Asymmetric Information on Non-cognitive Skills in the Indian Labor Market

An Experiment using an Online Job Portal[1]

Futoshi Yamauchi[2], Shinsaku Nomura[3], Ana Areias[3], Saori Imaizumi[3] and Afra Chowdhury[3]

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Abstract

This paper examines the impact of non-cognitive (socio-emotional) skills on job market outcomes using a randomized control trial implemented in an online job portal in India. Job seekers who registered in the portal were asked to take a Big Five personality test and, for a random sub-sample of the test takers, the results were displayed to potential employers. Outcomes are measured by whether a potential employer unlocks a seeker by opening his/her application and background information. The results show that the treatment group for whom test results were shown generally enjoyed a higher probability of unlock. That is, employers are more interested in those for whom they can see personality test results. Such a relationship was not detected in the pre-test period. The effect was more significant among female, more educated and/or more experienced applicants. We also found a significant impact among cooperative, organized, realistic, calm, and/or outgoing applicants, which seems to indicate employers' preferences.

Key works: On-line job portal, non-cognitive skills, asymmetric information, labor markets, India

JLE classifications: J23, D22, D82

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[2] Corresponding author. International Food Policy Research Institute, 1201 Eye Street, NW, Washington DC 20005; Email: f.yamauchi@cgiar.org; Phone: +1-202-862-6469.

[3] Education Global Practice, World Bank

1. Introduction

Asymmetric information on both workers and employers is one important source of friction in the labor market. Employers often have to rely on observables to infer unobservable characteristics of workers such as innate ability. In a classic example, educational attainment is taken as an observable signal of ability under some circumstances, which leads to an inefficient equilibrium in the labor market (Spencer 1973; Rothchild and Stiglitz 1976; Wilson 1977). In this setting, workers (students) are encouraged to invest in education simply to prove their ability rather than to augment their labor productivity, in contrast to the standard human capital theory (Becker 1962). Though roles played by non-cognitive (socio-emotional) skills are increasingly recognized as an important factor in the workplace (Heckman and Kautz 2002; Barrick and Mount 1991), such skills of job applicants are typically unobservable to employers. In this paper, we examine the impact of non-cognitive skills on job market outcomes by introducing a unique randomized control trial into an online job portal in India.

The recent literature highlights the importance of non-cognitive skills, including soft skills, personality traits, abilities, character skills, and socio-emotional skills, as a determinant of life outcomes (Almlund et al. 2011; Kautz et al. 2014). Non-cognitive skills and cognitive ability are equally significant to explain labor market outcomes (for example, reviewed in Kautz et al. 2014) and outcomes in many other fields.[4] Strikingly, non-cognitive skills can also be formed and malleable until later ages. Our study uses a relatively well-accepted taxonomy of non-cognitive skills called the Big Five (OCEAN: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism).[5] For example, of the Big Five, Conscientiousness—the tendency to be organized, responsible, and hardworking—is associated with job performance and wages (Barrick and Mount 1991; Hogan and Holland 2003; Nyhus and Pons 2005; Salgado 1997). The experiment we propose below aims to break a typical situation in the labor

[4] Our intuition comes from Japanese experience too. In elementary schools in Japan, we often see their emphasis on the importance of self-control, team work/manner, and, more generally, good behaviors. These skills are formable through their works to prepare meals for classmates in the lunch program, clean classrooms/toilets after academic sessions, and so on. In general, non-cognitive skill development and cognitive outcomes are positively correlated. Moreover, Kaizen and 3S (or 5S) introduced in Japanese manufacturing factories also require certain non-cognitive skills such as being organized and detail oriented, and, not to mention, patience and perseverance in the long run to achieve continuous improvements in Kaizen.

[5] See John and Srivastava (1999) for an overview and history of the Big Five. Other measurements are also proposed to capture a certain aspect of non-cognitive skills, such as Grit (Duckworth et al. 2007). The Big Five measurements depend on self-reported answers, but researchers also proposed to use actual behavioral decisions to measure non-cognitive skills, such as risky and reckless behaviors measured in adolescent years (Heckman et al. 2014) and tenth-grade participation in sports, academic clubs, and fine arts activities (Lleras 2008). As discussed in Section 3, the answers by job seekers might be biased as those who decided to take the test might have an intention to look good. However, the sample of test takers is randomly split into treatment and control, so our empirical results are unbiased under the above-mentioned conditionality.

market where, to a large extent, non-cognitive skills of job seekers are unknown to potential employers.[6] In this attempt, an online job portal proves very useful.

Currently, global online job portals such as LinkedIn, Indeed, Monster and Career Builder connect employers and job seekers in many countries. A growing number of local online job portals have also emerged including formerly Babajob (merged into Quikr Jobs in June 2017; all Babajob users were carried to Quikr Jobs).[7] The job portals provide information on job vacancies and help expand access to job information for those who have internet connectivity. These online platforms, global or local, provide real-time streams of labor market data that have remained largely unused by researchers as well as policy makers.[8]

A rapid expansion of job portals is a clear proof of the portals' usefulness for both job seekers and employers. A great advantage of online job portals is low marginal cost to acquire information. In online job portals, job seekers and employers can easily access each other. Kroft and Pope (2014) and Mang (2012) report that there has been a significant shift in posting job listings from newspapers and other print media to websites and that this process has lowered the cost of acquiring employment information. Moreover, several studies from developed countries have found that the use of employment websites has reduced unemployment rates (Beard et al. 2012; Kuhn and Mansour 2014), though an impact on wages remains unclear (Kuhn and Mansour 2014; Shahiri and Osman 2014). However, as Shahiri and Osman (2014) point out, it is important to keep in mind that a large number of employers and job seekers still cannot fully utilize employment websites due to limited internet infrastructure, high user fees, and/or a lack of knowledge about information technology. Some studies also found that a greater use of cell phones improves employment outcomes in developing countries (Klonner and Nolen [2010] for South Africa; Aker [2011] for Niger; Burga and Barreto [2014] for Peru), implying that information constraints are a significant source of inefficiency in the labor market.

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[6] Petre (2018) pointed out that employers learn about cognitive and non-cognitive skills of their employees over time. Her results show that employers reward self-esteem, internal control and schooling initially, while rewarding cognitive skills and motivation over time. Deming (2017) reports that labor market returns to social skills were much greater in the 2000s than in the mid-1980s and 1990s in the US. Thus, there was a shift in labor demands from math-intensive and less social jobs to more social skill intensive ones.

[7] Currently the platform developed in what was formerly Babajob is part of the Quikr Jobs platform. In this paper, we refer to Babajob since the randomized control trial was introduced into Babajob prior to their transition to Quikr Jobs (June 2017).

[8] For example, LinkedIn, a social networking service for businesses and professionals launched in 2003, had data on 433 million individuals as of Q1 2016. The site is available in over 200 countries worldwide and in 20 different languages. The data obtained through LinkedIn have been primarily used for business purposes, rather than for policy formulation, though various industry- and skills-focused analyses have been published on LinkedIn's official blog. Tambe (2014) used skills data from LinkedIn to measure employers' investment in big-data-related human resources management.

In this paper, we use an online job portal in India (Babajob described in the next section) to experiment on the information asymmetry of job seekers' non-cognitive skills. Job seekers who registered in the portal were asked to take a Big Five type personality test and, for a random sub-sample of the test takers, the results were displayed to potential employers. In this experiment, outcomes are measured by whether a potential employer assesses a seeker by opening (unlocking) his/her application and background information. Though whether or not to take the test is a voluntary decision (thus creating a selectivity issue), whether or not the results are displayed to potential employers in Babajob is random. Therefore, we can compare outcomes between those for whom the results were shown and not shown to analyze the impact of non-cognitive skills.[9] The execution of our experiment was fast once it was programmed and tested in the system, as the number of participants in Babajob is large (that is, a big-data environment).

