Matching Firms and Young Jobseekers through a Job Fair: A Field Experiment in Africa*

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Abstract

Matching frictions are believed to hurt the employment prospects of young jobseekers, particularly in rapidly growing labour markets. To remedy this perceived shortcoming, we organise job fairs that match large firms with young jobseekers with at least a high-school diploma. Invitations to the fair are randomized among workers as well as employers. For a random subset of the treated, a Gale-Shapley algorithm is used to recommend prospective applicants to employers. We look for direct effects on interviews, offers and jobs in the aftermath of the fairs, and for indirect effects on expectations and search strategy by firms and jobseekers. We find that the fairs and algorithmic recommendations succeed in generating interviews yet lead to few hires. But the fairs affect expectations and search strategy. Firms were over-optimistic about the availability of skilled workers with work experience, and they increase their search effort after the fair. High-school leavers start with reservation wages well above what firms offer but reduce their expectation after the fairs, accept more offers, and are more likely to hold a permanent or formal job at endline.

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1 A matching experiment

Policies designed to help young people find work often have limited success. Recent evidence has for instance shown that: worker training programs have modest effects on employment and earnings in both developed and developing countries (Crépon and Van den Berg, 2016; McKenzie, 2017);[1] wage subsidies do not perform in the same manner in different labour markets (De Mel et al., 2016); and job search assistance has positive short-term impacts but poorly understood long-term effects (Card et al., 2010; Abebe et al., 2016; Franklin, 2015). A common feature of these active labor policies is that they only target one side of the labour market. Yet obstacles to youth employment are likely to exist on both sides. On the supply side young people are prevented from searching optimally by liquidity constraints (Abebe et al., 2017). They may also have unrealistic expectations about their employment prospects (Groh et al., 2015). On the demand side, employers find screening young, inexperienced workers costly. Furthermore, if they hold overly pessimistic views about the employability of young job applicants, they may opt not to screen them at all (Glover et al., 2017; Beam et al., 2017; Caria et al., 2014). Policy interventions may thus be more effective if they address frictions incurred by *both* workers and firms – for instance, by reducing the costs of seach and signaling for young job candidates while simultaneously lowering screening costs for employers.

Job fairs aim to serve this dual purpose by reducing frictions affecting both sides of the market. The creation of a centralized clearing house allows applicants to investigate many employers and job openings at once, and to apply to those they prefer. It simultaneously enables firms to screen and interview many prospective workers at once. The ensuring reduction in search costs may encourage employers to interview marginal applicants, e.g., less experienced applicants whom they would not normally consider. Lower search costs should also allow young jobseekers to apply to more jobs, an issue known to hurt their probability of employment (e.g., Caria et al. 2018).

It is common for universities and vocational schools located in developed economies to organize job fairs for their prospective graduates.[2] This type of intervention, however, is not yet common in the rapidly growing economies of Africa.[3] The purpose of this paper is to organize a job fair for young jobseekers in a large African city and to test whether it improves their job prospects while allowing firms to fill their vacancies. Since job fairs are uncommon for unskilled manual work,[4] we focus on educated jobseekers for whom skill assessment is presumably more critical at the time of hiring.

[1] See, however, Alfonsi et al. (2017) for recent evidence of a positive impact for a six-month-long training in well-defined vocational skills.

[2] Large companies in the United Kingdom, for instance, use job fairs to select young IT graduates.

[3] With a few exceptions – e.g., in Ethiopia hotels regularly recruit their staff at large job fairs.

[4] There are important exceptions. Chinese manufacturing firms, for example, use job fairs to hire blue-collar workers (Chang, 2009). US employers organise job fairs in the Philippines to hire construction workers and domestic helpers (Beam, 2016).

Job fairs can affect labor market outcomes in two major ways. First they can serve the role of clearing house, allowing jobseekers to find jobs faster and firms to hire suitable employees more rapidly. This effect may dissipate over time, however, as non-participants progressively catch up. To test this search-cost-reduction effect, we randomize firms and jobseekers into a job fair intervention and compare treated and control subjects four months after the fair. We also collect precise data on all interviews, offers and postings arising as a direct consequence of the job fair. Secondly, participating firms and workers get an opportunity to observe a large number of market participants and can use this information to update their expectations and refine their search strategy. To investigate this possibility, we collect detailed information on expectations, reservation wage, and search activity. Relative to controls, subjects who did not get a job or fill a vacancy at the fair may nonetheless experience different endline employment outcomes as a result of improved search. While such finding would indicate that participants benefited from an information effect, it does not by itself demonstrate that job fairs are a cost effective tool to achieve it – a cheaper information dissemination intervention could possibly achieve the same result.

We invite randomly selected employers and job candidates to a large job fair. Randomizing both sides of the market at the same time sets our experiment apart from previous RCTs that have focused on a single side of the market (e.g., Beam 2016). We further facilitate search by including a matching intervention, itself randomized. Using a Gale-Shapley algorithm that combines information on jobs obtained from firms with information on candidates' profiles and preferences, we give randomly selected firms a list of recommended candidates that are likely to be interested in their vacancies, and that the firm is likely to attract given the jobs openings at other firms. This intervention should further improve matching by promoting employee-candidate encounters that have a higher chance of leading to an accepted offer. To investigate this, we add on the list some randomly selected candidates to test whether a chance recommendation increases a candidate's prospects. The inclusion of this matching intervention, itself randomized on both sides of the market, further sets our experiment apart from the literature on active labor market interventions[5], and it enables us to contribute to a nascent literature exploring the potential of algorithmic approaches for improving the matching efficiency of markets.[6]

For our intervention to work, we need a site where search costs are high for workers and firms. To this effect, we select a rapidly growing urban center in the developing world where the labour market is least likely to be frictionless. Addis Ababa, capital of Ethiopia, is a good choice

[5] In addition, randomly selected job seekers were treated with a certification intervention (Abebe et al., 2016).

[6] Algorithmic approaches have successfully been used in structured allocation problems — such as assigning doctors to hospitals (see, for example, Roth (1984), Roth (1991), Kagel and Roth (2000) and McKinney et al. (2005)). The relevance of matching algorithms in less structured markets remains an open empirical question. A funded research project by Magruder and Ksoll entitled "Labor Market Frictions in India – Evidence from the Introduction of a Job Information Platform" has experimented with offering job seekers a phone-based job matching app. Initial results seem to suggest that treated workers have worse endline outcomes due to the low quality of the jobs offered on the app (source: private communication).

because it combines all the above characteristics with the additional feature that, at the time of our study, the main avenue through which firms advertize openings is through job vacancy boards located in the centre of the city. While the purpose of these boards is to facilitate job search, they nonetheless entail sizeable transaction costs, especially for workers who not only must incur substantial transport costs to visit the boards, but must spend considerable time visually scanning the boards to identify suitable openings. Screening by firms is also challenging, given the limited information that firms can extract from the CVs of young labour market entrants (Abebe et al., 2016). In recent years Addis Ababa has experienced a large increase in the number of available jobs, coupled with high migration flows and volatile inflation. This makes it hard for firms and workers to have accurate beliefs about the distribution of wages and employment opportunities. All these features suggest that job fairs are an appropriate intervention in this context.

We randomly invited 250 firms and 1,000 jobseekers to take part in two separate one-day job fairs, held four months apart. Participating firms are some of the largest in the city, covering all the main sectors of economic activity. Almost all of them were actively looking to hire new staff at the time of the fair. The sample of jobseekers is representative of the population of young workers without a permanent job and looking for work. We limit our focus on jobseekers with at least a secondary school certificate, because they are naturally destined for jobs that require hard-to-measure skills, and thus for whom screening and signaling are more problematic.

