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April 2017

Working Paper No. 1006

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April 2017

Abstract

Do matching frictions affect youth employment in developing countries? We organise job fairs in Addis Ababa, to match firms with a representative sample of young, educated job-seekers. We create very few jobs: one for approximately 10 firms that attended. We explore reasons for this, and find significant evidence for mismatched expectations: about wages, about firms requirements and about the average quality of job-seekers. We find evidence of learning and updating of beliefs in the aftermath of the fair. This changes behaviour: both workers and firms invest more in formal job search after the fairs.

JEL codes: O18, J22, J24 , J61, J64.

Key words: *Matching, labour, job-search, firms, recruitment, experiment.*

*We thank audiences at the CSAE Conference 2017, SERC Work in Progress Seminar, SEEDEC Conference 2017, RES Annual Conference 2017 and NEUDC 2016; in particular Prithwiraj Choudhury and Pieter Serneels who provided helpful comments and feedback. We thank Jali Bekele, Biruk Tekle, Marc Witte, Alemayehu Woldu and Ibrahim Worku for outstanding research assistance. Data collection and experimental implementation were funded by The World Bank Research Support Budget (RSB), GLM — LIC, and by the International Growth Centre. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent. The project would not have been possible without the constant support of Rose Page and the Centre for the Study of African Economies (University of Oxford), nor without the support of the Ethiopian Development Research Institute in Addis Ababa. This RCT was registered in the American Economic Association Registry for randomized control trials under Trial number AEARCTR-0000911.

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1 A matching experiment

High youth unemployment is a major challenge for countries all over the world. Active labour market policies have attempted to help young people to move into work, but with limited success. Training programmes, in particular, have been found to have low returns in developing countries (McKenzie, 2017). Job search assistance programs have shown more promising results in terms of the cost effectiveness of getting young people into work (Franklin, 2015; Abebe et al., 2016). Yet getting workers into their first job might not be the ultimate solution to frictions in the labour market. Informational problems may prevent young people from finding out what work suits them, including having unrealistic expectations about what kind of work they could reasonably find (Groh et al., 2015; Blattman and Dercon, 2016); similarly, frictions may prevent firms and workers from making matches that workers are happy to keep. Workers thus may spend many years moving in and out of jobs, figuring out what sort of work suits then and the wages they can reasonably expect to earn.

What role can policy play to help young people and firms to find good matches? This paper tests whether a key friction in the labour market is simply a lack of contact between firms and workers — who may, respectively, be struggling to assess the relative merit of a particular worker, and struggling to assess the value of working at a particular firm. By allowing both sides of the market to meet, we test whether reducing these frictions allows workers and firms to find better matches in the labour market. To do this, we randomly invite 250 firms and 1000 unemployed job seekers to two job fairs in the centre of Addis Ababa. The firms were some of largest firms in the city, across all of the main sectors, and almost all of them were actively looking to hire new staff at the time of the fairs. The job-seekers, on the other hand, were all young and looking for work, and had different education levels and diverse backgrounds. Firms and workers met for a day, and suggested matches were made to facilitate meetings. At one of the two job fairs the job seekers attending were randomly selected to receive a certification intervention. We randomise invitations both for firms and workers.

The fairs are a new method of recruitment in this market.[1] The usual method of job search and recruitment centres around centrally located job vacancy boards, where firms post vacancies. Workers visit these boards, apply selectively, and firms assess workers on the basis of their CVs. This process is subject to high search costs for workers, and information asymmetries, because of the limited information contained in CVs (Abebe et al., 2016). The fairs were designed to cut down the costs involved in this process by bringing workers and jobs together directly, thus lowering the costs of finding a good match. At the fairs, both workers and firms have the opportunity to assess a large number of candidates at the same time, and

[1] Fairs have been used in this context by very large firms (such as large multi-national firms), but their use is not widespread.

draw inference about the distribution of job and worker quality, respectively. They are able to have meetings, make applications, and conduct interviews with zero effective marginal cost.

We find that the fairs generate a rich set of interactions between workers and firms. We estimate that 75% of workers at the fairs had an interview or in-depth discussion with a recruiter.[2] Among those who had meetings with firms, 11% report meeting with at least one firm after the job fair for a more formal interview. In total, the fairs lead to 105 job interviews. However, these meetings and interviews lead to only fourteen accepted jobs.[3] We therefore find no average impact of the job fairs on job seekers' main employment outcomes at endline. Similarly, we find no impact on firms' hiring outcomes in the last year, nor on the types of workers they hired.

Why did the fairs not create more jobs? We reject that the firms at the fair were not interested in looking for candidates. Most firms did hire many candidates outside of the job fairs, and firms typically spend a great deal of time and money on recruitment, receiving many formal applications. Similarly, job seekers search hard for employment, both at the fairs and elsewhere. Since our sample of job seekers was drawn in a representative way from the population of young, educated unemployed people in this labour market, and we find no evidence of negative selection into attendance, we do not think that firms just met an unusually weak entry level candidates.

Instead, firms are reluctant to hire entry-level workers who were present at the fairs for high-skill, professional positions — preferring to firm their recruits among employed workers at other firms, with formal work experience. Firms were disappointed with the quality of the applicants they met at the fairs: they reported that they were, on average, less employable than the applicants they usually see by direct applications. By comparison, firms *were* interested in hiring attendees with no tertiary education for low-skill positions: we find that firms made 55 job offers to low skilled workers, of which fewer than 15% were accepted. It seems that low skilled workers had unrealistically high expectations of the wages they could earn in these positions.

What do firms and workers learn from this (disappointing) experience at the job fairs? We find clear evidence that both firms and workers redouble efforts to search for work through formal channels after the fairs. Firms increase their advertising and recruitment at the main job vacancy boards. Workers increase their job search at those boards. For the workers, these effects are concentrated among low-type workers with low predicted probability of finding a good job. They also adjust downwards their reservation wages to more realistic levels. This

[2] Roughly 60% of invited workers came to the fairs.
[3] This is confirmed in the reports of both workers and firms.

combination of increased job search and more realistic expectations leads to considerably improved employment outcomes for low-type workers. By contrast, the fairs seem to be a discouraging experience for higher type workers, who learnt that firms have high experience requirements for formal jobs. They do not adjust their reservation wages, and in fact lower their aspirations. They are less likely to have good jobs at endline, and more likely to have switched to self-employment.

This is the first experiment, to our knowledge, to try to study the effects of labour market matching programs on both workers and firms. A growing but relatively new literature looks at the effects of labour market interventions that aim to reduce information asymmetries on job search outcomes. The closest study to ours is Beam (2016), where workers are encouraged to attend a job fair in the Philippines geared towards placing workers in overseas jobs. The paper focusses on a remote rural sample of workers who were not necessarily actively looking for jobs in an urban labour market, and finds that the job fairs changed people's perceptions of the labour market and encouraged job search in big cities (but had no effect on the probability of working overseas). Similarly Jensen (2012) finds that remote rural dwellers increase their employment when they are given information about available vacancies at nearby towns (see also Bassi and Nansamba (2017)).

Instead, we focus on a sample of active job-seekers who already know the labour market well. Our design is not intended to introduce workers to a new labour market or to motivate them to start looking for work. Rather, we aim to look at how lower barriers to talking to formal firms can improve workers' chances of getting jobs, and update their information about the jobs they are already looking to get. Similar work focussing on information frictions in large labour market includes Groh et al. (2015), who try to match workers and firm on the basis of observable characteristics. They are unable to get workers to take up offers for jobs and interviews, who seem to opt to remain unemployed to look for better work. Pallais (2014) shows how providing information about workers' abilities, which they can credibly communicate to hiring firms, can improve their prospects in an online labour market.[4] Finally, Abebe et al. (2016) conduct two parallel field experiments on how to get job seekers into jobs. They find that improving job-seekers' ability to engage in directed search through the existing channels increases their probability of finding a good job. In the second experiment, they find that improving job-seekers' applications — with a certification programme based on detailed testing — also improves employment outcomes, by making job search more effective. We extend this literature not only by testing job fairs as a new kind of intervention to reduce information frictions, but also by studying both sides of the market. We collect data on the recruitment decisions of firms where our job seekers looked for work, and we estimate the

[4] See also Horton (2017), who shows that algorithmic recommendations can increase hiring in the same online market. Stanton and Thomas (2015) shows that intermediaries in online markets can help workers and firms to overcome information asymmetries.

impact of the job fairs on the firms by randomly providing invitations to some of the firms.

While a literature from developing countries suggests that job-placement services have large short-run effects on employment outcomes (Card et al., 2010), other work has shown that these effects could be displacing other workers (Crépon et al., 2013).[5] A key research question is whether improved matching through any interventions of this kind can improve firms' ability to hire good workers; whether this is possible or not has important implications for whether such interventions can have an impact on the total number of jobs available, or whether the positive effects of all such programs are likely to be displaced elsewhere.[6]

We contribute to a literature on how biased beliefs can lead to sub-optimal job search and employment decisions (Spinnewijn, 2015). DellaVigna et al. (2016) and Krueger and Mueller (2016) show that recent income levels can cause the unemployed to anchor their reservation wages at levels that are too high. Our results suggest that the unemployed set their reservation wages too high because of unrealistic expectations of wages in big formal firms, which seems to stem specifically from a lack of contact with those firms.[7] Our results is the first evidence, to our knowledge, that formal employment rates can be increased through interventions that bring reservation wages down to more realistic levels.[8]

There is almost no experimental work focussing on firm recruitment.[9] While a growing literature uses field experiments with firms to test for binding constraints to growth faced by those firms (Bandiera et al., 2011), relatively little attention has been paid to how firms may be constrained by their inability to find the right workers to hire.[10] A large literature looks at how firm human resource management can improve firm performance Bloom and Van Reenen (2011). In a developing country context (Bloom et al., 2010) show that improved human resource management practices, which include, for instance, performance-based incentive systems for workers, can improve firm productivity. There is relatively little work on

[5] Other studies looking at the partial equilibrium effects of job search assistance programs include Altmann et al. (2015), Dammert et al. (2015), and Graversen and Van Ours (2008).