The paper is organized as follows. Section 2 describes the Indian labor market and Babajob. Section 3 describes in detail the experiment on non-cognitive skills. Section 4 displays empirical results. The results show that the treatment group for whom test results were shown generally enjoyed a higher probability of unlock (one step before being shortlisted). That is, employers are more interested in those for whom they can see personality test results. Such a relationship was not seen in the pre-test period, which confirms that the above results are unlikely to be spurious. The effect was more significant among female, more educated and/or more experienced applicants. We also found a significant impact among cooperative, organized, realistic, calm, and/or outgoing applicants, which seems to show employers' preferences. Implications are discussed in the concluding section.

2. Empirical Setting

India has made remarkable progress in economic growth as well as poverty reduction over the past few decades. India's gross domestic product (GDP) grew at an average rate of 7.3 percent per year between 2007 and 2012. This contributed to a substantial decline in the incidence of poverty, and an estimated 138 million people rose above the poverty line during the period. Despite its robust growth, India still faces major challenges to improve labor productivity and match the supply and demand of workforce skills.[10]

[9] We assume that the base population of job seekers in the portal is relatively homogenous. We maintain this assumption throughout the analysis. See Schmitt, et al. (2007) for the cautions required to compare the Big Five results across different nations and cultures.

[10] The Indian labor force is large, mostly informal, and relatively young. India's population reached 1.295 billion in 2014, including 497 million workers. The size of the labor force has been expanding at an annual net growth rate of 4.2 million for the past 10 years. The labor force participation rate is 54 percent, with a relatively high participation rate among men (80 percent) and low rate among women (26 percent). Only 16 percent of the labor force is engaged in wage employment (18 percent of male workers and 12 percent of female workers), and a large majority work in the informal sector. Moreover, 54 percent of the country's population is under 25 years of age. While the country's relatively young population has the potential to yield significant demographic dividends, ensuring sufficient

In India, online job portals emerged in the late 1990s, but only began to flourish in the past decade as mobile phone and internet use became more widespread and social networks expanded. The share of mobile phone subscribers more than tripled from 20 percent of the population in 2007 to 70 percent in 2014, and the number of fixed broadband subscriptions increased eightfold during the same period. There are now about 20 job search portals, many of them focusing solely on the Indian labor market.[11]

Babajob, once established in 2007, became one of the leading job-matching websites in the country. Between July 3, 2007, and May 24, 2017, there were 1,286,812 ads posted by 524,672 employers and 8,218,720 job seekers were registered in Babajob. Babajob matched workers and potential employers in both formal and informal sectors. In order to reach disadvantaged populations, Babajob provided a variety of access options including standard websites, mobile sites, interactive voice response (IVR), text messaging, and web applications.[12]

Figure 1 to be inserted

Figure 1 shows the number of advertisements posted and median real wage in 2011 to 2017. Babajob expanded in terms of the number of advertisements until 2016, but when Babajob introduced a system change, it significantly reduced the number of advertisements. In the peak time in 2016, the median wage dropped. Our experiment was introduced in the second quarter of 2017, when the number of advertisements resumed an upward trend again.

A large number of the jobs listed in Babajob are at the entry level, for example, with the largest share of listings in 2015 classified as clerical support. Seventy percent of the jobs advertised were in the 10 most

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employment opportunities for a young workforce also presents a critical challenge for the government. India faces a lack of highly trained workers and a large share of unskilled youth. As a result, job creation and skills development are critical priorities. To address these challenges, the government launched the National Policy for Skill Development and Entrepreneurship in 2015, and its 12th Five-Year Plan set a goal of training 400 million workers by 2022.

[11] Though not exhaustive, 22 firms were identified by compiling a list from government agencies and search engines. Of those firms, 77 percent provide job-search services, while a few provide job-matching services. Some platforms focus on entry-level jobs, while others mainly advertise technology or senior-management-level jobs. Job-matching platforms use different techniques to match workers with job opportunities, including leveraging social networks, providing curated job information based on an individual's profile and connecting local recruiters with candidates. Sixty-eight percent of the platforms focus on jobs located in India, with some portals concentrating on specific cities.

[12] The Babajob platform works to connect job seekers and employers. Job seekers can create a profile in Babajob or search and apply for jobs online or offline, all for free. Employers can create profiles in Babajob and post their hiring requirements for free in a service that resembles online job classifieds, or they can opt for the paid, premium service (*RapidHire*) that offers a facilitated hiring experience. All job posts are alive for 90 days. *RapidHire* jobs are promoted more heavily on the site for a certain period depending on the plan opted for (for example, the basic plan promotes jobs for 15 days). *RapidHire* also offers other services, such as additional screening, executive recruitment support, unlocking more information about candidates, and SMS promotion of the posted job to relevant job seekers within a certain radius.

populous cities: Bangalore, Delhi, Mumbai, Chennai, Hyderabad, Pune, Kolkata, Thane, Patna, and Lucknow. In 2015, the average offered salary was 13,182 rupees (Rs.) per month.[13] The average offered salary for professional-level jobs was Rs. 14,900, 17 percent higher than that for non-professional jobs, Rs. 12,739. By city, the average salary for professional jobs ranged from Rs. 16,970 in Mumbai to Rs. 12,757 in Patna, while the average for non-professional jobs ranged from Rs. 14,184 in Delhi to Rs. 10,742 in Patna.

Figures 2 and 3 to be inserted

Figures 2 and 3 display wage distributions by job category and gender, respectively, using the January-March 2017 data. Though Babajob is not representative of the Indian labor market and labor force, they illustrate the usefulness of the Babajob data as a source of the labor market analysis. In particular, Figure 3 clearly shows that gender gaps in wage are job category specific.

3. Experiment

In mid-February 2017, a shorter version of the Big Five personality test (Big Five Inventory-10 [BFI-10] in Rammstedt and John 2007) was introduced to job seekers who were relatively active in Babajob in the past three months.[14] Test takers were then randomly split into two groups: those for whom the results were displayed to potential employers and those for whom the results were kept confidential. Those who decided to take the test were informed that the results may be displayed in their profiles as additional information when they apply for a position.

Big Five Personality Test

The Big Five personality test aims to measure non-cognitive (socio-emotional) skills through the following five components: (i) openness (to experience), (ii) conscientiousness, (iii) extraversion, (iv) agreeableness and (v) neuroticism. Details on each component are below (Table 4.2 of Jonh, Naumann, and Soto 2008):

Openness to experience describes the breadth, depth, originality, and complexity of an individual's mental and experiential life.

[13] Using an exchange rate of US$1=Rs. 67 (the average rate during the first half of 2016) this amount is equivalent to about US$197.
[14] We used BFI-10 plus 1 additional item on Agreeableness suggested by Rammstedt and John (2007).

Conscientiousness describes socially prescribed impulse control that facilitates task- and goal-directed behavior, such as thinking before acting, delaying gratification, following norms and rules, and planning, organizing, and prioritizing tasks.

Extraversion implies an energetic approach toward the social and material world and includes traits such as sociability, activity, assertiveness, and positive emotionality.

Agreeableness contrasts a pro-social and communal orientation toward others with antagonism and includes traits such as altruism, tender-mindedness, trust, and modesty.

Neuroticism contrasts emotional stability and even-temperedness with negative emotionality, such as feeling anxious, nervous, sad, and tense.