As indicated earlier, job fairs can have an impact either directly by reducing search costs, or indirectly by updating expectations. If job fairs are effective in reducing frictions, we should observe to a higher employment probability on average among treated jobseekers, and fewer unfilled vacancies among treated firms. In contrast, if job fairs mostly cause participants to update their expectations about possible market outcomes, we should observe changes in search strategy among firms and workers with initially unrealistic expectations. For instance, if workers realize their initial wage expectation was too high, they may accept lower wage offers. Similarly, if firms realize that few jobseekers have the needed skills, they may increase their search effort. We investigate the effect of being invited to a fair on firms and jobseekers: direct effects of treatment on interviews, offers, and jobs in the immediate aftermath of the fair; and indirect effects on search strategy and endline employment outcomes. We note in passing that indirect effect are more likely to be observed if direct effects are absent or weak: if treated workers find a job and firms fill their vacancies, they have less cause to revise their expectations and search strategy than if they did not.

Regarding the first channel of impact, results show that the fairs generate a rich set of interactions between workers and firms. Three quarters of participating job candidates had an interview or in-depth discussion with at least one recruiter at the fair, a finding that is particularly strong among participants benefiting from our matching algorithm.[7] Among those who met with a

[7] Randomly recommended jobseekers see no improvement.

firm representative, 11% report visiting at least one firm for a job interview after the fair – making up 105 job interviews in total. These interviews, however, generate only 14 accepted job offers.[8] Given the small magnitude of this effect relative to the number of participating firms and applicants, we do not expect any persistent direct effect at endline – which is indeed what we find. Similarly, we find no significant impact on firms' hiring outcomes or the type of workers they hired. This is not because of low demand or supply of labour: most firms do hire many candidates outside of the job fairs, and they invest substantial amounts of time and money on recruitment; and jobseekers similarly search hard, both at the fairs and elsewhere. We also find no evidence of negative selection of workers into attendance,[9] confirming that firms did not meet an unusually weak pool of entry-level candidates at the fair. From this we conclude that the job fair did not play the role of clearing house, although it did reduce search costs for both firms and jobseekers.

As possible explanation, the evidence suggests that firms are reluctant to fill high-skill, professional positions with the entry-level (but highly educated) workers that we invited.[10] Firms seemed disappointed with the quality of the applicants they met and reported them to be, on average, less employable than the usual applicants they get when recruiting for high-skill positions. Firms *were*, however, interested in hiring attendees with no tertiary education for low-skill positions: firms made 55 job offers to these candidates, but fewer than 15% were accepted. The data further shows that attendees who did not study beyond high school came to the fairs with reservation wages far higher than the starting wages offered at the fairs – and than the wages earned by those who did take a job. Unrealistic expectations thus seem to have led these high-school graduates to turn down the job offers they received as an outcome of the fair.

Do firms and jobseekers adapt by revising their expectations and subsequent search? This is indeed what we find for both firms and jobseekers. Firms increase their advertising and recruitment at the main job vacancy boards, consistent with the idea that they had unrealistic expectations about skill availability in the market. This interpretation also tallies with what employers told us at the fairs. For jobseekers, indirect effects are concentrated among the group that had particularly unrealistic expectations at baseline – namely, high school graduates. Among these jobseekers, the evidence clearly shows that, after the fairs, reservation wages fall, job search effort increases, and visits to the job boards become more frequent. As a result, this category of jobseekers experiences a considerable improvement in employment outcomes at endline: permanent employment rates double and formal employment rates increase by almost 50 percent. In contrast, jobseekers with post-secondary education do not, on average hold unrealistic wage expectations. But they seem to have been discouraged by their lack of success at the job fair, and as a result appear somewhat demotivated in their job search. Although this

[8] This is confirmed in the reports of both workers and firms.
[9] 60% of invited jobseekers attend the fairs.
[10] Many firms said that the prefer to look for recruits among workers at other firms who already possess formal work experience.

effect is not statistically significant, it explains why the *average* treatment effect on employment is not different from zero.

Our main policy contribution is to identify two key constraints to youth employment in a rapidly growing African city, namely: firms' reluctance to hire inexperienced candidates; and unrealistic reservation wages. The first finding is already familiar, although the extent of this reluctance comes as a surprise. If, as our results indicate, limited information distorts firms' hiring strategies, policy makers may wish to target job market interventions towards firms so as to improve their recruitment effort directed at school leavers. The second finding is less widely known. It suggests that policy makers may want to correct unrealistic beliefs among secondary school leavers – something that can probably be achieved at a fraction of the cost of running a job fair.

The paper makes two methodological contributions. First, to the best of our knowledge, this is the first experiment to study the effect of a labour market matching intervention on both workers and firms. The richness of insights that this approach generates should encourage more work along this line. Second, we combine a job fair with an employer-employee matching algorithm. The recommendations we make to firms lead to more interviews for jobseekers suggested by the algorithm, but not for jobseekers recommended at random. This demonstrates that, even with limited data, matching algorithms can facilitate search. We expect such algorithms to play a bigger role in the future, as information about skills and job needs becomes more widely available (e.g., from social media).

The paper contributes to several distinct bodies of literature. A growing but relatively new literature looks at labour market interventions that offer matching and information services to workers. The study closest to ours is that of Beam (2016) who encourages rural Filipino workers to attend a job fair for overseas jobs. The author finds that treatment changes workers' perception of the labour market and encourage job search in big cities. But it has no effect on the probability of working overseas. We expand on this design along several important dimensions.[11] In the same vein, Jensen (2012) finds that remote rural dwellers are more likely to be employed when given information about available vacancies at nearby towns (see also Bassi and Nansamba (2017)). In contrast to these studies, we focus on a sample of active job-seekers already familiar with the labour market. Our design does not seek to introduce workers to a new labour market or to motivate them to start looking for work. Instead we investigate whether facilitating face-to-face contact with employers improves the chance of getting a job.

This paper also relates to work focussing on information in large labor markets, such as Groh et al. (2015) who match workers and firms on the basis of observable characteristics. The authors fail to increase the take-up of offers and interviews among participants, who instead remain unemployed to look for better work. In contrast, we do find that our matching algorithm generates more interaction between workers and firms. Pallais (2014) shows that providing

[11] We randomise both at the level of the worker and at the level of the firm; we focus on an urban population; and we invite a large number of local firms to attend the fairs, as opposed to firms based in a foreign country.

information about workers' abilities can improve their prospects in an online labour market.[12] We generalize this finding by showing that both firms and workers update their search strategy as a result of our intervention. Our paper also relates to a recent literature showing how biased beliefs can lead to sub-optimal job search and employment decisions (Spinnewijn, 2015). Abebe et al. (2017) find that workers are overconfident about the probability of being offered a job by an employer. Krueger and Mueller (2016) show that high reservation wages can delay exit from unemployment. We similarly find that some of our subjects have unrealistic expectations about starting wages in large firms, something that contact with those firms at the fair appars to correct.[13]

Finally, our results relate to the experimental work on firm recruitment.[14] Field experiments have tested different binding constraints to firm growth (Bandiera et al., 2011), but little attention has been paid to hiring constraints.[15] We provide original evidence about this. A large literature examines how human resource management can raise the performance of employees (Bloom and Van Reenen, 2011). For instance, Bloom et al. (2010) show that, in a developing country context, productivity increases performance-based pay. There is less work on recruitment practices as an HR tool.[16] Our contribution is to show how firms in a developing country use job fairs as a new recruitment and learning opportunity.

2 Data

2.1 Surveying of jobseekers

The job fairs intervention reported in this paper was run alongside the interventions studied in Abebe et al. (2016), drawing on the same sampling frame.[17] Specifically, we run our study with a representative sample of young unemployed people in Addis Ababa. To draw this sample, we first

[12] See also Stanton and Thomas (2015), who show that intermediaries in online markets can help workers and firms to overcome information asymmetries.

[13] 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).

[14] In Ethiopia, Abebe et al. (2017) show that firms can attract better candidates by offering monetary incentives to prospective applicants. Hoffman et al. (2015) 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.

