Final report

International Growth Centre

Labour market frictions in India

Evidence from the introduction of a Job Information Platform

JPAL South Asia

December 2016

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Final Report

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Contents

1 Introduction

The inability to find good workers is of critical importance for economic growth in India, as in many other developing countries. According to the Federation of Indian Chambers of Commerce and Industry (FICCI, 2011), employers frequently complain about the difficulty of filling vacant positions despite pervasive unemployment among semi-skilled labourers, and large cohorts of recent graduates from technical and vocational schools. Placement rates for the approximately 1 million graduates per year from existing government affiliated institutes are low; available data from three states, Orissa, Andhra Pradesh and Maharashtra, show that only 16%, 41% and 35%, respectively, of new graduates were wage or self-employed as of 2009 (National Knowledge Commission, 2009).

A candidate explanation for the simultaneous existence of open jobs and unemployed job seekers is search frictions: firms may not succeed in hiring qualified workers because of difficulties generating a match between a job and a worker who is qualified for this job. Traditionally, informal networks have been the dominant means of job search (e.g. Beaman and Magruder, 2012; Loury, 2006; Ioannides and Loury, 2004; Magruder, 2010; Munshi 2003; Wang, 2011); these networks have a number of characteristics that may prevent them from finding the best worker for a vacancy.

At the same time, job portals, which connect prospective employees with potential employers provide a potential new technological solution to this problem. Job portals in India work in a variety of ways: some allow applicants to post CVs online, or firms to post vacancies. Most create an algorithm to match workers with firms and then connect the two either on-line or through SMS. Compared to informal networks, which may exclude disadvantaged groups (Calvo-Armengol and Jackson, 2004) and which may fail to transmit information across geographical space, job portals may foster connections that provide equitable access to growth. Given that India has one of the largest and fastest growing populations of internet users in the world (an estimated 24% of Indians use the internet, up from 1% in 2001) there is reason to believe that job portals may help smooth search frictions sharply, reducing vacancy rates and increasing access to jobs for the poorly connected.

To date, there has been little focus on understanding how job portals actually benefit job seekers in the developing world. This project provides a rigorous assessment of the value of job portals - examining their effect on labour market outcomes for job seekers, as well as on job search behaviors. Specifically, the study sets out to answer the following two questions:

1. How does the portal affect outcomes for recent public vocational training graduates?
2. How does receiving more frequent information on open jobs via the portal affect outcomes for job seekers that are registered on the portal?

To this end, we designed a randomized control trial (RCT) in partnership with a job-matching platform (Job Shikari) where employers post job opportunities, and the portal send SMS messages to qualified candidates. Employees then follow up directly with the employer to set up interviews. The postings span a variety of sectors, including logistics, transport, services and telecoms. The RCT involves two samples of job-seekers we drew from (1) recent graduates from vocational training institutes managed by the National Skill Development Corporation India, NSDC (hereafter called the NSDC sample) and (2) existing job seekers currently on Job

Shikari's platform (hereafter called the Job Shikari sample). The NSDC sample was divided into two treatment arms and a control group:

1. **Control group**: These job-seekers were not enrolled on the platform.
2. **Treatment group**: These job-seekers were placed on the platform, received a welcoming sms introducing them to the platform, and received information about relevant job openings as they appeared on Job Shikari's platform via SMS.
3. **Treatment priority group**: These job seekers were given priority access on the portal, meaning that in addition to the effects of the treatment group they would always appear first on the list of relevant job-seekers generated by the portal, thereby receiving more job related SMSes from Job Shikari.

The Job Shikari sample was divided into two arms:

1. **Treatment group**: These job-seekers continued to receive information about relevant job openings as they appeared on Job Shikari's platform via SMS. (We decide to call this group "treatment group" to be consistent with the terminology used for the NSDC sample as this group of job-seekers are benefiting from access to Job Shikari. In terms of experimental variation, this group is the control group for the Job Shikari treatment priority group)
2. **Treatment priority group**: These job seekers were given priority access on the portal, meaning that in addition to the effects of the treatment group they would always appear first on the list of relevant job-seekers generated by the portal, thereby receiving more job related SMSes from Job Shikari.

Together with J-PAL South Asia, we conducted a total of three surveys with these job seekers: a baseline survey (before the RCT), a midline survey (approximately 5 months after treatment) and an endline survey (approximately 11 months after treatment). A call center was created for the purposes of the survey and an integrated computer software was designed to call the job seekers, and conduct the survey.

These surveys collect data on socioeconomic and demographic characteristics (in particular gender, religion, caste, location of origin) as well as data on job search and labor market outcomes. In addition to more conventional labor market outcomes like employment, occupation, and wages, our survey also elicits information on wage expectations and reservation wages, differentiated by the location of the potential job (rural / urban / metropolitan / regions). This information provides a unique snapshot of job markets in India, allowing us to investigate job market frictions and job market dynamics among (semi-) skilled workers.

Our primary research questions are impact questions, i.e. whether increased access to Job Shikari affects outcomes of job-seekers. Namely:

- Do individuals who receive access to Job Shikari and/or priority for jobs on the platform experience better labor market outcomes?
- Are they more likely to be employed?
- Do they receive higher wages?

In addition, the survey allows us to address potential mechanisms that might lead to these impacts, or that determine the size of potential impacts. For example:

- Does increased access to new job opportunities and information about the job market encourage migration and/or change wage expectations and reservation wages?
- Is the benefit of the platform (and access to formalized job matching) larger for rural graduates; for individuals who belong to a disadvantaged group (scheduled castes and tribes, women or religious minorities) who might lack access to occupation-specific networks?

The answers to these impact questions also provide information on the functioning of job markets in India. For example, if increased access to information leads to better job outcomes, then this is evidence for the existence of job search frictions. If groups that lack occupation-specific networks benefit most from increased access to Job Shikari access, this is evidence for the importance of occupation-specific networks in the current job market. This latter evidence will also show which demographics, skill, and regional groups face the strongest search frictions.

The following report presents the RCT in more detail and provides the first results of the effects of job portals on job-seekers in India.

2 Literature review

The research component of this project seeks to estimate the microeconomic importance of search frictions. Such frictions lead to job market inefficiencies through the reduction in productive match-specific gains. The effect on the economy as suggested by the FICCI study is a dampening of economic growth (FICCI 2011).

The role of search frictions in economic growth has been extensively modeled and studied, primarily in developed country environments. In a survey piece, Rogerson and Shimer (2011) discuss how job search frictions reduce productivity and growth and highlight how responses to productivity shocks can be better understood through the use of search and matching models. A broad literature in labor economics has focused on estimating the direct role of search frictions in wage dynamics and job turnover; wage inequality; and labor contracting. Differential labor market frictions play a role in sector specific productivity and inefficient allocations of resources (Charlot et al., 2016). With regards to the role of the internet and internet-based platforms, Kuhn and Mansour (2011) and Stevenson (2006, 2009) document that, in developed country contexts, internet job search is an increasing part of job search and reduces job market frictions, though these impacts are not unambiguous (Kroft and Pope (2010) find no evidence of the introduction of an internet platform called *craigslist* on local unemployment rates, for example).