<u>Pilots</u>

The experiment was first developed through pilots. Two different pilots were introduced to test both the content of the assessment and the survey tools planned for use. The first pilot was composed of a telephonic survey of 100 job seekers in our target population, using the Big Five Personality Test (24-question version adopted in the World Bank's Skills Toward Employment and Productivity [STEP] Measurement Survey (Pierre et al. 2014)). For this survey, Babajob's Consumer Insights Team was instructed to call job seekers and give the questions exactly as they were written without any explanation, even if the respondent requested it. The survey was administered from June 22 to June 24, 2016. Half of the job seekers were told that the results of this survey would be shared with potential employers, while the other half were told that the survey was purely for research purposes and the results would not be shared. The goals of this pilot were to ensure that job seekers understood the questions of the assessment and how to answer them and to investigate whether job seekers were likely to change their answers if they believed the results would be shown to employers. Overall, the job seekers understood the questions being asked (only 2.7 percent of all responses given were the "Respondent couldn't answer" option), and there was not significant deviation between the two groups.

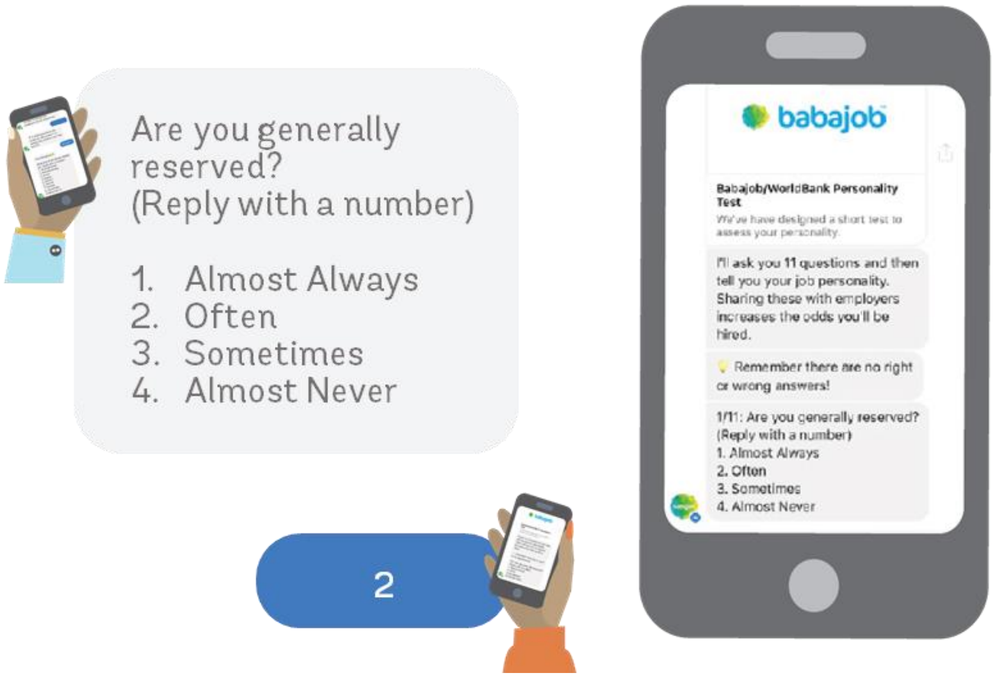
For the second pilot, the team tested our planned data collection methods. As described later, the team decided to pursue recruitment to the randomized control trial (RCT) primarily through SMS messages to job seekers, sending a link to the survey instrument in the text. This pilot aimed to test the effectiveness of the recruitment and also gave an opportunity to experiment with the combinations of messaging and SMS timing to determine how to increase the number of respondents.

From November 29 to December 1, 2016, a series of SMS blasts were sent to job seekers over a week with a link to a survey tool that allowed the users to fill out the Big Five Personality Test (11 question version). Overall, we sent approximately 124,000 SMS to 44,000 job seekers. The job seekers clicked the link in the SMS 3,865 times, with 1,010 completing the survey. The team experimented with different variations in the content and frequency of the messages, starting with sending three SMS, spread over three-hour intervals, to each seeker. In our final SMS blasts, sending one SMS and waiting at least 24 hours before subsequent blasts was found to be the most efficient method.

Technology Design

A variety of iterations were tested when determining how to run the main intervention/data collection (that is, getting job seekers to take the personality test). In the original design, the team was planning to build the functionality into the Android app, as users on this platform have data-rich profiles and high application per applicant numbers. Due to sample size requirements, and the smaller numbers seen in app downloads and usage, the team decided to focus on job seekers using Babajob's mobile web platform. Building the assessment into the registration process was also considered, but this would not allow for proper sampling and threatened Babajob's registration/application numbers, so the team switched to a direct recruitment method, prompting users through SMS to take the test.

The team planned to use a survey software outside of the Babajob platform to collect the required data (one stage of the RCT pilot), but this approach presented several technical difficulties and meant that updates to users' profiles with the personality test results would only happen periodically. Instead, the team decided to have job seekers take the test through Babajob's chatbot. Through this, job seekers would be able to click a link in the recruitment SMS, enter their registered mobile number, and begin the personality assessment. Below are screenshots of the test introduction, the process of answering the questions, and the job seeker's view of the results:



After a job seeker finishes the assessment, they get to see their scored results immediately. They can then go on to search local jobs that match their profile and apply for them over the chatbot itself, helping Babajob re-engage the participants of the study to increase the effect. The results of the test are also automatically uploaded to their Babajob profiles and will be shown on their applications to various jobs depending on whether the job seeker is in the treatment group. The job seeker is allotted to a group based on their Babajob User ID, a number created sequentially on their registration. Even-numbered User IDs are in the treatment group, while those with odd-numbered User IDs are in the control group (hidden results).

Test Results

The scores were constructed by giving each of the questions a four-option answer scale 10 = almost never, 30 = sometimes, 70 = often, and 90 = almost always. In each component, the scores were averaged. For example, if two answers are almost never (10) and often (70) in agreeableness, the score is (10+70)/2= 40.