[15] 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.

[16] 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."

[17] Abebe et al. (2016) conduct two parallel field experiments, to reduce respectively the spatial and informational barriers to job search.

defined geographic clusters using the Ethiopian Central Statistical Agency (CSA) enumeration areas.[18] Our sampling frame excluded clusters within 2.5 km of the center 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 minimize 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 aged between 18 and 29 (inclusive); (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 4,388 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 4,059 individuals who were are included in our experimental study. Of these 1006 were invited to the jobs fairs. Another 2226 were involved in the experimental interventions discussed in Abebe et al. (2016), while 823 remained in the control group.

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 interviews 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 included a module to study social networks. We called all study participants through the duration of the study. In these interviews we administered a short questionnaire focused on job search and employment.[19]

We have low attrition; in the endline survey, we find 93.3% of all job-seekers. We find that very few covariates predict attrition (see Table 9 in the Online Appendix). We are unable to reject a joint F-test that a range of covariates have a significant effect on attrition. However, we do find that the individuals invited to the job fairs are slightly more likely to respond to the endline survey. However, because attrition is so low overall (attrition is 8% in the control group and 5.6% in the treatment group) we are not concerned that this is influencing our main results. We

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

[19] 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.

show that our key findings are robust to bounding our estimates using the method of Lee (2009). Attrition in the phone survey is also low; for example, we still contact 90% of respondents in the final month.[20]

2.2 Surveying 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 first compiled a list of the largest 2,178 firms in Addis Ababa. Since no firm census exists for Ethiopia, we relied on a variety of data sources, including the lists of formal firms maintained by different government ministries. In all, we gathered data from more than eight different sources; many came from government-maintained lists of formal firms. For the manufacturing sector we could rely on a representative sample of the largest firms from the Large and Medium Enterprise surveys conducted by the Central Statistics Agency (CSA). In other cases we requested lists of the largest firms in each sector from the government agency in charge of that sector. Where firm size was available for the various sources, we imposed a minimum size cut-off off of 40 workers.

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 data.[21] 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. Detailed information on firm size is 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 expect to hire (at baseline) in the next 12 months amounts to 12% of their current workforce. The median rate of hiring is highest (16%) among service sector firms, which are also the most likely to come to the job fairs. The most common types of workers which firms expect to hire are white collar workers, usually requiring university degrees. These results are shown in Table 4 in the Online Appendix.

[20] Figure 1 in the Online Appendix shows the trajectory of monthly attrition rates over the course of the phone survey.

[21] Table 6 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.

2.3 Randomization of job-seekers

We assigned treatment at the level of the geographical 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 randomization procedure). We present extensive balance tests in Table 1. For each baseline outcome of interest, we report the p-values for a test of the null hypothesis that we have balance between the experiment and control groups. 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 industries (defined in Table 6, in the Online Appendix). Then firms were partitioned into nearest neighbour groups of four firms on the basis of Mahalanobis distance defined over the set of baseline variables.[22] After that, we randomized the firms into two groups within 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-randomization method. Following the recommendations of Bruhn and McKenzie (2009), we control in our estimations for the baseline covariates used for re-randomization (that is, the set of variables described in Table 2) and for the baseline covariates used to construct the randomization blocks.[23] With this sample we have 78% power to detect a small treatment effect (that is, only 0.2 standard deviations), using a significance level of 0.05%.

< Table 2 here. >

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 February 14 and 15, 2015. We

[22] These are listed in Table 7 in the Online Appendix.

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

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 minimize 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.[24]

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 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.

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, of our initial sample of job-seekers, only about 8% 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 study. On average, firms hired 52 workers in the year and four workers in the month after the job fairs.

[24] Weekend days were selected to maximize the oppurtunity for both firms and workers to attend. In preliminary discussions with firms, we realised that most would be unable to take the time off daily activities to attend during the week, but were interested in doing so on weekends. Similarly, many workers in our sample worked casual jobs and were more likely to be engaged during the week. Many Ethiopians attend religious services on the weekends: we allowed long enough time windows for job seekers to be able to attend on either side of such services.

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 whether the person used certificates for job search: it seems that workers who attended the fairs are the more active, and organized, job-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 personalized list of 15 firms that we suggested she or he should talk to during the job fair; each firm received a symmetric personalized 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, as we describe shortly, 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 randomized the order in which the 15 matches were presented.

In this context, the Gale-Shapley 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 stylized 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 previous 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 reasonable 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 analyze the impact of the job fairs on our sample of firms; this follows our pre-analysis plan.[25] 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 randomization. We use robust standard errors.[26] 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-skilled positions. For manufacturing firms, 'non-professional workers' refers mostly to labourers or 'production' workers; for service-based firms, these include mostly workers dedicated to 'client services' (tellers, waiters, receptionists, *etc.*) The main results on firm outcomes are presented in Tables 3, 4 and 9 (we place all other pre-specified outcome families to an online appendix); 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.

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

[26] Since randomisation was conducted at the firm level, we do not cluster our errors.

In each case, we report both p-values and False Discovery Rate q-values, calculated across the family of outcomes (Benjamini et al., 2006).

First, in Table 3, Panel A, 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 to 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 3, Panel B, we then look at the impact of the job fairs on firm hiring outcomes at the time of the endline survey, which took place about six months after the second job fair. We find no significant impact on the number of people hired by the firms in the last 12 months, nor on the types of people, 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.[27]

Unsurprisingly, therefore, we find no impact on the firms' overall work-force composition (Table 4). 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.[28]

< Table 4 here. >

4.2 Impact on jobseekers

We use the same specification as equation 1 to analyze the ITT for job-seekers; we report the main results on employment outcomes in Tables 5. In an online appendix we present additional results on employment amenities and job search at endline, in Tables 2 and 3, respectively. These tables show regressions of key employment and search outcomes at the time of the 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

[27] Similarly we find no impact on firms short term hiring, through a phone survey conducted immediately after the job fair. Table 11 shows the impacts on overall hiring. Table 12 shows the impacts on the types of workers hired.

[28] In addition, in Table 14 we show that the fairs had no impact overall firm productivity and growth. Table 13 shows no impact on firms' overall turnover and employee growth. Table 15 shows no overall impact on general HR practices at the treated firms.

that level. 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 (Table 5) or search methods (Table 3). This is hardly surprising, in light of our results on firms. The effect on key job quality outcomes such as 'formal' work or 'permanent' work are positive, but not significant.[29] We find that the fairs have no impacts on the types of jobs held by workers either.[30]

< Table 5 here. >

5 Why did the fairs not create more hires?

Why did the fairs not generate more hires, and what can we learn from this about labour market matching? We explore two main types of explanations for our results. First, we hypothesise that the fairs did not generate enough interaction between workers and firms to allow for hiring to happen (suggesting that fairs are not an appropriate mechanism for screening workers). Second, we investigate whether the workers who participated in the fairs were simply not good matches for the participating firms.

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 typically contacts multiple firms and was sometimes be interviewed by more than one firm. In total, we record 2,191 contacts between firms and workers and 105 interviews (spread among 67 workers). Finally, we find that 45 jobseekers were offered jobs, 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. 21 workers report that they rejected all of the offers that they received.

How does this compare to workers' search effectiveness outside the fairs? Between our baseline and endline interview, 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 figures, two conclusions emerge. First, there was rich interaction between firms and job-seekers at the fairs. Second, this

[29] 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 no 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.

[30] These results can be found in Table 2 in the online appendix, which reports effects on employment amenities. Table 3 shows the impacts on job search at enelin. Here we find only marginally significant impacts, which are not robust to our multiple hypothesis corrections.

interaction led to surprisingly few good matches. In this section, we combine data on job-seekers and on 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 — did indeed 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 actually met. We use a two-way cluster methodology, 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 6, 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 showing that suitable worker-firm pairs were likely to meet at the job fairs — and suggesting that even a stylised matching algorithm can be useful in highlighting suitable matches for market participants. This rules out the hypothesis that market design issues such as congestion and mis-coordination prevented suitable pairs from meeting during the job fairs. In other words, the fairs appear to have been well executed and attained their objective of facilitating meetings between jobseekers and the firms that suited them best.

