Formalized Employee Search and Labor Demand*

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Abstract

Firms in low- and middle-income countries rarely advertise their vacancies formally and instead use social networks to find employees. We experimentally reduce the cost of formal employee search for small and medium-sized enterprises in Ethiopia to test whether informal search constrains the number and type of positions firms create. We find that treated firms increase formal search and shift their labor demand towards more demanding white-collar positions. However, they struggle to fill these newly created vacancies, in particular, if they are not familiar with formal search channels. Additional applicant screening services do not affect treatment effects, suggesting that information asymmetries about applicants' skills do not limit formal search.

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1 Introduction

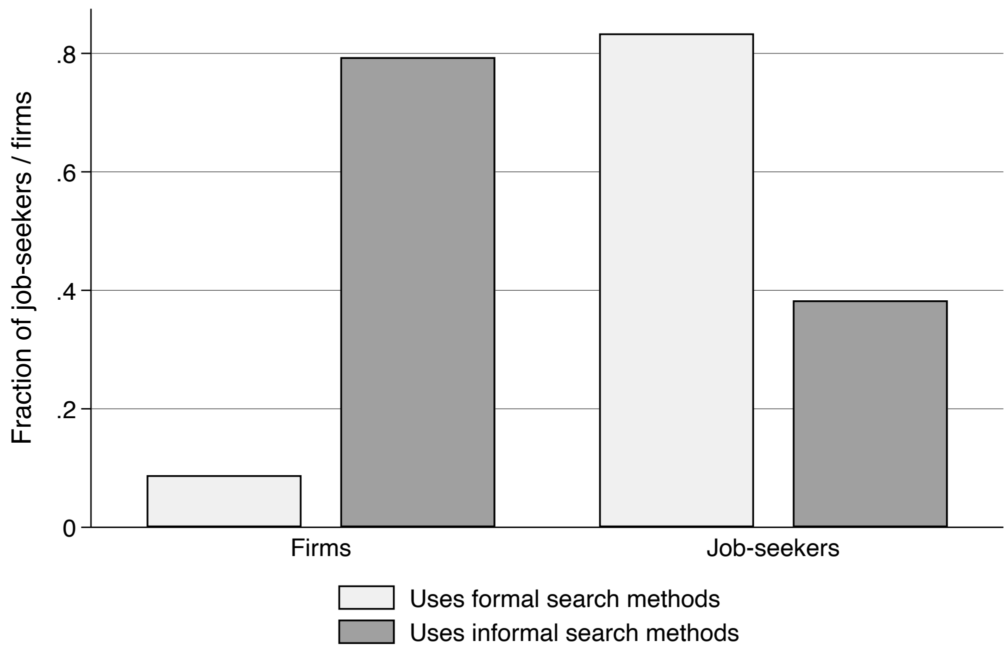
A long-standing question in development economics is how the prevalence of informal institutions affects socioeconomic outcomes. Informal relationships have been studied in credit markets (e.g. Banerjee et al., 2023), insurance (e.g. Mobarak and Rosenzweig, 2013), and work relationships (e.g. Ulyssea, 2018, 2020). This literature typically defines formality based on the existence of explicit contracts and registrations. However, this ignores the formality of the processes that generate economic outcomes.

We study informal search processes in the labor market. 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, leading to more productive employment relationships (Dustmann et al., 2016, Heath, 2018). On the other hand, sparse networks might limit firms' ability to expand their business, leading to aggregate welfare losses (Chandrasekhar et al., 2020). Crucially, labor 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, search channel-specific labor demand and supply can be mismatched, with potentially negative consequences for market outcomes.

Addis Ababa in Ethiopia displays such 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 our sample of small and medium-sized firms 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. This asymmetry suggests that firms forgo a large fraction of potential applicants in their search for employees, which might limit their ability to hire (specific types of) workers.

In this paper, we explore whether the use of informal employee search

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



Notes: **Figure 1 shows that the search channels of firms and job-seekers in Addis Ababa are mismatched.** It shows the fraction of either relying on formal or 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 experimental sample of 625 actively hiring firms in 2019. We describe the recruitment process and sample in detail in Section 3.1. 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).

indeed constrains firms' labor demand, both in terms of quantity and quality. 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. Second, we also cover the logistical costs of posting the vacancy. Taken together, we subsidize and post all job adverts of the firm, regardless of the posting costs, which exceed the average monthly wage of employees in our sample. 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.

We have three key findings. First, our intervention successfully increases formal vacancy posting: treated firms are 3.3 times 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 ads for 38% of created vacant positions 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, there is substantial heterogeneity by vacancy type: treated firms are a significant 7.2 percentage points more likely to create at least one white-collar vacancy.[1] 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 a corresponding 6.9 percentage point decrease in the fraction of firms creating at least one such vacancy. These results suggest that in response to the treatment, firms attempt to fill more high-skilled positions, which is consistent with firms anticipating being able to access a higher-skilled applicant pool through formal employee search.

Third, we find that treated firms struggle to fill newly created vacancies, suggesting their labor demand remains unmet. The share of filled vacancies

[1] 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.

decreases by 20 percentage points relative to the control group. This is results in a marginally significant decrease in the likelihood of any hire during the treatment period by 7.8 percentage points. The decrease in vacancy filling rates is even stronger for white-collar vacancies (-36 percentage points) relative to non–white-collar vacancies (-17 percentage points). The 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 significant decrease in the fraction of firms reporting any non–white-collar hires. In line with this reduction in non–white-collar hiring, treated firms actually report a 24% higher *share* of white-collar employees in their workforce at endline.

We provide suggestive evidence that this decrease in successful matches is driven by firms' lack of familiarity with formal search channels. Firms without experience in using formal search channels at baseline exhibit a significant reduction of 23 percentage points in vacancy filling rates. In contrast, firms that are familiar with formal search channels at baseline see an insignificant increase of 11 percentage points in the vacancy filling rate and sizable but noisily estimated increases in hiring numbers. Further supporting the role of familiarity, we find that managers at treated firms update their beliefs about both the quality and quantity of applicants in formal search channels in a downward direction. Their pre-treatment expectations 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).

One potential reason for the negative effects of inexperienced firms is a mismatch of wage expectations. 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 hire new employees through formal channels.

Fourth, we find that in the months following the treatment period firms revert to mostly using informal search channels. They also significantly reduce their labor demand for non–white-collar workers, leading to an increase in the relative demand for white-collar workers. This suggests that, while the intervention did not persistently alter search channels, it shifted the quality and quantity of labor demand post-treatment.

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 of their choice—on top of the vacancy posting subsidy.[2] 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 obtained applicants. This finding contrasts with a growing body of literature documenting the importance of such frictions for *job-seekers* (Abebe et al., 2021b, Carranza et al., 2022, Bassi and Nansamba, 2022, Abel et al., 2020).

With these findings, we make three main contributions to the literature.[3] First, ours is the first paper to study the firm-side effects of a reduction in vacancy posting costs on vacancy posting behavior.[4] Our results suggest that search frictions can be specific to the type of vacancy, which can ultimately

[2]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.

[3]Like much of the experimental literature on labor markets in developing countries, we encourage off-equilibrium behavior by reducing its cost to understand the constraints faced by firms. In contrast to much of the *published* literature (e.g., Franklin, 2018, Abebe et al., 2021b), we conclude that firms' ex-ante behavior is unlikely to have been constrained by cost (though costs seem to constrain their learning about the labor market).

[4]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 (2023) 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).

affect firms' labor force composition.[5] This finding also contributes to an emerging literature studying the constraints to hiring high skilled workers in developing countries. Hiring high-skilled (managerial) workers has been shown to constrain the growth and productivity of firms (Akcigit et al., 2021, Anderson and Mckenzie, 2022). We contribute by linking firms' lack of hiring white-collar employees to the structure of their search process.

Related to our study, Fernando et al. (2023) 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. Similarly, Wu and Wang (2023) provide firms in Ethiopia with subsidized access to employment agencies for a single vacancy. They also find that firms negatively update about applicant quality. However, contrary to our findings, firms increase vacancy filling rates and reduce their hiring of highly educated workers. A key difference to our study is that both studies randomize access to applicants for already existing vacancies. In contrast, we allow firms to adjust their vacancy posting behavior in response to our treatment, arguably estimating the more policy-relevant parameter.

In another related paper, Algan et al. (2022) 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 studied by Algan et al. (2022).

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. (2021b) study transport subsidies as a form of formal search subsidies for job-seekers—

[5] We also provide developing country evidence consistent with Rebien et al. (2020)'s finding that firms search more formally for high-skilled workers in Germany.

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.[6] Our evidence suggests 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., 2023). 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 created vacancies. This emphasizes the importance of firms' endogenous response to changes in the cost and availability of search methods.[7]

Finally, we speak to a nascent body of literature documenting unintended long-term consequences of labor market interventions on the beliefs and behavior 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[8], 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. As a specific example focusing on the job-seeker side of the labor

[6] Banerjee and Sequeira (2023) study transport subsidies in South Africa and find effects on beliefs and search behavior, but not employment outcomes.

[7] By emphasizing the importance of different search channels we provide additional evidence on the importance of search frictions for job-seekers (Carranza et al., 2022, Bassi and Nansamba, 2022, Abel et al., 2020, Wheeler et al., 2021, Kiss et al., 2023). 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., 2021a).

[8] Abebe et al. (2023) 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. (forthcoming) 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.

market, Kelley et al. (2024) 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. Sections 6 and 7 discuss the mechanisms behind our findings and present further impacts on downstream outcomes. Section 8 discusses how firm behavior changes in the post-treatment period. Section 9 concludes.

2 Labor market search in Addis Ababa

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.

To motivate our intervention, this section describes key facts about job and employee search in Addis Ababa. Our evidence is 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.

Experimental firm sample For our study, we recruited SMEs with between 5 and 50 employees 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 four criteria that ensured the relevance of our intervention for them.[9] While the firm data is not representative of the universe of firms in Addis Ababa, it describes a population that is likely to be most affected by employee search frictions in this context (Appendix D compares our sample to representative data from Addis Ababa). In total, we recruit 625 firms to take part in our experiment. These firms are spread out across Addis Ababa (see Online Appendix Figure A3).

2.1 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. We define white-collar vacancies 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. Formal employee search is relatively rare, with only 9% of firms posting vacancies in formal channels at baseline, and concentrated among white-collar vacancies.

Formal search is costly. Employee search via formal channels, defined as the public advertising of job adverts on offline and online job boards as well

[9] First, they had to have between 5 and 50 employees. Second, they had to not rule out hiring a new worker over the next three months. Third, they had to express interest in a generically-described service that would help their firm with job advertising. Finally, they could not exclusively hire through employment agencies. We chose these screening criteria to identify firms that were likely to use our intervention to increase statistical power. Among formally registered firms we reached out to, 50% met the employment criterion. Among those, 33% are interested in the intervention, and 24% plan to hire at least one worker. Only 16% of firms of the right size exclusively used the service of agencies in the last 12 months.

as in newspapers, is quite costly for firms in our sample.[10] 91% of firms mention the monetary cost of formal search as an important obstacle to posting vacancies on formal channels (Figure 2a).[11] In addition to the monetary costs, managers also mention the effort costs of formal search (41%) and difficulties in designing proper job adverts (65%).[12] These numbers suggest that the monetary and non-monetary costs are a major barrier preventing firms from using formal employee search. Our intervention is directly aimed at lowering this cost through monetary subsidies and logistical support, taking over part of the effort cost of formal search.

Formal vacancy posting is rare. 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 in 2019.[13] 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.[15]

[10] Numbers in the following paragraph are based on responses by 103 randomly sampled control group firms about the main factors preventing formal employee search. We conducted this additional descriptive survey in 2023, four years after the original experiment in 2019.

[11] The price of formal search is sizable relative to the prevailing wage level. 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 (198.12 USD PPP), which is more than the average monthly salary that firms in our sample pay their workers.

