816.011	21570.555	16840.012
Prop. delivered$_{\textbf{Non-P}}$	-0.017	-0.033*	0.031	0.019
	(0.019)	(0.017)	(0.020)	(0.021)
Prop. delivered$_{\textbf{P}}$	-0.027	-0.045***	0.007	0.008
	(0.019)	(0.017)	(0.020)	(0.020)
WT	[0.576]	[0.511]	[0.246]	[0.612]
Obs	3162	2845	3162	2845
Panel B - Female				
Prop. delivered	-0.024	-0.031	0.049**	0.069***
	(0.023)	(0.021)	(0.020)	(0.022)
First stage F value	13226.243	13445.156	13498.126	13628.899
Prop. delivered$_{\textbf{Non-P}}$	-0.020	-0.028	0.079***	0.079***
	(0.026)	(0.025)	(0.024)	(0.029)
Prop. delivered$_{\textbf{P}}$	-0.028	-0.034	0.022	0.059**
	(0.025)	(0.024)	(0.023)	(0.028)
WT	[0.745]	[0.820]	[0.023]	[0.559]
Obs	1675	1512	1675	1512
Panel C - Male				
Prop. delivered	-0.018	-0.048**	-0.014	-0.047*
	(0.021)	(0.020)	(0.027)	(0.027)
First stage F value	8519.612	6364.571	8460.047	6356.552
Prop. delivered$_{\textbf{Non-P}}$	-0.013	-0.040	-0.017	-0.046
	(0.025)	(0.026)	(0.032)	(0.033)
Prop. delivered$_{\textbf{P}}$	-0.023	-0.056**	-0.011	-0.048
	(0.023)	(0.022)	(0.029)	(0.030)
WT	[0.656]	[0.527]	[0.837]	[0.928]
Obs	1487	1333	1487	1333
Panel D - $H_0 : \beta(M) = \beta(F)$				
Treatment	[0.854]	[0.549]	[0.061]	[0.001]
Non-P	[0.849]	[0.745]	[0.017]	[0.004]
P	[0.892]	[0.495]	[0.373]	[0.008]

Note: The table reports ToT results using a 2SLS estimation model where we instrument the proportion of phone messages delivered with a dummy for assignment to Treatment, Non-P or P group. The dependent variables are indicator for job search that take a value of one if: ever searched for a job using any mode at Endline 1 (columns 1), at Endline 2 (columns 2), ever searched using digital or online mode at Endline 1 (columns 3), or Endline 2 (columns 4). **Panel A**includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel** D reports p-values for tests of equality of treatment effects between males and females. F-stat value range for regressions by treatment groups in Panel A (4677.009, 6313.955), Panel B (3459.243, 4302.803) and Panel C (1386.026, 2383.514). $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.10: Impact of information on ideal job expectations (2SLS)

	Working in an ideal job/ working towards it		Optimism for getting ideal job (if applied)	Perceived earnings gain in ideal job
	Endline 1	Endline 2	Endline 2	Endline 2
	(1)	(2)	(3)	(4)
Panel A - Full Sample				
Prop. delivered	-0.045*	-0.045*	0.001	-0.305
	(0.027)	(0.024)	(0.046)	(0.187)
First stage F value	21756.536	17086.694	16326.657	13019.584
Prop. delivered$_{\textbf{Non-P}}$	-0.018	-0.033	0.031	-0.150
	(0.030)	(0.028)	(0.055)	(0.229)
Prop. delivered$_{\textbf{P}}$	-0.070**	-0.056**	-0.027	-0.446**
	(0.032)	(0.027)	(0.053)	(0.223)
WT	[0.125]	[0.349]	[0.298]	[0.246]
Obs.	3162	2845	2672	2305
Panel B - Female				
Prop. delivered	-0.033	-0.041	-0.012	-0.291
	(0.034)	(0.030)	(0.050)	(0.225)
First stage F value	13553.913	13764.529	12950.858	9642.631
Prop. delivered$_{\textbf{Non-P}}$	-0.023	-0.033	0.027	-0.186
	(0.037)	(0.037)	(0.058)	(0.258)
Prop. delivered$_{\textbf{P}}$	-0.042	-0.048	-0.048	-0.386
	(0.042)	(0.032)	(0.057)	(0.276)
WT	[0.657]	[0.675]	[0.201]	[0.493]
Obs.	1675	1512	1405	1222
Panel C - Male				
Prop. delivered	-0.056*	-0.048	0.010	-0.298
	(0.031)	(0.034)	(0.066)	(0.200)
First stage F value	8486.366	6317.201	6289.288	5694.308
Prop. delivered$_{\textbf{Non-P}}$	-0.016	-0.032	0.030	-0.062
	(0.037)	(0.039)	(0.080)	(0.251)
Prop. delivered$_{\textbf{P}}$	-0.094***	-0.062*	-0.008	-0.513**
	(0.036)	(0.037)	(0.074)	(0.228)
WT	[0.045]	[0.373]	[0.640]	[0.090]
Obs.	1487	1333	1267	1083
Panel D - $H_0 : \beta(M) = \beta(F)$				
Treatment	[0.609]	[0.882]	[0.786]	[0.979]
Non-P	[0.881]	[0.977]	[0.971]	[0.729]
P	[0.339]	[0.777]	[0.669]	[0.723]

Note: In columns (1) - (2) the dependent variable is an indicator that takes a value of one if the respondent is working in their ideal job or looking for a job aligned with their ideal career path, and zero otherwise; in column (3) the dependent variable takes value 1 if very pessimistic, 2 if pessimistic, 3 if optimistic, 4 if very optimistic, and 5 if they are already in their ideal job. In column (4), the respondents choose from a range of monthly salary they expect to gain from ideal/aspiring job, which ranges from 1 if No change, 2 if Less than 1000 INR, 3 if 1000-5000 INR, 4 if 5001-7500 INR, 5 if 7501-10000 INR, 6 if 10001-20000 INR, 7 if 20001-50000 INR, 8 if 50001-100000 INR, and 9 if more than 100,000 INR. **Panel A** includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel** D reports p-values for tests of equality of treatment effects between males and females. F-stat value range for Panel A (3782.527, 6397.937), Panel B (2096.102, 4433.847) and Panel C (1367.707, 2369.984). $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.11: Attrition by individual and household characteristics at baseline