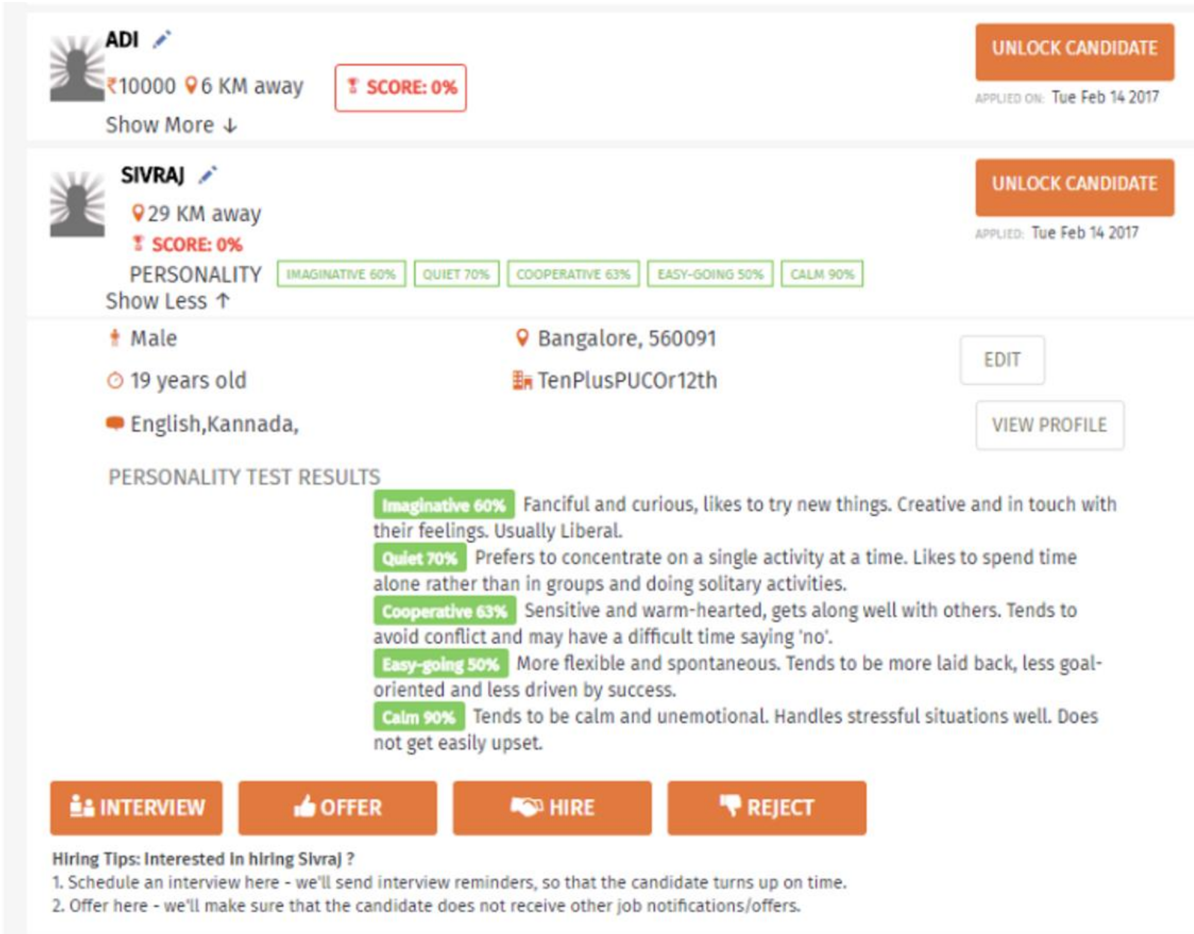
Personality traits are labelled by a simple word in each dimension using the cut-off point of 50. For example, if the extraversion score is above (not including) 50, the person is characterized as "outgoing"; if the score is below or equal to 50, the person is characterized as "quiet". To choose labels, we avoided negative words. Simple and intuitive words were identified to best describe the two opposite poles of Big

Five from Table 4.4 of John, Naumann and Soto (2008). Below is a table of the personality trait labels we decided to use in the experiment:

	Scores above 50	Scores below or equal to 50
Extraversion	Outgoing – Likes to be around people and enjoys being the center of attention. Is talkative and energetic. Prefers to work in groups.	Quiet – Likes to spend time alone and doing solitary activities such as reading and writing. Prefers to concentrate on a single activity at a time.
Agreeableness	Cooperative – Sensitive and warm-hearted, gets along well with others. Tends to avoid conflict and has a difficult time saying 'no'.	Competitive – Ambitious. Not afraid to criticize others or make difficult decisions. Is rational and may be perceived as insensitive.
Emotional stability (Neuroticism)	Sensitive – More emotional, can get worried and nervous easily. May be vulnerable to stress.	Calm – Tends to be calm and unemotional. Handles stressful situations well. Does not get easily upset.
Openness to experience	Imaginative – Fanciful and curious, likes to try new things. Creative and in touch with their feelings. Tends to be liberal.	Realistic – Practical, likes working with things rather than with ideas. Prefers familiar routines to new experiences. Tends to be conservative.
Conscientiousness	Organized – Hard-working and reliable, efficient. Likes to think carefully before acting. Prefers working in a structured setting.	Easy-going – Tends to be more laid back, less goal-oriented, and less driven by success. More flexible and spontaneous.

Display

For displaying the results of the assessments to potential employers, the team has modified our application tracking system to include the test results in an easy-to-read format where employers are likely to see them. Below is a screenshot of this new feature (expanded version - what an employer sees on clicking "Show More"):



As can be seen in the above screenshots, we include personality trait labels and scores. This reporting is done both on Babajob's Mobile and Desktop web platforms. For job seekers whose results are to be hidden, their profile would include only the normal information associated with an applicant without the personality test scores.

Data Collection

The data collection was started on February 18, 2017, through SMS blasting the link to a randomized list of job seekers who were active in the last three months (to increase the likelihood that they are still looking for jobs). Each day, we have messaged a new group of job seekers, waiting a few days before again messaging those who did not complete the personality test yet. Through this, we are recruiting participants to the RCT in a trackable fashion. The response rate was rather low, i.e., 3576 test takers out of 43574 job seekers who received the SMS at least once. The test takers do not represent the general population of job seekers in the Babajob system, but Appendix shows that the two groups resemble with respect to age and gender composition. In educational attainment, we observe test takers are more educated than non-takers. See Figure A1 and Table A1. However, this does not mean they are similar in unobserved characteristics such as non-cognitive abilities focused in this paper (note that non-cognitive abilities can be correlated with educational attainment).

Results Tracking

The team was able to track the results of the RCT without additional development based on Babajob's existing data tracking methods. Results tracking was performed through May 24, 2017.[15] Babajob tracked every application made by a user, storing a record of the same, as well as anytime an application is "Unlocked" (the primary result we are tracking, which signifies an employer is placing value on the applicant). In addition to this, Babajob has tracked which job seekers have completed the personality test and their answers.

Descriptive Analysis

In this sub-section we show descriptive results to characterize the experiment. Personality traits were distributed as follows (Table 1, including both treatment and control):

Tables 1 and 2 to be inserted

There is a potential bias in the distributions due to the voluntary decisions made by seekers to take the test. Therefore, the distribution is not representative of personality traits in the job seeker population. For the same reason, there can be differences between this result and the first pilot done by phone as the pilot was conducted under strict confidentiality. Except in extraversion, the traits are one-sided: cooperative in agreeableness, organized in conscientiousness, imaginative in openness, and calm in emotional stability. Those who decided to take the test might have an intention to make themselves look attractive to potential employers by choosing particular answers. It is important to compare more representative results on personality traits from a larger population and our results in the future to investigate the above issue, but this is beyond the scope of the current research. Similarly, the possibility that test takers game the results of the test is potentially alarming but, as described below, the treatment and control groups were split randomly, which at least ensures comparability between the two groups. To cross-check potential differences of personality trait patterns between males and females, Table 2 shows the percentage of test

[15] There are variations in the tracking period. The last test taker was recorded on May 16. This is one important reason why the number of applications needs to be controlled.

takers (by gender) who are labeled as cooperative, organized, imaginative, calm, and/or quiet. Though there are some differences by gender, we do not see any large gaps between the two groups.

Next, the treatment and control groups are compared in personality test scores as well as traits. In our experiment, 51.5 percent of the sample is in the treatment group (Table 3). Since the treatment is a random sub-sample of test takers, the treatment and control groups are designed to be probabilistically ex-ante identical. Table 4 shows that personality traits (defined in this study) are balanced between the treatment and control groups. Two-sided t tests could not differentiate the two groups (the equality of means is not rejected at the conventional level).

Tables 3 and 4 to be inserted

Table 5 compares gender and education distributions by treatment status.[16] Though we do not perform a test to compare the two groups, it is evident that the two distributions extraordinarily resemble each other. Similarly, age distributions are compared between the treatment and control groups (Figure 4), which confirms that the two groups are balanced in age. The above descriptive results appear to provide a good justification to identify the impact of non-cognitive skills (additional information on profiles) on job market outcomes.

