How do Online Job Portals affect Employment and Job Search? Evidence from India*

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June 24, 2022

Abstract

We use a randomized control trial to evaluate whether job portals improve employment outcomes among vocational training graduates in India. We uploaded a random subset of graduates to a job portal, and assigned some to receive many text messages about job opportunities. We find evidence of voluntary unemployment: job seekers respond to portal access by increasing their reservation wages, and by working significantly *less*. As good job offers fail to materialize on the platform, some job seekers adjust their expectations downwards and resume working. These findings suggest that job seekers' beliefs about the arrival rate of jobs mediate the effectiveness of matching interventions.

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1 Introduction

Youth unemployment is a policy priority throughout the developing world. In India, the importance of solving the youth unemployment problem was buoyed by 2017-18 job numbers which revealed that youth joblessness in both urban and rural areas had spiked to approximately 18% (Slater, 2019). In the last decade, there has been a big push to identify solutions to this problem. On the one hand, governments have responded by investing in large scale labor market policies such as wage subsidy and skills training programs (McKenzie, 2017). On the other hand, researchers have explored whether job search assistance programs can improve match rates between job seekers and prospective employers (McKenzie, 2017). The impact of these interventions have been modest, suggesting that some youth may be voluntary unemployed (Groh et al., 2015; Banerjee and Chiplunkar, 2018). In particular, young job seekers may have unrealistic expectations about their job market prospects, turning down the jobs they have access to through these interventions to hold out for better opportunities that fail to materialize(Abebe et al., 2018). This points to the need for longer, more sustainable interventions, that can provide new employment opportunities to young job seekers *while* setting their expectations and improving their understanding of the labor market.

Our paper proposes to investigate the benefits of online job platforms – a technology that continuously advertises new job opportunities, and has the potential to provide job seekers with a better understanding of the labor market and the jobs they can feasibly get. We partner with JobShikari.com,[1] an online portal that sends SMS information on low-skilled jobs to candidates registered on their platform. We enroll a randomly selected subset of vocational training graduates on the Job Shikari platform, and send them a brief text message indicating they will be registered with the portal. This is our first treatment group. For a second randomly-selected subset of new graduates, we provide access to the portal *and* grant them a priority ranking within Job Shikari's algorithm. We refer to this second sample as the priority treatment group. Job Shikari ultimately sent 1 additional SMS message about job opportunities per person to the treatment group, and an additional 17 messages to the priority treatment group for a truly intensive information intervention. We can compare these two groups to control respondents who are not registered on Job Shikari in order to estimate 1) the causal impact of portal access on search and employment outcomes, and 2) how these employment responses change as respondents receive more information about job opportunities from the portal.

We find a strong, but unexpected response to being enrolled on the portal: new graduates are 9 percentage points less likely to be working 12 months after being notified they would

[1] Job Shikari is no longer active. It was purchased by another job portal after study completion.

have access to Job Shikari. We also show that a steady stream of information for the priority treatment job seekers results in these graduates "catching up" to the control group. Priority treatment job seekers are only 4 percentage points less likely to be employed than control. This reversal in employment rates relative to the treatment group is statistically significant. These effects appear to be driven, at least in part, by changes in job seekers beliefs about what the portal can do for them: we see that reservation wages increase for the treatment group, and fall for priority treatment.

We also find that some job seekers "catch up" more quickly than others. We look at differences across four geographic zones in India (North, Delhi, South West, and East). We find that the reversal in employment rates is strongest among priority treatment job seekers located in the South West. This sample was older, from lower castes and more likely to be married relative to job seekers in the North or Delhi – features that may have increased the opportunity cost of holding out for a job on Job Shikari. They also were spatially mismatched relative to jobs advertised by the portal, which were largely in Delhi. While these positive priority treatment effects we observe for job seekers in the South West could be generated by new matches, several patterns in the data suggest that these job seekers learned the portal was delivering jobs they were unwilling to migrate for, which prompted them to accept outside offers rather than hold out for better opportunities on Job Shikari.

These results provide clear evidence of voluntary unemployment among the young adults in our sample, as predicted by seminal models of job search (McCall, 1970; Jovanovic, 1979): perceptions of access to new sources of job opportunities should boost reservation wages, and reduce employment in the short run. These effects may be larger and more persistent if job seekers have inaccurate expectations about the effectiveness of the portal, and if job opportunities fail to materialize. Nevertheless, as job seekers receive additional information about job opportunities they should update their perceptions of the new arrival rate of jobs and adjust their beliefs about their employment prospects. These predictions are borne out in our data: job seekers who are notified that they will be registered with a job portal increase their reservation wages, and reduce employment for at least 1 year. However, when we increase the amount of information that job seekers in our sample receive about jobs, it appears that a subset may have been able to overcome their biased beliefs.[2]

These results suggest that the impact of job portals depends crucially on job seekers expectations of what these platforms can deliver. If job seekers have high expectations when they join a job portal but the job offers are weak, we can expect to see some amount

[2]This is consistent with work by Bandiera et al. (2021) who show that job seekers revise their beliefs downwards in response to negative signals about their labor market prospects (when call back rates from employers are lower than they anticipated).

of voluntary unemployment as job seekers hold out for better jobs. The magnitude, and stickiness, of this effect will depend on the extent to which job seekers update their beliefs about the likelihood of finding a job. This concern may be magnified by the types of jobs that select onto platforms: platforms charge firms to make connections to job seekers, which is most valuable when matches are hard to find. For unskilled jobs, matches will be scarce when wages are low or working conditions are unappealing. If young graduates do not learn that portal jobs are negatively selected, they may stay unemployed for longer durations, as is the case in our study. This highlights the importance of educating youth about what they can expect from these new labor market interventions well ahead of time.

These findings speak to several literatures. First, there is a large literature evaluating the impacts of active labor market policies designed to reduce unemployment rates. Most closely connected to our own work are a series papers that aim to reduce search frictions through interventions that facilitate contact between job seekers and prospective employers (Abebe et al., 2018; Beam, 2016; Bassi and Nansamba, 2022; Groh et al., 2015); subsidize search costs (Abebe et al., 2021; Aeberhardt et al., 2019; Banerjee and Sequeira, 2020); and provide better information about applicants (Abebe et al., 2021; Abel, Burger, and Piraino, 2020; Banerjee and Chiplunkar, 2018). These researcher-led innovations often generate changes in the types of jobs acquired by at least some workers, but in general have had more muted impacts on employment rates (McKenzie, 2017).

Second, we contribute to a growing body of work on the role of job portals. Evidence from the US on the role of online job search has been somewhat mixed. In the early years of internet job search (1998-2000), Kuhn and Skuterud (2004) find that search durations were if anything longer for internet users once observable characteristics were controlled for. By contrast, Kuhn and Mansour (2014) find that by 2005-2008 online job search was associated with large reductions in unemployment durations. Wheeler et al. (2022) provide training to job seekers in South Africa on how to open Linkedin accounts and apply for jobs, which leads to a 7 percentage point increase in the probability of employment. Our work complements these two strands of research. Using a randomized control trial we can confirm that the impact of job portals varies based on the sophistication of the information they provide – a mechanism that could reconcile the findings of Kuhn and Skuterud (2004) and Kuhn and Mansour (2014). Our study differs from Wheeler et al. (2022) by studying how job seekers' respond to these platforms when they are introduced to them organically (without training). While we come to the opposite conclusion from Wheeler et al. (2022), our findings may be reconciled if their program's training component was crucial for setting expectations about the platform's impact. Work by Belot, Kircher, and Muller (2019) also highlights the benefits of receiving additional assistance on these online platforms. They show that job seekers with longer unemployment spells who search more narrowly obtain more interviews when they are nudged to consider a larger breadth of jobs.

Finally, our results add to the literature documenting job seekers unrealistic beliefs about their labor market prospects. In this paper, access to the job portal changed job seekers beliefs about their outside options, which induced a change in reservation wages, search and employment. The lack of positive matches created by the portal suggests this change in beliefs may not be rationalizable. These results link closely to work by (Jäger et al., 2022; Caldwell and Harmon, 2019) both of whom demonstrate that misperceptions about outside options influence worker bargaining, job transitions and mobility. Similarly, many of the papers studying labor market policies find that job seekers expectations about their job prospects are too high (Abebe et al., 2018; Banerjee and Chiplunkar, 2018; Banerjee and Sequeira, 2020). Our work formally tests this hypothesis by experimentally varying the amount of information that job seekers have to form their beliefs.

The rest of the paper is organized as follows: Section 2 discusses the context; Section 3 presents a model of job search with job portals; Section 4 details the field experiment; Section 5 discusses our results; Section 6 concludes.

2 Context

The proliferation of the internet has made it an increasingly popular tool for millions of job seekers searching for work. At the forefront of this surge are job portals connecting prospective employees with potential employers. In India, there are over 10 job portals operating nationwide – though when we launched our experiment, Job Shikari was one of the only ones advertising blue collar employment opportunities. Many of these platforms build online interfaces or mobile applications so that job seekers can browse job opportunities. Nevertheless these same job portals actively promote free job alert services because they recognize that most job seekers are passive users of the platform and rely on notifications about jobs that match their specific skills/requirements. In low income countries SMS-based platforms are also common – built on the principle that SMS are much easier for low income job seekers than computers or smart phones. While Job Shikari had an online interface, it is not clear that job seekers would have found it. Rather, they relied on the text messages that Job Shikari sent about new job opportunities.[3]

Table A.1 Panel B provides some basic statistics about the jobs in our sample. Most

[3]It is unclear how the results from our study will translate to job platforms that are dominated by active search using online interfaces because we cannot anticipate the extent to which job seekers digest the information they see online. Work by Kuhn and Mansour (2014) Kuhn and Skuterud (2004) suggests that job seekers can be relatively passive users of online platforms when they first start searching.

jobs require a high school education, and pay 10,000 rupees per month on average (141 USD). Employers on the platform are primarily hiring data entry operators, telecallers, and field executives – who perform a variety of administrative roles related to sales (Figure A1). Jobs are almost exclusively located in Delhi-NCR, while job seekers are located across the geographic zones we drew our sample from (North, South West, East and Delhi-NCR) (Figure A2).[4] This implies that some job seekers were much closer to the jobs being advertised than others (Figure A3). Figure A4 presents the average wage offers from Job Shikari relative to baseline wages. On average salary offers were comparable to the wages that employed job seekers at baseline were working for. This does, however, mask some heterogeneity across geographic zones which we discuss later (Figure A5).

Our sample of job seekers is drawn from vocational training institutes across India. These vocational institutes are part of the National Skill Development Corporation (NDSC), Pradhan Mantri Kaushal Vikas Yojana (PMKVY) scheme, which encourages youth to sign up for training programs and compensates them upon successful completion of the program. While completion rates for the 1 million graduates per year are high, placement rates are low (National Knowledge Comission, 2009). Work by Banerjee and Chiplunkar (2018) find placement rates of 10% amongst graduates of the training institute they partnered with. They establish that this is driven in part by job seekers' unrealistic expectations about their job prospects.

Table A.1 Panel A provides information about the basic demographic characteristics of graduates in our sample. Most of our sample is male – only 11% of the respondents are female. They are relatively young (approximately 24), and only a third are married. These vocational training programs typically cater to households from disadvantaged backgrounds, and over 65% of our sample comes from Scheduled Castes (SCs), Scheduled Tribes (STs), or Other Backward Class (OBCs). Compared to a nationally representative sample of the 68th Round of the National Sample Survey (NSS) from 2011-12 as in Banerjee and Chiplunkar (2018), our sample is similar in age and years of education, but has a higher concentration of unmarried males from SC/ST/OBCs.

Approximately 30% of the sample is employed, and 65% say they are actively looking for work. While the vast majority of graduates have access to the internet (approximately 76-80%), and many say they use the internet to find job opportunities, fewer than 25% are formally registered with a job portal. Job seekers say they would not be willing to work for less than 12,000 rupees (172 USD) per month. These reservation wages are considerably higher (20%) than the average wages that employed individuals in our sample report earning,

[4]Delhi-NCR encompasses Delhi and several surrounding districts. North refers to Northern India excluding Delhi-NCR. South West and East comprise areas to the South West and East of Delhi-NCR, respectively.

suggesting that job seekers are overly optimistic about their wage prospects – a fact that is consistent with work by (Banerjee and Sequeira, 2020) and (Abebe et al., 2018) among others.[5]

3 Model

3.1 Status Quo

We consider dynamic searcher responses to the web portal through the lens of a finite-time version of the seminal search model from McCall (1970); Jovanovic (1979). Absent the portal, in each period $\{t\}_0^T$ workers draw a wage offer w_t from known distribution $F(w)$ with associated density $f(w)$, and $F(\underline{\text{w}}) = 0, F(\overline{w}) = 1$. Workers decide to accept that offer or wait until the next period and draw a new offer. We normalize the utility of unemployment to zero and assume zero job destruction, so that in each period t workers solve

$$V_t(w) = \max_{\{accept, reject\}} \{u(w_t) + \beta V_{t+1}(w_t), \beta E[V_{t+1}(w')]\} \tag{1}$$

The solution to this problem is a series of reservation wages which are declining in t, w_t^*, where workers accept any job offer $w_t > w_t^*$ which they keep until T and reject any other offer (See proof in Appendix B.1).