Far less attention has been paid to job search in developing countries. There are several reasons to think that job search in developing countries may behave differently from search in OECD countries: perhaps most importantly, the presence of a (large) informal sector distorts wage-setting away from conventional equilibrium modeling (e.g. Meghir, Narita, and Robin 2012); different regulatory environments and degrees of wage inequality in the workforce affect solutions to search problems (e.g. Albrecht, Navarro, and Vroman 2009; Freeman 2009); credit constraints may affect the efficiency of job search; and the importance of social networks and traditional institutions in wage-setting and job search may strongly distort the information and opportunities held by the unemployed (e.g. Munshi and Rosenzweig 2006; Magruder 2010). While some existing literature has begun to adapt classic search models to a developing framework (e.g. Albrecht, Navarro, and Vroman 2009; Meghir, Narita and Robin 2012) the micro-empirical literature estimating search frictions in developing countries and relating those to economic outcomes remains minimal. Within the India context, we know even less; a search on econlit for the phrases "job search" and "India" in the abstract reveals 4 hits as of August 2013; of which none propose to directly estimate the role of search frictions on labor market outcomes (the closest, by Iversen et al (2009) examines whether informal networks are used for selective screening and incentive mechanisms rather than job search).

Our project is novel not only for estimating directly several characteristics of search frictions in the Indian context (such as eliciting location-specific reservation wages), but also for using randomized reductions in these frictions. As a result, we can provide a causal estimate of the impact of job search frictions.

2.1 Prediction

According to a job-search model with off-the-job search (e.g. Jovanovic 1979), job seekers will respond to additional information about job opportunities and wage offers by increasing their reservation wages. This, in turn, will reduce the employment rate among these job-seekers, as they hold out for higher paying jobs. In the long run however, as job-seekers continue to receive text messages, the probability of receiving a wage offer above their reservation wage increases, and we should see higher employment rates relative to the short run.

3 The econometric model

We estimate the effects of our intervention using three different specifications. The first specification uses the full panel structure of the data (with individual fixed effects) to identify the effect of the treatment for each survey round. This is particularly useful in a job-search framework where the short-run and long-run effects of an information treatment are likely to differ, as detailed above. The second specification also uses the panel structure of the data, but includes the number of job-related SMS received as the exogenous variable. Conditional on the trade and location, this is plausibly exogenous. The third specification pools data from all three rounds of data together to focus on average treatment effects after the program roll-out.

As the NSDC and Job Shikari samples are representative of different populations, we separately estimate these econometric models separately by sample.

We first test whether the effect of treatment varies across survey round using the following specification:

$$y_{it} = \beta_0 + \beta_1 Mid + \beta_2 End + \beta_3 T_{it} * Mid + \beta_4 T_{it} * End + \beta_5 TP_{it} * Mid + \beta_6 TP_{it} * End + \gamma_i + u_{it}$$

where y_{it} is an outcome of interest for job-seeker i in time period t (baseline, midline or endline). Mid and End are indicators for whether the survey was conducted at midline or endline (conducted 4 and 8 months after baseline respectively); T is a dummy equal to 1 if the job-seeker was assigned to treatment *or* treatment priority; TP denotes whether the job-seeker is in the treatment priority group specifically; and γ represents individual fixed effects. The two treatment arms differed in the intensity of text messages received. We cluster all regressions at the individual level. β_3 tells us the effect of being treated relative to control in midline, while β_4 represents the effect of treatment relative to control at endline. β_5 and β_6 represent the additional effect of being in the treatment priority group (relative to the treatment group) at midline and endline respectively.

The second regression specification replaces the exogenous assignment to treatment, with the number of SMS's received by each job seeker. The number of SMS a job-seeker received was based entirely on their location and preferred trade (these were the only two factors Job Shikari used to determine eligibility for a given job post). Conditional on modal trade and location, we can assume that the number of SMS received by a job-seeker is plausibly random. The results of these regressions are reported in the appendix.

$$y_{it} = \beta_0 + \beta_1 Mid + \beta_2 End + \beta_3 No\_SMS + \beta_4 No\_SMS\_recent + \beta_5 trade\_loc + \gamma_i + u_{it}$$

Third, as a simple means comparison, we can also pool the two follow-up rounds and estimate the following specification:

$$y_{it} = \beta_0 + \beta_1 Mid + \beta_2 End + \beta_3 T_{it} + \beta_4 TP_{it} + \gamma_i + u_{it}$$

where β_3 represents the average treatment effect across all survey rounds, and β_4 represents the average effect of being in the treatment priority group (relative to treatment) across all survey rounds.[1]

4 Sampling design

Samples

Our research sample is comprised of two distinct samples: existing job seekers currently on Job Shikari's platform, and recent graduates from vocational training institutes managed by the National Skill Development Corporation India (NSDC).

Job Shikari Sample

Job Shikari provided us with contact information for 18,105 job seekers currently registered with their portal. Applying three filters reducted this sampling frame to 8,277 job seekers. First, we only selected job seekers falling into one of four pre-selected trade categories: Telecom, Logistics, Sales & Marketing and Security. These trades have the most employers and the highest rate of job offers on Job Shikari's portal. Second, we restricted the sample to job seekers located in India's Northern States, in order to avoid any language barriers between the enumerators and the respondents. This includes: Delhi, Haryana, Punjab, Uttar Pradesh, Rajasthan, Uttarakhand, Chandigarh, Maharashtra, Madhya Pradesh, Bihar and Himachal Pradesh. Third, we eliminated all numbers listed on Do Not Disturb Registries, a service provided by telecom companies in India to avoid unwanted telemarketing calls or SMSes. We attempted calling all 8,277 job-seekers on the list. Over 80% of the calls did not lead to a completed interview: the

[1]These results will be presented in the first draft of our working paper

phone numbers either didn't exist, no one would pick up, or the number didn't belong to the respondent we had on file. We successfully completed 755 surveys.

NSDC Sample

The National Skills Development Corporation agreed to provide the names and contact information of recent graduates from 98 training institutes spanning the entire country (which means we received the information for over 829,812 recent graduates from October 2014 to March 2015). Training institutes often have multiple training centers, though not more than one per district. As a result we were able to uniquely identify each training center by the training institute they belonged to and the district they were located in. We only selected training centers that belonged to one of the same 4 pre-selected trades (Telecom, Logistics, Sales and Security) and that were located in the same Northern states as above (with the exception of Maharashtra). Training centers with less than 50 trainees were excluded: the contact rates suggested that we would not have enough observations for a meaningful treatment and control group selected at random within training institutes. The remaining training centers were given a random serial ID based on their trade (Telecom, Logistics, Sales and Security) and location (within vs. outside Delhi National Capital Region [hereafter referred to as Delhi NCR]). We first sampled centers with ID numbers from 1 to 20, then 21-40, and then 41-60. When specific trade-location pairs did not have at least 20 training centers, we sampled the universe of centers within that strata (for example, there were only 5 Security training centers in the original sample provided by NSDC, and we selected all 5). Finally, within each training center, we randomly selected 30 graduates to call. This resulted in 15,268 observations. We faced similar challenges contacting the selected sample of NSDC graduates, and we ultimately completed 2,662 surveys.

