Formalized Employee Search and Labor Demand[*]

Lukas Hensel[†], Tsegay Gebrekidan Tekleselassie[‡], Marc Witte[§]

November 2022

Abstract

Firms in low- and middle-income countries rarely advertise their vacancies formally and instead use social networks. This might limit the number and type of vacancies they can profitably create. We conduct a field experiment with small and medium-sized enterprises in Ethiopia to reduce firms' cost of formal search. Treated firms search for employees outside their networks and try to fill more demanding white-collar positions. However, they struggle to fill these newly created positions and their beliefs about the returns to formal employee search decrease. Providing additional screening services for firms does not affect the results, suggesting that information asymmetries about applicants' skills do not limit formal search. We conclude that informal employee search does not limit firms' hiring in our context.

[*]We thank Stefano Caria, Morgan Hardy, Rob Garlick, Clément Imbert, Erin Kelley, Pramila Krishnan, Jeremy Magruder, Mahreen Mahmud, Kate Orkin, Simon Quinn, Climent Quintana-Domeque, Jonas Radbruch, Chris Roth, Shuo Liu, Chris Woodruff, as well as seminar participants at Applied Development Conference, UC Berkeley, the Ethiopian Economics Association, EEA conference, ESPE conference, Exeter, IZA, Jobs and Development Conference, LEAP conference, NEUDC, NOVAFRICA, NYU Abu Dhabi and Oxford for useful comments and help. We thank Abis Getachew Makuria for outstanding research assistance. Financial support from grants by the International Growth Centre (Grant 32425), Private Enterprise Development in Low-Income Countries (PEDL Exploratory Research Grant 6023), and the Centre for the Study of African Economies is gratefully acknowledged. Lukas Hensel gratefully acknowledges financial support by the Wellspring Philanthropic Fund. IRB approval was obtained through by the Economics Departmental Research Ethics Committees at the University of Oxford (ECONCIA18-19-14).

[†]Peking University, lukas.hensel@pku.edu.cn.

[‡]Northeastern University, t.tekleselassie@northeastern.edu.

[§]IZA – Institute of Labor Economics, witte@iza.org.

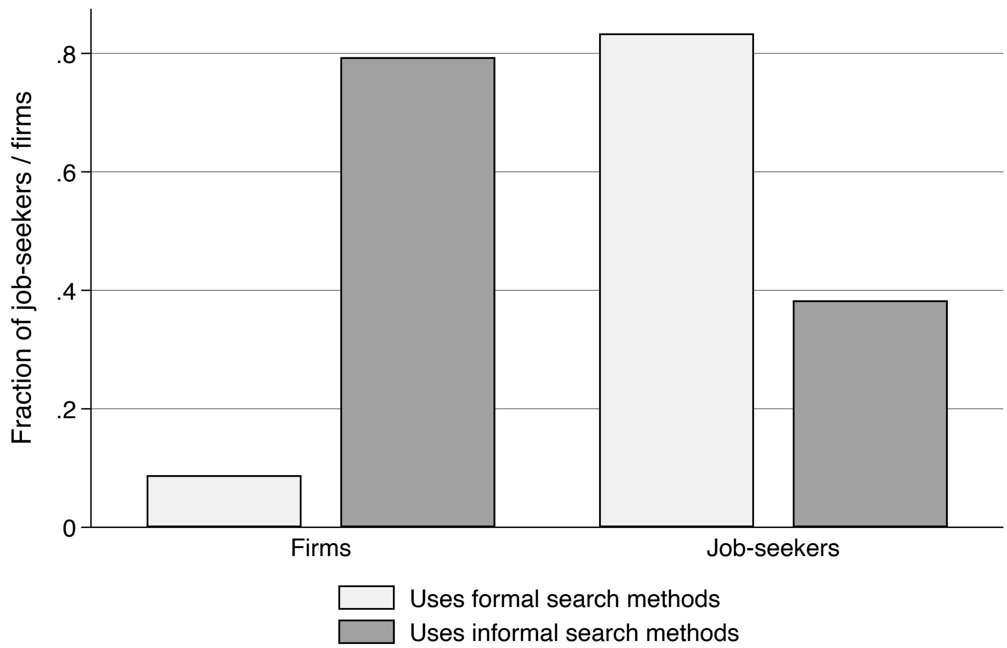
1 Introduction

A long-standing question in development economics is how the prevalence of informal institutions affects socioeconomic outcomes. Informality has been studied in areas as diverse as credit markets (e.g. Banerjee et al., 2021), insurance (e.g. Mobarak and Rosenzweig, 2013), and work relationships (e.g. Ulyssea, 2018, 2020). Much of this literature defines formality based on the existence of explicit contracts, registrations, or regulated markets. However, the formality of the processes that generate economic outcomes is another important dimension of (in)formality.

We study informal search processes in the labor market which can lead to market segmentation with important consequences for market outcomes. Consider a firm that wants to hire a new worker and searches informally through networks rather than advertising a job publicly. On the one hand, this can alleviate information frictions and moral hazard problems (Dustmann et al., 2016, Heath, 2018), leading to more productive employment relationships. On the other hand, sparse networks might limit firms' ability to expand their business, leading to aggregate welfare losses (Chandrasekhar et al., 2020). Crucially, market outcomes will also depend on the search behavior of job-seekers. If the two sides of the labor market differ in their use of formal search channels, this may lead to a mismatch of search channel specific labor demand and supply.

In the context of one of Africa's largest cities, Addis Ababa in Ethiopia, there is a striking mismatch between firms' and job-seekers' search channels. Figure 1 compares the prevalence of formal and informal search methods of both job-seekers and firms. While only ten percent of small and medium-size firms in our sample use formal search methods (such as posting vacancies on job-boards and in newspapers), over 80 percent of job-seekers in Addis Ababa search in these public channels. In comparison, almost 80 percent of firms use informal, network-based methods to identify suitable employees, while fewer than 40 percent of job-seekers search for work using their networks.

Figure 1: Formal and informal search on both sides of the labor market



This figure shows the fraction of firms and job-seekers in Addis Ababa, Ethiopia, relying on formal and informal methods of employee/job search. The responses are not mutually exclusive, meaning that both firms and job-seekers can search in more than one way. The firm data is based on baseline responses in our own sample of firms. The job-seeker data are from the Ethiopian National Labor Force Survey 2021. Formal search methods include online and offline job boards and newspapers. Informal search methods are through social contacts/networks (including family and co-workers).

This asymmetry suggests that firms forgo a large fraction of potential applicants in their search for employees, which might limit their ability to hire new workers and expand. In this paper, we explore whether the use of informal employee search indeed constrains firms' labor demand.

We conduct a field experiment in which we incentivize firms to advertise their vacancies through formal channels. We offer vacancy posting services to a randomly-selected subset of 625 small and medium-sized firms in Addis Ababa, Ethiopia. As part of these services, we first fully subsidize firms' vacancies in all commonly-used 'formal' channels, including online and offline job boards and newspaper advertisements.[1] Second, we also take care of the actual posting of the vacancy, thus covering logistical costs. Taken together, we subsidize and post all job adverts of the firm, regardless of the posting price.[2] Treated firms are eligible to use the vacancy services for about four months. We collect detailed data on vacancy creation and hiring behavior of all firms during and after the treatment period. To ensure that we capture all attempts at finding new employees across treatment groups, we also administer regular phone surveys during the treatment period, in addition to an in-person endline survey and multiple post-treatment surveys.

Informed by a theoretical framework, we hypothesize that the vacancy posting subsidy could affect firms' hiring behavior in four different ways. First, we expect a formalization of the hiring process during the study period. Second, a reduction in the cost of formal employee search might also affect vacancy creation: it might become more profitable for firms to create new vacancies and hire additional employees. Third, formalized search exposes firms to a different pool of job-seekers. Given the differential search costs for job-seekers across search channels, this pool is more likely to contain skilled workers looking for relatively well-paid jobs (Rebien et al., 2020).[3] Firms might adjust to the new pool of job-seekers by shifting the skill requirements of vacancies. Finally, the intervention might prompt firms to learn new information about the labor market, which could shift their labor market expectations and behavior beyond the treatment period.

Our study has the following key results that speak to our hypotheses.

[1]Specifically, we post the vacancies (i) on the five largest physical job-boards in Addis Ababa, (ii) in the largest national biweekly newspaper 'The Reporter', (iii) on the online job-board 'Ezega.com'.

[2]The costs of posting a formal vacancy exceed the average monthly wage of employees in our sample of firms.

[3]We also find evidence that formally-posted vacancies are disproportionately targeted at higher-skilled job-seekers. Based on all publicly-posted job advertisements in Addis Ababa during our study period, we find that 27% of vacancies require applicants to have a diploma, 37% a BA degree, and only 5% require less than 10 years of schooling. These requirements are high compared to the education levels in the population of job-seekers in Addis Ababa, where only 12% have at least a BA degree, 15% a diploma, and 34% have fewer than 10 years of schooling (according to the 2018 Ethiopian Labor Force Survey).

First, our intervention successfully increases formal vacancy posting: treated firms are 3.3 times and statistically significantly more likely than control firms to post at least one vacancy through formal search channels. However, firms are selective in their use of the subsidy. They only post 38% of created vacancies formally, suggesting that the perceived returns to formal search vary across vacancy types.

Second, we observe no average increase in the total number of vacancies created. However, we observe a marginally significant increase of 0.53 created vacancies conditional on posting any vacancy (equivalent to 23% of the control mean). This suggests that the cost of formal search is only a barrier to vacancy creation once firms bear the fixed cost of engaging in any worker search.

Our third result shows that firms' anticipation of obtaining better applicants through formal search channels affects the type of vacancy they post: treated firms are a significant 7.2 percentage points more likely to create at least one white-collar vacancy.[4] This is an increase of 91 percent relative to the control group mean. The overall number of white-collar vacancies and the share of white-collar postings among all vacancies also approximately double compared to control firms, suggesting a strong shift in the composition of firms' labor demand. For lower-skill, non–white-collar vacancies, we observe no significant change in vacancy creation. These results suggest that in response to the treatment, firms attempt to fill more high-skilled positions, which is consistent with firms ex-ante anticipating being able to access a higher-skilled applicant pool through formal employee search.[5]

As our fourth result, we find that treated firms struggle to fill a larger fraction of their vacancies. They exhibit a significant reduction in the share of filled vacancies by 20 percentage points relative to the control group. This effect is even stronger for white-collar vacancies (-36 percentage points). The

[4]White-collar vacancies are defined as "professional, managerial, or administrative" workers. Typical white-collar job titles include manager, accountant, and supervisor. Typical non–white-collar jobs are cooks, waiters, or carpenters.

[5]In line with this interpretation, we find that control group firms posted 41% of white-collar vacancies but only 4% of non–white-collar vacancies formally.

increase in white collar vacancy creation combined with decreased filling rates leads to an insignificant treatment effect on the number of white-collar hires with point estimates close to zero. In contrast, we observe a relatively large (8.6 percentage points) and a significant decrease in the fraction of firms reporting any non–white-collar hires.

We provide evidence for two potential mechanisms behind this reduction in successful matches between firms and high-skilled applicants. First, we find that managers at treated firms update their beliefs about both the quality and quantity of applicants in formal search channels downward. Their high expectations pre-treatment about the pool of formal job-seekers are not met and firms do not hire more white-collar employees. Firms' biased expectations about formal search could be driven by—potentially rational—under-experimentation (Chandrasekhar et al., 2020). Second, applicants obtained through formal search channels have high wage expectations and high reservation wages relative to the realized wages of filled vacancies and average baseline salaries. This might make it difficult for firms to successfully hire new employees through formal channels.

Finally, we find that information frictions about applicants' skills do not limit firms' use of formal search channels. We randomly offer half of the treated firms the option of having all applicants to their vacancies screened for three cognitive or socio-emotional skills—on top of the vacancy posting subsidy.[6] This additional treatment component does not differentially impact the uptake of the intervention, vacancy creation, or hiring outcomes. This suggests that an actual mismatch in applicants' and managers' expectations—not information asymmetries about applicants' skills—is behind firms' reluctance to hire formally attracted applicants. This finding contrasts with a growing body of literature documenting the importance of such frictions for job-seekers (Abebe et al., 2020a, Carranza et al., 2020, Bassi and Nansamba, 2021, Abel et al., 2020).

With these findings, we make four main contributions to the literature.

[6]While firms could have opted out of this screening service, all firms that used the vacancy posting subsidy in this treatment group also elected to add the screening component.

First, ours is the first paper to study the firm-side effects of a reduction in vacancy posting costs on vacancy posting behavior.[7] Our results suggest that search frictions can be specific to the type of vacancy which can ultimately affect firms' labor force composition.[8] Related to our study, Fernando et al. (2022) study the impact of increasing firms' applicant pool and providing identity verification services on firms' hiring outcomes on an Indian online job portal. They find that both interventions together, but not individually, increase hiring among treated firms. The authors study hiring outcomes for vacancies that were already posted on the online portal prior to the experiment. In contrast, we allow firms to adjust their vacancy posting behavior in response to vacancy posting subsidies. In another related paper, Algan et al. (2020) study an intensive bundled hiring support intervention for French small and medium-sized firms. In contrast to their bundled intervention, we disentangle the role of two specific frictions: vacancy posting cost and information frictions about work seekers. Moreover, our study is set in a labor market with a much higher prevalence of informal employee search and thus speaks to frictions that might prevent the development of more formal labor market institutions.

Second, we study the impact of reducing firm-side search frictions while most of the existing literature focuses on search frictions on the side of job-seekers. In particular, both Franklin (2018) and Abebe et al. (2020a) study formal search subsidies for job-seekers—the equivalent of our firm-side intervention—on the labor supply side. Both papers find short-run effects on the *quality* of jobs found, suggesting that formal search is beneficial for young job-seekers in the same context as ours. Our evidence suggests

[7]A separate literature studies the labor constraints faced by small and medium-sized enterprises (SMEs) in low- and middle-income countries and has found mixed results. Hardy and McCasland (2018) document that alleviating employee search constraints for SMEs in the manufacturing sector in Ghana through a local matchmaking process leads to increases in firm size and profits. Other experiments that use temporary wage subsidies to encourage hiring without alleviating search constraints find no evidence of permanent effects on firm outcomes (de Mel et al., 2019, Groh et al., 2016, Galasso et al., 2004).

[8]By showing that informal hiring practices affect the type of positions for which firms search and hire, we provide evidence from a developing country that is in line with Rebien et al. (2020)'s finding that firms search more formally for high-skilled workers in Germany.

the same is not true for firms. In studying the public advertisement of vacancies, we relate to the literature on different hiring channels such as networks (Calvó-Armengol and Jackson, 2004, Beaman and Magruder, 2012, Kramarz and Skans, 2014, Heath, 2018, Witte, 2021) and job fairs (Beam, 2016, Abebe et al., 2020b). Similar to the literature on job fairs, we do not find strong short-term effects on aggregate hiring numbers. However, we document a marked shift in the composition of posted vacancies and—for a subgroup of firms—hires. This emphasizes the importance of firms' endogenous response to changes in the cost and availability of search methods.[9]

Third, our paper speaks to a long-standing debate in development economics on the importance of formal versus informal institutions and markets. Recent papers have emphasized how the introduction of formal institutions can interact with (Comola and Prina, 2021) or even crowd out (Banerjee et al., 2021) pre-existing informal mechanisms; for instance, in credit or insurance markets. Similarly, firms in our study were exogenously incentivized towards formal vacancy posting, with the help of randomly-allocated subsidies. However, in contrast to much of the existing research, we do not find that this 'push towards formality' persistently reduces informal behavior. Instead, after the subsidy runs out, the market strongly reverts back to the informal mechanism. Firms downwards-revise their beliefs about the usefulness of formal search channels. This suggests that the informal search in our context might be optimal for firms given the current labor market conditions.[10]

Finally, we speak to a nascent body of literature documenting unintended long-term consequences of labor market interventions on the beliefs and be-

[9]By emphasizing the importance of different search channels we provide additional evidence on the importance of search frictions for job-seekers (Carranza et al., 2020, Bassi and Nansamba, 2021, Abel et al., 2020, Wheeler et al., 2021). In particular, our finding of a change in vacancy composition might in part be a response to the selection of job-seekers into different search channels. This is in line with evidence demonstrating an important role of liquidity constraints in application decisions (Abebe et al., 2021).