3.2 Job Portal

Searchers on the portal draw a second wage offer w_t^p, which can be interpreted as the distribution of the best wage offer received from the portal in that period.The portal will be relevant to the job search problem if $q \equiv \mathbb{P}(w_t^p > w_t^*) > 0$. For simplicity we suppose $w^p \in \{\underline{\text{w}}, \bar{w}\}$ so that $q = \mathbb{P}(w^p = \bar{w})$. To allow learning, we assume that searchers do not know q and instead form a belief $\hat{q}$. At baseline, searchers have uninformed priors so that $\hat{q} \sim U[0, 1]$. Each period, searchers now receive an offer on and off the portal, they decide which (if any) of those offers to accept, and they update priors over $\hat{q}$ by Bayes' rule. Finally, our framework does not allow on-the-job search on the portal, so that accepting a job offer on or off the portal ends the stream of portal offers. For our main results we need that on-the-job search is less efficient than off-the-job search. This would be true if adequately

[5]Figure A6 further computes where job seekers baseline stated reservation wages lie in the distribution of actual wages that employed job seekers from the same geo-zone and trade report at baseline. Most of the sample have reservation wages that are above the 50th percentile of wage offers, and the modal reported reservation wage is outside the winsorized support of observed wages.

responding to information from the portal (going to the place of employment, submitting an application, etc.) is more challenging for the employed.

In this set up, workers that receive an offer $w^p = \bar{w}$ accept the offer and retain it until period T. Thus, the interesting dynamics (and the dynamics which likely applied to most of our sample, who did not receive high wage offers) are those who have not yet made a match on the portal. This means that after they are enrolled in the portal in period k, everyone who has not received an acceptable wage offer from the portal has the same history of wage offers in any period $t+k$: $w^p_k = w^p_{k+1} = ... = w^p_{k+t} = \underline{\mathrm{w}}$. We use this framework to derive the following model predictions, with proofs in the Appendix.

Proposition 1 *Access to the job portal increases reservation wages for job searchers. The increase in reservation wages declines over time for searchers, and is smaller for older searchers.*

Access to the portal increases the expected future stream of high wage job offers, which increases the incentive to remain unemployed to receive those offers. Over time, the unemployed, who have by definition not yet received a high wage offer from the portal, update their priors $\hat{q}$ negatively.[6] In the appendix, we derive that after t periods of exposure to the portal the unemployed will form the posterior $E[\hat{q}] = \frac{1}{t+2}$ which clearly declines in t (See proof in Appendix B.2).

This increase in reservation wages has practical consequences for the graduates in our sample. As a result of reservation wages going up, employment may go up or down depending on whether the increase in the job arrival rate at higher wages outweighs the rate of declined jobs below the new reservation wage. This leads to an important corollary:

Corollary 1 *Suppose $\hat{q} > q = 0$. Then access to the job portal reduces employment.*

[6] In the model, job seekers perceive the portal as changing the probability they will receive a high quality job offer, which affects their reservation wage. Job seekers subsequently learn about the portal's effectiveness and further adjust their reservation wage. This approach is also consistent with other, less traditional reasons why portals may boost perceived offer rates. For example, individuals may update beliefs about their "type" in response to the portal, and similarly update the ambient offer rate they expect (either on or off the portal). This would trigger the same dynamics on reservation wages and employment that we observe in our model. Alternatively, portal access may allow job seekers to better motivate a lengthy unemployment spell to other household members if they believe that the job seeker's offer rate has been boosted. In the presence of these household bargaining dynamics, job seekers will behave according to a weighted combination of their own optimized search problem and that of the household's. As households update their beliefs about the portals' effectiveness over time they will renegotiate with individual job seekers, which will trigger the same dynamics on reservation wages and employment that we observe in our model.

4 Experimental Design and Data Collection

4.1 Design

We ran our experiment with Job Shikari, a job portal that charged companies a fee to send SMS messages to relevant job seekers. Once employers paid the fee associated with a fixed number of SMSs they waited for Job Shikari to run the platform's internal algorithm and send messages to relevant candidates. The algorithm prioritized job seekers working in the same trade and geographies as the jobs being advertised. The number of SMS that each recipient received was a function of the number of employers that contacted Job Shikari. In some cases that number was quite limited, particularly outside of Delhi (which we discuss in Section 5.2). All SMSs were constructed in the following way: *Data Entry Operator in Delhi, Salary 11500 Rupees, Please call +91**********. Interested job seekers contacted the phone number listed in the SMS to proceed with the next stages of the interview process (Job Shikari was no longer involved, and did not track whether job seekers applied to the jobs). Employers waited to receive phone calls from these candidates.

Our sample of job seekers consisted of recent graduates from vocational training institutes working under NSDC's PMKVY program. We randomly assigned these graduates to a control group and one of two treatment arms, stratifying by location and their registered trade. Job Shikari never contacted job seekers in the control group. The portal contacted job seekers in *both* treatment groups and sought their consent to upload their names to the job portal. No further information about why they were being uploaded to the portal was communicated to them. Once job seekers were uploaded to Job Shikari, they were sent another 'welcome SMS' introducing them to the platform. Job seekers assigned to the first treatment group were eligible to receive text messages, but in practice they typically did not – likely because the number of SMSs the platform was sending was relatively small (constrained by the number of employers using the platform and the number of SMS they were prepared to pay for). Job-seekers assigned to the second treatment group received priority status (hence the designation priority treatment): they appeared first on the list of job-seekers who matched a search query for a given job opportunity. Appearing first on these lists meant receiving many more SMSs. This priority status was never communicated to these job seekers. Table 1 presents the number of SMSs that job seekers received by treatment status. Job seekers in the treatment group received 1 text message on average (column 1), while job seekers in the priority treatment group received an average of 18 text messages. In other words, the intervention raised the probability of receiving a text message in the treatment group by 36 percentage points, and by 64 percentage points in the priority treatment group (column 2).[7]

4.2 Data

The NSDC provided contact information for recent PMKVY graduates from training institutes specializing in 4 pre-selected trades (Telecom, Logistics, Sales and Security). These trades had the most employers and the highest rate of job offers on Job Shikari's portal. We also restricted the sample to four broad geographic zones: Delhi-NCR, North, South West and East India (Figure A3). We randomly selected 30 graduates to call within each training center. Many calls did not lead to a completed interview: we ultimately reached 2,662 job seekers who were then randomized into our treatment and control groups.

We conducted three rounds of phone surveys. We reached the full sample for baseline between April and July 2015 (2,662 job seekers). Midline surveys took place 9 months later, and we managed to reach 83% of respondents (2,230 graduates). Finally, we conducted the endline survey between June and September 2016, and successfully reached 71% of respondents (1,905 job seekers). We allocated 30% of the sample to control, 40% to treatment, and 30% to priority treatment.[8] In addition to phone surveys, we also rely on a dataset shared by Job Shikari that has every text message that was ever sent to job seekers (both in and outside of our sample) over the course of the study period. Table A.1 shows that we are balanced across most variables at baseline, though a few variables demonstrate statistical imbalance. Reported reservation wage is the most concerning of these. We include individual fixed effects in our estimation strategy to account for any imbalance which is constant over time, and we will discuss additional checks we run for reservation wages in more detail in the results section.

4.3 Estimation

We estimate the effects of our intervention by pooling the two follow up survey rounds and running the following regression:

$$y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 TP_{it} + \gamma_i + \delta_t + u_{it}$$

where y_{it} is an outcome of interest for job seeker i in time period t. T_{it} is a dummy equal

[7] Figure A7 shows the distribution of SMS messages received by job seekers in the treatment and priority treatment groups. Figure A8 represents a timeline of when SMSs were sent by Job Shikari.

[8] While these response rates are high for phone surveys, attrition may still pose concerns for analysis. Nevertheless, we do not see differential attrition between treatment groups – Table A.2. We also investigate whether attrition varies by baseline characteristics. While younger men with lower reservation wages are slightly less likely to respond, overall we do not find that attrition is predicted by baseline characteristics.

to 1 if the job seeker was assigned to either of our treatments after enrollment to the portal (post-baseline); TP_{it} is an indicator equal to 1 for being in the priority treatment group after enrollment (post-baseline).[9] γ_i represents individual fixed effects; and δ_t represents a survey round fixed effect.[10] The coefficients of interest are β_1, which represents the average effect of being uploaded to the portal over time (relative to control); and β_2, which represents the average effect of receiving additional text messages over time as a result of being in the priority treatment group (relative to treatment). We cluster all regressions at the individual level (our unit of randomization).

5 Results

5.1 Employment and Job Search

Treatment job seekers were notified they would be uploaded to a job portal but only received 1 SMS on average. It follows that this treatment arm likely only shifted *expectations* about the new arrival rate of jobs. We predict this will increase unemployment rates as job seekers anticipate and hold out for jobs that fail to materialize. This prediction is confirmed in our data (Table 2 Panel A). We see that treatment job seekers' employment rate decreases by 9.2 percentage points in response to the notification that they were uploaded to Job Shikari (Column 1). Rather surprisingly, this translates into a 30 percent decrease in employment relative to the control group, and the effect persists for a full year. This result presents strong evidence of voluntary unemployment – job seekers prefer to remain unemployed for long periods of time rather than accept the types of jobs they can access on the open labor market. This effect appears to be concentrated among individuals whose baseline observable would predict they earn high wages (Table A.3). The negative employment result suggests that the effectiveness of job portals will depend on job seekers' expectations. This poses a challenge in the case of job portals in low-income labor markets. The benefits of a job portal accrue to employers who face significant matching frictions; and unskilled jobs with significant matching frictions may systematically have unattractive characteristics. Moreover, recent graduates in these markets may be ill-informed about the utility of job portals or their labor market prospects more broadly, generating a large gap between the perceived promise and the reality of the portal.

[9] T_{it} and TP_{it} are equal 0 for all respondents at baseline.

[10] We pool midline and endline. We have also tested whether these effects differ between the midline and endline. These differences are not sufficiently statistically precise to yield helpful interpretations (Appendix Table A.4). While we may have expected to see these effect sizes fall by endline, long unemployment spells are relatively common in India (Naraparaju, 2017; Dhingra and Kondirolli, 2021; Biswas, 2022; Young, 2014), and it may take more than a year for the dis-employment effects we observe to fade.

Nevertheless, we also establish that these effects on voluntary unemployment can be reversed. We predict that as job seekers learn more about the types of jobs on the portal, and the feasibility of getting one of these jobs, they will re-adjust their expectations. This effect can be tested in the priority treatment group, which received 17 more text messages on average. The text messages they received revealed that jobs on offer were located heavily in Delhi, and were relatively low paying. We find that the disemployment effect is muted in the priority treatment group: job seekers only experience a 4.8 percentage point (16%) decrease in employment relative to control. This suggests that new labor market interventions may need to find ways to set job seekers expectations about their job prospects by providing more information about the broader labor market. Consistent with this hypothesis we find suggestive evidence that job seekers in the priority treatment group are 3 percentage points less likely to say job portals are a helpful tool in their search for jobs (Table A.5).[11]

We also investigate whether accessing the portal has any impact on actual wages for employed job seekers, though this is difficult to interpret because the selection of workers is changing with treatment status. Table 2 presents the results on log wages (column 2). We do not see evidence of large effects on wages for the treatment group. The coefficient on wages for the priority treatment group is positive but insignificant. We might expect to see this positive result if more job seekers (not just low ability types) are accepting jobs.

We hypothesize that these employment results are driven, at least in part, by job seekers beliefs about what the portal can do for them. Table 2 Panel B presents the results on three different measures of job seeker beliefs. We find that being uploaded to the job portal leads to a small (3.1%) increase in reservation wages for the treatment group relative to control (Column 1), as job seekers expect and hold out for better jobs. Conversely, we see that reservation wages decrease significantly in the priority treatment group, by approximately 5.1% as job seekers realize the jobs on offer are not what they expected.[12] Similar trends, albeit not statistically significant, are visible in Column 2, which displays the treatment and

[11]Concerns about job seekers misreporting their employment status to receive additional SMSs are mitigated by a number of facts. First, the research team did not affiliate itself with the job portal, and its unlikely that job seekers would have attributed the 18 SMS they received over 12 months to our team, particularly given that promotional messaging via SMS is not unusual in India. Second, we asked respondents whether they were interested in hearing about jobs, and treatment job seekers were no more likely to say 'yes'. Finally, misreporting does not explain the differences between treatment and priority treatment.

[12]The priority treatment group has higher reservation wages at baseline. In our analysis throughout, we address this through the use of individual fixed effects. Even with fixed effects, the possibility remains that mean reversion could explain these differences. To test this, we split our sample into job seekers with baseline reservation wages above and below the mean. Table A.6 shows that job seekers with low baseline reservation wages experience the strongest movements in employment and reservation wages. This indicates that the imbalance in reservation wages in priority treatment is biasing us against finding these effects, rather than towards them. Note we can calculate baseline reservation wages differently (as deviations from a group) but the results do not change meaningfully.

priority treatment's assessment of the wages they can expect in their current location. In the last three columns of Table 2 we ask job seekers to estimate the probability they can get a job in their current location that pays 10,000, 16,000 and 20,000 rupees respectively. The stronger negative effects on the priority treatment group seem to suggest that job seekers who receive more text messages have a more negative assessment of their probability of actually getting a job at these wage rates.[13]

Are these changes in reservation wages meaningful? To answer this question we explore how reservation wages respond to two other metrics of interest: being employed and searching for a job. Table 3 compares how reservation wages respond to treatment (column 1), relative to finding a job and/or actively searching for work (column 2). While the estimates in column (2) cannot be interpreted as causal, their magnitudes are informative. They suggest that being uploaded to the portal has a similar impact on reservation wages to becoming employed or searching for a job. In columns (3) and (4) we focus on a subsample of job seekers who we expect to report reservation wages with less error. More specifically, while we refer to our sample as "job seekers" only about 63% of them actually report looking for work in our data. Reservation wages are poorly defined (both in the model and, likely, in survey responses) for individuals who are not searching: in effect, this means that accurate measurements of reservation wages are missing for those who are not presently searching. In order to avoid endogenous transitions in and out of search, we focus on the behavior of those engaged in search throughout our study period. The sample of always searchers is balanced (Table A.7), and exhibits similar employment and wage responses (Table A.8).[14] The impact on reservation wages is more pronounced for the always searchers: doubling from 3.1% to 7.7% in treatment, and from -5.1% to -8.0% for priority treatment. At the mean this suggests treatment status are changing reservation wages by approximately 500 rupees in the full sample, and 1000 rupees in the sample of searchers. Yet again the effects of treatment are similar in magnitude to becoming employed among this subsample.

