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ABSTRACT

Matching Frictions and Distorted Beliefs: Evidence from a Job Fair Experiment*

We evaluate the impacts of a job fair intervention that decreases meeting costs between large firms and young jobseekers, randomizing fair attendance among workers and among firms. The fairs generate a rich set of interactions between workers and firms, but very few hires: one for every twelve firms that attended. On the other hand, the fairs motivate both firms and workers to invest more in job search, which leads to better employment outcomes for some jobseekers. Using data from a unique two-sided survey with a new sample of young workers and firms alongside data from the fairs, we show that these impacts are driven by the fact that both firms and workers have inaccurate beliefs about fundamental aspects of the labor market – in particular, the distribution of skills and the competitiveness of specific occupations – which are corrected at the job fairs. Overall, our evidence suggests that, beyond directly slowing down efficient matching in the labour market, search frictions can impose a second, understudied cost: they entrench inaccurate beliefs, further distorting search strategies and the allocation of talent.

JEL Classification:
O18, J22, J24 , J61, J64

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1 A matching experiment

Matching frictions may prevent the efficient allocation of workers across firms, sectors and industries. The costs from this misallocation are likely to be large, especially in developing countries undergoing profound economic transformations (Bryan and Morten, 2019; Hsieh, Hurst, Jones, and Klenow, 2019). However, the precise channels through which matching frictions make it difficult for firms to hire the right workers or for workers to find the right firm are not fully understood.

In this paper, we provide new experimental evidence on the distortions generated by matching frictions in a fast-growing developing economy (Alfonsi, Bandiera, Bassi, Burgess, Rasul, Sulaiman, and Vitali, 2020; Abebe, Caria, Fafchamps, Falco, Franklin, and Quinn, 2020). In particular, we focus on the high costs that firms and workers have to bear to meet each other. These costs can have a direct effect on hiring and on job-finding, resulting from a lower probability of well-matched workers and firms meeting one another.[1] In addition, by reducing the exposure of firms to workers and of workers to firms, these costs can entrench inaccurate beliefs about the fundamentals of the labour market – e.g. beliefs on the distribution of jobseekers' ability. These inaccurate beliefs, in turn, are likely to distort key job-search and recruitment decisions, resulting in fewer and poorer matches. Our central contribution is to shed light on this little-explored second channel – through an experiment that provides a large one-time reduction in the cost of worker-firm meetings, and through a novel survey that captures workers and firms' beliefs about the labour market.

Our evidence comes from a country that is undergoing a rapid economic transformation: Ethiopia. Similar to many other fast-growing economies in Sub-Saharan Africa, Ethiopia is witnessing the expansion of non-traditional economic sectors, sustained workforce growth, a strong build-up of secondary education, and swift urbanization. In this context, labour market fundamentals – such as the distribution of worker ability or the competitiveness of particular occupations – are likely to change rapidly. At the same time, workers and firms have to pay substantial costs to acquire information, apply for suitable jobs, or to post vacancies and screen candidates (Abebe, Caria, and Ortiz-Ospina, 2020). These costs make it harder to develop accurate beliefs about the labour market.

We evaluate the impacts of reducing these meeting costs by inviting to a job fair a sample of young jobseekers and of medium-to-large formal employers. At the fair, workers can meet several employers at a low marginal cost, and employers can easily talk to many potential young recruits. As a result, meeting costs are low and each side of the market has the opportunity to gather a large amount of information about the other side. Our research design has several

[1] Eeckhout (2018) summarises some of the key theoretical literature. Additionally, recent structural work in both developed and developing countries consistently detects the presence of meaningful labour market search costs (DellaVigna, Lindner, Reizer, and Schmieder, 2017; Van den Berg and van der Klaauw, 2019; Abebe, Caria, and Ortiz-Ospina, 2020).

key features that enable us to fully explore the implications of the matching frictions we study. First, we randomize participation among firms as well as workers, allowing us to test for frictions affecting both employers and jobseekers. Second, we collect information about job interviews and offers arising as an immediate consequence of participation in the fairs, as well as detailed data on firms' and workers' labor market expectations, search strategies, and market outcomes over time. This allows us to test for immediate as well as delayed effects of participation on firms and workers. Third, we invite representative samples of young unemployed workers and of formal firms to participate in the fairs (subject to several eligibility criteria, discussed shortly). This increases the external validity of our findings.

Based on our initial experimental results – which suggested an important role for distorted beliefs on both side of the labour market – we returned to the field to run a unique survey administered to a new sample of firms and young workers, selected respectively during hiring and during job search. This survey enables us to measure carefully a set of beliefs that are central to the matching process, and may be impacted by participation in a job fair, but that have not yet been documented in the literature – for example, firms' beliefs about workers' ability, conditional on observable characteristics. Further, since we simultaneously observe representative samples of both sides of the market, we can contrast beliefs with actual data on the true distributions. This enables us to produce a more extensive set of evidence on labour market beliefs and their accuracy than the literature has presented so far.

We have three key results. First, we show that the fairs generate a rich set of interactions between workers and firms, but very few hires. Three quarters of participating job candidates had an interview or in-depth discussion with at least one recruiter at the fair. Among those who met with a 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, generated only 14 accepted job offers – one for every twelve firms that attended. From this we conclude that participation in the job fairs did not have a meaningful direct effect on hiring. This result is not due to adverse selection of participants, or to congestion during the job fair. Importantly, we facilitated search at the fair by including algorithmic recommendations. Using a Gale-Shapley algorithm that combines job information obtained from firms with data on candidates' profiles and preferences, we gave firms and jobseekers a list of recommended candidates who were likely to be interested in their vacancies, given existing jobs openings at other firms. This approach aimed to promote employee-candidate encounters with a higher chance of leading to an accepted offer.[2] Using dyadic data, we show that our approach facilitated meaningful interactions and did not cause congestion. Overall, this suggests that, if meeting costs prevent efficient matching

[2] 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, Niederle, and Roth (2005)). The relevance of matching algorithms in less structured markets, such as this one, remains an open empirical question.

in this market, the job fairs on their own are unable to remove this barrier.[3]

Second, we find that both firms and workers revise their search strategies after the fairs, suggesting that the information they acquired through the intervention led to a revision of their labour market beliefs. In particular, firms increase their advertising and recruitment through formal channels. Further, we have suggestive evidence that, while total hiring does not change, firms are less likely to require tertiary qualifications for white-collar positions and, among firms with an above-median number of white-collar jobs, we also observe a significant drop in hiring. For jobseekers, impacts 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, they reduce their reservation wages and increase their search effort. 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. These results are consistent with the hypothesis that firms have unrealistic expectations about the skills of highly educated jobseekers, and that jobseekers are optimistic about their labour market prospects.

Third, we investigate the hypothesis of unrealistic expectations. We show clear evidence that the labour market beliefs of both firms and workers are inaccurate. To do this, we use our novel survey on two-sided beliefs, as well as detailed data on the expectations of job fair participants before and after the job fairs. We show both that firms have an inaccurate perception of the skill premium of jobseekers with tertiary education, and that workers have overly optimistic beliefs about their prospects of obtaining higher-paid professional jobs, given their qualifications. Importantly, we also show that beliefs about facts that are easy to observe tend to be relatively accurate on both sides of the market (for example, beliefs about wages paid in particular occupations among job seekers). This suggests that, while market participants value and acquire relevant publicly available information, the natural interaction between firms and young jobseekers in the labour market is insufficient for participants to learn key parameters of the matching process that are only observed in a direct meeting (e.g. the ability of the worker). The job fairs correct this, by allowing both sides of the market to acquire an unusually large amount of information about each other. Crucially, updating these distorted beliefs has economically meaningful consequences: our second key result suggests that this updating leads workers and firms to re-optimize their search strategies. This leads, in the case of jobseekers, to better endline employment outcomes.

The key contribution of this paper, therefore, is to show that both firms and workers hold inaccurate beliefs about fundamental aspects of the labour market. Labour market participants, on both sides of the market, suffer not merely from a problem of information asymmetries but from a deeper misperception of the distribution of characteristics among other market partici-

[3] This is consistent with the result in Wheeler et al. (2019) that pecuniary job search costs are not the primary mechanism through which online job-matching platforms work.

pants. On the contrary, models of search and matching typically assume that market participants are uncertain about the skills of a specific jobseeker, or the competitiveness of a specific vacancy, but are aware of the distributions from which agents are drawn (Rogerson et al., 2005; Terviö, 2009; Wright et al., 2019). As a result, previous empirical work on market beliefs has mostly generated insights on uncertainty about the characteristics of specific individuals (Bassi and Nansamba, 2020; Carranza et al., 2020; Abebe et al., 2020). In this paper, we show that firms and jobseekers make decisions on the basis of information that is limited in a more fundamental sense.

This central finding advances two separate bodies of literature. First, we contribute in a number of ways to the literature cited above on information problems in the labour market. Importantly, a key innovation is our focus on beliefs about market fundamentals, relative to the literature on asymmetric information about the characteristics of individual workers. Second, we provide direct evidence on the beliefs of both firm managers and jobseekers. Evidence on the labour market beliefs of firm managers is particularly scarce. Third, while previous work has often been unable to measure the accuracy of labour market beliefs in relation to comparable empirical moments, our simultaneous survey and belief-elicitation exercise enables us to compare beliefs to true empirical values. These unique features enable us to show that firm managers hold beliefs that are substantially inaccurate, and that this has important implications for behaviour in the market.[4] Finally, we show that wrong beliefs can be partially corrected by a relatively short intervention that decreases the meeting costs of firms and workers. In other words, we show that distorted beliefs persist – at least in part – because workers and firms have relatively little contact.

Second, we contribute to a recent literature studying over-optimism among jobseekers in low-income settings. Banerjee and Sequeira (2020) show that distorted beliefs particularly due to spatial distance between workers and firms can make workers overoptimistic about finding formal jobs.[5] Correcting those beliefs reduces their search effort in the city centre. We contribute by showing that over-optimism among jobseekers can lead them to *under*-invest in job search. We find that – for the group who update their beliefs the most – correcting jobseekers beliefs' through direct contact with firms leads them to search harder and find employment faster. This finding relates to a similar literature from high-income settings, which finds that over-optimism can delay exit from unemployment (Spinnewijn, 2015; Krueger and Mueller, 2016; Mueller et al., 2020); we contribute to this literature by providing complementary evidence from a low-income setting, which lacks unemployment insurance. More generally, these results are related to other studies that have shown that providing shocks to jobseekers' information set can induce them to

[4] Our findings complement the results in Abebe et al. (2020), who show that firm managers make biased forecasts about the results a recruitment intervention, and of Caria and Falco (2020), who present lab-experimental evidence that small-firm managers are excessively concerned about worker trustworthiness.

[5] Other recent papers showing evidence for over-optimism among jobseekers in developing countries include Alfonsi et al. (2020) and Groh et al. (2015).

search harder (Bassi and Nansamba, 2020; Beam, 2016; Jensen, 2012). We add to this literature by providing evidence that distorted beliefs is the mechanism driving low baseline search effort, and that making beliefs more accurate can increase search effort.

2 The study population

We work in a rapidly growing urban center in a low-income setting, where frictions are likely to be prevalent in the labor market. Addis Ababa, capital of Ethiopia, is a good choice because it combines these characteristics with the additional feature that, at the time of our study, the main avenue through which firms advertise openings is through job-vacancy boards located in the center of the city. While the purpose of these boards is to facilitate job search, they nonetheless entail sizeable transaction costs – especially for jobseekers, who must incur substantial transport costs to visit, and then need to spend spend considerable time visually scanning the boards to identify suitable openings.

Screening by firms is also challenging, given the limited information that can be extracted from the CVs of young labor market entrants (Abebe et al., 2020). Like many growing cities in the developing world, Addis Ababa has recently experienced a large increase in the number of available jobs, coupled with high in-migration flows. This makes it hard for firms and jobseekers to have accurate beliefs about the distribution of wages, employment opportunities, and workers' abilities. All these features suggest that job fairs are a promising intervention in this context.

2.1 Surveying jobseekers

The job fair intervention reported in this paper draws on the same sampling frame as Abebe et al. (2020) and was partially run alongside it.[6] The study involves a representative sample of young educated jobseekers in Addis Ababa. To select our sample, we first define geographic clusters using enumeration areas from the Ethiopian Central Statistical Agency (CSA).[7] Our sampling frame excludes clusters within 2.5 kilometres of the center of Addis Ababa and clusters outside the city boundaries. Clusters are selected at random from the sampling frame. To minimize potential spillover effects across clusters, we impose the condition that directly adjacent clusters cannot be selected together.

In each selected cluster, we used door-to-door sampling to construct a list of all individuals who: (i) are aged between 18 and 29 (inclusive); (ii) have completed high school; (iii) are available to start working in the next three months; and (iv) are not currently working in a

[6] Abebe et al. (2020) report two parallel field experiments: a transport subsidy to visit job boards, and a workshop intervention to help jobseekers to signal their cognitive and non-cognitive skills to employers.

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

permanent job or enrolled in full time education. We randomly sample individuals from this list to be included in the study. The lists include individuals with different levels of education. We over-sample individuals with post-secondary education to ensure that they are sufficiently represented in our sample.

All randomly selected individuals were contacted to establish their willingness to participate in the study and be interviewed. 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) and dropped individuals who could not be reached after at least three attempts. We also dropped any individual who had found a permanent job at the time of baseline and had been in this job 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 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. (2020), while 823 remain in the control group.