[10]This does not mean that formal search processes, in aggregate, are not efficient. It is possible that, once a larger fraction of both firms and job-seekers use formal search channels, formal employee search will become profitable for firms.

havior of firms and job-seekers in developing countries. Recent papers study the impact of being negatively surprised by the quality of newly-created matching interventions[11], while we document that firms face negative surprises, even within *existing* labor market institutions. This suggests important information frictions during the hiring process and a lack of experimentation by firms, with potentially important consequences for firms' labor demand ('learning through noticing'; Hanna et al., 2014). As a specific example focusing on the job-seeker side of the labor market, Kelley et al. (2020) study the impact of using job portals for entry-level job-seekers in India. They find that treated job-seekers have higher reservation wages and end up working less in response to signing up for the platform. Our study emphasizes that unintended consequences of being exposed to existing labor market structures can also affect the firm side of the labor market.

The remainder of this paper proceeds as follows. In section 2 we describe the labor market context of our study. In section 3 we present the experimental setup and data collection activities. We link the labor market in our context theoretically to our intervention in section 4, before we present and discuss the treatment effects of our experiment in section 5. Section 6 concludes.

2 Labor market search in Addis Ababa

This section first describes the broader study context in Addis Ababa, before zooming in on some stylized facts about employee and job search in the local labor market.

[11] Abebe et al. (2020b) document that after attending a 'disappointing' job fair in the same context as our study, firms negatively update about the average quality of job-seekers and, as a consequence, shift towards more formal search channels and reduce hiring levels. This latter finding is in line with our results, which suggest that firms could become additionally disappointed by formal search. Similarly, Bandiera et al. (2020) show that lower-than-expected callback rates of a matching intervention have long-term impacts on the beliefs and search behavior of job-seekers, leading to substantially worse labor market outcomes.

2.1 Broader context

Our study took place between March and November 2019 in Addis Ababa, the capital of Ethiopia. With an average GDP growth rate of almost 10 percent over the last decade, Ethiopia is one of the fastest-growing countries in Sub-Saharan Africa (World Bank, 2020). At the same time, most of the country's young urban population is out of permanent or formal employment, while rural areas are traditionally dominated by subsistence agriculture. Unemployment is particularly high among young people who graduate from high school or higher education institutions, despite widely-reported shortages of qualified employees by Ethiopian firms, suggesting a problem with matching job-seekers to vacancies.

2.2 Search for jobs and employees

What does employee and job search in Addis Ababa look like? We provide descriptive evidence based on i) representative labor force data on job-seekers and workers, ii) a random subset of publicly posted vacancies during our study period, and iii) data on firms in our experimental sample (which is described in more detail in Section 3). We differentiate between formal and informal search channels. Formal search comprises the public advertising of job-adverts on offline and online job boards as well as in newspapers.

Similar to many other urban labor markets in low- and middle-income countries, the labor market in Addis Ababa is characterized by a large degree of informal network-based employee search (Serneels, 2007). In principle, this could both be a response to and a cause of the matching problem described above: firms might rely on social network search to overcome information asymmetries vis-à-vis the job candidates, but at the same time suffer from a restricted pool of applicants with a limited distribution of skills or abilities.

Firms' search behavior Firms' search behavior is characterized by a large degree of informality but clearly distinct patterns for white-collar and non–

white-collar vacancies. White-collar vacancies are defined as "professional, managerial, or administrative" workers. Typical white-collar job titles include manager, accountant, and supervisor. Typical non–white-collar jobs are cooks, waiters, or carpenters.

We first note that employee search via formal channels such as newspapers and job boards is quite costly for firms. For example, in the context of our study, posting a single job ad in a newspaper in the smallest available format costs about 3,800 ETB (105 USD), which is more than the average monthly salary that firms in our sample pay their workers.

Perhaps as a consequence of the substantial costs involved, formal vacancy posting is not very common among firms in Addis Ababa. To illustrate this, we create a database of publicly-posted vacancies in Addis Ababa, comprising 29,312 job advertisements posted over 36 weeks.[12] In February 2019, there were 438,747 formally registered firms in Addis Ababa. If we conservatively assume that every firm seeks to hire one employee per year, we should expect on average 438,747/52 $\simeq$ 8,437 posted vacancies per week. Instead, we find approximately 814 unique vacancies posted in the city per week. This means that only a small fraction of approximately 10 percent of firms publicly post vacancies.[13]

This is in line with firms' vacancy creation behavior in our experimental control group. Our inclusion criteria imply that the sample consists of relatively actively recruiting small- and medium-sized firms. Despite the prescreening, we observe that 50% of firms do not create any vacancies during the study period. This is despite baseline expectations of 3.5 hires over the next three months. This suggests that many firms believe that it is not prof-

[12]This database covers almost 100 percent of all posted vacancies in Addis Ababa. We collect data on job advertisements from the four main sources of job advertisements in the city: i) the ten largest physical vacancy boards located across the city, ii) vacancies in the three major newspapers, iii) the four largest online job boards (www.employethiopia.com, www.ethiojobs.com, www.ezega.com, www.mjobs.com), and iv) the largest social media job channel (on the messaging service 'Telegram'). We collect the data on a weekly basis between March and October 2019.

[13]If we compare this number to similarly-sized cities in rich countries, we note that in late 2021, on the single platform `indeed.com` alone, there are approximately 6,500 unique vacancies per week in Berlin, 7,000 in Birmingham, and 14,000 in Madrid.

itable to create new vacancies given the overall market environment during the study period.[14]

Firms in our control group mostly create non–white-collar vacancies but use formal search more for white-collar workers (Table 1). Specifically, we observe that non–white-collar vacancies make up 88% of all posted vacancies in the control group. This is in line with the structure of existing employees of firms (86% of existing employees are non–white-collar; Table 2). We also observe that only 12% of all vacancies in our control group are posted formally (at baseline 9% of firms report using formal search channels). This suggests that the returns to formal search are, on average, not perceived to be high enough to warrant the increased costs among most firms in our sample. When considering white-collar and non–white-collar vacancies separately, we find that 42% of white-collar vacancies are posted formally, while only 8% of non–white-collar vacancies are posted formally. This suggests that firms consider there to be substantially higher returns to formal search for white-collar vacancies compared to non–white-collar vacancies.

This difference we observe in our firm sample is also reflected in the characteristics of publicly posted vacancies in Addis Ababa. Table A2 describes the composition of the random sample of $N = 999$ vacancies for which we coded the white-collar classification. We find that 59% of all publicly posted vacancies are white-collar, while only 41% are non–white-collar vacancies. This is in line with the evidence from our firm sample and suggests that the returns to formal search are generally perceived to be higher for white-collar jobs.

Vacancy characteristics To understand how white-collar and non–white-collar vacancies differ from each other we use our representative sample of

[14]The lower-than-expected hiring activity is at least partly due to external events. In May and June of 2019, there were frequent power cuts due to nationwide electricity shortages that negatively affected the operations of firms in our sample. Around 35 percent of baseline firms reported that they changed their business activities in response to the electricity outages, with 20 percent of firms postponing hiring. Furthermore, there was a coup attempt on June 22, 2019, which lead to a nationwide internet shutdown and slowed down or stopped business activities for about two weeks.

Table 1: Descriptive evidence on vacancy posting and occupational type

	Formal advertising	Informal advertising	# of vacancies (column %)
Control group (row percentages):			
Pooled	12%	88%	249 (100%)
White-collar	42%	58%	31 (12%)
non–white-collar	8%	92%	218 (88%)

Notes: Table 1 displays the fraction of vacancies posted formally or informally by vacancy type (white-collar / non–white-collar) in the control group.

publicly posted vacancies and compare the characteristics of white-collar and non–white-collar vacancies. We present the results in Table A2.

We find that almost all white-collar vacancies require applicants to have an education beyond a high school degree. Almost 60% of white-collar vacancies require a university degree and the remaining require 40% vocational training. The educational requirements of non–white-collar vacancies are much lower. A quarter of non–white-collar vacancies requires at most high school education, while only 35% require a university degree. Similarly, white-collar vacancies require on average almost a year (or 38%) more experience than non–white-collar vacancies. Lastly, based on the selective subsample of vacancies for which firms decided to post salaries, white-collar vacancies on average pay two and a half times higher monthly salaries than non–white-collar vacancies (a 148% increase).

Taken together, we find that white-collar vacancies have relatively high education and experience requirements. They also offer substantially higher wages than non–white-collar vacancies. This pattern suggests that publicly posted vacancies represent the upper end of the observed labor market.

Job seekers' search behavior We already documented in Figure 1 that among job-seekers, formal job search is much more common than informal search. Over 80 percent of job-seekers in Addis Ababa search in public channels, such as online and offline job boards and newspapers, while fewer than

40 percent search in their networks.

Using data on Addis Ababa from the 2018 Urban Labor Force Survey, we further analyze how the characteristics of job-seekers using formal and informal search channels differ. We find a highly significant positive correlation between years of education and formal job search (columns (1) and (3) of Table A1). This means that better-educated job-seekers are more likely to use formal search channels. At the same time, job-seekers in formal channels are less experienced, even controlling for their years of education (columns (2) and (3) of Table A1). First, this is somewhat at odds with the higher experience requirements of white-collar vacancies, which dominate this formal market segment. And second, as a consequence of the higher experience requirements, job-seekers could lack signals that might help firms understand their quality, which in turn points to the potentially greater importance of applicant screening in the formal search segment. In contrast, we do not find a correlation between years of education and the likelihood of job-seekers engaging in informal (network) search. However, network seekers are around 10 percentage points ($\sim 25\%$) less likely to be first-time job-seekers, pointing to the importance of experience in building up social networks one can later rely on (columns (4)-(6)).

Considering the firm and job-seeker sides jointly, we observe a substantial mismatch of search activity. Job-seekers are much more likely to use formal search methods while firms in our sample hardly use them. This mismatch could have two important consequences. First, it could mean that firms forgo a large part of their potential applicant pool which might prevent them from growing (Chandrasekhar et al., 2020). Second, the lack of formal search activity by firms might exclude job-seekers without sufficient network connections from jobs. This might be particularly severe for young, inexperienced job-seekers.

However, while there is a mismatch in aggregate search activity, both vacancies and job-seekers in formal search channels are positively selected on education. This suggests that both sides of the labor market are aware that returns formal search are higher for more highly educated individuals and for white-collar vacancies that require higher education levels.

3 The experiment

This section describes our recruitment of firms into the experimental sample, the experimental design, as well as details on the data collection, summary statistics, and experimental integrity.

3.1 Sample recruitment

For our study, we recruited SMEs in Addis Ababa in two ways. First, we obtained a list of registered firms in Addis Ababa from the municipal authorities. Second, our field team went to recruit firms face-to-face in well-known business areas. To participate in our study, firms had to meet the following criteria. First, they had to in principle express interest in a generically-described service that would help their firm with job advertising. Second, they had to have between 5 and 50 employees. Third, they could not exclusively hire through employment agencies. Finally, they had to not rule out hiring a new worker over the next three months. We chose these screening criteria to identify firms that were likely to use our intervention to increase statistical power.[15] In total, we recruit 625 firms that meet our criteria during the screening survey. These firms are spread out across Addis Ababa (see Online Appendix Figure A3) and they form our experimental sample.

3.2 Design

Our field experiment is designed to study how subsidizing formal employee search channels affects firms' vacancy posting and employment flows. Figure 2 displays the experimental design of our study. We randomly allocate firms in our sample to one of two groups. Randomization happens at the firm

[15] This sampling strategy limits the external validity of our findings. We briefly discuss the generalizability of our findings in the conclusion.

level at the end of the baseline survey. Firms in the treatment group are offered the opportunity to post their job adverts on up to five physical vacancy boards, one major online job board (`www.ezega.com`) and the major newspaper "The Reporter" at no cost. To facilitate take-up of the intervention, firms are offered to send an electronic copy of the job advert or alternatively research staff would pick up a hard copy at the firm's premises. This offer covers all vacancies during the four-month treatment period.[16] We additionally randomize 50 percent of firms in the vacancy subsidy group to receive an applicant screening intervention in addition to the vacancy subsidy. Firms in this group are offered a screening of all applicants to their vacancies, for a range of cognitive and socio-emotional skills. The results of this screening are then passed on to the firm. We use this additional treatment to test whether a lack of information about job-seekers' skills affects firms' vacancy posting and hiring. For most of the analysis, we use the pooled treatment group to focus on the effect of the vacancy posting subsidy. This reflects the fact that there are few significant differences between the two arms. Where there are differences, we note them explicitly.

3.3 Data collection

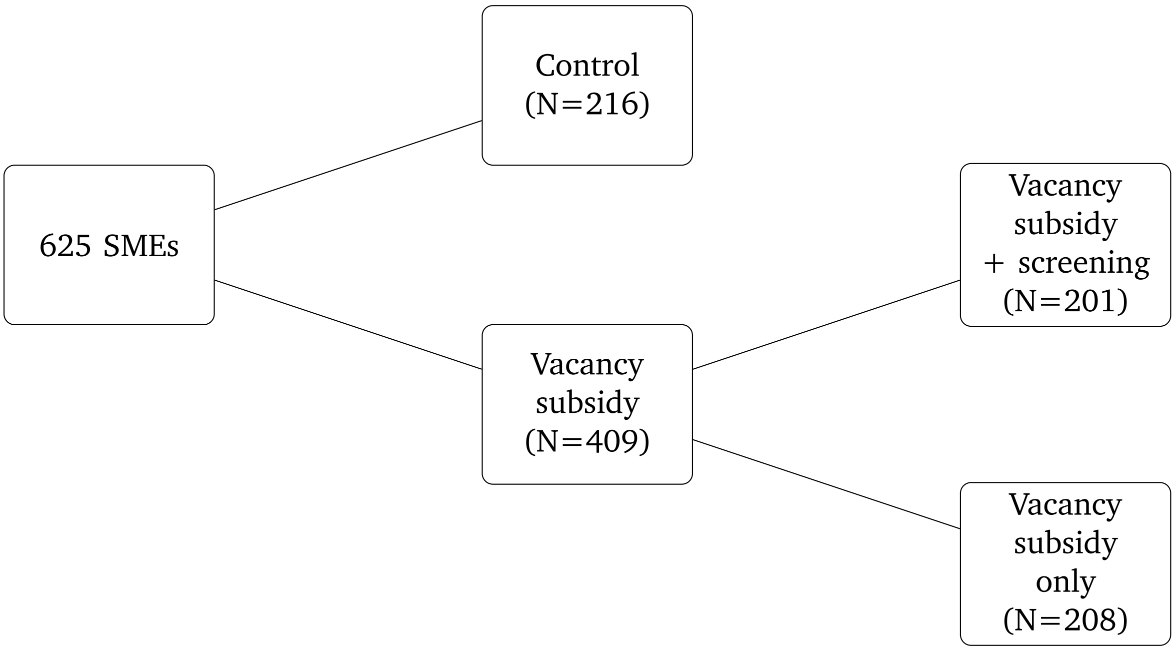
We survey the 625 firms in our sample before, during, and after the treatment period, for a total of 6,068 interviews. After an initial screening survey, we conduct an in-person baseline survey to capture manager and firm characteristics, expectations, as well as pre-existing hiring practices. The end of the baseline survey also marks the beginning of the four-month intervention period. During the intervention period, we carry out regular phone-based surveys to capture vacancy postings and hiring.[17] On average, we conduct more than five phone surveys during the treatment period per firm.