Table 5 and Figure 4 to be inserted

4. Results

We have confirmed that the treatment and control groups are similar in individual characteristics and personality test scores. The only difference between the two groups is whether the test scores were displayed to potential employers (treatment). Data were collected in the portal even before the test, so we have information on their job search behavior and outcomes prior to the experiment. Therefore, this setting offers us four different situations: (a) treatment after experiment, (b) control after experiment, (c) treatment before experiment, and (d) control before experiment. In (c) and (d), the distinction between treatment and control is trivial because they have not taken the test at that stage, thus whether or not the test results were displayed in the system has no significance. The situations in (a) and (b) are our primary

[16] Labor market experience can only be inferred from age and educational attainment. The length of active labor market experience cannot be compared since the Babajob portal did not ask about it. We use the length of period in which the applicant was registered in the system to screen the sample (see Table 6).

interest, and we conjecture that the difference between treatment and control after the experiment should not hold before the experiment if that is attributed to the intervention defined above.

The system records an incident where an employer opens (unlocks) an application. As described earlier, we use the unlock incidence as the outcome measure to detect the impact of displaying non-cognitive skill information on potential employers' reactions. In Babajob, there are two types of job advertisements: paid and unpaid. In paid advertisements, employers who post those advertisements pay fees to have additional services from Babajob, such as a preliminary screening to improve matching. In unpaid advertisements, such a service is not attached, so employers have to check applications by themselves. To unlock is the first action by employers to see details on the job applicant for short-listing. In the analysis, we use unpaid job advertisements because the number of unlocks in paid job advertisements was very small during the period under our experiment. Apparently, the number of unlocks is (positively) correlated with that of applications, so we include the number of applications (dummies) as control variables on the right-hand side.[17] Below we estimate the following equation to detect the impact:

$$unlock_{it} = \alpha + \beta_0 t_i + \beta_1 \mathrm{Tr}_i + \beta_2 t_i \times \mathrm{Tr}_i + \gamma \mathbf{Z}_{it} + \varepsilon_{it}$$

where $unlock_{it}$ is the number of unlocks by potential employers for seeker i at $t = 0, 1$ (0 for pre-test period and 1 for post-test period), t_i is the indicator that takes the value of one after the test, and zero before the test, Tr_i is the indicator of treatment status that takes the value of one if the test results are randomly disclosed and zero otherwise, $\mathbf{Z}_{it}$ is the vector of the number-of-applications dummies and ε_{it} is an error term. Each seeker, either in treatment or control, offers two observations from the pre-test and post-test periods. We assume that γ is common between the two periods.

Estimation is also executed in a sub-sample to identify differentiated effects by job seekers' characteristics. We look at their personality traits (revealed in the test) and gender. For example, results in the conscientiousness part of the test provide an indication as to whether the person is likely to be organized or easy-going, and it is possible that the impact of personality traits' information display could differ between organized applicants and easy-going applicants. Similarly, we can compare applicants who are cooperative and competitive; imaginative and realistic; calm and sensitive; quiet and out-going. Possible gender difference is also an interesting issue. If female and male applicants to a job vacancy are not treated equally for some cultural reasons (for example, the job is traditionally handled by males), the employer may want to know more details of the female applicant to assess her suitability to the job.

[17] It is possible that the number of applications in the observed period is correlated with the applicant's characteristics and treatment status.

Alternatively, if female characteristics, both observable and unobservable, are in small variations, employers may want to gather more information from male applicants.

Table 6 presents the benchmark results. In Column 1, the estimation used the sample of job seekers if they had been in the Babajob platform more than 20 days prior to the test and the number of applications is less than 20 in both pre-test and post-test periods. The specification includes treatment dummy, after-test dummy, and the number of applications dummies. As hypothesized earlier, we confirm that the disclosure of personality test results (treatment) has a positive and significant impact on the number of unlocks (dependent). Using the pre-intervention period, we confirmed that the treatment indicator is insignificant, which indicates that the above result is unlikely to be spurious (Yamauchi, et al., 2018). Even in the pre-test period, the number of applications is positive and significant, which confirms that the positive relationship between the numbers of applications and unlocks remains stable before and after the intervention. In Columns 2 and 3, we relax one of the assumptions to redefine the estimation sample. The time job seekers were in the system prior to the test is 40 days and 60 days respectively. The results remain qualitatively the same. The qualitatively same results were also confirmed even when gender, education, and age are controlled.

Table 6 to be inserted

Employers may be looking for job seekers who possess a certain set of personality traits. Our experimental design enables us to look deeply into this issue. Since we saw earlier that personality trait distributions are identical between the treatment and control groups, we can examine the treatment effect separately for different personality trait groups, for example, the organized versus the easy-going. Table 7 shows the results by component-wise personality trait. Interestingly, we found a significant impact among cooperative (high agreeableness), organized (high conscientiousness), calm (low neuroticism), realistic (high openness), and/or outgoing (high extraversion) applicants, which seems to display employers' preferences. Calm and sensitive are rather not easily differentiated in the above results. The results imply that employers generally prefer job seekers who are cooperative, organized, calm, realistic, and/or outgoing.

Table 7 to be inserted

Next, we split the sample by gender, educational attainment and age group to check group-specific treatment effects. Table 8 presents the results for each gender group. Interestingly, we observe a significant and positive (direct) effect of the intervention among females, but such an effect was not detected among males. One possible interpretation of the gender gap is generally personality related information tends to be scarce for female applicants in the given empirical setting, but this is highly speculative.

Tables 8 to 10 to be inserted

Similarly, the sample is split into those who attained secondary and post-secondary/tertiary levels (Table 9). The results confirm complementarities between schooling and non-cognitive skills (information); the impacts are more significant among those who attained higher than secondary level. In Table 10, the sample is split into two age groups in 15-29 and 30-44. On average, the group aged in 30-44 has more experience in the labor market, and the results show that the impacts are greater and significant in this group. Thus, the demand for the additional information on non-cognitive skills is higher in the more educated and/or more experienced groups.

5. Conclusions

The randomized control trial introduced in an online job portal has shown that (i) asymmetric information on non-cognitive (socio-emotional) skills could play potentially important roles in the labor market and (ii) employers seem to have certain (stereotypical) preferences when looking for employees. In other words, information on non-cognitive skills remains usually quite private, thus employers generally do not have such knowledge on job applicants and may have to imperfectly infer it from verifiable data such as actual actions taken by the individual. In this sense, asymmetric information on non-cognitive skills could be a source of inefficiency in the labor market.

Yet a few caveats follow. Our study based on the Big Five did not include other aspects of non-cognitive skills such as Grit (Duckworth, 2016), which is considered as a key factor to explain (long-term) success. While the Big Five measurements depend on self-reported answers, our analysis could have also used actual behavioral decisions to measure non-cognitive skills, such as risky and reckless behaviors measured in adolescent years (Heckman et al. 2014) and tenth-grade participation in sports, academic clubs, and fine arts activities (Lleras 2008). However, these decisions are also significantly affected by the environment in which the individual has grown up and, since the job portal normally does not have such information, we must resort to self-reported answers on actual behavioral decisions. Finally, it is important to recognize that non-cognitive skills can also be formed and malleable until later ages. Like growth mindedness as one answer to the question of how Grit can be formed among school-aged children (Dweck, 2006), competent concepts have been proposed but a large part of the formation of non-cognitive skills remains underexplored.

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Table 1 Personality traits

Agreeableness	Cooperative	2,017	Competitive	853
Conscientiousness	Organized	2,001	Easy-going	869
Openness	Realistic	1,022	Imaginative	1,848
Emotional stability	Calm	2,058	Sensitive	812
Extraversion	Outgoing	1,409	Quiet	1,461

Source: Authors.