	Overall						Female						Male					
	Control	Treatment		Difference			Control	Treatment		Difference			Control	Treatment		Difference		
	C (N=1,067)	Non-P (N=1,129)	P (N=1,147)	C-Non-P	C-P	Non-P-P	C (N=571)	Non-P (N=584)	P (N=593)	C-Non-P	C-P	Non-P-P	C (N=496)	Non-P (N=545)	P (N=554)	C-Non-P	C-P	Non-P-P
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Currently looking for work	-0.003	0.017	-0.015	0.020	-0.012	-0.032	-0.013	-0.012	0.002	0.001	0.015	0.014	0.008	0.041	-0.031	0.034	-0.038	-0.072
	(0.014)	(0.020)	(0.015)	(0.024)	(0.020)	(0.025)	(0.019)	(0.026)	(0.017)	(0.032)	(0.025)	(0.030)	(0.021)	(0.033)	(0.029)	(0.039)	(0.035)	(0.044)
Education level above 12th standard	0.034**	0.030	0.011	-0.005	-0.024	-0.019	0.026	0.059**	0.017	0.033	-0.010	-0.042	0.044*	-0.003	-0.002	-0.047	-0.046	0.001
	(0.015)	(0.018)	(0.015)	(0.023)	(0.021)	(0.023)	(0.017)	(0.025)	(0.020)	(0.030)	(0.026)	(0.032)	(0.025)	(0.024)	(0.026)	(0.034)	(0.036)	(0.035)
Married	-0.057	-0.016	-0.009	0.042	0.049	0.007	-0.091**	-0.046	0.009	0.046	0.100**	0.055	-0.014	0.006	-0.004	0.020	0.010	-0.010
	(0.035)	(0.027)	(0.028)	(0.044)	(0.045)	(0.039)	(0.038)	(0.033)	(0.017)	(0.050)	(0.042)	(0.037)	(0.052)	(0.043)	(0.058)	(0.067)	(0.077)	(0.072)
Age (in years)	0.001	0.002	0.002	0.001	0.001	0.000	0.004	0.003	-0.003	-0.001	-0.007	-0.006*	-0.003	0.000	0.009	0.003	0.011	0.008
	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.006)	(0.007)	(0.006)
Female	-0.012	-0.000	-0.047***	0.011	-0.035*	-0.047**	-	-	-	-	-	-	-	-	-	-	-	-
	(0.014)	(0.017)	(0.014)	(0.022)	(0.020)	(0.021)	.	.	.	.	.	.	.	.	.	.	.	.
Smartphone usage in a day (in hours)	-0.000	0.002	-0.002	0.002	-0.002	-0.004	0.007	-0.000	-0.001	-0.007	-0.008	-0.001	-0.007	0.004	-0.005	0.010	0.002	-0.008
	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.002)	(0.007)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Employed	0.024	0.024	0.009	0.001	-0.015	-0.015	0.021	0.005	0.007	-0.017	-0.014	0.003	0.018	0.041**	-0.010	0.023	-0.028	-0.051
	(0.016)	(0.015)	(0.012)	(0.022)	(0.020)	(0.019)	(0.021)	(0.025)	(0.016)	(0.032)	(0.026)	(0.029)	(0.024)	(0.020)	(0.025)	(0.031)	(0.034)	(0.031)
Uses/used online job platforms for job search	-0.013	-0.001	0.028	0.012	0.041	0.029	-0.015	0.021	0.027	0.035	0.042	0.007	-0.011	-0.019	0.022	-0.008	0.033	0.041
	(0.017)	(0.023)	(0.019)	(0.029)	(0.026)	(0.030)	(0.024)	(0.026)	(0.020)	(0.035)	(0.031)	(0.033)	(0.031)	(0.033)	(0.030)	(0.044)	(0.042)	(0.044)
Skill trained	0.000	-0.031*	-0.021	-0.031	-0.022	0.009	0.015	-0.025	-0.023*	-0.039	-0.037	0.002	-0.014	-0.043*	-0.012	-0.029	0.003	0.032
	(0.017)	(0.017)	(0.015)	(0.024)	(0.022)	(0.022)	(0.020)	(0.025)	(0.013)	(0.032)	(0.024)	(0.028)	(0.026)	(0.022)	(0.022)	(0.033)	(0.034)	(0.031)
Asset Index	-0.008	-0.005	0.007	0.003	0.015*	0.013	-0.002	-0.006	0.000	-0.004	0.003	0.007	-0.017	-0.005	0.013	0.012	0.030*	0.018
	(0.006)	(0.007)	(0.007)	(0.010)	(0.009)	(0.010)	(0.007)	(0.011)	(0.006)	(0.013)	(0.009)	(0.013)	(0.011)	(0.011)	(0.012)	(0.015)	(0.016)	(0.017)
Number of children below 10 years of age	0.024**	0.001	0.007	-0.023	-0.017	0.006	0.016	-0.013	0.016**	-0.029	-0.001	0.028	0.050*	0.027	-0.006	-0.023	-0.055*	-0.032
	(0.011)	(0.014)	(0.009)	(0.018)	(0.014)	(0.017)	(0.010)	(0.019)	(0.008)	(0.021)	(0.013)	(0.020)	(0.028)	(0.025)	(0.015)	(0.038)	(0.032)	(0.029)
Number of household members	-0.010**	-0.001	-0.014***	0.010	-0.003	-0.013**	-0.006	-0.002	-0.010**	0.004	-0.004	-0.008	-0.020**	0.001	-0.017**	0.020*	0.002	-0.018*
	(0.004)	(0.005)	(0.004)	(0.007)	(0.006)	(0.007)	(0.005)	(0.007)	(0.004)	(0.008)	(0.006)	(0.008)	(0.009)	(0.008)	(0.007)	(0.012)	(0.011)	(0.011)
SC/ST	-0.019	-0.010	0.017	0.009	0.036*	0.026	-0.016	-0.013	-0.014	0.003	0.003	-0.001	-0.023	-0.009	0.049*	0.015	0.072**	0.058
	(0.013)	(0.015)	(0.015)	(0.020)	(0.020)	(0.021)	(0.017)	(0.017)	(0.012)	(0.024)	(0.020)	(0.021)	(0.020)	(0.026)	(0.028)	(0.033)	(0.034)	(0.038)
Hindu	-0.029	-0.019	-0.027	0.009	0.001	-0.008	-0.026	-0.021	-0.031	0.005	-0.005	-0.010	-0.040	-0.021	-0.023	0.020	0.018	-0.002
	(0.023)	(0.028)	(0.019)	(0.036)	(0.030)	(0.034)	(0.025)	(0.038)	(0.024)	(0.046)	(0.035)	(0.045)	(0.040)	(0.037)	(0.041)	(0.054)	(0.057)	(0.055)
Years in Delhi	0.000	-0.001	0.001	-0.001	0.001	0.002	-0.001	0.000	0.002*	0.001	0.002	0.002	0.001	-0.003*	-0.000	-0.003	-0.001	0.002
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)	(0.003)	(0.004)	(0.003)
Native of Delhi	-0.001	-0.006	-0.029	-0.005	-0.028	-0.022	-0.016	-0.053	-0.022	-0.037	-0.006	0.031	0.017	0.044*	-0.025	0.027	-0.042	-0.069
	(0.023)	(0.023)	(0.021)	(0.033)	(0.032)	(0.031)	(0.034)	(0.035)	(0.019)	(0.049)	(0.039)	(0.040)	(0.034)	(0.025)	(0.035)	(0.042)	(0.049)	(0.043)
Test of joint significance	-	-	-	[0.544]	[0.218]	[0.036]	-	-	-	[0.619]	[0.127]	[0.309]	-	-	-	[0.249]	[0.222]	[0.008]

Note: The dependent variable is an indicator for attrition that takes value one if a respondent dropped out of the sample at Endline 2 and zero otherwise. The table presents coefficients from regressions of the attrition indicator on baseline characteristics, estimated separately for each treatment group (Control, Non-P, P) and by gender subgroups, to examine whether baseline characteristics predict attrition differently across treatment arms. Each coefficient represents the correlation between the respective baseline characteristic and the probability of attrition within that specific group. Significant differences in these correlations across treatment groups would suggest differential, non-random, attrition that could bias treatment effect estimates. The total number of observations is less than the 3,391 individuals at baseline because of missing data on control variables and outcome variables for some respondents. Robust standard errors, clustered at the PS level are in parentheses ($*p < 0.1, **p < 0.05, ***p < 0.01$).

