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

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December 17, 2020

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., 2018b). 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. 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 treatment-priority 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. They also were spatially mismatched relative to jobs advertised by the portal, which were largely in Delhi. Several patterns in the data suggest that job-seekers in the South West 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.

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 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., 2018b; Beam, 2016; Bassi and Nansamba, 2020; Groh et al., 2015); subsidize search costs (Abebe et al., 2018a; Crepon et al., 2019; Banerjee and Sequeira, 2020); and provide better information about applicants (Abebe et al., 2018a; 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). Many of these papers also find that job-seekers expectations about their job-prospects are too high. Our work formally tests this hypothesis by experimentally varying the amount of information that job-seekers have to form their beliefs.

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. Finally, Wheeler et al. (2019) 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. (2019) 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. (2019), our findings may be reconciled if their program's training component was crucial for setting expectations about the platform's impact.

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

2.1 Job Portals in India

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 nation-wide – though when we launched our experiment, Job-Shikari was one of the only ones advertising blue collar employment opportunities.

Table A2 provides some basic statistics about the jobs in our sample. Most 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 (Figure A2, Panel b), while job-seekers are located across the geographic zones we drew our sample from (North, South-West, East and Delhi-NCR - Figure A3).[2] This implies that some job-seekers were much closer to the jobs being advertised than others. 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).

2.2 Vocational Training Institutes in India

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 A2 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 23), and only a third are married. These vocational training

[2] 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.

programs typically cater to households from disadvantaged backgrounds, and over 60% of our sample comes from STs, SCs, or 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.

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 $F(\underline{w}) = 0, F(\overline{w}) = 1$. 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.[3] 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 $w^p \in \{\underline{w}, \bar{w}\}$ 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.

In this set up, workers that receive an offer $w^p = \bar{w}$ accept the offer and retain it until

[3] For simplicity, we do 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. This would be true if adequately responding to information from the portal (going to the place of employment, submitting an application, etc.) is not possible for the employed.

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 $t+k$: $w_k^p = w_{k+1}^p = ... = w_{k+t}^p = \underline{w}$. 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. 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.*

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 registered with the platform. There was no user interface for job-seekers to browse through job posts – all communication occurred via text. This model was built on the principle that accessing SMS is much easier for low-income job-seekers than computers or smart-phones. 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).

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-seekers assigned to the treatment group were uploaded to the platform, and received a welcoming SMS introducing them to the job-portal. In theory, they were then eligible to receive SMSs about various job opportunities on the platform. In practice, however, they did not. Job-seekers assigned to the priority treatment group, received the same 'onboarding' SMS. They were also provided with priority access on the portal by appearing first on the list of job-seekers who matched the portal's query for a given job opportunity. Appearing first on these lists meant receiving many more SMSs. Finally, job-seekers in the control group were not enrolled on the platform at all.

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 17 text messages. This translates into a 32 percentage point increase in the probability of receiving a text message in the treatment group, and a 58 percentage point increase in the probability of receiving a text message in the priority treatment group (column 2).

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. Midline surveys took place 9 months later, and we managed to reach 83% of respondents. Finally, we conducted the endline survey between June and September 2016, and successfully reached 71% of respondents.[4] 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.

[4] 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 A1)).

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 is a dummy equal to 1 if the job-seeker was assigned to either of our treatments; TP is an indicator equal to 1 for being in the priority treatment group specifically; γ represents individual fixed effects; and δ_t represents an time fixed effect (survey round). The coefficients of interest are β_1, which represents the average effect of being uploaded to the portal across all survey rounds, and β_2, which represents the average effect of receiving additional text messages as a result of being in the priority treatment group (relative to treatment) across all survey rounds. We cluster all regressions at the individual level (our unit of randomization).[5]

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 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 because featured jobs may not be very attractive, and recent graduates are less likely to know what their labor market prospects are.

Nevertheless, we also establish that these effects on voluntary unemployment can be

[5]We have also tested whether these effects differ between the midline and endline. These differences are not statistically precise enough to yield helpful interpretations (Appendix Table A8)

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 16 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 experiences a 4.4 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.[6]

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 (2.2%) 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 5.3% as job seekers realize the jobs on offer are not what they expected.[7] Similar trends, albeit not statistically significant, are visible in Column 2, which displays the treatment and 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.

We investigate whether accessing the portal has any impact on the actual wages for employed job-seekers, and overall earnings for the full sample. Table 2 presents the results

[6]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 17 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'. Third, while this disemployment effect is more heavily concentrated among job-seekers who are unemployed at baseline, the patterns are still visible among job-seekers who were employed at baseline. Finally misreporting does not explain the differences between T and TP.