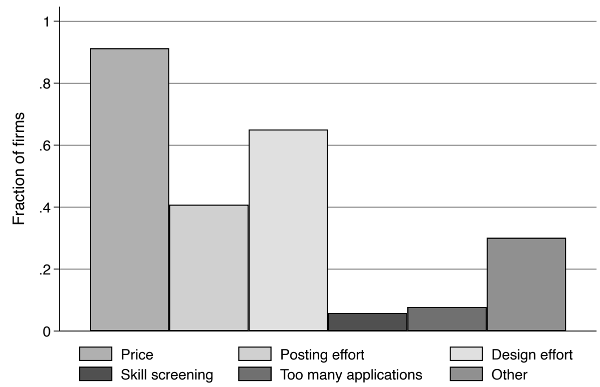
[12] Balgova et al. (2023) provide evidence in line with this observation and show that job adverts in Addis Ababa contain relatively little information, which in turn affects job-seekers' application choices.

[13] This database covers close to 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. [14] We collect the data on a weekly basis between March and October 2019.

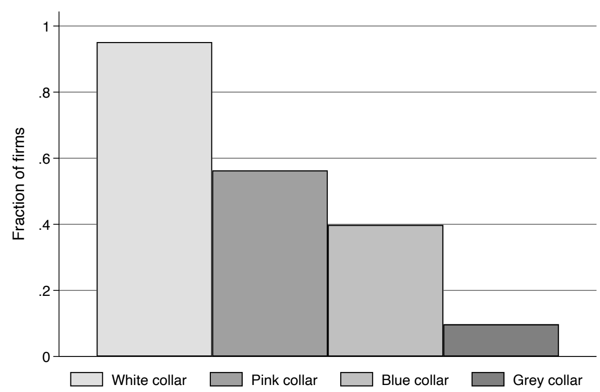
[15] If we compare this number to similarly-sized cities in rich countries, we note that in late 2021, on the single platform `indeed.com` alone, there are approximately 6,500 unique vacancies per week in Berlin, 7,000 in Birmingham, and 14,000 in Madrid.

Figure 2: Firms' perceptions of formal search

(a) Stated obstacles to using formal hiring channels



(b) Stated usefulness of formal hiring channels by position type



Notes: **Figure 2 shows that managers perceive formal search as expensive and most suitable for white-collar workers.** Figure 2a displays the fraction of firms that mention a given factor in an open question asking for the "main difficulties in using formal hiring channels". Each manager could mention multiple factors. Figure 2b displays managers' responses to the following question: "For the hiring of what type of worker are formal search channels most useful?" Managers could select one or more of four job types: white-, blue-, pink-, and grey-collar workers. Typical white-collar/professional job titles include manager, accountant, and supervisor. Typical blue-collar or production jobs are machine operators, builders, factory floor workers, and cooks. Typical pink-collar/service jobs are waiters, tellers, shop attendants, and hotel concierges. Typical grey-collar/ support workers are guards, drivers, cleaners, tea makers, and couriers/messengers. Data was collected in 2023 among 103 randomly sampled control group firms of the original experiment in 2019.

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 pre-screening, 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.[16]

Search strategies differ by vacancy type Firms in our control group mostly create non–white-collar vacancies but use formal search relatively more for white-collar workers (Table 1). Specifically, we observe that non–white-collar vacancies make up 88% of all created 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. Firms seem to perceive substantially higher returns to formal search for white-collar vacancies compared to non–white-collar vacancies. Figure 2b mirrors this directly: almost all firms consider formal search to be useful for white-collar positions, whereas this share decreases substantially for non-white collar (including blue-collar) positions.

This difference we observe in our firm sample is also reflected in the characteristics of publicly posted vacancies in Addis Ababa. Table A29 describes

[16]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 led to a nationwide internet shutdown and slowed down or stopped business activities for about two weeks.

the composition of the random sample of $N = 999$ vacancies for which we hand-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. Taken together, this suggests that reducing the cost of formal search might increase firms' propensity to create white-collar vacancies that rely more on formal employee search.[17]

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 shows that white-collar vacancies are much more likely to be posted formally.** It displays the fraction of vacancies posted formally or informally by vacancy type (white-collar / non–white-collar) by firms in the control group of the experiment ($N = 216$). White-collar vacancies are defined as office and knowledge workers (e.g., managers, lawyers, administrators, accountants, and clerks).

2.2 Job seekers' search behavior

We already documented in Figure 1 that among job-seekers, formal job search is much more common than informal search. Using data on Addis Ababa from the 2018 Urban Labor Force Survey, we see that 80 percent of job-seekers in Addis Ababa search in public channels, while fewer than 40 percent search in their networks.

We thus 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

[17] In Appendix Section E we further show that white-collar vacancies have higher demands in terms of experience and education than non–white-collar vacancies.

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.

While there is a mismatch in aggregate search activity, selection might mitigate the negative consequences of this mismatch. Job-seekers in formal search channels are positively selected on education, but not experience.[18] 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 Experiment design

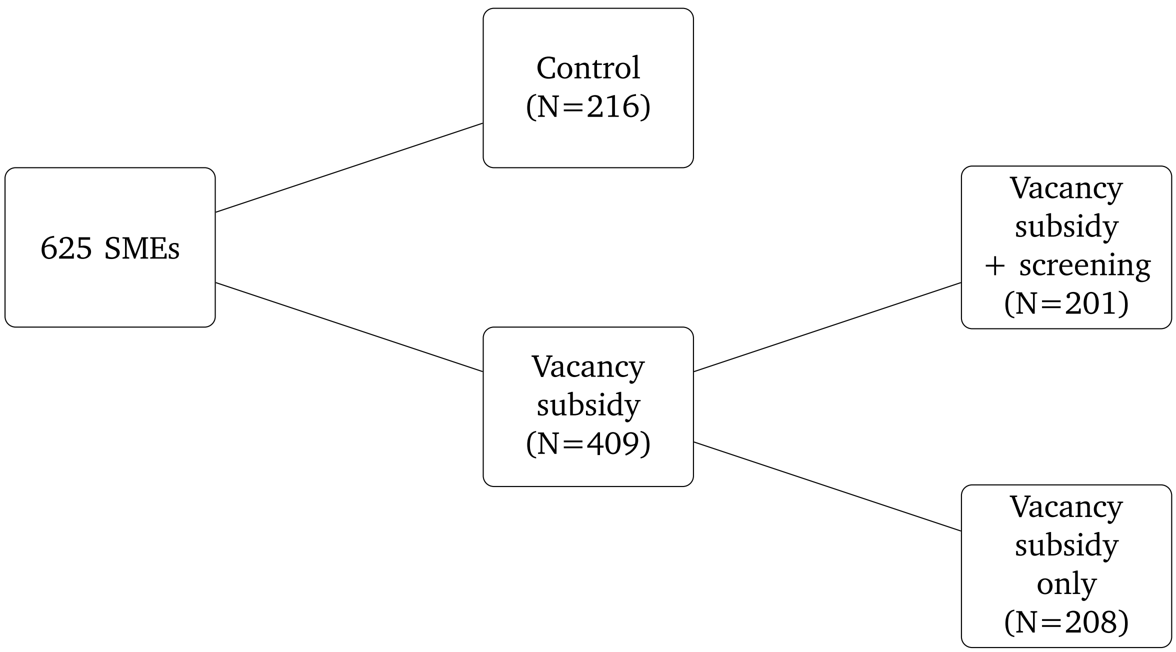
Our field experiment is designed to study how subsidizing formal employee search affects firms' vacancy posting and employment flows. Figure 3 displays the experimental design of our study. We randomly allocate firms in our sample to one of two groups. Randomization happens at the firm level at the end of the baseline survey without stratification. 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.[19] 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

[18] We find a highly significant positive correlation between years of education and formal job search (columns 1 and 3 of Table A1). 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). The pool of formal job-seekers is thus more likely to meet the more demanding education criteria of formally posted white-collar vacancies.

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

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 in endline firm outcomes between the two arms.[20]

Figure 3: Experimental design



Notes: **Figure 3 displays the experimental design.** Treatment allocation was randomized at the individual level.

3.1 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,

[20]We show and discuss the (lack of) differential treatment effects between both treatment arms in section 6.3.

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.[21] On average, we conduct more than five phone surveys per firm during the treatment period.

During every survey, we measure created vacancies as an "attempt to hire at least one worker since the last interview". We thus cover the complete period between surveys, even when firms are not reached for some survey rounds. If managers respond with yes, we then follow-up to ask about the nature of the position, the search process, and the search success for all hiring attempts. If they tell us that the hiring process has not yet been completed, we follow up on the same vacancy during our next scheduled survey round.

At the end of the treatment period, we conduct an in-person endline survey to capture employment flows and levels, firm-level characteristics, and 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 treatment period, we conduct further phone surveys with sampled firms to assess whether our intervention changes behavior in the following months.

3.2 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.[22] 51 percent of 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

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

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

respondent age is 35 years.[23] 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.[24]

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.

Firms' perceptions of their current hiring process are heterogeneous. 46% of firms were confident or very confident that they could find suitable candidates. 47% agree or absolutely agree that they attract the right kind of applicants. 23% of firms state that they receive too few applications (40% receive too many with the remainder being satisfied with current levels). Importantly, 72% of firms in our sample do not have positive views on at least one of finding candidates, attracting the right candidates, or receiving too few applications. This suggests that, while barriers vary, many firms do face barriers that could potentially be alleviated by the use of formal channels.

[23]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.

[24]39% percent of firms in our sample use employment agencies at baseline. However, these agencies typically focus on specific segments of the labor market and do not generally provide candidates that match firms' expectations (Wu and Wang, 2023). This suggests intermediaries are not able to overcome the existing labor market frictions.

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
Perceptions of hiring process						
(Very) confident to find suitable candidates	0.46	0.50	0.00	0.00	1.00	620
(Absolutely) agree attracts right applicants	0.47	0.50	0.00	0.00	1.00	625
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

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.

3.3 Experimental integrity

To check whether the randomization into treatment arms successfully achieves balance on baseline observable characteristics, we present Appendix Table A2. Out of sixteen tested variables, we only observe one significant baseline imbalance (at the ten percent level), which suggests that the randomization worked as intended. 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 A3). We reached 96 percent of firms to conduct at least one phone survey (we conducted 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.

4 Theoretical framework

This section summarizes the theoretical framework described in detail in Appendix F. It describes firms' decisions of whether to create a vacancy, how to advertise it, and what type of position to fill, in light of the descriptive patterns shown in Section 2. The framework considers a firm i deciding whether to create a vacancy or not. First, the firm chooses its optimal search strategy s_i^* and the vacancy type t_i^* to maximize the expected profits:

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

where $\pi(s_i, t_i)$ is firm i's expected profit of searching for an employee of type t_i (white-collar (wc) or non–white-collar positions (nwc)) through channel s_i

(formal or informal) excluding the search cost. $c(s_i)$ are the costs of searching for employees in search channel s_i. Iff $\pi(s_i^*, t_i^*) - c(s_i^*) > 0$ the firm decides to create a vacancy. We model our treatment as reducing formal search cost $c(formal)$ through subsidies.

To derive unambiguous predictions about treatment effects, we assume that the returns to informal search are higher for non–white-collar vacancies compared to white-collar vacancies ($\pi(informal, nwc) > \pi(informal, wc)$).[25] This is in line with the empirical observation that informal search channels are most commonly used for non–white-collar vacancies. This framework yields the following key predictions that we test empirically using the experimental variation:

Result 1: Reducing formal search cost increases 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. However, the model also implies that even with reduced formal search costs, there will still be firms who prefer to use informal search channels for their vacancies. Hence, the take-up of formal search channels will not be complete.

Result 2: Reducing formal search cost increases the number of created vacancies. The subsidy can induce non-searching firms to create a vacancy if they are close to being indifferent between creating a formally advertised vacancy and not posting at all. The magnitude of the effect depends on the mass of firms that fall into this category. If there are many firms who are close to being indifferent between posting a vacancy formally and not posting a vacancy at all, 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.

[25] We can relax this assumption to be about the share of firms for which this inequality holds.

Result 3: Reducing formal search cost leads to an increase in white-collar vacancies. The vacancy subsidy makes formal posting more attractive overall, leading to a substitution of informal with formal search channels for some firms. The subsidy reduces the number of informally posted vacancies, which are (disproportionately) non–white-collar. Conversely, it increases the number of formally posted vacancies. As firms use formal channels disproportionately use formal channels for white-collar positions, the overall share of white-collar vacancies increases. Intuitively, some firms are induced to switch from informal non–white-collar vacancies to formal white-collar vacancies as the relative profitability of both types is a function of the cost of formal posting.[26]

Result 4: Reducing formal search cost might negatively affect hiring for inexperienced firms So far, we have assumed that the firm managers have full information about the expected returns to search through different channels. This is a reasonable assumption for managers with experience in using formal channels. However, managers without such experience might be overoptimistic about the returns to formal search, for example, because they have not experimented with those channels in the past.[27] This might lead to unsuccessful searches as managers have unrealistic expectations about the quality and quantity of applicants and, consequently, to negative treatment effects on hiring levels. If this were the case, we would expect firm managers to update their beliefs and revert back to informal search methods in the longer run.