[6] Hardy and McCasland (2015) show that very small firms seem to be labour constrained: the introduction of improved screening mechanisms improves revenues and profits. A long literature suggests that job referrals can be used by information constrained firms to learn about work ability; see for example, Pallais and Sands (2016) and Heath (2016).

[7] By constrast, evidence from South Africa suggests that reservation wages are not out line of available wages, and thus are not a contributor to the unemployment problem (Nattrass and Walker, 2005).

[8] Groh et al. (2015) suggest that young people choose unemployment due to preferences over non-wage benefits. By contrast, workers in our sample do not reject offers to remain unemployed. They seem to increase their search effort, and indeed find jobs shortly after the fairs in other positions.

[9] One notable exception is Hoffman et al. (2015), who show that firms can improve the quality of workers hired by limiting managerial discretion in hiring and relying more directly in standardized test results. In another experiment related to ours Hardy and McCasland (2015) study the use of an apprentice placement system, which they argue can be used as a novel screening mechanisms for firms.

[10] Work on audit studies (Bertrand and Mullainathan, 2004) suggest that firms face time constraints that in some cases lead them to make sub-optimal hiring decisions based on statistical discrimination.

recruitment and hiring as a tool of human resource management.[11] We contribute to this literature by studying how firms recruit, in a developing country, and by looking at how they respond to an opportunity to recruit in a completely new way.

2 Data

2.1 Surveys of job seekers

We run the job fairs study with a representative sample of young unemployed people in Addis Ababa. To draw this sample, we first defined geographic clusters using the Ethiopian Central Statistical Agency (CSA) enumeration areas.[12] Our sampling frame excluded clusters within 2.5 km of the centre of Addis Ababa, and clusters outside the city boundaries. Clusters were selected at random from our sampling frame, with the condition that directly adjacent clusters could not be selected, to minimise potential spill-over effects across clusters.

In each selected cluster, we used door-to-door sampling to construct a list of all individuals in the cluster who: (i) were 18 or older, but younger than 30; (ii) had completed high school; (iii) were available to start working in the next three months; and (iv) were not currently working in a permanent job or enrolled in full time education. We randomly sampled individuals from this list to be included in the study. Our lists included individuals with different levels of education. We sampled with higher frequency from the groups with higher education. This ensured that individuals with vocational training and university degrees are well represented in the study. All selected individuals were contacted for an interview.

We completed baseline interviews with 4388 eligible respondents. We attempted to contact individuals by phone for at least a month (three months, on average); we dropped individuals who could not be reached after at least three attempted calls. We also dropped any individual who had found a permanent job and who retained the job for at least six weeks. Finally, we dropped individuals who had migrated away from Addis Ababa during the phone survey. In all we were left with 4059 individuals who were are included in our experimental study.

We collected data on study participants through both face-to-face and phone interviews. We completed baseline face-to-face interviews between May and July 2014 and endline inter-

[11] Oyer and Schaefer (2010) review the literature on hiring, writing, "The literature has been less successful at explaining how firms can find the right employees in the first place. Economists understand the broad economic forces–matching with costly search and bilateral asymmetric information–that firms face in trying to hire. But the main models in this area treat firms as simple black-box production functions. Less work has been done to understand how different firms approach the hiring problem, what determines the firm-level heterogeneity in hiring strategies, and whether these patterns conform to theory."

[12] CSA defines enumeration areas as small, non-overlapping geographical areas. In urban areas, these typically consist of 150 to 200 housing units.

views between June and August 2015. We collected information about the socio-demographic characteristics of study participants, their education, work history, finances and their expectations and attitudes. We also include a module to study social networks. We call all study participants through the duration of the study. In these interviews we administer a short questionnaire focused on job search and employment.[13]

We have low attrition; in the endline survey, we find 93.5% of all job-seekers. We cannot reject the null hypothesis that there are no differences in attrition rates between treatment and control individuals when we study each treatment individually, or when we run a joint test for all treatments. A number of covariates predict attrition. Since neither these variables are correlated with treatment, we are not worried that this is affecting our results. Table A.7 in the Online Appendix presents the analysis of attrition. Attrition in the phone survey is also low; for example, we still contact 90% of respondents in the final month. Figure A.1 in the Online Appendix shows the trajectory of monthly attrition rates over the course of the phone survey.[14]

2.2 Surveys of firms

We surveyed 498 large firms in Addis Ababa. We sampled these firms to be representative of the largest employers in the city, stratified by sector. We included all major sectors in the economy, including construction, manufacturing, banking and financial services, hotels and hospitality, and other professional services. To sample firms, we constructed a list of the largest 2,178 firms in Addis Ababa. Since no firm census exists for Ethiopia, we formed our own firm sample using a variety of data sources. In all, we gathered data from more than eight different sources; many came from government-maintained lists of formal firms, from each ministry for the respective sector covered by that ministry. For the manufacturing sector we used a representative sample of the largest firms from the Large and Medium Enterprise surveys, conducted by the Central Statistics Agency (CSA). Where firm size was available for the various sources, we imposed a minimum size cut-off off of 40 workers. In other cases we requested lists of the largest firms in each sector.

We drew the firms in our sample using sector-level weights that reflect the number of employers in that sector in the city. We constructed these weights using representative labour force

[13] Franklin (2015) shows that high-frequency phone surveys of this type do not generate Hawthorne effects — for example, they do not affect job-seekers' responses during the endline interview.

[14] We do not report attrition rates at the very beginning of the phone survey since many respondents were only contacted for the first time in months 2 and 3 of the phone survey, either because they were surveyed towards the end of the baseline survey, and because of lags in setting up the phone survey.

data.[15] The firms are, on average, very large by Ethiopian and African standards. The mean number of employees per firm is 171.5 workers, but this masks considerable heterogeneity, particularly in the 'Tours & Hospitality' sector, which is dominated by relatively small hotels and restaurants. Average firm size, when this sector is excluded, is 326 workers per firm. These firms size numbers are given in Table 1 below. Note that these numbers exclude casual daily labourers: on average, firms report employing 34 casual labourers per day.

< Table 1 here. >

The firms in our sample are growing in size and looking to hire new workers. At the median, the number of workers that firms expected to hire in the next 12 months amounts to 12% of their current workforce. The median rate of hiring was highest (16%) among service sector firms, which were also the most likely to come to the job fairs. The most common types of workers which firms expected to hire were white collar workers, usually requiring university degrees. These results are shown in Table A.2 in the Online Appendix.

2.3 Randomisation of job-seekers

We assign treatment at the level of geographic cluster, after blocking on cluster characteristics (see Abebe et al. (2016) for further details). Our sample is balanced across all treatment and control groups, and across a wide range of outcomes (including outcomes that were not used in the randomisation procedure). We present extensive balance tests in Table . For each baseline outcome of interest, we report the p-values for a test of the null hypothesis that all experimental groups are balanced. We cannot reject this null for any of variables that we study.

2.4 Randomisation of firms

We assigned firms to either a treatment group or a control group using block level randomization techniques suggested by Bruhn and McKenzie (2009). Firms in the treatment group were invited to attend the job fairs, while firms in the control group did not receive an invitation. The following method was used to group firms together: firstly, firms were partitioned by five main groups of industry (defined in Table A.4, in the Online Appendix). Then firms were partitioned into nearest neighbour groups of four firms on the basis of Mahalanobis

[15] Table A.4 in the Online Appendix shows the number of firms surveyed in our sample, divided into five main categories. Column (2) provides weighted percentages obtained by applying the inverse of the weights used to sample the firms. For instance we surveyed NGOs ("Education, Health, Aid") relatively infrequently because of the large number of NGOs in the data.

distance defined over the set of baseline variables.[16] After that we randomized the firms into two groups in each block of four firms: two firms were invited to the job fairs, one firm on each of the days, at random. The other two firms in the group were assigned to the control group, who were not to be invited to the fairs.

Additionally, we assigned treatment using a re-randomisation method. Following the recommendations of Bruhn and McKenzie (2009), we will control in our estimations for the baseline covariates used for re-randomisation (that is, the set of variables described in Table 2) and for the baseline covariates used to construct the randomisation blocks.[17]

< Table 2 here. >

With this sample we have 78% power to detect a small treatment effect on the total number of pay-roll employees (that is, only 0.2 standard deviations), using a significance level of 0.05%.

3 Design and Implementation

3.1 The job fairs

We invited treated job-seekers and treated firms to attend two job fairs. The first fair took place on October 25 and 26, 2014. The second fair took place on 14 and 15 February, 2015. We ran two fairs to ensure that each job-seeker and firm would have the chance to participate in at least one of them. The job fairs were held at the Addis Ababa University campus, a central and well-known location in the capital city. To minimise congestion, each job fair lasted two days and only half of the firms and job-seekers were invited to attend on each day. The firms that were invited to attend on Saturday 25th (Sunday 26th) of October were then invited to attend on Sunday 15th (Saturday 14th) of February. On the other hand, job-seekers invited to attend on the Saturday (Sunday) of the first fair were also invited to attend on the Saturday (Sunday) of the second fair. This ensured that, in each job fair, job-seekers were exposed to a different pool of firms and firms were exposed to a different pool of job-seekers.

At the beginning of both fairs, we gave job-seekers (i) a list of all firms invited to the fair and (ii) a list of recommended meetings. We created these recommended meetings using information on firms' vacancies obtained from the phone survey which we ran shortly before the fairs (see the data section). After creating a ranking of workers for each vacancy and

[16] These are listed in Table A.5 in the Online Appendix.