Table A.12: Robustness (Lee Bounds): Impact of information on job search

	Full Sample				Youth Sample			
	Ever searched using any mode		Ever searched using any digital/online mode		Ever searched using any mode		Ever searched using any digital/online mode	
	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Full Sample								
Treatment								
Lower	-0.010	-0.047**	0.010	-0.009	-0.039*	-0.061**	-0.023	-0.033
	(0.018)	(0.020)	(0.019)	(0.022)	(0.022)	(0.026)	(0.025)	(0.028)
Upper	-0.009	-0.021	0.010	0.016	-0.035	-0.031	-0.019	-0.002
	(0.017)	(0.017)	(0.019)	(0.021)	(0.023)	(0.021)	(0.025)	(0.026)
Non-P								
Lower	0.004	-0.025	0.018	-0.010	-0.026	-0.042	-0.032	-0.050*
	(0.018)	(0.021)	(0.019)	(0.022)	(0.024)	(0.027)	(0.025)	(0.028)
Upper	0.014	0.011	0.028	0.026	-0.008	-0.002	-0.014	-0.010
	(0.017)	(0.017)	(0.019)	(0.021)	(0.023)	(0.022)	(0.025)	(0.026)
P								
Lower	-0.023	-0.031*	-0.018	-0.010	-0.031	-0.029	-0.010	0.007
	(0.017)	(0.017)	(0.019)	(0.021)	(0.023)	(0.022)	(0.025)	(0.026)
Upper	-0.014	-0.020	-0.009	0.001	-0.009	-0.019	0.013	0.017
	(0.018)	(0.020)	(0.019)	(0.021)	(0.024)	(0.026)	(0.025)	(0.028)
Observations	3,391	3,391	3,391	3,391	2,050	2,050	2,050	2,050
Panel B - Female								
Treatment								
Lower	0.003	-0.025	0.047*	0.050*	-0.006	-0.021	0.034	0.015
	(0.024)	(0.028)	(0.026)	(0.029)	(0.031)	(0.035)	(0.034)	(0.038)
Upper	0.005	-0.009	0.049*	0.066**	-0.003	0.003	0.037	0.039
	(0.025)	(0.023)	(0.026)	(0.029)	(0.032)	(0.030)	(0.034)	(0.036)
Non-P								
Lower	-0.000	-0.024	0.052*	0.019	-0.008	-0.026	0.009	-0.034
	(0.025)	(0.029)	(0.027)	(0.030)	(0.033)	(0.037)	(0.035)	(0.040)
Upper	0.028	0.014	0.080***	0.057**	0.015	0.024	0.032	0.016
	(0.024)	(0.024)	(0.027)	(0.029)	(0.032)	(0.030)	(0.035)	(0.037)
P								
Lower	-0.024	-0.022	-0.032	0.009	-0.021	-0.020	0.004	0.025
	(0.024)	(0.024)	(0.027)	(0.028)	(0.032)	(0.031)	(0.035)	(0.036)
Upper	0.005	-0.000	-0.003	0.031	0.005	0.005	0.030	0.050
	(0.025)	(0.028)	(0.026)	(0.029)	(0.033)	(0.036)	(0.035)	(0.039)
Observations	1,768	1,768	1,768	1,768	1,017	1,017	1,017	1,017
Panel C - Male								
Treatment								
Lower	-0.027	-0.072**	-0.035	-0.077**	-0.072**	-0.101***	-0.081**	-0.082**
	(0.027)	(0.030)	(0.029)	(0.033)	(0.032)	(0.038)	(0.035)	(0.041)
Upper	-0.024	-0.037	-0.032	-0.042	-0.066**	-0.066**	-0.075**	-0.046
	(0.025)	(0.023)	(0.029)	(0.030)	(0.033)	(0.031)	(0.035)	(0.038)
Non-P								
Lower	-0.001	-0.026	-0.028	-0.041	-0.043	-0.057	-0.070**	-0.066
	(0.025)	(0.031)	(0.028)	(0.032)	(0.034)	(0.039)	(0.035)	(0.040)
Upper	0.010	0.007	-0.018	-0.008	-0.030	-0.027	-0.057*	-0.035
	(0.026)	(0.024)	(0.028)	(0.030)	(0.033)	(0.032)	(0.035)	(0.038)
P								
Lower	-0.036	-0.043	-0.015	-0.033	-0.039	-0.040	-0.021	-0.013
	(0.027)	(0.030)	(0.028)	(0.032)	(0.033)	(0.038)	(0.035)	(0.039)
Upper	-0.023	-0.042*	-0.002	-0.032	-0.020	-0.036	-0.002	-0.009
	(0.025)	(0.024)	(0.028)	(0.030)	(0.033)	(0.032)	(0.035)	(0.037)
Observations	1,623	1,623	1,623	1,623	1,033	1,033	1,033	1,033

Note: The lower and upper bounds indicate the minimum and maximum possible impact of assignment, respectively, to treatment on the outcomes reported in Table 4, with their std errors in parentheses. The dependent variables are indicator for job search that take a value of one if: ever searched using any mode at Endline 1 (columns 1 and 5), or Endline 2 (columns 2 and 6), ever searched using any digital or online mode at Endline 1 (columns 3 and 7), or Endline 2 (columns 4 and 8). Columns (1)-(4) are for the full sample and columns (5)-(8) are for the youth (aged 18-24 years) sample. Panel A includes the full sample, Panel B includes the female sample and Panel C includes the male sample. Robust standard errors clustered at the PS level are in parentheses. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.13: Robustness (Lee Bounds): Impact of information on ideal job expectations

	Working in an ideal job/ working towards it		Optimism for getting ideal job (if applied)	Perceived earnings gain in ideal job
	Endline 1	Endline 2	Endline 2	Endline 2
	(1)	(2)	(3)	(4)
Panel A - Full Sample				
Treatment				
Lower	-0.036**	-0.052**	-0.048	-0.337**
	(0.018)	(0.021)	(0.038)	(0.143)
Upper	-0.035**	-0.027	0.063	-0.208
	(0.017)	(0.019)	(0.043)	(0.131)
Non-P				
Lower	0.011	-0.022	-0.039	-0.093
	(0.018)	(0.022)	(0.039)	(0.145)
Upper	0.021	0.014	0.117**	0.236*
	(0.017)	(0.019)	(0.046)	(0.122)
P				
Lower	-0.055***	-0.040**	-0.052	-0.443***
	(0.017)	(0.019)	(0.043)	(0.121)
Upper	-0.046**	-0.029	0.000	-0.236*
	(0.018)	(0.021)	(0.037)	(0.136)
Observations	3,391	3,391	3,391	3,391
Panel B - Female				
Treatment				
Lower	-0.028	-0.049*	-0.058	-0.315*
	(0.024)	(0.029)	(0.050)	(0.188)
Upper	-0.026	-0.034	0.056	-0.252
	(0.025)	(0.026)	(0.059)	(0.182)
Non-P				
Lower	-0.020	-0.034	-0.035	-0.189
	(0.026)	(0.030)	(0.052)	(0.191)
Upper	0.008	0.005	0.102**	0.129
	(0.024)	(0.027)	(0.045)	(0.169)
P				
Lower	-0.036	-0.038	-0.066	-0.376**
	(0.024)	(0.027)	(0.042)	(0.168)
Upper	-0.006	-0.016	-0.016	-0.129
	(0.025)	(0.029)	(0.047)	(0.181)
Observations	1,768	1,768	1,768	1,768
Panel C - Male				
Treatment				
Lower	-0.049*	-0.056*	-0.040	-0.376*
	(0.025)	(0.032)	(0.058)	(0.220)
Upper	-0.046**	-0.022	0.066	-0.182
	(0.023)	(0.028)	(0.064)	(0.186)
Non-P				
Lower	0.033	-0.010	-0.046	0.004
	(0.022)	(0.032)	(0.059)	(0.219)
Upper	0.044*	0.022	0.098	0.341*
	(0.025)	(0.028)	(0.066)	(0.198)
P				
Lower	-0.091***	-0.043	-0.033	-0.507**
	(0.026)	(0.031)	(0.063)	(0.198)
Upper	-0.078***	-0.042	0.017	-0.361*
	(0.024)	(0.027)	(0.057)	(0.206)
Observations	1,623	1,623	1,623	1,623