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

[27]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.

5 Results

How do the theoretical predictions hold up empirically? We estimate the treatment effects of the vacancy subsidy intervention using the following equation:[28]

$$y_i = \beta_0 + \beta_1 vacsub_i + \varepsilon_i \quad (2)$$

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.[29]

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 ($p<0.01$).[30]

[28] 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. 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 treatment duration as we do not observe differential timing 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 Appendix Section G.

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

[30] Table A4 compares compliers to non-compliers. Complying firms are larger, are more likely to work in the service sector, and less likely to be in manufacturing. They have an

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 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 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

insignificant 2.5pp higher share of white-collar employees and pay white-collar workers 16% more (there is no difference in average baseline wages). Thus, compliers are not negatively selected in terms of offered salaries.

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 shows that the vacancy subsidy increased 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. Columns 4 to 6 show 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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; $p < 0.1$). This suggests that there might be some fixed costs associated with starting the search for new employees.

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 mea-

Table 4: Impacts on vacancy postings

	Pooled			White collar			Non-white collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any	# vacs	# vacs | any	Any vac	# vacs	% vacs	Any vac	# vacs
Treatment	-0.048	0.124	0.529*	0.072***	0.173***	0.118***	-0.069*	-0.051
	(0.042)	(0.171)	(0.283)	(0.026)	(0.066)	(0.040)	(0.042)	(0.147)
	[0.188]	[0.252]	[0.085]*	[0.021]**	[0.021]**	[0.021]**	[0.110]	[0.376]
Control mean	0.495	1.153	2.327	0.079	0.144	0.119	0.449	1.009
Observations	621	621	288	621	621	288	621	621

Notes: **Table 4 shows that the treatment increased white-collar but not non–white-collar vacancy creation.** Columns 1 to 3 shows effects on overall vacancy creation by firms. Column 1 shows effects on a dummy indicating at least one created vacancy. Column 2 shows the effect on the number of created vacancies. Column 3 shows effects on the number of vacancies conditional on creating at least one vacancy. Columns 4 to 6 show the impact on the creation of white-collar vacancies. Column 4 shows effects on a dummy indicating at least one created white-collar vacancy. Column 5 shows the effect on the number of created white-collar vacancies. Column 6 shows effects on the fraction of white-collar vacancies. Columns 7 and 8 show the impact on the creation of non–white-collar vacancies. Column 7 shows effects on a dummy indicating at least one created non–white-collar vacancy. Column 8 shows the effect on the number of created 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. Heteroskedasticity robust standard errors are displayed in parenthesis. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

sure 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.[31] 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.[32]

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—together with managers' perceived usefulness of formal hiring channels by position type shown in Figure 2b—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. Columns 4 to 8 of Table 4 show 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 4 and 5). On average, the number of white-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

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

[32] 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.

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 (6)). This suggests that the treatment leads firms to use white-collar vacancies as a substitute for non–white-collar vacancies as hypothesized in result 3 of our framework.[33]

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.

In terms of overall hiring, we observe a significant reduction in the fraction of vacancies successfully filled (Table 5). 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 decrease in the number of hires (0.21 hires or 17 percent of the control group mean). 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.

[33] This substitution can be interpreted as evidence for convex cost of posting vacancies in a given time period. Our framework abstracts from this interpretation by only considering the decision post a single vacancy.

Table 5: Impacts on hiring

	Pooled			White collar				Non-white collar		
	(1) Any hire	(2) # hires	(3) % vacs filled	(4) Any hire	(5) # hires	(6) % hires	(7) % vacs filled	(8) Any hire	(9) # hires	(10) % vacs filled
Treatment	-0.078*	-0.210	-0.203***	0.019	0.005	0.062	-0.357***	-0.086**	-0.215	-0.167***
	(0.042)	(0.171)	(0.041)	(0.022)	(0.062)	(0.042)	(0.102)	(0.041)	(0.154)	(0.043)
	[0.092]*	[0.159]	[0.001]***	[0.273]	[0.379]	[0.137]	[0.003]***	[0.067]*	[0.137]	[0.001]***
Control mean	0.454	1.218	0.877	0.069	0.153	0.118	0.847	0.412	1.065	0.877
Observations	621	621	288	621	621	250	78	621	621	252

Notes: **Table 5 shows that the treatment had negative effects on vacancy filling rates.** Columns 1 to 3 shows effects on average hiring outcomes. Column 1 shows effects on a dummy indicating at least one hire during the treatment period. Column 2 shows the effect on the number of hires. Column 3 shows effects on the fraction of filled vacancies. Columns 4 to 7 show the impact on the creation of white-collar vacancies. Column 4 shows effects on a dummy indicating at least one white-collar hire. Column 5 shows the effect on the number of white-collar hires. Column 6 shows effects on the fraction of white-collar hires. Column 7 shows effects on the fraction of filled white-collar vacancies. Columns 8 to 10 show the impact on non–white-collar hires. Column 8 shows effects on a dummy indicating at least one non–white-collar hire. Column 9 shows the effect on the number of non–white-collar hires. Column 10 shows effects on the fraction of filled non–white-collar vacancies. Column 9 shows the effect on the number of non–white-collar hires. 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. Heteroskedasticity robust standard errors are displayed in parenthesis. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 are present for both white-collar and non–white-collar vacancies (columns 7 and 10 of Table 5). 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).[34] Table 5 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 A12 that at endline the share of white-collar employees is a significant 2.4 percentage points (or 24%) higher in treated firms.

6 Mechanisms

In this section we explore mechanisms that could explain the decrease in vacancy filling rates in the experiment. We first show that firms' familiarity with formal search channels is related to treatment effects. We then consider the applicant side and explore the role of expectation mismatches between firms and job seekers. Finally, we provide evidence against a series of other potential mechanisms, such as imperfect information about skills, lack of formally qualified applicants, and extended search duration.

[34] The fact that 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.

6.1 The role of experience

We provide two pieces of evidence consistent with the decrease in successful matches being driven by firms' lack of familiarity with formal search channels: First, firm managers in the treatment group negatively update their beliefs about formal search channels at endline. Second, the negative treatment effects on hiring are driven by firms that did not regularly use formal channels at baseline.

Lower beliefs about the returns to using formal search We measure managers' beliefs about the returns to formal search in two ways. First, we once again make use of the question asking our respondents whether different types of applicants obtained through different formal channels are of better or worse quality than those obtained through networks (introduced in section 5.1).[35] 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. 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% 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).[36]

Second, we also ask about the *expected* number of applicants after posting a vacancy for different collar types through the various formal channels. We also find a significant decrease in managers' beliefs about the number of applicants (0.21 standard deviations, significant at the 10% level after MHC).

[35] Specifically, we ask managers "Imagine that you posted a vacancy for a [white/blue/pink/grey]-collar employee [on one of the central job-boards/on ezega.com/in The Reporter]. What do you think would be the quality of applicants compared to hiring through family and friends?" with answers on a 7-point Likert-scale from 1, "Much better", to 7, "Much worse".

[36] Our findings on belief updating are mirrored by Wu and Wang (2023) who document negative belief updating after being offered access to applicants through an employment agency. They also relate to Caria and Falco (2024) who find that employers' overly pessimistic beliefs about potential employees limit hiring in Ghana.

These effects are more noisily estimated due to the unbounded nature of the variable. As Appendix Figure A4 shows, this is not driven by a negative treatment effect on the number of applicants received through the intervention, but rather by unrealistically high control group expectations.[37]

This decrease in expected applicant numbers need not negatively affect firms, as 40% of firms say that receive too many applications at baseline. These firms, maybe unsurprisingly, drive most of the negative updating about applicant numbers. However, they exhibit no heterogeneity of treatment effects on vacancy related outcomes. This suggests that learning about the relatively low number of applicants is unlikely to drive our main effects.

Lack of experience with formal search channels To investigate the role of familiarity with formal search channels more broadly, we test whether firms that regularly used formal search channels at baseline exhibit differential treatment effects.

For these experienced firms, we find relatively large positive effects of 14 percentage points on the likelihood of creating at least one vacancy, but the effects are not statistically significant ($p < 0.34$; column 1 of Table A8). Inexperienced firms have an insignificant decrease in the likelihood of creating at least one vacancy of 7 percentage points. The p-value for a test of equality across both groups of firms is $p = 0.16$.

The difference between inexperienced and experienced firms is more pronounced for white-collar vacancies. Treated experienced firms exhibit a 20 percentage points larger treatment effect on the probability of creating at least one white-collar vacancy ($p < 0.1$, column 3). Compared to control firms, they are 26 percentage points more likely to create at least one white-collar vacancy, in contrast to a 6 percentage point increase for inexperienced

[37] At baseline, firms expect, on average, 11 additional applicants per vacancy just from posting on a single job board without taking other formal channels into account. Appendix Figure A6 shows that, in the control group, the average number of expected applicants per vacancy for formal search channels used in the experiment ranges between 32 and 50 per channel. This is substantially below our largest treatment effect estimate of just about 9 applicants (Appendix Figure A4). Firms' self-reported estimate is even lower at less than three applicants per vacancy.

firms (both $p < 0.05$). The substitution away from non–white-collar vacancies is also driven by inexperienced firms, whereas we see no significant decrease for experienced firms (column 5).

In line with this, we also observe fewer negative treatment effects on the vacancy-filling rates of experienced firms. Table 6 shows that the negative treatment effects on vacancy filling rates are driven by firms that are relatively unfamiliar with formal search channels (-23pp, $p < 0.01$; column 1). The effect on firms that were already using formal channels at baseline is significantly higher (35pp, $p < 0.05$), with sizable positive but noisily estimated treatment effects for this subgroup (11pp, $p = 0.47$). This pattern holds for both white-collar and non–white-collar vacancies (columns 2 and 3).

This effect is not driven by firms familiar with formal channels being better at filling vacancies in general. In the control group, these firms are 35pp *less* likely to fill vacancies compared to firms that did not use formal channels at baseline ($p < 0.01$, Table 6, column (1)). The treatment thus roughly equalizes vacancy filling rates between familiar and unfamiliar firms. One interpretation is that our treatment induces unfamiliar firms to create marginal vacancies that are more difficult to fill, while there is no such gradient for firms already familiar with formal employee search channels. These familiar firms already create such difficult-to-fill vacancies at baseline, before our experimental intervention.

Combining the effects on vacancy creation and vacancy filling rates, we also see suggestive evidence that experienced firms manage to increase their hiring rates (Table A8). On average, they are a nosily estimated 14 percentage points more likely to hire at least one employee ($p = 0.30$) whereas we see a 10 percentage point reduction for inexperienced firms ($p < 0.05$). While treatment effects for experienced firms are noisily estimated, the difference between the two groups is significant at the 10% level.

In relative terms, this difference is even more pronounced for white-collar hires, though effects are again noisily estimated (columns (9) and (10) of Table A8). We find that experienced treated firms have a 15 percentage points higher probability of hiring at least one white-collar worker ($p = 0.12$) rela-

Table 6: Effects on vacancy filling rates by experience

	Fraction filled		
	(1) pooled	(2) white-collar	(3) non-white-collar
Treatment	-0.232***	-0.455***	-0.190***
	(0.041)	(0.098)	(0.044)
Treatment × Used formal channels at baseline	0.345**	0.540*	0.320*
	(0.160)	(0.293)	(0.166)
Used formal channels at baseline	-0.349***	-0.462*	-0.327**
	(0.128)	(0.254)	(0.127)
Treatment effect: Used formal channels at baseline	0.113	0.085	0.130
	(0.155)	(0.276)	(0.160)
Control mean	0.877	0.847	0.877
Observations	288	78	252

Notes: **Table 6 shows that the negative effects on vacancy filling rates are driven by firms without previous experience with formal search channels.** Column 1 shows the impact on the overall vacancy-filling rate. Column 2 shows effects on the vacancy filling rate for white-collar vacancies. Column 3 shows effects on the vacancy filling rate for non–white-collar vacancies. At baseline, 8.8% of firms used formal search channels. 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. Heteroskedasticity robust standard errors are displayed in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

tive to an overall control mean of 7%. This contrasts with a point estimate of almost exactly zero for inexperienced firms. One important caveat is that only 9% of all firms (and also 9% of vacancy posting firms) reported regularly using formal search channels at baseline.[38] Hence, the cell sizes for this analysis are relatively small and the evidence should be considered suggestive.