At the end of the treatment period, we conduct an in-person endline survey to capture employment flows and levels, firm-level characteristics, and

[16] The timeline of the study is shown in Appendix figure A2.

[17] For firms that were not responsive to the phone calls, we conduct the surveys in person.

Figure 2: Experimental design



This figure shows the randomly-allocated treatment arms and corresponding sample sizes of our experimental design.

manager beliefs regarding the effectiveness of different hiring channels. For the main analysis of vacancy posting and employment flow data, we aggregate the phone surveys and the endline survey at the firm level to facilitate interpretability (McKenzie, 2012). After the end of the treatment period, we conduct further phone surveys with sampled firms to assess whether our intervention changes behavior in the two months following the treatment period.

3.4 Summary statistics

Baseline summary statistics based on our firm-level data collection are presented in Table 2. Firms in our sample have on average 14.5 employees, of which 14 percent are highly-educated white-collar workers.[18] 51 percent of

[18]Two firms report more than 50 employees due to changes between the screening and baseline survey.

firms are in the manufacturing sector and 27 percent are in the hospitality or retail sectors. 26 percent of our firm respondents are female and the average age is 35 years.[19] They are well-educated, with 45 percent of respondents having a university degree.

Existing employee search channels are largely informal and network-based. 79 percent of sampled firms use network-based search for employees, and 50 percent of firms exclusively rely on network-based employee search. Only 9 percent of firms post their vacancies through formal channels (i.e., in newspapers or on job boards; no firm uses online job boards at baseline), closely mirroring our city-wide back-of-the-envelope calculations.

Overall, the firms in our sample are relatively optimistic about their business. 62 percent and 77 percent of firms have a positive business outlook for the next three and twelve months following the baseline survey, respectively. Furthermore, in the three months after the intervention firms expect to hire on average 3.46 new workers.

We observe stark heterogeneity in the firms' current application volumes. At baseline, 37 percent receive about the appropriate number of applications, while 23 percent of firms state that they receive too few applications and 40 percent receive too many. 11 percent of firms do not know. On average, firms think that by posting their vacancy on one (additional) job board in the city center, they would receive eleven more applications.

3.5 Experimental integrity

To check whether the randomization into treatment arms successfully achieves balance on baseline observable characteristics, we present Appendix Table A3. Out of sixteen tested variables, we only observe one significant baseline imbalance (at the ten percent level), which suggests that the randomization

[19] For all of our data collection activities, we asked to speak with *the person in charge of hiring decisions*. In the vast majority of cases, this is the firm manager or owner. In the few cases where there was managerial turnover during the study period, we instead interviewed the new person in charge of hiring decisions.

Table 2: Summary statistics

	Mean	SD	Median	Min	Max	# obs
Firm characteristics						
Age of firm (in years)	7.19	7.99	5.00	0.10	63.00	616
# of employees	14.49	11.60	10.00	4.00	88.00	625
Share of white-collar employees	0.14	0.15	0.11	0.00	0.94	625
Manufacturing sector	0.51	0.50	1.00	0.00	1.00	625
Service sector (retail, hospitality)	0.27	0.45	0.00	0.00	1.00	625
Health Sector	0.11	0.31	0.00	0.00	1.00	625
Hiring practices						
Uses formal hiring channels	0.09	0.28	0.00	0.00	1.00	625
Uses network hiring channels	0.79	0.41	1.00	0.00	1.00	625
Uses employment agencies	0.39	0.49	0.00	0.00	1.00	625
Manager expectations						
Expected number of hires in next 3 months	3.46	5.93	2.00	0.00	90.00	624
Positive bus. outlook next 3 months	0.62	0.49	1.00	0.00	1.00	611
Positive bus. outlook next 12 months	0.77	0.42	1.00	0.00	1.00	584
Manager characteristics						
Female	0.26	0.44	0.00	0.00	1.00	625
Manager age	35.32	10.30	32.00	19.00	84.00	625
Manager has univ. degree	0.45	0.50	0.00	0.00	1.00	625
Application volumes						
Right amount of applications	0.37	0.48	0.00	0.00	1.00	556
Too few applications	0.23	0.42	0.00	0.00	1.00	556
Too many applications	0.40	0.49	0.00	0.00	1.00	556
Don't know about application volumes	0.11	0.31	0.00	0.00	1.00	625
# of add. applications if posting on one more job board	11.13	14.46	5.00	0.00	100.00	418

Notes: Table 2 presents baseline summary statistics of firm and firm manager characteristics. The number of observations varies due to "don't know" answers and refusals to answer. The total number of firms is 625.

worked as intended.[20] Controlling for this variable does not affect the results in systematic ways.

Attrition levels are generally low and mostly balanced across treatment groups (Appendix Table A4). We manage to reach 96 percent of firms to conduct at least one phone survey (5.6 surveys per firm on average). Furthermore, we successfully reach 97 percent of firms for our in-person endline survey. For our main analysis, we pool both phone and endline data sources, which means that we have outcome data for 100 percent of control group firms and 99 percent of treatment firms (four firms in the treatment group could neither be reached during phone surveys nor the endline survey, meaning that they also did not take up the intervention). While the latter difference is significant at the 5 percent level, it is very small and very unlikely to influence our results. Finally, we manage to contact 88 percent of firms at least once during the two-month post-treatment period (for an average of 2.6 surveys). Reassuringly, there is no statistical difference between the treatment and control group attrition rates during the post-treatment period.

4 Theoretical framework

This section lays out a theoretical framework that rationalizes the descriptive patterns shown in Section 2 and makes predictions about treatment effects. It describes firms' decisions of whether to create a vacancy, how to advertise it, and what type of position to fill.

4.1 Setup

Consider a firm deciding whether to attempt to hire a new employee. Firm i chooses the optimal search strategy s_i^* and the vacancy type t_i^* to maximize the expected profits:

$$(s_i^*, t_i^*) = argmax_{s_i,t_i}\ \pi(s_i, t_i) - c(s_i) \tag{1}$$

[20]The exception is the gender of the interviewed firm manager.

where $\pi(s_i, t_i)$ is firm i's expected profit of searching for an employee of type t (white-collar (wc) or non–white-collar positions (nwc)) through channel s_i (formal or informal)[21] excluding the search cost. $c(s_i)$ are the costs of searching for employees in search channel s_i.

Firms' expected profit from search The expected profit from employee search $\pi(s_i, t_i)$ varies across search channels and vacancy types. We assume that the returns to informal search are higher for non–white-collar vacancies compared to white-collar vacancies ($\pi(informal, wc) < \pi(formal, nwc)$). This assumption is in line with non–white-collar vacancies being posted informally at much higher rates than white-collar vacancies.

Cost of search Firms' costs of searching applicants in channel s_i have two components: $c(s_i) = c^{adv}(s_i) + c^{scr}(s_i)$, where $c^{adv}(s_i)$ are costs of advertising the position on channel s_i, and $c^{scr}(s_i)$ are the total costs of screening applicants obtained through channel s_i, to learn the applicants' true quality.[22] We assume that formal search is more costly than informal search: $c(formal > c(informal)$. This reflects both higher advertising cost $c^{adv}(formal)$ and, potentially, higher screening cost $c^{scr}(formal)$, e.g. because informal network-search can provide more information about applicants.

Choosing the search channel We first consider firms' choice of search channel conditional on job type t. Firm i chooses formal search for job type t if the expected profit from doing so is larger than the expected profit from searching informally:

$$\pi(t, formal) - \pi(t, informal) > c(formal) - c(informal) = \Delta c \qquad (2)$$

That is, firms will use formal job search for type t if the difference in expected benefit between formal and informal search is larger than the cost differential between the two search methods. This condition yields two thresholds

[21] For simplicity, we assume that these two are mutually exclusive.
[22] For simplicity, we assume that screening is always optimal for firms.

for the profitability of formal search below which firms would prefer informal search channels for type t: $\pi^*(wc, formal) = \Delta c + \pi(wc, informal)$ and $\pi^*(nwc, formal) = \Delta c + \pi(nwc, informal)$.

Choosing the vacancy type Next, we consider firms' optimal choice of vacancy type. Firms choose the vacancy type to maximize expected profits, taking into account the optimal search strategy for each type of job $s^*(t)$. They choose a white-collar vacancy if:

$$\pi(s^*(wc), wc) - c(s^*(wc), wc) > \pi(s^*(nwc), nwc) - c(s^*(nwc), nwc) \tag{3}$$

We can combine this condition with the choice of search channel to completely characterize firms' search behavior.

Combining type and search choice Figure 3 displays firms' optimal choices in the $\pi(wc, formal)$—$\pi(nwc, formal)$ space.

First, if it is optimal to use informal search channels for both job types ($\pi(t_i, formal) < \pi^*(t_i, formal), \forall t_i.$), firms' type decision will only depend on their profitability of informal search $\pi_i(informal, t)$. Hence, firms will choose a non–white-collar vacancy.[23] This corresponds to area A in Figure 3.

Second, if formal search is optimal for all types, that is $\pi(t_i, formal) > \pi^*(t_i, formal), \forall t_i$), firms will post a white-collar vacancy if $\pi(wc, formal) > \pi(nwc, formal)$ (area F). Otherwise they will choose to post a non–white-collar vacancy formally (area E).

Third, if formal search is optimal for white-collar jobs but not for non–white-collar jobs ($\pi(wc, formal) < \pi^*(wc, formal)$ and $\pi(nwc, formal) > \pi^*(nwc, formal)$; areas B and C), we need to compare the profits of informal search for both options. Firms will post white-collar vacancies if $\pi(wc, formal) > \pi(nwc, informal) + \delta c = \pi^*(nwc)$ (area C). If $\pi^*(nwc) > \pi(wc, formal)$ firms will post informal non–white-collar vacancies (area B).

[23]Remember that we assumed $\pi(wc, informal) < \pi(nwc, informal)$, i.e. that non-formal search has higher returns for non–white-collar vacancies.

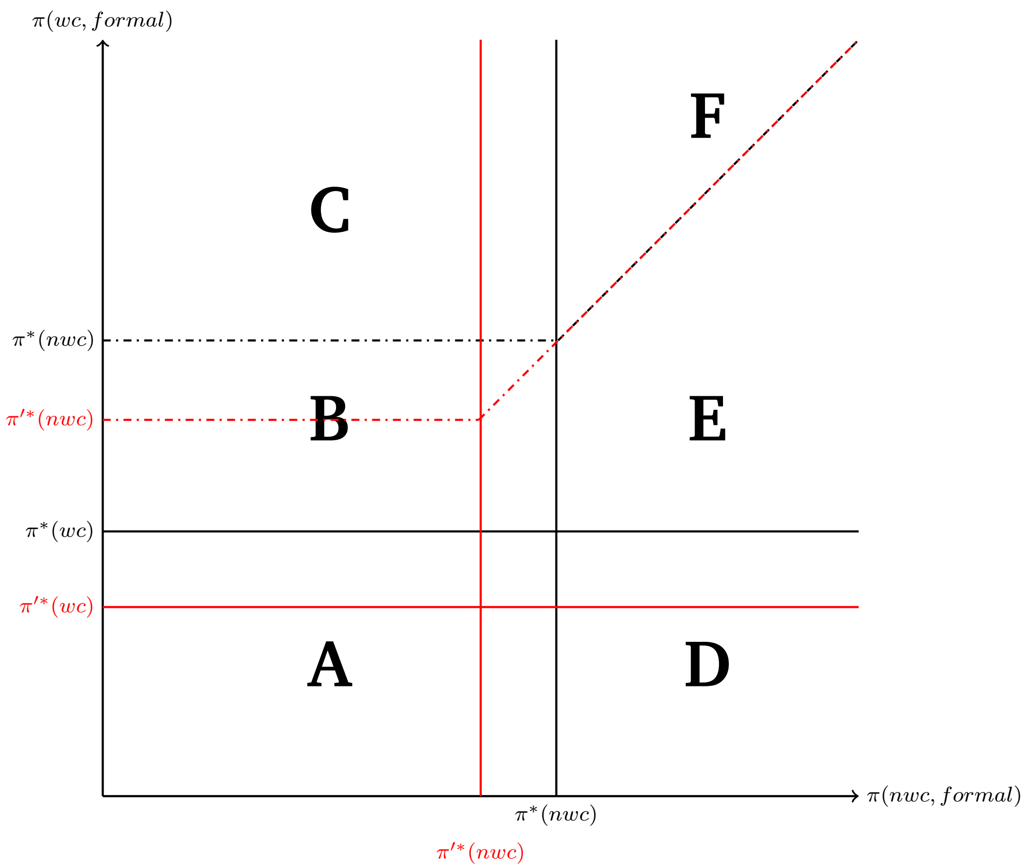


Figure 3: Vacancy search and type decision

Notes: Figure 3 displays the choice of search channel and vacancy type in the $\pi(nwc, formal)$—$\pi(wc, formal)$ space. Red lines indicate what happens when formal search cost are reduced. Firms that fall in the area above the dashed lines post white-collar vacancies (areas C and F). Firms that fall below the dashed line post non–white-collar vacancies (areas A, B, D, and E).

Hence, both formal white-collar and informal non–white-collar posting will occur in this regime.

Finally, if formal search is optimal for non–white-collar jobs but not for white-collar jobs, firms will only create non–white-collar vacancies (that is $\pi(wc, formal) > \pi^*(wc, formal)$ and $\pi(nwc, formal) < \pi^*(nwc, formal)$; area D). Firms would post white-collar vacancies if it were profitable, that is $\pi_i(nwc, formal) < \pi(wc, informal) + \delta c = \pi^*(wc)$. However, to be in this search regime we require $\pi_i(nwc, formal) > \pi^*(nwc)$. As we assume $\pi_i(wc, informal) < \pi_i(nwc, informal)$ we know that $\pi^*(wc) < \pi^*(nwc)$, which implies that firms will not post white-collar vacancies in this regime.

The dashed line in Figure 3 summarizes this pattern. If firms fall above the dashed line, they will choose to create a white-collar vacancy (areas C and F). Conversely, if firms fall below the dashed line, they will choose to create a non–white-collar vacancy (areas A, B, D, and E). All white-collar vacancies will be posted formally (areas C and F), while only a subset of non–white-collar vacancies will be posted formally (areas B and E). Firms that fall in areas A and D will search informally for non–white-collar employees.[24]

Vacancy creation decision Finally, firms decide whether or not to create the vacancy in the first place. They do so if the expected return is positive:

$$\max_{t,s} \pi(t_i, s_i) - c(s_i) > 0 \tag{4}$$

This implies that the vacancy creation decision depends on the anticipated vacancy type and search channel.

[24] If the returns to informal search were higher for white collar vacancies ($\pi(wc, informal) > \pi(nwc, informal)$), all non–white-collar vacancies would be posted formally and some white-collar vacancies will be posted informally (see Figure A1).

4.2 Subsidizing formal search

Our field experiment effectively subsidizes the cost of formal search. In the model, this means that $c'(formal) < c(formal)$. This implies that the cost differential between formal and informal search channels is also reduced ($\Delta c' < \Delta c$). The red lines in Figure 3 display the effect of the subsidy graphically. We derive four predictions from the model that we will test empirically using our experimental data.

Result 1: Subsidies increase take-up of formal search. This result follows from the intuition that reducing the price of formal search will allow firms with lower benefits from formal search to use formal search. Graphically, we observe that the areas C+F and E which contain all formal posting grow unambiguously larger. This is the case because the subsidy shifts both formal posting thresholds $\pi^*(wc) = \Delta c + \pi(wc, informal)$ and $\pi^*(nwc) = \Delta c + \pi(nwc, informal)$ closer to the origin as Δc decreases. Moreover, this subsidy will not dissuade any firms from creating vacancies as none of the cost increase. Hence, subsidizing formal search will make firms with lower benefits from formal search choose formal search. However, the model also implies that there will still be firms who prefer to use informal search channels for their vacancies, implying that take-up will not be perfect.