[7]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 reservation wages above and below the mean. Table A7 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.

on log wages (column 2), wages (column 3) and earnings (column 4). The results suggest that being in the treatment group is associated with an 11% decrease in wages. In light of the observed increase in reservation wages, we might have expected the opposite outcome. However, this effect is difficult to interpret because of selection. It is conceivable that "low-ability" or poor job-seekers with relatively limited outside options are the only ones to accept low-paying jobs in the treatment group because they can ill afford to wait for better offers. 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. The results on earnings (Column 4) follow the same trends as those on wages.

Finally, we look at whether job-seekers in the treatment groups spend more or less time searching and applying for jobs. There is very little evidence that being uploaded to the portal has any significant impacts on whether job-seekers are searching for a job, the number of hours that they search, or the number of applications that they submit (Table A4).This is true for both employed and unemployed job-seekers.[8] This result is not altogether surprising, however, as job-seekers can be passive users of the portal as they wait for additional text messages. However, 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 can use the experiment's geographic stratification to explore this further. 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 A3 demonstrates that job-seekers in the South and West zone 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 A3 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 and 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 treatment-priority job-seekers in Delhi NCR saw 54 text messages on average, while job-seekers in the North

[8]The number of hours unemployed job-seekers spend searching for a job is the only variable that decreases significantly (at the 10%)

and East saw 18 and 12 job offers respectively. Job seekers in the South and West received only 4 text messages on average. 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 3 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 South West experience a 8.9 percentage point increase in the probability of being employed relative to treatment. Similarly, 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 4 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 4. 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.[9]

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 A5).

To test whether the priority treatment effects we observe are primarily a withdrawal from voluntary unemployment, we investigate whether that 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 A6 shows that this is indeed the case. The younger priority treatment job-seekers experience a 2 percentage points 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 negative employment effect disappears altogether for older job-seekers. The impact of age becomes even more stark as we focus on older cohorts (Figure 1). The coefficient on priority treatment increases from 0.09 to 0.20 as we move from 23 year olds to 28 year olds.[10]

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

[9]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. (2018a) 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

[10]Though outside the scope of our model, Table A6 presents the results for other groups that may be unable to afford long unemployment spells: married, highly educated, general caste and rural job-seekers

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 re-locate to Delhi, where most of the portal's jobs are located. Instead, they re-adjust their expectations and are more likely to be 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.

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Tables

Table 1: SMS receipt

	(1) SMS Received	(2) =1 SMS Received	(3) SMS Received	(4) =1 SMS Received
Treatment	1.437	0.322		
	(0.096)	(0.014)		
Priority Treatment	16.405	0.267		
	(0.977)	(0.021)		
Treatment DelhiNCR			6.132	0.728
			(0.503)	(0.034)
Treatment North			1.043	0.319
			(0.101)	(0.024)
Treatment East			0.758	0.288
			(0.087)	(0.024)
Treatment SouthWest			0.307	0.143
			(0.059)	(0.021)
Priority Treatment			48.039	0.179
DelhiNCR			(4.537)	(0.041)
Priority Treatment			17.429	0.467
North			(1.130)	(0.032)
Priority Treatment			11.634	0.206
East			(1.279)	(0.038)
Priority Treatment			3.627	0.102
SouthWest			(0.863)	(0.037)
Respondent Fixed Effects	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	7986	7986	7986	7986

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)	(3) Wage	(4) Earnings
Treatment	-0.092	-0.041	-1354.580	-1145.932
	(0.022)	(0.071)	(796.593)	(357.399)
Priority Treatment	0.048	0.069	369.564	493.411
	(0.021)	(0.078)	(588.904)	(322.057)
Mean in Control	0.30	9.09	11220.12	3368.86
Respondent Fixed Effects	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	6866	2311	2326	6475

	Panel B: Beliefs				
	(1) Reservation Wage	(2) Expected Wage	(3) Prob10	(4) Prob16	(5) Prob20
Treatment	274.541	-37.234	-0.010	-0.165	0.099
	(306.323)	(356.674)	(0.216)	(0.192)	(0.175)
Priority Treatment	-659.004	209.527	-0.399	-0.239	-0.252
	(315.462)	(344.058)	(0.207)	(0.187)	(0.178)
Mean in Control	12308.9	12174.1	4.9	3.0	2.0
Respondent Fixed Effects	Yes	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Observations	6505	6442	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), the logarithm of wages (column 2), their wages winzorised at the 1% (column 3), and their earnings (imputing earnings of zero for job-seekers who are not working) (column 4). Columns 1 and 4 include all respondents in the sample while column 2 and 3 only include respondents who were employed at the time of survey. Panel B illustrates the impact of the treatments on beliefs. The dependent variables are respondents reservation wages (column 1), their expected wages (column 2), and the probability that job-seekers' think they will get a job that pays 10,000, 16,000 and 20,000 rupees respectively. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 3: Employment by Geographic Zone