As a whole, these results suggest that firms' experiences with formal channels shape how they are able to leverage the vacancy subsidy. Inexperienced firms struggle to fill the vacancies they create and see no positive impact. Experienced firms see no decline in filling rates and see nosily estimated increases in hiring outcomes.

6.2 Mismatch in wage expectations

Why do some firms struggle to fill their vacancies? We provide suggestive evidence that applicants have unrealistic wage expectations relative to prevailing wages. 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). This discrepancy is qualitatively consistent but smaller for larger firms in our sample. It is more pronounced when considering the average salary of vacancy posting firms at baseline. This suggests that applicants are generally over-optimistic about the possible

[38] Table A9 shows effects on expected returns by baseline experience. The effects on applicant quality are driven by inexperienced firms, while those on applicant numbers are driven by experienced firms.

remuneration.[39] 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.

6.3 Ruling out alternative explanations

Alternative mechanisms, such as a low absolute number of formally qualified applicants and information frictions about workers' skills, are unlikely to explain the low vacancy-filling rates in the treatment group.

6.3.1 Lack of formally qualified applicants

A first alternative explanation of why firms struggle to hire candidates through formal channels is that they receive too few applicants who 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 a reduction in filled vacancies. Moreover, more than 75% of applicants fulfill all required

[39] This is not driven by a negative selection of firms into our sample. Applicants are also over-optimistic relative to the average earnings of workers in Addis Ababa in comparable positions (see Section D).

criteria for the posted vacancy (such as education or experience requirements). Thus, formal employee search, thus, yields more *formally qualified* applicants.

6.3.2 Extended search duration

Another potential explanation for reduced vacancy filling rates is that search through formal channels might take longer. This could lead us to overestimate the share of unfilled vacancies. However, we think that this channel is unlikely to explain the effects we observe. If, in one survey round, firms tell us that the search for a created vacancy is still ongoing, we follow-up on this same vacancy in the next rounds of surveys until they tell us that the search has been concluded. We continue to do that during the post-treatment follow-up period. Hence, we capture hiring outcomes at least a few months after vacancy creation, which is an order of magnitude longer than the average search duration of five days in the control group.[40]

6.3.3 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., 2022, Abebe et al., 2019, Bassi and Nansamba, 2022). The theoretical framework in Appendix F models screening cost as part of the overall search cost through formal channels. It implies that reducing screening costs can further amplify the effect of subsidies on vacancy creation and shift towards white-collar vacancies.

To test whether limited information about candidate skills constrains the use of formal search channels, we offer half the firms in the treatment

[40]This could be more relevant for the post-treatment period where we have a limited amount of follow-up. However, we observe that effects during this period are concentrated among the vacancy creation margin and not vacancy filling rates.

group the option to have all applicants screened for three cognitive or socio-emotional skills of the firm's choice.[41] We invite all applicants to a screening center in downtown Addis Ababa for a screening session. We 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 A10). 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 hires (Appendix Table A11). 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.

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' lack of familiarity with formal job search, exemplified by unrealistic baseline expectations about potential candidate quality. 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.

[41] 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.

7 Treatment effects on downstream outcomes

We find that providing vacancy posting subsidies does affect the treated firms' workforce composition in line with the previously reported effects on hiring. However, we do not see any impact on further downstream outcomes, potentially because we lack statistical power to detect small effects.

Impact on firms' workforce Firms' overall workforce 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 (column (1) of Table A12). At the same time, and consistent with the negative hiring effects being driven by non–white-collar workers, we observe that the share of white-collar employees at endline is a significant 2.4 percentage points (or 24%) higher in treated firms (column (2)). The negative hiring effects for non–white-collar workers might also have affected the remuneration of the treated firms' existing non–white-collar employees: we find that firms in the treatment group have a slightly higher average salary level at endline, driven by their non–white-collar workers (Table A13).

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.

While our posting subsidy led to more applicants for treated firms (Figure A4), it also simplified the search logistics in terms of time and direct costs. Thus, the overall impacts on search inputs are ambiguous. We observe no treatment effect on the firms' candidate search inputs, such as search duration as well as screening and non-screening time and costs (Table A15).

Impact on firm outcomes There are no significant effects of the vacancy posting subsidy on downstream firm outcomes (Table A16). 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. More broadly, we often 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.

8 Search beyond the experiment

Does our intervention affect firms' employee search behavior beyond the duration of the subsidy? To answer this question we use data from a two-month post-treatment follow-up period. We attempt to recontact all firms for four more further surveys after their treatment period has lapsed. On average, we conduct 2.9 surveys with 554 firms. Attrition is unrelated to treatment status (columns 5 and 6 Table A3).

In line with negative experiences with formal channels, we find that the usage of formal channels does not persist beyond the treatment. Column 3 of Table 7 shows an insignificant but sizable 1.9pp (25%) reduction in the fraction of formally posted vacancies ($p = 0.69$, column 3).[42] While not conclusive, this is consistent with firms' changed beliefs about the returns to formal search shifting their behavior in the longer term.[43] Our finding contrasts with Abebe et al. (2023) who find an increase in formal search after negative search experiences using job fairs. Our results suggest that learning about specific search channels is an important factor for firms' choice of

[42] Interpreting heterogeneity by baseline usage of formal channels is complicated by the fact that less than 2% of baseline non-users in the control group post formally. This means that there is very little scope for a further reduction and the interaction coefficients in column 3 of Table A17 are hard to interpret.

[43] However, we find no significant treatment effects on firms' willingness-to-pay for the continuation of our intervention's vacancy posting services or for formal vacancy posting more generally, potentially because statistical power is limited with an MDE of 62% of the control group mean (column (1) of Table A18).

Table 7: Impact on post-treatment behavior

	Vacancy posting					Hires		
	(1) Any	(2) #	(3) % formal	(4) % network	(5) % wc	(6) Any	(7) #	(8) % wc
Treatment	-0.075**	-0.178***	-0.019	-0.005	0.205***	-0.081**	-0.255***	0.171**
	(0.035)	(0.068)	(0.048)	(0.092)	(0.071)	(0.035)	(0.083)	(0.070)
	[0.029]**	[0.020]**	[0.248]	[0.315]	[0.018]**	[0.024]**	[0.018]**	[0.024]**
Control mean	0.221	0.379	0.075	0.312	0.087	0.221	0.458	0.087
Observations	554	554	95	95	95	554	554	93

Notes: **Table 7 shows that treated firms continued to shift their labor demand composition after the end of the intervention.** It displays the impact of the effects of the vacancy subsidy intervention on formal vacancy posting in the four months following the four-month treatment period. Columns 1 to 5 show treatment effects on vacancy creation. Column 1 shows the effects on creating any vacancy post-treatment. Column 2 shows the effect on the number of created vacancies. Column 3 shows the effect on the fraction of formally posted vacancies. Column 4 shows the effect on the fraction of vacancies searched through networks. Column 5 shows the effect on the fraction of white-collar vacancies. Columns 6 to 8 show effects on hiring outcomes. Column 6 shows the effect on having any hire post-treatment. Column 7 shows the effect on the number of post-treatment hires. Column 8 shows the effect on the fraction of white-collar hires. Outcomes in columns 3, 4, 5, and 8 are only defined for firms with at least one created vacancy or hire. Heteroskedasticity robust standard errors are displayed in parenthesis. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

search method.

We further find that treated firms significantly reduce their labor demand in the post-treatment period (Table 7). They are 7.5pp less likely to create at least one vacancy ($p < 0.05$, column 1) and create 0.18 fewer vacancies ($p < 0.001$, column 2). This goes along with fewer hires, both at the extensive margin (-8.1pp, $p < 0.05$, column 6) and the intensive margin (-0.26 hires, $p < 0.05$, column 7). The reduction in labor demand is driven by firms that did not use formal search channels at baseline, the firms most likely to learn from experimenting with formal search channels (Table A17).

However, we do observe a persistent post-treatment shift towards more white-collar vacancies and hires. The share of white-collar vacancies in the treatment group is 20.5pp higher than the 8.7% mean in the control group ($p < 0.01$). This also results in a 17.1pp larger fraction of white-collar hires relative to the 8.7% mean in the control group ($p < 0.05$). This effect is mostly driven by a decrease in non–white-collar labor demand whereas there is little movement in the demand for white-collar workers, again in line with the behavior during the treatment period.

What can explain this change in behavior? Learning about formal search channels alone cannot explain the pattern, as firms were not using these channels at baseline and less than 2% of baseline non-users in the control group used a formal channel after the treatment period. Instead, firms seem to have updated their beliefs about the cost of hiring non–white-collar employees in general, in line with their behavior during the treatment period.[44]

The persistent shift in behavior post-treatment suggests that firms were ex-ante misinformed about the returns to formal search and did learn about the cost of employee search. However, they updated negatively leading to a reduction in overall labor demand and a shift in its composition toward more white-collar workers. Our results highlight how labor market experiences persistently shape both the quantity and relative quality of firms' labor demand.

9 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 employee search and 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, partially at the expense of network-based search. This alteration in posting strategies does not increase overall vacancy creation; instead, it prompts firms to predominantly create higher-skilled white-

[44]Firms' behavior is unlikely to reflect a front-loading of vacancy posting during the treatment period as we do not observe an increase in created vacancies during the treatment period.

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. This negative effect is driven by inexperienced firms, whereas we observe suggestive evidence of positive effects on hiring numbers for experienced firms. After the end of the treatment period, firms revert to using informal channels and reduce their labor demand, potentially due to, on average, negative experiences with formal search channels. That suggests that firms' prevailing search practices are potentially overoptimistic, given the market environment.

Our findings also suggest that the existing labor market institutions in Addis Ababa affect the quality of firms' labor demand. They lead to firms trying to fill less demanding positions than they would if they had cheaper access to formal search channels. However, the supply side of the labor market seems unable to meet firms' demand for 'high quality' workers, at least not at offered wage levels.

Do our results imply that firms made a costly mistake in taking up the treatment? They reduce hiring after the treatment period, which might limit growth and output. However, the persistent effect on hiring suggests that firms updated their beliefs and now make potentially better-informed profit maximizing decisions. Moreover, we observe a shift in the composition of both firms' labor demand and labor force, suggesting that they updated their beliefs about the optimal labor force composition in response to our treatment. We cannot draw strong conclusions about whether these changes are profitable for firms. Treatment effects on business outcomes are negative but too noisily estimated to draw strong conclusions.

Finally, when extrapolating from this study, it is important to keep in mind the partial equilibrium nature of our research. Our experiment was too small to affect the search behavior of job-seekers in this market, 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. Studying the general equilibrium characteristics of coexisting formal and informal search processes is a promising avenue for future work.

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Appendix
For Online Publication

The Online Appendix contains additional tables and figures referenced in the main text. Section A contains additional result tables.

Table A1 shows correlates of formal and informal job search based on labor force data. Table A2 tests for balance between the treatment and control groups. Table A3 tests for differential attrition by treatment groups. Table A4 describes how compliers differ from non-compliers. Table A5 shows wage expectations and realized wages for different vacancy types. Table A6 displays heterogeneous treatment effects by a wide range of observable characteristics. Table A7 displays treatment effects on managers' beliefs. Table A8 presents heterogeneous treatment effects on vacancy creation and hiring by baseline use of formal channels, whereas Table A9 shows the same heterogeneity effects on firm expectations about applicant quality and quantity. Table A10 shows the additional impact of the screening intervention on vacancy posting and creation, and hiring outcomes. Table A11 shows the additional impact of the screening intervention on the composition of vacancy creation and hires. Table A12 shows treatment effects on firms' endline employee numbers and collar shares. Table A13 shows the impact on average salaries at endline. Table A14 shows the impacts on characteristics of hired individuals. Table A15 shows the impact on search inputs. Table A16 shows the impact on downstream business outcomes. Table A17 shows heterogeneous treatment effects on post-treatment behavior by baseline usage of formal search channels. Table A18 presents effects on firms' willingness to pay for the services offered as part of the treatments.