Table 2 Personality traits by gender

	Males	Females
Agreeableness (% Cooperative)	69.38	73.14
Conscientiousness (% Organized)	69.24	70.93
Openness to experience (% Realistic)	34.34	39.41
Emotional stability (% Calm)	72.35	69.35
Extraversion (% Outgoing)	48.05	50.71

Source: Authors.

Table 3 Sample composition by treatment status

	# obs	%
Treatment	1,478	51.50
Control	1,392	48.50
Total	2,870	100.00

Source: Authors.

Table 4 Personality traits by treatment status and t-test results

	Treatment		Control		
	# obs	Mean	# obs	Mean	p value
Agreeableness	1,478	61.857	1,392	60.944	0.1322
Conscientiousness	1,478	67.896	1,392	67.787	0.8736
Openness	1,478	62.465	1,392	62.098	0.6462
Emotional stability	1,478	69.133	1,392	68.671	0.5298
Extraversion	1,478	57.410	1,392	56.983	0.5959

Source: Authors.

Note: Mean equality is tested under two side and unequal standard deviation assumptions.

Table 5 Characteristics by treatment status (number of applicants)

Gender	Treatment	Control
Uninformed	2	4
Male	1,099	1,024
Female	329	329
Education	Treatment	Control
Uninformed	558	522
No education	0	0
Primary	1	3
Secondary	334	302
Post-secondary/Tertiary	585	565

Source: Authors.

Note: Gender reported had 179 and 147 uninformed cases in treatment and control, respectively. The results shown above are gender imputed from their given names in cases of being uninformed.

Table 6 Benchmark results

Dependent: # unlocks	# days>20	# days>40	# days>60
Treatment *after	0.0349***	0.0326**	0.0343*
	(2.81)	(2.25)	(2.01)
Treatment	-0.0160*	-0.0148	-0.0166
	(1.75)	(1.41)	(1.35)
After	-0.0098	-0.0118	-0.0168
	(1.15)	(1.20)	(1.41)
R squared	0.0563	0.0565	0.0577
# obs	3,944	2,996	2,452

Source: Authors.
Note: *** 1%, ** 5%, * 10% significance. Numbers in parentheses are absolute t values using robust standard errors. The specification includes treatment dummy, after-test dummy, and the number of applications dummies. The benchmark sample consists of job seekers who were in the system for more than 20 days at the time of taking the test and applied for fewer than 20 positions during the tracking period.

Table 7 Personality

Dependent: # unlocks		
Agreebleness	**Cooperative**	Competitive
Treatment*after	0.0362**	0.0277
	(2.46)	(1.30)
Conscientiousness	**Organized**	Easy-going
Treatment*after	0.0511***	-0.0037
	(3.24)	(0.20)
Openness to experience	Imaginative	**Realistic**
Treatment*after	0.0241	0.0463**
	(1.51)	(2.39)
Emotional stability (neuroticism)	**Calm**	Sensitive
Treatment*after	0.0297**	0.0401*
	(2.04)	(1.79)
Extraversion	**Outgoing**	Quiet
Treatment*after	0.0534***	0.0167
	(2.98)	(0.99)

Source: Authors.

Note: *** 1%, ** 5%, * 10% significance. Numbers in parentheses are absolute t values using robust standard errors. The specification includes treatment dummy, after-test dummy, and the number of applications dummies. The sample consists of job seekers who were in the system for more than 30 days at the time of taking the test and applied for fewer than 20 positions during the tracking period.

Table 8 Gender

Dependent: # unlocks	Males	Females
Treatment*after	0.0167	0.0927***
	(1.24)	(3.04)
R squared	0.0564	0.1083
N obs	3,024	868

Source: Authors.
Note: *** 1%, ** 5%, * 10% significance. Numbers in parentheses are absolute t values using robust standard errors. The specification includes treatment dummy, after-test dummy, and the number of applications dummies. The sample consists of job seekers who were in the system for more than 20 days at the time of taking the test and applied for fewer than 20 positions during the tracking period.

Table 9 Education

Dependent: # unlocks	Secondary	Post-secondary/Tertiary
Treatment*after	0.0215	0.0442**
	(0.82)	(2.20)
R squared	0.0673	0.0845
N obs	900	1,792

Source: Authors.
Note: *** 1%, ** 5%, * 10% significance. Numbers in parentheses are absolute t values using robust standard errors. The specification includes treatment dummy, after-test dummy, and the number of applications dummies. The sample consists of job seekers who were in the system for more than 20 days at the time of taking the test and applied for fewer than 20 positions during the tracking period.

Table 10 Age

Dependent: # unlocks	15<= age < 30	30<= age <45
Treatment*after	0.0074	0.1155***
	(0.42)	(2.64)
R squared	0.0716	0.1496
N obs	2,108	528

Source: Authors.
Note: *** 1%, ** 5%, * 10% significance. Numbers in parentheses are absolute t values using robust standard errors. The specification includes treatment dummy, after-test dummy, and the number of applications dummies. The sample consists of job seekers who were in the system for more than 20 days at the time of taking the test and applied for fewer than 20 positions during the tracking period.