We collected data 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. Information was collected on the socio-demographic characteristics of study participants, their education, work history, finances, and their expectations and attitudes. We also kept in touch with all study participants by phone throughout the duration of the study, at which time we administered a short questionnaire on job search and employment.[8]

We have low attrition: 93.3% of baseline respondents were re-interviewed at endline. Few covariates predict attrition and we are unable to reject a joint F-test that a range of covariates have no effect on attrition (see Appendix Table A9 in the Online Appendix). However, we do find that the individuals invited to the job fairs are slightly more likely to respond to the endline survey. Yet, because attrition is low overall (8% in the control group and 5.6% in the treatment group), we are not concerned that this affects our main results. 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 were still able contact 90% of the respondents in the final month of the study.[9]

2.2 Surveying firms

We surveyed 498 large firms in Addis Ababa. These firms were sampled so as to be representative of largest employers in the city, stratified by sector. All major sectors in the economy are covered, including construction, manufacturing, banking and financial services, hotels and hospitality,

[8] Franklin (2018) shows that high-frequency phone surveys of this type do not generate Hawthorne effects and do not affect jobseekers' responses at endline.

[9] Appendix Figure A1 shows the trajectory of monthly attrition rates over the course of the phone survey.

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 rely on a variety of data sources, including lists of formal firms maintained by different government ministries. In all, we gathered data from more than eight different sources. For the manufacturing sector, we rely on a representative sample of large firms that took part in the Large and Medium Enterprise surveys conducted by the Central Statistics Agency (CSA). For other sectors we requested lists of the largest firms from the government agency in charge of that sector. Whenever information on firm size is available, we impose a minimum size cut-off of 40 workers.

We draw the firms in our sample using sector-level weights to reflect the number of employers in that sector in the city. We construct these weights using representative labour-force data.[10] The firms are, on average, large by Ethiopian and African standards. The mean number of employees per firm is 171.5 workers. This masks considerable heterogeneity, particularly in the 'Tours & Hospitality' sector which is dominated by small hotels and restaurants; when this sector is excluded, average firm size is 326 workers. Detailed information on firms' total employment is given in Table 1, excluding casual daily laborers. On average, firms report employing 34 casual laborers per day.

The firms in our sample are growing in size and looking to hire new workers. At baseline, the median number of workers that a firm expects to hire in the next 12 months amounts to 12% of its 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 whom firms expect to hire are white-collar workers, usually requiring university degrees. For details, see Appendix Table A4.

3 Experimental design

3.1 Randomization to the job fair

We assign treatment of jobseekers to the job fairs by geographical cluster, after blocking on cluster characteristics (see Abebe et al. (2020) for further details). The sample is balanced across all treatment and control groups, and across a wide range of outcomes – including baseline outcomes that are not used in the stratified randomization procedure. We present extensive balance tests in Appendix Table A1. For each baseline outcome of interest, we report the p-values for a test of the null hypothesis that we have balance between treatment and control groups. We cannot reject the null for any of variables that we study.

[10] Table A6 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.

We assign 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 are invited to attend the job fairs; control firms are not. The following method is used to block firms for sampling. Firms are first partitioned into five main industries (see Appendix Table A6). Within each industry, firms are partitioned into blocks of four nearest neighbors on the basis of their Mahalanobis distance over a set of baseline variables.[11] We then randomize the firms in each block into two groups of two firms: one firm is invited to the first day of the job fair; the second is invited to the second day (see below for details); and the other two are assigned to serve as controls. Given the relatively small size of the firm sample, we use a re-randomization approach to ensure balance on a set of baseline covariates listed in Table 2.[12]

3.2 Implementation of the job fairs

We invited treated jobseekers 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 run two fairs to increase the chance that each jobseeker and firm is able 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 a randomly selected half of the firms and jobseekers were invited to attend on each day. The firms that were invited to attend on Saturday 25 October were then invited to attend on Sunday 15 February; firms invited for Sunday 26 October were invited for Saturday 14 February. In contrast, jobseekers invited to attend on the Saturday of the first fair were also invited to attend on the Saturday of the second fair; jobseekers invited for the Sunday of the first fair were invited for the Sunday of the second fair. This ensures that, in each job fair, jobseekers are exposed to a different pool of firms, and that firms are exposed to a different pool of jobseekers.[13]

During each fair, jobseekers and firms are free to interact as they see fit. Each firm sets up a stall before the jobseekers arrive. These stalls are typically staffed by the firm's HR team who bring with them printed material advertising the firm. In a typical interaction, a jobseeker approaches the stall of a firm and asks questions about the firm and its vacancies. The firm's HR staff is then free to check his or her CV and to ask about the jobseeker's skills and work experience. If the jobseeker looks suitable for one of the firm's vacancies, the firm invites her or

[11] The variables used for blocking are listed in Appendix Table A7.

[12] Following the recommendations of Bruhn and McKenzie (2009), we control for these covariates in our estimation, as well as for the baseline covariates used to construct the randomization blocks. Details of these variables and how they are defined are contained in our detailed pre-analysis plan. Simulations show that, with this sampling strategy, we have 78% power to detect a small treatment effect of 0.2 standard deviations at a significance level of 0.05%.

[13] Weekend days are selected to maximize the opportunity for both firms and jobseekers to attend. In preliminary discussions with firms, we realized that most would be unable to take time off from daily activities to attend during the week, but they were interested in attending on a weekend. Similarly, many jobseekers in our sample work in casual jobs and are more likely to be unavailable during the week. Since many Ethiopians attend religious services on the weekend, we set a long enough time window for jobseekers to be able to attend.

him for a formal job interview a few days after the job fair.

To avoid self-selection out of the sampling frame, we do not restrict invitations to the fairs to currently unemployed jobseekers, or to firms that have open vacancies at the time of the fair. Of our initial sample of jobseekers, only about 8% had permanent jobs by the time of the first job fair, and thus most jobseekers were still searching for work. Similarly, most firms were hiring at the time that the job fairs were held. 89% hired at least one worker in the year of the study and, on average, firms hired four workers in the month after the job fairs and 52 workers in the year of the fairs.

In total, we invited 1,007 jobseekers and 248 firms to attend the fairs. Both jobseekers and firms were contacted by phone, were given some information about the nature of the fairs, and had the opportunity to ask questions. Among firms, 170 attend at least one job fair, which represents quite a successful take-up rate of 68.5%. Of the firms that do not attend the fairs, 12% say it is because they do not have an open vacancy at the time. The remaining firms tend to cite logistical issues or previous commitments. Only 13 firms respond that they would not find the job fair useful.[14]

Of the 1007 invited jobseekers, 606 attend at least one fair, a 60% take-up rate. The most common reason that jobseekers give for not attending the fairs is that they are busy during that particular weekend. This reason is given by 226 jobseekers in the first fair and 229 jobseekers in the second. Other reasons include not being able to take a new job (9 jobseekers at the first fair and 83 at the second) and finding the venue of the fair hard to reach (31 respondents for the first fair and 25 for the second).

Two baseline characteristics predict higher attendance by jobseekers: search effort at baseline; and whether the jobseeker uses a school certificate during job search. It follows that jobseekers who attend the fairs are, if anything, more active and organized in their job search. Those who attend are also more likely to have a university degree or diploma, but this is not statistically significant. Taken together, this evidence provides reassurance that results are not driven by negative selection of jobseekers coming to the fairs.

3.3 Matching at the fairs

At the beginning of each fair, we give jobseekers a list of all the firms invited. In the second fair, we also give jobseekers the list of all vacancies, and we give firms a list of all jobseekers invited to the fairs, with some information about their education and past work experience. We then ask firms to list up to 10 jobseekers with whom they would like to talk at the job fair. After collecting the list of requested meetings from each firm, we post them on a board at the fair.[15]

[14] In Appendix Table A8, we run a descriptive regression to explore correlates of firm attendance at job fairs.

[15] Given the logistics of collecting lists of names from more than a hundred employers, the lists were posted a few hours after the beginning of the fair.

In order to increase match efficiency and avoid congestion at the fairs, we create a list of 15 recommended meetings that we give to each jobseeker at the beginning of the fair. Of the 15 firms on the recommended list, 10 are selected using a Gale-Shapley Deferred Acceptance algorithm described below (Gale and Shapley, 1962); the other five are selected at random. The order of presentation on each list is similarly randomized. We tell jobseekers that these are the firms they should talk to during the fair. Each firm similarly receives a personalized list showing the names of all the jobseekers who have been recommended to meet that firm. The recommendations are based on information about firms' vacancies that we obtain through a phone survey shortly before the fair.

The purpose of the Gale-Shapley algorithm is to suggest sensible matches for these vacancies, given baseline characteristics of both jobseekers and firms. Indeed, not all jobseekers are qualified for certain positions, and not all firms can attract the best jobseekers. To avoid firms and jobseekers wasting time in unsuccessful meetings, we seek to pair those firms and jobseekers who, given the distribution of firms and jobseekers at the fair, stand a higher chance of leading to a hire. To this end, we start by constructing a synthetic ranking of all vacant positions for each jobseeker, and similarly a synthetic ranking of all jobseekers for each firm. The rankings of jobseekers by firms are constructed using lexicographic preferences over: (i) whether the jobseeker held a previous occupation that matches that of the vacancy; (ii) the jobseeker's educational qualification for the job; and (iii) the jobseeker's years of wage employment. The rankings of jobseekers vary across firms. For the jobseeker's rankings of vacancies, we use a simple ranking over the advertised wage. This means that, for the purposes of forming recommendations, all jobseekers synthetically rank vacancies in the same way.

These rankings are not intended to represent literally the true preferences of all participants over all possible matches. Indeed, gathering information on all these preferences would have been logistically impossible in the allotted time – and any attempt to impose such a ranking burden on jobseekers or firms would undoubtedly have reduced substantially the participation in the experiment. Rather, the rankings are intended to provide a fast way of improving on random encounters at the fairs that takes into account the heterogeneous set of vacancies and jobseeker skills that are present at the fair. After creating a ranking of jobseekers for each vacancy and a ranking of vacancies for each jobseeker, a Gale-Shapley algorithm is used to match jobseekers and firms. Specifically, the algorithm generates a single set of matches; we then iterate the algorithm 10 times, requiring a different set of recommended matches each time.[16] This generates the 10 recommended matches mentioned above; to this list, we then add five random matches.

Figure 1 illustrates the outcome of the matching algorithm. Each point represents a stable match recommended by the algorithm. The figure shows which combinations of firm rankings and jobseeker rankings generated these recommended matches. The graph provides a visual

[16] We implement this requirement by taking the matches recommended in iteration t and placing those matches at the bottom of the firms' and jobseekers' rankings in iterations $s > t$.

illustration that the algorithm worked well in the sense of generating matches between firms and jobseekers who are, on the basis of jobseeker skills and experience, reasonably suitable for each other. Note the substantial mass at the bottom-left of the graph. It shows that, for those firms paying higher wages, the algorithm recommend matches that provide a reasonable occupational fit. For example, for top 100 firms in the jobseekers' ranking, the median match is to a jobseeker with a firm ranking of just 14, that is, a jobseeker ranked quite high according to our synthetic firm preferences.

4 The effects of the fairs

We study the impacts of the job fairs on employment outcomes, as well as on the subsequent search behaviour of jobseekers and firms. If job fairs are effective in reducing frictions, we should observe a higher employment probability among treated jobseekers and fewer unfilled vacancies or more hires among treated firms. Further, we should observe subsequent search and recruitment activities to slow down, since several firms and workers have found a productive match. In contrast, if job fairs mostly cause participants to update their expectations about possible market outcomes, we may observe a negligible or modest initial impact on employment, but changes in search strategy among firms and jobseekers with initially unrealistic expectations subsequent to the job fair. For instance, if jobseekers with high reservation wages at the job fairs realize their initial wage expectation was too high, they may subsequently accept lower wage offers. Similarly, if firms realize that few jobseekers have the needed skills, they may increase their search effort.

In what follows, we present separate evidence on the effect on firms and the effect on jobseekers of being invited to a fair. Employment outcomes are measured through data on job interviews, offers, and hiring in the immediate aftermath of a fair, as well as hiring outcomes at endline, six months after the second job fair. To test for impacts on search behaviour, we look at impacts on reservation wages and on the search strategies used by firms and jobseekers at endline. Impacts on search behaviour are more likely to be observed if a direct effect on hiring is absent or weak: if treated jobseekers find a job and firms fill their vacancies as a direct outcome of the fairs, they have little cause to revise their expectations and search strategy.[17]

4.1 Hiring at the job fairs

The fairs generated rich interactions between firms and jobseekers. 454 jobseekers (75% of those attending) interacted with at least one firm at the job fair, either through an informal

[17] The pre-analysis plan that we filed for this experiment can be found at https://www.socialscienceregistry.org/trials/1495. Most pre-specified outcome families are presented in the order in which they appear in the PAP. Those that are not documented here in detail can be found in the Online Appendix.

interview or an in-depth discussion with a recruiter. This finding is particularly strong among participants who benefited from the matching algorithm treatment. In total, we record 2,191 contacts between firms and jobseekers.

However, these numerous interactions between employers and jobseekers seldom translated into formal job interviews. As a whole, the two job fairs generated a total of 105 formal job interviews conducted at a participating firm in the immediate aftermath of a fair – implying a conversion rate of 1 interview for each 20.9 contacts established at the fair. Further, these 105 interviews are concentrated on 67 jobseekers only, representing 11% of those attending the fairs. These interviews led to 76 offers to a total of 45 jobseekers, which represents a healthy conversion rate of one offer for each 1.4 interviews. Contrary to what one might expect in a job fair for educated jobseekers, offers were disproportionately made to less-educated applicants: 55 offers (72%) went to jobseekers with at most a high-school diploma, even though they represented a minority of the jobseekers attending.

Although a few offers were made at the fairs, most of them were rejected. Only 14 jobseekers – 2% of those attending the fairs – accepted an offer, while 31 jobseekers rejected all the offers they received. This high rejection rate explains why only one job was created for every 12 firms that attended the fair (that is, one job was created for every 7.5 interviews). The offer rejection rate is particularly high among less educated jobseekers: 85% for applicants with a high-school diploma compared with 71% for those with tertiary education. Only 33% of offer recipients with a high-school diploma accepted one of their offers.