In section B, we show all main results with control variables selected according to the pre-analysis plan. Table A19 and A20 show the main effects on vacancy creation and hiring. Tables A21 and A22 display the effects on the skill composition of vacancy creation and hires. Table A23 displays the impact on manager beliefs. Table A24 displays the impact on turnover. Table A25 displays the impact on search inputs. Table A26 shows the impacts on the characteristics of new hires. Table A27 shows the impacts on post-treatment behavior.

Section C contains additional figures. Figure A1 shows our theoretical predictions for vacancy search and type decision if white-collar positions are optimal for informal search. Figure A2 displays the timeline of the experiment. Figure A3 shows the geographical distribution of firms in our sample. Figure A4 shows different measures of treatment effects on the number of job applicants. Figure A5 shows control group firm expectations about the relative quality of formal applicants compared to candidates obtained through social networks. Figure A6 shows control group firm expectations about the number of applicants that can be obtained through different formal posting channels. Figure A7 shows the difference between the actual and expected number of applicants by collar type for control group firms.

Section D compares our sample to more representative data sources using Table A28. Section E shows differences between white-collar and non–white-collar vacancies based on publicly posted vacancy data using Table A29. Section F describes the details of our theoretical framework, which is introduced in the main text section 4. Lastly, section G lists the deviations from the pre-anaysis plan.

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 shows that education level and experience are correlated with formal search among job seekers in Addis Ababa.** It presents correlates of formal and informal (network-based) job search. In columns (1)-(3), an indicator whether a job seeker searches in formal channels is regressed on her years of education, whether she is a first-time job seeker, 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: 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
Raven score	8.99	8.86	-0.128	0.716

Notes: **Table A2 shows that treatment and control groups have similar observable characteristics.** It presents tests for equality of means across the treatment and control groups.

Table A3: 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 A3 shows that attrition levels are very low and mostly balanced across treatment groups.** Columns indicate different attrition measures. Columns 1 to 4 test for differential attrition during the treatment period. Columns 5 and 6 test for differential attrition during the post-treatment period. Heteroskedasticity robust standard errors are in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Characteristics of employers

	Control	Non-compliers	Compliers	Δ	p(Non-compliers=Compliers)
Firm characteristics					
Age of firm (in years)	7.45	7.14	6.88	-0.260	0.799
# of employees	15.12	13.15	18.01	4.861	0.002
Share of white-collar employees	0.13	0.14	0.16	0.025	0.222
Share of white-collar employees	0.13	0.14	0.16	0.025	0.222
Av. salary of workers	3216.24	2983.93	2935.97	-47.965	0.836
Av. salary of white-collar workers	5183.02	4791.61	5568.57	776.959	0.143
Manufacturing sector	0.52	0.56	0.25	-0.310	0.000
Service sector (retail, hospitality)	0.27	0.25	0.37	0.113	0.049
Health Sector	0.07	0.09	0.26	0.170	0.001
Hiring practices					
Uses formal hiring channels	0.10	0.08	0.09	0.013	0.700
Uses network hiring channels	0.81	0.78	0.82	0.039	0.410
Uses employment agencies	0.36	0.37	0.57	0.207	0.001
Manager expectations					
Expected number of hires in next 3 months	3.06	3.36	4.84	1.483	0.111
Positive bus. outlook next 3 months	0.62	0.59	0.68	0.086	0.136
Positive bus. outlook next 12 months	0.79	0.75	0.82	0.073	0.136
Manager characteristics					
Female	0.30	0.22	0.28	0.056	0.297
Manager age	34.98	35.40	35.83	0.428	0.718
Manager has univ. degree	0.42	0.45	0.56	0.117	0.053
Raven's Matrix score (out of 10)	5.01	4.71	5.34	0.631	0.039

Notes: **Table A4 shows that firms who make use of the vacancy posting subsidy work in different sectors and differ on further characteristics.** All variables are measured at baseline. Column 5 tests for equality of means between compliers and non-compliers.

Table A5: Expected and realized earnings

	Applicant data		Realized salary data		
	(1) Reservation wage (mean)	(2) Wage expectation	(3) All firms	(4) Large firms	(5) Average salary at bl
Panel A: All vacancies					
All vacancies	5059	5490	.	.	3563
Vacancies with hires	4066	4700	3256	3935	2960
Vacancies without hires	5601	5907	.	.	3665
Panel B: White-collar vacancies					
All white-collar vacancies	5848	6791	.	.	4794
White-collar vacancies with hires	4728	5892	4184	4653	3148
White-collar vacancies without hires	6435	7233	.	.	5398
Panel C: Non–white-collar vacancies					
All non–white-collar vacancies	4384	4329	.	.	3661
Non–white-collar vacancies with hires	3507	3741	2813	3438	2822
Non–white-collar vacancies without hires	4822	4621	.	.	3774

Notes: **Table A5 shows that applicants are generally overoptimistic about offered salaries, and relatively more so for white-collar vacancies.** It compares average reservation salaries and salary expectations to realized salaries and average baseline salaries. All values are in Ethiopian Birr per month (100 Birr were worth around 5.21 USD PPP in 2019). Samples are restricted to the vacancy subsidy plus screening treatment group because reservation salary and salary expectation data are 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 is the average salary of newly hired employees for vacancies posted during the treatment group (at the vacancy level). Column 4 is the average salary of newly hired employees for vacancies posted during the treatment group by the firms with an above-median number of employees. The sample in column 5 displays firm-level averages with the sample defined to be comparable to columns 1 to 3.

Table A6: Heterogeneous treatment effects on vacancy creation and hires.

	Firm characteristics			Sector		Hiring practices			Expectations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Bus. age	# bl_employees	% wc employees	Manufactoring	Service	Exp. hires (3m)	Pos. bus. outlook (3m)	Pos. bus. outlook (12m)	Female	Age	Univ. degree	Raven's score
Panel A: Impact on number of vacancies posted												
Treatment	0.008	-0.272	0.190	0.250	0.124	0.018	0.486^{**}	0.545^{**}	0.040	0.493	0.106	-0.366
	(0.226)	(0.287)	(0.217)	(0.287)	(0.192)	(0.216)	(0.228)	(0.275)	(0.220)	(0.753)	(0.206)	(0.453)
Treatment $\times$ hetero. var	0.018	0.029	-0.517	-0.291	-0.033	0.020	-0.509	-0.469	0.242	-0.011	0.011	0.055
	(0.026)	(0.024)	(1.185)	(0.340)	(0.392)	(0.053)	(0.327)	(0.349)	(0.312)	(0.022)	(0.357)	(0.043)
Hetero. var	0.006	0.034^{*}	0.672	-0.673^{***}	0.828^{***}	0.045	0.777^{***}	0.825^{***}	-0.395^{*}	0.014	0.249	-0.045
	(0.015)	(0.019)	(1.021)	(0.260)	(0.292)	(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
Observations	613	609	621	621	621	620	607	580	621	621	621	621
Panel B: Impact on number of hires												
Treatment	-0.229	-0.640^{**}	-0.106	-0.348	-0.129	-0.274	0.183	0.225	-0.243	0.221	-0.203	-0.535
	(0.230)	(0.265)	(0.243)	(0.262)	(0.193)	(0.200)	(0.206)	(0.277)	(0.210)	(0.661)	(0.196)	(0.389)
Treatment $\times$ hetero. var	0.004	0.031	-0.730	0.242	-0.325	0.011	-0.541^{*}	-0.491	0.064	-0.012	-0.045	0.036
	(0.024)	(0.022)	(1.148)	(0.342)	(0.393)	(0.048)	(0.319)	(0.351)	(0.350)	(0.018)	(0.360)	(0.041)
Hetero. var	0.003	0.032^{**}	0.135	-0.642^{**}	0.928^{***}	0.039	0.773^{***}	0.761^{***}	-0.267	0.003	0.289	-0.014
	(0.019)	(0.016)	(1.056)	(0.280)	(0.318)	(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
Observations	613	609	621	621	621	620	607	580	621	621	621	621

Notes: **Table A6 show that there are no further heterogeneous treatment effects on the number of posted vacancies and on the number of hires by baseline firm and manager characteristics.** The dependent variable in Panel A is the number of created vacancies. The dependent variable in Panel B is the number of hires. Columns indicate heterogeneity variables. Columns (1) to (3) show heterogeneity by firm characteristics (firm age, size, and share of white-collar employees). Columns (4) and (5) show heterogeneity by sector of the firm (manufacturing and service). Columns (6) to (8) show effects by managers baseline expectations (expected number of hires and dummies indicating a positive business outlook for the next 3 and 12 months). Columns (9) to (12) show heterogeneity by manager characteristics (gender, age, education, and Raven's score). Heteroskedasticity robust standard errors are in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 shows that managers negatively update their beliefs about the returns to formal search.** It 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 measured by binary variables equal to 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. Heteroskedasticity robust standard errors are in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Treatment effects by baseline use of formal channels

	Vacancy creation						Hires					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Any	#	Any wc	# wc	Any non-wc	# non-wc	Any	#	Any wc	# wc	Any non-wc	# non-wc
Treatment	-0.067	0.141	0.057**	0.166***	-0.088**	-0.027	-0.101**	-0.278	0.008	0.003	-0.105**	-0.281*
	(0.044)	(0.162)	(0.026)	(0.060)	(0.044)	(0.147)	(0.044)	(0.174)	(0.023)	(0.054)	(0.043)	(0.161)
Treatment ×	0.203	-0.081	0.201*	0.167	0.194	-0.245	0.237*	0.824	0.143	0.103	0.196	0.720
Used formal channels at baseline	(0.143)	(0.902)	(0.115)	(0.367)	(0.139)	(0.646)	(0.139)	(0.744)	(0.099)	(0.387)	(0.134)	(0.552)
Used formal channels at baseline	-0.096	0.538	0.064	0.346	-0.146	0.192	-0.151	-0.040	0.024	0.285	-0.155	-0.325
	(0.111)	(0.783)	(0.076)	(0.281)	(0.106)	(0.578)	(0.106)	(0.534)	(0.064)	(0.323)	(0.102)	(0.388)
Treatment effect:	0.136	0.061	0.258**	0.333	0.106	-0.273	0.136	0.545	0.152	0.106	0.091	0.439
Used formal channels at baseline	(0.136)	(0.887)	(0.113)	(0.362)	(0.132)	(0.629)	(0.132)	(0.724)	(0.097)	(0.384)	(0.127)	(0.528)
Control mean	0.495	1.153	0.079	0.144	0.449	1.009	0.454	1.218	0.069	0.153	0.412	1.065
Observations	621	621	621	621	621	621	621	621	621	621	621	621

Notes: **Table A8 shows that effects on vacancy posting and vacancy composition are driven by firms without experience using formal search channels.** It displays the effects on vacancy posting (columns (1) to (6)) and hires (columns (7) to (12)) parallel to our main outcomes. At baseline, 8.8% of firms used formal search channels. 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. Heteroskedasticity robust standard errors are displayed in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Treatment effects on expectations by baseline use of formal channels

	Expected applicant quality (index)			Expected applicant numbers (index)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	wc	non-wc	Pooled	wc	non-wc
Treatment	-0.168*	-0.137	-0.178**	-0.158	-0.150	-0.155
	(0.089)	(0.090)	(0.089)	(0.108)	(0.107)	(0.112)
Treatment × Used formal channels at baseline	0.137	0.159	0.097	-0.465	-0.383	-0.393
	(0.251)	(0.251)	(0.247)	(0.498)	(0.565)	(0.419)
Used formal channels at baseline	0.362*	0.260	0.418**	0.572	0.510	0.483
	(0.198)	(0.200)	(0.194)	(0.480)	(0.551)	(0.399)
Treatment effect: Used formal channels at baseline	-0.032	0.021	-0.081	-0.622	-0.533	-0.548
	(0.235)	(0.234)	(0.231)	(0.486)	(0.555)	(0.404)
Control mean	0.109	0.086	0.118	0.141	0.131	0.134
Observations	606	606	606	561	553	560