	(1) Employed	(2) Log(Wage)	(3) Wage	(4) Earnings
Treatment East	-0.051	0.135	-401.620	-368.486
	(0.037)	(0.258)	(2398.994)	(499.010)
Treatment DelhiNCR	-0.112	-0.204	-1151.970	-1805.379
	(0.059)	(0.143)	(1977.652)	(1455.493)
Treatment North	-0.087	-0.057	-1279.226	-1476.530
	(0.039)	(0.139)	(1578.961)	(672.761)
Treatment SouthWest	-0.144	-0.023	-1846.838	-1394.088
	(0.046)	(0.090)	(1077.126)	(626.391)
Priority Treatment	0.075	0.147	1202.693	479.340
East	(0.033)	(0.156)	(1952.018)	(461.859)
Priority Treatment	-0.013	-0.007	-613.708	-887.203
DelhiNCR	(0.055)	(0.069)	(1149.410)	(1176.568)
Priority Treatment	0.016	0.189	1004.258	671.047
North	(0.039)	(0.211)	(1335.243)	(608.971)
Priority Treatment	0.089	-0.021	15.429	1012.121
SouthWest	(0.044)	(0.091)	(695.208)	(619.477)
Respondent Fixed Effects	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes
Geo-Specifc Time Trend	Yes	Yes	Yes	Yes
Number of Observations	6866	2311	2326	6475

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), the logarithm of wages (column 2), the wage winzorised at the 1% (column 3), and earnings (imputing earnings of zero for job-seekers who are not working) (column 4). Columns 1 and 4 include all respondents in the sample while columns 2 and 3 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.

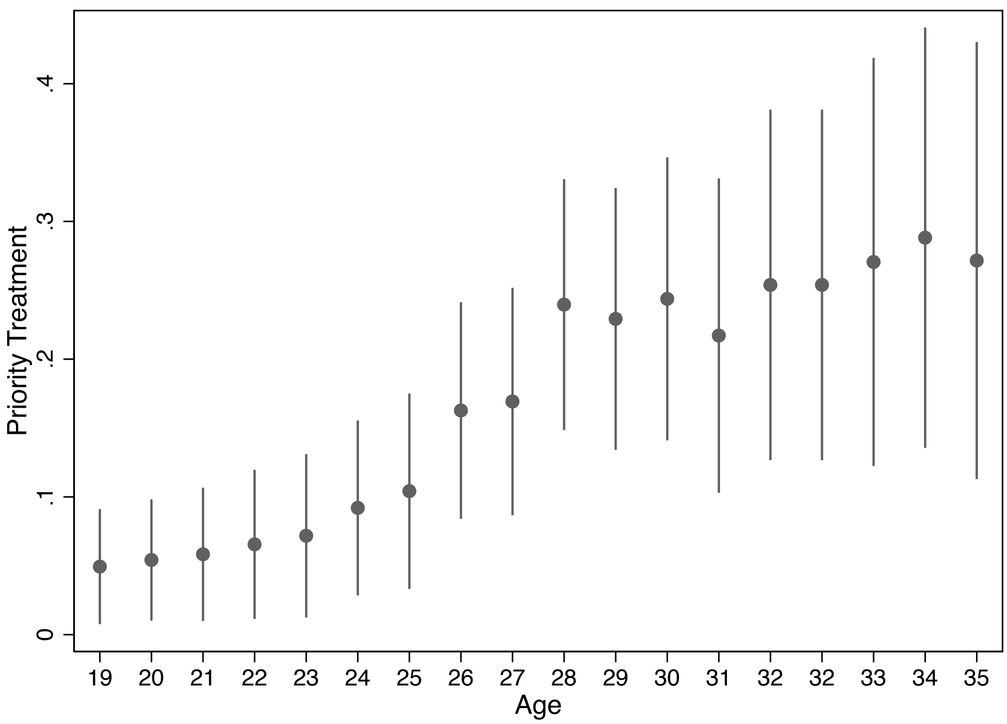
Table 4: Living in a City

	(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)
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.