How do these conversion rates compare to jobseeker search effectiveness outside the fairs? First, in the open market, jobseekers secured an interview for every 3.5 job applications, an offer for every 1.9 interviews, and a job for every 3.3 interviews over the period between the baseline and endline surveys. This implies that contacts with employers at the fair (20 on average) were much less likely to result in an interview than a formal job application. The contrast is particularly striking for highly educated jobseekers, who tend to do better in the labour market but did particularly poorly at the fair. Second, the 1.4 conversion rate of interviews into offers compares favorably to the 1.9 conversion rate observed outside the fairs. Third, the conversion of interviews into jobs is much lower at the fair: one job for 7.5 interviews instead of 3.5 outside the fairs. A large majority (81%) of offers made in the aftermath of the fairs were rejected. To verify these findings, we conducted a phone survey of firms immediately after each job fair. Appendix Tables A11 and A12 show the immediate impact on overall hiring and the type of job candidate hired, respectively. These results confirm that the fairs had no significant impact on short-term hiring by treated firms.

4.1.1 Was the market at the job fairs too thin?

One possible explanation for this small direct effect is the market at the job fairs was too thin: there were too few high-quality worker-firm matches available. We present evidence against this hypothesis both from the jobseeker and the firm side. First, we investigate whether the jobs on offer were too few or did not match jobseekers' interests. To study this issue, we use data that was collected from participating firms prior to arriving at the fairs. Firms were to provide a roster of all their open vacancies at the time of the fairs.[18] The average firm at the fair had two vacancies open and was looking to hire seven workers. 70% of participating firms had at least one vacancy. In total, there were 711 vacancies and 1,751 jobs available at the fairs. The occupational composition of the vacancies exhibits considerable overlap with the distribution of occupations desired by jobseekers invited to the job fairs. It is therefore unlikely that firms did not have enough vacancies of the kind that jobseekers wanted.

Second, we investigate whether jobseekers were negatively selected and hence firms were reluctant to hire them. To explore this possibility, we compare the jobseekers who attended (about 60% of those invited) to those in the full sample, which is near-representative of educated young jobseekers in Addis Ababa at the time of the study. In Appendix Table A5 we regress attendance at the fairs on a rich set of baseline characteristics. We find no evidence suggesting that observably weaker candidates are more likely to attend the fairs: education and current employment do not significantly predict attendance. The only two robust predictors of attendance are instead associated with a positive motivation to work: attendance is higher among those jobseekers who search the most at baseline and who produce a formal certificate to employers.[19] Further, in the second job fair, we showed firms the list of qualifications of jobseekers at the fair and asked them whether they were interested in interviewing some of them. Most responded positively and provided the names of several candidates of interest to them. Across both fairs, firms report meeting 20 jobseekers on average. We can therefore rule out that firms were in principle uninterested in the jobseekers that attended the fairs.

4.1.2 Did the fairs suffer from congestion and mis-coordination?

Since both employers and jobseekers were interested in each other and willing to interact, could the small direct effect of the fairs be due to congestion and miscoordination? That is, could the effect be explained by firms and jobseekers having wasted their time and effort talking to the wrong people? To investigate this possibility, we test whether the jobseeker-firm pairs that

[18] We define a vacancy as an open position for a specific occupation. Firms first produced a list of vacancies (e.g. a firm could report that they were both looking for clerical workers and for drivers) and, then, for every vacancy, they reported the number of workers they were planning to hire in that position.

[19] Invitees already in permanent employment at the time of the fairs are slightly less likely to attend. But the effect is unlikely drive our results: 4% of those attending the fairs have a permanent job compared to only 5.6% of the total sample.

met are those that were most suitable for each other, given the mix of employers and jobseekers at the fairs. We use two types of variables to assess mutual suitability: the synthetic rankings, and the proposed matches that we suggested to participants. The two ranking variables are $\texttt{Rank}_{fj}$, which is firm f's ranking of jobseeker j, and $\texttt{Rank}_{jf}$, which is jobseeker j's ranking of firm f. The two proposed match variables are: $\texttt{Gale\_Shapley}_{fj}$, which is equal to 1 if jobseeker j and firm f were recommended to each other by our Gale-Shapley algorithm, and $\texttt{Random}_{fj}$, which is 1 if jobseeker j and firm f were randomly recommended to each other by us. If firms and jobseekers are able to engage in promising interactions, we expect participants' rankings to predict who wishes to meet with whom and who actually meets whom. If our matching algorithm was capable of identifying promising matches instead of random matches, we expect meetings and willingness to meet to be predicted by $\texttt{Gale\_Shapley}_{jw}$ but not by $\texttt{Random}_{jw}$.

To test these hypotheses, we estimate two dyadic regression models:

$$y_{fj} = \beta_0 + \beta_1 \cdot \texttt{Rank}_{fj} + \beta_2 \cdot \texttt{Rank}_{jf} + \mu_{fj}; \tag{1}$$

$$y_{fj} = \beta_0 + \beta_1 \cdot \texttt{Gale\_Shapley}_{fj} + \beta_2 \cdot \texttt{Random}_{fj} + \mu_{fj}, \tag{2}$$

where y_{fj} is either $request_{fj}$, a dummy equal to one if firm f requested a meeting with jobseeker j, or $meet_{fj}$, which equals one if firm f and jobseeker j actually met. Standard errors are clustered two-way at the level of the firm and jobseeker (Cameron, Gelbach, and Miller, 2011).

We report estimates in Table 3, using the jobseekers and firms who attended the fairs. We find that the synthetic rankings predict both requested meetings 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. We interpret these results as showing that the fairs are effective in bringing together jobseeker-firm pairs who – at least on the basis of observable characteristics – value each other. Algorithmic recommendations are also shown to have a strong predictive power: matches suggested by our algorithm are about 200 percent more likely take place than non-suggested matches. In contrast, the coefficient on randomly suggested matches is small and never significant. This contrast suggests that our stylized matching algorithm was useful in identifying matches that were deemed worth pursuing by market participants. The fairs thus appear to have reached their objective of facilitating meetings between jobseekers and the firms that suited them best.

4.2 Impact on search behaviour and on outcomes *after* the fairs

In this section, we examine the impacts of the intervention on the search behavior and outcomes of firms and workers after the job fairs. We first leverage a high-frequency survey that lets us document jobseekers' search behavior in the months following the job fairs. We then report endline impacts for both jobseekers and firms. Overall, we find clear evidence that both jobseekers and firms increase their search effort as a result of being invited to the fairs, and this leads to changes in outcomes that are particularly evident for the groups that revised beliefs the most.

4.2.1 Short-term jobseeker impacts from the high-frequency survey

To examine jobseekers' immediate response to the intervention, we rely on the fortnightly phone surveys conducted throughout the study with all treated and control individuals. From this data we plot in Figure 2 the fortnightly change in the probability that treated jobseekers visit the job boards relative to controls.[20] Fortnight 0 in the Figure is when the first job fair was held; the second fair was held in fortnight 8. We find that treated jobseekers are significantly more likely to visit the job boards after the fairs. On average, the probability of visiting the job boards goes up by about 8.3 percentage points (26% percent) in six weeks following the first job fair. Since the job boards are the main source of information on vacancies, this implies that jobseekers search harder for employment as a result of treatment.

4.2.2 Endline firm and jobseeker impacts

We study the impacts of the intervention on firms using an ITT approach with an ANCOVA specification. Following current practice, covariates used for balancing the randomization are included as controls. For each outcome of interest, we estimate regressions of the form:

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

with robust standard errors. Variable $y_{ic,pre}$ is the dependent variable measured at baseline and $\boldsymbol{x}_{i0}$ includes the randomization variables listed in Table 2. In the tables, we show each regression as a row and we report the estimated ITT ($\hat{\beta}_1$), the mean of the control group, and the number of observations. We report both p-values and False Discovery Rate q-values, the latter being calculated across the family of outcomes (Benjamini et al., 2006).[21]

Our first finding is that, as a result of the job fairs, firms invested more in worker search and recruitment. Our regression estimates, presented in Table 4, show that treated firms are six percentage points more likely to advertise new vacancies in the last 12 months, relative to

[20] Specifically, we estimate this difference in probabilities using a Linear Probability Model in an ANCOVA specification, in which we regress job search on treatment, baseline search status and a sector of baseline balancing variables. We cluster at the level of individual jobseekers, and show both point estimates and 90% confidence intervals; we do this both by regressing on fortnight dummies, and by imposing a quadratic shape.

[21] Throughout this paper, we report the average treatment effect of the job fairs. As outlined in the pre-analysis plan, our study was designed to enable us to estimate separately an effect of the fairs both with and without additional information revelation about workers' abilities. Since we found no direct effect of the fairs on hiring for either treatment arm, and the experimental information revelation was designed specifically to improve direct hiring at the fairs, we took the decision to pool the treatment arms. This also improves the precision of our null estimates of the direct effects of the fairs.

a control mean of about 79%. They are also 12 percentage points more likely to advertise for professional positions, relative to a control mean of 60%.[22] Firms are also almost 10 percentage points more likely to publicize their vacancies on the job boards, relative to a control mean of 33 percent. All three effects are statistically significant after controlling for multiple hypothesis testing. This suggests that the intervention leads both firms and jobseekers to search more intensely through the main channels available to them at the time of the study.[23]

Our second finding is that the job fairs do not significantly change whom the average firm hires over the 12 months period between baseline and endline. In Panel A of Table A10, we test whether treatment has an impact on firms' ability to fill vacancies at endline. We find no impact on the time taken to fill open positions or on firms' reported costs of recruitment. We do find a small but significant increase in the proportion of unfilled vacancies, but this effect disappears after correction for multiple hypothesis testing. In Panel B of Table A10, we look at the impact of the job fairs on the number of people hired in the last 12 months, the hiring of job candidates with a degree, and hiring on a permanent contract.[24] We find no effect of treatment. Thus, the main average treatment effect on firms is the way they look for new recruits.

Our last finding is that firms seem to reorient their hiring away from highly educated workers, in particular for professional positions. Among firms that hire above the median number of professional workers – a pre-specified dimension of heterogeneity – we find that, beyond raising recruitment investments, the fairs also (i) significantly reduce the proportion of professional workers with degrees by about 7 percentage points (relative to a control mean of 72 percent), (ii) reduce hiring by an average of 17 workers (over a control mean of 62 workers), and (iii) reduce overall firm size.[25] These results are consistent with the observation, discussed in the previous section, that firms at the job fairs did not extend interviews to workers with degrees. Further, in the next section, we will show that firms seem to be overly optimistic about the ability premium of highly educated workers.

Next we use a similar methodology to examine the effect of treatment on jobseekers' reservation wages, search, and employment outcomes. We use the same specification as equation 4.2.2. To account for the fact that jobseekers were randomized to treatment according to their

[22] Throughout the 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 production workers; for service-based firms, these include mostly workers dedicated to client services (tellers, waiters, receptionists, *etc*).

[23] We do not find significant heterogeneity in these impacts. However, effects on recruitment appear to be larger among firms that did not hire many young people at baseline (Table A19). This result is consistent with a learning story, as those firms likely have noisier and more inaccurate priors about young people in the labour market.

[24] This is reflected in the fact that we find no impact on the firms' overall workforce composition (Appendix Table A13), overall turnover and employee growth (Appendix Table A14), and general HR practices (Appendix Table A15). Also, unsurprisingly, overall firm productivity and growth does not change in treated firms (Appendix Table A16).

[25] Results (i) and (ii) are presented in Table A23 in the Appendix, result (iii) is shown in Table A22.

enumeration area of residence, standard errors are clustered by enumeration area. We report both conventional p-values and False Discovery Rate q-values.

We have two key findings on jobseeker impacts. First, the fairs reduce reservation wages, bringing them more in line with market wages. We show these results in Panel A of Table 5. In column (1), we see that treatment results in a significant 7 percent reduction in endline reservation wages. Further, to test whether treatment makes reservation wages more in line with market conditions, we construct a 'wage mismatch' variable equal to the absolute difference between the log of the reported reservation wage, and the log of the average wage earned by a worker with the jobseeker's skill and education. We present data on the mismatch between market wages and reservation wages in Table 6, and treatment effects on wage mismatch in column (2) of Table 5. We find that treatment reduces the wage mismatch by a significant 4 percent. Table 5 also shows that treatment causes an increase in visits to job boards at endline: treated jobseekers report roughly three more visits to the job boards, relative to a control mean of 15.[26]

Second, the impacts of the fairs are concentrated among the least educated jobseekers, who experience a large fall in reservation wages and large increases in job search and employment quality due to the intervention. In Panel B of Table 5 we disaggregate treatment effects by whether or not the respondent has more than secondary education. We find that the average effect on reservation wages is mostly driven by low-education jobseekers, who reduce their reservation wage by 9 percent as a result of treatment, closing the mismatch between reservation wages and market wages by 7 percent. We also find that low-education jobseekers increase their visit to the job boards by 4.2 percent relative to a control mean of 11 visits. As a result of these changes, we observe a positive impact of the fairs on employment at endline among the least educated jobseekers. For this group, the fairs have a large significant impact on job quality. In particular, we document an increase of 6 percentage points in the probability of having a permanent job relative to a control mean of just 6 percent – i.e., a doubling of the probability of permanent employment. We similarly find an increase in the probability of having a formal job by 5 percentage points relative to a control mean of about 11 percent – i.e., a 45% improvement.[27]

[26] Treatment effects on employment outcomes are reported in Appendix Table A10; additional results on employment amenities and job search at endline are presented in Appendix Tables A2 and A3. We find no average treatment effect on whether respondents have any work at endline. The effects on whether they hold a permanent or formal job are positive but not significant. These average results, however, hide sharply contrasted treatment effect between low and high education jobseekers who, as we have documented earlier, had different experiences at the job fairs.

[27] In the bottom row of Table 5 we report p-values for the null hypothesis that treatment effects are equal across educational categories. The null is rejected for wage mismatch and having a permanent job, and it is close to being rejected ($p < 0.12$) for visiting job board and having a formal job.