[13] We might expect people with more biased beliefs to respond more as they see lower wage offers coming in. While this is an interesting dimension of heterogeneity, most of the job seekers in our sample report beliefs that are somewhat inconsistent with the reality of the labor market they are searching in. Figure A6 shows that many job seekers in our sample report reservation wages that would be difficult to rationalize based on the actual job market. Those with the most biased beliefs are either misreporting their reservation wages or else do not use observed wage distributions to inform their reservation wages. In either case it is hard to predict whether we should anticipate seeing larger (they update more) or smaller (they are remain overly optimistic) impacts on reservation wages for this group.

[14] If treatment influenced transitions in and out of search, this may mean that this group is differently selected depending on which treatment group they belong to. We nonetheless think this is the most sensible group to focus on as accurate reservation wage data is missing for non-searchers and are somewhat reassured by the fact that search behavior is not associated with treatment (column 2 of Table A.9) and that the inclusion of individual fixed effects will remove any differential attributes of these always searchers which do not change over time.

While these reservation wage effects are large, the employment effects are more tightly estimated and larger in magnitude than what we would have expected from our estimated reservation wage effects. This could be because search behavior is not fully described by the simple search and matching model, or due to attenuation bias from the measurement error in reservation wages. We anticipate that measurement error in reservation wages is large which means that the two treatment effect estimates (employment and reservation wages) are not directly comparable. As a result, we emphasize the part of the story that is well captured by the neoclassical model even if other factors may also be at play.[15]

Finally, we look at whether job seekers in the treatment groups spend more or less time searching and applying for jobs. We do not see any significant impacts on the extensive margin. Column 1 Table A.9 shows that the probability of engaging in any type of search does not change among treatment and priority treatment groups. This result is not altogether surprising, however, as job seekers can be passive users of the portal as they wait for additional text messages. Nevertheless, we do see suggestive evidence that the portal has a large (albeit statistically insignificant) effects on the number of applications job seekers submit (Column 3). The point estimates are consistent with the treatment group applying less (3%) and the priority treatment group applying more (13%). These results become even more pronounced when we look at the subset of always searchers: the treatment group applies to 15% fewer jobs while the priority treatment group applies to 13% more. We still interpret these results with some caution. We are not able to measure job search intensity on different platforms, and it could be that Job Shikari changes the amount of effort job seekers invest in certain job search tools over others.

5.2 Learning on the Portal

We find that sending additional SMS's to priority treatment job seekers results in higher reservation wages and employment rates relative to the treatment group. While our results on reservation wages suggest this effect is driven by changes in job seekers beliefs, it is also possible that match rates were higher among this group. We do not have direct evidence on matches generated by the portal, but we can use the experiment's geographic stratification to explore this further.[16] The geographic stratification is particularly informative as job seekers in the four zones differ strongly in baseline characteristics, and also experienced treatment in very different ways. Table A.10 demonstrates that job seekers in the South West zone

[15] The fact that non-searchers report reservation wages makes clear that some respondents interpret this question differently than the model does.

[16] It was important that the survey not be associated with the Job Shikari treatment, and that enumerators not be aware of individuals' treatment status. This meant that we did not ask treated job seekers about whether they applied to the jobs they saw.

are much older, more likely to be married, with less educated parents and less likely to be General Caste than those in Delhi NCR. Table A.10 also suggests that job seekers in the East and North zones are disadvantaged in some characteristics relative to those in Delhi, though not always as significantly so as those in the South West.

The experience of being assigned to priority treatment was also very different by geography. Looking first at the quantity of jobs, Table 1 confirms that priority treatment job seekers in Delhi NCR saw 56 text messages on average, while priority treatment job seekers in the North and East saw 20 and 13 job offers respectively. Priority treatment job seekers in the South West received only 4 text messages on average. These differences were driven by the differential success that Job Shikari had in identifying employers in these different regions. The quality of jobs differs significantly by geographic zone as well. Figure A3 shows the location of the advertised jobs relative to job seekers' primary residence in each part of the country. Job seekers in Delhi NCR were seeing jobs exclusively in the city where they live. Job seekers in the North were living in and around Delhi, which is where most of the SMSs were advertising work opportunities. Job seekers in the East and the South West were seeing jobs located much further away. Despite living in Madhya Pradesh, Eastern UP, Bihar and Jharkand, job seekers were receiving notifications about jobs in Delhi. Turning next to the distribution of wage offers, we can see that they are differentially attractive across geographic zones. The platform's wage offers were more appealing in the South West and the East, where the baseline wages were lower (Figure A5).

These differences affect priority treatment job seekers' probability of employment. Table 4 demonstrates that while treatment job seekers in all four regions experience similar voluntary unemployment effects, the impact of being in the priority treatment group is only detected in the South West and the East. Job seekers in the priority group in the South West experience a 8.9 percentage point increase in the probability of being employed relative to treatment. Similarly, priority group job seekers in the East experience a 7.5 percentage point increase in the probability of being employed relative to treatment. The priority treatment effects in the North and Delhi NCR are approximately 0 and statistically insignificant. We conclude that the positive priority treatment effect in the whole sample is driven by job seekers who are older and less well-off, who received information about jobs that were well matched on wage offers but poorly matched spatially.

In principle, the positive priority treatment effects we observe for job seekers far from Delhi could be generated by new matches, or by differences in how these job seekers allow the portal to boost their reservation wages. If the positive priority treatment effects in the South West, and East were attributable to newly generated matches, we would expect to see a migration response to rectify the spatial mismatch. Table 5 shows that on average, job seekers do become more urbanized in response to priority treatment, providing evidence that job seekers did respond to the information on job locations. To test whether this information led to new matches in the South West and East, we compare the heterogeneous results on employment by geographic zone to those on migration patterns, presented in Table 5. Focusing on the priority treatment group, we see that job seekers in the North drive the urbanization results, as they are 12 percentage points more likely to be living in a city. Despite experiencing the largest bounce back in employment rates, job seekers in the South West do not differentially move in response to priority treatment. We therefore conclude that the job seekers in our sample did learn something meaningful about job location, namely that most job offers were located in urban Delhi. However the different patterns of employment and migration responses suggest that the portal itself did not lead to many new matches.[17]

Alternatively, the strong employment effects in the South West and East could be driven by job seekers updating their beliefs about the likelihood of finding a job on the portal, and choosing to end voluntary unemployment spells more quickly. In particular, job seekers in the South West and East may infer the portal is unlikely to deliver a job opportunity close to home, and respond by accepting employment opportunities closer to where they live. Job seekers in the South West and East are also older, married, and poorer which means the opportunity costs of holding out for a good job on the portal could be higher; our model suggests this directly for older job seekers. These job seekers may choose to end voluntary unemployment spells more quickly either due to the physical distance between regions, or to differences in the characteristics of our sample across regions. Somewhat strikingly, we find that the heterogeneity in priority treatment effects across geographical zones can be largely explained by differences in demographic characteristics (Table 6).

To test whether the priority treatment effects we observe are primarily a withdrawal from voluntary unemployment, we investigate whether the effects are largest for job seekers who are unable to afford long unemployment spells. Proposition 1 suggests that the option value of waiting for a portal job should be lower for older job seekers, so that they may revise their beliefs about the portal more quickly than their younger, single counterparts. Table A.11 shows that this is indeed the case.[18] The younger priority treatment job seekers experience a 2 percentage point increase in their probability of employment, while the older priority treatment job seekers are 10.4 percentage points more likely to be employed. In fact, the

[17]The idea that job seekers could be learning something about the spatial distribution of jobs, and respond accordingly is consistent with other papers in this literature. Banerjee and Sequeira (2020) find evidence that job seekers have biased beliefs about the disutility of commuting to different job locations. Similarly, Abebe et al. (2021) find that providing job seekers in Ethiopia with transport subsidies induces people to search more efficiently for work and find employment closer to the city center.

[18]Though outside the scope of our model, Table A.11 also presents the results for other groups that may be unable to afford long unemployment spells: married, highly educated, general caste and rural job seekers.

negative employment effect disappears altogether for older job seekers. Figure 1 confirms this result: both younger and older job seekers are less likely to be employed in response to treatment, but being in the priority treatment group helps only older job seekers bounce back relative to treatment. Job seekers in the oldest quintile are no less likely to be employed at endline than the control group.[19]

6 Conclusion

Matching young job seekers to prospective employers has become a policy priority for many governments – global youth unemployment rates currently stand at 13% and continue to rise. While there have been numerous attempts to design interventions that will facilitate matches between job seekers and potential employers, they have had modest impacts on employment rates. The literature suggests this may be because youth are voluntary unemployed because of a "mismatch of expectations" (Banerjee and Duflo, 2019). Job seekers hold out for better jobs rather than accept jobs they can feasibly get.

In this paper we directly test this hypothesis by evaluating the impact of enrolling job seekers onto a job portal, and providing them with information about jobs. We find that job seekers who were notified that they would be uploaded to a job portal are 9 percentage points less likely to be employed for at least 1 year. We interpret this result as strong evidence for voluntary unemployment: job seekers prefer to wait for good jobs than accept those they have access on and off the portal. The priority treatment group receives more information from the job portal, and experiences a less strong disemployment effect. This result is driven by older job seekers in the South West who choose not to relocate to Delhi, where most of the portal's jobs are located. Instead, they re-adjust their expectations and are more likely to accept a job off the platform.

Overall our results suggest that these employment platforms raise job seekers' expectations in ways that may not be rational; and these expectations effects can only be overcome when job seekers have sufficient information about the types of jobs that the portal has to offer. From a policy standpoint these results suggest that more needs to be done to set expectations for youth searching via internet platforms; and to encourage job seekers to be more active on these platforms so they can learn about the quality of jobs, and the distribution of offer rates in the locations and trades they are interested in.

[19] In examining treatment effect heterogeneity, we also investigated the possibility of spillovers across alumni from the same training institute. Table A.12 finds that the negative employment effects from treatment are concentrated on those who are actually treated, but the priority treatment effects are largest when the share of our sample in priority treatment within the NSDC institute is high.

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Tables

Table 1: SMS receipt

	(1) SMS Received	(2) Any SMS Received	(3) SMS Received	(4) Any SMS Received
Treatment	1.608***	0.361***		
	(0.112)	(0.016)		
Priority Treatment	17.401***	0.289***		
	(1.059)	(0.023)		
Treatment DelhiNCR			7.028***	0.851***
			(0.581)	(0.033)
Treatment North			1.208***	0.363***
			(0.124)	(0.028)
Treatment East			0.917***	0.331***
			(0.106)	(0.028)
Treatment SouthWest			0.392***	0.156***
			(0.076)	(0.024)
Priority Treatment DelhiNCR			49.586***	0.151***
			(4.876)	(0.033)
Priority Treatment North			19.135***	0.492***
			(1.251)	(0.035)
Priority Treatment East			12.763***	0.231***
			(1.400)	(0.042)
Priority Treatment SouthWest			3.766***	0.124***
			(0.922)	(0.042)
Respondent Fixed Effects	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	6797	6797	6797	6797

Column 1 is the *number* of SMS's that job seekers' received from Job Shikari, and Column 2 is an *indicator* for whether the respondent received an SMS from Job Shikari (column 2). Columns 3 and 4 consider the same two outcomes by geographic zones. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 2: Employment and Beliefs

	Panel A: Employment	
	(1) Employed	(2) Log(Wage)
Treatment	-0.092***	-0.003
	(0.022)	(0.065)
Priority Treatment	0.048**	0.060
	(0.021)	(0.077)
Mean in Control	0.30	9.08
F-test T + PT	0.06	0.49
Respondent Fixed Effects	Yes	Yes
Survey Round Fixed Effects	Yes	Yes
Number of Observations	6866	2311

	Panel B: Beliefs				
	(1) Log(Reservation Wage)	(2) Log(Expected Wage)	(3) Prob10	(4) Prob16	(5) Prob20
Treatment	0.031	0.010	-0.010	-0.165	0.099
	(0.024)	(0.031)	(0.216)	(0.192)	(0.175)
Priority Treatment	-0.051**	-0.008	-0.399*	-0.239	-0.252
	(0.025)	(0.030)	(0.207)	(0.187)	(0.178)
Mean in Control	9.3	9.3	4.9	3.0	2.0
F-test T + PT	0.44	0.95	0.07	0.05	0.42
Respondent Fixed Effects	Yes	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Observations	6489	6424	6337	6179	6097