Note: The lower and upper bounds indicate the minimum and maximum possible impact of assignment, respectively, to treatment on the outcomes reported in Table 3, with their std errors in parentheses. In columns (1) - (2) the dependent variable is an indicator that takes a value of one if the respondent is working in their ideal job or looking for a job aligned with their ideal career path, and zero otherwise; in column (3) the dependent variable takes value 1 if very pessimistic, 2 if pessimistic, 3 if optimistic, 4 if very optimistic, and 5 if they are already in their ideal job. In column (4), the respondents choose from a range of monthly salary they expect to gain from ideal/aspiring job, which ranges from 1 if No change, 2 if Less than 1000 INR, 3 if 1000-5000 INR, 4 if 5001-7500 INR, 5 if 7501-10000 INR, 6 if 10001-20000 INR, 7 if 20001-50000 INR, 8 if 50001-100000 INR, and 9 if more than 100,000 INR. Panel A includes the full sample, Panel B includes the female sample and Panel C includes the male sample. Robust standard errors clustered at the PS level are in parentheses. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.14: Robustness (IPW Weights): Impact of information on job search

	Full Sample				Youth Sample			
	Ever searched using any mode		Ever searched using any digital/online mode		Ever searched using any mode		Ever searched using any digital/online mode	
	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Full Sample								
Treatment	-0.019	-0.034***	0.017	0.012	-0.034*	-0.040**	-0.007	-0.014
	(0.015)	(0.013)	(0.015)	(0.016)	(0.019)	(0.016)	(0.019)	(0.018)
Non-P	-0.014	-0.029*	0.027	0.016	-0.025	-0.032	0.001	-0.011
	(0.016)	(0.015)	(0.018)	(0.018)	(0.022)	(0.020)	(0.022)	(0.023)
P	-0.023	-0.039**	0.007	0.008	-0.043**	-0.048***	-0.014	-0.018
	(0.017)	(0.015)	(0.018)	(0.019)	(0.020)	(0.018)	(0.022)	(0.021)
WT	[0.558]	[0.488]	[0.266]	[0.666]	[0.356]	[0.431]	[0.491]	[0.776]
Observations	3162	2845	3162	2845	1932	1727	1932	1727
Panel B - Female								
Treatment	-0.020	-0.027	0.043**	0.061***	-0.025	-0.018	0.032	0.025
	(0.020)	(0.018)	(0.018)	(0.020)	(0.025)	(0.023)	(0.025)	(0.026)
Non-P	-0.017	-0.024	0.068***	0.069***	-0.017	-0.005	0.055*	0.038
	(0.022)	(0.022)	(0.021)	(0.025)	(0.030)	(0.029)	(0.032)	(0.037)
P	-0.024	-0.029	0.019	0.053**	-0.034	-0.031	0.008	0.011
	(0.022)	(0.021)	(0.021)	(0.025)	(0.026)	(0.026)	(0.027)	(0.030)
WT	[0.720]	[0.834]	[0.027]	[0.610]	[0.540]	[0.410]	[0.149]	[0.517]
Observations	1675	1512	1675	1512	966	875	966	875
Panel C - Male								
Treatment	-0.015	-0.042**	-0.011	-0.040	-0.037	-0.064***	-0.040	-0.053*
	(0.018)	(0.017)	(0.024)	(0.024)	(0.025)	(0.021)	(0.028)	(0.028)
Non-P	-0.010	-0.034	-0.013	-0.038	-0.031	-0.062**	-0.048	-0.058*
	(0.021)	(0.022)	(0.028)	(0.028)	(0.030)	(0.028)	(0.032)	(0.031)
P	-0.019	-0.050**	-0.009	-0.042	-0.043*	-0.065***	-0.032	-0.047
	(0.020)	(0.020)	(0.026)	(0.027)	(0.026)	(0.024)	(0.031)	(0.032)
WT	[0.659]	[0.497]	[0.849]	[0.891]	[0.623]	[0.921]	[0.575]	[0.711]
Observations	1487	1333	1487	1333	966	852	966	852

Note: We re-estimate Table 4 using the propensity scores generated using the controls to model the likelihood of being present at Endline 1 and Endline 2 as weights. The dependent variables are indicator for job search that take a value of one if: ever searched using any mode at Endline 1 (columns 1 and 5), or Endline 2 (columns 2 and 6), ever searched using any digital or online mode at Endline 1 (columns 3 and 7), or Endline 2 (columns 4 and 8). Columns (1)-(4) are for the full sample and columns (5)-(8) are for the youth (aged 18-24 years) sample. Panel A includes the full sample, Panel B includes the female sample and Panel C includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values in square brackets. Panel D reports p-values for tests of equality of treatment effects between males and females. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.15: Robustness (IPW Weights): Impact of information on ideal job expectations

	Working in an ideal job/ working towards it		Optimism for getting ideal job (if applied)	Perceived earnings gain in ideal job
	Endline 1	Endline 2	Endline 2	Endline 2
	(1)	(2)	(3)	(4)
Panel A - Full Sample				
Treatment	-0.039*	-0.040*	0.002	-0.269
	(0.023)	(0.021)	(0.041)	(0.164)
Non-P	-0.016	-0.030	0.027	-0.129
	(0.026)	(0.024)	(0.048)	(0.198)
P	-0.062**	-0.051**	-0.022	-0.402**
	(0.028)	(0.024)	(0.048)	(0.199)
WT	[0.118]	[0.344]	[0.331]	[0.222]
Obs.	3162	2845	2672	2305
Panel B - Female				
Treatment	-0.029	-0.038	-0.011	-0.253
	(0.030)	(0.026)	(0.044)	(0.199)
Non-P	-0.021	-0.030	0.022	-0.157
	(0.033)	(0.033)	(0.051)	(0.224)
P	-0.038	-0.045	-0.043	-0.344
	(0.037)	(0.028)	(0.051)	(0.249)
WT	[0.647]	[0.617]	[0.208]	[0.468]
Obs.	1675	1512	1405	1222
Panel C - Male				
Treatment	-0.049*	-0.043	0.011	-0.265
	(0.027)	(0.030)	(0.058)	(0.178)
Non-P	-0.013	-0.030	0.026	-0.054
	(0.032)	(0.034)	(0.069)	(0.219)
P	-0.083***	-0.055	-0.002	-0.464**
	(0.032)	(0.033)	(0.067)	(0.206)
WT	[0.044]	[0.420]	[0.696]	[0.082]
Obs.	1487	1333	1267	1083