[17] Details of these variables and how they are defined are contained in our detailed pre-analysis plan.

a ranking of vacancies for each worker, a matching algorithm matched workers and firms; we discuss this shortly. In the second fair, we introduced two further elements. First, we gave job-seekers the list of all vacancies, on top of the list of firms. Second, we gave firms a list of all job-seekers invited to the fairs, with some information about their educational qualifications and previous work experience. We asked firms to indicate up to 10 job-seekers whom they would like to talk to at the job fair. These 'requested meetings' were posted on a small board a few hours after the beginning of the fair. We plan to do in-depth analysis using data on recommended and requested meetings in future drafts of the paper.

During each fair, workers and firms were free to interact as they preferred. Each firm set up a stall before the job seekers arrived. These stalls were typically staffed by the firm's HR team, who brought with them printed material advertising the firms. In a typical interaction, a job-seeker would approach the stall of a firm and ask questions about the firm and its vacancies. The firm's HR staff would then often also ask about the job-seeker's skills and experience and check his or her CV. If the job-seeker looked suitable for one of the vacancies, the firm would then invite her or him to attend a formal job interview a few days after the job fair.

We did not restrict the invitation to the fair to unemployed job-seekers or to firms that had open vacancies. However, only about 8% of job-seekers had permanent jobs by the time of the first job fair, and thus most job-seekers were still searching for work. Similarly, most firms were hiring during the period that the job fairs were held. 89% hired at least one worker in the year of the experiment. On average firms hired 52 workers in the year and 4 workers in the month after the job fairs.

In total, we invited 1,007 job-seekers and 248 firms to attend fairs. Both job-seekers and firms were contacted over the phone, were given some information about the nature of the fairs and had the opportunity to ask questions. 606 job-seekers attended at least one fair: a 60% take-up rate. The most common reason that job-seekers gave for not attending the fairs was that they were busy during that particular weekend. This reason was given by 226 job-seekers in the first fair and 229 job-seekers in the second fair. Other reasons included not being able to take up a job at that time (83 respondents for the second fair, but only nine respondents for the first fair) and finding that the fair venue was too difficult to reach (31 respondents for the first fair and 25 respondents for the second fair). We find that very few baseline characteristics predict this attendance. This reassures us that our results are not driven by negative selection of workers into attendance. In fact the two variables that do predict attendance positively are search effort at baseline, and the use of certificates for job search at baseline: it seems that workers who attended the fairs are the more active, organized, jobs seekers. Those who attended are more likely to have a university degree or diploma, though the effect is not significant.

Similarly, 170 firms attended at least one job fair: a take-up rate of 68.5%. Of the firms that did not attend the fairs, 12% reported that this was because they did not have vacancies at the time. The remaining firms often cited reasons related to logistics and previous commitments. 13 firms reported that they thought they would not find the job fairs useful.

3.2 The matching algorithm

We provided each job-seeker with a personalised list of 15 firms that we suggested he or she should talk to during the job fair; each firm received a symmetric personalised list, showing the names of all those job-seekers who had been recommended to meet that firm. We formed the list of 15 firms in two distinct ways. First, we used a Gale-Shapley Deferred Acceptance algorithm to recommend 10 of the matches (Gale and Shapley, 1962). Second, we augmented this list by randomly selecting five additional matches. We randomised the order in which the 15 matches were presented.

In this context, the matching algorithm was applied as a computational tool to suggest sensible matches, given baseline characteristics on both job-seekers and firms. To this end, we constructed stylised synthetic rankings of vacant positions (for each job-seeker), and of job-seekers (for each firm). We constructed firm rankings of job-seekers using lexicographic preferences over (i) whether the job-seeker's occupation matched that of the vacancy, then (ii) job-seekers' educational qualifications, and then (iii) the job-seekers' number of years in wage employment. We constructed job-seeker rankings of vacancies using a simple ranking over the advertised wage (that is, we applied identical rankings for each job-seeker). Of course, these rankings were not intended literally to represent the true preferences of participants; rather, they were intended to provide a simple method of purposive matching given a heterogeneous set of vacancies and job-seeker skills. With these rankings in hand, we then looped 10 times over the Gale-Shapley Algorithm; for each iteration of the loop, we formed a stable assignment, subject to the constraint that we not match any firm and job-seeker who had been matched in any earlier iteration.

Figure 1 illustrates the output of the ranking algorithm. Each point represents a match recommended by the algorithm; the graph shows which combinations of firm rankings and job-seeker rankings generated these recommended matches. The graph illustrates that the algorithm worked well — in the sense of generally generating matches between firms and job-seekers who were, at least on the basis of job-seeker skills and experience, reasonably suitable for each other. Note the substantial mass at the bottom-left of the graph; this shows that, at least for those firms paying reasonably well, the algorithm recommended matches of suitable occupational fit. (For example, for firms in the top 100 of job-seekers' rankings, the median match was to a job-seeker with a firm ranking of just 14.)

< Figure 1 here. >

4 Results: Average Effects

4.1 Impact on firms

In this section, we analyse the impact of the job fairs on our sample of firms; this follows our pre-analysis plan.[18] We divide outcomes into families. For each outcome of interest we use an ITT approach with an ANCOVA specification; we also include the set of covariates used for the randomisation. We use robust standard errors.[19] Specifically, we estimate:

$$y_i = \beta_0 + \beta_1 \cdot \texttt{fairs}_i + \alpha \cdot y_{i,pre} + \boldsymbol{\delta} \cdot \boldsymbol{x}_{i0} + \mu_i \tag{1}$$

In this specification, the 'balance' variables included in $\boldsymbol{x}_{i0}$ are all the variables listed in Table 2. Variable $y_{ic,pre}$ is the dependent variable measured at baseline. Throughout this analysis we distinguish between professional workers and non-professional workers. 'Professional workers' refers to traditional notions of 'white-collar employees': typically those with some degree or diploma, working in relatively highly-trained positions. For manufacturing firms, 'non-professional workers' refers mostly to labourers or 'production' workers; for service-based firms, these include mostly 'client services' (tellers, waiters, receptionists, *etc.*) The main results on firm outcomes are presented in Tables 3, 4, 10, and 5; in each table, we show each regression as a row, in which we report the estimated ITT ($\hat{\beta}_1$), the mean of the control group, and the number of observations. In each case, we report both p-values and False Discovery Rate q-values, taken across the family of outcomes (Benjamini et al., 2006).

First, in Table 3, we test whether the fairs had an impact on firms' recruitment processes, as measured by firms' ability to fill vacancies. We find no impact on these outcomes, nor on how long it took fill positions that were made available, nor on firms' reported costs of recruitment. We do find a small but significant positive impact of the fairs on unfilled vacancies. That is, firms reported having more vacancies that they were unable to fill during the year. (However, this effect becomes marginally insignificant after we apply multiple hypothesis testing corrections.)

< Table 3 here. >

In Table 4, we then look at the impact of the job fairs on firm hiring outcomes at the main endline survey, which took place about six months after the second job fair. We find that

[18] This is available at https://www.socialscienceregistry.org/trials/1495.

[19] We do not cluster our errors since randomisation was conducted at the firm level.

no significant impact on the number of people hired by the firms in the last 12 months, nor on the types of people hired by the firms, whether it be hiring of candidates with degrees, or hiring more candidates on permanent contracts. This suggests that the job fairs did not significantly change how, and whom, firms hired, over the 12 month period.

< Table 4 here. >

Unsurprisingly, therefore, we find no impact of the firms overall work-force composition (Table 5). We asked firms about their entire current workforce (not just workers hired in the last few months). We find no impacts on the types of contracts held by different workers, their starting salaries, or the firms assessment of how well qualified their workers are, on average.

< Table 5 here. >

4.2 Impact on job seekers

We use the same specification as equation 1 to analyse the ITT for job-seekers; we report results in Tables 6, A.1 and 7. These tables show regressions of key employment and search outcomes at an endline survey conducted four months after the second job fair. We cluster errors at the level of the enumeration area in which respondents live, to correct for the fact that the treatments were randomized at the level of the enumeration area. As in our earlier results, we report both conventional p-values and False Discovery Rate q-values.

We find no average effect on either endline employment outcomes or search methods. This is hardly surprising, in light of our results on firms. Table 6 reports effects on employment outcomes. The effect on key job quality outcomes such as 'formal' work or 'permanent' work are positive, but not significant. (These estimates are very much in line with the results suggesting that about 14 job seekers found jobs at the large formal firms at the job fairs, which would not doubt have been formal and permanent contracts; this effect would register as a 1.5 percentage point increase in the probability of having such a job.) We find that the fairs have no impacts on the types of jobs held by workers either.[20]

< Table 6 here. >

Table 7, we consider average effects on search methods. We find that treated individuals were more likely to have found jobs by interview. Similarly, we find that treated respondents

[20] These results can be found in Table A.1 in the online appendix, which reports effects on employment amenities.

were more successful in converting job applications into interviews, and then into offers, when applying for permanent jobs. However, each of these three results are only marginal significant, and not robust to our multiple hypothesis correction.

< Table 7 here. >

5 Why did we not create more hires?

Why did our fairs not generate more hires, and what can we learn from this about matching in this labour market? We explore two main types of explanations for our results: first, that the fairs didn't generate enough interaction between workers and firms to allow for hiring to happen (suggesting that fairs are not an appropriate mechanism for screening workers, or that they were badly executed events in our case), and second, we look at whether there simply were not good matches available at the fairs.

5.1 Did the fairs provide enough scope for interaction?

We find that 454 job-seekers (75% of those attending) interacted with at least one firm at the job fair, according to job-seekers' reports. Of these, 69 job-seekers (11%) were then formally interviewed after the job fairs. The same job-seeker would typically contact multiple firms and would sometimes be interviewed by more than one firm. In total, we record 2191 contacts between firms and workers and 105 interviews. Finally, we find that 76 job offers were made at the fairs (to 45 job seekers); in total, 14 job-seekers (2%) were hired. Overall, the job-seekers who attended a fair secured one interview every 21 informal inquires with the firms, one job offer every 1.4 interview and one job every 6.2 interviews approximately. Between our baseline and endline interview, on the other hand, job-seekers in our sample obtained an interview every 3.5 job applications, an offer every 1.9 interviews, and a job every 3.3 interviews. From these numbers, two conclusions emerge. First, there was rich interaction between firms and job-seekers at the fairs. Second, this interaction lead to surprisingly few good matches. In this section, we combine data from job-seekers and from firms to explore this second finding.