Panel A illustrates the impact of the treatments on employment outcomes. The dependent variables are an indicator for whether the respondent is employed (column 1), and the logarithm of wages winzorised at the 1% (column 2). Columns 1 includes all respondents in the sample while column 2 only include respondents who were employed at the time of survey. Panel B illustrates the impact of the treatments on beliefs. Column 1 presents the logarithm of respondents reservation wages (where we asked job seekers "What is the minimum salary that you would accept if you are looking for a job in your field/sector and location"). Column 2 shows respondents expected wages (where we ask "What is the normal salary that someone with your level of training and your experience would earn in your location"). Column 3-5 shows the probability that job seekers' think they will get a job that pays 10,000, 16,000 and 20,000 rupees respectively (where we ask "On a scale of 1-10, how likely is it that you will be offered a job that pays at least 10,000 in your location next month?"). Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 3: Reservation Wages

	All		Searchers	
	(1) Log(RW)	(2) Log(RW)	(3) Log(RW)	(4) Log(RW)
Treatment	0.031		0.077**	
	(0.024)		(0.037)	
Priority Treatment	-0.051**		-0.080**	
	(0.025)		(0.037)	
Employed		0.058***		0.071***
		(0.018)		(0.026)
Searching		-0.030*		
		(0.016)		
Mean in Control	9.29	9.29	9.26	9.26
F-test T + PT	0.44		0.94	
Respondent Fixed Effects	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	6489	6479	2551	2551

Column 1 and 3 in this table show the impact of treatment on log reservation wages winzorised at the 1%. Column 2 and 4 show the impact of being employed and searching for a job on log reservation wages winzorised at the 1%. In columns 1 and 2 we focus on the full sample, whereas in columns 3 and 4 we focus on the sample of job seekers who are searching throughout the study period. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 4: Employment by Geographic Zone

	(1) Employed	(2) Log(Wage)
Treatment East	-0.051	0.205
	(0.037)	(0.239)
Treatment DelhiNCR	-0.112*	-0.230*
	(0.059)	(0.136)
Treatment North	-0.087**	0.018
	(0.039)	(0.123)
Treatment SouthWest	-0.144***	0.007
	(0.046)	(0.085)
Priority Treatment	0.075**	0.125
East	(0.033)	(0.142)
Priority Treatment	-0.013	-0.003
DelhiNCR	(0.055)	(0.069)
Priority Treatment	0.016	0.165
North	(0.039)	(0.207)
Priority Treatment	0.089**	-0.021
SouthWest	(0.044)	(0.091)
Mean in Control	0.30	9.08
Respondent Fixed Effects	Yes	Yes
Survey Round Fixed Effects	Yes	Yes
Geo-Specifc Time Trend	Yes	Yes
Number of Observations	6866	2311

This table shows the impact of the treatments on employment outcomes - broken out by geographic zone. The dependent variables are an indicator for whether the respondent is employed (column 1), and the logarithm of wages winzorised at the 1% (column 2). Column 1 includes all respondents in the sample while column 2 only includes respondents who were employed at the time of survey. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 5: Living in a City

	(1) In-City	(2) In-City
Treatment	-0.020	
	(0.024)	
Priority Treatment	0.060***	
	(0.022)	
Treatment East		0.002
		(0.044)
Treatment DelhiNCR		0.046
		(0.032)
Treatment North		-0.038
		(0.043)
Treatment SouthWest		-0.061
		(0.048)
Priority Treatment East		0.029
		(0.042)
Priority Treatment DelhiNCR		0.014
		(0.033)
Priority Treatment North		0.120***
		(0.040)
Priority Treatment SouthWest		0.042
		(0.048)
Mean in Control	0.51	0.51
F-test T + PT	0.11	
Respondent Fixed Effects	Yes	Yes
Survey Round Fixed Effects	Yes	Yes
Number of Observations	6889	6889

The dependent variable in both columns is an indicator for whether the respondent is currently living in a city. Column 1 estimates the impact of treatment and priority treatment for the pooled sample, while Column 2 estimates the impact of treatment and priority treatment for the sample broken out by geographic zone. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

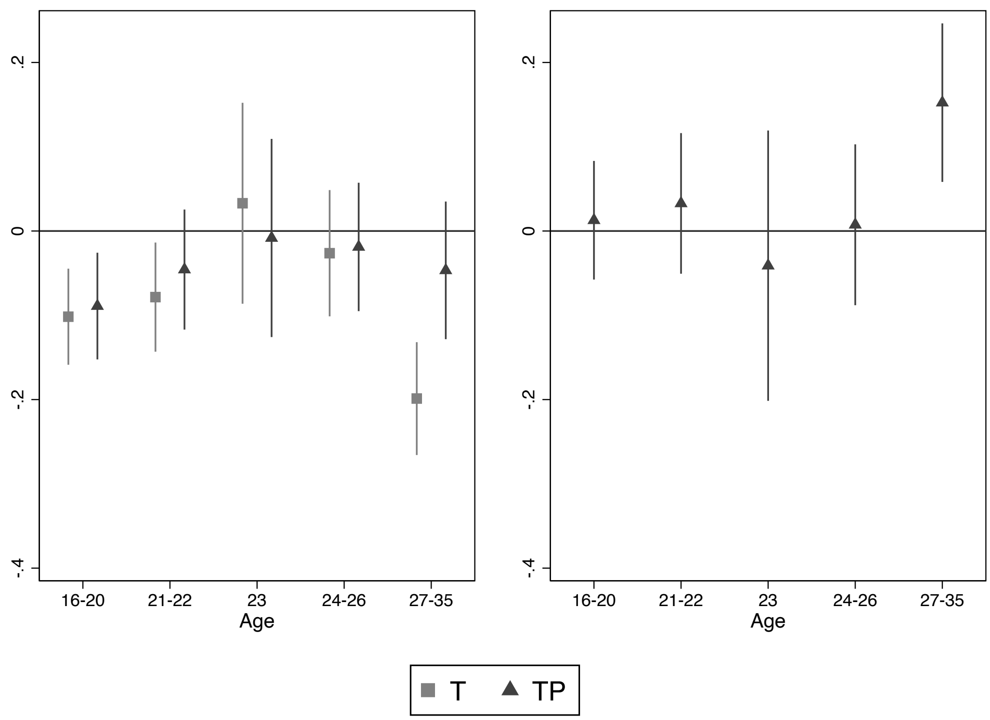
Table 6: Employment, Migration and Search (controlling for Predicted Geographic Zone)

	Main			Predict		
	(1) Emp	(2) City	(3) Hours	(4) Emp	(5) City	(6) Hours
Treatment East	-0.051	0.002	-1.653	-0.284	-1.422***	1.605
	(0.037)	(0.044)	(1.130)	(0.323)	(0.231)	(8.942)
Treatment DelhiNCR	-0.112*	0.046	2.470*	-0.329	-1.080***	4.477
	(0.059)	(0.032)	(1.435)	(0.316)	(0.217)	(8.538)
Treatment North	-0.087**	-0.038	-0.013	-0.319	-1.385***	2.527
	(0.039)	(0.043)	(1.034)	(0.327)	(0.229)	(8.900)
Treatment SouthWest	-0.144***	-0.061	-0.366	-0.359	-1.405***	2.409
	(0.046)	(0.048)	(1.193)	(0.327)	(0.225)	(9.009)
Priority Treatment	0.075**	0.029	-0.620	0.403	0.345	-12.376
East	(0.033)	(0.042)	(1.120)	(0.431)	(0.347)	(11.587)
Priority Treatment	-0.013	0.014	0.523	0.295	0.381	-9.603
DelhiNCR	(0.055)	(0.033)	(1.250)	(0.419)	(0.331)	(11.239)
Priority Treatment	0.016	0.120***	0.486	0.352	0.497	-10.556
North	(0.039)	(0.040)	(0.945)	(0.435)	(0.343)	(11.484)
Priority Treatment	0.089**	0.042	-0.731	0.366	0.446	-12.254
SouthWest	(0.044)	(0.048)	(1.189)	(0.434)	(0.342)	(11.756)
Mean in Control	0.30	0.51	4.78	0.29	0.50	5.12
Respondent Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	6866	6889	6589	5478	5479	5281

The first 3 columns present the standard regression specifications for our main outcomes of interest (employment status, living in a city, and hours spent searching) interacted with geo-zone. The next three columns take these same regressions and control for a predicted geo-zone measure, which we constructed by regressing indicators for being in these zones on a set of demographic characteristics. Both the estimated treatment and priority treatment effects on all dependent variables are remarkably similar across geo-zones when we do so. This confirms that the heterogeneous treatment effects we observe in our geographic strata are at least partly attributable to the underlying characteristics that correlate with location and mediate search behavior. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Figures

Figure 1: Priority Treatment by age



This figure plots our treatment effects on employment for progressively older samples. We bin ages into quintiles. In the left panel we display the estimates on treatment and priority treatment from running a specification of employment status on an indicator for being in treatment (not including priority treatment) and priority treatment, interacted with age quintiles. In the right panel we display the estimates on priority treatment from running our standard specification of employment status on any treatment and priority treatment interacted with age quintiles. For example, from the left panel we read that the impact of being in the treatment group (excluding priority treatment) is -0.10 relative to control for job seekers who are 16-20 years old, and the impact of being in the priority treatment group is -0.089 relative to control for job seekers ages 16-20. From the right panel we read that the impact of being in the priority treatment group relative to treatment is 0.01 for job seekers ages 16-20.

Appendix for “How do Online Job Portals affect Employment and Job Search? Evidence from India”

Contents

A Appendix for Online Publication Only - Tables and Figure

A.1 Tables

A.1.1 Balance (Main)

Table A.1: Job Seeker Characteristics

Panel A: Job-seeker Characteristics

	(1) Control	(2) Treatment	(3) Priority Treatment	(4) (1) vs. (2), p-value	(5) (1) vs. (3), p-value	(6) (2) vs. (3), p-value	(7) Joint F-test
=1 if male	0.86	0.89	0.88	0.04	0.20	0.53	0.13
Age	24.17	24.01	24.30	0.53	0.64	0.26	0.52
Education (Yrs)	14.17	14.22	14.29	0.63	0.28	0.50	0.55
=1 if married	0.27	0.28	0.26	0.46	0.57	0.18	0.40
=1 if Hindu	0.92	0.94	0.94	0.08	0.19	0.72	0.19
=1 if ST/SC caste	0.38	0.34	0.35	0.03	0.13	0.59	0.09
=1 if OBC caste	0.29	0.34	0.35	0.01	0.01	0.73	0.01
=1 if general caste	0.33	0.32	0.30	0.59	0.18	0.37	0.39
Father's education>0	0.80	0.83	0.81	0.14	0.63	0.34	0.31
Mother's education>0	0.55	0.58	0.52	0.26	0.34	0.03	0.10
=1 if live in village	0.49	0.48	0.48	0.65	0.98	0.66	0.87
=1 access to Internet	0.76	0.80	0.80	0.02	0.05	0.85	0.05
=1 access Internet for jobs	0.49	0.52	0.55	0.16	0.01	0.19	0.04
=1 if registered with a job portal	0.23	0.23	0.28	0.92	0.03	0.03	0.04
=1 family is helpful for search	0.65	0.64	0.64	0.49	0.78	0.69	0.78
=1 friends are helpful for search	0.60	0.61	0.62	0.71	0.34	0.52	0.63
=1 if currently employed	0.30	0.34	0.32	0.07	0.51	0.26	0.18
=1 if looking for job	0.65	0.66	0.65	0.69	0.95	0.74	0.91
Hours search (winz, 0.01)	5.79	6.50	5.58	0.29	0.79	0.18	0.35
Reservation wage winzorized (rupees)	12285.89	12215.82	13153.77	0.77	0.01	0.00	0.01
Current wage winzorized (rupees)	10950.84	10884.03	10650.77	0.85	0.55	0.64	0.82
= 1 if Telecom	0.38	0.38	0.38	.	.	.	.
= 1 if Logistics	0.36	0.36	0.36	.	.	.	.
= 1 if SalesMarketing	0.18	0.18	0.18	.	.	.	.
= 1 if Security	0.08	0.09	0.08	.	.	.	.

Panel B: Job Characteristics

	Mean
Salary Offered	10011.21
Requires 10th pass	0.68
Requires 12th pass	0.27
Requires Diploma/Undergraduate	0.05

Panel A presents summary statistics for job seekers, which are calculated using the baseline survey. Columns 1-3 show mean values of each variable for the control group and treatment groups at baseline. Columns 4-6 tests whether these characteristics differ significantly across groups (controlling for geographic and trade strata). Column 7 presents a joint F-test of treatment orthogonality. Panel B presents job characteristics, as they were advertised in the SMSs that Job Shikari sent to the treatment group.