Comparison of JS and NSDC Sample

Table 1 shows that, relative to the NSDC sample, the respondents from the Job Shikari sample are more likely to be employed, have more years of work experience in their current trade sector, have spent more years in their current job, have higher current wages (for the employed respondents), and higher reservations wages.

Table 1: Summary statistics

	NSDC Sample		JS Sample		
	Mean	SD	Mean	SD	p-value
Employed	0.32	0.47	0.52	0.50	0.00
Unemployed	0.47	0.50	0.41	0.49	0.00
Fresher	0.21	0.41	0.07	0.26	0.00
Work experience (years)	3.16	5.10	6.19	9.36	0.00
Monthly salary	11412.36	11658.16	31030.95	146439.10	0.00
Months in current job	24.64	21.78	33.05	26.29	0.00
Informal contract	0.80	0.40	0.79	0.41	0.60
Reservation wage	12988.83	14097.39	17491.05	39172.11	0.00

5 Evaluation design

5.1 Assignment to treatment status

The 3417 respondents who completed the baseline survey were included in our intervention sample. A respondent was either assigned to the control group or to one of two the treatment groups, treatment or priority treatment. We first stratified the sample across geographic zones (Delhi NCR, Northern part of our sample regions, Western and Southern part of our sample regions, and Eastern part of our sample region) and trade professions (Logistics, Security, Telecom, Sales & Marketing). We chose to stratify on region-trade to ensure balance, and to facilitate analysis at the level of these subgroups (some of which were more likely to be intensely treated by Job Shikari due to the number of listed jobs in these location/trade combinations). Within each strata we assigned control, treatment and treatment priority status at random. This produced the following breakdown:

Table 2: Randomization

	Control	Treatment	Treatment Priority
NSDC Sample	799(30%)	1518(40%)	798(30%)
Job Shikari Sample	-	453(60%)	302(40%)

5.2 Implementation of priority status

When contracted to post a job opportunity (often for a large number of open positions for an employer), Job Shikari applies an algorithm to generate a list of eligible job-seekers most suited to a particular job post by an employer. The platform then sends SMS messages about the job opportunity to the first job-seekers on the list. The matching algorithm takes into account a job-seekers preferred trade and location.

Job-seekers in the treatment priority group received more SMS than those in the treatment group as they were systematically ranked above all other job-seekers in the list of eligible candidates for the SMS. Job-seekers in the treatment group would receive more SMS's than the control group by construction (the control group was not uploaded to the portal for the duration of the study). Initially, there was no cap placed on the number of SMS's each job seeker could receive. However, with some job-seekers receiving more than 50 SMS's per day, a cap of 2 SMS's per day was implemented.

6 Data Collection

Survey Rounds

The baseline survey was conducted between April and July, 2015. Here, we managed to complete surveys with 3417 respondents who were included in our sample. In the midline, which was conducted between December, 2015 and April, 2016, we managed to reach 81.80% of respondents (N=2795). The endline was conducted between June and September 30, 2016, and we managed to reach 70% of respondents (N= 2392).

Survey Process

Enumerators followed a specific protocol when contacting respondents. First an SMS was sent out to each individual. This message included: a greeting, a brief sentence about the research, and details of the mobile recharge they would receive. The enumerators followed up by calling individuals directly. They followed a detailed script introducing themselves and the project. Once this introduction was complete and interviewers had obtained job-seekers consent to participate in the survey, the survey was initiated. Surveys took approximately 20-30 minutes to complete. At the end of the survey, the respondent was thanked for his or her time and sent a mobile recharge as financial compensation. At baseline, every respondent who successfully completed the survey was automatically awarded a mobile recharge of INR 50. In the following survey rounds, the immediate recharge amount was increased to INR 70. In the midline and endline surveys, participants could also receive higher amounts based on the outcome of a time discounting game that was played at the end of the survey (with a maximum of INR 120).

Figure 1: Data collection in progress

Computer Software

An integrated digital data collection software was custom made for the purposes of this survey. The software used a cloud telephonic service, Exotel to make calls to the respondents. This service allowed all respondents to receive the call from the same number. To minimize enumerator errors, the software produced a list of numbers for each enumerator to call, which updated periodically. A detailed tracking system was designed and implemented to monitor the status of each survey. Specifically, each call was assigned a code, which detailed whether or not the call successfully reached the respondent, and why (wrong number, busy signal, respondent refused to be part of the survey etc.). The software was designed to send the recruitment SMS to the respondents before they were initially contacted by the enumerators on the phone. Moreover, the software sent mobile recharges to those who successfully completed the survey. The software produced 11 different tracking datasets to monitor outgoing calls, incoming data, SMS receipts, recharge receipts, and surveyor productivity. Moreover, the system maintained a record of all the respondents on the secure central server and updated the response codes as the survey operations progressed.

Below are some screenshots of the software. The first picture illustrates the interface that enumerators would see before making a call. The enumerator was provided with both the respondent's ID, and response code status and would simply click the "Click2Call" button to initiate the call. If Exotel's service was poor, the enumerator could switch to another service provider by tapping the "Bypass Exotel" button and calling directly with a regular cell-phone. The second image depicts the screen used by the field manager to obtain the tracking data, and export the raw data to Excel.