We begin by exploring whether the more suitable worker-firm pairs attending the fair — according to the rankings we created and the matching algorithm we ran — were likely to meet. We interpret this as a basic descriptive test of coordination: *do participants' rankings predict meetings?* And, following this, *do participants' synthetic rankings also predict meetings?* To test this, we estimate the following dyadic regression models:

$$\texttt{meet}_{fw} = \beta_0 + \beta_1 \cdot \texttt{Rank}_{fw} + \beta_2 \cdot \texttt{Rank}_{wf} + \mu_{fw} \tag{2}$$

$$\texttt{meet}_{fw} = \beta_0 + \beta_1 \cdot \texttt{Gale\_Shapley}_{fw} + \beta_2 \cdot \texttt{Random}_{fw} + \mu_{fw}. \tag{3}$$

Depending on the regression, $\texttt{meet}_{fw}$ is a dummy capturing either whether firm f requested a meeting with worker w, or whether firm f and worker w had an actual meeting. We use a two-way cluster, clustering standard errors both at the level of the firm and at the level of the worker (Cameron et al., 2011). We report model estimates in Table 8 below, which we obtain using the sample of workers and firms who attended the fairs. We find that both rankings and algorithmic recommendations are predictive of both requested and actual meetings. The effects are large and significant. Moving from the highest to the lowest rank is associated with an almost 100 percent decrease in the probability of a requested meeting, and about a halving of the probability of an actual meeting. Further matches suggested by the algorithm are about 200 percent more likely to happen than matches that were not suggested to workers. On the other hand, the coefficient on randomly suggested matches is much smaller and is never significant. In one specification we can reject that the two coefficients are equal at the 5 percent level. In the other specifications, the F-test is on the margin of significance. We interpret these figures as suggesting that suitable worker-firm pairs were likely to meet at the job fairs. This rules out that market design issues such as congestion and miscoordination prevented suitable pairs from meeting each other during the job fairs.

< Table 8 here. >

5.2 Were there not enough good matches available at the fairs?

Prior to arriving at the fairs, firms were surveyed to ask about their current vacancies: a roster of different positions for which, at the time, they were looking to hire. On average, we find that each firm was looking to hire for two different occupations, and had a total of seven vacancies available. Only 30% of reporting firms told us that they had no vacancies at all. In total, going into the fair, firms were hiring for 711 different vacancies, and looking to hire a total of 1751 workers. The occupational composition of the vacancies available at the firms exhibits considerable overlap with the occupation composition of the job seekers invited to the job fairs. Therefore, we can rule out that the firms did not have sufficient vacancies. We can also rule out that firms did not interact sufficiently with workers. On average, each firm reports meeting 20 job-seekers through the job fairs that they attended. In the second job fair, we asked firms — based on list of job-seekers' qualifications — whether there were individuals whom they were interested in interviewing. Most responded positively, by listing names of several candidates who were of interest to them.

We would only see hires if the expected returns to hiring someone with a signal observed at the fair was higher than the expected quality of the best recruit made through the usual hiring channels. Indeed firms may have already received applications for the positions that they had open at the time of the fairs. If we assume that the job fairs did work for firms as a low cost route to get a more accurate signal of worker ability, then firms must assess the quality of a candidate for whom they have a very tight signal of ability against a range of anonymous CVs received as applications. If the workers at the fairs simply were not very employable, it would be unlikely that firms would be likely to invite them for interviews. If they were invited to the interview stage, they would only be hired if they were indeed stronger candidates than all other interviewees.

Were the workers who attended the fairs negatively selected from our sample of workers? Only about 60% of workers came to the fairs: if only those with very low education, motivation and prospects of employment arrived, it is perhaps not surprising that they didn't get hired. In Table A.3 we regress job-seekers' attendance at the fairs on a rich set of baseline characteristics; we find no evidence that observably weaker candidates attended. In fact, the only two outcomes that robustly predict attendance were related to search motivation: those who were searching the most at baseline, and who were using formal certificates to search were mostly likely to attend. Education, gender, and even employment do not predict attendance. We do find that invited youth who were already working at permanent jobs at the time of the fairs were slightly less likely to attend, but the effect is unlikely to be driving our results: 4% of attendants at the fairs had permanent jobs, relative to only 5.6% of the total sample.

5.2.1 Education and experience mismatch?

Given our random sampling strategy, the job seekers in attendance could thus be said to be representative of the population of young, educated job-seekers. Perhaps large firms simply do not hire from this population? In other words, could it be that young people who struggle to find a job immediately out of education will never be able to find work at a formal firm, and thus any hopes of active labour market policies to get young people into work are doomed to fail?

We certainly *do* find that firms prefer to hire from a population that is it different to the one at the fairs. Most importantly, firms place a high premium on work experience. In the phone questionnaire after the second job fair, we asked firms to rate the most employable job-seekers they met at the job fair, compared to the candidates whom the firm would have selected for interviews through its normal recruitment channels. Only 12 percent of firms report that the most employable job-seeker at the fair would be in the top 20 percent of candidates in their usual recruitment round. 54 percent of firms, on the other hand, report that the most employable job-seeker at the fair would be in the *bottom* 50 percent of candidates in their usual recruitment. This is is consistent with the fact that the most common reasons firms reported for not hiring more job-seekers at the fairs are 'insufficient work experience' (34% of firms) and 'wrong educational qualifications' (23%). On the other side of the market, even workers themselves report that they did not have the required experience for the firms present at the job fairs. Many reported that firms 'asked for experience', which few of them have in the formal sector. More than 65% reported that the main problem with the fairs was that there weren't enough jobs for which they were qualified.

However, we also find evidence that firms *do* hire entry level workers without previous normal experience. After the job fair, we interviewed all firms about the vacancies they were had open before the fairs and how successful they were at filling them. 424 firms hired 2018 workers in one month after the job fairs. We find that more than 30% of vacancies were filled with average experience of zero years. Because firms often hired many people at once to fill a particular vacancy, and because they hired more workers for vacancies not requiring experience, this translates into 65% of all hires made around the time of the fairs being filled with inexperienced workers. We compare these hiring patterns to the same firms' intentions when they posted these vacancies: only 13% of vacancies (or a total of 33% of workers the firm intended to hire) were meant to workers with no experience. This suggests that firms strongly prefer work experience, but are often forced to hire the best entry level candidate that the can, due to a lack of suitable candidates. Attendance at the job fair had no discernible effect on whether firms hired entry level candidates.

Finally, we note that our job-seekers were not mismatched in terms of education. A substantial proportion of our sample (31%) had not continued to post-secondary education. However, 55% of firm hires made after the fair, and 28% of all vacancies filled, were of job-seekers who had not finished high-school.

5.2.2 Mismatched expectations

It is not implausible, then, that firms might have hired the types of workers attending the fairs. However, there may have been other kinds of mismatch leading to a lack of hires at the fairs. In this section, we explore the related roles of expectations and reservation wages. In particular, we find that firms came to the fairs with the expectation that they would be hiring highly skilled professionals, for which higher education (degree or diploma) was essential. Hiring lower skilled workers for low wage jobs does not usually recruit considerable recruitment effort on the part of firms, so the fairs were seen as a chance to head-hunt the best candidates.

So why were our highly educated workers, with university degrees, not hired at the fairs? Firms report paying their new recruits with university degrees an average of 4500 Birr per month. This sum lies well above the reservation wages of university graduates at the fairs: this was 2500 Birr at the median, and only 10% of workers in our sample had reservation wages above the average paid for professionals at these firms. So it is unlikely that the workers were not interested in the high-skill positions available at the fairs.

Rather, a key constraint emerges: firms hiring for high-skilled professional position put a particular premium on work experience for these positions. In particular, only 22% of vacancies filled by workers with post-secondary education were filled by workers with no experience, compared to 52% of vacancies filled for high-school graduates (or below). Yet very few of the tertiary educated job seekers in our sample had any experience at all (only 20% had had any kind formal work experiences). Firms may have been unwilling to hire them because of the costs of training a worker with no experience, or to take the risk of hiring someone without a reference letter from a previous employee.

By contrast, however, lower-skilled workers may have had over-inflated expectations about the salaries they could aspire to in the market. We explore this possibility in Table 9. Workers without degrees in our sample report reservation wages with median 1400 Birr per month. Yet firms that hired individuals with no degree (or diploma) and no experience paid a median wage of only 855 Birr. It may be the case that any possible low-skilled vacancies that might have been filled at the fairs did not happen because the workers were unhappy with the wages they were offered. So, even though firms have been willing to hire entry level workers without experience, the workers did not take the offers because of unrealistic expectations. Recall that workers reported receiving quite a few job offers at the fairs, but only 33% of workers accepted at least one of those offers. Do the offers and rejections fit with this story of mismatched expectations across different levels of education? We find that a total of 76 offers were made to 45 different workers. Of those offers fully 55 were made to low skilled workers, with the remaining 21 going to those with diplomas or degrees. All offers made to low-skilled workers were to workers with no previous work experience. The low skilled workers accepted only 8 of those positions (14.5%) while higher skilled workers accepted 6 (28.5%).

< **Table 9 here.** >

It also seems that workers and firms had mismatched expectations: firms have may have overestimated the ease with which they could find experienced workers with tertiary education at the fairs; workers with degrees may have been impressed by the salaries on offer by the firms, but disappointed to find that the experience required to get those jobs was beyond their reach. Finally, while firms seem to have met low educated workers at the fairs and had an interest in hiring them, these firms were used to recruiting such workers very easily, and with low wages, on the open market. The job seekers at the fairs, though ambitious, may have been surprised to hear how little even these formal firms were offering for low skilled positions. In the next section we study how the experience of attended the fairs may have influence the expectations of both workers and firms, and thus may have altered their job search and recruitment behaviour.