Result 2: Subsidies increase the number of created vacancies. Introducing vacancy subsidies can never decrease the expected profits, as it either reduces cost or leaves cost unchanged. Consider firms who are close to indifferent between creating a formally advertised vacancy and not posting at all but optimally decide to not create a vacancy without the subsidy. Such firms will be induced to create a vacancy as the cost of formal search decrease.[25] The magnitude of the effect depends on the mass of firms that fall

[25]Formally, consider a firm for which formal search for white-collar is most profitable ($\pi(wc, formal) - c(formal) \geq \pi(t, s) - c(s)\ \forall t_i, s_i$). This firm will post a vacancy if $\pi_i(wc, formal) - c(formal) > 0$. Define $\bar{\pi}_i(wc, formal) = c(formal)$ as the threshold

into this category. If there are many firms who are close to being indifferent between posting a vacancy formally and not posting a vacancy, we would expect relatively large effects of the subsidy. However, if most firms without initial vacancies are far from the threshold values for formal search, we would expect relatively small treatment effects.

Result 3: Subsidies lead to an increase in white-collar vacancies. The vacancy subsidy increases white-collar vacancy posting by making formal posting more attractive. This leads to some informal non–white-collar vacancies being substituted by formally posted white-collar vacancies. This happens as the range of $\pi(t_i, s_i)$ for which firms post informal non–white-collar vacancies rather than formal white-collar vacancies (area B in Figure 3) shrinks because formal posting is more profitable for both white-collar and non–white-collar vacancies. Put differently, the area in which formal white-collar posting is optimal (area C+F in Figure 3) increases as the cost of formal search decreases. As there are no informally posted white-collar vacancies in the model, the additional formal white-collar vacancies substitute non–white-collar vacancies. This effect is driven by firms with relatively high returns to formal search for white-collar compared to non–white-collar vacancies (i.e. firms that fall above the 45 degree line in Figure 3).[26]

Result 4: Reducing screening cost can further amplify the effect of subsidies. This result directly follows from the above results. If we further reduce the screening cost that firms face when using formal search channels ($c^{scr}(formal)$), we further reduce the cost of formal search to $c''(formal) < c'(formal) < c(formal)$. If the cost of screening is a constraining factor for firms, then we would expect the additional reduction to lead to additional

value above which this firm posts a vacancy. The vacancy subsidy reduces this threshold to $\bar{\pi}'_i(wc, formal) = c'(formal)$. Now, other firms with $\bar{\pi}_i(wc, formal) > \pi_i(wc, formal) > \bar{\pi}'_i(wc, formal)$ and for which $\pi(wc, formal) - c(formal) \geq \pi(t_i, s_i) - c(s_i)\ \forall t_i, s_i$ holds will be induced to post formal white-collar vacancies.

[26] Subsidies could also increase white-collar vacancies by causing non-posting firms to start posting white-collar vacancies (as argued in result 2).

uptake of formal search. It could also imply a further shift to white-collar vacancies following the same logic as in result 3.

Beliefs about returns to formal employee search So far we have assumed that the firms' managers have full information about the expected returns to search through different channels ($\pi(t_i, s_i)$). However, in practice that may not be the case. The overwhelming prevalence of informal search and low demand for white-collar employees means that few managers might have direct experience in using these channels, which could help them form accurate beliefs. Indeed, Chandrasekhar et al. (2020) show that—in the presence of informal search—even rational firms might fail to learn about the true returns to formal search.

If firm managers are too pessimistic about the returns to formal search, subsidizing formal search could lead to learning and permanent behavioral change. Conversely, if managers are overoptimistic about the returns to formal search, they might attempt to use subsidized formal search initially. The overoptimism might lead to unsuccessful searches for example, because managers have unrealistic expectations about the quality and quantity of applicants. This could lead to reduced hiring rates among treated firms. If this were the case, we would expect firm managers to update their beliefs and revert back to informal search methods in long-run.

5 Results

How do the theoretical predictions hold up empirically? We estimate treatment effects of the vacancy subsidy intervention using the following equation:[27]

[27]We registered a pre-analysis plan for this project with this as the main specification. We deviate from the pre-analysis plan in the following main ways. First, we expand the number of outcomes, as we consider studying both the extensive and intensive margins and the success ratio of vacancy creation. To account for this we include all variables in the multiple hypothesis test correction (MHC). In line with these changes, we do not normalize outcomes over time to be able to use extensive margin outcomes. Second, we do not normalize by

$$y_i = \beta_0 + \beta_1 vacsub_i + \varepsilon_i \tag{5}$$

where y_i is the firm-level outcome of interest. y_i is aggregated across phone surveys and the endline survey whenever possible. $vacsub_i$ is a dummy variable equal to one if firm i is eligible for the vacancy posting subsidy treatment. We use heteroskedasticity robust standard errors throughout the analysis and include sharpened q-values to correct for multiple hypothesis testing within each outcome family in brackets.[28]

Take-up and formalization of employee search We find that the treatment causes a large and highly significant increase in the use of formal vacancy posting (columns (1) to (6) of Table 3). We see a decrease in the use of networks for employee search (columns (7) to (9) of Table 3). In particular, we find a 17-percentage-point increase in the fraction of firms posting vacancies through formal channels for at least one of their vacancies ($p<0.01$). This is equivalent to a 331 percent increase relative to the control mean. This goes hand in hand with a substantial increase in the absolute number of formally-posted vacancies (by 0.46 vacancies per firm or 320 percent, $p<0.01$) and the fraction of vacancies posted through formal means (31 percentage points or 447 percent, $p<0.01$). These large effect sizes suggest that our intervention succeeds in increasing the formalization of vacancy posting among treated firms, in line with result 1 of our theoretical framework.

Furthermore, firms are selective in using our intervention to post job adverts. Column (3) of Table 3 shows that on average firms in the treatment group post 0.56 vacancies through our intervention, which amounts to 73

---

treatment duration as we do not observe differential attrition by treatment group. Third, we use pooled treatment effect estimation instead of separate effects for a screening add-on intervention as our main specification. Finally, we do not show hire- and vacancy-level specifications and outcomes for which the data quality is insufficient. More details can be found in Online Appendix Section D.

[28] In Online Appendix Section B we estimate treatment effects controlling for observable firm and manager characteristics. Specifically, we control for pre-specified covariates by using the post-double LASSO method for each outcome separately (Belloni et al., 2013). The results remain quantitatively and qualitatively unchanged.

Table 3: Formalization of employee search

	Take-up			Formal search			Network based search		
	(1) Any	(2) Any | any vacs	(3) # vacs	(4) Any	(5) # vacs	(6) % vacs	(7) Any	(8) # vacs	(9) % vacs
Treatment	0.215***	0.481***	0.558***	0.169***	0.461***	0.313***	-0.078**	-0.055	-0.094*
	(0.020)	(0.037)	(0.081)	(0.025)	(0.111)	(0.039)	(0.036)	(0.063)	(0.054)
	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.038]**	[0.380]	[0.095]*
Control mean	0.000	0.000	0.000	0.051	0.144	0.070	0.269	0.398	0.462
Observations	621	288	621	621	621	288	621	621	288

Notes: Table 3 displays the impact of the vacancy subsidy on formal employee search. Column (1) shows the fraction of firms posting at least one vacancy through our intervention. Column (2) shows the number of vacancies posted through our intervention conditional on using the subsidy for at least one subsidy. Column (3) shows the number of vacancies for which the vacancy subsidy was used. Column (4) to (6) shows the impact of the vacancy subsidy on formal employee search. Columns (7) to (9) show the impact of the vacancy subsidy on exclusively using network-based employee search. Heteroskedasticity robust standard errors are displayed in parenthesis. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

percent of vacancies of firms that use the intervention at least once (or 35 percent of all posted vacancies in the treatment group). In total, among firms that posted any vacancy during the treatment period, 48 percent use the vacancy subsidy at least once. This suggests that despite initially being interested in using the intervention, firms are selective in their use of formal search channels. Moreover, this indicates that the expected returns to formal employee search might vary substantially across firms and vacancies.

5.1 Impact on vacancy creation

The vacancy subsidy intervention was designed to reduce the marginal cost of posting vacancies through formal channels. This decrease in marginal costs should make it more attractive for firms to post vacancies, as result 2 of our theoretical framework suggests. To test this hypothesis, we estimate treatment effects on vacancy creation in Table 4.

We find no significant treatment effect on overall firm-level vacancy creation on either the intensive or intensive margin of vacancy creation. On

Table 4: Impacts on vacancy postings

	(1) Any	(2) # vacs	(3) # vacs $\mid$ any
Treatment	-0.048	0.124	0.529*
	(0.042)	(0.171)	(0.283)
	[0.333]	[0.454]	[0.230]
Control mean	0.495	1.153	2.327
Observations	621	621	288

Notes: Table 4 displays the treatment effects on vacancy creation. Heteroskedasticity robust standard errors are displayed in parenthesis. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

average, we observe an increase in the total number of vacancies by 0.12 (column (2)). However, this effect is not statistically significant. The treatment group also exhibits a 4.8-percentage-point, non-significant decrease in the fraction of firms posting any vacancy (column (1)). Interpreted within our theoretical framework, this implies there are few firms who are close to indifferent between not posting and posting formal vacancies. We do find a significant increase of 23% or 0.53 vacancies in the number of vacancies posted for those firms that post any vacancy during the study period (column (3); significant at 10% before multiple hypothesis correction (MHC)). This suggests that there might be some fixed costs associated with starting the search for any new worker.

Composition effects Result 3 of our theoretical framework establishes the possibility that vacancy subsidies might shift the composition of created vacancies. We present two descriptive pieces of analysis that explain why vacancy subsidies might induce changes in the *type* of vacancies firms search for in our specific context. First, we make use of the following survey question in which we ask firm respondents about the expected quality of applicants obtained through formal channels: *"Imagine that you posted a vacancy for a (non-)white-collar employee on [search channel]. What do think would be the quality of applicants compared to hiring through family and friends?"* We measure this for two types of jobs (white-collar and non–white-collar) and three formal search channels (newspapers, offline job boards, online job boards).

We show firms' beliefs about the returns to formal search in Appendix figure A5.[29] We find that a sizable share between 40% and 55% of respondents expects to get better applicants through formal channels compared to social networks. Across different search channels and worker types, the share of respondents expecting to get better applicants through formal channels compared to social networks is never smaller than the share of respondents expecting worse applicants. Yet, there are stark differences between higher-skilled white-collar applicants—where over 50% of respondents expect better applicants from formal channels—and non–white-collar applicants, where the corresponding number is only 40%, on par with the share of respondents expecting worse applicants.[30]

Second, in line with these expectations, we find that among firms in the control group, white-collar vacancies are more than four times as likely to be posted formally compared to non–white-collar vacancies (42 vs 8 percent, respectively, see Table 1). This suggests that the returns to formal employee search are higher for white-collar positions, which could affect how firms use the vacancy posting subsidy.

In line with these patterns, we find that the intervention significantly affects the composition of vacancies created during the treatment period. Table 5 shows the impact on the skill composition of posted vacancies. We observe a significant increase in the level of white-collar vacancy creation at all margins, (columns (1) and (2)). On average, the number of white-

[29]We only asked this set of questions at endline, which is why we present data from the control group firms, unaffected by treatment.

[30]We also ask firm respondents about the expected number of applicants when posting a vacancy in the same three formal channels, for both white-collar and non–white-collar vacancies. Here, the differences between the two collar types are very small and insignificant, Figure A6.

Table 5: Composition effects: vacancy creation

	White collar			Non-white collar	
	(1) Any vac	(2) # vacs	(3) % vacs	(4) Any vac	(5) # vacs
Treatment	0.072***	0.173***	0.118***	-0.069*	-0.051
	(0.026)	(0.066)	(0.040)	(0.042)	(0.147)
	[0.012]**	[0.012]**	[0.012]**	[0.051]*	[0.170]
Control mean	0.079	0.144	0.119	0.449	1.009
Observations	621	621	288	621	621

Notes: Table 5 displays the effect of our intervention on the skill composition of vacancy postings. Columns (1) to (3) show the impact on white-collar vacancies. Columns (4) and (5) show the impact on non–white-collar vacancies. Heteroskedasticity robust standard errors are displayed in parenthesis. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

collar vacancies increases by 0.173, which is equivalent to an increase of 120 percent relative to the control group mean. We also observe a relatively sizable decrease in the likelihood of posting any non–white-collar vacancy by 6.9 percentage points or 15 percent of the control group. The two results combined yield a significant increase in the fraction of white-collar vacancies by 11.8 percentage points on average (column (4)). This suggests that the treatment leads firms to use white-collar vacancies as substitute for non–white-collar vacancies as hypothesized in result 3 of our framework.

5.2 Impact on hiring

Next, we investigate to what extent the treatment effects on formal vacancy creation and vacancy composition translate into effects on firms' hiring of employees. First, we look at overall hiring levels, followed by a composition analysis.

Table 6: Impacts on hiring

	(1) Any	(2) # hires	(3) % vacs filled
Treatment	-0.078*	-0.210	-0.203***
	(0.042)	(0.171)	(0.041)
	[0.063]*	[0.099]*	[0.001]***
Control mean	0.454	1.218	0.877
Observations	621	621	288

Notes: Table 6 displays the treatment effects on hiring outcomes. Heteroskedasticity robust standard errors are displayed in parenthesis. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In terms of overall hiring, we observe a significant reduction in the fraction of vacancies successfully filled (Table 6). Specifically, we observe a reduction of 20 percentage points in the fraction of successfully-filled vacancies (down from a control group mean of 88 percent and significant at the 1 percent level even after MHC, column (3)). Similarly, the fraction of firms filling any vacancy (and thus making any hire) falls by 8 percentage points, which is significant at the 10 percent level after MHC. This could be due to various factors, including a shift in the nature of posted vacancies or the observed shift in employee search channels. This pattern translates into a sizable (0.21 hires or 17 percent of the control group mean) decrease in the number of hires. This decrease is driven by a reduction of firms successfully hiring any candidate rather than by the number of hires of actively-hiring firms. Put differently, we observe marginally significant treatment effects on the extensive but not the intensive hiring margin.

Composition effects. The composition effect in vacancy posting does not translate into more white-collar hires. We observe that the negative effects on the fraction of filled vacancies is present for both white-collar and non–

white-collar vacancies (columns (4) and (7) of Table 7). However, the point estimate for white-collar vacancies is over twice as large in absolute terms (-35.7 percentage points for white-collar vacancies vs -16.7 percentage points for non–white-collar vacancies).[31] Table 7 also explores hiring numbers and shows no significant impacts and overall small effect sizes for white-collar hires. This is true for the fraction of firms hiring any white-collar workers, the total number of white-collar hires, and the fraction of white-collar hires. In contrast, we observe a marginally significant (after MHC) decrease of 8.6 percentage points in the number of firms conducting any non–white-collar hire, in line with the results on overall hiring numbers. Consistent with the negative hiring effects being driven by non–white-collar workers, we show in Appendix Table A13 that at endline the share of white-collar employees is a significant 2.4 percentage points (or 24%) higher in treated firms.

5.3 Why do firms fail to fill vacancies?

We explore two potential explanations of why we observe negative treatment effects on the vacancy filling rate. We clearly observe that firms use the subsidy to post more high-skilled vacancies with more stringent selection criteria. Moreover, there is the possibility that firms also increase the requirements of their formally posted vacancies in other ways. For example, they could require specific types of work experience that potential applicants in their network lack. If formal search methods do not yield applicants that meet these stringent criteria and would accept a job-offer, this could explain the decrease in hiring rates.