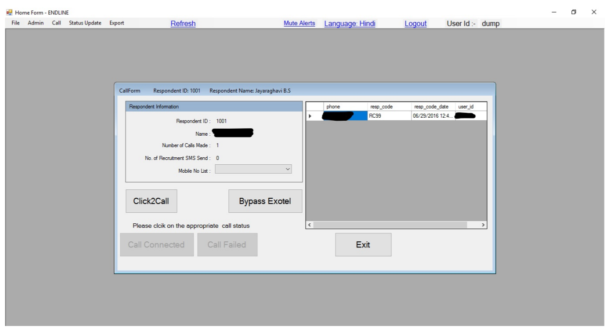

Figure 2: Calling Screen

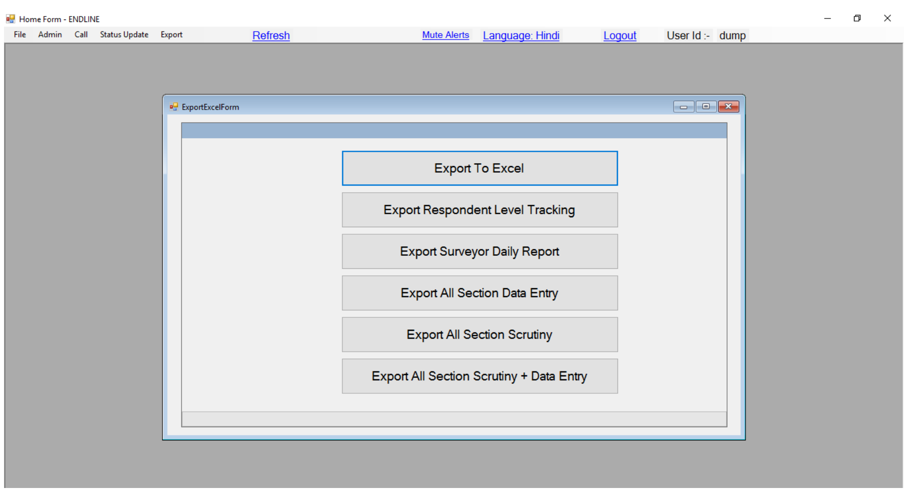

Figure 3: Export Screen

Survey Instrument

The surveys provide information on a wide range of topics, asking almost the same questions across all three survey rounds. The survey starts by collecting basic demographic information (gender, education, language fluency, parents' education and occupation, caste and religion), and the type of location the respondent lives in. We also collected detailed information on formal skills trainings, and employment history (including details about the trade, location ,wage, and benefits of all jobs held in the last two years). In addition, details were asked about job search strategies, the usefulness of their occupational network, and knowledge/use of job portals. We also elicited their reservation wages. Finally, a time discounting game was played with the respondents in the midline and endline. The game asked job seekers to choose between a recharge of INR 70 now or a higher amount in two weeks time. In the midline, the respondents were asked to play the same game twice - once for an immediate recharge and another time for a recharge paying out in 4 months time versus 4 months and two weeks (around the time of endline). During the endline we followed up with jobseekers by asking whether they would like to change their decision from midline.

7 Results

Validating the experimental design

Job-seekers were randomized into three groups: control, treatment and treatment priority. Table 3 and Table 4 present the means of each group across a range of observables, for the JS and NSDC samples respectively. The differences between each group are small, but there remains some imbalance for the NSDC sample across caste, reservation wage, access to the Internet and religion. Table A1 in the Appendix presents the same balance table for the NSDC sample after controlling for strata, training institute, age and gender. The imbalance we see across these few observables largely disappears, confirming the importance of including individual fixed effects in our main specifications.

Table 3: Balance table - JS sample

	(1) Treatment	(2) Priority Treatment	(3) (1) vs. (2), p-value
=1 if Male	0.94	0.94	0.98
Age	29.55	31.58	0.11
=1 if Married	0.47	0.49	0.53
Religion=Hindu	0.89	0.91	0.41
Religion=Muslim	0.08	0.06	0.42
Caste=SC	0.19	0.15	0.16
Caste=General	0.50	0.52	0.61
Father's education>0	0.83	0.85	0.67
Mother's education>0	0.59	0.57	0.67
Location=Village	0.31	0.28	0.36
Location=City	0.32	0.36	0.26
Location=Metro City	0.22	0.23	0.84
Received training	0.45	0.44	0.84
Employed	0.50	0.54	0.32
Access to internet	0.76	0.78	0.59
Use portals	0.49	0.51	0.55
Read/Understand English	0.22	0.22	0.86
Read/Understand Hindi	1.00	0.99	0.68
Reservation wage (winsorized)	15431.37	14943.26	0.36
Log of Reservation Wage	9.51	9.52	0.82
=1 if looking for job	0.57	0.59	0.48

Table 4: Balance table - NSDC sample

	(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 test
=1 if Male	0.86	0.89	0.88	0.04	0.20	0.52	0.13
Age	23.88	23.74	23.96	0.60	0.78	0.41	0.70
=1 if Married	0.27	0.28	0.26	0.47	0.58	0.19	0.41
Religion=Hindu	0.92	0.94	0.94	0.07	0.19	0.70	0.18
Religion=Muslim	0.08	0.05	0.06	0.08	0.22	0.64	0.20
Caste=SC	0.35	0.30	0.31	0.01	0.09	0.53	0.04
Caste=General	0.33	0.32	0.30	0.64	0.18	0.34	0.39
Father's education>0	0.79	0.82	0.80	0.17	0.78	0.28	0.33
Mother's education>0	0.55	0.57	0.52	0.35	0.28	0.04	0.12
Location=Village	0.49	0.48	0.48	0.68	0.98	0.70	0.90
Location=City	0.22	0.23	0.22	0.38	0.96	0.35	0.56
Location=Metro City	0.08	0.07	0.07	0.68	0.38	0.61	0.68
Received training	0.68	0.66	0.66	0.29	0.54	0.68	0.56
Employed	0.30	0.34	0.32	0.08	0.53	0.29	0.21
Access to internet	0.76	0.80	0.80	0.03	0.06	0.87	0.07
Use portals	0.40	0.42	0.42	0.32	0.50	0.79	0.60
Read/Understand English	0.16	0.14	0.15	0.49	0.90	0.57	0.75
Read/Understand Hindi	1.00	1.00	1.00	1.00	0.20	0.17	0.31
Reservation wage	12587.26	12558.22	13973.44	0.97	0.06	0.04	0.08
Reservation wage (winsorized)	12332.19	12305.14	13282.10	0.94	0.01	0.00	0.01
Log of Reservation Wage	9.29	9.28	9.35	0.72	0.06	0.02	0.05
=1 if looking for job	0.65	0.66	0.65	0.69	0.95	0.74	0.91

Table 5 presents survey attrition for the midline and endline surveys. We were successful in re-contacting 2,808 respondents (82%) at midline and 2,392 (70%) at endline, attributable to many attempts per phone number, as well as different sources (company line versus mobile lines), and efforts to contact job-seekers at times that most suited their schedules. We find some evidence of differential attrition for the treatment group at endline, though none for the treatment priority group.

Table 5: Differential Attrition

	Midline	Endline
Treatment	0.0129	0.0397**
	(0.0169)	(0.0200)
Priority Treatment	-0.0160	0.0140
	(0.0179)	(0.0213)
Constant	0.181***	0.278***
	(0.0136)	(0.0162)
N	3417	3417

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Results validating treatment

Job seekers assigned to the treatment and treatment priority groups were enrolled in the portal and received text messages listing available job opportunities. Table 6 demonstrates that job-seekers in the treatment group received 1 more text message from Job Shikari on average than the control group (which received none), while job-seekers in the treatment priority group received approximately 12 more text messages than the treatment group. Table 6 and Table 7 mask a fair amount of heterogeneity across strata (constructed based on geographic location and trade). The job portal we were working with received more job-posts (employer interest) in certain trades/location pairs than others. Figures 4 and 5 demonstrate the substantial amount of heterogeneity in the number of text messages received. Most job-seekers received between 0-10 text messages, while some job-seekers received upwards of 50 text messages.