A.1.2 Attrition

Table A.2: Attrition

	(1) Midline	(2) Midline	(3) Endline	(4) Endline
Treatment	0.017		-0.017	
	(0.017)		(0.021)	
Priority Treatment	0.024		0.018	
	(0.017)		(0.021)	
=1 if male		0.028**		0.000
		(0.012)		(0.002)
Age		-0.002**		0.000
		(0.001)		(0.000)
Education (Yrs)		-0.002		-0.000
		(0.002)		(0.000)
=1 if married		0.005		-0.002
		(0.010)		(0.002)
=1 if Hindu		0.020		-0.001
		(0.015)		(0.002)
=1 if ST/SC caste		-0.001		0.001
		(0.008)		(0.001)
=1 if live in village		-0.002		-0.001
		(0.008)		(0.001)
=1 if currently employed		0.012		-0.002
		(0.009)		(0.001)
=1 if looking for job		0.011		-0.001
		(0.008)		(0.001)
=1 access to Internet		-0.000		-0.000
		(0.011)		(0.002)
=1 access Internet for jobs		0.003		-0.001
		(0.009)		(0.002)
=1 if registered with a job portal		0.004		0.002
		(0.009)		(0.002)
Log(RW)		-0.015*		0.001
		(0.008)		(0.001)
Number of Observations	2662	1696	2662	1696

We investigate differential attrition at midline (column 1) and endline (column 2) by regressing an indicator for responding to our survey on an indicator for being in the treatment and priority treatment groups. We also investigate how attrition varies by baseline characteristics at midline (column 2) and endline (column 4). Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

A.1.3 Employment by Baseline Expected Wage

Table A.3: Employment by Baseline Expected Wage

	(1) Low	(2) High	(3) Full
Treatment	-0.067**	-0.111***	-0.067**
	(0.031)	(0.030)	(0.031)
Priority Treatment	0.036	0.058**	0.036
	(0.029)	(0.029)	(0.029)
Treatment X High Exp. Wage			-0.044
			(0.043)
Priority Treatment X High Exp. Wage			0.022
			(0.041)
Mean in Control	0.19	0.36	0.29
Respondent Fixed Effects	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes
Number of Observations	2880	3632	6512

This table shows how the impact of treatment and priority treatment on employment vary based on baseline expected wages. We use baseline observables (living in a village, gender, age, marital status, religion, caste) to predict baseline wages. We then define high (low) predicted baseline expected wages as wages above (below) the median. Column 1 restricts the sample to job seekers with below median predicted baseline wages. Column 2 restricts the sample to job seekers with above median predicted baseline wages. Columns 3 considers the full sample and interacts treatment and priority treatment with an indicator for above median predicted wages at baseline. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

A.1.4 Outcomes at Midline and Endline

Table A.4: Outcomes by Midline/Endline

	(1) Emp	(2) Log(RWage)	(3) City	(4) Searching	(5) Log(Hours)	(6) Log(Apps)
Treatment X Midline	-0.087***	0.035	-0.010	0.004	-0.097	-0.125
	(0.023)	(0.026)	(0.028)	(0.030)	(0.151)	(0.094)
Treatment X Endline	-0.098***	0.027	-0.033	0.007	0.109	0.089
	(0.027)	(0.028)	(0.028)	(0.032)	(0.156)	(0.104)
Priority Treatment X Midline	0.054**	-0.043	0.047*	-0.010	0.070	0.113
	(0.022)	(0.029)	(0.027)	(0.030)	(0.140)	(0.097)
Priority Treatment X Endline	0.041	-0.061**	0.076***	0.019	-0.170	0.158
	(0.026)	(0.030)	(0.027)	(0.031)	(0.148)	(0.106)
Mean in Control	0.30	9.29	0.51	0.65	2.06	1.32
Treat_Mid = Treat_End	0.66	0.77	0.44	0.91	0.13	0.02
PTreat_Mid = PTreat_End	0.58	0.57	0.35	0.36	0.08	0.62
Respondent Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	6866	6489	6889	6828	2986	3333

This table presents the impact of treatment and priority treatment at midline and endline. The dependent variables are an indicator for being employed (column 1), log reservation wages (column 2), whether the job seeker lives in a city (column 3), whether the job seeker is looking for work (column 4), the number of hours spent searching in the past week (column 5), and the number of applications made in the last 3 months (column 6). We test whether the coefficients at midline and endline are statistically Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

A.1.5 Assessment of Job Portals

Table A.5: Job Seeker Assessment of Job Portals

	(1) Helpful
Treatment	0.022
	(0.017)
Priority Treatment	-0.026
	(0.017)
Mean in Control	0.77
F-test T + PT	0.82
Survey Round Fixed Effects	Yes
Geo Round Fixed Effects	Yes
Trade Round Fixed Effects	Yes
Number of Observations	3769

We ask job seekers whether websites which have information about jobs can be/or have been helpful in searching for employment. We only collected this variable at midline and endline, which means we cannot include individual fixed effects in this specification. We include our strata fixed effects (geography and trade), as well as survey round fixed effects. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

A.1.6 Employment and Beliefs by Baseline Reservation Wage

Table A.6: Employment and Beliefs by Baseline Reservation Wage

	Emp			Reservation Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	High	Full	Low	High	Full
Treatment	-0.107***	-0.058*	-0.107***	0.045	-0.007	0.045
	(0.029)	(0.035)	(0.029)	(0.028)	(0.036)	(0.028)
Priority Treatment	0.063**	0.033	0.063**	-0.053*	-0.009	-0.053*
	(0.027)	(0.036)	(0.027)	(0.031)	(0.034)	(0.031)
Treatment X High Res Wage			0.049			-0.052
			(0.045)			(0.046)
Priority Treatment X High Res Wage			-0.029			0.043
			(0.045)			(0.047)
Mean in Control	0.23	0.44	0.30	9.01	9.82	9.28
Respondent Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3965	2053	6018	3862	1985	5847

This table shows how the impact of treatment and priority treatment vary based on baseline reservation wages. The dependent variable in columns 1, 2 and 3 is an indicator for being employed, while the dependent variable in columns 4, 5 and 6 is log reservation wages. Column 1 and 4 restricts the sample to job seekers with below median reservation wages at baseline. Column 2 and 5 restricts the sample to job seekers with above median reservation wages. Columns 3 and 6 consider the full sample and interact treatment and priority treatment with an indicator for above median reservation wages at baseline. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

A.1.7 Balance (Always Searchers)

Table A.7: Job Seeker (Always-Searchers) Characteristics

	Panel A: Job-seeker Characteristics						
	(1) Control	(2) Treatment	(3) Priority Treatment	(4) (1) vs. (2), p-value	(5) (1) vs. (3), p-value	(6) (2) vs. (3), p-value	(7) Joint F-test
=1 if male	0.90	0.93	0.89	0.12	0.90	0.09	0.16
Age	23.74	23.49	23.73	0.41	0.91	0.48	0.66
Education (Yrs)	14.21	14.32	14.40	0.56	0.34	0.66	0.64
=1 if married	0.26	0.27	0.25	0.71	0.74	0.47	0.77
=1 if Hindu	0.92	0.96	0.97	0.09	0.04	0.59	0.09
=1 if ST/SC caste	0.40	0.40	0.36	0.95	0.27	0.21	0.40
=1 if OBC caste	0.30	0.35	0.36	0.16	0.17	0.95	0.29
=1 if general caste	0.30	0.25	0.29	0.11	0.76	0.21	0.23
Father's education>0	0.80	0.77	0.82	0.46	0.59	0.19	0.41
Mother's education>0	0.56	0.55	0.57	0.79	0.95	0.74	0.94
=1 if live in village	0.49	0.52	0.52	0.32	0.28	0.88	0.50
=1 access to Internet	0.78	0.83	0.82	0.15	0.34	0.67	0.34
=1 access Internet for jobs	0.57	0.61	0.65	0.38	0.12	0.42	0.29
=1 if registered with a job portal	0.27	0.25	0.32	0.53	0.17	0.03	0.10
=1 family is helpful for search	0.68	0.65	0.65	0.45	0.44	0.93	0.68
=1 friends are helpful for search	0.63	0.63	0.62	0.91	0.74	0.80	0.94
=1 if currently employed	0.28	0.30	0.27	0.62	0.70	0.36	0.65
=1 if looking for job	1.00	1.00	1.00	.	.	.	.
Hours search (winz, 0.01)	9.92	10.65	8.77	0.61	0.45	0.19	0.42
Reservation wage winzorized (rupees)	11707.80	11216.59	12113.83	0.28	0.31	0.03	0.09
Current wage winzorized (rupees)	10573.45	9347.76	8448.70	0.26	0.03	0.23	0.11
= 1 if Telecom	0.32	0.35	0.34	.	.	.	.
= 1 if Logistics	0.39	0.40	0.42	.	.	.	.
= 1 if SalesMarketing	0.18	0.17	0.13	.	.	.	.
= 1 if Security	0.11	0.08	0.10	.	.	.	.

This table presents summary statistics for the sample of job seekers who are searching throughout the study period, which are calculated using the baseline survey. Columns 1-3 show mean values of each variable for the control group and treatment groups at baseline. Columns 4-6 tests whether these characteristics differ significantly across groups (controlling for geographic and trade strata). Column 7 presents a joint F-test of treatment orthogonality. Panel B presents job characteristics, as they were advertised in the SMSs that Job Shikari sent to the treatment group.

A.1.8 Outcomes for Always Searchers

Table A.8: Employment and Beliefs (Always Searchers)

	Panel A: Employment	
	(1) Employed	(2) Log(Wage)
Treatment	-0.048	0.010
	(0.036)	(0.075)
Priority Treatment	0.049	0.122
	(0.033)	(0.170)
Mean in Control	0.28	9.03
F-test T + PT	0.96	0.45
Respondent Fixed Effects	Yes	Yes
Survey Round Fixed Effects	Yes	Yes
Number of Observations	2665	795

	Panel B: Beliefs				
	(1) Log(Reservation Wage)	(2) Log(Expected Wage)	(3) Prob10	(4) Prob16	(5) Prob20
Treatment	0.077**	0.009	0.128	-0.061	0.114
	(0.037)	(0.051)	(0.333)	(0.288)	(0.272)
Priority Treatment	-0.080**	0.001	-0.376	-0.421	-0.353
	(0.037)	(0.050)	(0.333)	(0.288)	(0.265)
Mean in Control	9.3	9.2	4.7	2.9	2.0
F-test T + PT	0.94	0.82	0.50	0.12	0.40
Respondent Fixed Effects	Yes	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Observations	2551	2516	2471	2408	2386

Panel A illustrates the impact of the treatments on employment outcomes for job seekers who are always searching. The dependent variables are an indicator for whether the respondent is employed (column 1), and the logarithm of wages winzorised at the 1% (column 2). Columns 1 includes all respondents in the sample while column 2 only include respondents who were employed at the time of survey. Panel B illustrates the impact of the treatments on beliefs for job seekers who are always searching. Column 1 presents the logarithm of respondents reservation wages (where we asked job seekers "What is the minimum salary that you would accept if you are looking for a job in your field/sector and location"). Column 2 shows respondents expected wages (where we ask "What is the normal salary that someone with your level of training and your experience would earn in your location"). Column 3-5 shows the probability that job seekers' think they will get a job that pays 10,000, 16,000 and 20,000 rupees respectively (where we ask "On a scale of 1-10, how likely is it that you will be offered a job that pays at least 10,000 in your location next month?"). Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

A.1.9 Job Search

Table A.9: Job Search

	All			Searchers	
	(1) Search	(2) Log(Hours)	(3) Log(Apps)	(4) Log(Hours)	(5) Log(Apps)
Treatment	0.005	-0.003	-0.037	0.015	-0.153
	(0.027)	(0.138)	(0.088)	(0.151)	(0.112)
Priority Treatment	0.003	-0.042	0.131	0.003	0.133
	(0.026)	(0.127)	(0.090)	(0.139)	(0.116)
Mean in Control	0.65	2.06	1.32	2.06	1.31
F-test T + PT	0.78	0.74	0.33	0.90	0.87
Respondent Fixed Effects	Yes	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Observations	6828	2986	3333	1908	1768

This table shows how treatment affects different measures of job search. The dependent variables are an indicator for whether the respondent is actively searching for employment (column 1), the log number of hours spent searching in the past week (winzorised at the 1%)- where people who are not searching are assigned a value of 0 hours (column 2/4), the log number of job applications submitted in the last 3 months (winzorised at the 1%) (column 3/5). Columns 1, 2 and 3 include all respondents in the sample at baseline, while columns 4 and 5 include all respondents who report consistently searching for work throughout the study. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

A.1.10 Balance (by Geo-Zones)

Table A.10: Job Seeker Characteristics by Geographic Zone

	(1) DelhiNCR	(2) North	(3) SouthWest	(4) East	(5) (1) vs. (2), p-value	(6) (1) vs. (3), p-value	(7) (1) vs. (4), p-value
=1 if male	0.81	0.89	0.87	0.90	0.00	0.01	0.00
Age	23.33	22.97	26.95	23.69	0.30	0.00	0.32
Education (Yrs)	14.78	14.28	14.54	13.70	0.00	0.10	0.00
=1 if married	0.17	0.21	0.41	0.28	0.15	0.00	0.00
=1 if Hindu	0.86	0.91	0.95	0.97	0.01	0.00	0.00
=1 if ST/SC caste	0.16	0.27	0.27	0.59	0.00	0.00	0.00
=1 if OBC caste	0.20	0.37	0.45	0.24	0.00	0.00	0.12
=1 if general caste	0.64	0.36	0.27	0.17	0.00	0.00	0.00
Father's education>0	0.89	0.80	0.82	0.79	0.00	0.03	0.00
Mother's education>0	0.77	0.53	0.61	0.46	0.00	0.00	0.00
=1 if live in village	0.06	0.46	0.46	0.69	0.00	0.00	0.00
=1 access to Internet	0.96	0.83	0.79	0.66	0.00	0.00	0.00
=1 access Internet for jobs	0.61	0.54	0.55	0.43	0.03	0.08	0.00
=1 if registered with a job portal	0.49	0.25	0.22	0.17	0.00	0.00	0.00
=1 family is helpful for search	0.62	0.66	0.61	0.66	0.17	0.85	0.19
=1 friends are helpful for search	0.54	0.63	0.62	0.61	0.01	0.02	0.05
=1 if currently employed	0.45	0.32	0.48	0.16	0.00	0.38	0.00
=1 if looking for job	0.54	0.64	0.65	0.72	0.00	0.00	0.00
Hours search (winz, 0.01)	3.20	6.17	5.99	7.09	0.00	0.00	0.00
Reservation wage winzorized (rupees)	17321.81	12278.82	12055.50	11019.78	0.00	0.00	0.00
Current wage winzorized (rupees)	15958.12	11440.36	8330.73	9042.25	0.00	0.00	0.00

This table presents summary statistics for job seekers across geographic zones, which are calculated using the baseline survey. Columns 1-3 show mean values of each variable across geographic zones. Columns 4-6 tests whether these characteristics differ significantly across geography.