< **Table 6 here.** >

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

Prior to arriving at the fairs, firms were surveyed and asked 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 1,751 workers. The occupational composition of the vacancies available at the firms exhibits considerable overlap with the occupational composition of the jobseekers invited to the job fairs. Therefore, we can rule out the possibility that the firms did not have sufficient vacancies of the kind that participating jobseekers could have filled. 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 a 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 at least as high as 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 precise 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 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.

Was the selected group of workers who chose to attend the fair of lower quality than the full sample? Only about 60% of invited 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 did not get hired. As discussed above, in Table 5 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 most likely to attend. Education, gender, and even employment do not predict attendance. We do find that invitees 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 pool of participants was representative of the population of young, educated job-seekers with little prior work experience. Could one explanation for the lack of hiring be that large firms 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 active labour market policies that aim to get young adults into work are unlikely to succeed?

First, we note that our job-seekers were not mismatched in terms of education. A substantial proportion of our sample (31%) had on 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.

Second, we investigate the role of work experience. Only 13% of workers had some experience in a formal job. Could it be that the workers didn't match firms experience requirements? Firms do hire entry level workers without experience outside of the job fairs. After the job fair, we interviewed all firms about the vacancies they had open before the fairs and how successful they were at filling them. 424 firms hired 2,018 workers in one month after the job fairs. We find that more than 30% of vacancies were filled with workers with zero years of work experience. 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.

That said, we find that firms exhibit a strong preference for experienced workers. We collected data on firms' open vacancies at the time that they attended the jobs fairs. Only 13% of vacancies open at the fairs were intended for workers with no experience. This suggests that firms do not think it is difficult to find candiates without work experience, so they used the fairs as oppurtunity to focus on finding experienced workers. Firms may strongly prefer work experience, but are often forced to hire the best entry level candidate they can find, due to a lack of suitable candidates. Indeed, we find that although firms came to the fairs expecting to find experienced workers for more skilled positions, they ended up making job offers to inexperienced workers for lower paid positions. We explore the role of these expectations in the next section.

5.2.2 Mismatched expectations

We conclude, therefore, that firms *did* meet the kinds of workers whom they usually hire, both in terms of education and work experience: it seems that matches were possible. However, there may have been other kinds of mismatch preventing the hires from happening, related to the expectations and reservation wages. In particular, we find that firms came to the fairs with the expectation that they would be hiring experienced, skilled professionals, for which higher education (degree or diploma) was essential. Hiring lower-skilled workers for low wage jobs does not usually require considerable recruitment effort on the part of firms, so the fairs were seen as a chance to head-hunt the best candidates. On this interpretation, when firms realised that their expectations were not matched by the pool of available candidates, which was a representative sample of the labour market, the result was a very low number of jobs generated.

So why were our highly educated workers, with university degrees, not hired at the fairs? Firms report paying their recruits with university degrees an average of 4,500 birr per month. This sum lies well above the reservation wages of university graduates at the fairs: these were equal to 2,500 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 positions put a particular premium on work experience for these positions. In particular, only 22% of vacancies filled by job-seekers 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 jobseekers in our sample had any experience at all (only 20% had had any kind of formal work experience). Firms may have been unwilling to hire them because of the costs of training a worker with no experience, or because of the risk associated with hiring someone without a reference letter from a previous employer.

To investigate this channel further, we return to our dyadic framework and to our data on firm-requested meetings, to investigate what types of workers firms want to meet. We find that the single strongest predictor of whether firms wanted to meet a worker was that workers' previous job experience, even after controlling for worker and firm characteristics. The results are not driven only by firms who intended to hire experienced workers before the fairs: even firms that said they were willing to hire fresh graduates (without experience) were more likely to request meetings with experienced workers. Unfortunately for these firms, when we look at actual worker-firm meetings, we do not find that experienced workers were more likely to meet up with the firms. Firms report that a lack of experience among workers was indeed a key constraint for them not making more offers for high-skill positions.[31] So firms that attended the job fairs came with the intention of finding workers with work experience for relatively high skilled positions, and seem to have overestimated how easy it would be find such a candidate from the presentative group of jobseekers in attendence.

They did not miss the opportunity, however, to recruit for lower paid positions. We find that a total of 76 offers were made to 45 different workers. Of those offers, 55 were made to low skilled workers (workers with no post-secondary education), with the remaining 21 going to those with diplomas or degrees. All offers made to low-skilled workers were to workers with no previous

[31] 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 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 were not enough jobs for which they were qualified.

work experience. Yet the low skilled workers accepted only 8 of those positions (14.5%) while higher skilled workers accepted 6 (28.5%). This, ultimately, is why so few matches were made at the fairs.

We argue that this was because of mismatched wage expectations. Lower-skilled workers had over-inflated expectations about the salaries they could aspire to in the market. We explore this possibility in Table 7. Workers without degrees in our sample report reservation wages with a median of 1,400 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, therefore, that even the relatively few low-skilled vacancies that could have been filled at the fairs did not attract a match because workers were unhappy with the offered wages. So, even though firms were willing to hire entry-level workers without experience (and indeed made offers at the job fairs), the workers did not take the offers because of unrealistic expectations. Recall that workers reported receiving a sizeable number of job offers at the fairs, but only 33% of workers accepted at least one of those offers.

< Table 7 here. >

In sum, it appears that workers and firms had mismatched expectations. Firms 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. On the other hand, they were not particularly interested in hiring low-skilled workers, whom they could have easily recruited on the open market at low wages without needing to invest in time-consuming interviews and screening processes. Low-skilled workers, on the other hand, had reservation wages well above those that firms were willing to offer. In the next section, we study how the experience of attending the fairs influenced the expectations of both workers and firms, and thus altered their search and recruitment behaviour later on.

6 Effects of the fairs on expectations and search

The analysis in the previous sections suggests that firms and workers came to the fairs with inconsistent expectations about the types of matches they were likely to make. Did the fairs have an impact, then, on expectations, and therefore firms' and job-seekers' search and recruitment behaviour afterwards? Workers may have realised that their reservations wages were too high. Given that so few workers recieved job offers, and also possibly because they saw the competition they faced from other jobseekers in the market, they may have come to believe that formal jobs were harder to get than they had originally thought. This updating of the beliefs would lead them to increase their search effort and reduce their reservations wages in order to increase their probability of finding a good job. In testing this new hypothesis, we go beyond what was pre-specified in our original analysis plan.

To answer this question, we now explore changes in job-seekers' search behaviour and in firms' recruitment activities in the months after the job fairs. 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 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 are estimated using weekly phone call surveys conducted with all jobseekers 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 8, we study impacts on firms' recruitment activities outside the job fairs. That is, after the fairs 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 to have advertised new vacancies in the last 12 months (compared to a control mean of about 79%), and 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. 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.

< Table 8 here. >

In Table 9, we test the effect of our treatment on expectations, search and employment. In Panel A of that table, we show that our treatment had a large and significant effect on the reservation wages (namely, a reduction of about 7 percent). This resulted in reservation wages becoming more realistic: when we test effects on 'wage mismatch' (which we define as the absolute difference between the reservation wage and the expected wage for a worker of that skill/education level, in logs), we find a highly significant negative effect (of about 4 percent). This was accompanied by a significant increase in visits to the job boards (an increase of about three visits, on a control mean of about 15 visits). We find no significant average effects on employment outcomes (namely, whether respondents had any work, and then either a permanent job or a formal job).