Figure 1 The number of advertisements posted and median wage in 2011 to 2017

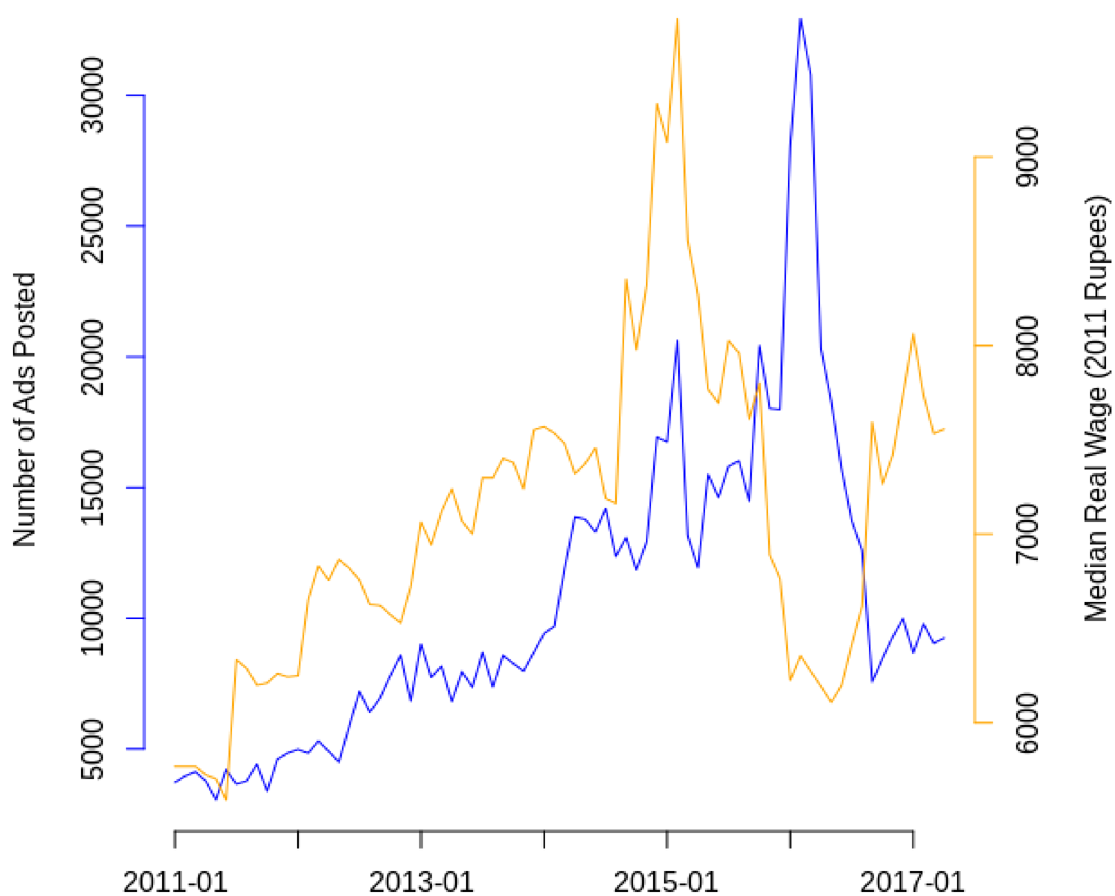
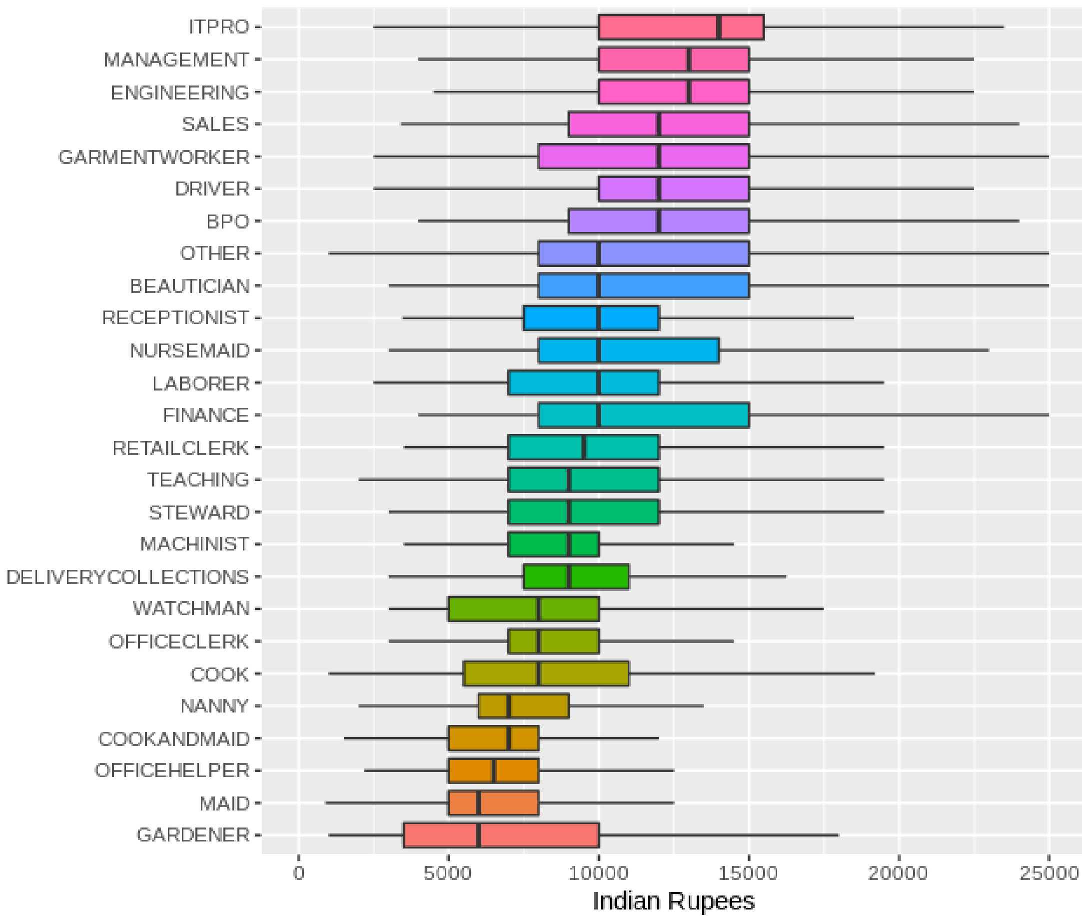
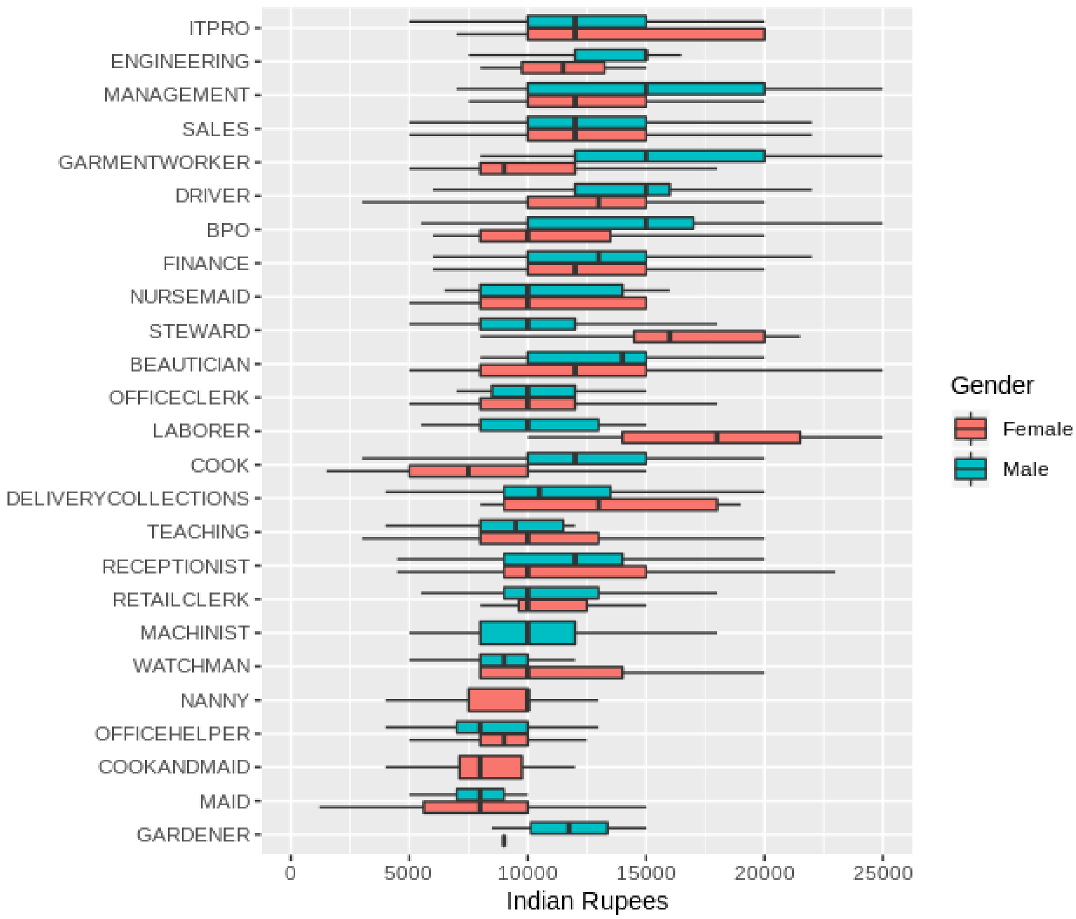