A.1.11 Employment by Characteristic

Table A.11: Employment by Characteristic

	(1) Emp	(2) Emp	(3) Emp	(4) Emp	(5) Emp
Treat	-0.075***	-0.075***	-0.108**	-0.106***	-0.075***
	(0.026)	(0.026)	(0.043)	(0.032)	(0.026)
Priority Treat	0.020	0.030	0.040	0.028	0.058**
	(0.025)	(0.024)	(0.043)	(0.030)	(0.024)
Treat X Old	-0.052				
	(0.047)				
Priority Treat X Old	0.084*				
	(0.044)				
Treat X Mar		-0.059			
		(0.048)			
Priority Treat X Mar		0.065			
		(0.047)			
Treat X Ed			0.023		
			(0.050)		
Priority Treat X Ed			0.008		
			(0.049)		
Treat X Vil				0.027	
				(0.043)	
Priority Treat X Vil				0.040	
				(0.041)	
Treat X Gen					-0.051
					(0.047)
Priority Treat X Gen					-0.052
					(0.047)
Mean in Control	0.29	0.29	0.29	0.29	0.29
Respondent Fixed Effects	Yes	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Observations	6510	6504	6480	6512	6407

This table shows how the impact of treatment and priority varies with different job seeker characteristics. The dependent variable across all columns is an indicator for being employed. The specification in column 1 interacts treatment and priority treatment with an indicator for being above the median age in our sample ("Old"). The specification in column 2 interacts treatment and priority treatment with an indicator being married ("Mar"). The specification in column 3 interacts treatment and priority treatment with an indicator for being above the median education in our sample ("Ed"). The specification in column 4 interacts treatment and priority treatment with an indicator being in a village ("Vil"). Finally the specification in column 5 interacts treatment and priority treatment with an indicator for being general caste ("Gen"). Standard errors are clustered at the respondent level. Older job seekers react more strongly to priority treatment. None of the estimates on columns 2-5 are statistically significant, though it appears that married job seekers (who may have dependents) are more likely to respond to priority treatment status. Similarly, lower caste job seekers and those based in villages respond more strongly to priority treatment. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

A.1.12 Spillovers

Table A.12: Spillovers

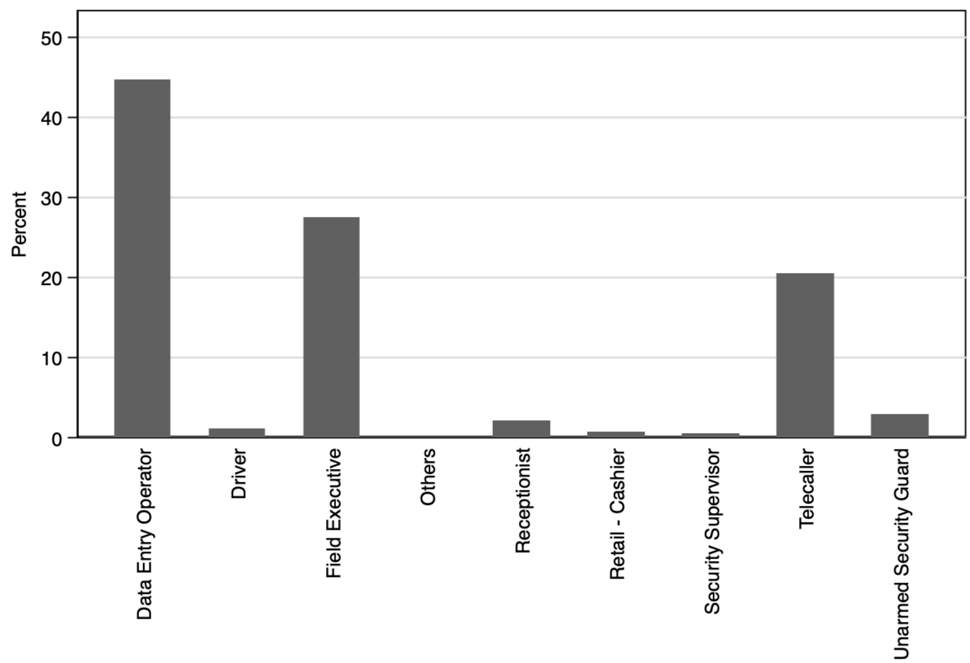
	(1) Employed	(2) Log(Wage)
Treatment	-0.095***	-0.001
	(0.023)	(0.068)
Priority Treatment	0.038*	0.057
	(0.021)	(0.074)
Share of Sample in Treatment (per NSDC)	0.064	-0.013
	(0.092)	(0.359)
Share of Sample in Priority Treated (per NSDC)	0.183**	0.063
	(0.087)	(0.236)
Mean in Control	0.30	9.08
F-test T + PT	0.01	0.54
Respondent Fixed Effects	Yes	Yes
Survey Round Fixed Effects	Yes	Yes
Number of Observations	6866	2311

This table presents evidence of spillovers. The dependent variables are an indicator for being employed (column 1), and log reservation wages (column 2). We regress these measures on our indicators for treatment and priority treatment, as well as the share of the sample within the NSDC institute that is assigned to treatment and priority treatment. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

A.2 Figures

A.2.1 Job Types that Job Shikari sent via SMS

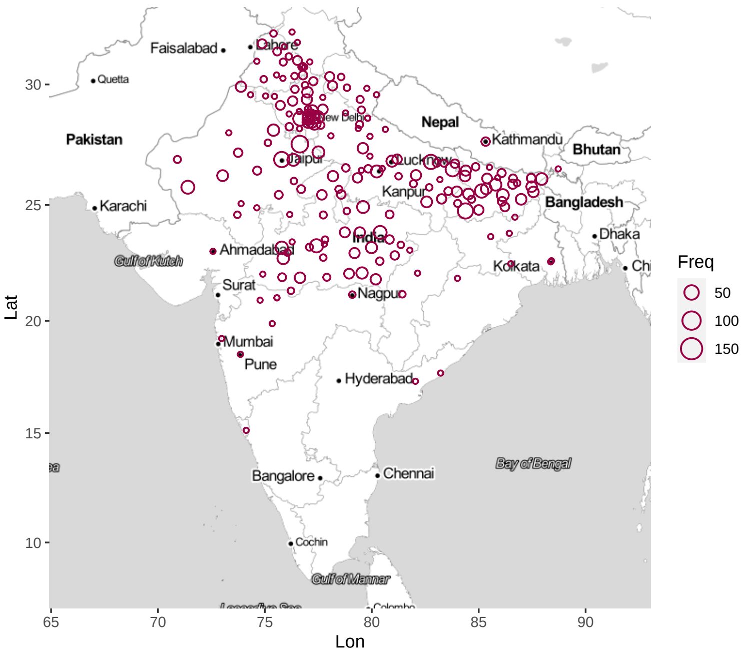
Figure A1: Job Types that Job Shikari sent via SMS



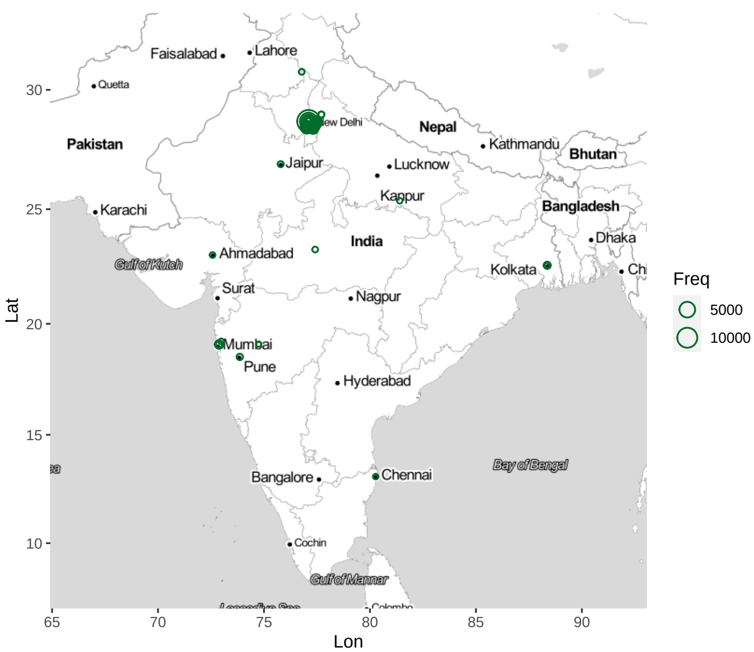
This figure represents the trades that were advertised in the SMSs that Job Shikari sent to our sample from August 2015 to September 2016.

A.2.2 Location of Job seekers and Jobs across India

Figure A2: Location of Job seekers and Jobs across India



(a) Job Seekers



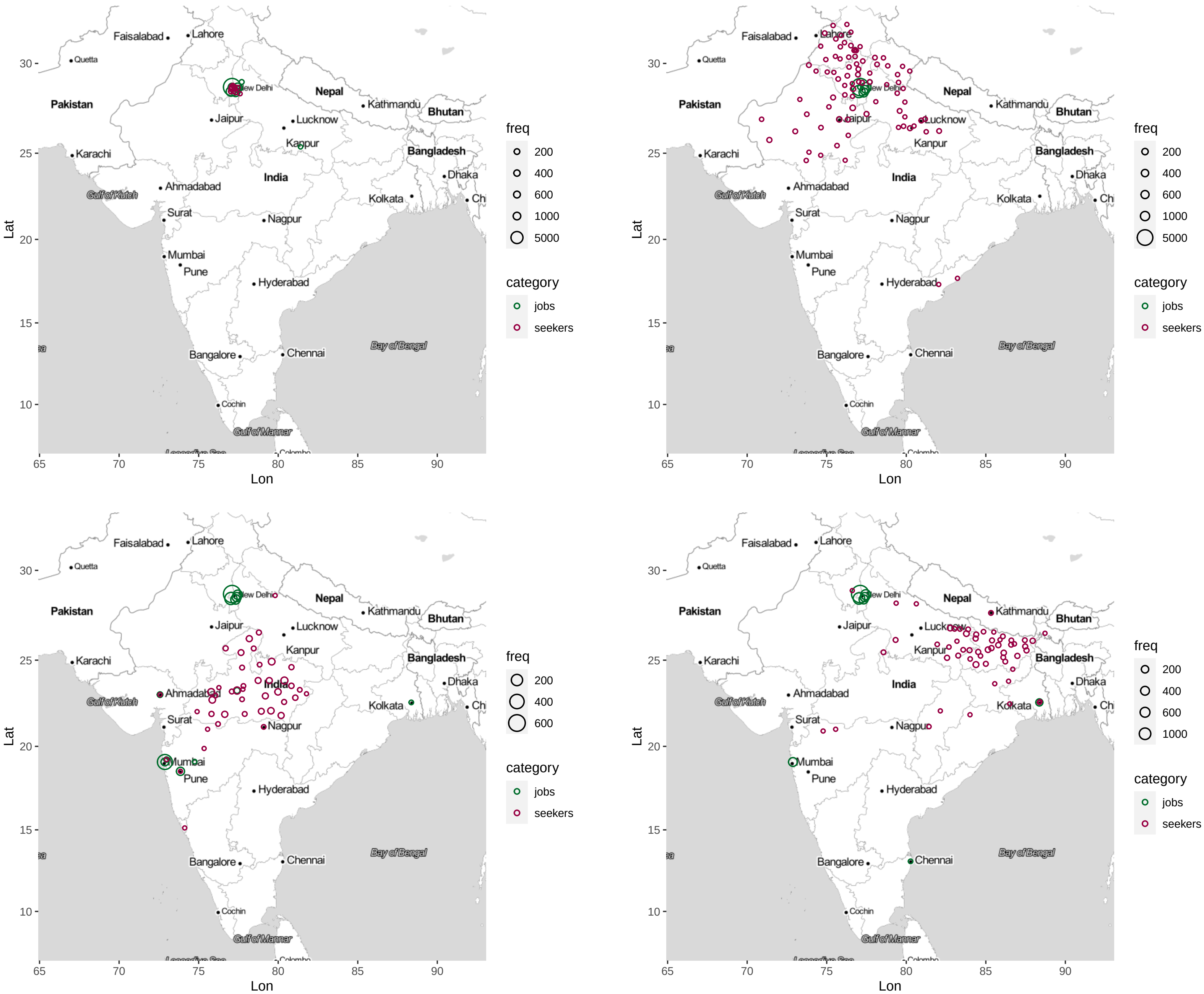
(b) Jobs

This figure presents the location of job seekers (Panel A) at baseline, and the location of the jobs that Job Shikari sent to our sample from August 2015 to September 2016.