< Table 9 here. >

Earlier, in Table 7, we showed descriptively that education is centrally important for explaining heterogeneity in both reservation wages and offered wages — and that expectations appear to be most unrealistic among those workers who do not have a degree qualification. With this stylised fact in mind, we then disaggregate our treatment estimates by whether or not respondents have a post-secondary education; we report results in Panel B of Table 9. We find that the average effects on reservation wages can wholly be explained by large effects on those with only a high-school education — who, on average, reduced their reservation wage by 9 percent, reduced wage mismatch by 7 percent, and increased board visits by 4.2 percent (on a control mean of about 11 visits). Further, for respondents with high-school education, we find large and significant effects on employment in 'good jobs': an increase of about 6 percentage points in the probability of having a permanent job (on a control mean of just 6 percent), and an increase in the probability of having a formal job of about 5 percentage points (on a control mean of about 11 percent).[32]

7 Conclusion

We run one of the first experimental studies of job fairs, bringing together a random sample of young jobseekers and firms with vacancies. The jobseekers invited to the fairs are representative of the type of young workers that firms usually hire. We facilitate interactions between workers and firms by providing information about workers' education and firms' vacancies, and by suggesting matches based on a Gale-Shapley algorithm. We find that the fairs generate a rich set of interactions between workers and firms. But only 14 jobseekers were hired as a direct result of interactions at the job fairs.

Our analysis of the mechanisms generating these results sheds new light on the workings of the urban labour markets, and bears important implications for active labour market policies in developing countries. First, we find that lack of work experience is a binding requirement for the most qualified jobs and a crucial obstacle for young jobseekers. Firms see the fairs as an opportunity to select highly qualified and experienced workers but find the pool of participating jobseekers to be less experienced than they expected. As a result, they refrain from making offers for highly qualified positions at the fair.[33] Firms do make offers for low-skilled positions, but many of these offers are turned down, consistent with the fact that low-skilled workers have a reservation wage above the going wage rate.

Given the apparent mismatch of expectations between firms and workers, we investigate whether subjects learn from their experience. The fairs induce an updating of expectations among high-school graduates who have the most misguided expectations at baseline. After the fairs, these

[32] In the bottom row of Table 9, we report p-values for tests of the null hypothesis that these effects are equal between educational groups. We reject this null for measures of wage mismatch and of having a permanent job; we are very close to rejecting at conventional levels ($p < 0.12$) for board visits and for having a formal job.

[33] 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.

jobseekers revise their reservation wage downwards to more accurately reflect the wages offered at the fairs and those that people of their education and skill level usually get in Addis Ababa. These jobseekers also increase their job search effort through formal channels and, four months after the job fairs, they are more likely to have found a formal job.

How do these results compare to other job search interventions directed at young jobseekers? In other work (Abebe et al., 2016) we find that reducing search costs by giving out a transport subsidy increases visits to the job boards by about 30%. The indirect effect of the job fairs is about half that, and their effect on formal and permanent employment is similarly half the size of the effect of the transport subsidy. However, unlike the job fairs that bring jobseekers in contact with hundreds of firms, the transport subsidy does not reduce reservation wages. It just allows young jobseekers to search more persistently and look at more vacancies, without causing them to meet more firms face-to-face. Although recipients of the transport subsidy do not update their beliefs, they nonetheless enjoy a short-term positive effect on employment. Taken together with the findings of this paper, these results suggest that multiple frictions are at play that potentially compound each other – especially among high-school graduates who benefit most form both the reduction in search cost allowed by the transport subsidy, and the revision in misguided expectations enabled by the job fairs.

What have we learned about the possible usefulness of job fairs in urban Africa? Based on the frequent use of job fairs by schools elsewhere, we were hoping that they could serve as clearing house to reduce friction and facilate the matching of young educated jobseekers to jobs in a rapidly growing city. This is not what we find. The behavior of employers at the fair instead suggest that, at this point in time, job fairs could be more appropriate for specific skills that are hard to search for, such as job experience particular to a sector or technology. With time, employers may start looking for university and vocational school graduates with specific interests or internship experience – just like they do in the US. But this time does not seem to have been reached yet in Addis Ababa. We can only hope that employers disappointed by what they saw at the job fairs will, in the future, put more emphasis on providing task-specific training to young jobseekers themselves.

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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
Panel A: Short term recruitment outcomes			
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
Panel B: Characteristics of workers recruited			
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, corrected for the tests conducted within each panel.

Table 4: **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 5: **Worker employment outcomes**

Outcome	Estimated ITT	Control Mean	Observations
Worked	-0.00500 (.863) [1]	0.562	1702
Hours worked	-0.901 (.6) [1]	26.20	1697
Formal work	0.0230 (.258) [1]	0.224	1702
Perm. work	0.0140 (.543) [1]	0.171	1702
Self-employed	0.00600 (.711) [1]	0.0950	1702
Monthly earnings	77.58 (.352) [1]	1145	1684
Satis. with work	0.0430 (.152) [1]	0.237	1702

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: **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 equations 2 and 3. 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 7: **Mismatched expectations: Reservation wages of workers and wages paid by firms and wages earned at endline (Medians)**

	Education of worker			
	High-school only	Vocational	Diploma	Degree
Panel A: Wages expected and paid at the job fairs				
Worker Reservation Wages before Fairs				
With Experience (13%)	1400	1900	2000	3000
Without Experience (87%)	1300	1500	1900	2400
Firm Wages paid for positions at Fairs				
Require Experience	1588	1900	3250	5685
Don't require Experience	855	1018	1168	3500
All Jobs	973	1500	2900	4500
Panel B: Individual Realised Employment outcomes at endline				
Worker employment rates at endline				
All jobs	49%	57%	49%	64%
Permanent jobs	9%	16%	18%	31%
Worker Earnings at Endline by Experience				
With Experience	1500	1800	1722	3130
Without Experience	1000	1500	1500	2190
All Experience levels	1000	1500	1500	2373
Worker Earnings at Endline by Job type				
Permanent work	1000	1500	1527	2500
Non-permanent work	1000	1500	1400	2282

Notes: This table describes self-reported reservation wages (for job-seekers) and offered wages (from firms), disaggregating by types of worker and types of job. Workers data comes from the full representative sample of jobs seekers.

Table 8: **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.

Table 9: **Workers' job search and employment outcomes after the fairs**

	(1) Reserv. Wage	(2) Wage Mismatch	(3) Board visits	(4) Worked	(5) Perm. job	(6) Formal job
Panel A: Average Treatment Effect						
Fairs	-0.0669*	-0.0438**	3.012**	-0.004	0.024	0.026
	(0.0369)	(0.0223)	(1.285)	(0.0273)	(0.0183)	(0.0193)
Observations	1,503	1,503	1,705	1,705	1,705	1,705
R-squared	0.005	0.003	0.006	0.000	0.001	0.001
Control mean	7.417	0.529	14.780	0.562	0.171	0.224
Panel B: Treatment Effect by Education						
Fairs × High-school	-0.0879*	-0.0742**	4.197**	-0.012	0.0576**	0.0482*
	(0.0484)	(0.0335)	(1.719)	(0.0397)	(0.0262)	(0.0275)
Fairs × Post-secondary	-0.036	0.001	1.251	0.006	-0.026	-0.008
	(0.0352)	(0.0218)	(1.335)	(0.0313)	(0.0234)	(0.0236)
Observations	1,503	1,503	1,705	1,705	1,705	1,705
R-squared	0.005	0.006	0.008	0.000	0.005	0.003
Control mean: High-school	7.183	0.561	10.980	0.508	0.058	0.108
Control mean: Post-secondary	7.522	0.514	16.550	0.587	0.223	0.277
Test: High=Post (p)	0.268	0.051*	0.118	0.718	0.018**	0.116

Notes: Each row reports a separate regression. 'Wage mismatch' refers to the absolute difference between the worker's reservation wage (in logs) and the expected wage for a worker of that skill/education level (in logs). For each regression, we report the estimated ITT from participating in the job fair (disaggregated, in Panel B, by whether the worker has post-secondary education or merely high school). Standard errors are reported in parentheses. In the bottom row, we report p-values for a test of the null hypothesis that the effect of treatment is equal between high-school and post-secondary sub-samples.