6 Indirect effects and learning

The job fairs did not generate very many hires. But workers and firms came into the fairs with mismatched expectations about the types of matches they were likely to make. Did the fairs have some impact on their search and recruitment behaviour after the fairs?

To answer this question, we now explore changes in job-seekers' search behaviour and in firms' recruitment activities. We find clear evidence that both job-seekers and firms increased their efforts at search through formal channels. In particular, workers were more likely to visit the job boards during the weeks after the job fairs. Figure 2 below plots the fortnight-specific treatment effect of the job fairs, relative to fortnight 0 (when the first job fairs were held) and fortnight 8 (when the second job fair was held). These effects were estimated using weekly phone call surveys conducted with all job seekers in our sample, throughout the course of the study. We find significant effects — albeit short-lived — on the probability of visiting the job boards after each of the two fairs.

< Figure 2 here. >

In Table 10, we study the impacts on firms' recruitment activities outside of the job fairs. That is, we asked firms about their methods of advertising for vacant positions, and whether they conducted interviews with the applicants who applied. We find that firms invited to the job fairs were about six percentage points more likely in the last 12 months to have advertised for new hires (on a control mean of about 79%); they were 12 percentage points more likely to have advertised for professional positions (control mean: about 60%). They were also more likely to be using the job vacancy boards: the main place for attracting formal applications. All three results are significant, including after controlling for multiple hypothesis testing.

< Table 10 here. >

This suggests that the fairs increased beliefs about the returns to searching for jobs through the usual formal methods, for both workers and firms that attended. The discussion in the previous section suggests that these impacts on beliefs should differ between high- and low-skilled workers. Low-skilled workers came to the fairs with unrealistically high expectations of the wages they could earn if they were hired, while the high-skilled workers were over-optimistic about their chances of finding a job without a strong record of work previous work experience.

To pursue this analysis further, we look at how different workers were influenced differently by the fairs. First, we find that job seekers with worse employment prospects (lower education, and no previous work experience) are driving the overall effect on formal job search. We generate a single measure of labour market attachment, based on the predicted probability of finding a permanent or formal job at endline determined with a set of pre-specified baseline covariates, and using the 'leave-one-out' estimator developed by Abadie et al. (2013).[21] We find that the strongest predictors of permanent work at endline are education, use of certificates in applications, and previous work experience. While women and individuals living further from the city have lower labour market attachment on average, they are not significantly worse after controlling for education and experience.

In Figure 3, we look at the shape of treatment effects by baseline predictions of access to good work; we look separately at the number of visits to the job boards (Panel A) and at the probability of having permanent work in the past week (Panel B). In each case, we show point estimates and 90% confidence intervals for both treated and control job-seekers.

< Figure 3 here. >

We find that job seekers with low predicted baseline probability of finding a good formal job significantly increased their number of trips to the boards, with no similar effect for those with a high labour market attachment (indeed, if anything, higher types reduce their job search after the fairs, though the result is not significant). Further, in Panel B, we show that this increased job search lead to significantly higher probability of finding a permanent job for this low attachment group. Again, this increase in good employment is unlikely to have come through direct hiring at the job fairs, but rather though the channel of increased job search outside of the fairs. Interestingly, we also find suggestive evidence of negative impacts on permanent employment among those with higher predicted probability of good work.

To test more formally for heterogeneous effects, we split our sample in two, at the median of predicted probability of formal work, and study differences in the effect of the fairs in the

[21] The results are robust to predicting just permanent work, and to using a larger range of dependent variables, in addition to our core set of heterogeneity variables.

two groups. The results (in Figure 4) are stark: among the high-types, the fairs reduced substantially the probability of having wage employment, and the probabilities of having formal employment and permanent work — leading to a shift into self-employment. By contrast, the low-types experience an increase in formal and permanent work. They are also more likely to be working at larger firms. We find that overall the fair helped bring jobseekers connect to large firms. In particular, individuals invited to the job fair are a significant 4.2 points (15 percent) more likely to work in a firm with more than 10 employees. These effects are overwhelmingly concentrated among the low skilled workers. We confirm this result by looking at heterogeneous outcomes according to whether a job seeker only completed high school or went on to tertiary education. Figure A.2 in the Online Appendix confirms that high school (low-skilled) graduates experienced increases in formal work, while those with tertiary education were more likely to be in self-employment.

< **Figure 4 here.** >

What could explain these effects? Recall that wages paid for high-skilled work by firms at the fairs are much higher than reservation wages of workers, while wages page for low-skilled work were much lower. If high-type workers have unrealistic expectations about their ability to get high-paying formal jobs, they may have been unpleasantly surprised by the strict experience requirements imposed by firms at the fairs. Given that many of the firms at the fair were well-known brands in the local market, where they may have aspired to find work, this might have lead them to give up hope for finding a good formal job. In response, they were less likely to take wage employment, and shifted into the entrepreneurial sector. By contrast, the low-types may also have been impressed by the wages available in higher-skilled positions, but also realised that they were substantially over-estimating the wages available to them from formal firms for low skill work. This may have prompted a stark realisation: the high-skill professional jobs were much harder to get than they thought, while the the low-skilled jobs that they were offered paid very low wages. They may have adjusted their expectations downward. To test this, we test the effect of the job fairs on reservation wages. In Panel A Figure 5, we find that low skilled workers significantly reduce their reservation wages after the job fairs, while the higher type candidates did not. By contrast, higher type candidates did become less optimistic about their prospects for being offered wage work: Panel B of 5 shows an increase the numbers of weeks that expected to wait for a job offer.

< **Figure 5 here.** >

7 Conclusion

We run a job fair in Addis Ababa, Ethiopia, where we bring together unemployed job-seekers and firms looking to hire. We facilitate interactions between workers by suggesting matches based a Gale-Shapley algorithm — and by providing information about workers education and firms vacancies. We find that the workers who attended the fair were not very different from the types whom the firms usually hired, and that the fairs generated a rich set of interactions between workers and firms. However, only 14 workers were hired as a direct result of interactions at the job fairs. Firms invited to the fairs were not significantly more likely to hire; invited job-seekers were no more likely to find work.

The reasons for the failure of the job fairs to generate jobs provide several lessons about the working of labour markets. Two key problems arose. First, for high-skilled professional jobs, firms prefer to hire workers with more experience.[22] Therefore, more educated job seekers at the fairs received few offers at the fairs, and reported that they didn't have the required experience for this formal sector jobs. Second, for low-skilled vacancies, firms seemed willing to hire at the fairs, but lower-skilled workers received offers comfortably below their reservation wages; indeed, lower-skilled workers received many offers, but rejected most of them.

We find evidence of learning in the aftermath of the fairs. High-skilled workers seem to have realised that their lack of experience put most of these formal jobs beyond their reach. They were less optimistic about their chances of finding work in the future, and less likely to be engaged in formal employment, but more likely to be self-employment. Low-skilled workers seem to have revised down their reservation wages after the fairs, and also to have significantly increased their job search effort through formal methods. Four months after the job fairs, they are considerably more likely to have found a formal job. In short, we conclude that mismatched expectations — among both job-seekers and firms — can generate important labour market frictions.

[22] This is consistent with Terviö (2009), who shows that firms can often over-invest in hiring among workers with existing experience, instead of investing more in the recruitment of talented workers with less observable skills.

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Tables

Table 1: **Firm size by sector**

	Worker Type					Sample
Industry	Client services	Production	Support staff	White collar	All workers	Size
Construction, Mining, Farming	2.7	92.7	21.7	21.8	143.2	92
Tours-Hospitality	15.8	7.4	13.2	7.4	46.4	102
Finanace, Services, Retail	146.6	33.7	96.6	183.3	473.3	104
Education, Health, Aid	12.6	5.2	31.2	73.6	131.0	126
Manufacturing	24.4	149.0	37.4	33.7	250.2	69
All Industries	26.9	52.4	33.1	52.8	171.5	493

Notes: This table describes the firms in our sample, disaggregating by primary sector and by type of occupations.

Table 2: **Summary of variables used in blocking/re-randomisation**

	N	Mean	S.Dev.	1st Q.	Median	3rd Q.	Min.	Max.	p-value
Private limited company	493	0.51	0.50	0.00	1.00	1.00	0.0	1.0	0.963
NGO	493	0.13	0.34	0.00	0.00	0.00	0.0	1.0	0.958
Tours & Hospitality	493	0.19	0.39	0.00	0.00	0.00	0.0	1.0	0.949
Services & Finances	493	0.21	0.41	0.00	0.00	0.00	0.0	1.0	0.878
Education & Health	493	0.21	0.41	0.00	0.00	0.00	0.0	1.0	0.944
Manufacturing	493	0.26	0.44	0.00	0.00	1.00	0.0	1.0	0.937
Construction & Mining	493	0.14	0.35	0.00	0.00	0.00	0.0	1.0	0.940
Distance to centre	491	4.93	8.85	1.96	3.42	5.80	0.2	123.6	0.886
Total employees	493	288.11	972.98	37.00	87.00	225.00	4.0	18524.0	0.598
Workforce composition (job category)									
Professionals	493	0.29	0.23	0.10	0.21	0.45	0.0	0.9	0.921
Support staff	493	0.24	0.15	0.13	0.22	0.32	0.0	0.8	0.401
Production	493	0.26	0.29	0.00	0.17	0.50	0.0	1.0	0.863
Customer services	493	0.14	0.16	0.00	0.07	0.22	0.0	0.7	0.873
Workforce composition (education)									
Degree	493	0.23	0.24	0.04	0.13	0.37	0.0	1.0	0.901
Diploma	493	0.17	0.15	0.05	0.13	0.24	0.0	1.0	0.519
Turnover	493	0.21	0.88	0.05	0.10	0.19	0.0	14.3	0.150
Total annual new years	493	54.45	218.42	4.00	11.00	35.00	0.0	3901.0	0.268
Hiring rate	493	54.45	218.42	4.00	11.00	35.00	0.0	3901.0	0.268
Use formal recruitment	493	0.65	0.48	0.00	1.00	1.00	0.0	1.0	0.703
Would come to a fair	493	0.79	0.41	1.00	1.00	1.00	0.0	1.0	0.711
Total sales (1000s)	339	554.75	3.84e+03	7.1750	23.017	121.8310	0.0	6.0e+04	0.492
Average salary (Birr)	493	2885.07	3010.35	1303.03	1990.18	3190.00	0.0	27683.2	0.812
Expected hiring rate	493	0.22	0.85	0.00	0.08	0.19	0.0	14.9	0.571

Notes: This table provides basic descriptive statistics on sample firms; in doing so, it also shows the variables used for blocking and re-randomisation. The 'p-value' column shows individual p-values for tests of covariate balance.