Note: We re-estimate Table 3 using the propensity scores generated using the controls to model the likelihood of being present at the Endline 1 and Endline 2 as weights. In columns (1) - (2) the dependent variable is an indicator that takes a value of one if the respondent is working in their ideal job or looking for a job aligned with their ideal career path, and zero otherwise; in column (3) the dependent variable takes value 1 if very pessimistic, 2 if pessimistic, 3 if optimistic, 4 if very optimistic, and 5 if they are already in their ideal job. In column (4), the respondents choose from a range of monthly salary they expect to gain from ideal/aspiring job, which ranges from 1 if No change, 2 if Less than 1000 INR, 3 if 1000-5000 INR, 4 if 5001-7500 INR, 5 if 7501-10000 INR, 6 if 10001-20000 INR, 7 if 20001-50000 INR, 8 if 50001-100000 INR, and 9 if more than 100,000 INR. Panel A includes the full sample, Panel B includes the female sample and Panel C includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values in square brackets. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.16: Robustness (Multiple Hypothesis Testing): Impact of information on job search

	Full Sample		**Youth Sample**	
	Ever searched using any mode	Ever searched using any digital/online mode	Ever searched using any mode	Ever searched using any digital/online mode
	Endline 2	Endline 2	Endline 2	Endline 2
	(1)	(2)	(3)	(4)
		Panel A - Full Sample		
Treatment	-0.035**	0.012	-0.040**	-0.014
	(0.010)	(0.447)	(0.018)	(0.451)
	[0.021]	[0.288]	[0.038]	[0.292]
Non-P	-0.029*	0.017	-0.032	-0.010
	(0.060)	(0.363)	(0.126)	(0.656)
	[0.099]	[0.320]	[0.234]	[0.489]
P	-0.040**	0.007	-0.047**	-0.017
	(0.011)	(0.699)	(0.011)	(0.404)
	[0.047]	[0.538]	[0.047]	[0.369]
Obs	2845	2845	1727	1727
		Panel B - Female		
Treatment	-0.027	0.060***	-0.017	0.025
	(0.147)	(0.003)	(0.468)	(0.338)
	[0.080]	[0.007]	[0.880]	[0.880]
Non-P	-0.024	0.069***	-0.004	0.040
	(0.273)	(0.008)	(0.899)	(0.286)
	[0.159]	[0.034]	[1.000]	[1.000]
P	-0.030	0.052**	-0.030	0.011
	(0.171)	(0.036)	(0.263)	(0.713)
	[0.129]	[0.058]	[1.000]	[1.000]
Obs	1512	1512	875	875
		Panel C - Male		
Treatment	-0.042**	-0.041*	-0.064***	-0.054*
	(0.017)	(0.091)	(0.004)	(0.052)
	[0.036]	[0.048]	[0.009]	[0.027]
Non-P	-0.034	-0.039	-0.063**	-0.060*
	(0.127)	(0.165)	(0.029)	(0.054)
	[0.142]	[0.142]	[0.046]	[0.058]
P	-0.050**	-0.043	-0.065***	-0.048
	(0.013)	(0.108)	(0.008)	(0.137)
	[0.055]	[0.142]	[0.034]	[0.074]
Obs	1333	1333	852	852

Note: Endline 2 coefficients from Table 4 are reported with original p-values in parentheses, while p-values of Anderson's sharpened False Discovery Rate (FDR) q-values which adjust for multiple hypothesis testing are reported in square brackets (*** p<0.01, ** p<0.05, * p<0.1). The dependent variables are indicator for job search that take a value of one if: ever searched using any mode at Endline 1 (columns 1 and 5), or Endline 2 (columns 2 and 6), ever searched using any digital or online mode at Endline 1 (columns 3 and 7), or Endline 2 (columns 4 and 8). Columns (1)-(4) are for the full sample and columns (5)-(8) are for the youth (aged 18-24 years) sample. Panel A includes the full sample, Panel B includes the female sample and Panel C includes the male sample. Robust standard errors clustered at the PS level are in parentheses. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.17: Robustness (Multiple Hypothesis Testing): Impact of information on ideal job expectations

	Working in an ideal job/ working towards it	Optimism for getting ideal job (if applied)	Perceived earnings gain in ideal job
	Endline 2	Endline 2	Endline 2
	(1)	(2)	(3)
Panel A - Full Sample			
Treatment	-0.039*	0.001	-0.268
	(0.071)	(0.988)	(0.108)
	[0.194]	[0.492]	[0.194]
Non-P	-0.028	0.027	-0.130
	(0.250)	(0.574)	(0.515)
	[0.500]	[0.680]	[0.680]
P	-0.050**	-0.024	-0.398**
	(0.039)	(0.607)	(0.048)
	[0.169]	[0.680]	[0.169]
Obs	2845	2672	2305
Panel B - Female			
Treatment	-0.036	-0.011	-0.256
	(0.176)	(0.808)	(0.202)
	[0.435]	[0.435]	[0.435]
Non-P	-0.029	0.023	-0.162
	(0.373)	(0.652)	(0.475)
	[1.000]	[1.000]	[1.000]
P	-0.043	-0.043	-0.345
	(0.140)	(0.407)	(0.168)
	[1.000]	[1.000]	[1.000]
Obs	1512	1405	1222
Panel C - Male			
Treatment	-0.042	0.009	-0.262
	(0.167)	(0.879)	(0.141)
	[0.335]	[0.415]	[0.335]
Non-P	-0.027	0.026	-0.053
	(0.417)	(0.710)	(0.808)
	[1.000]	[1.000]	[1.000]
P	-0.056	-0.007	-0.458**
	(0.100)	(0.915)	(0.027)
	[0.334]	[1.000]	[0.194]
Obs	1333	1267	1083

Note: Endline 2 coefficients from Table 3 are reported with original p-values in parentheses, while p-values of Anderson's sharpened False Discovery Rate (FDR) q-values which adjust for multiple hypothesis testing are reported in square brackets (*** p<0.01, ** p<0.05, * p<0.1).In columns (1) - (2) the dependent variable is an indicator that takes a value of one if the respondent is working in their ideal job or looking for a job aligned with their ideal career path, and zero otherwise; in column (3) the dependent variable takes value 1 if very pessimistic, 2 if pessimistic, 3 if optimistic, 4 if very optimistic, and 5 if they are already in their ideal job. In column (4), the respondents choose from a range of monthly salary they expect to gain from ideal/aspiring job, which ranges from 1 if No change, 2 if Less than 1000 INR, 3 if 1000-5000 INR, 4 if 5001-7500 INR, 5 if 7501-10000 INR, 6 if 10001-20000 INR, 7 if 20001-50000 INR, 8 if 50001-100000 INR, and 9 if more than 100,000 INR. Panel A includes the full sample, Panel B includes the female sample and Panel C includes the male sample. Robust standard errors clustered at the PS level are in parentheses. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.18: Impact of information on enrollment in educational institution (Youth)