5 Distorted beliefs

In this section, we provide evidence that firms and jobseekers hold inaccurate beliefs about each other. We focus on a core set of beliefs that are central to the search problem faced by firms and jobseekers. For firms, we investigate the perceived availability of skills in different segments of the labour market and the price of these skills (i.e. the reservation wage set by workers). For jobseekers, we study their beliefs about the distribution of wages in various occupations and the probability of receiving a job offer in that occupation.[28] Importantly, the job fairs provided direct information on these key parameters: firms observed jobseekers' ability by scrutinising CVs and by interacting with them, while jobseekers learnt about wages and interview invitations in various occupations. Further, indirectly, the fairs provided information about the effectiveness of search strategies based on these beliefs: firms had some of their offers rejected and jobseekers could compare the rejected offers to those they received subsequently on the market.[29]

The distorted beliefs that we document provide a coherent explanation for our key findings on the impacts of the job fairs. First, distorted perceptions led participants to set ineffective strategies at the job fairs – e.g. firms extended offers that were rejected and jobseekers targeted jobs they were not likely to get – which resulted in a low number of hires. Second, the fairs provided an opportunity to correct firm and jobseeker misperceptions. Jobseekers likely realised that their wage expectations were overly optimistic, while firms understood that the education ability premium was lower than they anticipated. In our context, where firms need to fill vacancies in a short time frame and jobseekers have insufficient liquidity for long search spells, these negative beliefs revisions plausibly increased the returns to job and worker search. As a result, search effort increased on both sides of the market (Spinnewijn, 2015).

5.1 Belief elicitation with firms and jobseekers

To shed additional light on the beliefs of market participants we fielded a new survey in 2019 that contemporaneously sampled firms that were advertising vacancies on Addis Ababa's job boards and jobseekers that were looking for vacancies at those job boards. This survey has three unique features. First, it focuses on a real, well-defined labour market. Second, it elicits beliefs on both sides of the market. While many papers study jobseeker beliefs, systematic data on the beliefs of firm managers is rare, especially in developing countries. Third, the survey enables us to measure the accuracy of beliefs. In particular, we can contrast firms' answers with the true empirical counterparts obtained from the jobseeker survey and viceversa; this improves over

[28] Search strategies will also likely depend on search costs and on government policies such as the provision of insurance. However, the job fairs did not plausibly provide any information about these parameters. We thus abstract from these in the following analysis.

[29] Approximately one year after rejecting the offers, 60 percent of the workers in this group are still unemployed and, among those who have a job, only 10 (20) percent of them earn a wage above 2000 (1000) Birr – well below the average entry level wage in the firms that attended the fairs.

existing studies that collect beliefs but cannot measure their accuracy.[30]

Overall, we are able to complete interviews with 395 firm managers and 779 jobseekers. We recruited jobseekers between the age of 18 and 29, who had at least a high school diploma. We contacted a random sample of firms that were advertising a position on the job boards or in the newspaper between the end of November and the end of December 2019. We also contacted some of the firms that jobseekers were applying to. In this way, we select samples of firms and jobseekers that resemble on key dimensions our original experimental participants.

The firm survey carefully elicits firm managers' beliefs about the ability of jobseekers. We document expectations both with respect to tertiary-educated applicants and high-school graduates. Ability is measured as a jobseeker performance on a Raven test. We took a number of steps to make sure that lack of familiarity with the Raven test would not distort our results. First, we provided that test to the managers, so that they would familiarise themselves with it. Second, before managers answered the ability questions, we provided them with real statistics on the difference in ability between workers with a high (75th percentile) and an average GPA in our sample. Thus, we generated a realistic anchor based on the Raven premium associated with an observable characteristic commonly used in hiring. We also elicited managers' beliefs about the jobseekers' reservation wages and their work experience. The elicitation of managers' expectations was incentivised.[31]

The jobseeker survey focused on reservation wages, the distribution of wages across sectors and the expected duration of unemployment. We elicited beliefs about the distribution of wages by asking the jobseeker what proportion of jobs currently advertised paid a wage lower than a set of thresholds (from 10,000 ETB to 1,000 ETB per month). Similarly, we elicited reservation wages by asking the jobseeker whether they would accept a job that would pay at least a a certain amount. This amount was decreased until we found the wage bracket corresponding to the jobseeker reservation wage. To minimise complexity, we did not incentivise the elicitation of beliefs among jobseekers. Finally, after belief elicitation was completed, jobseekers took a 12-item Raven test.

5.2 Firms' beliefs

The data we gathered on managers' beliefs offers four pieces of evidence supporting the conclusion that firms hold distorted beliefs about jobseekers. First, there is a large dispersion in firm beliefs. We show this Figure 3 through a series of 'raincloud plots' of manager beliefs, with su-

[30] Additional, our survey focuses on a new sample of market participants as opposed to the original experimental subjects. This has two distinct advantages. First, attrition after several years may have biased our sample. Second, the subjects that took part in the intervention were exposed to the information they gained at the fairs. Our interest, on the other hand, is in uncovering perceptions biases that may have existed prior to the fair.

[31] Participants were told that one of the questions they were asked would be randomly drawn at the end of the survey and they would receive a prize based on the accuracy of their answer.

perimposed vertical lines showing the average jobseeker characteristic. For example, when asked to forecast the proportion of tertiary educated jobseekers with work experience, firms' answers range from 20% (at the 25th percentile of the distribution) to 60% (at the 75th percentile of the distribution).

Second, firms underestimate the ability of secondary-educated jobseekers and overestimate the ability of tertiary-educated jobseekers. The average secondary-educated jobseeker answers about 5 questions on the Raven test correctly, while the average tertiary-educated jobseeker answers about 5.3 questions correctly. In contrast, the median firm forecasts that secondary-educated jobseekers answer 4 questions correctly, while tertiary-educated jobseekers answer 6 questions correctly. This difference is twice as the large as the difference in Raven performance between individuals at the 75th percentile and at the mean of the GPA distribution – the anchoring information we gave to firms before these forecasts. The true ability premium associated with tertiary education is less than one fourth of what firms expect. Additionally, while there is large variation in firm beliefs, about 90% of firms overestimate the ability premium.

Third, firms underestimate work experience among secondary educated jobseekers and overestimate it among the tertiary educated – a result that is consistent with the underlying misperception of relative ability. The bias in beliefs about secondary-educated jobseekers is particularly evident when managers forecast the share of the sample that has any work experience. About 55% of secondary-educated jobseekers have some work experience, while managers expect that about 30% of them have work experience. For tertiary-educated jobseekers, the bias is larger when managers forecast the proportion of jobseekers that have at least two years of work experience. In the last panel of Figure 3 we report evidence on the expected share of jobseekers who are currently employed that confirms the direction of these biases.

Lastly, firms underestimate the reservation wages of jobseekers with secondary education and overestimate the reservation wage of jobseekers with tertiary education. In the survey, we asked firms to indicate the proportion of jobseekers who would accept different wage levels for the most common job available at the firm. Figure 4 shows how firms overestimate the reservation wages of tertiary-educated jobseekers across occupations – but most starkly with respect to professional roles. In Figure A2, we show the results for secondary educated jobseekers.

In sum, firms expect young tertiary-educated jobseekers to have a strong ability premium and a good level of work experience. On the contrary, they are more pessimistic about secondary-educated jobseekers. This can explain why hiring at the job fairs was modest: firms were disappointed by the tertiary-educated jobseekers they met, while they underestimated the ability and reservation wages of the secondary-jobseekers, so the offers they extended to this group were rejected.

We provide three pieces of evidence in support of this interpretation. First, the most common reason firms report for not hiring more at the fair is 'insufficient work experience' (34%

of firms). Other common reasons relate to the perceived expertise of workers or poor interview performance (see Table A17). Educational mismatch plays a role, but is certainly not the most important factor.[32] Second, we examine our data on firm-requested meetings to find out what type of jobseekers firms wanted to meet. We apply the same dyadic regression approach as in equations (1) and (2) and report the results in Table A18. The dependent variable is $request_{fj}$, a dummy equal to one if firm f requested a meeting with jobseeker j, using a centralized meeting-request algorithm that we offered to firms at the fair. Regressors include jobseeker and firm characteristics. We find that the strongest predictor of a requested meeting is past job experience and, consistent with our story, this effect is present only for workers with post-secondary education.[33] Third, the behavior of the firms after the fairs — in particular, the increase in search efforts and, among a key subgroup, the reduced hiring of tertiary educated jobseekers — are also consistent with the interpretation that firms have an incorrect perception of the ability premium of tertiary-educated jobseekers.

5.3 Jobseekers' beliefs

On the jobseeker side, our results show that beliefs about available job opportunities are not always aligned with reality. Specifically, we find that jobseekers with secondary education overestimate the probability of being hired in highly-paid professional jobs and have unrealistically high reservation wages. In contrast, the expectations of tertiary educated jobseekers are better aligned with actual labour-market opportunities. Several pieces of evidence corroborate these observations.

First we turn to our original experimental sample. This shows that less educated jobseekers who came to the fairs had reservation wages that were completely misaligned with the wages that firms at the fairs were expecting to pay. As shown in Table 6, jobseekers invited to the fairs with a high-school diploma and no experience report a median reservation wage of 1,300 Birr per month. This stands in sharp contrast to the median salary of 855 Birr that firms report offering to high-school graduates with no work experience. Such misalignment is also consistent with the high offer-rejection rate by less educated jobseekers: only 33% of jobseekers with secondary education and no work experience who were offered a job at the fairs accepted the offer. In contrast, Table 6 shows that jobseekers with tertiary education that were invited

[32] Additional evidence is provided by the phone survey we conducted after the second job fair. We asked firms to rate the most employable jobseekers they met at the job fair, compared to candidates the firm would normally interview through its regular recruitment process (who may include candidates who are older and thus on average more experienced than those in our sample). Only 12 percent of firms report that the most employable jobseeker at the fair is in the top 20 percent of candidates they see in their usual recruitment process. In fact, 54 percent of firms report that the most employable jobseeker at the fair is in the *bottom* half of the candidates they normally interview.

[33] These results are not driven by firms who sought experienced jobseekers outside the fair: even firms willing to hire graduates without work experience at baseline are more likely to request experienced jobseekers at the fair.

to the fairs have reservation wages that are well within the boundaries of what is available in the market. On average firms report paying recruits with a university degree around 4,500 Birr per month, which is well above the median reservation wage of 2,500 Birr reported by university graduates without exprience at the fairs. Only 10% of tertiary graduates in our sample have a reservation wage above the average wage paid for employees with their qualifications.[34] We see these unrealistic reservation wages as the proximate reason for less-educated workers rejecting job offers from the job fairs. Recall that in Table 5 we established that job seekers reduced their reservation wages in the aftermath of the job fairs.

Next, we turn to the follow-up beliefs survey of jobseekers to shed light on the reasons behind these unrealistic reservation wages. Most importantly, we find that jobseekers with secondary education often seek positions for which firms largely hire tertiary educated jobseekers. Figure 5 shows this clearly. A large proportion of jobseekers with secondary education (Panel A) seek employment in professional categories such as 'Technicians and professionals' and 'Services and sales workers', even though firms offer relatively few opportunities in those roles to jobseekers with secondary education. Conversely, the search efforts of jobseekers with tertiary education (Panel B) are better aligned with available opportunities: the occupations they seek (e.g., 'Technicians and professionals') are the most commonly offered to tertiary graduates by employers in our sample.

On the other hand, jobseekers with secondary education have fairly accurate beliefs about the distribution of wages in specific occupations (Figure A4; the same is true for jobseekers with tertiary education, as shown in Figure A3). If anything, they tend to overestimate the proportion of jobs at the bottom of the wage distribution. High reservation wages among high-school graduates are thus plausibly linked to having an unrealistic occupation target, rather than an inaccurate perception of the wages paid in the market.

We corroborate this point by showing that, contrary to wage expectations, beliefs about the length of unemployment appear to be substantially inaccurate. This is shown in Figure 6, which compares the expected duration of unemployed among jobseekers in the new survey to the typical unemployment spells among individuals in the control group of our experimental sample.[35] For example, 55% of jobseekers with only a high-school diploma expect to find a job with a permanent contract in less than 1 year. In reality, only 5.8% of our experimental sample found a permanent job within 1 year. Furthermore, when asked about jobseekers in the same age

[34] Data from our beliefs survey confirms the finding in experimental sample that jobseekers have reservation wages that are well above what firms are willing to offer. 70% percent of jobseekers with only high-school and no permanent work experience would reject a job paying 2000 ETB per month. However, 44 % of jobs in the market for that occupation and level of experience pay less than 2000 ETB per month.

[35] Since we only interview jobseekers once, we do not have data on the length of their unemployment spell. However, there are a number of reasons to believe that statistics from our experimental sample can provide a useful benchmark. First, the two populations were selected using similar screening criteria based on age and education. Thus, when we re-weight by observables to ensure comparability between the two samples, there are no qualitative changes in our findings. Second, although the two samples were interviewed a few years apart, aggregate labour market conditions are not significantly different across the two periods.

cohort with the same education and work experience, respondents expect 30% of them to have found permanent jobs. This suggests that jobseekers are not only over-confident about their own ability relative to the rest of their cohort, they are also over-optimistic about the prospects of the average individual *like themselves*. We argue that this stems from the mistaken belief that a jobseeker with only a high-school qualification can easily get a professional job with a permanent contract. In contrast, jobseekers with a tertiary degree have accurate beliefs about the prospects of their cohort as a whole, reflecting their accurate beliefs about the distribution of occupations available to them (shown in Figure 5) and have largely accurate beliefs about the distribution of wages within these occupations (shown in Figure A3). But they are over-confident about their own ability to find a permanent job relative to the rest of their cohort, which results in them being optimistic about their probability of finding a good job within one year.