Figures

Figure 1: Priority Treatment by age



This figure plots the effect of being in the priority treatment group for progressively older samples. The estimate associated with age "19" corresponds to the coefficient on priority treatment from running our standard specification of employment status on treatment and priority treatment, restricted to the sample of job-seekers who are 19 and above. Similarly, the estimate associated with age "20" corresponds to the coefficient on priority treatment from running our standard specification of employment status on treatment and priority treatment, restricted to the sample of job-seekers who are 20 and above.

A Appendix for Online Publication Only - Tables and Figure

A.1 Tables

Table A1: Attrition

	(1) Midline	(2) Endline
Treatment	0.017	-0.017
	(0.017)	(0.021)
Priority Treatment	0.024	0.018
	(0.017)	(0.021)
Number of Observations	2662	2662

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. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A2: Job-seeker Characteristics and Balance

	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
=1 if male	0.86	0.89	0.88	0.04	0.20	0.52
Age	24.17	24.01	24.30	0.56	0.65	0.28
Education (Years)	14.17	14.22	14.29	0.66	0.30	0.50
=1 if married	0.27	0.28	0.26	0.47	0.58	0.19
=1 if Hindu	0.92	0.94	0.94	0.07	0.19	0.70
=1 if ST/SC caste	0.38	0.34	0.35	0.04	0.17	0.53
=1 if OBC caste	0.29	0.34	0.35	0.01	0.01	0.76
=1 if general caste	0.33	0.32	0.30	0.64	0.18	0.34
Father's education>0	0.80	0.83	0.81	0.19	0.66	0.39
Mother's education>0	0.55	0.58	0.52	0.36	0.30	0.04
=1 if live in village	0.49	0.48	0.48	0.68	0.98	0.70
=1 if currently employed	0.30	0.34	0.32	0.08	0.53	0.29
=1 if looking for job	0.65	0.66	0.65	0.69	0.95	0.74
=1 access to Internet	0.76	0.80	0.80	0.03	0.06	0.87
=1 access Internet for jobs	0.49	0.52	0.55	0.18	0.01	0.19
=1 if registered with a job portal	0.23	0.23	0.28	0.94	0.04	0.03
Reservation wage (winsorized)	12308.90	12245.72	13186.48	0.85	0.01	0.00
= 1 if Telecom	0.38	0.38	0.38	0.92	0.97	0.94
= 1 if Logistics	0.36	0.36	0.36	0.96	0.99	0.98
= 1 if SalesMarketing	0.18	0.18	0.18	0.99	0.99	0.98
= 1 if Security	0.08	0.09	0.08	0.90	0.99	0.91

	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. Columns 4-6 tests whether these characteristics differ significantly across groups. Panel B presents job characteristics, as they were advertised in the SMSs that Job Shikari sent to the treatment group.

Table A3: 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 (Years)	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 Muslim	0.14	0.08	0.04	0.03	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
Received formal skills training	1.30	1.28	1.42	1.35	0.43	0.00	0.10
=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
=1 access to Internet	0.96	0.83	0.79	0.66	0.00	0.00	0.00
Reservation wage (winsorized)	17337.38	12294.29	12090.75	11064.49	0.00	0.00	0.00

Columns 1-3 show mean values of each variable across geographic zones. Columns 4-6 tests whether these characteristics differ significantly across geography.

Table A4: Job Search

	Unemployed			Employed		
	(1) Searching	(2) Hours	(3) Applications	(4) Searching	(5) Hours	(6) Applications
Treatment	-0.019	-1.579	-0.056	-0.023	0.019	-0.073
	(0.036)	(0.899)	(0.315)	(0.051)	(0.754)	(0.434)
Priority Treatment	-0.000	0.332	0.015	-0.024	-0.073	0.068
	(0.035)	(0.844)	(0.327)	(0.050)	(0.768)	(0.408)
Respondent Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	4134	3951	3870	2694	2638	2505

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 1/4), the number of hours spent searching in the past week - where people who are not searching are assigned a value of 0 hours (column 2/5), the number of job applications submitted in the last 3 months (column 3/6). Columns 1, 2 and 3 include all unemployed respondents in the sample, while columns 4, 5 and 6 include all employed respondents in the sample. Standard errors are clustered at the respondent level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A5: 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)
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.

Table A6: Employed 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)
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.

Table A7: 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	474.870	-224.988	474.870
	(0.029)	(0.035)	(0.029)	(295.729)	(639.945)	(295.741)
Priority Treatment	0.063	0.033	0.063	-601.071	-327.714	-601.071
	(0.027)	(0.036)	(0.027)	(293.167)	(656.101)	(293.179)
Treatment X High Res Wage			0.049			-699.859
			(0.045)			(704.521)
Priority Treatment X High Res Wage			-0.029			273.358
			(0.045)			(718.156)
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	3870	1990	5860

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 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.