	Youth Sample		Enrolled (at baseline)		Not enrolled (at baseline)	
	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Full Sample						
Treatment	0.017	0.014	0.016	0.014	0.008	0.012
	(0.027)	(0.010)	(0.035)	(0.013)	(0.031)	(0.009)
Non-P	0.008	0.005	0.009	0.005	-0.012	0.004
	(0.032)	(0.012)	(0.042)	(0.016)	(0.033)	(0.011)
P	0.025	0.022*	0.023	0.023	0.025	0.018
	(0.030)	(0.012)	(0.039)	(0.016)	(0.035)	(0.013)
WT	[0.580]	[0.179]	[0.726]	[0.303]	[0.223]	[0.342]
Obs.	1932	1727	1356	1215	576	512
Panel B - Female						
Treatment	0.030	0.003	0.017	-0.011	0.049	0.027**
	(0.035)	(0.013)	(0.047)	(0.019)	(0.042)	(0.012)
Non-P	0.013	-0.001	0.000	-0.012	0.025	0.014
	(0.043)	(0.016)	(0.059)	(0.022)	(0.046)	(0.015)
P	0.047	0.007	0.035	-0.010	0.070	0.038*
	(0.037)	(0.015)	(0.050)	(0.022)	(0.047)	(0.020)
WT	[0.394]	[0.638]	[0.515]	[0.950]	[0.291]	[0.362]
Obs.	966	875	653	591	313	284
Panel C - Male						
Treatment	0.002	0.025*	0.008	0.043**	-0.038	-0.011
	(0.036)	(0.015)	(0.044)	(0.019)	(0.049)	(0.015)
Non-P	0.002	0.010	0.011	0.024	-0.049	-0.018
	(0.041)	(0.016)	(0.051)	(0.021)	(0.051)	(0.015)
P	0.002	0.040**	0.006	0.062**	-0.028	-0.005
	(0.041)	(0.020)	(0.052)	(0.025)	(0.057)	(0.017)
WT	[0.995]	[0.142]	[0.922]	[0.151]	[0.641]	[0.322]
Obs.	966	852	703	624	263	228
Panel D - $H_0 : \beta(M) = \beta(F)$						
Treatment	[0.542]	[0.274]	[0.878]	[0.047]	[0.180]	[0.037]
Non-P	[0.849]	[0.625]	[0.876]	[0.207]	[0.280]	[0.122]
P	[0.371]	[0.195]	[0.650]	[0.035]	[0.185]	[0.095]

Note: Sample is restricted to the young respondents aged 18-24 years at baseline. The dependent variables are indicators of enrollment for any educational qualification from the date of intervention to Endline 1 (column 1, 3 and 5) and between Endline 1 and Endline 2 (column 2, 4 and 6). Panel A includes the full sample, Panel B includes the female sample and Panel C includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. Panel D reports p-values for tests of equality of treatment effects between males and females. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.19: Impact of information on job satisfaction

	Overall satisfaction	Monetary satisfaction	Non-monetary satisfaction	Work flexibility satisfaction	Work environment satisfaction	Job location satisfaction
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Full Sample						
Treatment	0.136***	0.146**	0.254***	0.083	0.109*	0.063
	(0.046)	(0.064)	(0.064)	(0.059)	(0.061)	(0.063)
Non-P	0.073	0.103	0.232***	0.017	0.038	-0.028
	(0.053)	(0.075)	(0.072)	(0.070)	(0.069)	(0.070)
P	0.195***	0.185**	0.275***	0.143**	0.175**	0.147**
	(0.054)	(0.074)	(0.081)	(0.069)	(0.070)	(0.072)
WT	[0.029]	[0.280]	[0.597]	[0.105]	[0.053]	[0.012]
Obs	1221	1354	1227	1354	1331	1348
Panel B - Female						
Treatment	0.101	0.170*	0.343***	-0.078	0.091	-0.076
	(0.063)	(0.099)	(0.105)	(0.096)	(0.086)	(0.098)
Non-P	0.048	0.124	0.340***	-0.138	0.056	-0.099
	(0.080)	(0.122)	(0.118)	(0.116)	(0.099)	(0.113)
P	0.147**	0.211**	0.346***	-0.025	0.122	-0.055
	(0.066)	(0.105)	(0.122)	(0.108)	(0.098)	(0.111)
WT	[0.172]	[0.426]	[0.959]	[0.336]	[0.488]	[0.685]
Obs	464	527	468	526	511	520
Panel C - Male						
Treatment	0.148**	0.134	0.207**	0.179**	0.102	0.125
	(0.062)	(0.086)	(0.086)	(0.078)	(0.082)	(0.077)
Non-P	0.080	0.092	0.178*	0.108	0.010	-0.001
	(0.066)	(0.094)	(0.093)	(0.089)	(0.095)	(0.089)
P	0.215***	0.173*	0.237**	0.244***	0.187**	0.242***
	(0.073)	(0.100)	(0.105)	(0.093)	(0.088)	(0.085)
WT	[0.043]	[0.365]	[0.554]	[0.154]	[0.040]	[0.005]
Obs	757	827	759	828	820	828
Panel D - $H_0 : \beta(M) = \beta(F)$						
Treatment	[0.560]	[0.782]	[0.320]	[0.038]	[0.924]	[0.075]
Non-P	[0.735]	[0.834]	[0.275]	[0.088]	[0.732]	[0.477]
P	[0.430]	[0.779]	[0.481]	[0.055]	[0.577]	[0.015]

Note: The job satisfaction question was asked only at Endline 2, conditional on the individual being employed. The dependent variables are standardized Z-scores ($Z(y) = \frac{y-\bar{Y}}{sd}$ where, $\bar{Y}$ is the mean value of y for the control group and sd is the standard-deviation for the control group) of the response (yes/no) to the statement, "How satisfied are you with the various characteristics of your current job?": Column (2): monetary compensation (salary, bonuses); Column (3): non-monetary compensation (such as benefits, healthcare, insurance, meals, and transportation); Column (4): work flexibility and working hours; Column (5): nature of the work environment (such as safety and gender composition); Column (6): job location (distance and locality). Column (1) is the *'Overall satisfaction'* measure constructed as an equal weighted average of the five satisfaction components in columns (2)-(6). The response were - 1: Not at all satisfied; 2: Somewhat dissatisfied; 3: Neutral; 4: Somewhat satisfied; and 5: Very satisfied. ANOVA specification is used in this analysis as baseline satisfaction data is not available. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. Panel D reports p-values for tests of equality of treatment effects between males and females. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.20: Impact of information on job search (Youth, by earnings mis-match at baseline)