[31] The fact hat we also observe an effect on non–white-collar vacancies can potentially be explained by two factors. First, it could be driven by endogenous changes in unobserved vacancy characteristics that make the vacancy harder to fill. For example, firms might try to fill positions that require specialized experience that workers in their network lack. Second, it could be that they generally have inflated expectations about the quality of job-seekers which leads to them choosing a hiring threshold that is high relative to the realized quality distribution.

Table 7: Composition effects: hiring decision

	White collar				Non-white collar		
	(1) Any hire	(2) # hires	(3) % hires	(4) % vacs filled	(5) Any hire	(6) # hires	(7) % vacs filled
Treatment	0.019	0.005	0.062	-0.357***	-0.086**	-0.215	-0.167***
	(0.022)	(0.062)	(0.042)	(0.102)	(0.041)	(0.154)	(0.043)
	[0.291]	[0.363]	[0.147]	[0.002]***	[0.062]*	[0.147]	[0.001]***
Control mean	0.069	0.153	0.118	0.847	0.412	1.065	0.877
Observations	621	621	250	78	621	621	252

Notes: Table 7 displays the displays the effect of our intervention on the skill composition of hiring. Columns (1) to (4) show the impact on white-collar hiring. Columns (5) to (7) show the impact on non–white-collar hiring. Heteroskedasticity robust standard errors are displayed in parenthesis. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Applicant numbers and quality The first possible explanation is that firms receive too few applicants that meet the formal education and experience requirements stated by the firm. We find that this is unlikely to be the driver of this result. Appendix Figure A4 shows that treated firms, on average, roughly double their number of applicants compared to control firms, for approximately 5-6 applicants per vacancy. This goes against the idea that a lack of applicants brings about the reduction in filled vacancies. Moreover, more than 75% of applicants fulfill all required criteria for the posted vacancy (such as education or experience requirements). Thus, formal employee search thus yields, in principle, more *formally qualified* applicants.

However, despite these positive impacts, we find that firms update negatively about the returns to formal search. We first consider if candidates are worse than managers expected, which both prevented hiring and led managers to update their beliefs about formal vacancy posting. To document belief updating, we once more make use of the question from the previous section, asking managers whether different types of applicants obtained through different formal channels are of better quality than those obtained through networks. Using these data, we construct a normalized belief index, with higher values indicating a higher expected quality of applicants through formal search channels relative to network-based search.[32] We find that on average firm managers in the treatment group have significantly lower expectations about the quality of applicants obtained through formal channels (-0.17 standard deviations, significant at the 10 percent level after MHC) than the control group (see Appendix Table A7). The impact on expectations for white-collar and non–white-collar applicants are of a similar size (columns (2) and (3)). The negative updating while most candidates meet the stated requirements suggests that firms update negatively about quality dimensions other than formal education and experience.

We also find negative average treatment effects on the *expected* number of applicants after posting a vacancy in formal channels (0.21 standard deviations, significant at the 10 percent level after MHC), with no discernible differences between expectations about white-collar and non–white-collar applicants. These effects are more noisily estimated due to the unbounded nature of the variable. Again, this is not driven by a negative treatment effect on the number of applicants, but rather by unrealistically high expectations to begin with.

In summary, we find that managers negatively update their beliefs about the quality and quantity of applicants obtained through formal search channels, thus updating negatively about the prospects of formal employee search overall. If they set the quality thresholds for hiring according to their initial expectations, this could explain why treated firms struggle to fill their vacancies.

Moreover, the fact that our treatment affects endline beliefs about the usefulness of formal search channels indicates that firm managers had incomplete information about the properties of such search channels. This in turn suggests that firms experiment little with different types of employee search. In the context of our experiment, such a lack of experimentation

[32]The index summarizes answers across the three different formal search channels (online, job board, newspaper) and the two job types (white-collar, non–white-collar).

might well be optimal for firms. However, a broader lack of accurate information might slow down or even prevent firms from adapting formal search channels as these channels improve over time (for example, because more firms and job-seekers start using them).

Applicant expectations about salaries Another potential reason for low hiring rates is that applicants have unrealistic wage expectations and are not willing to work at the relatively small firms in our sample. We show descriptively—using data from our applicant screening center—that applicants to formally-posted job advertisements indeed have unrealistically high wage expectations.

We observe a strong mismatch between applicants' expectations and realized salaries for the position to which they applied. Table A5 uses the applicant data we collect for firms in the screening treatment group to show applicants' reservation wages, wage expectations, realized salaries, and average baseline salaries. Three facts emerge. First, wage expectations and reservation wages are on average significantly higher than both the realized wage (when the vacancy is filled) and the average salary of vacancy posting firms at baseline. This suggest that applicants are generally over-optimistic about the possible remuneration. Second, applicants to unfilled vacancies have 38% higher reservation wages and 26% higher wage expectations compared to applicants to filled vacancies, despite the fact that average baseline salaries between firms with filled and unfilled vacancies do not strongly differ. Overall, this pattern is consistent with overly optimistic expectations at least partially explaining why firms face difficulties filling vacancies. Finally, the discrepancy between expectations of applicants for filled and unfilled vacancies is larger for white-collar compared to non–white-collar vacancies (59% difference in reservation wages vs 31% difference in reservation wages). Hence, applicants to unfilled white-collar vacancies are more over-optimistic than those to unfilled non–white-collar vacancies. This pattern is further in line with the observed heterogeneity in the decrease in filling rates across vacancy types.

5.4 Treatment effects on downstream outcomes

In this section, we study the treatment effects on the characteristics of successful hires and outcomes related to business performance.

Impact on hire characteristics We find no evidence that our intervention affected the average characteristics of successful hires. In principle, the observed change in the type of vacancies created could also lead to a change in the quality or type of worker hired, even without affecting overall hiring numbers. To study this, we estimate the impact of the intervention on indicators that measure the match quality of new hires, namely the salary and the satisfaction of the manager with the new hire. Appendix Table A14 shows insignificant impacts with point estimates close to zero for both outcomes. We also find no effect on the share of female hires.

Impact on firm outcomes There is no significant effects of the vacancy posting subsidy on downstream firm outcomes (Table A11). Column (1) shows a sizable (ca. -29%) but insignificant negative impact on reported profits. The effect on revenues is much smaller (-2.5%) and far from significant. Similarly, the impact on managers' business outlook is slightly negative but far from significant. Finally, the total number of employees decreases by an insignificant 2.5 employees or 15% of the control group mean in line with the observed decrease in hiring in the treatment group. Overall, we lack statistical power to detect small effects on firm performance and outcomes, not least because of the relatively low vacancy posting levels during our study period.

Summary Taken together, our results suggest that the vacancy posting subsidy shifts firms' vacancy posting patterns. Firms use the intervention to post white-collar vacancies that they would not have posted otherwise. At the same time, the fraction of firms posting any non–white-collar vacancies decreases. This pattern suggests that firms substitute non–white-collar vacancies with white-collar vacancies when offered the subsidy. However, this shift does not lead to an increase in white-collar hiring, and many vacancies remain unfilled. We provide suggestive evidence for two potential mechanisms. First, this could be due to managers' unrealistic expectations about the quality (and quantity) of applicants obtainable through formal job-search. Second, we show descriptively that applicants to unfilled vacancies have high reservation wages and wage expectations, which plausibly makes it more difficult for firms to fill vacancies.

5.5 The role of information frictions about worker skills

Is the usefulness of our intervention constrained by firms' inability to pre-screen applicants obtained through formal networks? Information frictions have been found to be an important aspect in many labor markets in developing countries—including in Ethiopia—and could limit the effectiveness of formal employee search (Carranza et al., 2020, Abebe et al., 2019, Bassi and Nansamba, 2021). To test whether limited information about candidate skills constrains the use of formal search channels, we offer half the firms in the treatment group the option to have all applicants screened for three cognitive or socio-emotional skills of the firm's choice.[33] We invite all applicants to a screening center in downtown Addis Ababa for a screening session. When then pass their test results (grouped in terciles among all applicants) on to the hiring managers who are then free to arrange interviews according to the results.

Overall, we find very little heterogeneity based on whether firms receive an additional screening intervention (Appendix Table A9). Columns (1) to (3) show no difference in the formalization of employee search by treatment group. Similarly, columns (4) to (8) show that there are no statistically significant differences in vacancy creation or hiring numbers. The screening add-on also does not affect the skill composition of created vacancies and

[33]To ensure that the screening is relevant for firms, we let them choose from a list of ten skills that are commonly associated with labor market success.

hires (Appendix Table A10). This suggests that even if firms face more severe information frictions when using formal search channels, these frictions do not seem to limit firms' use of formal vacancy posting or affect their vacancy creation when posting costs are subsidized.

5.6 Search beyond the experiment

Does our intervention affect firms' employee search behavior beyond the duration of the subsidy? The belief updating results suggest that firms had, on average, a negative experience with the use of formal search channels. This suggests that treated firms should not continue their increased use of formal search channels past the treatment period. If anything, they should reduce their use of formal search channels relative to the control group. We use data from post-treatment surveys to analyze firms' search behavior after the intervention.

We find that firms do not increase their use of formal search channels beyond the treatment period. Table A16 shows that there is no significant impact on either the quantity or share of formally posted vacancies. However, the point estimates for formal posting are non-negligible. For example, the share of formally posted vacancies decreases by 1.9 percentage points which is equivalent to 25% of the control group mean. This behavior is in line with managers' negative updating about the returns to formal search. Our finding contrasts with Abebe et al. (2020b) who find an increase in formal search after negative search experiences using job fairs. This suggests that learning about specific search channels is an important factor for firms' choice of search method.

6 Conclusion

In this paper, we randomly provide vacancy posting subsidies to 625 SMEs in Addis Ababa, Ethiopia, to test whether incentivizing firms' formal vacancy posting changes their hiring practices. We pay for all formal job advertisements of treated firms over a period of four months and survey firms extensively before, during, and after the treatment.

Our intervention successfully increases the share of firms posting in formal channels four-fold. This shift in posting techniques does not lead to more vacancy creation, but rather induces firms to gravitate towards creating higher-skill white-collar vacancies. However, not all of these new, high-skill vacancies get filled, with treated firms' probability of filling a given vacancy decreasing by 20 percentage points. Treated firms update negatively about the quality of applicants recruited through formal channels and reduce formal posting again after the end of the intervention period.

Alleviating information frictions about applicant skills—which has been found to increase job-seekers' labor market outcomes in the literature—does not change the impact of the vacancy posting subsidy. This suggests that the lack of information about job-seekers' skills is not a binding constraint for firms in the context of Addis Ababa. Their difficulty in filling vacancies posted through formal channels instead suggests that an actual mismatch in applicants' and managers' expectations constrains firms' formal search and hiring activities.

Our findings suggest that firms have incomplete information about the returns to formal search, potentially because of low usage rates of formal search. At the same time, it might be that firms' ex-ante vacancy posting behavior without the formal posting subsidies is also ex-post optimal, given the type and number of applicants firms receive through formal channels.

When extrapolating from this study, it is important to keep in mind the partial equilibrium nature of our research. In all likelihood, our experiment did not affect the search behavior of job-seekers, which already is predominantly formal. As such, this study only speaks to the effect of formalized employee search given current job search habits. If a large fraction of firms were to switch to using more formal search channels, this could also incentivize job-seekers to rely even more on these channels. This in turn might have important consequences for the composition of the applicant pool and the resulting incentives for firms to use formal channels. We think that studying the general equilibrium characteristics of coexisting formal and informal search processes is an interesting avenue for future work.

References

Abebe, Girum, A. Stefano Caria, and Esteban Ortiz-Ospina, "The Selection of Talent: Experimental and Structural Evidence from Ethiopia," *American Economic Review*, June 2021, *111* (6), 1757–1806.

_ , Marcel Fafchamps, Michael Koelle, and Simon Quinn, "Learning Management Through Matching: A Field Experiment Using Mechanism Design," *NBER Working Paper 26035*, 2019.

_ , Stefano Caria, Marcel Fafchamps, Paolo Falco, Simon Franklin, and Simon Quinn, "Anonymity or Distance? Job Search and Labour Market Exclusion in a Growing African City," *Review of Economic Studies*, 2020.

_ , _ , _ , _ , _ , _ , and Forhad Shilpi, "Matching Frictions and Distorted Beliefs: Evidence from a Job Fair Experiment," *Working Paper*, 2020.

Abel, Martin, Rulof Burger, and Patrizio Piraino, "The Value of Reference Letters -Experimental Evidence from South Africa," *American Economic Journal: Applied Economics*, 2020, *12* (3), 40–71.

Algan, Yann, Bruno Crépon, and Dylan Glover, "Are active labor market policies directed at firms effective? Evidence from a randomized evaluation with local employment agencies," *Working Paper*, 2020.

Bandiera, Oriana, Vittorio Bassi, Robin Burgess, Imran Rasul, Munshi Sulaiman, and Anna Vitali, "Worker Heterogeneity and Job Search: Evidence from a Six-Year Experiment in Uganda," *Working Paper*, 2020.

Banerjee, Abhijit, Emily Breza, Arun G Chandrasekhar, Esther Duflo, Matthew O Jackson, and Cynthia Kinnan, "Changes in social network structure in response to exposure to formal credit markets," Technical Report, National Bureau of Economic Research 2021.

Bassi, Vittorio and Aisha Nansamba, "Screening and Signaling Non-Cognitive Skills: Experimental Evidence from Uganda," *Economic Journal*, 2021.

Beam, Emily A., "Do job fairs matter? Experimental evidence on the impact of job-fair attendance," *Journal of Development Economics*, 2016, *120*, 32–40.

Beaman, Lori and Jeremy Magruder, "Who Gets the Job Referral? Evidence from a Social Networks Experiment," *The American Economic Review*, 2012, *102* (1027), 3574–3593.

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen, "Inference on Treatment Effects After Selection Among High-Dimensional Controls," *Review of Economic Studies*, 2013, *81* (2), 608–650.

Calvó-Armengol, Author Antoni and Matthew O. Jackson, "The Effects of Social Networks on Employment and Inequality," *American Economic Review*, 2004, *94* (3), 426–454.

Carranza, Eliana, Rob Garlick, Kate Orkin, and Neil Rankin, "Job Search and Matching with Two-Sided Limited Information ," *Working Paper*, 2020.

Chandrasekhar, Arun G, Melanie Morten, and Alessandra Peter, "Network-Based Hiring: Local benefits; Global Costs," *Working Paper*, 2020.

Comola, Margherita and Silvia Prina, "Treatment Effect Accounting for Network Changes," *The Review of Economics and Statistics*, 07 2021, *103* (3), 597–604.

de Mel, Suresh, David McKenzie, and Christopher Woodruff, "Labor drops: Experimental evidence on the return to additional labor in microenterprises," *American Economic Journal: Applied Economics*, 2019, *11* (1), 202–235.

Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker, "Referral-based job search networks," *Review of Economic Studies*, 2016, *83* (2), 514–546.

Fernando, A. Nilesh, Nihirika Singh, and Gabriel Tourek, "Hiring Frictions and the Promise of Online Job Portals: Evidence from India," *Working Paper*, 2022.

Franklin, Simon, "Location, Search Costs and Youth Unemployment: Experimental Evidence from Transport Subsidies," *The Economic Journal*, 2018, *128* (614), 2353–2379.

Galasso, Emanuela, Martin Ravallion, and Agustin Salvia, "Assisting the Transition from Workfare to Work: A Randomized Experiment," *ILR Review*, 2004, *58* (1), 128–142.

Groh, Matthew, Nandini Krishnan, David Mckenzie, and Tara Vishwanath, "Do Wage Subsidies Provide a Stepping-Stone to Employment for Recent College Graduates? Evidence from a Randomized Experiment in Jordan," *Review of Economics and Statistics*, 2016, *98* (3), 488–502.