Table A8: Outcomes by Midline/Endline

	(1) Emp	(2) RWage	(3) City	(4) Searching	(5) Hours	(6) Applications
Treatment X Midline	-0.087	275.135	-0.010	0.004	-0.485	-0.112
	(0.023)	(329.103)	(0.028)	(0.030)	(0.658)	(0.260)
Treatment X Endline	-0.098	277.614	-0.033	0.007	-0.046	0.379
	(0.027)	(382.419)	(0.028)	(0.032)	(0.716)	(0.279)
Priority Treatment X Midline	0.054	-507.648	0.047	-0.010	0.029	-0.104
	(0.022)	(327.691)	(0.027)	(0.030)	(0.638)	(0.251)
Priority Treatment X Endline	0.041	-847.957	0.076	0.019	-0.326	0.030
	(0.026)	(410.953)	(0.027)	(0.031)	(0.672)	(0.276)
Treat_Mid = Treat_End	0.66	0.99	0.44	0.91	0.52	0.05
PTreat_Mid = PTreat_End	0.58	0.37	0.35	0.36	0.59	0.57
Respondent Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Survey Round Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	6866	6505	6889	6828	6589	6375

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), 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.2 Figures

Figure A1: Job Types that Job Shikari sent via SMS

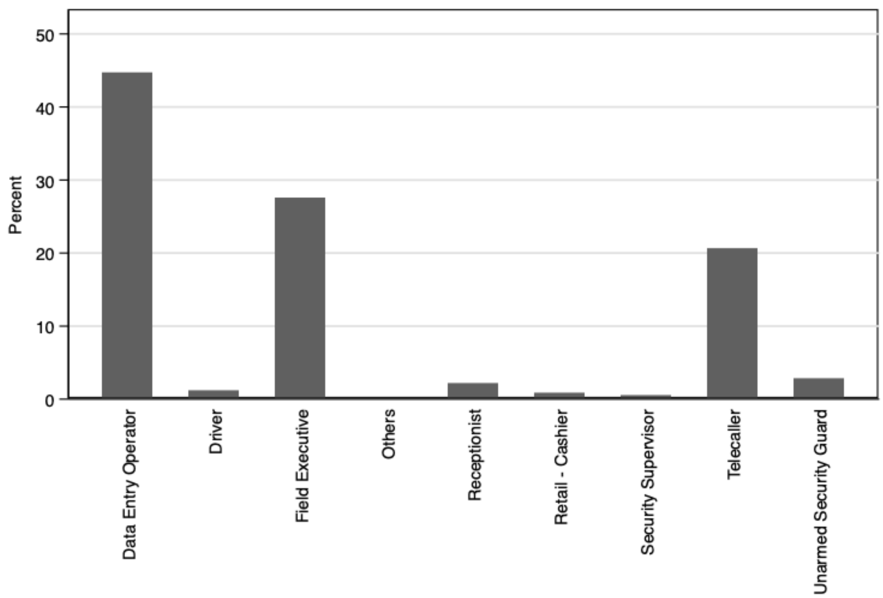
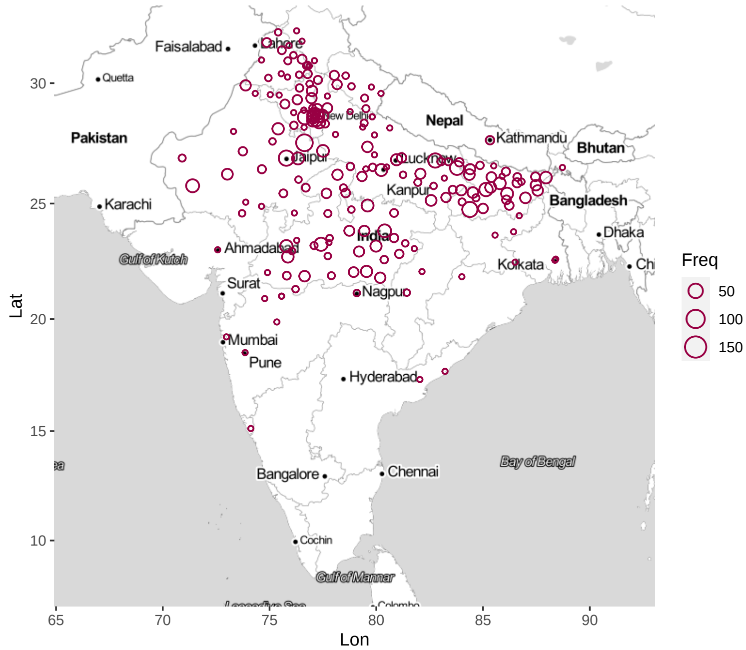
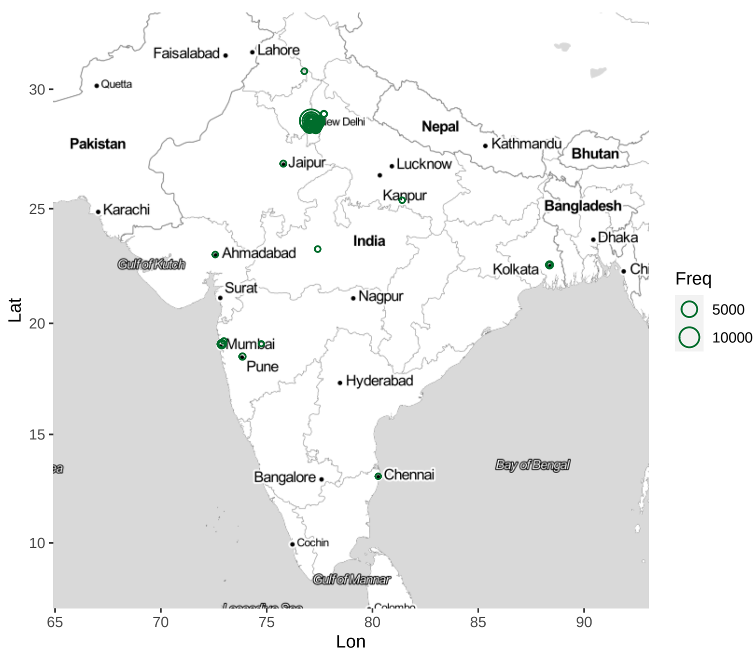