Table 3: **Firm recruitment in the last year**

Outcome	Estimated ITT	Control Mean	Observations
Time taken to fill professional vacancies	-2.344 (.238) [.658]	24.11	338
Time taken to fill non-professional vacancies	0.724 (.679) [.909]	15.66	109
Number of interviews per position (professional)	0.312 (.895) [.909]	8.818	361
Pay per recruitment (professional)	746.7 (.469) [.909]	2818	382
Pay per recruitment (non-professional)	-437.8 (.172) [.658]	1259	406
Proportion of vacancies unfilled, as percentage of vacancies opened	0.601 (.015)** [.101]	0.859	305

Notes: Each row reports a separate regression. For each regression, we report the estimated ITT from participating in the job fair, the mean in the control group, and the number of observations. p-values are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Table 4: **Firm recruitment in the last year: Worker characteristics**

Outcome	Estimated ITT	Control Mean	Observations
Number of new hires for the year (professional)	-1.604 (.551) [1]	11.73	472
Number of new hires for the year (non-professional)	-9.704 (.183) [1]	44.64	472
Did firms mostly hire people with degrees (professional positions)?	-0.00800 (.845) [1]	0.574	473
Percentage of new hires hired in permanent positions (non-professional)	-0.00900 (.76) [1]	0.892	337
Percentage of new hires hired in permanent positions (professional)	-0.00800 (.791) [1]	0.876	308

Notes: Each row reports a separate regression. For each regression, we report the estimated ITT from participating in the job fair, the mean in the control group, and the number of observations. p-values are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Table 5: **Firms' total workforce composition**

Outcome	Estimated ITT	Control Mean	Observations
Total number of employees	-18.38 (.268) [.847]	350.5	473
Proportion of professional workers on permanent contracts	0.0190 (.332) [.847]	0.908	462
Proportion of non-professional workers on permanent contracts	0.0280 (.169) [.67]	0.896	408
Average starting salary (professional)	-90.01 (.708) [1]	4190	461
Average starting salary (non-professional)	102.9 (.417) [.847]	1059	400
Proportion of professional workers with degree	-0.0570 (.033)** [.366]	0.645	461
Proportion of workers with post-secondary education (non-professionals)	0.0370 (.172) [.67]	0.355	407
Average worker is not under-qualified in any of the worker categories	0.00200 (.949) [1]	0.773	473

Notes: Each row reports a separate regression. For each regression, we report the estimated ITT from participating in the job fair, the mean in the control group, and the number of observations. p-values are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Table 6: **Worker employment outcomes**

Outcome	Estimated ITT	Control Mean	Observations
Worked	-0.0120 (.731) [1]	0.562	3786
Hours worked	-1.109 (.559) [1]	26.20	3779
Formal work	0.0260 (.192) [1]	0.224	3786
Permanent work	0.0180 (.42) [1]	0.171	3786
Self-employed	0.00700 (.722) [1]	0.0950	3786
Monthly earnings	75.70 (.417) [1]	1145	3733
Satisfied with work	0.0340 (.266) [1]	0.237	3786

Notes: Each row reports a separate regression. For each regression, we report the estimated ITT from participating in the job fair, the mean in the control group, and the number of observations. p-values are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Table 7: **Worker job search outcomes**

Outcome	Estimated ITT	Control Mean	Observations
Applied to temporary jobs	0.321 (.241) [.702]	1.311	3770
Applied to permanent jobs	0.0420 (.877) [.938]	2.279	3765
Interviews/Applications	0.0150 (.678) [.932]	0.354	2140
Offers/Applications	0.00200 (.976) [.938]	0.248	2141
Interviews/Applications (Perm)	0.0890 (.077)* [.702]	0.327	1660
Offers/Applications (Perm)	0.0880 (.099)* [.702]	0.164	1659
Interviews/Applications (Temp)	-0.0680 (.124) [.702]	0.389	1315
Offers/Applications (Temp)	-0.0590 (.29) [.702]	0.332	1315
Uses CV for applications	-0.0160 (.617) [.932]	0.401	3786
Uses certificates	0.0660 (.222) [.702]	0.479	3786

Notes: Each row reports a separate regression. For each regression, we report the estimated ITT from participating in the job fair, the mean in the control group, and the number of observations. p-values are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Table 8: **Dyadic regressions: Rankings, matches and meetings**

	Requested	Actual	Requested	Actual	Requested	Actual
	(1)	(2)	(3)	(4)	(5)	(6)
Firm ranking of workers	-.006	-.002			-.006	-.001
	(.001)***	(.0006)**			(.001)***	(.0006)**
Worker ranking of firms	-.002	-.001			-.002	-.001
	(.002)	(.002)			(.002)	(.002)
Algorithm suggestion			.020	.015	.014	.014
			(.007)***	(.006)**	(.006)**	(.006)**
Random suggestion			.0006	.003	.0009	.003
			(.006)	(.007)	(.006)	(.007)
Const.	.027	.012	.012	.006	.026	.011
	(.004)***	(.004)***	(.001)***	(.001)***	(.004)***	(.003)***
Obs.	27778	27778	27778	27778	27778	27778
Effect size: max to min rank	.024	.006			.024	.005
Algorithm = Random			.029**	.14	.123	.178

Notes: This table report the estimates of model 2. The highest ranked worker and firm are assigned a value of zero. Lower ranks corresponds to higher numbers. Standard errors are corrected for two-way clustering at the level of the worker and at the level of the firm. The last row reports the p-value of an F-test of the hypothesis that the effect of the algorithmic and the random suggestion are the same.

Table 9: **Reservation wages of workers and wages paid by firms**

	Sample of workers		Wage paid by hiring firms		
	N	Reservation Wage	Experience	No Experience	All
High school only	1108	1400	1588	855	973
Vocational training	1563	1500	1900	1017.5	1500
Diploma	242	1900	3250	1168	2900
Degree	665	2500	5685	3500	4500

Notes: This table describes self-reported reservation wages (for job-seekers) and offered wages (from firms), disaggregating by educational qualification.

Table 10: **Firm recruitment methods**

Outcome	Estimated ITT	Control Mean	Observations
Firm performed formal interviews (professionals)	0.0440 (.242) [.138]	0.682	473
Firm performed formal interviews (non-professionals)	-0.0140 (.715) [.401]	0.607	473
Did any advertising for new hires	0.0580 (.069)* [.074]*	0.789	473
Did advertising for professional positions	0.120 (.002)*** [.009]***	0.595	473
Did advertising on the job boards	0.0960 (.021)** [.044]**	0.331	473

Notes: Each row reports a separate regression. For each regression, we report the estimated ITT from participating in the job fair, the mean in the control group, and the number of observations. p-values are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Graphs