Notes: **Table A9 shows that effects on beliefs about applicant quality are driven by firms without experience of using formal search channels.** It displays the effects on standardized beliefs about the quality of applicants obtained through formal search channels (columns (1) to (3)) and the number of applicants obtained (columns (4) to (6)) parallel to our main outcomes. At baseline, 8.8% of firms used formal search channels. 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. Heteroskedasticity robust standard errors are displayed in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: 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 A10 shows that providing applicant screening services on top of vacancy posting subsidies does not affect average treatment effects on our main outcomes.** It displays heterogeneous treatment effects on main outcomes by whether firms in the treatment group were offered a service to screen all applicants to their vacancies on three skills of their choice. 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 A11: 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 A11 shows that providing applicant screening services on top of vacancy posting subsidies does not affect average treatment effects on the composition of posted vacancies.** It displays heterogeneous treatment effects on the composition vacancy posting and hires by whether firms in the treatment group were offered a service to screen all applicants to their vacancies on three skills of their choice. Columns (1) to (5) show impacts on the composition of vacancy creation. Columns (6) and (10) show impacts on the composition of hires. 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. Heteroskedasticity robust standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: 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 A12 shows that treated firms have a higher share of white-collar employees at endline.** It 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 A13: 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 A13 shows that firms in the treatment group have a slightly higher average salary level at endline.** It displays the effect of our intervention on average monthly salaries at endline (transformed using the inverse hyperbolic sine). Column (2) shows the impact on white-collar wages conditional on having white-collar employees. Column (3) shows the 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. Heteroskedasticity robust standard errors are in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Effects on characteristics of hires

	(1) Salary (ETB, IHS)	(2) Satisfaction	(3) Share female	(4) Share with degree
Panel A: Pooled				
Treatment	0.035	-0.034	-0.023	-0.007
	(0.083)	(0.126)	(0.057)	(0.054)
	[1.000]	[1.000]	[1.000]	[1.000]
Control mean	8.165	0.020	0.586	0.408
Observations	232	236	250	250

Notes: **Table A14 shows that the intervention had no measurable effect on the characteristics of new hires.** It displays the effect of our intervention on the characteristics of new hires. Column (1) shows effects on the inverse hyperbolic sine of the average salary of new hires. Column (2) shows the effect on a standardized measure of satisfaction with new hires. Column (3) shows the effect on the fraction of women among new hires. Column (4) shows the effect on the fraction of hires with a university degree among 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 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 A15 shows that the intervention did not affect firms search inputs.** It 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 A16: Effects on downstream firm outcomes

	(1) Profit (IHS)	(2) Revenue (IHS)	(3) Outlook 3m	(4) Outlook 12m
Treatment	-0.287	-0.025	-0.021	-0.036
	(0.229)	(0.217)	(0.087)	(0.089)
	[1.000]	[1.000]	[1.000]	[1.000]
Control mean	4.128	5.563	0.000	-0.000
Observations	581	580	619	552

Notes: **Table A16 shows that the intervention had no significant effect on firms' business outcomes and outlook at endline.** It displays the effect of our intervention on revenue (column (1)), profit (column (2)), and standardized business outlook for the next three and twelve months (columns (3) and (4)). 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 A17: Impact on post-treatment behavior by baseline usage of formal search

	Vacancy posting					Hires		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any	#	% formal	% network	% wc	Any	#	% wc
Treatment	-0.088**	-0.188***	0.002	0.022	0.197***	-0.091**	-0.274***	0.177**
	(0.037)	(0.070)	(0.033)	(0.100)	(0.070)	(0.037)	(0.088)	(0.069)
Treatment × Used formal channels at baseline	0.147	0.153	-0.288	-0.213	-0.043	0.115	0.238	-0.121
	(0.125)	(0.274)	(0.293)	(0.268)	(0.282)	(0.122)	(0.279)	(0.289)
Used formal channels at baseline	-0.034	0.056	0.469*	0.024	0.364	-0.034	-0.033	0.364
	(0.092)	(0.218)	(0.256)	(0.221)	(0.223)	(0.092)	(0.225)	(0.224)
Treatment effect: Used formal channels at baseline	0.060	-0.036	-0.286	-0.190	0.155	0.024	-0.036	0.056
	(0.119)	(0.265)	(0.292)	(0.249)	(0.274)	(0.116)	(0.265)	(0.280)
Control mean	0.221	0.379	0.075	0.312	0.087	0.221	0.458	0.087
Observations	554	554	95	95	95	554	554	93

Notes: **Table A17 shows heterogeneous treatment effects on post-treatment behavior by baseline usage of formal search channels.** It displays the impact of the effects of the vacancy subsidy intervention on formal vacancy posting in the four months following the four-month treatment period. "Used formal channels at baseline" is a dummy indicating the use of formal search channels Columns 1 to 5 show treatment effects on vacancy creation. Column 1 shows the effects on creating any vacancy post-treatment. Column 2 shows the effect on the number of created vacancies. Column 3 shows the effect on the fraction of formally posted vacancies. Column 4 shows the effect on the fraction of vacancies searched through networks. Column 5 shows the effect on the fraction of white-collar vacancies. Columns 6 to 8 show effects on hiring outcomes. Column 6 shows the effect on having any hire post-treatment. Column 7 shows the effect on the number of post-treatment hires. Column 8 shows the effect on the fraction of white-collar hires. Outcomes in columns 3, 4, 5, and 8 are only defined for firms with at least one created vacancy or hire. 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. 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 A18: 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 A18 shows that the intervention had no significant effect on firms' willingness-to-pay for formal vacancy postings.** It displays the effect of our intervention on firms' incentivized willingness-to-pay for an additional three months of the subsidy treatment in column (1). Column (2) displays treatment effects on a hypothetical willingness-to-pay for formal vacancy posting (calculated as the standardized average willingness-to-pay for advertising on offline and online job boards and in the major newspaper "The Reporter"). Heteroskedasticity robust standard errors are displayed in parentheses. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Results including control variables

This section presents all main results with control variables following the pre-analysis plan. We select control variables separately for each outcome using a LASSO algorithm (Belloni et al., 2013) with the same list of potential control variables. The results remain qualitatively unchanged. The list of control variables includes the following categories:

- Manager characteristics (age, gender, education, ethnicity, general intelligence, beliefs)
- Firm characteristics (firm age, sector, labor demand, management practices, hiring practices)
- Employee characteristics (demographics, collar shares, salaries, turnover)

Table A19: Main impacts on vacancy creation - including control variables

	(1) Any	(2) # vacs	(3) # vacs $\mid$ 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 A19 displays the treatment effects on vacancy creation with control variables.** Control variables selected from a pre-specified set of variables using LASSO algorithms for each outcome separately. 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: 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 A20 displays the treatment effects on hiring outcomes including control variables.** Control variables selected from a pre-specified set of variables using LASSO algorithms for each outcome separately. 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 A21: 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 A21 displays the effect of our intervention on the skill composition of vacancy creation including control variables.** Control variables selected from a pre-specified set of variables using LASSO algorithms for each outcome separately. Columns (1) to (3) show the impact on white-collar vacancies. Columns (4) and (5) show the impact on 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. 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 A22: 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 A22 displays the effect of our intervention on the skill composition of new hires including control variables.** All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms. Columns (1) to (4) show the impact on white-collar hires. Columns (5) to (7) show the impact on non–white-collar hires. 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. 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 A23: 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 A23 displays the treatment effects on beliefs about the quality and number of applicants obtained through formal search channels including control variables.** All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms. 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. 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. 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 A24: 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 A24 displays the impact of the effects of the vacancy subsidy intervention on employee turnover including control variables.** All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms for each outcome separately. 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. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A25: 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 A25 displays the effect of our intervention on candidate search inputs including control variables.** All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms for each outcome separately. 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 A26: 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 A26 displays the effect of our intervention on the characteristics of new hires including control variables.** All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms for each outcome separately. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

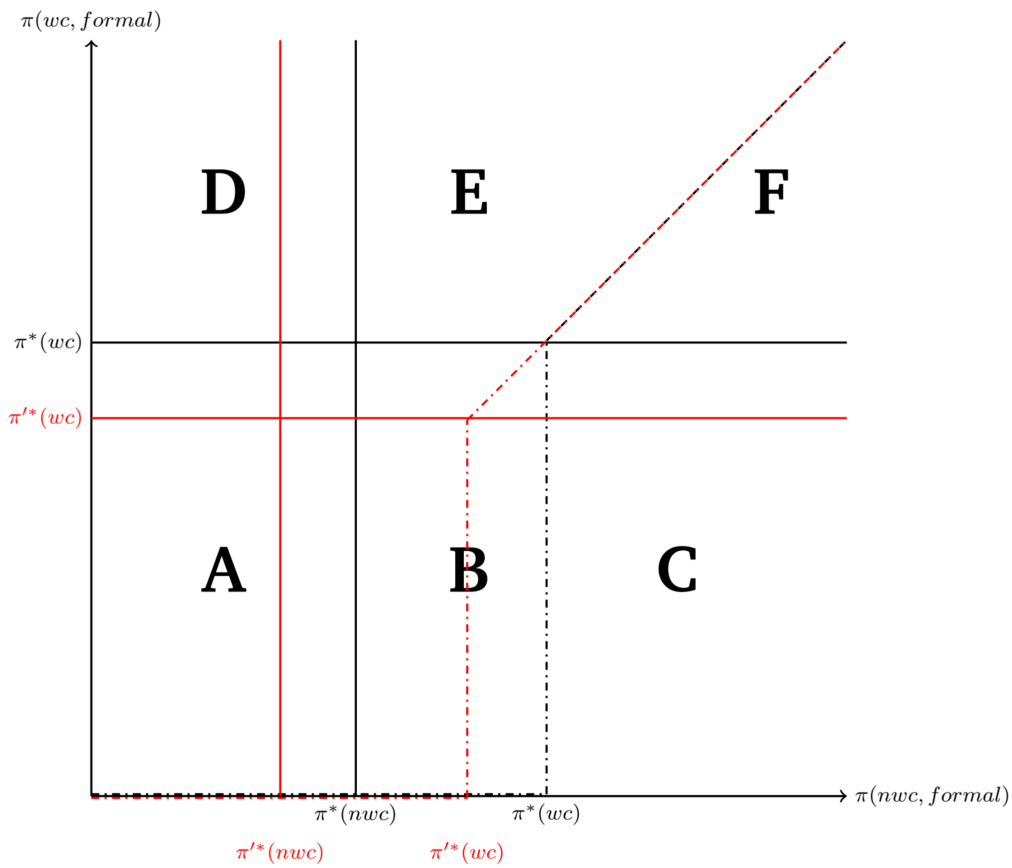
Table A27: Impact on post-treatment behavior by baseline usage of formal search - including control variables

	Vacancy posting					Hires		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any	#	% formal	% network	% wc	Any	#	% wc
Treatment	-0.074**	-0.164**	-0.019	-0.024	0.183***	-0.082**	-0.251***	0.118*
	(0.035)	(0.066)	(0.048)	(0.074)	(0.062)	(0.034)	(0.080)	(0.070)
	[0.034]**	[0.025]**	[0.229]	[0.229]	[0.015]**	[0.025]**	[0.015]**	[0.054]*
Control mean	0.221	0.379	0.075	0.312	0.087	0.221	0.458	0.087
Observations	554	554	95	95	95	554	554	93

Notes: **Table A27 shows treatment effects on post-treatment behavior including control variables.** It displays the impact of the effects of the vacancy subsidy intervention on formal vacancy posting in the four months following the four-month treatment period. "Used formal channels at baseline" is a dummy indicating the use of formal search channels Columns 1 to 5 show treatment effects on vacancy creation. Column 1 shows the effects on creating any vacancy post-treatment. Column 2 shows the effect on the number of created vacancies. Column 3 shows the effect on the fraction of formally posted vacancies. Column 4 shows the effect on the fraction of vacancies searched through networks. Column 5 shows the effect on the fraction of white-collar vacancies. Columns 6 to 8 show effects on hiring outcomes. Column 6 shows the effect on having any hire post-treatment. Column 7 shows the effect on the number of post-treatment hires. Column 8 shows the effect on the fraction of white-collar hires. Outcomes in columns 3, 4, 5, and 8 are only defined for firms with at least one created vacancy or hire. 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. All specifications include control variables selected from a pre-specified set of variables using LASSO algorithms for each outcome separately. Heteroskedasticity robust standard errors are displayed in parenthesis. Minimum q-values from two-stage false discovery rate correction are displayed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