Figure A2: Location of Job seekers and Jobs across India



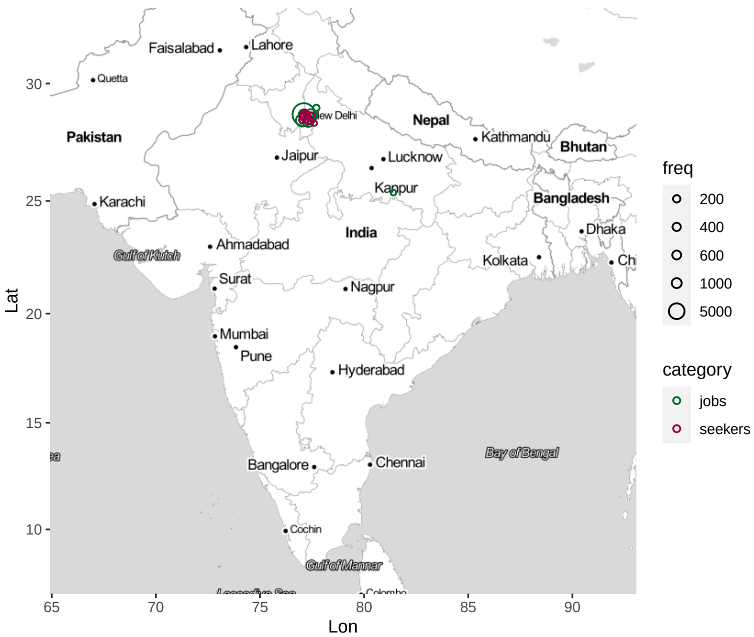
(a) Job-Seekers



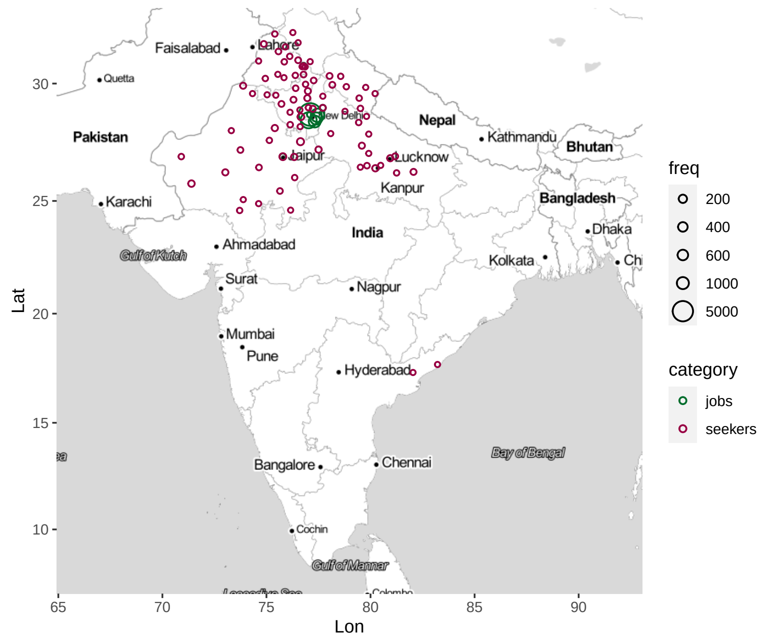
(b) Jobs

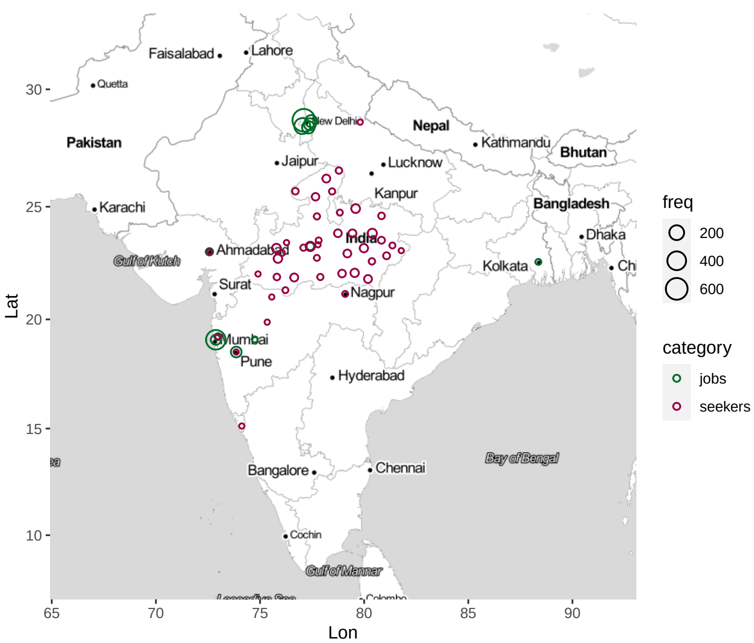
Figure A3: Locations of Job seekers and jJob offers by Initial Geographic Zone