	Upward biased expectations (at baseline)				Downward biased expectations (at baseline)			
	Ever searched using any mode		Ever searched using any digital/online mode		Ever searched using any mode		Ever searched using any digital/online mode	
	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A - Full Sample								
Treatment	-0.038**	-0.046***	-0.009	-0.011	0.024	0.051	0.030	-0.022
	(0.019)	(0.016)	(0.020)	(0.019)	(0.057)	(0.056)	(0.059)	(0.058)
Non-P	-0.030	-0.038*	-0.004	-0.008	0.055	0.082	0.068	-0.004
	(0.022)	(0.021)	(0.023)	(0.023)	(0.068)	(0.060)	(0.075)	(0.072)
P	-0.046**	-0.053***	-0.015	-0.015	0.000	0.027	0.002	-0.035
	(0.020)	(0.018)	(0.024)	(0.022)	(0.061)	(0.063)	(0.058)	(0.061)
WT	[0.388]	[0.468]	[0.667]	[0.755]	[0.369]	[0.320]	[0.264]	[0.620]
Obs.	1692	1512	1692	1512	240	215	240	215
Panel B - Female								
Treatment	-0.027	-0.013	0.030	0.039	0.023	0.020	0.085	-0.009
	(0.026)	(0.025)	(0.027)	(0.029)	(0.064)	(0.057)	(0.071)	(0.076)
Non-P	-0.013	0.005	0.056*	0.058	0.012	0.010	0.109	-0.011
	(0.032)	(0.032)	(0.033)	(0.039)	(0.084)	(0.067)	(0.101)	(0.094)
P	-0.041	-0.031	0.004	0.021	0.031	0.027	0.067	-0.007
	(0.026)	(0.027)	(0.029)	(0.033)	(0.072)	(0.067)	(0.070)	(0.082)
WT	[0.343]	[0.279]	[0.130]	[0.393]	[0.823]	[0.799]	[0.654]	[0.969]
Obs.	826	742	826	742	140	133	140	133
Panel C - Male								
Treatment	-0.043*	-0.080***	-0.043	-0.063**	0.047	0.164*	0.002	0.065
	(0.025)	(0.021)	(0.030)	(0.029)	(0.080)	(0.090)	(0.086)	(0.105)
Non-P	-0.043	-0.083***	-0.059*	-0.071**	0.133	0.254**	0.056	0.083
	(0.030)	(0.028)	(0.033)	(0.032)	(0.094)	(0.097)	(0.108)	(0.129)
P	-0.043	-0.077***	-0.028	-0.055	-0.016	0.094	-0.036	0.052
	(0.027)	(0.024)	(0.034)	(0.034)	(0.083)	(0.102)	(0.083)	(0.113)
WT	[0.982]	[0.831]	[0.310]	[0.601]	[0.053]	[0.081]	[0.237]	[0.788]
Obs.	866	770	866	770	100	82	100	82
Panel D - $H_0 : \beta(M) = \beta(F)$								
Treatment	[0.618]	[0.037]	[0.057]	[0.014]	[0.787]	[0.128]	[0.417]	[0.555]
Non-P	[0.481]	[0.034]	[0.015]	[0.014]	[0.255]	[0.018]	[0.688]	[0.534]
P	[0.954]	[0.217]	[0.442]	[0.115]	[0.621]	[0.528]	[0.312]	[0.655]

Note: Sample is restricted to the young respondents aged 18-24 years at baseline. The dependent variables is an indicator that takes a value of one if the respondent reports having ever searched for a job using any mode at Endline 1 (columns (1) and (5)) or at Endline 2 (columns (2) and (6)); ever searched for a job using any digital or online mode at Endline 1 (columns (3) and (7)) or Endline 2 (columns (4) and (8)). An individual is classified as having 'Upward biased' ('Downward biased') expectations if their average expected salary was more (less) than the average weighted monthly earnings from PLFS 2022-23 urban sample, at baseline. **Panel A** includes the full sample, **Panel B** includes the female sample and **Panel C** includes the male sample. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. **Panel D** reports p-values for tests of equality of treatment effects between males and females within each group. $***p < 0.01, **p < 0.05, *p < 0.10$. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A.21: Impact of information on govt portal engagement

	Know about govt portal NCS/Delhi Online Employment exhange portal		Job ads viewed via govt portals		Jobs applied via govt portals	
	Endline 1	Endline 2	Endline 1	Endline 2	Endline 1	Endline 2
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Full Sample						
Treatment	0.054**	0.011	0.244	0.032	-0.011	-0.025*
	(0.022)	(0.015)	(0.260)	(0.162)	(0.017)	(0.015)
Non-P	0.041	-0.004	-0.169	-0.059	-0.019	-0.024
	(0.025)	(0.017)	(0.142)	(0.168)	(0.019)	(0.016)
P	0.068**	0.025	0.644	0.119	-0.003	-0.026
	(0.026)	(0.019)	(0.478)	(0.245)	(0.020)	(0.016)
WT	[0.348]	[0.151]	[0.099]	[0.514]	[0.368]	[0.912]
Obs.	3162	2845	3162	2845	3162	2845
Panel B - Female						
Treatment	0.074***	0.014	0.388*	-0.079	-0.019	-0.008
	(0.024)	(0.019)	(0.223)	(0.171)	(0.024)	(0.015)
Non-P	0.061**	-0.003	-0.006	-0.262*	-0.020	-0.018
	(0.030)	(0.021)	(0.142)	(0.137)	(0.026)	(0.014)
P	0.086***	0.030	0.764*	0.095	-0.018	0.000
	(0.027)	(0.024)	(0.413)	(0.250)	(0.026)	(0.018)
WT	[0.444]	[0.199]	[0.084]	[0.107]	[0.930]	[0.197]
Obs.	1675	1512	1675	1512	1675	1512
Panel C - Male						
Treatment	0.034	0.008	0.068	0.100	-0.003	-0.048*
	(0.028)	(0.024)	(0.331)	(0.251)	(0.021)	(0.029)
Non-P	0.021	-0.005	-0.366	0.096	-0.019	-0.037
	(0.030)	(0.027)	(0.234)	(0.307)	(0.020)	(0.032)
P	0.047	0.020	0.493	0.104	0.014	-0.059**
	(0.035)	(0.028)	(0.558)	(0.358)	(0.029)	(0.028)
WT	[0.440]	[0.388]	[0.123]	[0.985]	[0.234]	[0.243]
Obs.	1487	1333	1487	1333	1487	1333
Panel D - $H_0 : \beta(M) = \beta(F)$						
Treatment	[0.169]	[0.832]	[0.193]	[0.525]	[0.559]	[0.230]
Non-P	[0.225]	[0.956]	[0.151]	[0.276]	[0.991]	[0.586]
P	[0.250]	[0.767]	[0.361]	[0.980]	[0.371]	[0.088]

Note: In columns (1) - (2) the dependent variable is an indicator that takes a value of one if the respondent says 'Yes' to 'Do you know about the govt job platform National Career Service (NCS)/Delhi Online Employment exchange portal and it's activities?', and zero otherwise; column (3) and (4): 'How many job ads you viewed through the govt portal?'; column (5) and (6): 'How many jobs you applied through the govt portal?'. Robust standard errors clustered at the PS level are in parentheses. Wald test (WT) p-values of equality of P and Non-P estimates are reported in square brackets. Panel D reports p-values for tests of equality of treatment effects between males and females. $***p < 0.01, **p < 0.05, *p < 0.10$.

B Phone Messages - Event study

After the in-person intervention, six phone messages were sent at an interval of 10 - 15 days each to all individuals assigned to the treatment group (irrespective of their platform registration status). Messages were sent to all individuals in a treatment group polling station (PS) on the same date. Message 1 was sent after 10 days of the in-person intervention date in each polling station, starting September 11, 2023. Since the in-person intervention date varied across PS, the date by which all 6 messages were sent to all sampled PSs was February 9, 2024. Given that the platform data on job seeker usage are available until May 30, 2024, we restrict our analysis to the first 14 weeks post the in-person intervention for all individuals in both treatment groups.