Hanna, Rema, Joshua Schwartzstein, and Sendhil Mullainathan, "Learning Through Noticing: Theory and Evidence From a Field Experiment," *The Quarterly Journal of Economics*, 2014, pp. 1311–1353.

Hardy, Morgan and Jamie McCasland, "Are Small Firms Labor Constrained? Experimental Evidence from Ghana," *Working Paper*, 2018.

Heath, Rachel, "Why do Firms Hire using Referrals? Evidence from Bangladeshi Garment Factories," *Journal of Political Economy*, 2018.

Kelley, Erin M, Christopher Ksoll, and Jeremy Magruder, "How do Online Job Portals affect Employment and Job Search? Evidence from India," *Working Paper*, 2020.

Kramarz, Francis and Oskar Nordström Skans, "When strong ties are strong: Networks and youth labour market entry," *Review of Economic Studies*, 2014, *81* (3), 1164–1200.

McKenzie, David, "Beyond baseline and follow-up: The case for more T in experiments," *Journal of Development Economics*, 2012, *99* (2), 210–221.

Mobarak, Ahmed Mushfiq and Mark R. Rosenzweig, "Informal Risk Sharing, Index Insurance, and Risk Taking in Developing Countries," *American Economic Review*, May 2013, *103* (3), 375–80.

Rebien, Martina, Michael Stops, and Anna Zaharieva, "Formal Search and Referrals from a Firm's Perspective," *International Economic Review*, 2020, *61* (4), 1679–1748.

Serneels, Pieter, "The nature of unemployment among young men in Urban Ethiopia," *Review of Development Economics*, 2007, *11* (1), 170–186.

Ulyssea, Gabriel, "Firms, Informality, and Development: Theory and Evidence from Brazil," *American Economic Review*, August 2018, *108* (8), 2015–47.

_ , "Informality: Causes and Consequences for Development," *Annual Review of Economics*, 2020, *12* (1), 525–546.

Wheeler, Laurel, Robert Garlick, Eric Johnson, Patrick Shaw, and Marissa Gargano, "LinkedIn (to) Job Opportunities : Experimental Evidence from Job Readiness Training," *American Economic Journal: Applied Economics*, 2021.

Witte, Marc, "Why do workers make job referrals? Experimental Evidence from Ethiopia," *Working Paper*, 2021.

World Bank, *World Development Indicators*, World Bank, 2020.

Appendix
For Online Publication

The Online Appendix contains additional tables and figures referenced to in the main text. Online Appendix Section A contains additional result tables. Online Appendix Table A3 tests for balance between treatment and control group. Online Appendix Table A4 tests for differential attrition by treatment groups. Online Appendix Table A5 shows wage expectations and realized wages for different vacancy types. Online Appendix Table A6 displays heterogeneous treatment effects by a wide range of observable characteristics. Online Appendix Table A7 displays treatment effects on managers' beliefs. Online Appendix Table A8 shows the impact on average salaries at endline. Online Appendix Table A9 shows the additional impact of the screening intervention on vacancy posting and creation, and hiring outcomes. Online Appendix Table A10 shows the additional impact of the screening intervention on the composition of vacancy creation and hires. Online Appendix Table A11 shows the impact on downstream business outcomes. Online Appendix Table A12 shows the impact average search inputs. Online Appendix Table A14 show the impacts on characteristics of hired individuals. Online Appendix Table 7 shows the impacts on the skill composition of new hires. Online Appendix Table A16 shows impacts on search channels after the treatment period.

In section B, we show all main results with control variables selected according to the pre-analysis plan. Online Appendix Table A17 shows the main effects. Online Appendix Tables A19 and A20 display the effects on the skill composition of vacancy creation and hires. Online Appendix Table A21 displays the impact on manager beliefs. Online Appendix Table A22 displays the impact on turnover. Online Appendix Table A23 displays the impact on search inputs. Online Appendix Table A24 shows the impacts on the characteristics of new hires.

Section C contains additional figures. Online Appendix Figure A2 displays the timeline of the experiment. Online Appendix Figure A3 shows the geographical distribution of firms in our sample.

A Additional tables

Table A1: Correlates of formal and informal job search

	Formal search			Informal (network) search		
	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.01***		0.01***	0.00		0.00
	(0.00)		(0.00)	(0.00)		(0.00)
First-time job-seekers		0.13***	0.10***		-0.09*	-0.11**
		(0.04)	(0.04)		(0.05)	(0.05)
Mean dep. var.	0.84	0.83	0.84	0.38	0.38	0.38
Observations	329	355	329	329	355	329

Notes: Table A1 presents correlates of formal and informal (network-based) job search. In columns (1)-(3), an indicator whether a jobseeker searches in formal channels is regressed on her years of education, whether she is a first-time jobseeker, or both. Columns (4)-(6) repeat the same for informal job search as dependent variable. Based on data from the Ethiopian National Labor Force Survey 2021. Formal job search methods include online and offline job boards and newspapers. Informal job search methods are through social contacts/networks. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Differences between white-collar and non–white-collar vacancies

	White-collar (WC)	Non–white-collar (NWC)	Δ	p(WC=NWC)	Obs.
Number of vacancies	593	406	187	.	999
Share of vacancies	0.59	0.41	0.19	.	999
Education requirements					
High school or less	0.01	0.25	-0.23	0.00	999
Vocational/other post-secondary	0.40	0.41	-0.01	0.87	999
University	0.59	0.35	0.24	0.00	999
Other characteristics					
Years of experience	3.28	2.38	0.90	0.00	877
Monthly salary	10086	4052	6034	0.00	134

Notes: Table A2 compares various vacancy characteristics betwee white-collar and non–white-collar vacancies. The monthly salary in row five is in Ethiopian Birr. Based on a random subsample of our database of publicly-posted vacancies in Addis Ababa in 2019, where we coded the collar details of a random sample of $N = 999$ vacancies. The differences in number of observations from the total sample of $N = 999$ is due to missing experience requirements or salary information.

Table A3: Treatment balance

	Control	Treatment	Δ	p(Control=Treatment)
Firm characteristics				
Age of firm (in years)	7.45	7.05	-0.404	0.548
# of employees	15.12	14.16	-0.952	0.352
Share of white-collar employees	0.13	0.15	0.014	0.271
Share of pink-collar employees	0.17	0.18	0.008	0.635
Share of blue-collar employees	0.59	0.56	-0.024	0.316
Share of grey-collar employees	0.11	0.11	0.002	0.816
Manufacturing sector	0.52	0.50	-0.024	0.563
Service sector (retail, hospitality)	0.27	0.28	0.008	0.836
Hiring practices				
Uses formal hiring channels	0.10	0.08	-0.021	0.391
Uses network hiring channels	0.81	0.79	-0.018	0.588
Uses employment agencies	0.36	0.41	0.054	0.183
Manager expectations				
Expected number of hires over the next three months	3.06	3.67	0.618	0.159
Positive bus. outlook next 3 months	0.62	0.61	-0.008	0.840
Positive bus. outlook next 12 months	0.79	0.76	-0.028	0.441
Optimistic firms	0.59	0.61	0.018	0.673
Manager characteristics				
Female	0.30	0.23	-0.069	0.068
Manager age	34.98	35.50	0.519	0.565
Manager has univ. degree	0.42	0.47	0.051	0.226
bl_raven_score_m	8.99	8.86	-0.128	0.716

Notes: Table A3 presents tests for equality of means across the treatment and control group.

Table A4: Attrition analysis

	During treatment period				Post treatment period	
	(1) Any highfreq survey	(2) # highfreq surveys	(3) Has endline survey	(4) Has highfreq or endline survey	(5) Any post treatment survey	(6) # post treatment surveys
Treatment	-0.005	0.171	0.003	-0.010**	0.010	-0.002
	(0.017)	(0.193)	(0.015)	(0.005)	(0.027)	(0.123)
Control mean	0.958	5.440	0.968	1.000	0.880	2.569
Observations	625	625	625	625	625	625

Notes: Table A4 test whether attrition rates differ across treatment groups.

Table A5: Expected and realized earnings

	Applicant data		Realized salary data	
	(1) Reservation wage (mean)	(2) Wage expectation	(3) Realized salary	(4) Average salary at baseline
Panel A: All vacancies				
All vacancies	5059	5490	-	2945
Vacancies with hires	4066	4670	3256	2996
Vacancies without hires	5601	5907	-	2804
Panel B: White collar vacancies				
All white collar vacancies	6281	7695	-	2993
White collar vacancies with hires	4678	6127	4314	2940
White collar vacancies without hires	7454	8740	-	2895
Panel C: Non white collar vacancies				
All non white collar vacancies	4532	4463	-	3045
Non white collar vacancies with hires	3729	3898	2955	3010
Non white collar vacancies without hires	4874	4702	-	2956

Notes: Table A5 compares average reservation salaries, salary expectations to realized salaries and average baseline salaries. All values are in Ethiopian Birr per month (at the end of 2019 100 Birr were worth around 3.5 USD). Samples are restricted to to the vacancy subsidy plus screening treatment group because reservation salary and salary expectation data is only available for applicants applying to vacancies posted in the screening group. Columns (1) and (2) are applicant level averages (applicants to vacancies with hires but without salary information are excluded to make results comparable to column (3)). Column (3) three is the average salary of newly hired employees for vacancies posted during the treatment group (at the vacancy level). The sample in column (4) displays firm level averages with the sample defined to be comparable to columns (1) to (3).

Table A6: Heterogeneous impacts by observable characteristics

	Firm characteristics			Sector			Hiring practices		Expectations			Manager characteristics			
	(1) Bus. age	(2) % wc employees	(3) Manufactoring sector	(4) Service sector	(5) Health	(6) Formal	(7) Network	(8) Exp. hires (3m)	(9) Pos. bus. outlook (3m)	(10) Pos. bus. outlook (12m)	(11) Female	(12) Age	(13) Univ. degree	(14) Raven's score	(15) col15
Panel A: Impact on number of vacancies posted															
Treatment	0.008	0.190	-0.327	0.250	0.124	-0.007	0.141	-0.523	0.018	0.486**	0.545**	0.040	0.493	0.106	-0.366
	(0.226)	(0.217)	(1.064)	(0.287)	(0.192)	(0.179)	(0.162)	(0.540)	(0.216)	(0.228)	(0.275)	(0.220)	(0.753)	(0.206)	(0.453)
Treatment × hetero. var	0.018	-0.517	0.517	-0.291	-0.033	1.274**	-0.081	0.791	0.020	-0.509	-0.469	0.242	-0.011	0.011	0.055
	(0.026)	(1.185)	(1.185)	(0.340)	(0.392)	(0.522)	(0.902)	(0.563)	(0.053)	(0.327)	(0.349)	(0.312)	(0.022)	(0.357)	(0.043)
Hetero. var	0.006	0.672	-0.672	-0.673***	0.828***	-0.594	0.538	-1.259***	0.045	0.777***	0.825***	-0.395*	0.014	0.249	-0.045
	(0.015)	(1.021)	(1.021)	(0.260)	(0.292)	(0.365)	(0.783)	(0.460)	(0.031)	(0.221)	(0.230)	(0.226)	(0.019)	(0.277)	(0.035)
Control mean	1.153	1.153	1.153	1.153	1.153	1.153	1.153	1.153	1.153	1.153	1.153	1.153	1.153	1.153	1.153
Observations	613	621	621	621	621	621	621	621	620	607	580	621	621	621	621
Panel B: Impact on number of hires															
Treatment	-0.229	-0.106	-0.836	-0.348	-0.129	-0.234	-0.278	-0.507	-0.274	0.183	0.225	-0.243	0.221	-0.203	-0.535
	(0.230)	(0.243)	(0.991)	(0.262)	(0.193)	(0.181)	(0.174)	(0.418)	(0.200)	(0.206)	(0.277)	(0.210)	(0.661)	(0.196)	(0.389)
Treatment × hetero. var	0.004	-0.730	0.730	0.242	-0.325	0.425	0.824	0.352	0.011	-0.541*	-0.491	0.064	-0.012	-0.045	0.036
	(0.024)	(1.148)	(1.148)	(0.342)	(0.393)	(0.552)	(0.744)	(0.456)	(0.048)	(0.319)	(0.351)	(0.350)	(0.018)	(0.360)	(0.041)
Hetero. var	0.003	0.135	-0.135	-0.642**	0.928***	-0.520	-0.040	-1.030***	0.039	0.773***	0.761***	-0.267	0.003	0.289	-0.014
	(0.019)	(1.056)	(1.056)	(0.280)	(0.318)	(0.481)	(0.534)	(0.372)	(0.036)	(0.249)	(0.279)	(0.288)	(0.015)	(0.301)	(0.033)
Control mean	1.218	1.218	1.218	1.218	1.218	1.218	1.218	1.218	1.218	1.218	1.218	1.218	1.218	1.218	1.218
Observations	613	621	621	621	621	621	621	621	620	607	580	621	621	621	621

Notes: Table A6 displays the heterogeneous treatment effects on number of posted vacancies and number of hires by observable firm and manager characteristics. Columns indicate heterogeneity variable. Dependent variable in Panel A is the number of posted vacancies. Dependent variable in Panel B is the number of hires. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Effects on managers' beliefs about formal employee search

	Applicant quality			Applicant numbers (standardized)		
	(1) Index	(2) WC	(3) Non-WC	(4) Index	(5) WC	(6) Non-WC
Treatment	-0.169**	-0.133	-0.183**	-0.214*	-0.198*	-0.203*
	(0.084)	(0.084)	(0.084)	(0.111)	(0.115)	(0.110)
	[0.072]*	[0.072]*	[0.072]*	[0.091]*	[0.091]*	[0.091]*
Control mean	0.110	0.087	0.120	0.141	0.131	0.134
Observations	605	605	605	561	553	560

Notes: Table A7 displays the treatment effects on beliefs about the quality and number of applicants obtained through formal search channels. Columns (1) to (3) show the impacts on beliefs of beliefs about applicant quality. Applicant quality is measures by binary variables equal one if managers believe that they can obtain better quality candidates through different formal search channels relative to network-based hiring. Columns (4) to (6) show the impacts on beliefs of beliefs about absolute applicant numbers. All variables normalized sums of non-missing normalized beliefs across different formal search channels (online, job board, newspaper) and vacancy type (white-collar, blue collar, pink collar). Number of observations varies for beliefs about applicant numbers due to "don't know" answers. Heteroskedasticity robust standard errors are displayed in parentheses. Minimum q-values from two-stage false discovery rate correction within families (columns (1)-(3) and (4)-(6)) are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Effects on average monthly salaries

	Averages salaries at endline (ihs)		
	(1) Pooled	(2) White collar	(3) Non-white collar
Treatment	0.120*	-0.015	0.121*
	(0.063)	(0.070)	(0.062)
	[0.094]*	[0.381]	[0.094]*
Control mean	8.412	8.944	8.327
Observations	597	418	596

Notes: Table A8 displays the effect of our intervention on average monthly salaries at endline (transformed using the inverse hyperbolic sine). Column (2) shows impact on white-collar wages conditional on having white-collar employees. Column (3) shows impact on non–white-collar wages conditional on having non–white-collar employees. Heteroskedasticity robust standard errors are displayed in parentheses. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: The effect of the worker screening add-on on vacancy creation and hires