(a) DelhiNCR

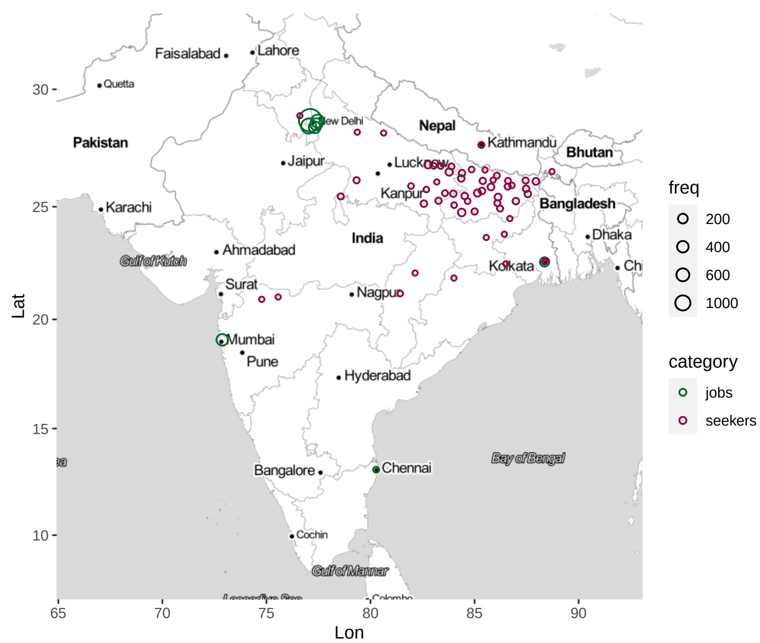


(b) North





(c) South



(d) East

Figure A4: Distribution of Baseline Wages and Salary Offers

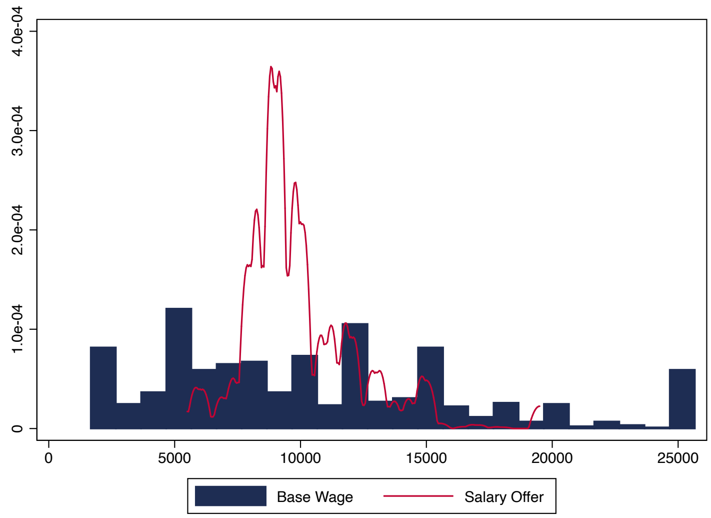
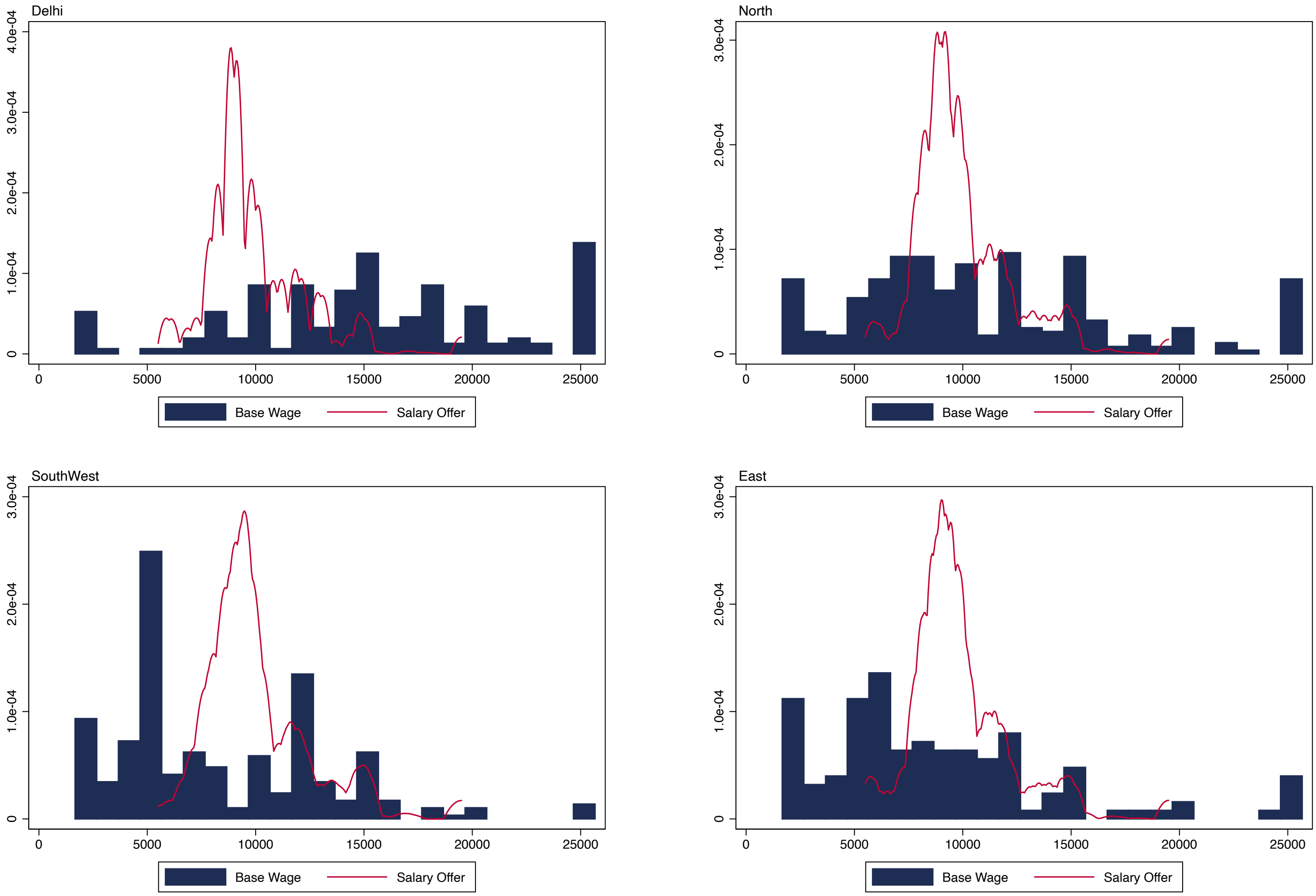


Figure A5: Distribution of Baseline Wages and Salary Offers by Geographic Zone

(a) DelhiNCR

(b) North



(c) South

(d) East

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 $h_T(w) = \textit{accept}$ 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:

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

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 $\underline{w}$, $\underline{w}$, ... $\underline{w}$ 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

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