Figure 1: **Output of the matching algorithm**

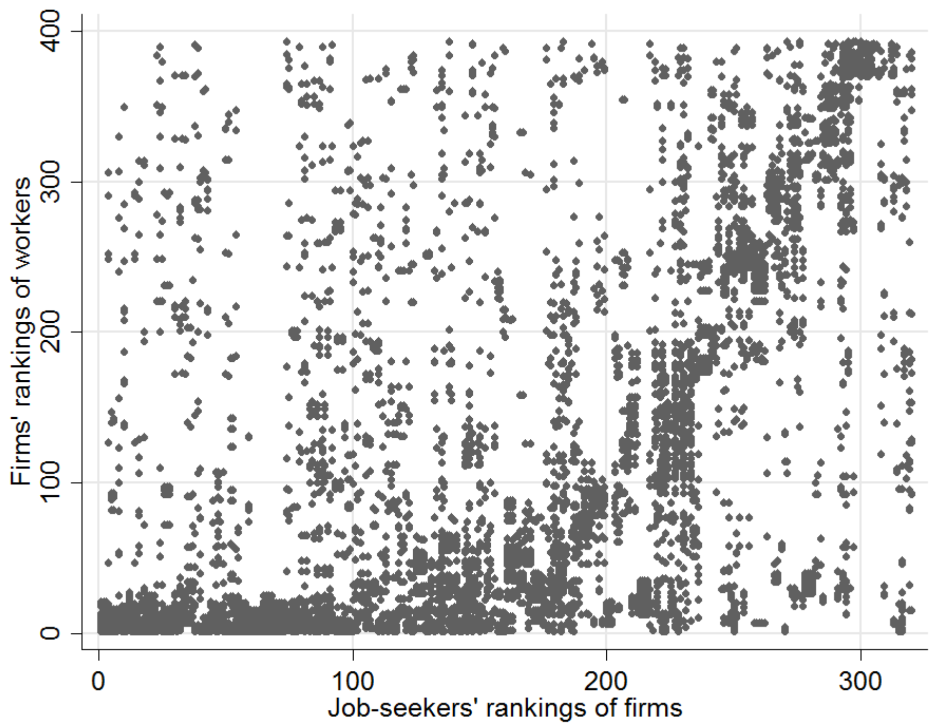


Figure 2: **Impacts on Job Search by Fortnight**

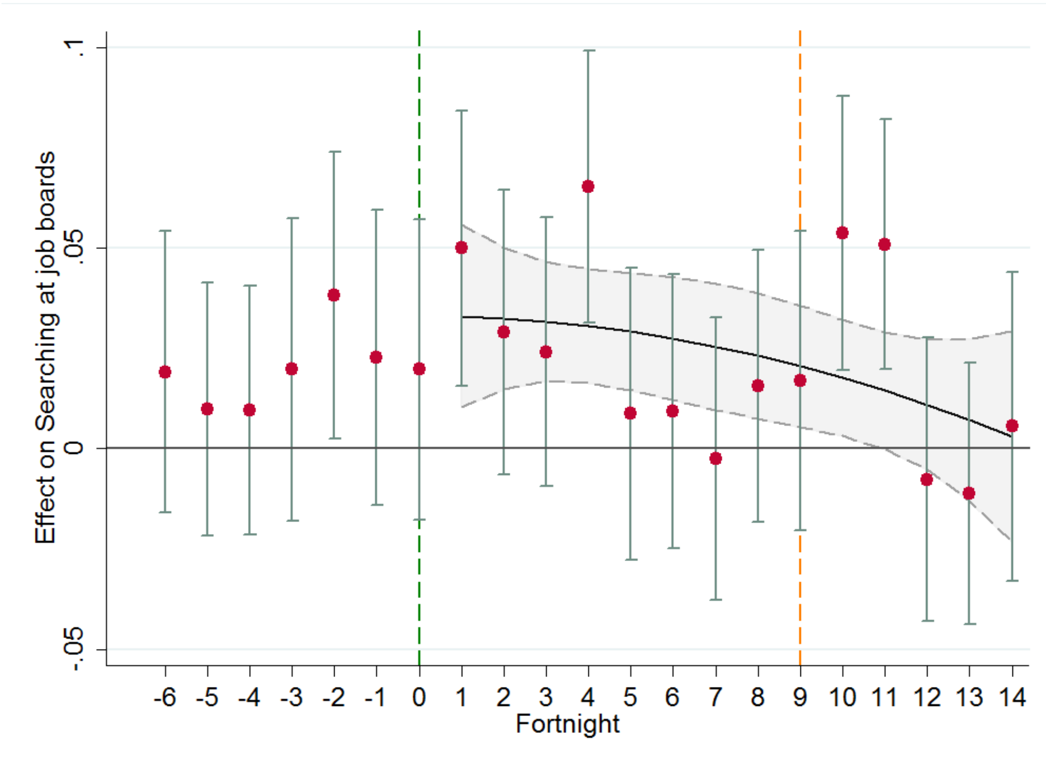
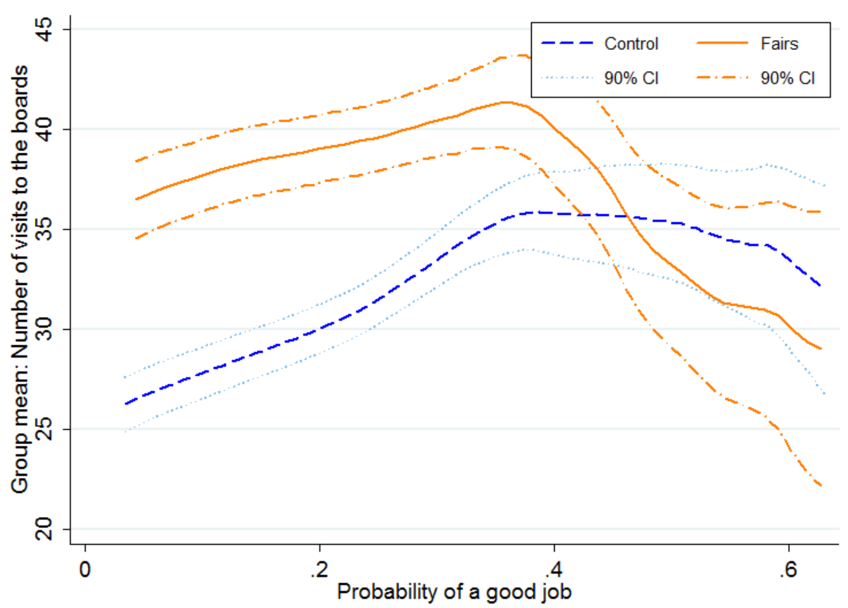


Figure 3: **Shape of treatment effects by predicted access to good work**

Panel A: Number of trips to search at the job vacancy boards



Panel B: Probability of having permanent job

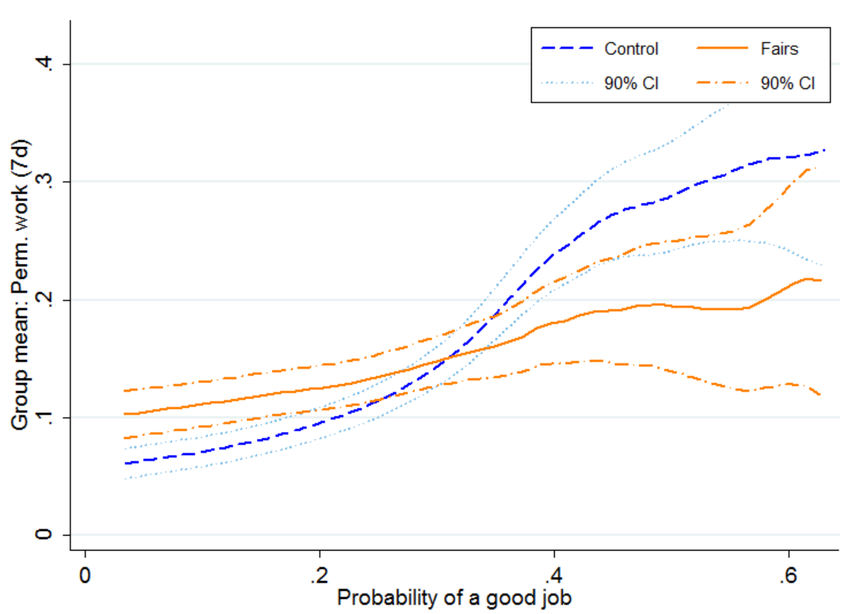


Figure 4: **Impacts on Employment Outcomes by Probability of Good Work**

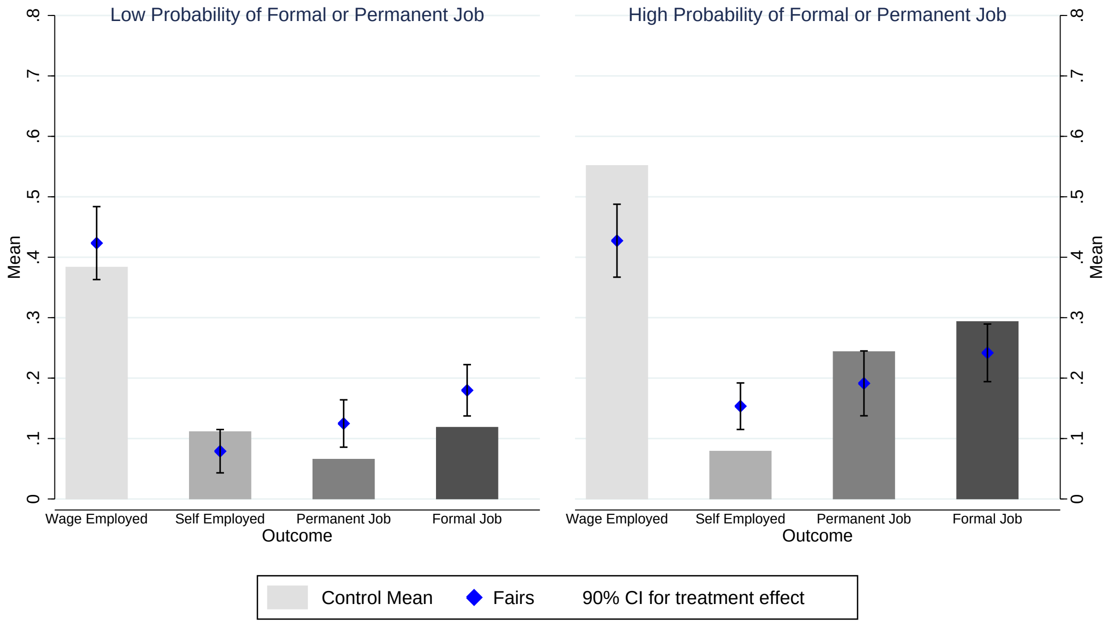
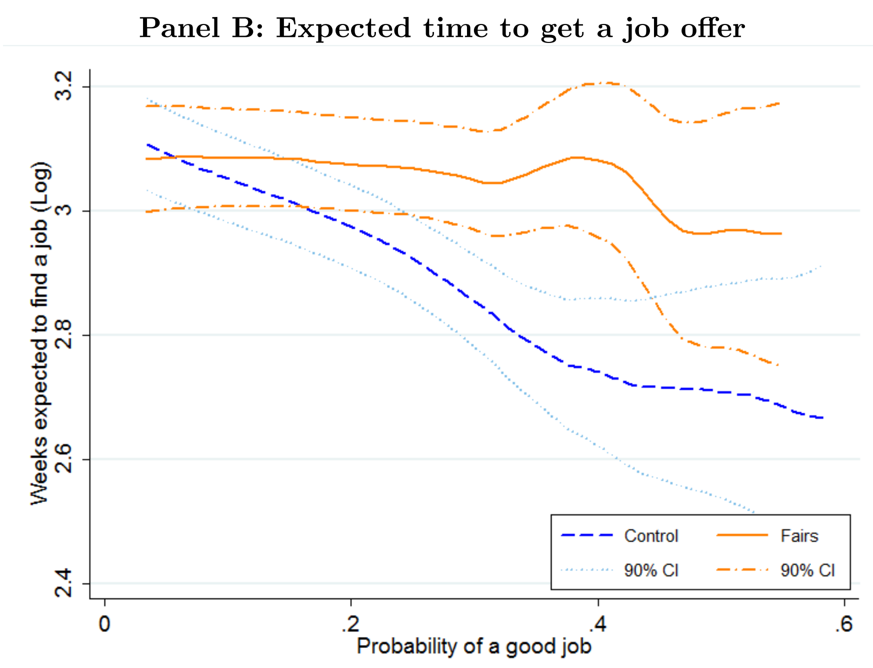