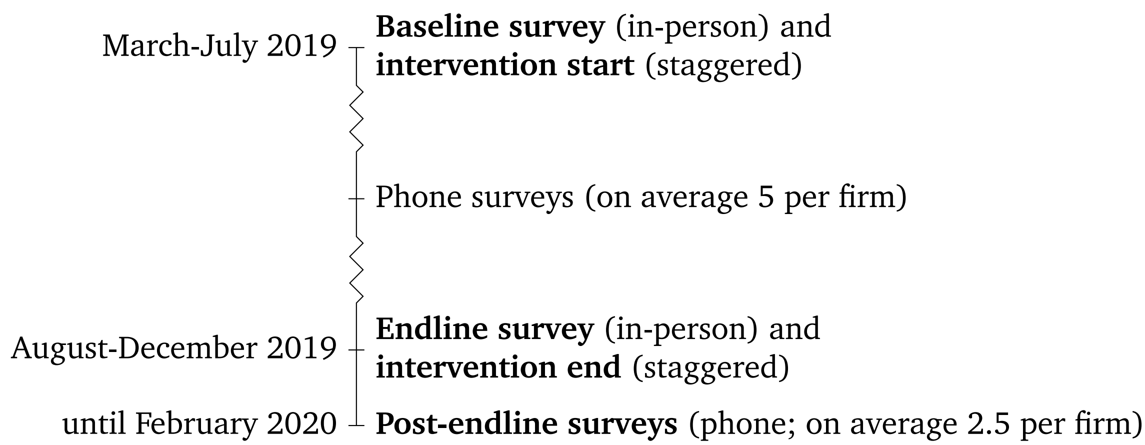
C Additional figures

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



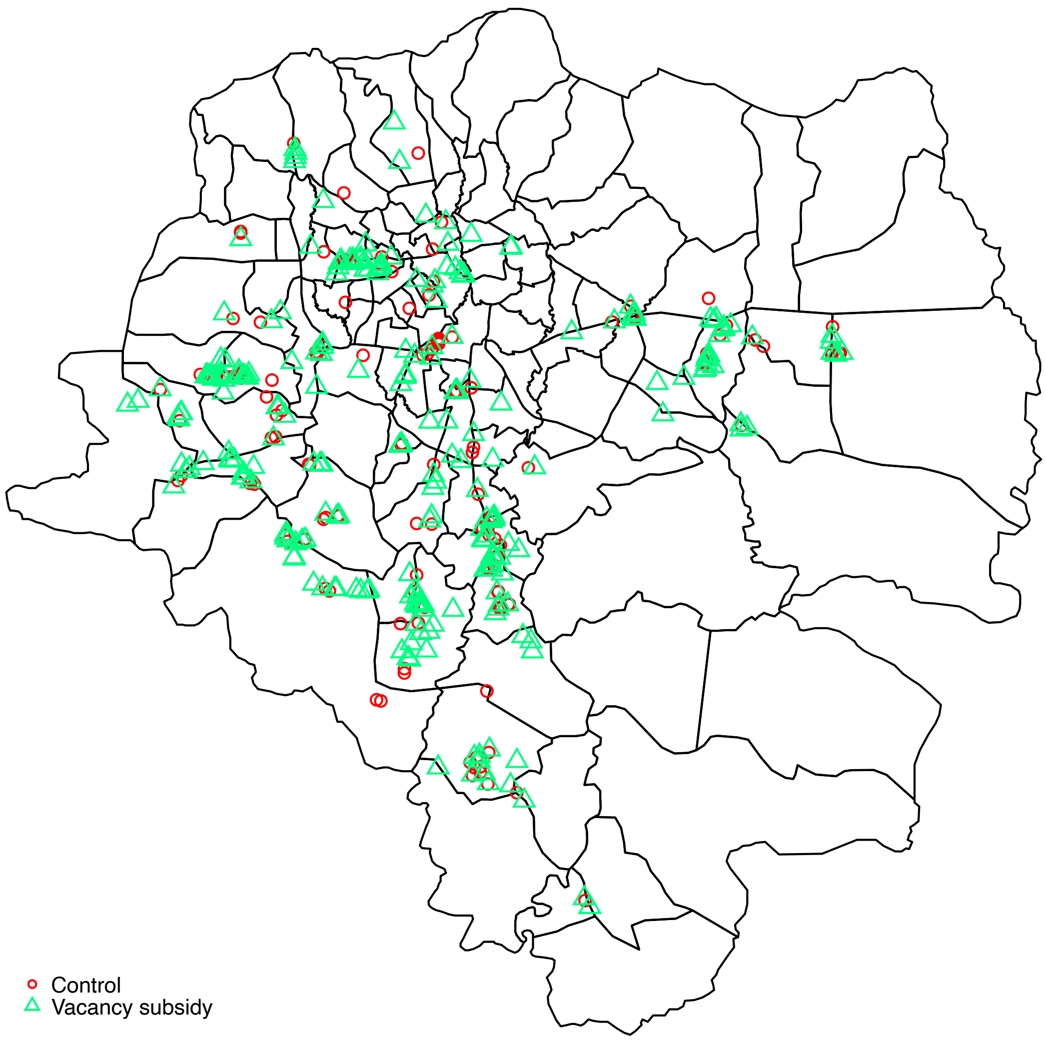
Notes: **Figure A1 displays the choice of search channel and vacancy type for firms in the $\pi(wc, formal)$–$\pi(nwc, formal)$ space.** It assumes that informal search for non–white-collar positions has lower returns than informal search for white-collar positions ($\pi(nwc, informal) < \pi(wc, informal)$). 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



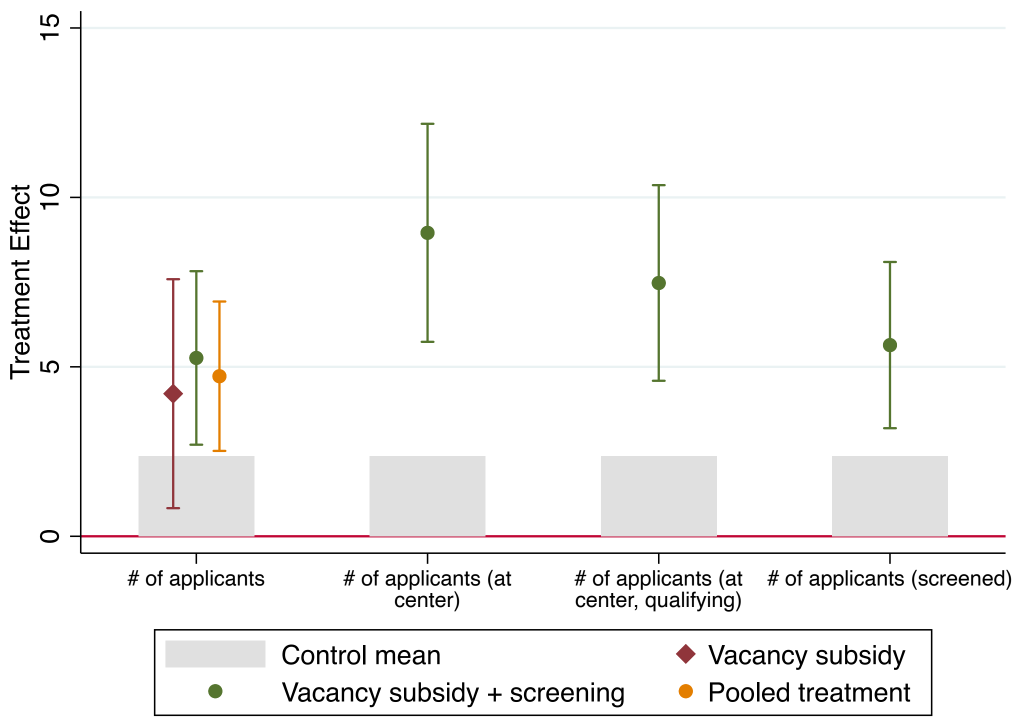
Notes: **Figure A2 displays the timeline of the experiment.**

Figure A3: Geographical distribution of firms



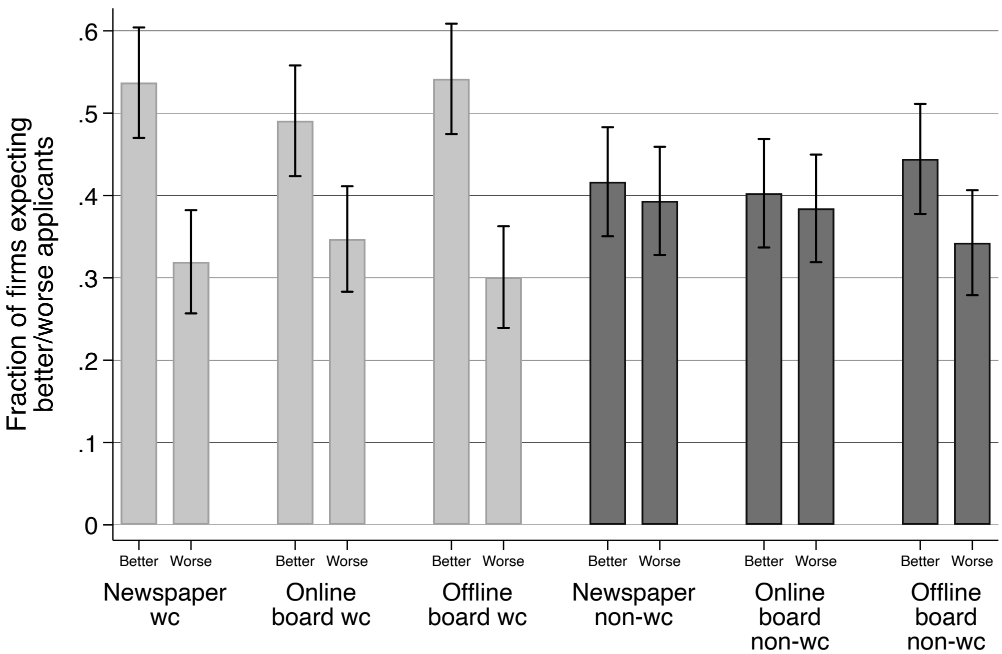
Notes: **Figure A3 displays the spatial distribution of sampled firms across Addis Ababa, Ethiopia.**

Figure A4: Treatment effects on the number of job applicants



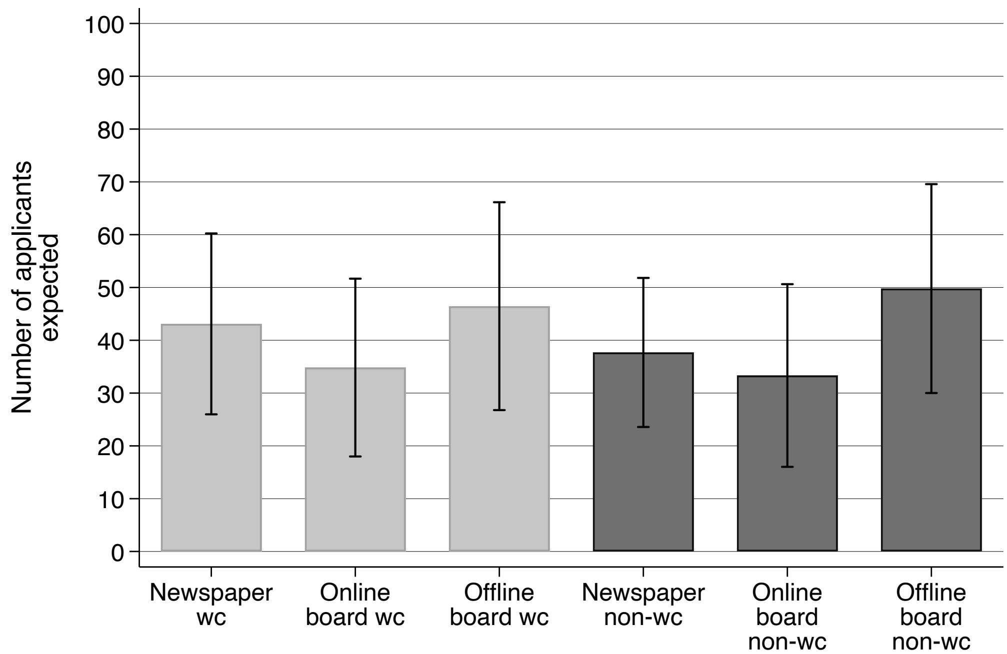
Notes: **Figure A4 shows that the treatment lead to an increase in the average number of applicants per vacancy.** Grey bars display the control group mean. 90% confidence intervals are displayed. Bar 1 shows the separate effects of the vacancy subsidy treatment, the vacancy subsidy treatment plus screening 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 is 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