No of SMSes

Table 6: Number of SMSes - NSDC Sample

	Midline	Endline
Treatment	1.331***	1.544***
	(0.0942)	(0.105)
Priority Treatment	12.52***	19.55***
	(0.786)	(1.166)
Constant	-4.17e-14***	6.93e-14***
	(4.31e-15)	(6.53e-15)
N	2662	2662

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 7: Number of SMSes - JS Sample

	Midline	Endline
Priority Treatment	18.76***	24.78***
	(2.045)	(2.444)
Constant	3.865***	4.512***
	(0.352)	(0.479)
N	755	755

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

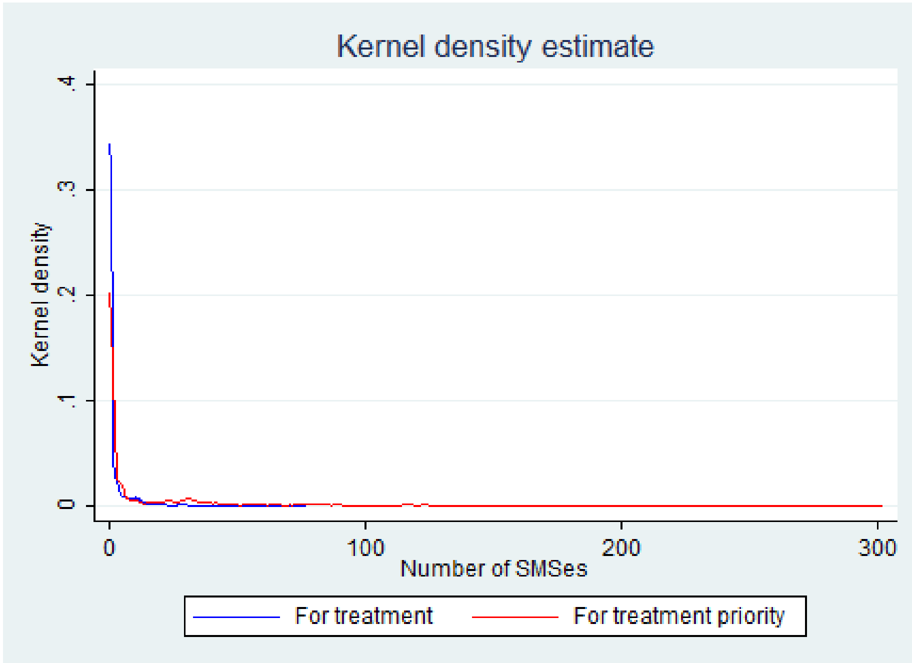

Figure 4: No of SMSes

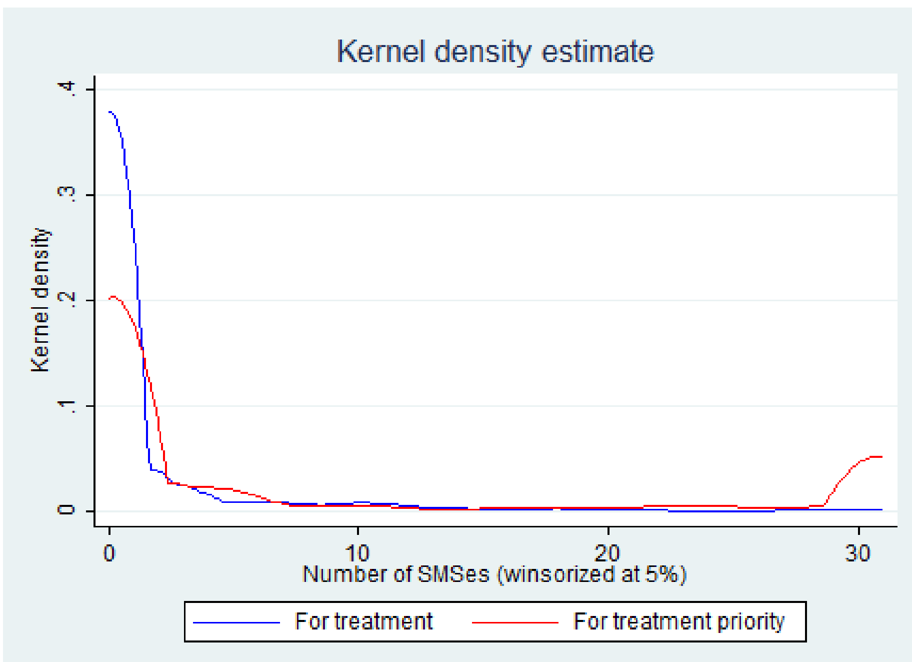

Figure 5: No of SMSes (winsorized)

Impact of Job Shikari

The tables below detail the effect of treatment on employment outcomes and job-search behavior. The impact of the treatment is almost exclusively observed in the NSDC sample. The JS sample was already enrolled in the portal when the intervention began, and may have been less likely to pay attention to text messages from Job Shikari, and/or had already adjusted their behavior in response to the types of text messages they were receiving. They were also more likely to be employed than the NSDC sample, with higher current wages at baseline.[2]

Employment outcomes

In a traditional search model with off-the-job search, we would expect job-seekers to respond to an increase in the number of wage offers by increasing their reservation wage in the short-run, thereby reducing the probability of accepting a job-offer. In the long run however, as the probability of receiving a wage offer above the reservation wage increases, we would expect more job-seekers to accept these offers. Table 8 presents the results from a regression of employment status (= 1 if the job-seeker is employed, and = 0 otherwise) on indicators for survey round, survey round interacted with treatment, and individual fixed effects. We find that being in the *treatment* group at midline is associated with a 8.7 percentage point decrease in the probability of being employed relative to the control group, suggesting an increase in reservation wages. The probability of being employed increases slightly at endline relative to midline (3 percentage points), however the two coefficients are not significantly different. The same trends are visible in the treatment priority group. Job-seekers in the *treatment priority* group are significantly more likely to be employed than job seekers in the treatment group at both midline and endline. Adding these results suggests that treatment priority resulted in job seekers being only 3.2% less likely to be employed than job-seekers in the control group at midline, and 1% less likely to be employed at endline (the difference between midline and endline is not statistically significant).

We further investigate the employment response of job-seekers by breaking up the sample according to caste and gender for the NSDC sample. In theory, job portals should expand *equality* of access to employment for job-seekers from traditionally marginalized groups. Prior to their existence, social connections and informal networks were the dominant means of searching for employment, thereby favoring well connected individuals, and further entrenching existing inequalities. Equality of access to online portals can mitigate this implicit discrimination in access to both formal and informal jobs. Table 17 and Table 18 display the employment responses of job-seekers by gender and caste. We find that females react more strongly to the information about job opportunities from the portal relative to males. The probability of employment decreases by 20% for females and 7% for males in the treatment group at midline. This significant decrease for females relative to males (at the 10%) signals an important increase in their reservation wage as a result of the intervention. This trend reverses at endline, with the probability of employment increasing by 3 percentage points for males relative to midline and 7 percentage points for females, as the probability of finding a job above the reservation wage increases (note the difference is not statistically significant). We observe similar trends for the treatment priority group. Turning to caste, the differences across groups are harder to detect. While the decrease in employment at midline is more pronounced among the general castes for the treatment and treatment priority groups, the response at endline is muted. Other castes in

[2] The discussion of the results will focus on the NSDC sample

the treatment group see a rather small (7% decrease) at both midline and endline, while the other castes in the treatment priority group witness almost no changes in employment over the entire study period.