6 Conclusion

We run a novel experimental job fair, with a unique dual randomization – both on the side of jobseekers and of participating firms. The jobseekers invited to the fairs are representative of the type of young jobseekers whom firms usually hire, and participating firms are a representative sample of large employers. We facilitate interactions between jobseekers and firms by providing information about jobseekers' education and firms' vacancies, and by suggesting matches based on a Gale-Shapley algorithm. We study both the direct effects of the treatment on jobseekers' and firms' outcomes, and subsequent effects on both learning and search.

We find that the fairs generate a rich set of interactions between jobseekers and firms, and that the matching algorithm is successful in increasing the efficiency of the matching process. However, the direct impact of the treatment on employment outcomes is very limited: only 14 hires are made as a direct consequence of two job fairs that bring together hundreds of firms and jobseekers. Crucially, however, we find clear evidence of delayed effects of treatment, as both firms and jobseekers appear to learn from the experience at the fairs: they change their expectations accordingly and adjust their search strategies. Treated jobseekers with at most a high-school diploma had misaligned reservation wages prior to treatment; after the fairs, they search harder and experience a significant increase in their probability of obtaining a formal job. Treated firms increase their efforts to search, both for professional positions and through advertising at the job boards. Follow-up survey work with similar jobseekers and firms confirms both that firms have an inaccurate perception of the skill premium of jobseekers with tertiary education, and that jobseekers have overly optimistic beliefs about the probability of obtaining professional jobs given their qualifications.

The main contribution of our paper is to show that both firms and jobseekers hold inaccurate beliefs about market fundamentals – that is, that labour market participants suffer not merely from a problem of information asymmetries, but from a deeper misperception of the distribution of characteristics among other market participants. Although we find that the fairs did not directly facilitate matches – suggesting that reducing the costs of face-to-face meetings alone is not sufficient to overcome matching frictions in this context – we do find that the fairs serve to reduce these deep misperceptions. These results show that active labour market policies that increase contact between jobseekers and firms – such as job fairs, and including many other classes of policy intervention – are likely to generate important learning effects on both sides of the market.

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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	492	0.31	0.97	0.05	0.13	0.26	0.0	14.3	0.433
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: **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 1 and 2. The highest ranked worker and firm are assigned a value of zero. Lower ranks corresponds to higher numbers. Standard errors are corrected for two-way clustering at the level of the worker and at the level of the firm. The last row reports the p-value of an F-test of the hypothesis that the effect of the algorithmic and the random suggestion are the same.

Table 4: **Firm recruitment methods**

Outcome	Estimated ITT	Control Mean	Observations
Firm performed formal interviews (professionals)	0.0440 (.038) [.138]	0.682	473
Firm performed formal interviews (non-professionals)	-0.0140 (.039) [.401]	0.607	473
Did any advertising for new hires	0.0580 (.032)* [.074]*	0.789	473
Did advertising for professional positions	0.120 (.038)*** [.009]***	0.595	473
Did advertising on the job boards	0.0960 (.042)** [.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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Table 5: **Workers' job search and employment outcomes after the fairs**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Reserv. Wage	Wage Mismatch	Board visits	Worked	Perm. job	Formal job	Earnings
Panel A: Average Treatment Effect							
Fairs	-0.0669*	-0.0438**	3.012**	-0.004	0.024	0.026	34.110
	(0.0369)	(0.0223)	(1.285)	(0.0273)	(0.0183)	(0.0193)	(75.89)
Observations	1,503	1,503	1,705	1,705	1,705	1,705	1,690
R-squared	0.005	0.003	0.006	0.000	0.001	0.001	0.000
Control Mean	7.417	0.529	14.780	0.562	0.171	0.224	0.224
Panel B: Treatment Effect by Education							
Fairs*HighSchool	-0.0879*	-0.0742**	4.197**	-0.012	0.0576**	0.0482*	0.421
	(0.0484)	(0.0335)	(1.719)	(0.0397)	(0.0262)	(0.0275)	(86.82)
Fairs*PostSecondary	-0.036	0.001	1.251	0.006	-0.026	-0.008	84.360
	(0.0352)	(0.0218)	(1.335)	(0.0313)	(0.0234)	(0.0236)	(128.6)
Observations	1,503	1,503	1,705	1,705	1,705	1,705	1,690
R-squared	0.005	0.006	0.008	0.000	0.005	0.003	0.000
ControlMean HighSchool	7.183	0.561	10.980	0.508	0.058	0.108	0.108
ControlMean PostSecond	7.522	0.514	16.550	0.587	0.223	0.277	0.277
Test High=Post (p)	0.268	0.051	0.118	0.718	0.018	0.116	0.577

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.

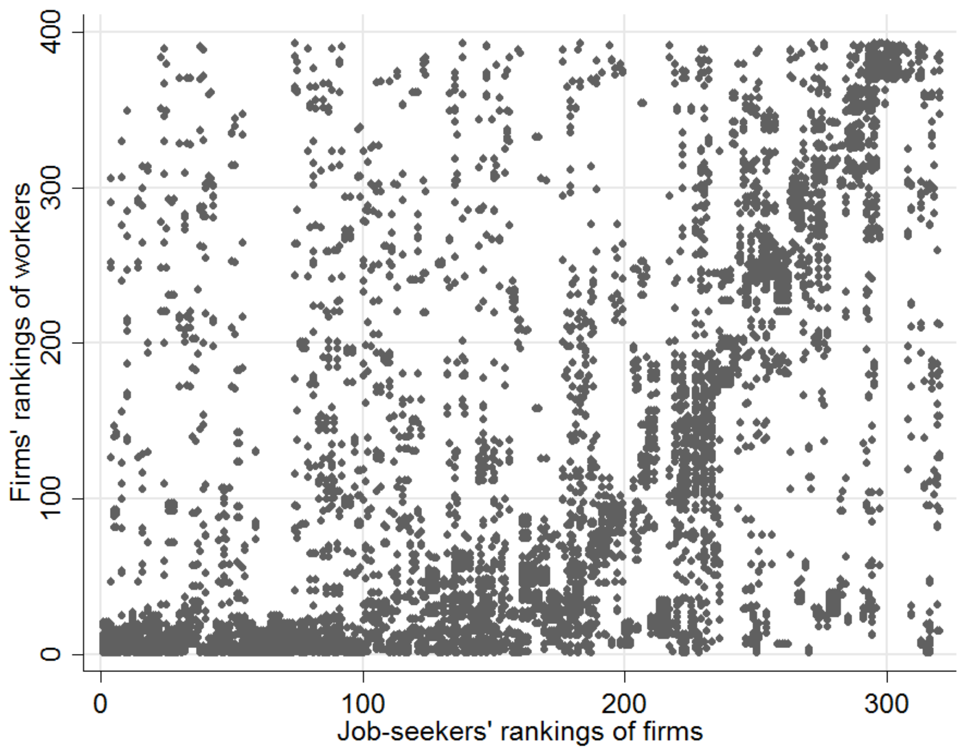
Table 6: **Mismatched expectations: Reservation wages of workers before the fairs, wages offered at the fairs, and endline employment outcomes (Medians)**

	Education of worker			
	High-school	Vocational	Diploma	Degree
Panel A: Workers' reservation wages and firms wages for jobs offered at the job fairs				
Worker reservation wages before fairs				
With Experience (13%)	1500	2000	2000	3000
Without Experience (87%)	1300	1500	1600	2500
Firm wages 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: Workers' employment outcomes at endline				
Worker employment rates at endline				
All jobs	50%	46%	43%	69%
Permanent jobs	6%	17%	19%	35%
Worker wages at endline by experience				
With Experience	1450	1450	1743	3000
Without Experience	975	1400	1350	2100
All Experience levels	1000	1400	1500	2300
Worker wages at endline by job type				
Permanent work	950	1400	1662	2373
Non-permanent work	1000	1400	1200	2291

Notes: This table describes self-reported reservation wages (for jobseekers) using phone survey data in the weeks just prior to the first job fair, offered wages at the job fair (for firms), and endline wages (for jobseekers), disaggregated by types of worker and type of job.

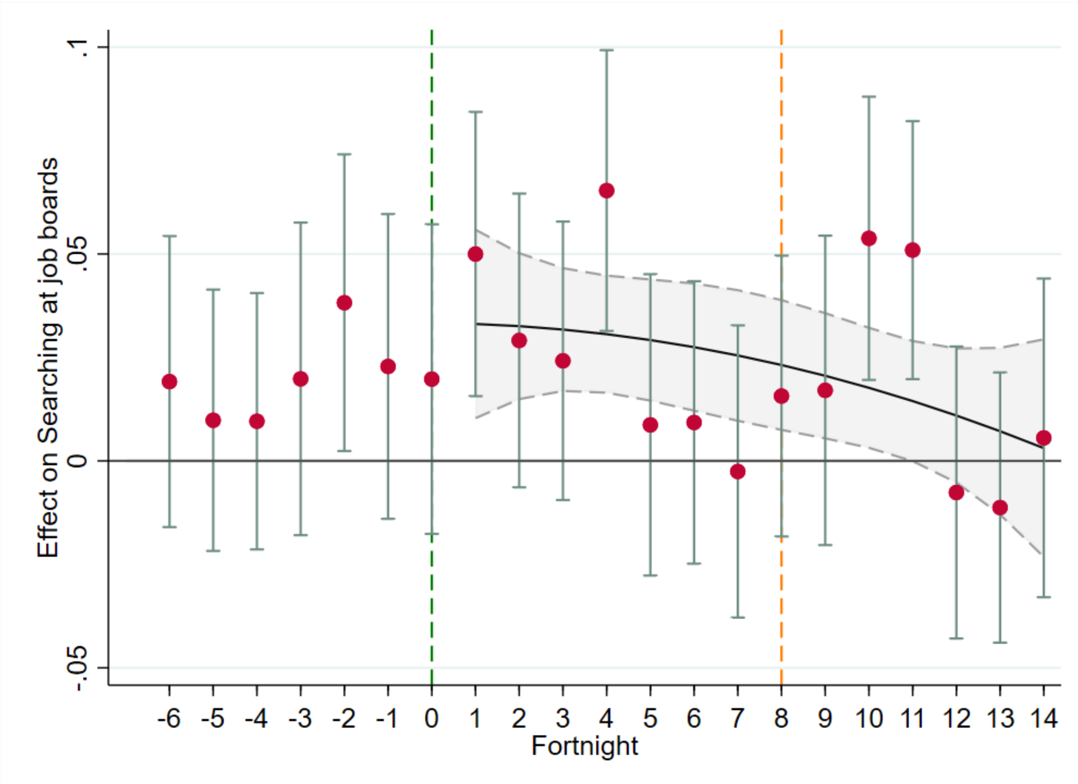
Figures

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



Notes: This figure illustrates the outcome of the matching algorithm. Each point represents a stable match recommended by the algorithm. The figure shows which combinations of firm rankings and job-seeker rankings generated these recommended matches. The graph provides a visual illustration that the algorithm worked well in the sense of generating matches between firms and job-seekers who are, on the basis of job-seeker skills and experience, reasonably well-suited to each other.

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

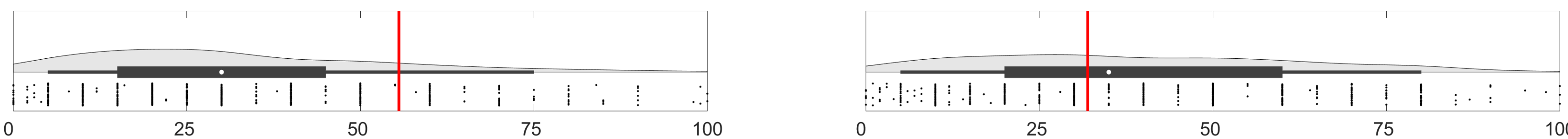


Notes: This figure shows the probability, for each fortnight, that treated job-seekers visit the job board, relative to job-seekers in the control group. Fortnight 0 is when the first job fair was held; the second fair was held in fortnight 8. We estimate the difference in probabilities using a Linear Probability Model in an ANCOVA specification, in which we regress job search on treatment, baseline search status and a bector of baseline balancing variables. We cluster at the level of individual job-seekers, and show both point estimates and 90% confidence intervals; we do this both by regressing on forntight dummies, and by imposing a quadratic shape.