A.2.3 Locations of Job seekers and Job offers by Initial Geographic Zone

Figure A3: Locations of Job seekers and Job offers by Initial Geographic Zone

(a) DelhiNCR (b) North

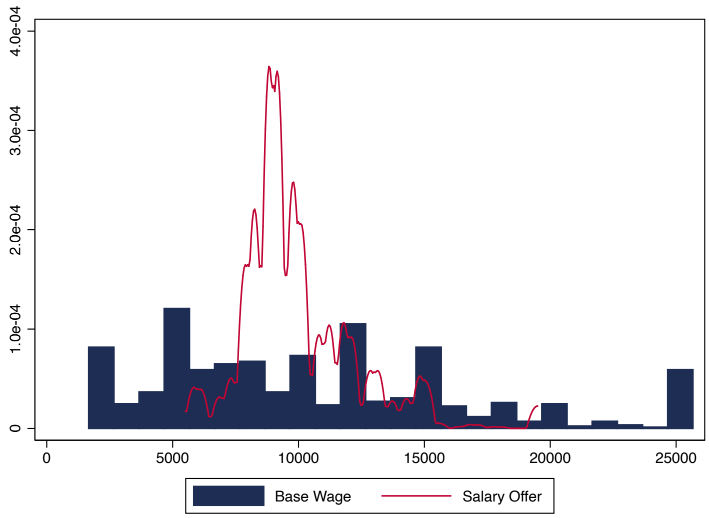


(c) South West (d) East

This figure presents the location of job seekers (Panel A) at baseline broken out by geographic zone at baseline, and the location of the jobs that Job Shikari sent to our sample in those respective geographic zones from August 2015 to September 2016.

A.2.4 Distribution of Baseline Wages and Salary Offers

Figure A4: Distribution of Baseline Wages and Salary Offers

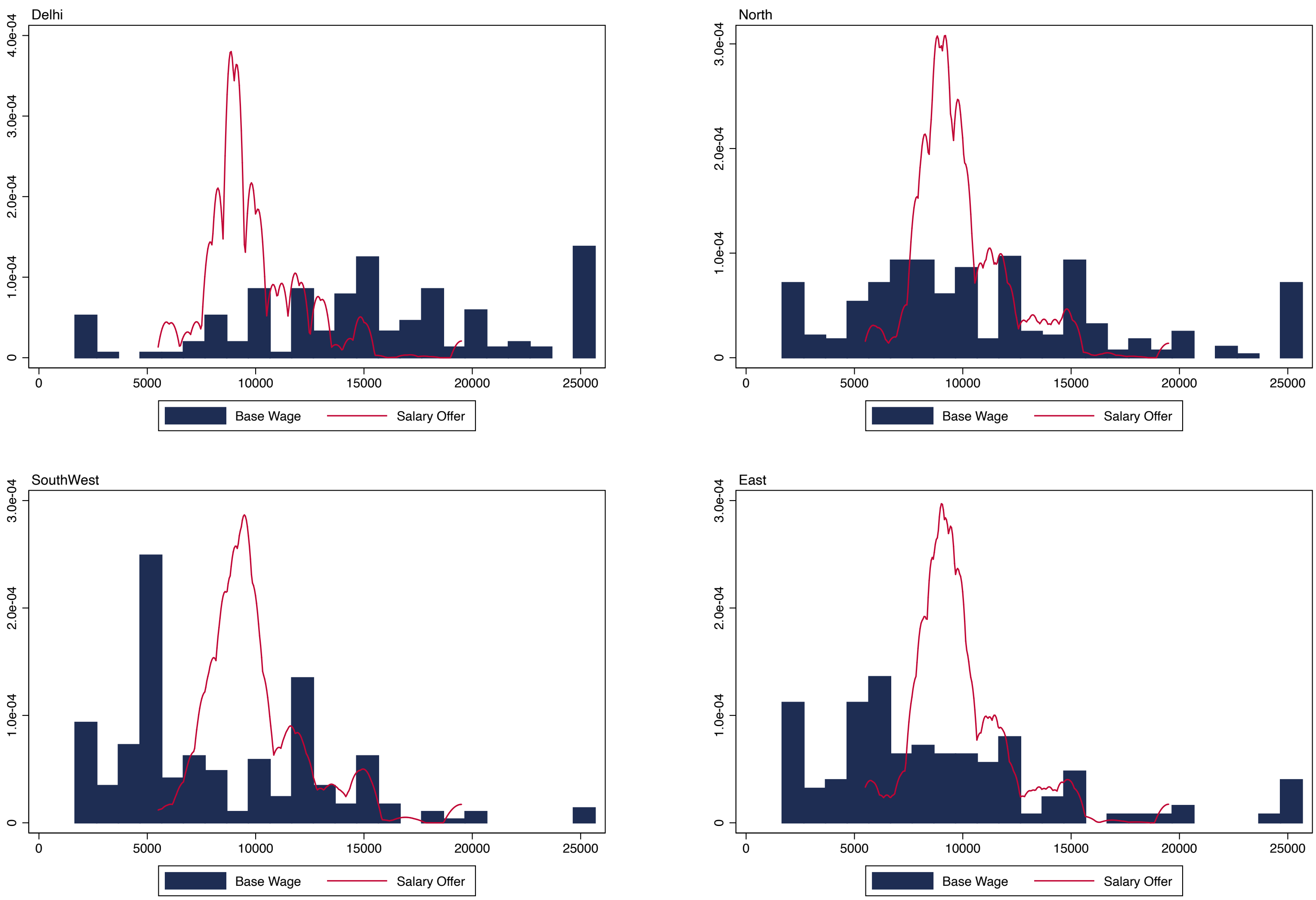


This histogram reflects the distribution of wages that employed job seekers in our sample report at baseline. The k-density plot displays the set of salary offers that were advertised in the set of SMS that job seekers could apply for from August 2015 to September 2016.

A.2.5 Distribution of Baseline Wages and Salary Offers by Geographic Zone

Figure A5: Distribution of Baseline Wages and Salary Offers by Geographic Zone

(a) DelhiNCR (b) North

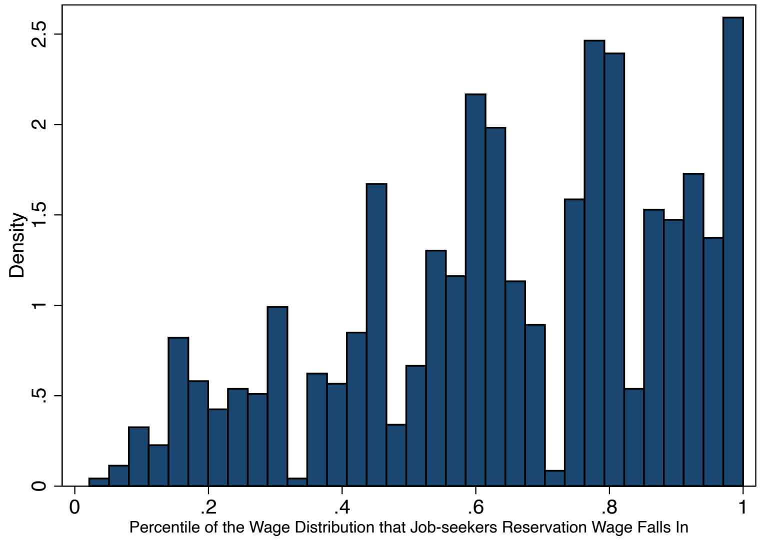


(c) South West (d) East

This histogram reflects the distribution of wages that employed job seekers in our sample report at baseline, where each panel focuses on the set of job seekers in that geographic zone at baseline. The k-density plot displays the set of salary offers that were advertised in the set of SMS that job seekers in that geographic zone could apply for from August 2015 to September 2016.

A.2.6 Biased Beliefs

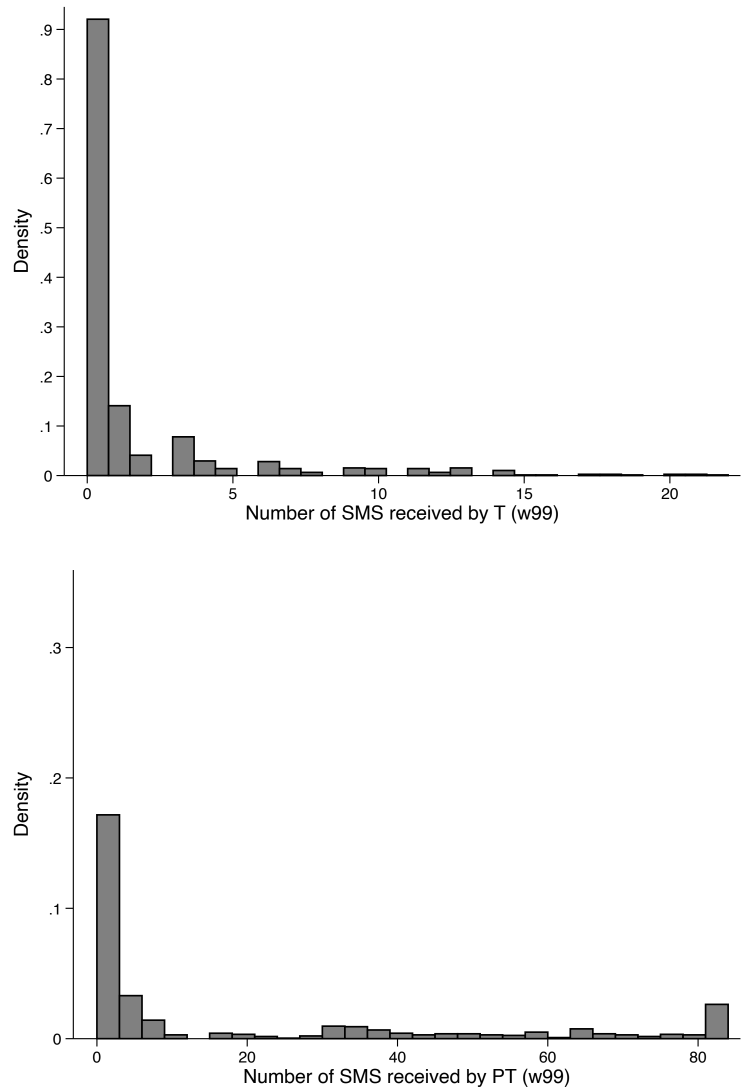
Figure A6: Biased Beliefs



This figure computes where job seekers baseline stated reservation wages lie in the distribution of actual wages that employed job seekers from the same geo-zone and trade report at baseline.

A.2.7 Distribution of SMS received

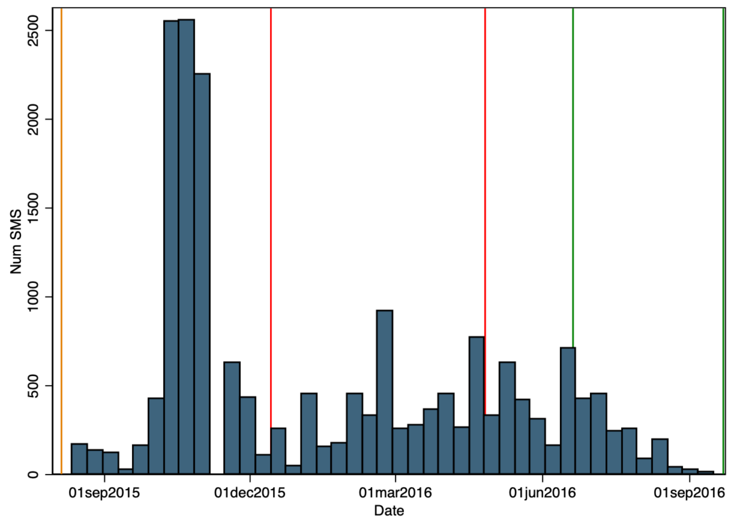
Figure A7: Distribution of SMS received



This figure presents the number of SMS that job seekers received in the treatment (Panel A) and priority treatment (Panel B) groups.

A.2.8 Timeline of SMS sent by Job Shikari

Figure A8: Timeline of SMS sent by Job Shikari



This figure represents a timeline of when SMSs were sent by Job Shikari to the job seekers in our sample. The orange line represents the end of baseline, the red lines represent the start and end dates for mildine (since we could not midline everyone on the exact same date), and the green lines represent the start and end dates for endline (since we could not endline everyone on the exact same date).

B Appendix for Online Publication Only - Model

B.1 Status Quo

In period T the worker armed with wage offer w solves:

$$V_T(w) = \max_{accept,reject} [u(w_T), 0]$$

The worker will accept the wage offer this period if:

$$u(w_T) > 0 \tag{1}$$

The worker will accept any wage offer.

In period T-1, the worker solves:

$$V_{T-1}(w) = \max_{accept,reject} [u(w) + \beta V_T(w), \beta E[V_T(w')]]$$

The worker will accept the wage offer this period if

$$\begin{aligned} u(w_{T-1}) + \beta u(w_{T-1}) &> \beta E[u(w')] \\ (1+\beta)u(w_{T-1}) &> \beta E[u(w')] \\ u(w_{T-1}) &> \frac{\beta}{1+\beta} E[u(w')] \\ u(w_{T-1}) &> \frac{\beta}{1+\beta} \int u(w') f(u(w') dw' \end{aligned} \tag{2}$$

Based on the utility function, the discount rate, and the density of to wage offers $f(\cdot)$, this implicity defines the reservation wage $\bar{w}_{T-1}$; clearly some wages will not be acceptable at time $T-1$ that were acceptable at time t.

Next, we demonstrate that reservation wages are declining in t. To see this, note that if the decision vector $(h_{T-k}(w), ..., h_T(w))$ is $(accept, accept, ..., accept)$ in time periods $(T-k, T-k+1, .., T)$ for a worker who receives offer w in any period $T-k$, then $V_{T-k}(w) = \frac{1-\beta^{k+1}}{1-\beta} u(w)$. Therefore, to demonstrate that reservation wages are declining in t we demonstrate that if w_{T-k} is acceptable in period $T-k$, it is acceptable forever, which means we can write $V_{T-k}(w_{T-k}) = \frac{1-\beta^{k+1}}{1-\beta} u(w_{T-k})$.