Table 8: Employment Status

	NSDC	JS
=1 if midline	0.159***	0.132***
	(0.0180)	(0.0276)
=1 if endline	0.0857***	0.0283
	(0.0173)	(0.0271)
Midline*Treatment	-0.0879***	
	(0.0230)	
Endline*Treatment	-0.0557**	
	(0.0229)	
Midline*Treatment Priority	0.0543**	-0.0126
	(0.0225)	(0.0429)
Endline*Treatment Priority	0.0479**	0.0128
	(0.0226)	(0.0387)
Constant	0.316***	0.516***
	(0.00451)	(0.00944)
N	6866	1850

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

We find similar trends in the number of hours worked (Table 9). Focusing on column 2 (where we assign a zero to those who are unemployed), we find that job seekers in the treatment group work approximately 2 hours less per week relative to the control group in both midline and endline. Job-seekers in the treatment priority group work slightly fewer hours at midline, but increase their hours worked at endline, consistent with the prediction that job-seekers at endline are accepting wage offers above their higher reservation wage.

Table 9: Hours worked per week

	NSDC	NSDC (0 for unemployed)	JS	JS (0 for unemployed)
=1 if midline	-1.002	1.994**	0.00939	0.949
	(1.478)	(0.842)	(1.150)	(1.541)
=1 if endline	1.050	-0.559	-0.117	-2.542*
	(1.345)	(0.764)	(1.234)	(1.492)
Midline*Treatment	-0.333	-2.497**		
	(1.871)	(1.098)		
Endline*Treatment	-1.022	-1.848*		
	(1.854)	(1.067)		
Midline*Treatment Priority	2.683	2.318**	2.462	2.395
	(1.853)	(1.108)	(1.864)	(2.464)
Endline*Treatment Priority	2.048	2.989***	1.481	2.325
	(1.940)	(1.073)	(1.954)	(2.203)
Constant	50.26***	16.36***	53.87***	28.71***
	(0.437)	(0.217)	(0.509)	(0.536)
N	2224	6403	946	1708

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Finally we investigate the effects of the intervention on monthly salaries and job satisfaction (Table 10 and Table 11, respectively). Job Shikari does not have significant effects on monthly salaries or job satisfaction. We find that wages are lower for the treatment group at midline and endline relative to control (both when we include and exclude the unemployed with wages of zero). The treatment priority group has slighlty lower wages relative the control group at midline and endline as well, but the results are not statistically significant. While we might expect job-seekers to report higher job-satisfaction in the treatment and treatment-priority groups, we do not find any significant evidence of this in the data. We note that there are selection problems in interpreting these effects: as access to the portal changed who is employed, and only the employed report wages and job satisfaction, it is difficult to interpret these changes.

Table 10: Monthly Salary

	NSDC	NSDC (0 for unemployed)	JS	JS (0 for unemployed)
=1 if midline	4884.8*	2629.7***	-32012.0*	-12671.1
	(2559.6)	(841.6)	(18837.2)	(8049.7)
=1 if endline	12711.6	4227.5*	-18846.8	-7764.4
	(9551.3)	(2341.2)	(21975.8)	(8865.8)
Midline*Treatment	-5639.2*	-2131.5**		
	(2907.9)	(914.2)		
Endline*Treatment	-10694.4	-3016.9		
	(9688.5)	(2469.5)		
Midline*Treatment Priority	1978.0	1749.9	27097.6	11114.7
	(1421.4)	(1222.1)	(19273.7)	(8290.6)
Endline*Treatment Priority	7.016	770.9	14514.5	6116.2
	(1657.9)	(1041.2)	(22355.6)	(9076.2)
Constant	11686.8***	3606.6***	34100.2***	16675.2***
	(879.5)	(285.4)	(6786.6)	(2784.3)
N	2324	6643	935	1738

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 11: Job Satisfaction

	NSDC	JS
Treatment	0.104	
	(0.112)	
Priority Treatment	0.115	-0.121
	(0.116)	(0.120)
Constant	2.550***	2.500***
	(0.0843)	(0.0813)
N	453	189

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Job search outcomes

Next we look at the effect of the treatment on various job search outcomes, including whether the job-seeker is still living in a village, their reservation wage, whether they are actively searching for a job, and the number of hours spent looking for a job. The primary dimension of change is in the decision to migrate. The text messages being sent to job-seekers were concentrated in major metropolitan areas such as Delhi (76%), Gurgaon (10%), and Mumbai (5%). We would expect that job-seekers receiving these text messages would focus their search more heavily in these urban areas, thereby increasing the probability of finding employment in these locations. The data (Table 12) corroborate this hypothesis: the treatment priority group is 3% less likely to live in a village than the control group at midline and 5% less likely at endline.

Table 12: Living in a village

	NSDC	JS
=1 if midline	-0.176***	-0.125***
	(0.0215)	(0.0259)
=1 if endline	-0.0516**	-0.0512**
	(0.0212)	(0.0255)
Midline*Treatment	0.0102	
	(0.0277)	
Endline*Treatment	0.0327	
	(0.0275)	
Midline*Treatment Priority	-0.0474*	0.0305
	(0.0266)	(0.0403)
Endline*Treatment Priority	-0.0757***	0.0438
	(0.0273)	(0.0401)
Constant	0.490***	0.304***
	(0.00583)	(0.0102)
N	6889	1858

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

We also elicited job-seekers reservation wage by asking the “minimum wage you would accept if you were looking for a job in [your current location]". We expect job-seekers’ reservation wage to increase in the short run as they see more wage offers, though the migration results above suggest that some caution must be taken: since respondents in the treatment priority group are less likely to remain in low-wage villages, the “current location” reservation wage is changing endogenously with treatment. Eliciting reservation wages is difficult to do with great accuracy, and the regressions with reservation wages are too imprecisely measured to draw concrete conclusions (Table 13). Nevertheless, we present the kernel density functions for job-seekers reservation wage at midline and endline (Figure 6, Figure 7), where we see that the treatment and treatment priority distributions are shifted to the right relative to the control group suggesting an increase in their reservation wage. Finally we don’t find any evidence that job-seekers spend more time searching for a job as a result of the treatment (Table 14, Table 15).