Graphs

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

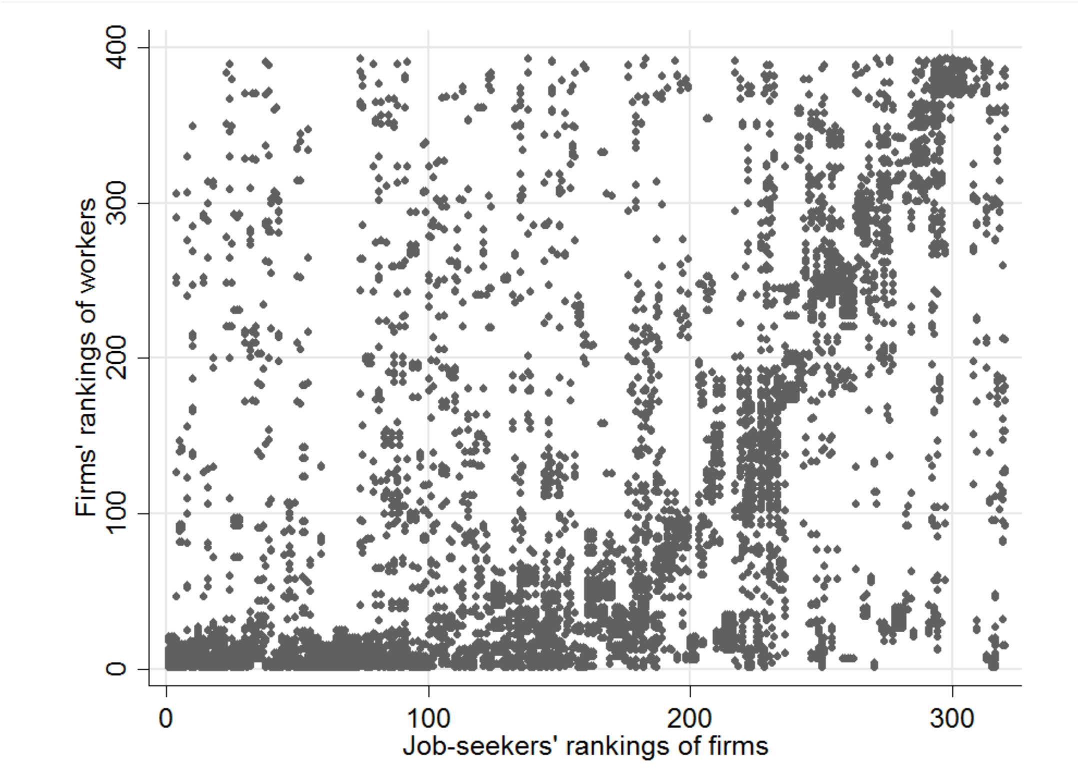
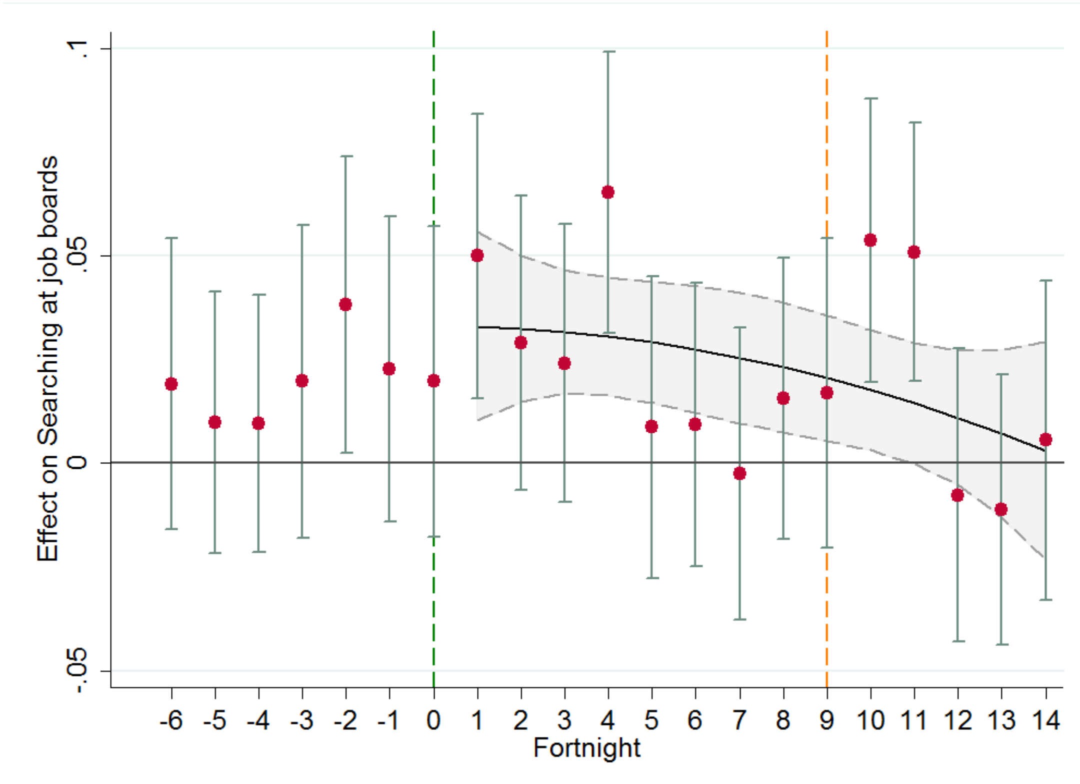


Figure 2: **Impacts on Job Search by Fortnight**



Online Appendix: Additional Figures and Tables

Table 1: **Summary and tests of balance**

	(1) **Control Mean**	(2) **(SD)**	(3) **Job Fairs**	(4) **N**	(5) **F-test P**
degree	0.18	0.39	-0.01	1829	0.619
			(0.62)		
vocational	0.43	0.49	-0.00	1829	0.910
			(0.91)		
work	0.31	0.46	-0.04	1829	0.155
			(0.15)		
search	0.50	0.50	-0.01	1829	0.763
			(0.76)		
dipdeg	0.25	0.43	-0.00	1829	0.993
			(0.99)		
female	0.52	0.50	0.01	1829	0.848
			(0.85)		
migrant_birth	0.37	0.48	-0.03	1829	0.459
			(0.46)		
amhara	0.46	0.50	-0.02	1829	0.590
			(0.59)		
oromo	0.26	0.44	-0.04	1829	0.171
			(0.17)		
work_wage_6months	0.46	0.50	-0.04	1829	0.186
			(0.19)		
married	0.20	0.40	-0.00	1829	0.842
			(0.84)		
live_parents	0.52	0.50	0.02	1829	0.521
			(0.52)		
experience_perm	0.13	0.34	-0.01	1829	0.730
			(0.73)		
search_6months	0.75	0.43	0.01	1829	0.832
			(0.83)		
respondent_age	23.44	3.00	0.22	1829	0.230
			(0.23)		
years_since_school	42.30	273.93	-10.95	1826	0.492
			(0.49)		
search_freq	0.57	0.31	0.00	1829	0.889
			(0.89)		
work_freq	0.34	0.38	-0.01	1829	0.611
			(0.61)		
self_employed	0.05	0.22	0.01	1829	0.601
			(0.60)		
work_cas	0.06	0.23	-0.02	1829	0.087
			(0.09)		
work_satisfaction	0.09	0.28	-0.01	1829	0.659
			(0.66)		
total_savings	2279.23	6203.56	290.89	1829	0.346
			(0.35)		
res_wage	1327.22	1235.30	34.35	1808	0.632
			(0.63)		
cent_dist	5.92	2.24	-0.60	1829	0.229
			(0.23)		

travel	1.83	2.03	0.21 (0.19)	1826	0.185
written_agreement	0.06	0.23	0.00 (0.81)	1829	0.810
cv_application	0.28	0.45	-0.00 (0.90)	1829	0.903
expect_offer	1.46	2.09	-0.21 (0.24)	1697	0.245
aspiration	5583.33	5830.85	191.89 (0.64)	1694	0.636
network_size	6.74	9.63	0.89 (0.53)	1818	0.529
respondent_age	23.44	3.00	0.22 (0.23)	1829	0.230
present_bias	0.12	0.33	0.00 (0.89)	1252	0.889
future_bias	0.08	0.27	-0.02 (0.28)	1252	0.282
life_satisfaction	4.20	1.85	-0.08 (0.63)	1828	0.633