	Vacancies posted formally			Vacancy creation		Hiring outcomes		
	(1) Any	(2) # vacs	(3) %	(4) Any vacancy	(5) # vacs	(6) Any hire	(7) # hires	(8) % vacancies filled
Treatment	0.152***	0.446***	0.297***	-0.065	0.142	-0.082*	-0.140	-0.178***
	(0.032)	(0.135)	(0.050)	(0.049)	(0.197)	(0.048)	(0.200)	(0.049)
Treatment × screening	0.034	0.032	0.031	0.035	-0.037	0.007	-0.143	-0.049
	(0.041)	(0.168)	(0.065)	(0.050)	(0.225)	(0.048)	(0.197)	(0.058)
Treatment effect screening	0.186***	0.478***	0.328***	-0.031	0.105	-0.075	-0.283	-0.227***
	(0.034)	(0.145)	(0.051)	(0.049)	(0.212)	(0.048)	(0.195)	(0.051)
Control mean	0.051	0.144	0.070	0.495	1.153	0.454	1.218	0.877
Observations	621	621	288	621	621	621	621	288

Notes: Table A9 displays the treatment effects of the screening add-on on vacancy posting and hires. Columns (1) to (3) show impacts on formal vacancy posting. Columns (4) and (5) show impacts on vacancy creation. Columns (6) to (8) show impacts on hiring numbers. Heteroskedasticity robust standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: The effect of the worker screening add-on on skill composition of vacancy creation and hires

	Vacancies					Hires				
	(1) Any wc vac	(2) # wc vacs	(3) % wc vacs	(4) Any non-wc	(5) # non-wc vacs	(6) Any wc hire	(7) # wc hires	(8) % wc hires	(9) Any non-wc hire	(10) # non-wc hires
Treatment	0.066**	0.121*	0.073*	-0.067	0.021	0.007	-0.010	0.024	-0.078*	-0.131
	(0.029)	(0.073)	(0.041)	(0.048)	(0.164)	(0.024)	(0.052)	(0.041)	(0.047)	(0.188)
Treatment $\times$ screening	-0.019	-0.055	-0.017	0.033	0.018	0.003	0.015	0.018	0.001	-0.158
	(0.033)	(0.076)	(0.045)	(0.049)	(0.197)	(0.025)	(0.051)	(0.047)	(0.047)	(0.183)
Treatment effect screening	0.047	0.066	0.055	-0.034	0.038	0.011	0.005	0.042	-0.077	-0.288
	(0.029)	(0.056)	(0.040)	(0.049)	(0.192)	(0.024)	(0.056)	(0.043)	(0.048)	(0.179)
Control mean	0.069	0.120	0.094	0.463	1.032	0.060	0.111	0.088	0.426	1.106
Observations	621	621	288	621	621	621	621	250	621	621

Notes: Table A10 displays the heterogeneous treatment effects of the screening add-on on the skill composition vacancy posting and hires. Columns (1) to (5) show impacts on the composition of vacancy creation. Columns (6) and (10) show impacts on the composition of hires. Heteroskedasticity robust standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Effects on downstream firm outcomes

	(1) Profit (IHS)	(2) Revenue (IHS)	(3) Outlook 3m	(4) Outlook 12m	(5) # of employees
Panel A: Pooled					
Treatment	-0.287	-0.025	-0.021	-0.036	-2.488
	(0.229)	(0.217)	(0.087)	(0.089)	(1.605)
	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
Control mean	4.128	5.563	0.000	-0.000	16.818
Observations	581	580	619	552	606

Notes: Table A11 displays the effect of our intervention on downstream firm outcomes. Profits and revenues are inverse hyperbolic sine (IHS)-transformed. Heteroskedasticity robust standard errors are displayed in parentheses. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Effects on candidate search inputs

	Index	Days	Hours			Cost (ETB)		
	(1) Search costs	(2) Search duration	(3) Screening	(4) Non-screening	(5) Total	(6) Screening	(7) Non-screening	(8) Total
Treatment	-0.019	-1.055	-1.051	1.277	0.168	22.323	19.060	48.872
	(0.144)	(1.170)	(0.860)	(0.843)	(1.295)	(118.531)	(17.208)	(120.154)
	[0.897]	[0.736]	[0.717]	[0.717]	[0.897]	[0.897]	[0.717]	[0.897]
Control mean	0.000	4.951	4.410	1.046	5.448	228.528	17.512	241.887
Observations	240	234	227	226	227	236	233	234

Notes: Table A12 displays the effect of our intervention on candidate search inputs. The outcomes are calculated as firm-level averages and are only defined for firms that posted at least one vacancy during the treatment period. Heteroskedasticity robust standard errors are displayed in parentheses. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Effects on employee numbers and shares

	(1) # of employees	(2) Share of WC employees
Treatment	-2.488	0.024**
	(1.605)	(0.011)
	[0.121]	[0.068]*
Control mean	16.818	0.099
Observations	606	600

Notes: Table A13 displays the effect of our intervention on the number of employees and the share of white-collar employees. Heteroskedasticity robust standard errors are displayed in parentheses. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Effects on characteristics of hires

	(1) Salary (ETB, IHS)	(2) Satisfaction	(3) Share female
Treatment	0.035	-0.034	-0.023
	(0.083)	(0.126)	(0.057)
	[1.000]	[1.000]	[1.000]
Control mean	8.165	0.020	0.586
Observations	232	236	250

Notes: Table A14 displays the effect of our intervention on the characteristics of new hires. The outcomes are only defined for firms that hired at least one person during the treatment period. Heteroskedasticity robust standard errors are displayed in parentheses. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Effects on willingness to pay for services

	(1) Subsidy	(2) Formal posting
Treatment	69.321	0.053
	(61.784)	(0.078)
	[0.972]	[0.972]
Control mean	278.565	-0.035
Observations	604	594

Notes: Table A15 displays the effect of our intervention on willingness to pay for the subsidy treatment and formal vacancy posting more generally (winsorized at the 99th percentile). Heteroskedasticity robust standard errors are displayed in parentheses. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Impact on search channels - post-treatment

	Formal search		
	(1) Any	(2) # vacs	(3) % vacs
Treatment	-0.009	-0.025	-0.019
	(0.010)	(0.021)	(0.048)
	[1.000]	[1.000]	[1.000]
Control mean	0.019	0.037	0.075
Observations	625	625	95

Notes: Table A16 displays the impact of the effects of the vacancy subsidy intervention on formal vacancy posting in the two months following the four-month treatment period. Heteroskedasticity robust standard errors are displayed in parenthesis. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Results including control variables

Table A17: Main impacts on vacancy creation - including control variables

	(1) Any	(2) # vacs	(3) # vacs | any
Treatment	-0.046	0.082	0.384
	(0.040)	(0.157)	(0.259)
	[0.616]	[0.616]	[0.616]
Control mean	0.495	1.153	2.327
Observations	621	621	288

Notes: Table A17 displays the treatment effects on vacancy creation. Heteroskedasticity robust standard errors are displayed in parenthesis. All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A18: Main impacts on hiring - including control variables

	(1) Any	(2) # hires	(3) % vacs filled
Treatment	-0.079*	-0.182	-0.197***
	(0.041)	(0.165)	(0.038)
	[0.055]*	[0.098]*	[0.001]***
Control mean	0.454	1.218	0.877
Observations	621	621	288

Notes: Table A18 displays the treatment effects on hiring outcomes. Heteroskedasticity robust standard errors are displayed in parenthesis. All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A19: Composition of vacancy creation - including control variables

	White collar			Non-white collar	
	(1) Any vac	(2) # vacs	(3) % vacs	(4) Any vac	(5) # vacs
Treatment	0.061**	0.155**	0.045	-0.071*	-0.054
	(0.024)	(0.063)	(0.035)	(0.039)	(0.136)
	[0.035]**	[0.035]**	[0.135]	[0.076]*	[0.321]
Control mean	0.079	0.144	0.119	0.449	1.009
Observations	621	621	288	621	621

Notes: Table A19 displays the effect of our intervention on the skill composition of vacancy creation. Columns (1) to (3) show the impact on white-collar vacancies. Columns (4) and (5) show the impact on non–white-collar vacancies. Heteroskedasticity robust standard errors are displayed in parenthesis. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: Composition of new hires - including control variables

	White collar				Non-white collar		
	(1) Any hire	(2) # hires	(3) % hires	(4) % vacs filled	(5) Any hire	(6) # hires	(7) % vacs filled
Treatment	0.014	0.011	-0.007	-0.357***	-0.085**	-0.203	-0.163***
	(0.021)	(0.060)	(0.036)	(0.102)	(0.039)	(0.146)	(0.040)
	[0.424]	[0.583]	[0.583]	[0.002]***	[0.054]*	[0.195]	[0.001]***
Control mean	0.069	0.153	0.118	0.847	0.412	1.065	0.877
Observations	621	621	250	78	621	621	252

Notes: Table A20 displays the effect of our intervention on the skill composition of new hires. Columns (1) to (4) show the impact on white-collar hires. Columns (5) to (7) show the impact on non–white-collar hires. Heteroskedasticity robust standard errors are displayed in parenthesis. All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A21: Effects on managers' beliefs - including control variables

	Applicant quality			Applicant numbers (standardized)		
	(1) Index	(2) WC	(3) Non-WC	(4) Index	(5) WC	(6) Non-WC
Treatment	-0.156*	-0.117	-0.201**	-0.225**	-0.204*	-0.211*
	(0.082)	(0.082)	(0.082)	(0.111)	(0.122)	(0.109)
	[0.086]*	[0.154]	[0.086]*	[0.086]*	[0.112]	[0.086]*
Control mean	0.109	0.086	0.118	0.141	0.131	0.134
Observations	606	606	606	561	553	560

Notes: Table A21 displays the treatment effects on beliefs about the quality and number of applicants obtained through formal search channels. Columns (1) to (3) show the impacts on beliefs of beliefs about applicant quality. Applicant quality is measures by binary variables equal one if managers believe that they can obtain better quality candidates through different formal search channels relative to network-based hiring. Columns (4) to (6) show the impacts on beliefs of beliefs about absolute applicant numbers. All variables normalized sums of non-missing normalized beliefs across different formal search channels (online, job-board, newspaper) and vacancy type (white-collar, blue collar, pink collar). Number of observations varies for beliefs about applicant numbers due to "don't know" answers. Heteroskedasticity robust standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A22: Effects on turnover - including control variables

	Employees left		Leaving reasons		
	(1)	(2)	(3)	(4)	(5)
	Any	#	Personal	Better opportunities	Fired for performance
Treatment	-0.005	-0.324	-0.080**	-0.010	-0.014
	(0.040)	(0.277)	(0.033)	(0.022)	(0.019)
	[0.904]	[0.605]	[0.077]*	[0.815]	[0.767]
Control mean	0.597	2.435	0.241	0.079	0.060
Observations	621	621	621	621	621

Notes: Table A22 displays the impact of the effects of the vacancy subsidy intervention on employee turnover. Columns (1) to (3) show the impact on a dummy variable indicating any turnover during this period. Column (2) shows the impact on the number of employees who left the firm (winsorized at the 99th percentile). Heteroskedasticity robust standard errors are displayed in parenthesis. All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A23: Effects on candidate search inputs - including control variables

	Index	Days	Hours			Cost (ETB)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Search costs	Search duration	Screening	Non-screening	Total	Screening	Non-screening	Total
Treatment	-0.019	-1.055	-1.051	1.277	0.168	22.323	19.060	48.872
	(0.144)	(1.170)	(0.860)	(0.843)	(1.295)	(118.531)	(17.208)	(120.154)
	[0.897]	[0.736]	[0.717]	[0.717]	[0.897]	[0.897]	[0.717]	[0.897]
Control mean	0.000	4.951	4.410	1.046	5.448	228.528	17.512	241.887
Observations	240	234	227	226	227	236	233	234

Notes: Table A23 displays the effect of our intervention on candidate search inputs. The outcomes are calculated as firm-level averages and are only defined for firms that posted at least one vacancy during the treatment period. Heteroskedasticity robust standard errors are displayed in parentheses. All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A24: Effects on characteristics of hires - including control variables

	(1) Salary (ETB)	(2) Satisfaction	(3) Share female
Treatment	-155.282	-0.034	-0.046
	(196.870)	(0.126)	(0.047)
	[0.646]	[0.786]	[0.646]
Control mean	2199.932	0.020	0.586
Observations	232	236	250

Notes: Table A24 displays the effect of our intervention on the characteristics of new hires. The outcomes are only defined for firms that hired at least one person during the treatment period. Heteroskedasticity robust standard errors are displayed in parentheses. All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Additional figures

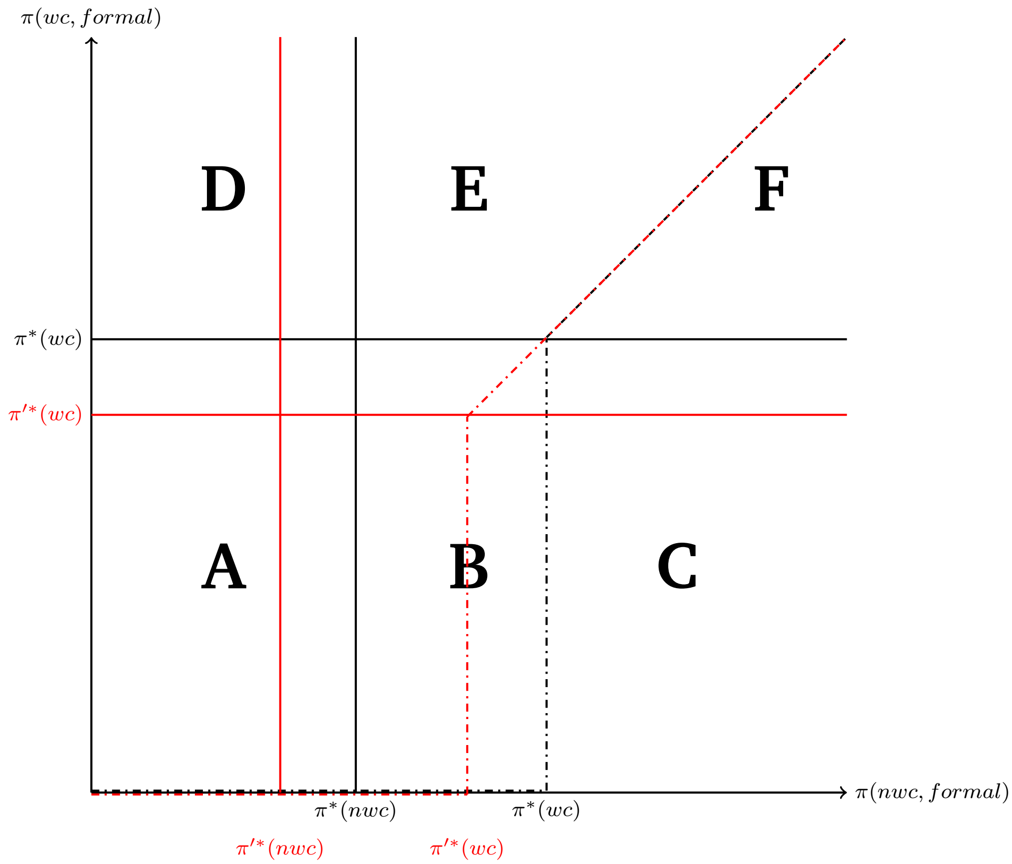


Figure A1: Vacancy search and type decision if white-collar positions are optimal for informal search

Notes: Figure A1 displays the choice of search channel and vacancy type for firms in the $\pi(wc, formal)$–$\pi(nwc, formal)$ space assuming that informal search for non–white-collar positions has lower returns than informal search for white-collar positions ($\pi(nwc, informal) < \pi(wc, informal)$). Red lines indicate what happens when formal search cost are reduced. Firms that fall in the area above the dashed lines post white-collar vacancies (areas A, B, D, and E). Firms that fall below the dashed line post non–white-collar vacancies (areas C and F).