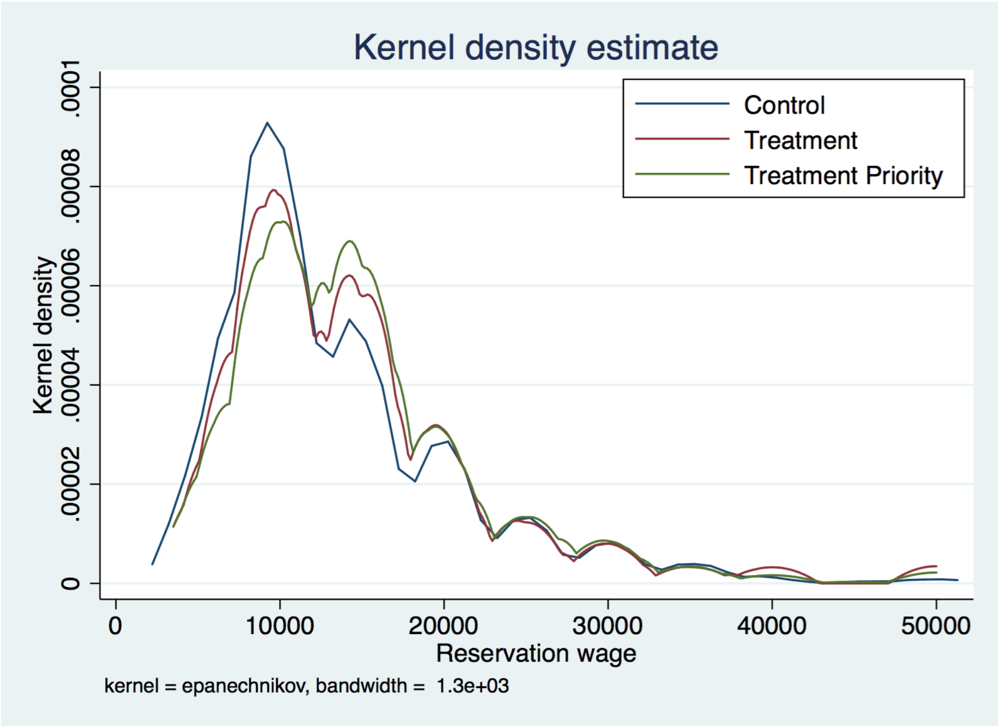

Figure 6: Reservation wage at midline (winsorized)

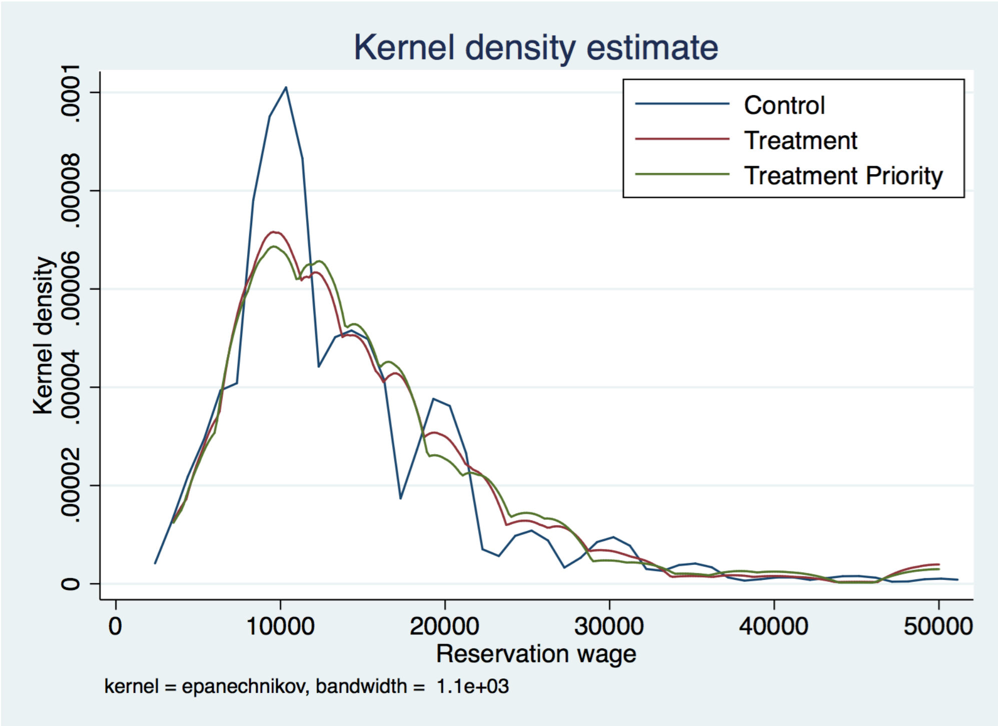

Figure 7: Reservation wage at endline (winsorized)

Table 13: Reservation Wage

	NSDC	JS
=1 if midline	1376.8***	1012.7***
	(223.1)	(370.8)
=1 if endline	1767.7***	1560.8***
	(246.9)	(395.7)
Midline*Treatment	191.6	
	(300.9)	
Endline*Treatment	187.1	
	(340.2)	
Midline*Treatment Priority	-412.4	173.9
	(296.4)	(560.2)
Endline*Treatment Priority	-795.6**	615.6
	(351.8)	(610.2)
Constant	12170.2***	15095.1***
	(71.67)	(155.2)
N	6504	1716

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 14: Is looking for a job

	NSDC	JS
=1 if midline	-0.0490**	-0.0123
	(0.0230)	(0.0288)
=1 if endline	-0.0705***	-0.0822**
	(0.0242)	(0.0331)
Midline*Treatment	0.00358	
	(0.0301)	
Endline*Treatment	0.00726	
	(0.0316)	
Midline*Treatment Priority	-0.00990	-0.0324
	(0.0297)	(0.0456)
Endline*Treatment Priority	0.0187	-0.0289
	(0.0310)	(0.0530)
Constant	0.666***	0.592***
	(0.00667)	(0.0123)
N	6828	1828

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 15: Hours spent looking for a job per week

	NSDC	JS
=1 if midline	34.91***	51.93***
	(6.348)	(17.97)
=1 if endline	25.95***	17.77**
	(5.551)	(7.401)
Midline*Treatment	-3.659	
	(8.035)	
Endline*Treatment	-3.862	
	(7.129)	
Midline*Treatment Priority	6.261	-15.05
	(8.243)	(22.72)
Endline*Treatment Priority	-0.851	21.10
	(7.245)	(16.41)
Constant	11.69***	6.416
	(1.565)	(4.838)
N	3941	925

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

8 Conclusion: Policy Implications & Recommendations

Traditionally job seekers in India - in particular in the informal sector - have had to rely on social connections and informal networks to find employment opportunities. These job search methods are costly and tend to favor the well-connected, thereby entrenching existing inequalities. In recent years job portals have emerged to facilitate the connection between job-seekers and employers. The idea behind these online marketplaces is straightforward but novel: create an easily accessible platform where job seekers can learn about employment opportunities and employers can search through thousands of job candidates. The goal of this work is to understand the impact of job portals, and their ability to ease search frictions for job-seekers. Such frictions can lead to inefficiencies and an absence of productive match-specific gains dampening economic growth.