Table 2: **Worker employment ameneties**

Outcome	Estimated ITT	Control Mean	Observations
Received job by interview	0.0270 (.141) [1]	0.167	1702
Office work (7d)	0.00700 (.803) [1]	0.201	1702
Skills match with tasks	-0.0380 (.219) [1]	0.130	1702
Overqualified	0.0290 (.395) [1]	0.291	1702
Underqualified	-0.0130 (.468) [1]	0.0820	1702

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 3: **Worker job search outcomes**

Outcome	Estimated ITT	Control Mean	Observations
Applied to temporary jobs	0.242 (.347) [.533]	1.311	1693
Applied to permanent jobs	-0.0670 (.749) [.713]	2.279	1692
Interviews/Applications	0.0190 (.539) [.706]	0.354	972
Offers/Applications	-0.00300 (.937) [.881]	0.248	975
Interviews/Applications (Perm)	0.0850 (.039)** [.365]	0.327	742
Offers/Applications (Perm)	0.0790 (.114) [.365]	0.164	742
Interviews/Applications (Temp)	-0.0680 (.08)* [.365]	0.389	586
Offers/Applications (Temp)	-0.0630 (.207) [.401]	0.332	586
Uses CV for applications	-0.0530 (.074)* [.365]	0.401	1702
Uses certificates	0.0180 (.711) [.713]	0.479	1702

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: **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 5: **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 6: **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 7: **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 8: **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 9: **Determinants of Attrition among workers**

Fairs	-0.025**	Oromo	-0.007
	(0.012)		(0.016)
bs work freq	0.007	Wage empl (6m)	0.017
	(0.018)		(0.014)
Degree	-0.024	Married	-0.015
	(0.017)		(0.017)
Worked (7d)	-0.015	Years since school	0.000
	(0.016)		(0.0027)
Searched job (7d)	0.008	Lives with parents	0.008
	(0.014)		(0.015)
Female	0.029**	Ever had permanent job	0.002
	(0.013)		(0.019)
Respondent age	0.000	Searched job (6m)	-0.020
	(0.0027)		(0.017)
Born outside Addis	0.031**	Amhara	0.000
	(0.015)		(0.014)
		Constant	0.061
			(0.060)
Average Attrition	6.7%		
Observations	1,827	R-squared	0.012
F-test (covariates)	1.130	F-test (treatment)	4.320
Pval (covariates)	0.320	Pval (treatment)	0.038

Table 10: **Lee Bounds for Main Impacts on Workers (Table 6)**

Outcome	Upper Bound (95% CI)	Lower Bound (95% CI)
Work	0.0410	-0.0863
Hours Worked	2.202	-5.594
Formal Work	0.060	-0.052
Permanent Work	0.054	-0.047
Self Employment	0.031	-0.060
Earnings	203.4	-362.9
Work Satisfication	0.049	-0.060

Table 11: **Impacts on firm hiring after job fairs**

Outcome	Job Fair	Control Mean	N
Number of vacancies	0.136 (.587) [1]	1.722	418
New Hires	-1.492 (.471) [1]	5.782	418
Hiring short fall	-0.0160 (.641) [1]	0.0290	193
Unfilled vacancies	-0.137 (.913) [1]	2.707	418

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 12: **Impacts on firm hire quality after job fairs**

Outcome	Job Fair	Control Mean	N
Permanent workers hired (%)	0.0190 (.697) [1]	0.341	418
Days taken to recruit for position (avg)	0.0460 (.976) [1]	11.96	190
Starting salary of new recruits (avg)	-278.9 (.629) [1]	3401	160
Workers with degrees hired (%)	-0.0430 (.339) [1]	0.240	418

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 13: **Impacts on firm turnover and employye growth**

Outcome	Job Fair	Control Mean	N
Firing rate (professionals)	0.00400 (.343) [1]	0.00600	458
Firing rate (non-professionals)	0.00300 (.535) [1]	0.0130	319
Quit rate (professionals)	0.00800 (.685) [1]	0.143	458
Quit rate (non-professionals)	0.0250 (.49) [1]	0.134	320
Employee growth rate	0.0170 (.29) [1]	0.0140	472
Employee growth rate (professionals)	-0.0140 (.638) [1]	0.0310	467

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 14: **Impacts on firm growth and productivity**

Outcome	Job Fair	Control Mean	N
Firm is for-profit	-0.0140 (.216) [1]	0.867	471
Sales Revenue (last year)	-17575 (.452) [1]	144370	331
Value Added	-15491 (.196) [1]	80851	327
Profit (inferred)	6026 (.209) [1]	12975	326
Self-reported profit	1853 (.796) [1]	29626	313
Capital stock	60034 (.628) [1]	185398	279
Investment (12 months)	-6452 (.276) [1]	20147	398
Sales per worker	-57.12 (.454) [1]	604.5	330
Value added per worker	19.45 (.489) [1]	220.3	326

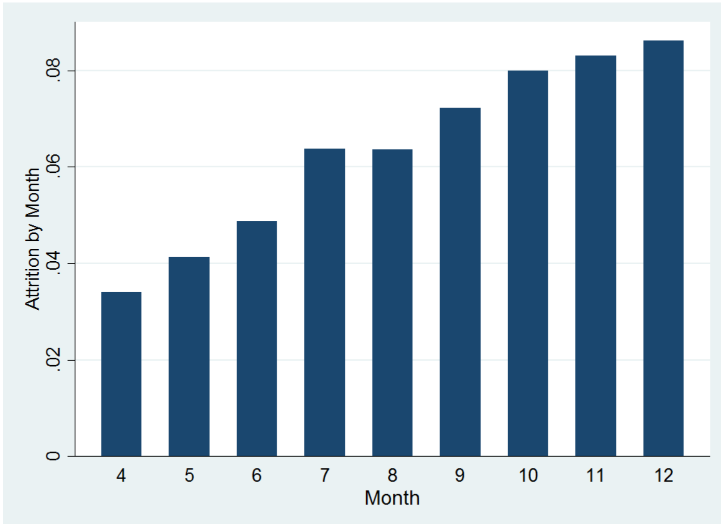
Notes: Each row reports a separate regression. For each regression, we report the estimated ITT from participating in the job fair, the mean in the control group, and the number of observations. p-values are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Table 15: **Impacts on firm human resources policies and attitudes**

Outcome	Job Fair	Control Mean	N
Firm reports HR problem	0.0820 (.025)** [.217]	0.752	473
Uses incentives in HR	0.0390 (.37) [.588]	0.595	473
Firm estimate of a fair wage	201.2 (.52) [.592]	5463	452
Uses short term contractors	0.0480 (.282) [.588]	0.479	473
Uses performance rewards (professionals)	-0.0300 (.51) [.592]	0.545	473
Uses performance rewards (non-professionals)	-0.0740 (.098)* [.417]	0.562	473
Retrains poor performers	0.0390 (.336) [.588]	0.719	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.