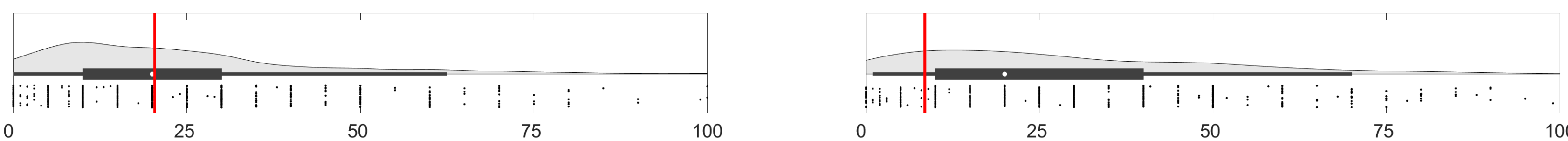
Figure 3: **Distribution of employer beliefs by education**

PANEL A: BELIEFS ABOUT THE AVERAGE RAVEN'S TEST SCORE (LEFT: HIGH SCHOOL; RIGHT: TERTIARY)

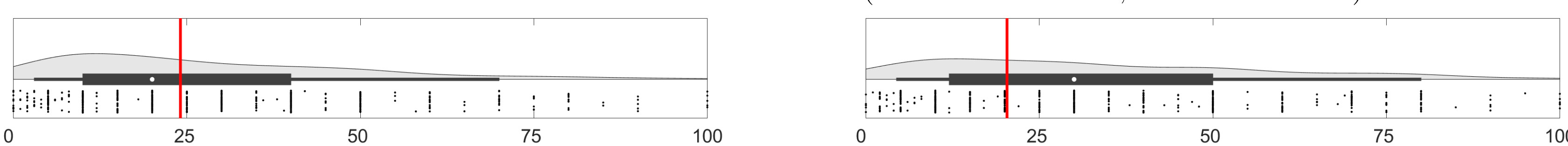
PANEL B: BELIEFS ABOUT THE SHARE HAVING ANY EXPERIENCE (LEFT: HIGH SCHOOL; RIGHT: TERTIARY)



PANEL C: BELIEFS ABOUT THE SHARE HAVING AT LEAST 2 YEARS' EXPERIENCE (LEFT: HIGH SCHOOL; RIGHT: TERTIARY)

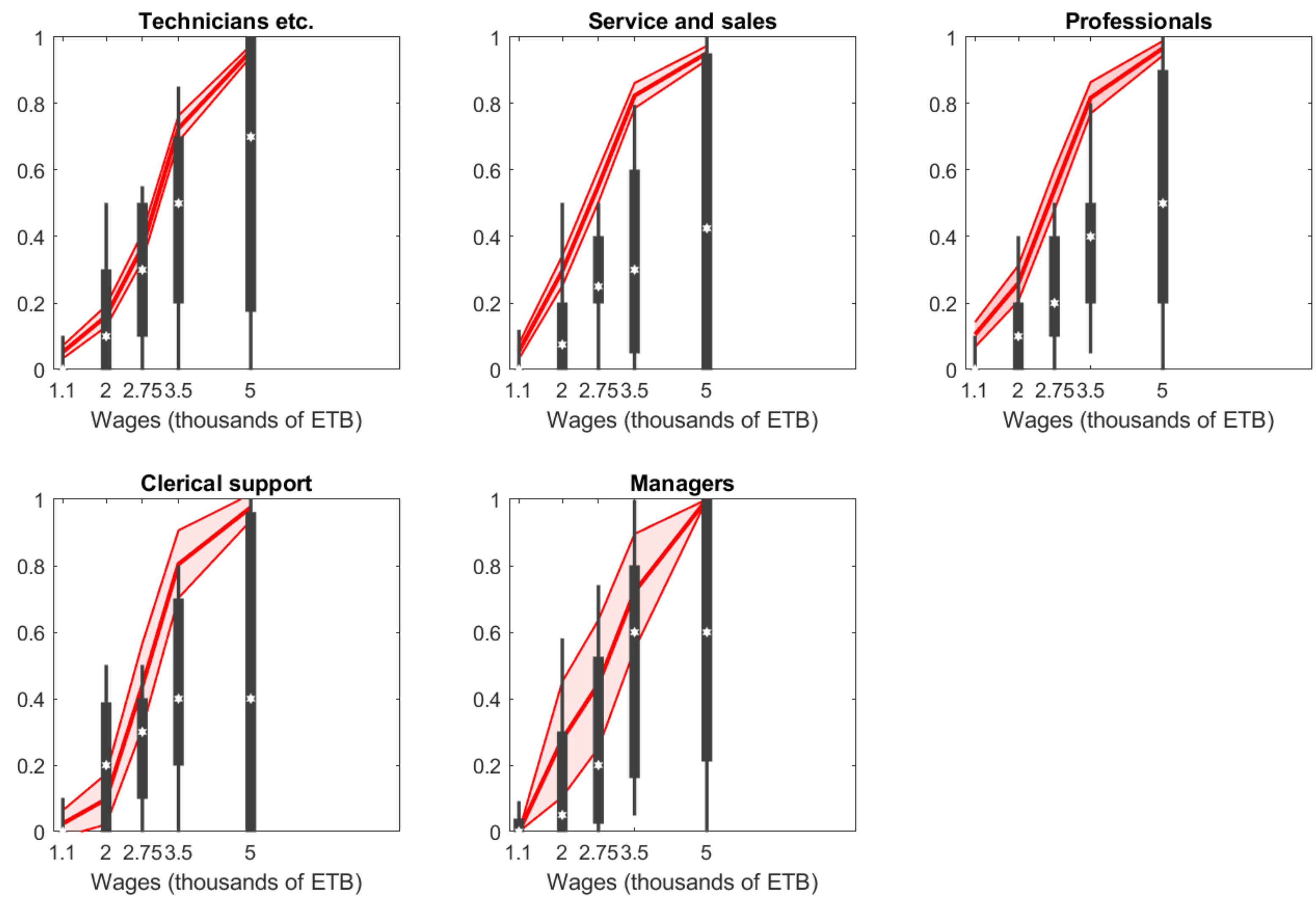


PANEL D: BELIEFS ABOUT THE EMPLOYMENT RATE (LEFT: HIGH SCHOOL; RIGHT: TERTIARY)



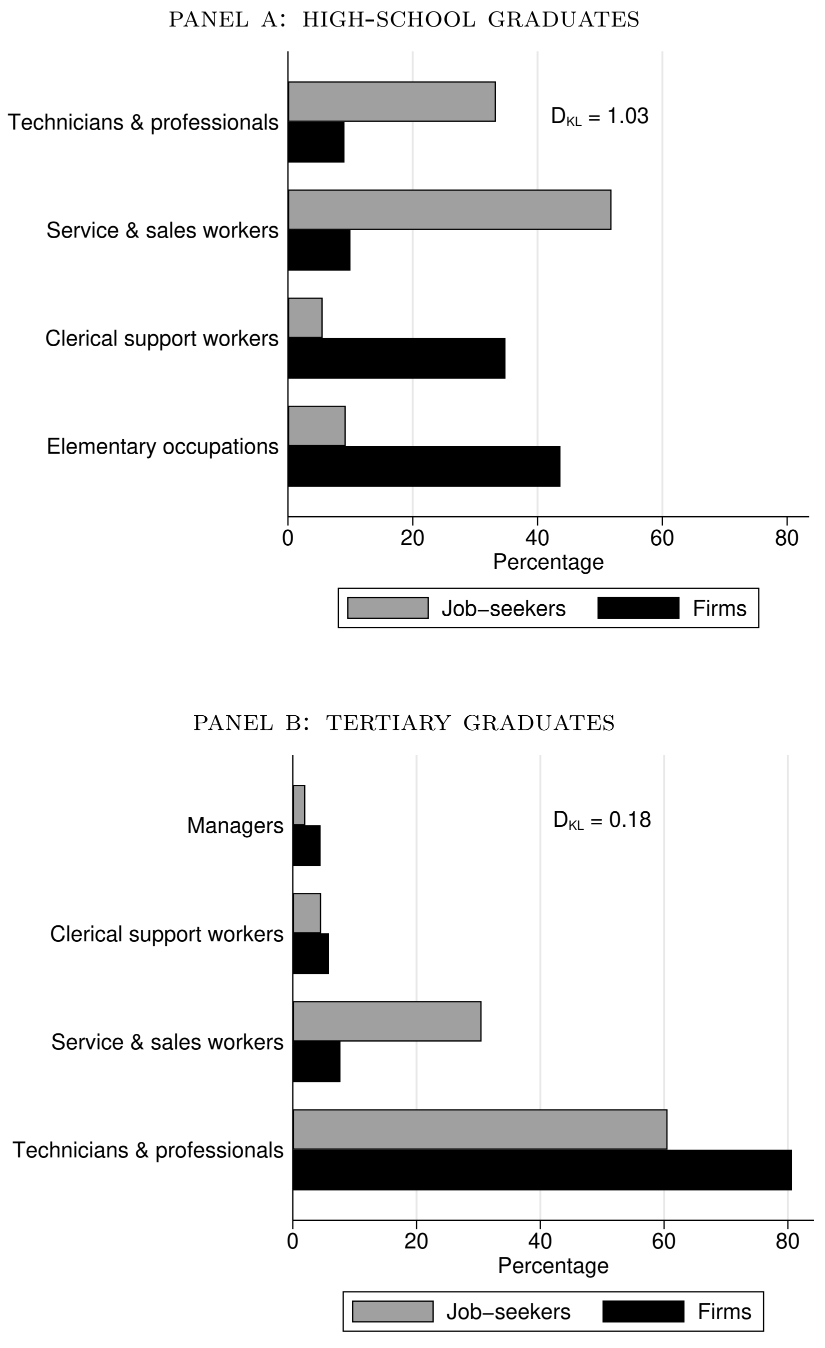
Notes: Each panel shows the distribution of employer beliefs, for some specific job-seeker characteristic. Each panel shows a kernel density plot (with bandwidth chosen using Silverman's plug-in), then a box-plot (showing 5th, 25th, 50th, 75th and 95th percentiles), followed by a direct visualisation of data (with random vertical jitter). For each panel, we superimpose a vertical line at the true value of the statistic in our sample.

Figure 4: **Firms' beliefs about the distribution of job-seekers' reservation wages: Tertiary-educated job-seekers**



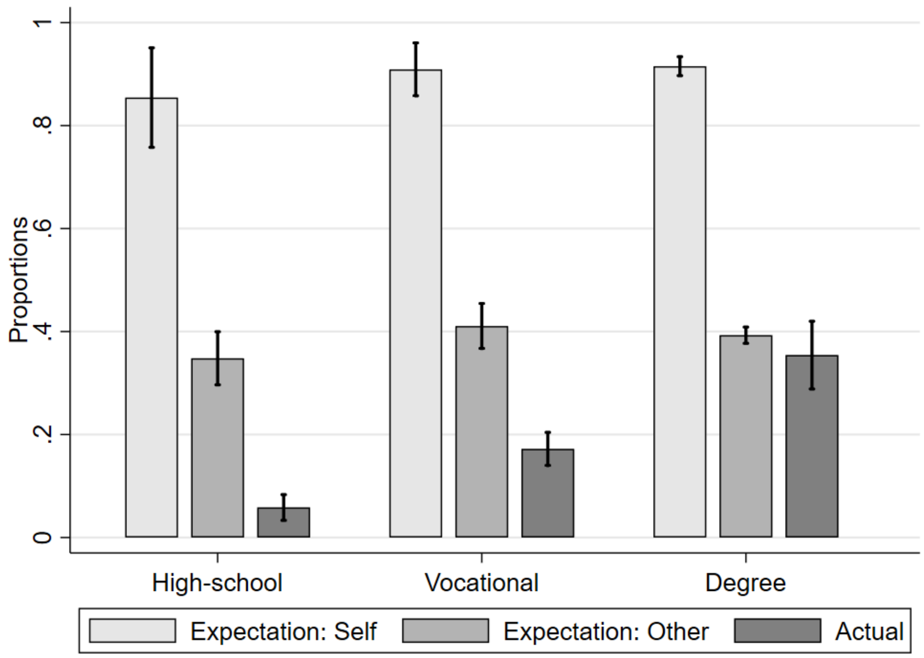
Notes: These figures show the distribution of firm beliefs about job-seekers' reservation wages. In each graph, we show this at five wage points: in each case, we show the distribution of firm beliefs (using thin bars to show the 10th and 90th percentiles, thick bars to show the 25th and 75th percentiles, and a star symbol to show the median). The coloured lines show the true proportion of our job-seekers with a given reservation wage (where the shaded area represents the 90% confidence interval for the proportion).

Figure 5: **Distribution of occupation sectors**



Note: This figure shows the distribution of (i) the proportion of total jobs in the most common occupations in each firm, and (ii) the sector of the job most commonly looked at by job-seekers in the last week. We show both bars for the five most common sectors for the firm side. We report D_{KL}*, the Kullback-Leibler distance from the distribution of job-seeker sectors to the distribution of firm occupation sectors.*

Figure 6: **Jobseekers' expectations of finding a job with a permanent contract in the next 12 months**



Note: 'Expectation: Self' refers to jobseekers' stated probabilities that they will be employed with a permanent contract in the next 12 months, as measured in our 2019 follow-up survey. 'Expectation: Other' refers to jobseekers' stated probabilities that others like them will be employed with a permanent contract in the next 12 months, as measured in our 2019 follow-up survey. 'Actual' refers to the actual proportion of jobseekers who found a job with a permanent contract, using our original survey data.

Online Appendix:
Additional Figures and Tables

Appendix Table A1: **Summary at baseline 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)		
Employed	0.31	0.46	-0.04	1829	0.155
			(0.15)		
Searched for work	0.50	0.50	-0.01	1829	0.763
			(0.76)		
Diploma or degree	0.25	0.43	-0.00	1829	0.993
			(0.99)		
Female	0.52	0.50	0.01	1829	0.848
			(0.85)		
Born outside of Addis Ababa	0.37	0.48	-0.03	1829	0.459
			(0.46)		
Amhara ethnic group	0.46	0.50	-0.02	1829	0.590
			(0.59)		
Oromo ethnic group	0.26	0.44	-0.04	1829	0.171
			(0.17)		
Worked in the last 6 months	0.46	0.50	-0.04	1829	0.186
			(0.19)		
Married	0.20	0.40	-0.00	1829	0.842
			(0.84)		
Lives with parents	0.52	0.50	0.02	1829	0.521
			(0.52)		
Any permanent work experience	0.13	0.34	-0.01	1829	0.730
			(0.73)		
Searched for work (last 6 months)	0.75	0.43	0.01	1829	0.832
			(0.83)		
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 frequency (weeks of last 2 months)	0.57	0.31	0.00	1829	0.889
			(0.89)		
Work frequency (weeks of last 2 months)	0.34	0.38	-0.01	1829	0.611
			(0.61)		
Self employed	0.05	0.22	0.01	1829	0.601
			(0.60)		
Casual labourer	0.06	0.23	-0.02	1829	0.087
			(0.09)		
Satisfied with job	0.09	0.28	-0.01	1829	0.659
			(0.66)		
Total savings	2279.23	6203.56	290.89	1829	0.346
			(0.35)		
Reservation wages	1327.22	1235.30	34.35	1808	0.632
			(0.63)		
Distance from city centre (km)	5.92	2.24	-0.60	1829	0.229
			(0.23)		

Trips to the city centre (7d)	1.83	2.03	0.21	1826	0.185
			(0.19)		
Has formal job	0.06	0.23	0.00	1829	0.810
			(0.81)		
Uses CV in applications	0.28	0.45	-0.00	1829	0.903
			(0.90)		
Expected no. job offers	1.46	2.09	-0.21	1697	0.245
			(0.24)		
Aspired wage	5583.33	5830.85	191.89	1694	0.636
			(0.64)		
No. job contacts	6.74	9.63	0.89	1818	0.529
			(0.53)		
Present biased	0.12	0.33	0.00	1252	0.889
			(0.89)		
Future biased	0.08	0.27	-0.02	1252	0.282
			(0.28)		
Life satisfaction	4.20	1.85	-0.08	1828	0.633
			(0.63)		

Note: This table reports our baseline balance tests. For each baseline outcome of interest, we report the p-values for a test of the null hypothesis that we have balance between treatment and control groups. We cannot reject the null for any of the variables.