Figure 5: **Shape of treatment effects on expectations by predicted access to good work**



Online Appendix: Additional Figures and Tables

Table A.1: **Worker employment ameneties**

Outcome	Estimated ITT	Control Mean	Observations
Received job by interview	0.0340 (.051)* [.339]	0.167	3786
Office work (7d)	0.0190 (.5) [1]	0.201	3786
Skills match with tasks	-0.0150 (.641) [1]	0.130	3786
Overqualified	0.0140 (.721) [1]	0.291	3786
Underqualified	-0.0210 (.326) [1]	0.0820	3786

Notes: Each row reports a separate regression. For each regression, we report the estimated ITT from participating in the job fair, the mean in the control group, and the number of observations. p-values are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Table A.2: **Median rate of expected number rof new hires in the coming 12 months, as a percentage of current workforce**

	Worker Type				
Industry	Client services	Production	Support staff	White collar	All workers
Construction, Mining, Farming	0.0%	14.3%	9.2%	15.4%	20.0%
Tours-Hospitality	16.7%	10.8%	10.2%	10.6%	14.8%
Finanace, Services, Retail	10.5%	6.3%	10.1%	16.0%	16.1%
Education, Health, Aid	4.5%	5.7%	5.0%	14.3%	13.0%
Manufacturing	0.0%	8.0%	1.6%	3.4%	8.8%
All Industries	7.4%	9.3%	7.4%	11.1%	12.6%

Table A.3: **Correlates of worker attendance at the job fairs**

	(1) Background	(2) Search Effort	(3) Employment	(4) All
Degree	0.0639			0.0330
	(0.198)			(0.209)
Vocational	0.00802			0.00559
	(0.0395)			(0.0398)
Post_secondary	0.000127			-0.0294
	(0.191)			(0.201)
Female	-0.0109			-0.0115
	(0.0307)			(0.0310)
Migrant	0.0154			-0.00141
	(0.0362)			(0.0358)
Amhara	0.00957			0.0148
	(0.0376)			(0.0338)
Oromo	-0.0181			-0.0164
	(0.0506)			(0.0488)
Experience	-0.0590			-0.0433
	(0.0547)			(0.0533)
Age	-0.00861			-0.00924*
	(0.00528)			(0.00518)
Certificate	0.0984***			0.0654*
	(0.0304)			(0.0357)
Distance (center)	0.00214			0.00167
	(0.00722)			(0.00715)
Search_6months		0.0418		0.0155
		(0.0409)		(0.0469)
Plan Self Empl		0.0399		0.0297
		(0.0898)		(0.0891)
Search frequency		0.304***		0.293***
		(0.0497)		(0.0505)
Wage Empl (6 months)			-0.0164	-0.0446
			(0.0304)	(0.0289)
Work frequency			-0.0291	-0.00877
			(0.0496)	(0.0524)
Employment at the time of the job fair				
Permanent Job			-0.161**	-0.160**
			(0.0646)	(0.0692)
Any Job			-0.00143	-0.00576
			(0.0338)	(0.0335)
Constant	0.748***	0.398***	0.631***	0.664**
	(0.253)	(0.0376)	(0.0270)	(0.263)
Observations	1,006	1,006	1,006	1,006
R-squared	0.018	0.045	0.007	0.063

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.4: **Main industry classifications**

Main Industry	Freq.	Percent
Tours-Hospitality	92	18.66
Finanace, Services, Retail	102	20.69
Education, Health, Aid	104	21.1
Manufacturing	126	25.56
Construction, Mining, Farming	69	14
Total	493	100

Table A.5: **Blocking variables**

VARIABLE	DEFINITION	SOURCE (QUESTION NUMBER)
plc	Firm is a private limited company	$g3 = 3$
total_n_all	Total number of pay-roll employees at the firm	$l1\_1\_n$
prop_p	Proportion of workers who are professionals	l1_5_n/l1_1_n
ed_deg	Number of workers at the firm with a degree	$rowtotal(l1\_19\_ * \_1)/rowtotal(ed * \_total)$
to_all	Rate of turnover in the last year	$rowtotal(l2\_1\_*)/total\_n\_all$
formal_adv	Firms advertise when recruiting for jobs	l4_2_1=1 or l4_2_2=1
fairs	Firms expressed interest in attending a job fair	$l4\_31$
hire_all	Rate of new hiring in the last year	$rowtotal(l3\_2\_*)/total\_n\_all$

Table A.6: **Correlates of firm attendance at the job fairs**

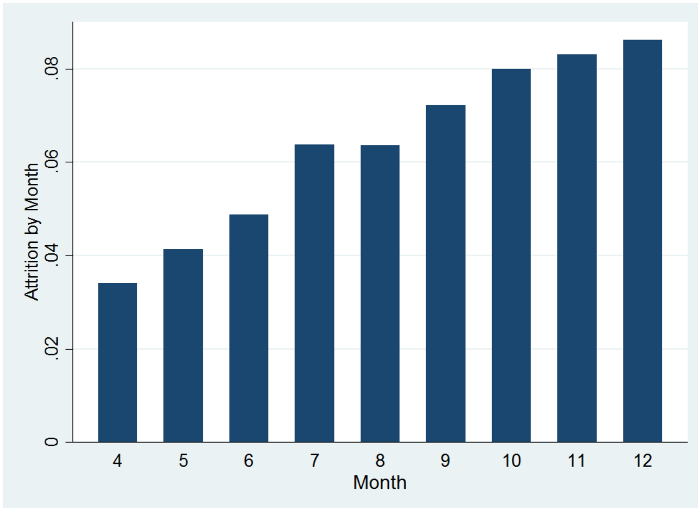
	(1) Blocking	(2) Others	(3) Salaries	(4) All
Tours-Hospitality	-0.210*			-0.742**
	(0.117)			(0.351)
Finanace, Services, Retail	-0.0150			-0.244
	(0.119)			(0.347)
Education, Health, Aid	-0.105			-0.674
	(0.130)			(0.652)
Manufacturing	-0.0556			-0.425
	(0.108)			(0.301)
bs_stad_dist	0.00270			0.0352
	(0.00385)			(0.0231)
Total employees (100s)	0.00171			-0.00377
	(0.00586)			(0.0203)
Respondent is owner	0.0306			0.0573
	(0.0869)			(0.251)
Turnover Rate	-0.0600			1.343
	(0.223)			(1.505)
Quit rate	-0.0268			0.453
	(0.252)			(1.799)
Workers with degrees	-0.427**			-0.772
	(0.197)			(0.912)
Workers with highschool	-0.0534			0.962**
	(0.174)			(0.456)
Proportion professionals	0.0114			1.611*
	(0.228)			(0.922)
Proportion female	0.144			0.460
	(0.175)			(0.397)
Total sales (log)		-0.0377		-0.0578
		(0.0340)		(0.0628)
Hiring Rate		0.248		-0.633
		(0.304)		(0.595)
Number permanent hires		0.0686		0.166
		(0.142)		(0.154)
Employee growth rate		-1.477		-2.275
		(1.347)		(1.765)
Growth rate (professionals)		0.120		0.704
		(0.437)		(0.500)
Growth rate (service)		0.0176		0.289*
		(0.137)		(0.157)
Growth rate (production)		0.917		1.122
		(0.689)		(0.947)
Growth rate (support)		0.0536		-0.309
		(0.366)		(0.414)
Starting salaries (professionals)			-0.0517	-0.106
			(0.192)	(0.260)
Starting salaries (services)			0.279	0.204
			(0.184)	(0.354)
Starting salaries (production)			0.163	0.254
			(0.187)	(0.303)
Starting salaries (support)			-0.142	-0.181
			(0.214)	(0.272)
5 year salary (professionals)			-0.116	0.0375
			(0.207)	(0.278)
5 year salary (services)			-0.0966	-0.328
			(0.224)	(0.321)
5 year salary (production)			-0.169	-0.228
			(0.195)	(0.266)
5 year salary (support)			0.0915	0.367
			(0.196)	(0.284)
Constant	0.834***	1.051**	1.302	0.835
	(0.128)	(0.411)	(0.987)	(1.465)
Observations	232	70	87	61
R-squared	0.075	0.075	0.102	0.576

Ommitted industry dummy is “Construction, Mining”.
*** p<0.01, ** p<0.05, * p<0.1

Table A.7: **Determinants of Attrition**

Fairs	-0.032**	Amhara	-0.025
	(0.015)		(0.017)
search freq	-0.051	Oromo	-0.014
	(0.032)		(0.020)
work freq	0.000	Wage empl (6m)	0.008
	(0.021)		(0.017)
Degree	-0.030*	Married	-0.027
	(0.017)		(0.019)
Worked (7d)	-0.004	Years since school	-0.002
	(0.019)		(0.0030)
Searched job (7d)	0.022	Lives with parents	0.015
	(0.020)		(0.015)
Female	0.051***	Ever had permanent job	0.017
	(0.015)		(0.025)
Respondent age	0.003	Searched job (6m)	-0.020
	(0.0031)		(0.020)
Born outside Addis	0.026	Constant	0.037
	(0.016)		(0.073)
Observations	1,827	R-squared	0.021
F-test (covariates)	1.320	F-test (treatments)	4.780
Prob > F	0.170	Prob > F	0.029

Figure A.1: **Attrition rate from the Phone Survey by Month**



Note. Attrition is defined as failure to complete one interview.

Figure A.2: **Impacts on Employment Outcomes by Education**