Figure 2 Wage distributions by job category



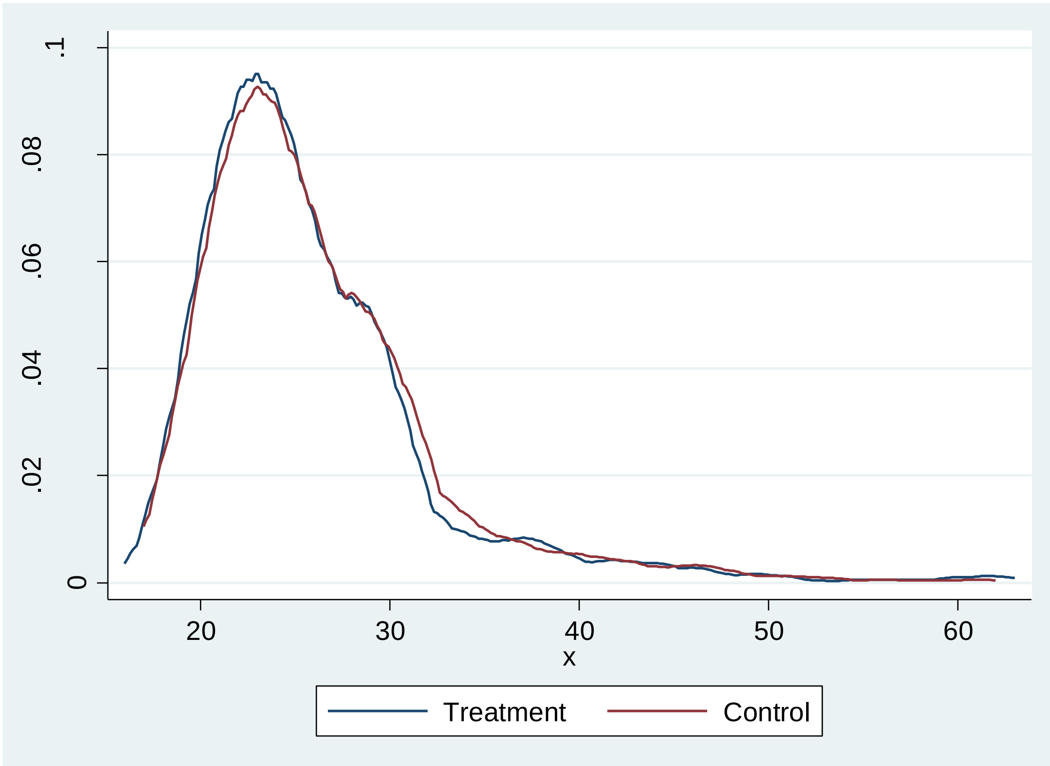
Note: January-April 2017 nominal wages. The boxplots boxes show median, 25th and 75th percentile and the lines extend up to the smallest/largest value no further than 1.5 * inter-quantile range.

Figure 3 Wage distributions by job category and gender



Note: January-April 2017 nominal wages. The boxplots boxes show median, 25th and 75th percentile and the lines extend up to the smallest/largest value no further than 1.5 * inter-quantile range.

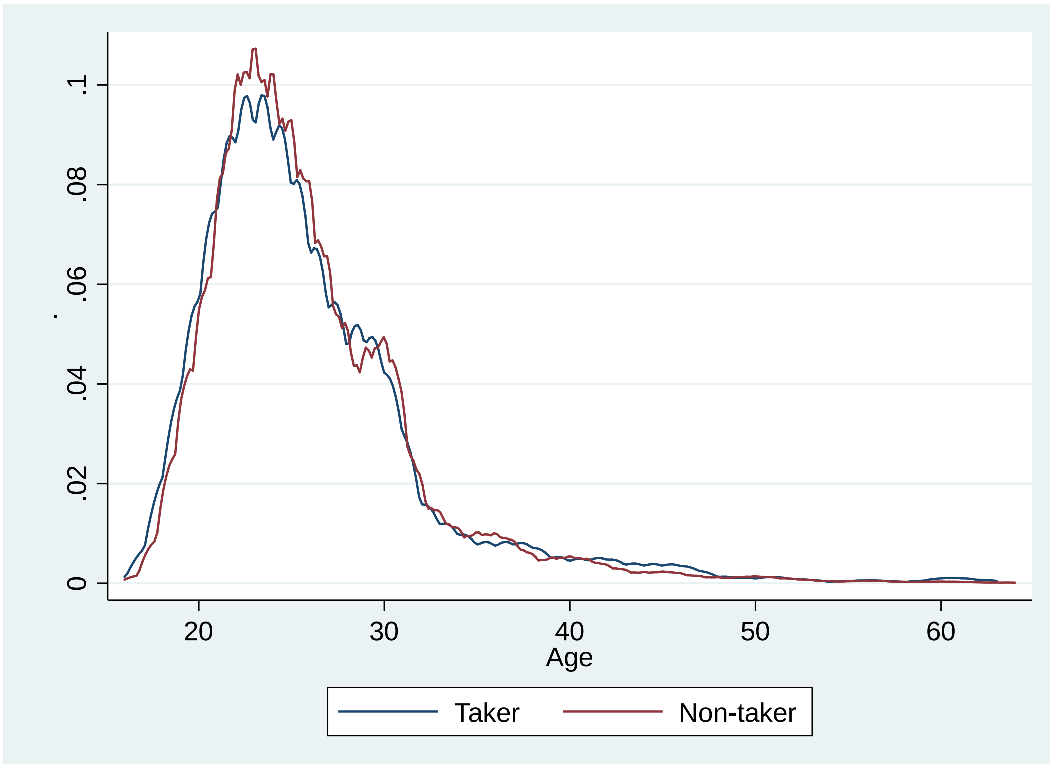
Figure 4 Age distribution by treatment status (kernel density)



Source: Authors.

Appendix

Figure A1 Age distribution by test taker status (kernel density)



Source: Authors.

Table A1 Characteristics by test taker status (proportion)

Gender	Taker	Non-taker	Taker	Non-taker
Uninformed	4.19	13.62		
Male	74.52	67.15	77.79	77.73
Female	21.18	19.23	22.21	22.27

Education	Taker	Non-taker	Taker	Non-taker
Uninformed	40.32	63.07		
No education	0.03	0.01	0.05	0.02
Primary	0.14	0.25	0.23	0.66
Secondary	21.34	15.44	35.75	41.82
Post-secondary/Tertiary	38.17	21.23	63.96	57.49

Source: Authors.

Table A2 Personality test questions used in the first pilot test

1	Are you talkative?
2	When doing a task, are you very careful?
3	Do you come up with ideas other people haven't thought of before?
4	Do you like to share your thoughts and opinions with other people, even if you don't know them very well?
5	Do you get very upset in stressful situations?
6	Do you finish whatever you begin?
7	Do people take advantage of you?
8	Do you work very hard? For example, do you keep working when others stop to take a break?
9	Do you forgive other people easily?
10	Do you tend to worry?
11	Are you very interested in learning new things?
12	Do you prefer relaxation more than hard work?
13	Do you enjoy working on things that take a very long time (at least several months) to complete?
14	Do you enjoy beautiful things, like nature, art and music?
15	Do you think about how the things you do will affect you in the future?
16	Are you very polite to other people?
17	Do you work very well and quickly?
18	Do you get nervous easily?
19	Are you generous to other people with your time or money?
20	Are you outgoing and sociable, for example, do you make friends very easily?
21	Do you think carefully before you make an important decision?
22	Are people mean/not nice to you?
23	Do you ask for help when you don’t understand something?
24	Do you think about how the things you will do will affect others?

Personality test questions (Big Five Inventory-11) used in the randomized control trial

1	Is reserved
2	Is generally trusting
3	Tends to be lazy
4	Is relaxed, handles stress well
5	Has few artistic interests
6	Is outgoing, sociable
7	Tends to find fault with others
8	Does a thorough job
9	Gets nervous easily
10	Has an active imagination
11	Is considerate and kind to almost everyone