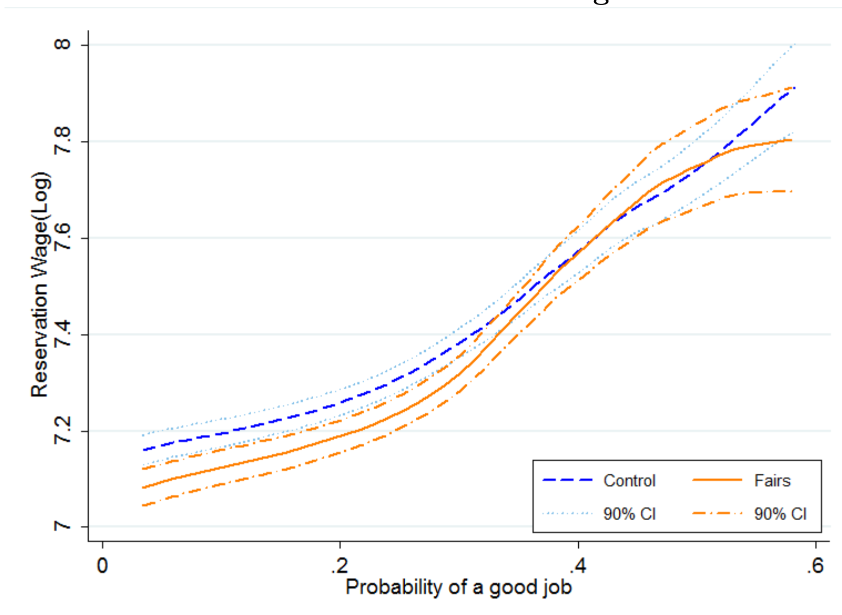
Figure 1: **Attrition rate from the Phone Survey by Month**



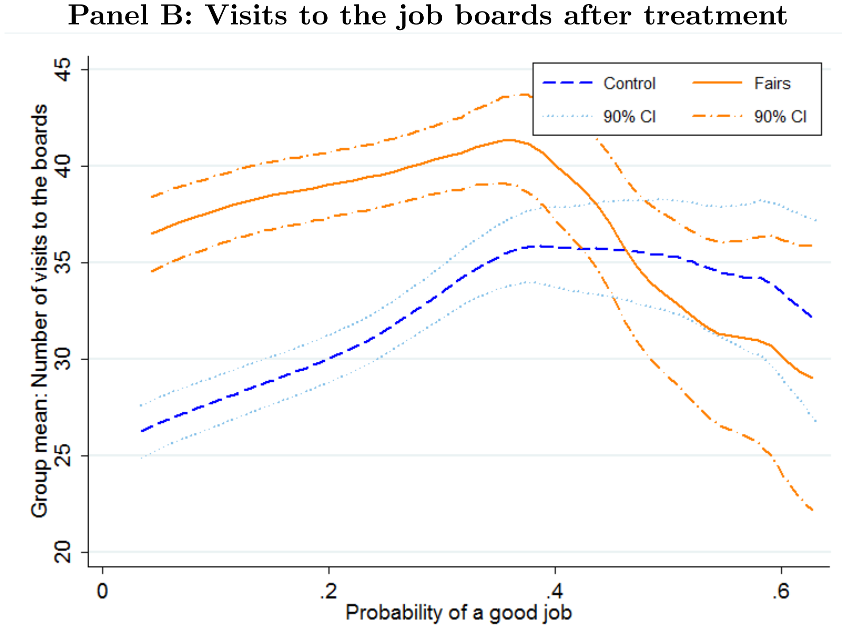
Note. Attrition is defined as failure to complete one interview.

Figure 2: **Shape of treatment effects on expectations and job search by predicted access to good work**

Panel A: Reservation wage



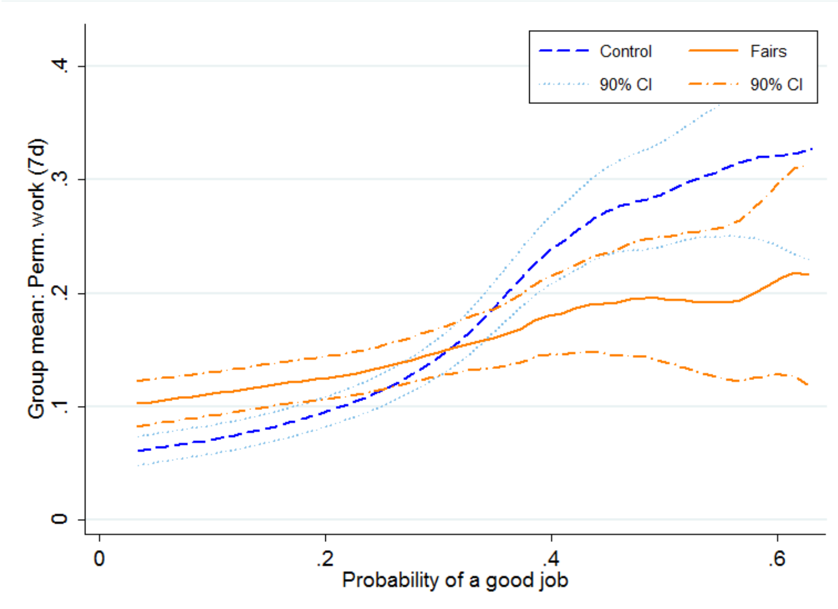
Panel B: Visits to the job boards after treatment



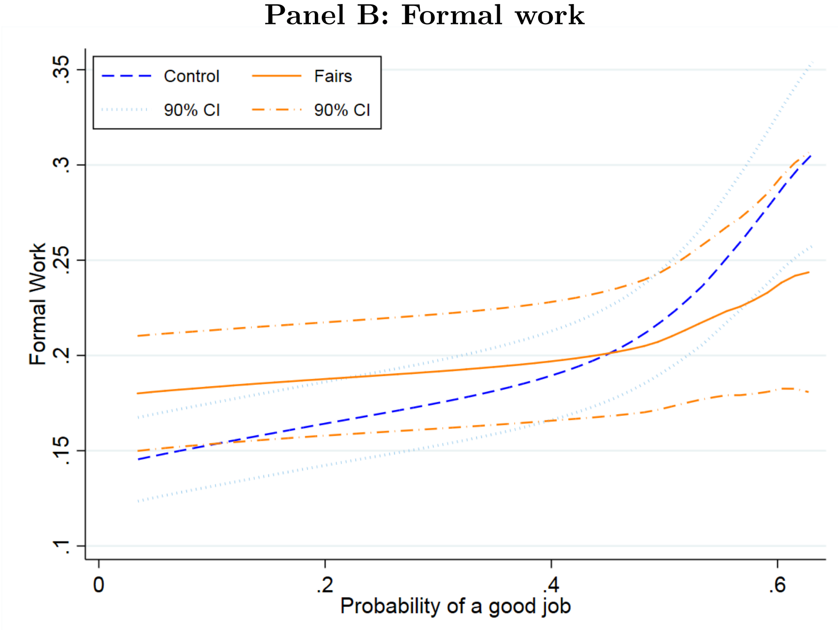
In this Figure we generate a predicted probability of having a good job based on a baseline characteristics. Specifically we regress, for the control group, having a good job (either permanent or formal) on 7 baseline covariates that we pre-specified as key sources of heterogeneity (we find that the strongest predictors of permanent work at endline are education, use of certifcates in applications, and previous work experience). Then, we generated predicted probability of good work for the entire sample. Finally, we use local-polynomial regression to estimate the relationship between predicted good work and job search, expectations and employment outcomes at endline. We do this for the control group and the treatment group separately, to show how the fairs has impacts that vary with level of predicted work.

Figure 3: **Shape of treatment effects on expectations and job search by predicted access to good work**

Panel A: Permanent work



Panel B: Formal work



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