We prove this by induction on V.

First, consider period $T-1$, and an offer w_{T-1} where $h_{T-1}(w_{T-1}) = accept$ (the wage offer is accepted in period T-1). We know this same wage offer will be accepted in time T since all offers are accepted at time T. Therefore we can write

$$V_{T-1}(w_{T-1}) = u(w_{T-1}) + \beta u(w_{T-1})) = \frac{1-\beta^2}{1-\beta} u(w_{T-1}) \tag{3}$$

Next, consider period $T-k$, and assume $V_{T-k+1}(w_{T-k+1}) = \frac{1-\beta^k}{1-\beta} u(w_{T-k+1}) \; \forall \; w_{T-k+1} > w^*_{T-k+1}$, where w^*_{T-k+1} is the reservation wage at time $T-k+1$. That is, that any acceptable wage offer at time $T-k+1$ would be accepted at all future wage offers. Then consider the decision to accept a wage offer w_{T-k+1} at time $T-k+1$:

$$V_{T-k+1}(w) = \max_{accept, reject} \left[u(w) + \beta V_{T-k+2}(w), \beta E\left[V_{T-k+2}(w')\right]\right]$$

Where by the definition of the reservation wage:

$$V_{T-k+1}(w) = \beta E[V_{T-k+2}(w')] = \frac{1-\beta^k}{1-\beta} u(w^*_{T-k+1}) \tag{4}$$

In **period T-k**, consider $w < w^*_{T-k+1}$, so that $h_{T-k+1}(w) = reject$. Then $h_{T-k}(w) = reject$ if:

$$\begin{aligned}
u(w) + \beta V_{T-k+1} &< \beta E[V_{T-K+1}(w')] \\
u(w) + \beta^2 E[V_{T-k+2}(w')] &< \beta E[V_{T-k+1}(w')] \qquad \text{by (4)} \\
\underbrace{u(w) + \beta \frac{1-\beta^k}{1-\beta} u(w^*_{T-k+1})}_{A} &< \underbrace{\beta E[V_{T-k+1}(w')]}_{B}
\end{aligned}$$

Since $w < w^*_{T-k+1}$

$$\begin{aligned}
\underbrace{u(w) + \beta \frac{1-\beta^k}{1-\beta} u(w^*_{T-k+1})}_{A} &< u(w^*_{T-k+1}) + \beta \frac{1-\beta^k}{1-\beta} u(w^*_{T-k+1}) \\
&< u(w^*_{T-k+1}) \frac{1-\beta^{k+1}}{1-\beta} \\
&< u(w^*_{T-k+1}) \frac{1-\beta^k}{1-\beta} + u(w^*_{T-k+1}) \beta^k \\
&< \beta E[V_{T-k+2}(w')] + \beta^k u(w^*_{T-k+1}) \qquad \text{by (4)}
\end{aligned}$$

Thus, the searcher in time $T-k$ will reject all wage offers $w < w^*_{T-k+1}$ if

$$\beta E[V_{T-k+2}(w')] + \beta^k u(w^*_{T-k+1}) < \underbrace{\beta E[V_{T-k+1}(w')]}_{B}$$
$$E[V_{T-k+1}(w')] - E[V_{T-k+2}(w')] > \beta^{k-1} u(w^*_{T-k+1})$$

To evaluate this expression note two things.

First, the searcher could play strategy $h_{T-k+2}(w), h_{T-k+3}(w), ..., h_T(w)$ in periods $T-k+1, T-k+2, ..., T-1$ and $h_T(w) = accept$ in period T. If the searcher did that, because the wage offer distribution is stable she would receive in expectation $E[V_{T-k+2}(w')]$ in periods $T-k, ..., T-1$ plus an additional utility payment $\beta^{k-1}E_{t-k+1}[u(w_T)|h_{T-k+1}(w), h_{T-k+2}(w), ..., h_T(w), h_T(w)]$ in period T. Since $V_{T-k+1}(w)$ is an optimum, we know that

$$E[V_{T-k+1}(w)] > E[V_{T-k+2}(w)] + \beta^{k-1}E_{t-k+1}[u(w_T)|h_{T-k+1}(w), h_{T-k+2}(w), ..., h_T(w), h_T(w)]$$

Second, define ω_t as the received wage in time t, i.e. $\omega_t = 0$ if the wage offer is rejected at time t and $\omega_t = w$ for an accepted wage offer. Note that he time $t-k+1$ expectation of the $t-k+1+\tau$ expected received wage is increasing in τ.

$$E_{T-k+1}[u(\omega_{T-k+1+\tau})|h_{T-k+1}(w), h_{T-k+2}(w), ..., h_T(w)] = (1-F(w^*_{T-k+1}))E[u(w)|w > w^*_{T-k+1}] + \sum_{d=1}^{\tau}\prod_{a=1}^{d} F(w^*_{T-k+a})(1-F(w^*_{T-k+1+d}))E[u(w)|w > w^*_{T-k+1+d}]$$

Since τ only adds positive numbers to this expectation, it is clearly increasing in τ. Thus, from the perspective of time $t-k$, the searcher expects to receive higher wages in more distant future periods τ: intuitively, each period further in the future allows more chances at a high wage accepted offer. So your expected value of a new wage draw, which is just a weighted sum of expected wages in future periods, will have the property where the expected wage in each future period is higher the more distant that period is. This means that the expected wage in period T is going to be larger than the average of the expected wages. Now, we also know that the expected value of a new wage draw is equal to the weighted sum of utility at the reservation wage in T-k+1 (the average of the expected wages), by definition of the reservation wage:

$$\beta E[V_{T-k+2}(w')] = \beta \sum_{\tau=0}^{T-k+2} \beta^\tau E[u(\omega_{T-k+2+\tau})|h_{T-k+2}, ..., h_T] = \frac{1-\beta^{T-k+1}}{1-\beta} u(w^*_{T-k+1})$$

Thus, we can be guaranteed that the average expected wage from following the $T-k+2, ..., T$ strategies is w^*_{T-k+1} and that $E_{T-k+1}[u(\omega_T)|h_{T-k+2,...,h_T,h_T}] > u(w^*_{T-k+1})$. Thus

$$E[V_{T-k+1}(w')] - E[V_{T-k+2}(w')] > \beta^{k-1}u(w^*_{T-k+1})$$

And the searcher would reject any offer at time $T-k$ that she would reject at $T-k+1$. In turn, this means that

$$V_{T-k}(w) = \frac{1-\beta^{k+1}}{1-\beta}u(w^*_{T-k})$$

which implies that any wage accepted at $T-k$ is always accepted at later time periods and reservation wages are declining in t.

B.2 Job Portal

B.2.1 Job seeker beliefs

Each period the job seeker updates their prior about the probability of receiving a better wage offer from the portal. They follow Bayes Rule:

$$f(q|x) = \frac{p(x|q)f(q)}{\int p(x|q)f(q)dq}$$

Where the job portal can successfully produce a good wage draw with *unknown probability* q, and we hypothesize that q is anywhere in the range [0,1]. The value of q is random and we suppose that q follows a *continuous prior density function* f(q) = 1. We have simplified the problem to having a discrete likelihood because the portal only has two outcomes $x = \bar{w}$ and $x = \underline{w}$ such that $p(x = \bar{w}|q) = q$ and $p(x = \underline{w}|q) = 1 - q$. In this case, anyone who receives an offer of $\bar{w}$ from the portal will accept it; so the only interesting history is that for a seeker who has only received offers for $\underline{w}$ from the portal. Suppose in time **period 1**, the job seeker gets 1 SMS and it's a bad offer. We can compute the posterior pdf for q after seeing one bad draw:

$$
\begin{aligned}
Hypothesis &= q \\
Prior &= f(q)dq = 1 \cdot dq \\
Likelihood &= p(x = \underline{w}|q) = 1 - q \\
Bayes\ Numerator &= p(x = \underline{w}|q) * f(q) = 1 - q \\
Total\ Probability &= p(x = \underline{w}) = \int_0^1 p(x = \bar{w}|q) f(q) dq = \int_0^1 (1 - q) dq
\end{aligned}
$$

In time **period t**, where the job seeker gets bad offers each period, we can compute the posterior pdf for q after seeing t bad draws:

$$
\begin{aligned}
f(q|x = \underline{w}) &= \frac{p(x = \underline{w}|q) * f(q)}{\int_0^1 p(x = \bar{w}|q) f(q) dq} \\
&= (t + 1)(1 - q)^t
\end{aligned}
$$

We are interested in the expected value of q given these t bad draws:

$$
\begin{aligned}
E[q|x = \underline{w}] &= \int_0^1 q f(q|x = \underline{w}) dq \\
&= \int_0^1 q \cdot (t + 1)(1 - q)^t dq \\
&= (t + 1) \int_0^1 q \cdot (1 - q)^t dq \\
&= (t + 1) \left[\frac{1}{t + 1} q (1 - q)^{t+1} \mid_0^1 - \int \frac{1}{t + 1} (1 - q)^{t+1} \right] \quad \text{Int. by parts} \\
&= q(1 - q)^{t+1} \mid_0^1 - \int (1 - q)^{t+1} \\
&= -\frac{1}{t + 2} (1 - q)^{t+2} \mid_0^1 \\
&= \frac{1}{t + 2}
\end{aligned}
$$

Which shows that the job seekers' posterior q declines over time, they are less likely to think the portal can provide a higher wage offer.

B.2.2 Value function

A job seeker who has not yet received an offer of $\bar{w}$ from the portal and has a wage offer in hand of w "off-the-portal" must decide whether or not to accept the off-the-portal wage each period. They can accept, and get w this period and the continuation value of this wage offer in the future. They can reject, at which point they will receive a new wage draw on and off the portal. They expect the portal to provide a high wage offer with probability $\frac{1}{t+2}$. If they see this wage draw $\bar{w}$, they will accept it because it dominates all other non-portal wage offers. With probability $\frac{t+1}{t+2}$ they believe the portal will yield a bad wage offer $\underline{w}$, which they won't accept and they will be left with the continuation value of some wage offer w'.

We define a new value function for a seeker with access to the portal, who has a history of $\underline{\mathrm{w}}$, $\underline{\mathrm{w}}$, ... $\underline{\mathrm{w}}$ in the t periods that they have received offers from the portal and a current wage offer off of the portal of w as $W_t(w)$.

$$W_t(w) = \max_{accept,reject} u(w) + \beta W_{t+1}(w), \beta \frac{t+1}{t+2} \int W_{t+1}(w')f(w')dw' + \frac{1}{t+2} W_{t+1}(\bar{w})$$

Since a person will accept and retain any job offer of $\bar{w}$, we know that $W_{t+1}(\bar{w}) = \frac{(1-\beta^{T-t})}{(1-\beta)} u(\bar{w})$. Moreover, given that the continuation value of rejecting a particular job offer is declining in t, we know that a person who accepts a job at wage w will retain it. Therefore:

$$W_t(w) = \max_{accept,reject} u(w) + \beta \frac{1-\beta^{T-t}}{1-\beta} u(w), \beta[\frac{t+1}{t+2} \int W_{t+1}(w')f(w')d(w') + \frac{1}{t+2} \frac{1-\beta^{T-t}}{1-\beta} u(\bar{w})] \tag{5}$$

Since $F(\bar{w}) = 1$, we know that the payoff associated with rejecting a wage offer of w is higher with access to the portal than it would be without (because you now have the chance to get this better offer). This gives the result in Proposition 1 and Corollary 1 that access to the portal increases reservation wages and that unemployment increases in the event that $\hat{q} > q = 0$ (job seekers believe the job portal will deliver a high wage draw, but the true probability is zero, so they don't get a job).

Note that the difference between W and V is the option value of continued search allowed by the portal

$$W^O = \beta \frac{1}{t+2} [\frac{1-\beta^{T-t}}{1-\beta} u(\bar{w})] \tag{6}$$

whereas if the searcher chooses according to value function V, then we know that with a similar probability $1/(t+2)$

$$V^O = \frac{1}{t+2} \beta E[V_{t+1}(w')] = \frac{1}{t+2} \frac{1-\beta^{T-t}}{1-\beta} u(w^*_{T-t}) \tag{7}$$

Taking the derivative with respect to t, we have

$$\frac{dW^0 - V^0}{dt} = [u(\bar{w}) - u(w^*_{T-t})][ln(\beta)\frac{1}{t+2}(\frac{\beta^{T-t}}{1-\beta}) - \frac{1}{(t+2)^2}\frac{1-\beta^{T-t}}{1-\beta}] - \frac{1}{t+2}\frac{1-\beta^{T-t}}{1-\beta}u'(w^*_{T-t})\frac{dw^*_{T-t}}{dt} < 0 \tag{8}$$

since $ln(\beta) < 0$, $\bar{w} > w^*_{T-t}$, and $dw^*_{T-t}/dt > 0$. This suggest that over time, the gap between W and$V$ shrinks, consistent with the fact that $W_T(w) = V_T(w)$: in the final period the two value functions are identical.

Finally, note that W also shrinks faster towards V for older searchers

$$\frac{dW^O - V^O}{dT} = [u(\bar{w}) - u(w^*_{T-t})][-ln(\beta)\frac{1}{t+2}\beta^{T-t}1-\beta] + \frac{1}{t+2}\frac{1-\beta^{T-t}}{1-\beta}u'(w^*_{T-t})\frac{dw^*_{T-t}}{dT} > 0 \tag{9}$$