Figure A2: Timeline

March-July 2019	**Baseline survey** (in-person) and **intervention start** (staggered)
	Phone surveys (on average 5 per firm)
August-December 2019	**Endline survey** (in-person) and **intervention end** (staggered)
until February 2020	**Post-endline surveys** (phone; on average 2.5 per firm)

Figure A3: Geographical distribution of firms

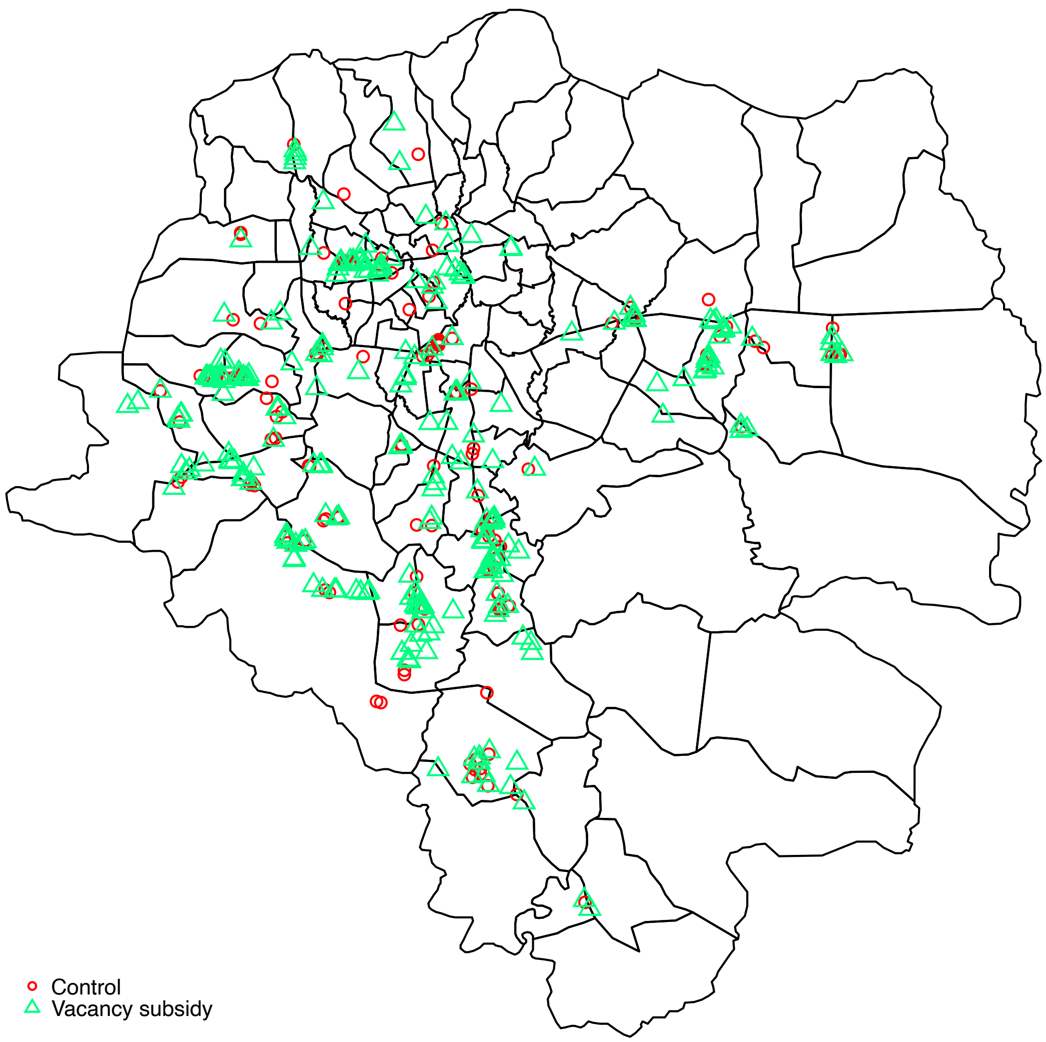
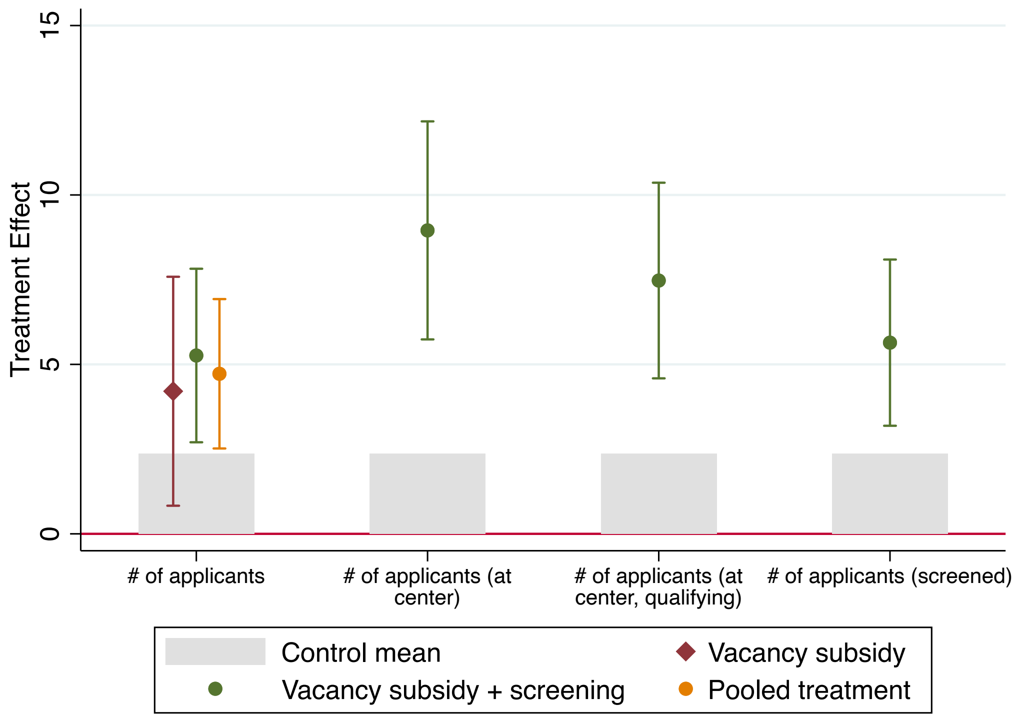


Figure A4: Treatment effects on the number of job applicants



This figure shows the treatment effects on the number of applicants. The grey bars display the control group mean. 90% confidence intervals are displayed. Bar 1 shows the separate effects of the vacancy subsidy treatment, the vacancy subsidy treatment plus screening add-on, as well as the pooled treatment on the number of applicants per firm (as reported by the firms). Bars 2-4 show the effects on applicant numbers as collected by our screening center, for the vacancy subsidy treatment plus screening add-on. The applicant numbers are displayed based on whether a candidate simply called the number specified on the vacancy (bar 2), fulfilled all the criteria specified in the job advertisement (bar 3), and actually completed the screening procedure (bar 4). Bar 4 should be approximately equivalent to the number of candidates actually applying directly at the firm (bar 1).

Figure A5: Firm expectations about relative quality of formal applicants

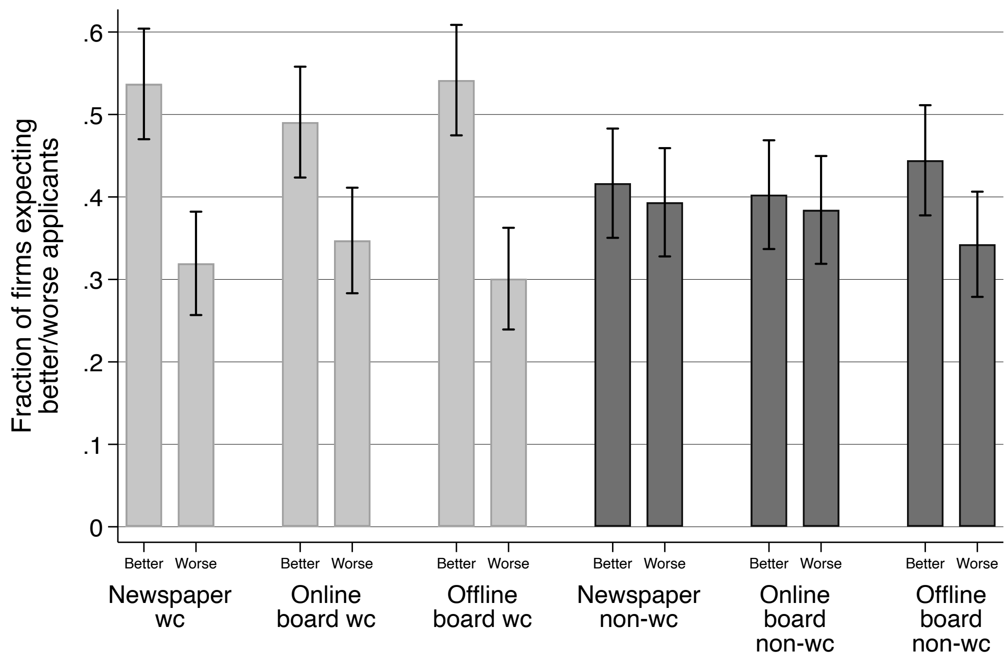


Figure A5 shows share of firms who expect applicants to vacancies posted in formal channels of better or worse quality compared to applicants obtained through social networks. The figure is shown for control group firms only, based on endline data. The three formal channels are newspapers, online job boards, and offline job boards. In every pair of bars, i) the left bar shows the share of firms that expect applicants obtained through the respective channel to be of better quality than those obtained through social networks (based on the top three responses on a seven-point Likert scale question); ii) the right bar shows the share of firms that expect these applicants to be of worse quality. The three left pairs of bars show expectations over applicants to white-collar positions, the three right pairs of bars show expectations over applicants to non–white-collar positions.

Figure A6: Firm expectations about applicant numbers

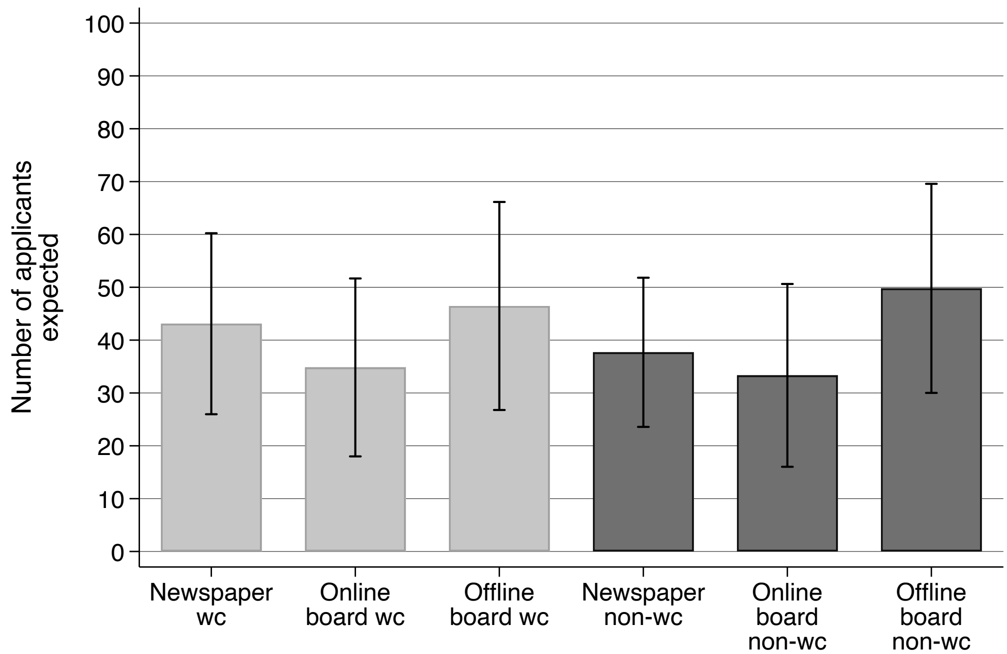


Figure A6 shows the number of applicants firms expect to receive when posting a vacancy in a given formal channel. The figure is shown for control group firms only, based on endline data. The three formal channels are newspapers, online job boards, and offline job boards. The three left bars show expectations over applicant numbers to white-collar positions, the three right bars show expectations over applicants numbers to non–white-collar positions.

Figure A7: Difference between actual and expected number of applicants

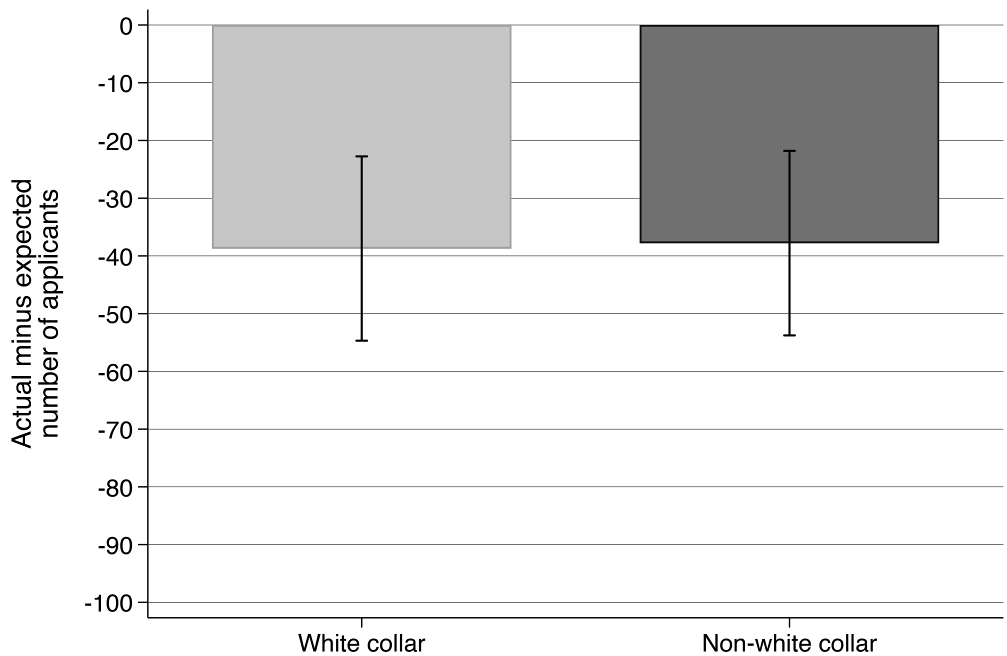


Figure A7 shows the firm-level difference between actual and expected number of applicants, by collar type. The figure is shown for control group firms only, based on endline data. The left bar shows the difference for applicant numbers to white-collar positions, the right bar shows the difference for applicants numbers to non–white-collar positions.

D Deviation from the pre-analysis plan

In our analysis we make the following deviations from our pre-analysis plan:

- We expand the number of outcomes to study both the extensive and intensive margins of vacancy creation, as well as the ratio of filled vacancies to overall vacancies. To accommodate the larger number of outcomes, we spread these across multiple tables and correct for multiple hypothesis testing across the different margins.

- We collapse all different non–white-collar employment categories (blue collar, pink collar, grey collar) into a single non–white-collar category to improve power. We also collapse managers' expectations in the same way.

- We do not normalize outcomes over time, in order to be able to use extensive margin outcomes.

- We do not winsorize the number of vacancies and number of hires because there are no outliers.

- For our main specification, we estimate pooled treatment effects instead of separate effects for a screening add-on intervention, because we do not find consistent differences across treatment arms.

- We only show firm-level regression specifications. We do not show hire- and vacancy-level specifications as they are subject to selection bias and add little additional information beyond the firm-level specification.

- We drop outcomes for which the data quality is insufficient. This mostly affects hire-level outcomes, where we struggled to get adequate data on variables such as ethnicity and religion of new hires (as well as variables derived from these). In addition, this list includes respondents' knowledge about prices of formal employee search methods.

- We include some outcomes that we did not pre-specify in the online appendix (e.g., number of employees at endline and share of white-collar employees at endline).
- We do not display all pre-specified heterogeneity analyses to simplify the presentation of results. We show a subset of this heterogeneity in Table A6.