Appendix Table A2: **Worker employment amenities**

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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Appendix Table A3: **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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Appendix Table A4: **Median rate of expected number of 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%

Note: This table shows firms' stated expectations about new hires in the coming 12 months.

Appendix Table A5: **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

Note: This table reports regression coefficients from a Linear Probability Model, in which we regress attendance at the fairs on a rich set of baseline characteristics; we provide robust standard errors in parentheses. We find no evidence suggesting that observably weaker candidates are more likely to attend the fairs: education, gender, and current employment do not significantly predict attendance. The only two robust predictors of attendance are instead associated with a positive motivation to work: attendance is higher among those job-seekers who search the most at baseline and who produce a formal certificate to employers.

Appendix Table A6: **Main industry classifications**

Main Industry	Frequency	Percent
Tours-Hospitality	92	18.7
Finance, Services, Retail	102	20.7
Education, Health, Aid	104	21.1
Manufacturing	126	25.6
Construction, Mining, Farming	69	14.0
Total	493	100

Note: This table shows the initial partitioning of firms into five main industries prior to randomisation.

Appendix Table A7: **Blocking variables for the firm randomisation**

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	$rowtotal(l3\_2\_*)/total\_n\_all$

Note: This table defines the variables used for blocking for firm randomisation.

Appendix Table A8: **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)
Distance from city centre (km)	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

Note: This table reports results from a series of Linear Probability Models; in each case, the outcome variable is a dummy for whether a firm attended the job fairs, conditional upon having been invited. Parentheses show heteroskedasticity-robust standard errors. The omitted industry dummy is for 'construction/mining'.

Appendix Table A9: **Determinants of attrition among job-seekers**

Fairs	-0.025**	Oromo	-0.007
	(0.012)		(0.016)
Work frequency (weeks of 2 months)	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
p-value (covariates)	0.320	p-value (treatment)	0.038

Note: This table reports regression results from a Linear Probability Model, in which the dependent variable is a dummy for whether a job-seeker attrited between baseline and endline; parentheses show heteroskedasticity-robust standard errors.

Appendix Table A10: **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 (1.986) [.658]	24.11	338
Time taken to fill non-professional vacancies	0.724 (1.751) [.909]	15.66	109
Number of interviews per position (professional)	0.312 (2.355) [.909]	8.818	361
Pay per recruitment (professional)	746.7 (1030.791) [.909]	2818	382
Pay per recruitment (non-professional)	-437.8 (320.543) [.658]	1259	406
Proportion of vacancies unfilled, as percentage of vacancies opened	0.601 (.247)** [.101]	0.859	305
Panel B: Characteristics of workers recruited			
Number of new hires for the year (professional)	-1.604 (2.688) [1]	11.73	472
Number of new hires for the year (non-professional)	-9.704 (7.283) [1]	44.64	472
Did firms mostly hire people with degrees (professional positions)?	-0.00800 (.041) [1]	0.574	473
Percentage of new hires hired in permanent positions (non-professional)	-0.00900 (.03) [1]	0.892	337
Percentage of new hires hired in permanent positions (professional)	-0.00800 (.031) [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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets, corrected for the tests conducted within each panel.

Appendix Table A11: **Impacts on firm hiring after job fairs**

Outcome	Estimated ITT	Control Mean	Observations
Number of vacancies	0.169 (.266) [1]	1.115	422
New Hires	-0.671 (.866) [1]	3.907	422
Hiring shortfall	-0.0160 (.034) [1]	0.0290	193
Unfilled vacancies	0.380 (.785) [1]	2.143	422

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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Appendix Table A12: **Impacts on firm hire quality after job fairs**

Outcome	Estimated ITT	Control Mean	Observations
Permanent workers hired	0.0200 (.049) [1]	0.336	422
Days taken to recruit for position (avg)	0.311 (1.386) [1]	11.75	190
Starting salary of new recruits (avg)	-673.9 (636.454) [1]	1031	160
Workers with degrees hired (%)	-0.0430 (.044) [1]	0.237	422

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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Appendix Table A13: **Firms' total workforce composition**

Outcome	Estimated ITT	Control Mean	Observations
Total number of employees	-18.38 (16.581) [.847]	350.5	473
Proportion of professional workers on permanent contracts	0.0190 (.019) [.847]	0.908	462
Proportion of non-professional workers on permanent contracts	0.0280 (.02) [.67]	0.896	408
Average starting salary (professional)	-53.52 (235.925) [1]	4280	454
Average starting salary (non-professional)	102.9 (126.66) [.847]	1059	400
Proportion of professional workers with degree	-0.0570 (.027)** [.366]	0.645	461
Proportion of workers with post-secondary education (non-professionals)	0.0370 (.027) [.67]	0.355	407
Average worker is not under-qualified in any of the worker categories	0.00300 (.038) [1]	0.752	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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Appendix Table A14: **Impacts on firm turnover and employee growth**

Outcome	Estimated ITT	Control Mean	Observations
Firing rate (professionals)	0.00400 (.004) [1]	0.00600	458
Firing rate (non-professionals)	0.00300 (.005) [1]	0.0130	319
Quit rate (professionals)	0.00800 (.02) [1]	0.143	458
Quit rate (non-professionals)	0.0250 (.037) [1]	0.134	320
Employee growth rate	0.0170 (.016) [1]	0.0140	472
Employee growth rate (professionals)	-0.0140 (.03) [1]	0.0310	467

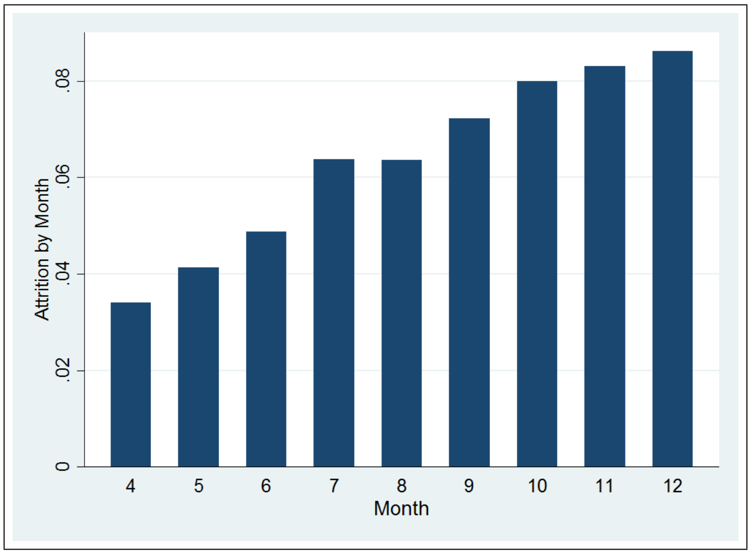
Notes: Each row reports a separate regression. For each regression, we report the estimated ITT from participating in the job fair, the mean in the control group, and the number of observations. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Appendix Table A15: **Impacts on firm human resources policies and attitudes**

Outcome	Estimated ITT	Control Mean	Observations
Firm reports HR problem	0.0820 (.037)** [.217]	0.752	473
Uses incentives in HR	0.0390 (.043) [.588]	0.595	473
Firm estimate of a fair wage	201.2 (312.897) [.592]	5463	452
Uses short term contractors	0.0480 (.045) [.588]	0.479	473
Uses performance rewards (professionals)	-0.0300 (.045) [.592]	0.545	473
Uses performance rewards (non-professionals)	-0.0740 (.045)* [.417]	0.562	473
Retrains poor performers	0.0390 (.04) [.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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Appendix Figure A1: **Attrition rate from the Phone Survey by Month**



Notes: This figure shows the trajectory of monthly attrition rates over the course of the phone survey. Attrition is defined as failure to complete one interview.

Appendix Table A16: **Impacts on firm growth and productivity**

Outcome	Estimated ITT	Control Mean	Observations
Firm is for-profit	-0.0140 (.011) [1]	0.867	471
Sales Revenue (last year)	-17575 (23388.044) [1]	144370	331
Value Added	-15491 (11969.701) [1]	80851	327
Profit (inferred)	6026 (4791.574) [1]	12975	326
Self-reported profit	1853 (7175.053) [1]	29626	313
Capital stock	60034 (123774.721) [1]	185398	279
Investment (12 months)	-6452 (5920.8) [1]	20147	398
Sales per worker	-57.12 (76.278) [1]	604.5	330
Value added per worker	19.45 (28.102) [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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets.

Appendix Table A17: **Firms' reasons for not hiring workers they met at the fairs**

Main self-reported reason	Percent
Insufficient work experience	34.38
Wrong expertise	7.03
Wrong educational qualifications	23.44
Poor performance at the interview	7.03
The candidates we wanted were hired by other firms	3.91
Poor references	2.34
Salary disagreement	2.42
Workers were not interested or did not apply	1.61
Workers arrived late	1.61
Firm did not have vacancies at the time of the fair	3.23
Other	10.48

Appendix Table A18: **Dyadic regressions: Firm requests to meet workers as function of worker characteristics**

	(1)	(2)	(3)	(4)
	Firm requested to meet worker			
Worker has some permanent work experience	0.0173***		0.0151**	0.0132**
	(0.00657)		(0.00652)	(0.00617)
Worker is recent graduate	0.00185	0.00185	-0.000304	0.00153
	(0.00379)	(0.00379)	(0.00450)	(0.00479)
Worker has certificate with application	0.00190	0.00190	0.00136	0.00182
	(0.00273)	(0.00273)	(0.00285)	(0.00286)
Worker has postsecondary education	0.00729***	0.00729***	0.00783***	0.00808***
	(0.00257)	(0.00257)	(0.00270)	(0.00279)
Permanent work experience * fresh graduate	-0.00610	-0.00610	-0.00317	-0.000833
	(0.00948)	(0.00948)	(0.01000)	(0.0107)
Permanent work experience * Highschool only	-0.0180***	-0.000785	-0.0162**	-0.0139**
	(0.00663)	(0.00421)	(0.00679)	(0.00652)
Permanent work experience * postsecondary education		0.0173***		
		(0.00657)		
GS- algorithm suggested match			0.0256***	0.0266***
			(0.00805)	(0.00833)
GS- matches we randomly suggested			-0.000233	-0.00527
			(0.00792)	(0.00661)
Controls: Firms' vacancy characteristics	No	No	Yes	Yes
Controls: Firm baselien characteristics	No	No	No	Yes
Observations	19,110	19,110	18,185	17,491
R-squared	0.003	0.003	0.005	0.007

Notes: We regress on worker-firm dyadic data for all workers and firms who were invited to the same job fair, whether the firm requested to meet that worker in person, using a centralized meeting-request system facilitated at the job fairs. We include controls for worker characteristics, firm characteristics, and vacancy characteristics (vacancies held by the firm in question at the time of the job fairs).

Appendix Table A19: **Heterogeneous effects: firm recruitment by baseline proportion of youth in workforce**

	(1) Firm performed formal interviews (professionals)	(2) Firm performed formal interviews (non-professionals)	(3) Did any advertising for new hires	(4) Did advertising for professional positions	(5) Did advertising on the job boards
Proportion young high	0.0121	-0.0501	0.0545	0.0492	0.0846
	(0.0556)	(0.0568)	(0.0461)	(0.0558)	(0.0607)
Proportion young low	0.0689	0.0123	0.0554	0.177***	0.0959
	(0.0534)	(0.0546)	(0.0443)	(0.0535)	(0.0583)
Observations	473	473	473	473	473
R-squared	0.009	0.013	0.017	0.027	0.010
ControlMean 1	0.715	0.659	0.805	0.634	0.325
ControlMean 2	0.647	0.555	0.773	0.555	0.336
Test 1=0 (p)	0.462	0.430	0.989	0.0997	0.893

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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets, corrected for the tests conducted within each panel.

Appendix Table A20: **Heterogeneous effects: firm recruitment by baseline use of formal recruitment methods**

	(1) Firm performed formal interviews (professionals)	(2) Firm performed formal interviews (non-professionals)	(3) Did any advertising for new hires	(4) Did advertising for professional positions	(5) Did advertising on the job boards
Used formal methods	0.0666	0.00436	0.0781**	0.155***	0.0827
	(0.0473)	(0.0486)	(0.0393)	(0.0475)	(0.0517)
Did not use formal methods	-0.0159	-0.0737	-0.00102	0.0309	0.103
	(0.0661)	(0.0679)	(0.0550)	(0.0664)	(0.0721)
Observations	473	473	473	473	473
R-squared	0.004	0.003	0.008	0.023	0.010
ControlMean 1	0.776	0.671	0.888	0.714	0.410
ControlMean 2	0.494	0.481	0.593	0.358	0.173
Test 1=0 (p)	0.311	0.350	0.242	0.128	0.816

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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets, corrected for the tests conducted within each panel.

Appendix Table A21: **Heterogeneous effects: firm workforce composition at endline by proportion of workforce in professional occupations**

	(1) Firm performed formal interviews (professionals)	(2) Firm performed formal interviews (non-professionals)	(3) Did any advertising for new hires	(4) Did advertising for professional positions	(5) Did advertising on the job boards
Proportion professional high	-0.0223	-0.0331	0.0573	0.105*	0.0530
	(0.0542)	(0.0557)	(0.0452)	(0.0546)	(0.0592)
Proportion professional low	0.100*	-0.0110	0.0452	0.121**	0.127**
	(0.0544)	(0.0560)	(0.0454)	(0.0549)	(0.0595)
Observations	473	473	473	473	473
R-squared	0.007	0.001	0.005	0.018	0.011
ControlMean 1	0.788	0.559	0.822	0.678	0.356
ControlMean 2	0.581	0.653	0.758	0.516	0.306
Test 1=0 (p)	0.111	0.780	0.849	0.829	0.380

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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets, corrected for the tests conducted within each panel.