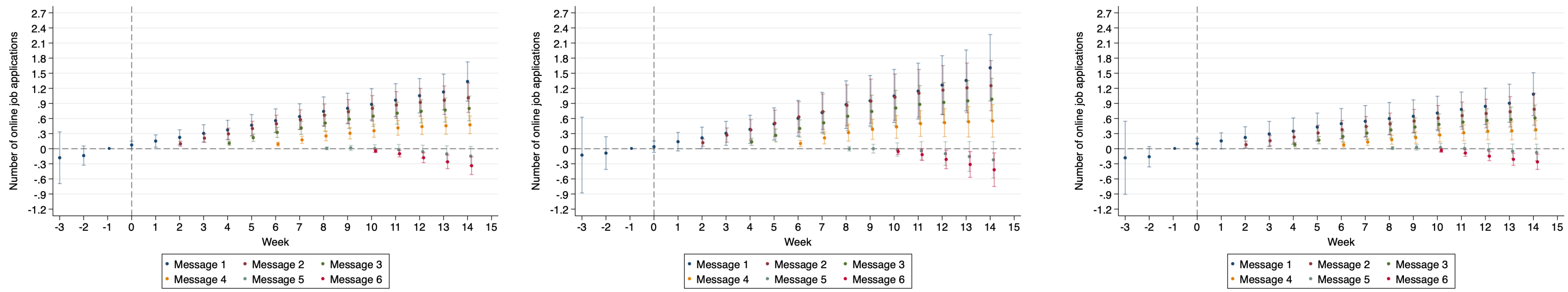
Using an event study framework, we explore whether the phone messages nudged the job search behavior of individuals on the platform over the first 14 weeks of messaging, estimating effects of the 6 messages separately and cumulatively. For this analysis, we combine the weekly administrative data on user behavior from the platform with the survey data on message timing. We use the following specification for estimation:

$$Y_{isw} = \alpha_i + \delta_w + \sum_{m=1}^{6} \sum_{k \neq -1} \beta_w^k \cdot Message_{sw}^k + \epsilon_{isw} \tag{B.4}$$

where, Y_{isw} is the outcome variable for individual i, in polling station s in week w. α_i are the individual fixed effects, δ_w is week fixed effects, $Message_{sw}^k$ is a dummy variable for the polling station level messages that equals 1 if the polling station s had received the kth message in week w, and 0 otherwise. The six messages are represented by $k = 1$ to $k = 6$. β_k is the coefficient capturing the cumulative effect of the messages starting from the kth message onwards relative to one week before the kth message was received. ϵ_{it} is the error term. For instance, the coefficient for Message 3 ($k = 3$), sent in Week 4, captures the effect of all messages (i.e. Message 1 sent in Week 0 and Message 2 sent in Week 2) in Week 4 relative to the previous week. We estimate this equation separately for all individuals in each PS assigned to treatment for each message and report the average estimate across all PS for each message. Y_{isw} equals 0 for individuals who did not register on the platform.

The following figures plot the estimated effects on the number of jobs applied online for each message.

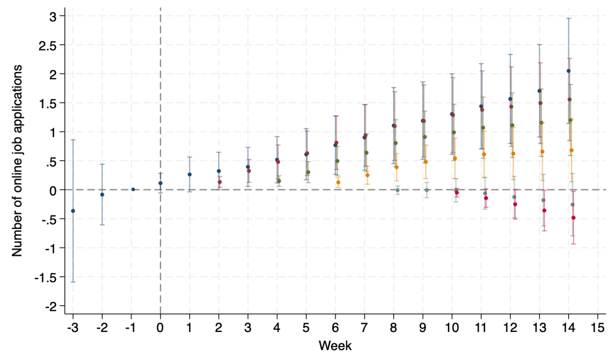
Figure B.1: Effect of messages on number of online job applications on the platform



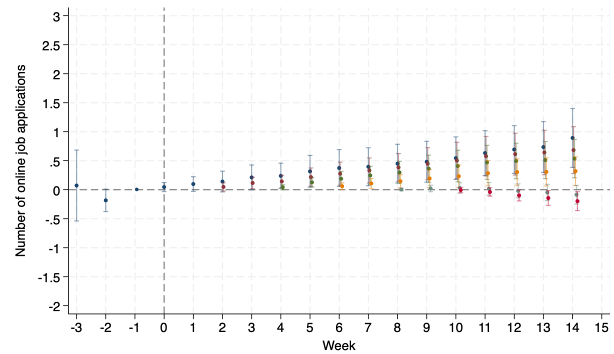
(a) **Overall** (b) **Non-Personalized (Non-P)** (c) **Personalized (P)**

Source: Platform data
Note: The event study plots the number of online jobs applied for on the platform during the 14 weeks post-intervention. Figure (a) reports the overall estimates for all respondents offered the platform registration (N=2299), Figures (b) and (c) report estimates for the two treatment groups Non-P (N=1144) and P (N=1155), respectively. Each of the six messages is treated as a separate event, represented with color coded average estimates, and 90% confidence bands. For the ease of visualization of impacts, we pool all the event study plots together by the timing of each message. All specifications control for individual fixed effects and week of observation by default and plot the event-time path. The coefficient for the $t-1$ week is normalized to zero, implying that the plotted coefficients are the estimated effects relative to before the first message was received. If we focus on the interpretation of the coefficients for the events plot of the first message (*Message 1* plotted in blue color), the blue colored dots and 90% confidence bands corresponding to the zeroth and first week's observations ($Week = 0\&1$) will capture the effect of the first message. The bars corresponding to the second and third observations ($Week = 2\&3$) will capture the cumulative effect of the first and the second message as the second message was sent after two weeks of the first message, i.e. at $Week = 2$, and so on for the rest of the messages. On the tenth week from the start of the platform data collection, everyone has received all the six messages. Thus, the blue coefficients from $Week = 10$ onwards capture the cumulative effect of all the messages.

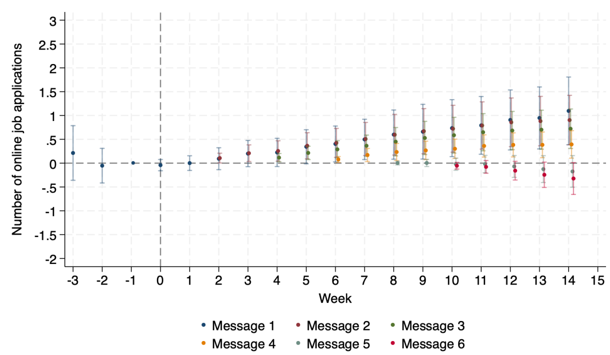
Figure B.2: Effect of messages on number of online job applications on the platform (by gender)



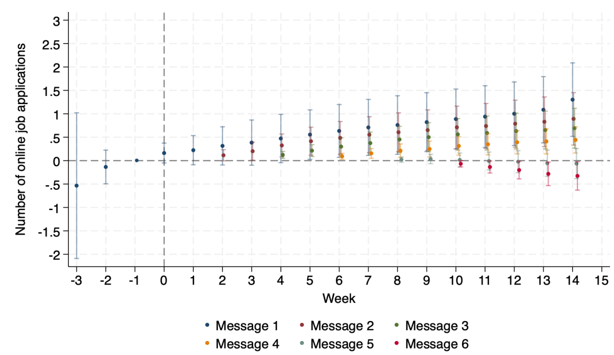
(a) **Female (Non-P)**



(b) **Female (P)**



(c) **Male (Non-P)**



(d) **Male (P)**

Source: Platform data

Note: The event study plots the number of online jobs applied for on the platform during the 14 weeks post-intervention. Figures (a) and (b) shows the event study estimates for female respondents (N=1186) and Figure (c) and (d) for male respondents (N=1113). Figure (a) & (c) report the estimates for Non-P and Figures (b) & (d) for P group, respectively. Each of the six messages in each figure is treated as a separate event and have been represented with color coded average estimates and 90% confidence bands around these estimates. On the tenth week from the start of the platform data collection, everyone has received all the six messages. Thus, the blue coefficients from $Week = 10$ onwards capture the cumulative effect of all the messages.