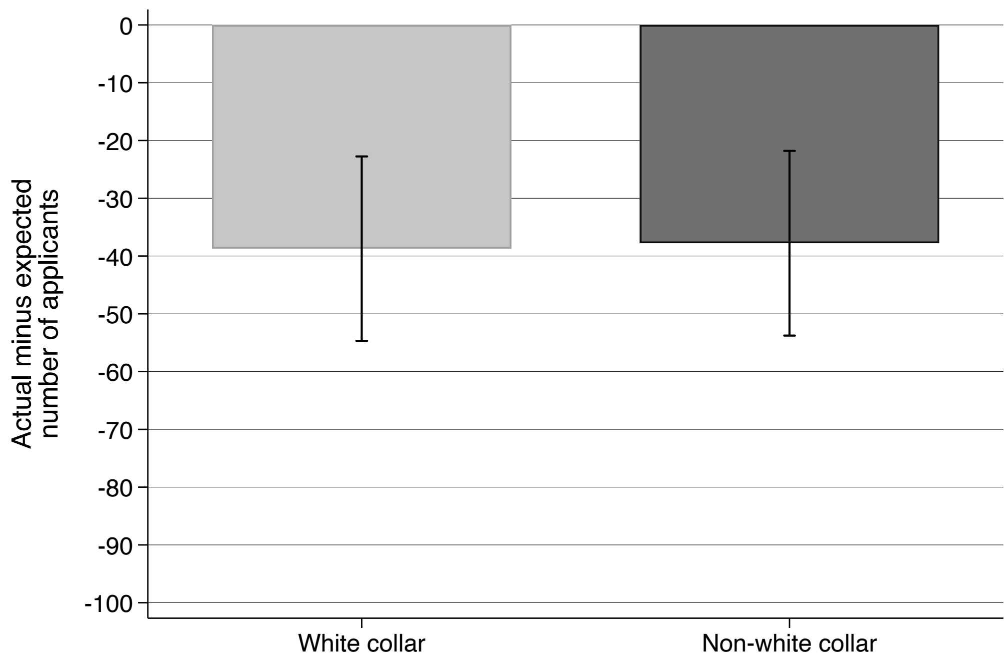
Notes: **Figure A5 shows that managers perceive formal channels to be more useful for white-collar positions.** It shows share of firms who expect applicants to vacancies posted in formal channels of better or worse quality compared to applicants obtained through social networks. The figure is shown 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



Notes: **Figure A6 shows that the number of applicants firms expect to receive when posting a vacancy in a given formal channel is relatively high.** The numbers are substantially higher than the ones observed in Figure A4.The figure is based on control group 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



Notes: **Figure A7 shows that firms are overoptimistic about the number of applicants they can attract through formal channels.** It 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 applicant numbers to non–white-collar positions.

D Sample representativeness

Table A28: Representativeness of sample

Panel A: Firm Characteristics			
Share of firms	**AALEID data**	**Among SMEs**	**Our Sample**
Micro Enterprises	63%		0%
Small and Medium Enterprises	36%		100%
Manufacturing Sector	28%	39%	51%
Service Sector	40%	34%	38%
Other	33%	32%	11%

Panel B: Labor market data		
Employment Shares	**Repr. Data**	**Our Sample**
Share Manufacturing	13%	47%
Share Service Sector	76%	31%
Share White-Collar	21%	13%
Share Non-White-Collar	79%	87%
Monthly salaries (Birr)		
All	3086	3779
Manufacturing	3385	4183
Service	3401	2219
White-Collar	5432	6021
Non-White-Collar	2479	3436

Notes: **Table A28 compares our sample to other data sources.** Panel A compares our sample to data on active firms with up to 50 employees from the Addis Ababa Labor, Enterprise, and Industry Development Bureau (AALEID). Micro enterprises are defined as 1 to 4 workers. SMEs are defined as 5 to 50 employees. Panel B uses data from the Urban Employment Unemployment Survey in 2018, for wages and occupations, and data from the Labor Force and Migration Survey of 2020 for sectoral composition.

This section compares our sample to representative samples from Addis Ababa. Panel A of Table A28 shows firm-level statistics comparing data collected in 2020 by the Addis Ababa Labor, Enterprise, and Industry Development Bureau (AALEID) to our sample. The AALEID data is a complete data set of micro-, small-, and medium-sized active firms in Addis Ababa. Larger firms are under the auspices by federal agencies.[45] Panel B shows aggregated employment share and salary statistics based on the Urban Employment Unemployment Survey in 2018 and the Labor Force and Migration Survey of 2020 both of which are conducted by the Central Statistical Agency. This data source is representative at the worker level, and covers employment at firms of all sizes. We focus our descriptive analysis on the subsample of wage employed individuals.

Our sample falls, by design, into the upper tail of the size distribution of the AALEID sample. 63% of firms are micro-enterprises with five or fewer employees, whereas 37% have between 6 and 50 employees.[46] Our sample, consist of SMEs with between 5 and 50 employees, with only two firms reporting more than 50 employees and one firm reporting 4 employees. The small discrepancy to our screening criteria stems from hiring between prescreening and baseline surveys.

The manufacturing sector makes up 28% of all AALEID firms and 39% of small- and medium-sized firms in Addis Ababa, but it only employs 13% of workers. Our sample consists of 51% manufacturing firms, which comprise 47% of employment in our sample. The service sector makes up 76% of AALEID firms and only 34% of small- and medium-sized firms in Addis Ababa. In our sample, 38% of firms work in the service sector. The employment share of the service sector in Addis Ababa is 76%, substantially more than the 31% in our sample.

Firms in our sample employ 13% white-collar workers at baseline, which is somewhat less than the share of 21% white-collar positions among wage employed individuals. This suggests that our sample employs relatively fewer high-skilled workers.

Finally, our sample is somewhat positively selected in terms of workers'

[45]There is, to our knowledge, no representative firm data from Addis Ababa that covers all sectors and firm sizes. The 2015 World Bank Enterprise survey of small, medium, and large firms documents a ratio of one large firm with more than 50 employees per four firms with between 5 and 50 employees.

[46]Extrapolating from the World Bank Enterprise Survey yields 58% micro enterprises, 33% SMEs, and 9% large enterprises.

salaries. The average worker at firms in our sample is paid 3779 Birr per month whereas workers in Addis Ababa earn 3086 Birr per months. The selection differs by sector: workers at service sector firms earn less than in the representative sample, whereas workers in the manufacturing sector earn slightly more than in the representative sample.

When splitting the sample by occupation, we find positive selection for both white-collar and non–white-collar workers. This implies that the over-optimistic expectations of applicants document in section 6.3 is unlikely to be the result of negative selection of firms into our experimental sample.

E Vacancy characteristics

This Appendix Section describes the differences between white-collar and non–white-collar vacancies based on our representative sample of publicly posted vacancies in Addis Ababa in 2019. Table A29 shows 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 require 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). Note that this comparison only considers formally posted vacancies. We do not directly observe differences between informally posted white-collar and non–white-collar vacancies but expect qualitatively similar differences among informally posted vacancies.

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 white-

Table A29: 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 A29 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.

collar vacancies are more attractive and more demanding than non–white-collar vacancies. Considering that white-collar vacancies are more likey to be posted formally, this also implies that formally posted vacancies are positively selected.

F 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.

F.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:

$$(s_i^*, t_i^*) = argmax_{s_i,t_i}\ \pi(s_i, t_i) - c(s_i) \tag{3}$$

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)[47] 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.[48] 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

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

t if the expected profit from doing so is larger than the expected profit from searching informally:

$$\pi(t, formal) - \pi(t, informal) > c(formal) - c(informal) = \Delta c \qquad (4)$$

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 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:

$$\pi(s^*(wc), wc) - c(s^*(wc), wc) > \pi(s^*(nwc), nwc) - c(s^*(nwc), nwc) \qquad (5)$$

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

Combining type and search choice Figure A8 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.[49] This corresponds to area A in Figure A8.

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 $\pi(wc, formal) >$

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

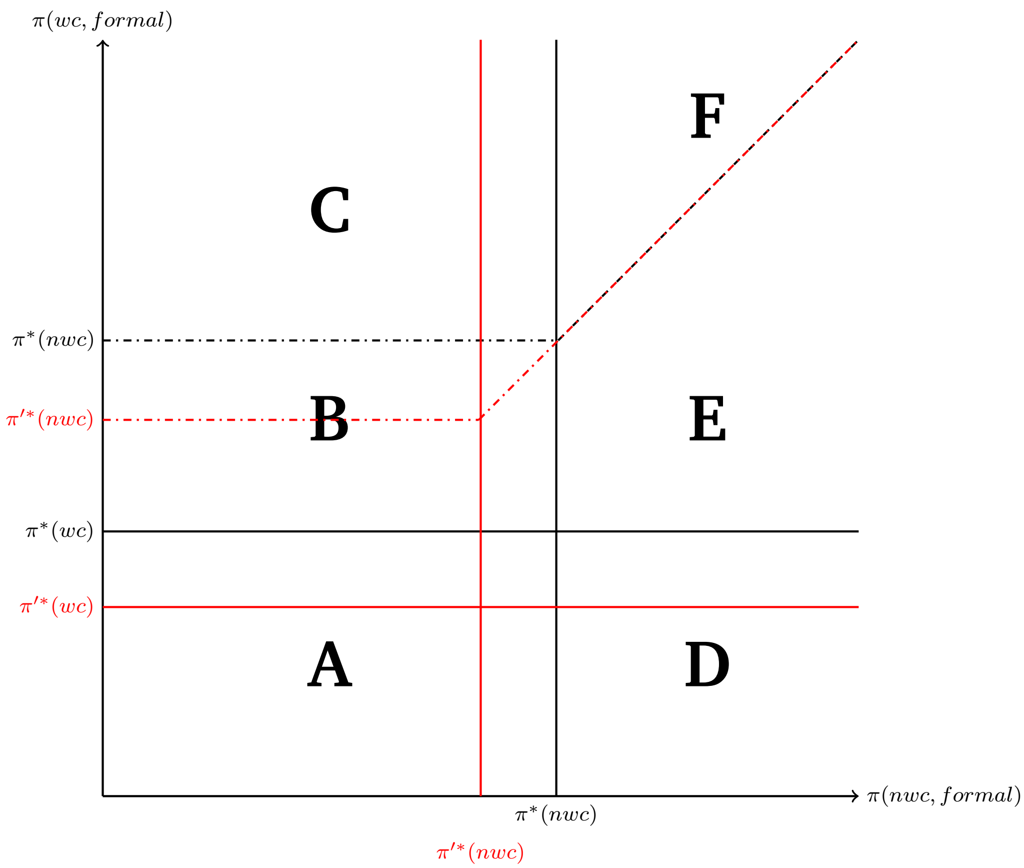


Figure A8: Vacancy search and type decision

Notes: Figure A8 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).

$\pi(nwc, formal)$ (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). 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 $\pi(nwc, formal) < \pi(wc, informal) + \delta c = \pi^*(wc)$. However, to be in this search regime we require $\pi(nwc, formal) > \pi^*(nwc)$. As we assume $\pi(wc, informal) < \pi(nwc, informal)$ 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 A8 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.[50]

[50] 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).

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

$$\max_{t,s} \pi(t_i, s_i) - c(s_i) > 0 \tag{6}$$

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

F.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 A8 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 postings, 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 costs 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 costs of formal search decrease.[51] The magnitude of the effect depends on the mass of firms that fall 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 A8) 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 A8) 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 A8).[52]

[51] 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 $\pi(wc, formal) - c(formal) > 0$. Define $\bar{\pi}_i(wc, formal) = c(formal)$ as the threshold 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 $\bar{\pi}_i(wc, formal) > \pi(wc, formal) > \bar{\pi'}_i(wc, formal)$ 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.

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

Result 4: Reducing screening costs 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 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.

G 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 the 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.