Appendix Table A22: **Heterogeneous effects: firm hiring after the fairs by proportion of workforce in professional occupations**

	(1) Num. new hires (professional)	(2) Num. new hires (non-prof)	(3) Most hires with degrees (professionals)	(4) Percentage new hires perm. positions (non-prof)	(5) Percentage new hires perm positions (prof)
Proportion professional high	-4.761	-17.89*	-0.0815	0.00427	-0.0210
	(3.825)	(10.35)	(0.0580)	(0.0402)	(0.0478)
Proportion professional low	0.422	1.430	0.0624	-0.0214	0.00920
	(3.836)	(10.38)	(0.0583)	(0.0447)	(0.0409)
Observations	472	472	473	337	308
R-squared	0.003	0.006	0.007	0.001	0.001
ControlMean 1	20.51	62.43	0.669	0.840	0.892
ControlMean 2	3.444	27.85	0.484	0.958	0.864
Test 1=0 (p)	0.339	0.188	0.0800	0.669	0.633

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

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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets, corrected for the tests conducted within each panel.

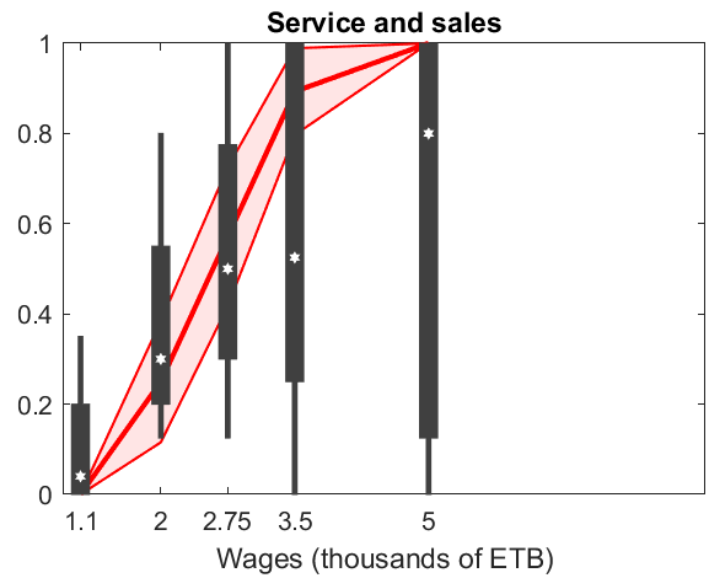
Appendix Table A23: **Heterogeneous effects: firm recruitment by proportion of workforce in professional occupations**

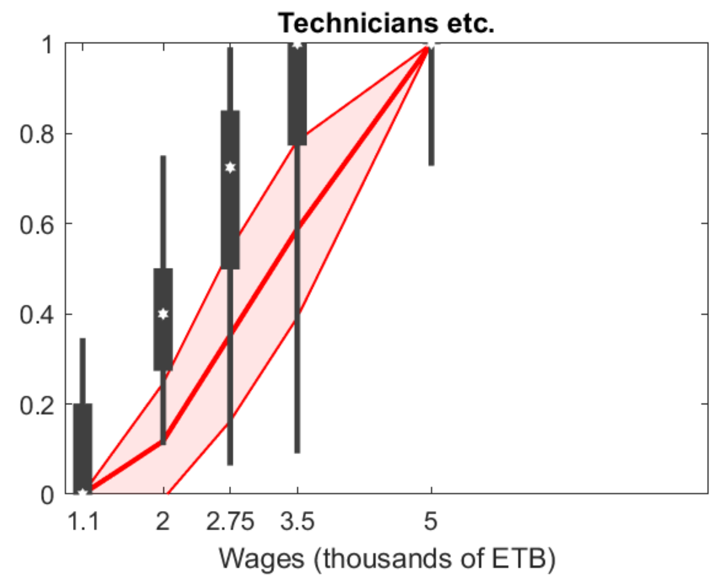
	(1) Total number of employees	(2) Prop. professional workers on perm. contract	(3) Prop. non-prof workers on perm. contract	(4) Av. starting salary (professionals)	(5) Av. starting salary (non-prof's)	(6) Prop. prof workers with degree	(7) Prop. non-prof workers with degree	(8) Average worker not under-qualified s
Prop. professional high	-46.96**	0.0352	0.0438	181.1	180.7	-0.0698*	0.0824**	-0.0262
	(23.54)	(0.0272)	(0.0302)	(338.0)	(188.4)	(0.0375)	(0.0397)	(0.0536)
Prop. professional low	14.86	0.00629	0.0180	-187.9	63.95	-0.0427	0.00720	0.0331
	(23.66)	(0.0274)	(0.0275)	(340.1)	(170.4)	(0.0380)	(0.0363)	(0.0538)
Observations	473	462	408	454	400	461	407	473
R-squared	0.009	0.004	0.006	0.001	0.003	0.010	0.011	0.001
ControlMean 1	501.5	0.862	0.881	4818	653.6	0.728	0.502	0.814
ControlMean 2	206.8	0.951	0.908	3760	1398	0.564	0.231	0.694
Test 1=0 (p)	0.0641	0.454	0.528	0.442	0.646	0.612	0.163	0.435

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

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. Standard errors are reported in parentheses; False Discovery Rate q-values are reported in square brackets, corrected for the tests conducted within each panel.

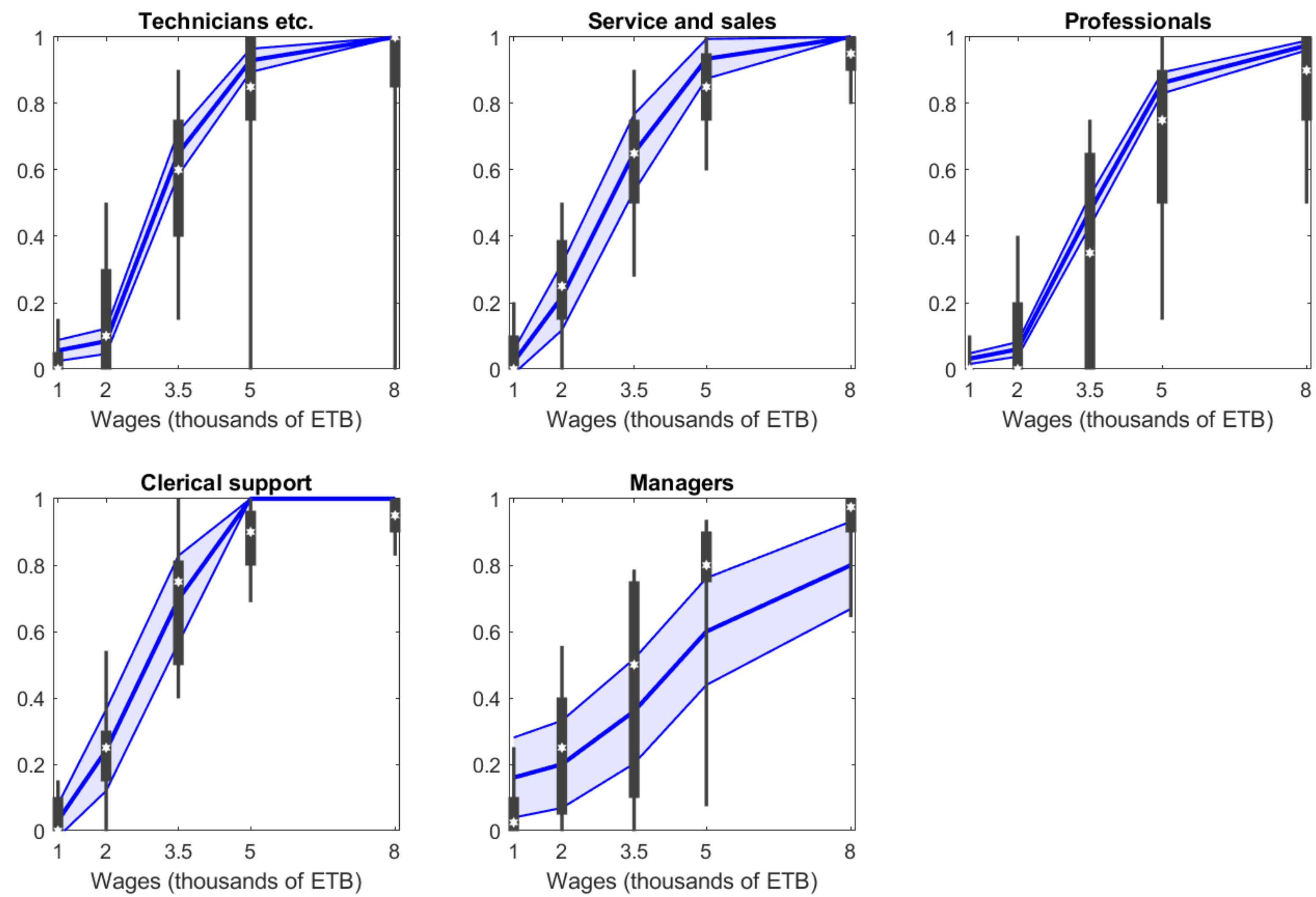
Appendix Figure A2: **Firms' beliefs about the distribution of job-seekers' reservation wages: Secondary-educated job-seekers**





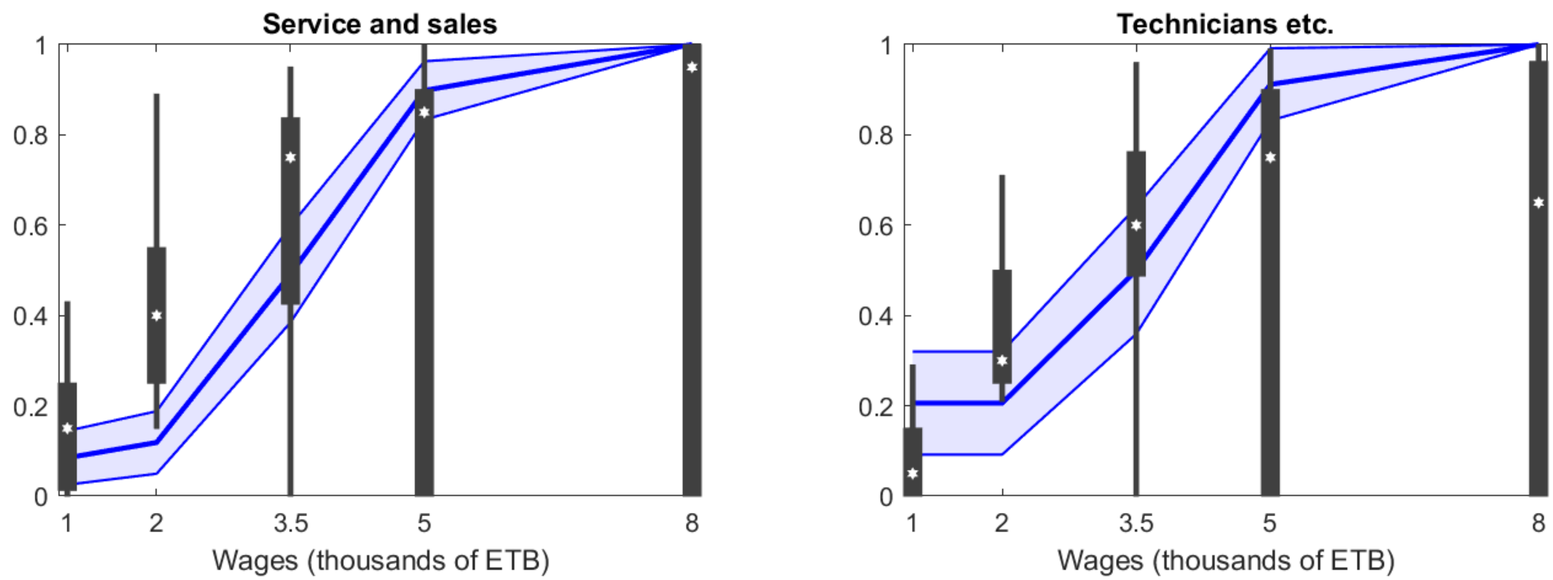
Notes: These figures show the distribution of firm beliefs about job-seekers' reservation wages. In each graph, we show this at five wage points: in each case, we show the distribution of firm beliefs (using thin bars to show the 10th and 90th percentiles, thick bars to show the 25th and 75th percentiles, and a star symbol to show the median). The coloured lines show the true proportion of our job-seekers with a given reservation wage (where the shaded area represents the 90% confidence interval for the proportion).

Appendix Figure A3: **Job-seekers' beliefs about the distribution of firm wages: Tertiary-educated job-seekers**



Notes: These figures show the distribution of job-seeker beliefs about firms' wages. In each graph, we show this at five wage points: in each case, we show the distribution of job-seeker beliefs (using thin bars to show the 10th and 90th percentiles, thick bars to show the 25th and 75th percentiles, and a star symbol to show the median). The coloured lines show the true proportion of our firms with a given wage (where the shaded area represents the 90% confidence interval for the proportion).

Appendix Figure A4: **Job-seekers' beliefs about the distribution of firm wages: Secondary-educated job-seekers**



Notes: These figures show the distribution of job-seeker beliefs about firms' wages. In each graph, we show this at five wage points: in each case, we show the distribution of job-seeker beliefs (using thin bars to show the 10th and 90th percentiles, thick bars to show the 25th and 75th percentiles, and a star symbol to show the median). The coloured lines show the true proportion of our firms with a given wage (where the shaded area represents the 90% confidence interval for the proportion).