Preliminary results suggest that job-portals can have important effects on job-search behavior and employment outcomes for job-seekers, particularly among those who face difficulties accessing the labor market using traditional means (for example, women). We find that job portals have significant effects on where people search for job-opportunities (larger cities instead of their own villages) and on employment outcomes (whether they are working, and the number of hours worked). These effects are stronger among women. These preliminary results suggest that job portals may benefit some groups more than others, and may be able to help overcome natural inequalities. This information is particularly valuable for government entities: departments such as the National Skill Development Corporation (NSDC), the Directorate General of Employment and Training (DGET) at the Ministry of Labor, and the Ministry of Corporate affairs have all expressed their firm commitment to ensuring that all job-seekers have equal access to the labor market, and to reduce search frictions so that more successful matches are made between employers and job seekers.

Appendix

Balance

NSDC sample, controlling for training centre, age, sex, category of location (add joint test)

Table 16: NSDC sample- using controls

	(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 test
Reservation wage	8278.99	-287.59	1116.10	0.97	0.06	0.04	0.08
Log of Reservation Wage	7.33	-0.05	0.03	0.72	0.06	0.02	0.05
Caste=SC	0.73	-0.03	-0.03	0.01	0.09	0.53	0.04
Access to internet	0.89	0.03	0.02	0.03	0.06	0.87	0.07

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Employment Status

Employment Status by By Gender

Table 17: Employment Status - by Gender (for NSDC)

	Male	Female
=1 if midline	0.149***	0.234***
	(0.0189)	(0.0563)
=1 if endline	0.0782***	0.141**
	(0.0181)	(0.0567)
Midline*Treatment	-0.0744***	-0.192**
	(0.0241)	(0.0748)
Endline*Treatment	-0.0462*	-0.128*
	(0.0240)	(0.0760)
Midline*Treatment Priority	0.0421*	0.159**
	(0.0236)	(0.0738)
Endline*Treatment Priority	0.0468**	0.0557
	(0.0238)	(0.0712)
Constant	0.334***	0.175***
	(0.00474)	(0.0142)
N	6092	771

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Employment Status by Caste

Table 18: Employment Status - by Caste (for NSDC)

	General	Other Castes
=1 if midline	0.215***	0.129***
	(0.0323)	(0.0218)
=1 if endline	0.0774**	0.0895***
	(0.0319)	(0.0214)
Midline*Treatment	-0.129***	-0.0645**
	(0.0405)	(0.0282)
Endline*Treatment	-0.0535	-0.0725**
	(0.0426)	(0.0283)
Midline*Treatment Priority	-0.00634	0.0685**
	(0.0429)	(0.0266)
Endline*Treatment Priority	0.0374	0.0717***
	(0.0459)	(0.0269)
Constant	0.432***	0.269***
	(0.00852)	(0.00545)
N	2111	4663

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Results with No of SMSes as independent covariate

Employment outcomes

Table 19: Employment Status

	NSDC	JS
=1 if midline	0.112***	0.125***
	(0.00965)	(0.0224)
=1 if endline	0.0576***	0.0327
	(0.0100)	(0.0225)
Number of SMSes sent	0.00134**	-0.000174
	(0.000678)	(0.000794)
Number of SMSes sent last month	-0.0127*	0.00375
	(0.00674)	(0.00938)
Constant	0.316***	0.516***
	(0.00452)	(0.00945)
N	6866	1850

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 20: Hours worked per week

	NSDC	NSDC(0 for unemployed)	JS	JS(0 for unemployed)
=1 if midline	-0.353	0.881*	0.762	1.584
	(0.802)	(0.471)	(0.938)	(1.284)
=1 if endline	1.125	-1.066**	0.149	-1.941
	(0.838)	(0.476)	(1.050)	(1.272)
Number of SMSes sent	-0.0839*	0.0393	-0.00772	-0.0453
	(0.0474)	(0.0252)	(0.0326)	(0.0388)
Number of SMSes sent last month	0.787*	-0.343	0.470	1.067**
	(0.455)	(0.253)	(0.422)	(0.490)
Constant	50.28***	16.35***	53.88***	28.72***
	(0.437)	(0.217)	(0.508)	(0.537)
N	2224	6403	946	1708

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 21: Monthly Salary

	NSDC	NSDC(0 for unemployed)	JS	JS(0 for unemployed)
=1 if midline	1486.8	1411.1***	-23763.9*	-9706.8*
	(950.9)	(304.3)	(13012.9)	(5797.5)
=1 if endline	5225.4*	1934.9**	-17164.8	-7358.6
	(3095.3)	(943.5)	(15374.0)	(6661.5)
Number of SMSes sent	-36.59	60.45	252.5	120.0
	(48.80)	(74.58)	(189.1)	(82.54)
Number of SMSes sent last month	158.4	-112.4	322.1	-45.28
	(221.0)	(150.1)	(471.5)	(200.9)
Constant	11820.3***	3604.8***	33828.4***	16660.9***
	(818.9)	(287.0)	(6561.4)	(2771.4)
N	2324	6643	935	1738

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 22: Job Satisfaction

	NSDC	JS
Number of SMSes sent	0.000246	0.00478
	(0.00456)	(0.00393)
Number of SMSes sent last month	0.0212	-0.0683
	(0.0525)	(0.0485)
Constant	2.614***	2.438***
	(0.0482)	(0.0680)
N	453	189

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Job search outcomes

Table 23: Living in a village

	NSDC	JS
=1 if midline	-0.184***	-0.124***
	(0.0116)	(0.0220)
=1 if endline	-0.0528***	-0.0497**
	(0.0122)	(0.0226)
Number of SMSes sent	0.000173	0.00152***
	(0.000656)	(0.000531)
Number of SMSes sent last month	-0.000628	-0.0102
	(0.00707)	(0.00720)
Constant	0.490***	0.304***
	(0.00584)	(0.0102)
N	6889	1858

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 24: Reservation Wage

	NSDC	JS
=1 if midline	1434.1***	915.1***
	(127.4)	(301.4)
=1 if endline	1742.8***	1590.2***
	(151.4)	(332.5)
Number of SMSes sent	-16.32*	8.715
	(9.058)	(10.50)
Number of SMSes sent last month	83.20	46.54
	(92.84)	(130.9)
Constant	12168.9***	15101.7***
	(71.72)	(155.4)
N	6504	1716

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 25: Is looking for a job

	NSDC	JS
=1 if midline	-0.0525***	-0.0232
	(0.0127)	(0.0237)
=1 if endline	-0.0643***	-0.0933***
	(0.0138)	(0.0288)
Number of SMSes sent	0.000315	0.00106
	(0.000878)	(0.000980)
Number of SMSes sent last month	0.00349	-0.0183*
	(0.00851)	(0.0110)
Constant	0.666***	0.592***
	(0.00667)	(0.0123)
N	6828	1828

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 26: Hours spent looking for a job per week

	NSDC	JS
=1 if midline	35.00***	51.05***
	(3.485)	(13.06)
=1 if endline	24.20***	33.65***
	(3.248)	(8.651)
Number of SMSes sent	-0.101	-0.498***
	(0.126)	(0.161)
Number of SMSes sent last month	-1.352	2.074
	(1.313)	(1.798)
Constant	11.80***	6.456
	(1.556)	(4.823)
N	3941	925

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

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