Search Costs, Belief Formation, and Firm Hiring: Evidence from Ethiopia*

David Qihang Wu† Samuel Zicheng Wang‡

This version: March, 2025

For the latest version please click here

Abstract

Active labor market policies that lower search costs often do not increase hiring. We provide a new explanation: Lowering search costs may induce an indirect effect on hiring through belief formation. In a hiring intervention with 799 private firms with an active job vacancy in Addis Ababa, Ethiopia, we introduced a subset of the firms to a specialized type of employment agency which helps them find more college-educated applicants. First, we observe an overall null effect on hiring. Five months after the intervention, treated firms received 35% more college-educated applicants, but were not more likely to interview or fill the vacancy. Second, we discover a learning effect. Treated firms became significantly less optimistic about the productivity of college graduates in general; among firms that requested a college graduate at baseline, treated firms became 19% and 34% less likely to interview and hire any college graduate. This learning effect could be partially triggered by the noisy productivity signals from applicants due to ineffective résumé writing. Guided by a search model with imperfect information, we show that our intervention has ambiguous implications on matching efficiency and potentially induces a persisting decrease in the labor demand for college graduates.

JEL Classification: O12, J23, M51

Keywords: Firm Hiring, Search Costs, Belief Formation, Matching Efficiency, Labor Demand, Employment Agency, Ethiopia

---

*We are extremely grateful to Edward Miguel, Supreet Kaur, Christopher Walters, and Benjamin Schoefer for their support and advice over the course of the project. We also thank Girum Abebe, Jie Bai, Abhijit Banerjee, Philipp Barteska, Vittorio Bassi, Sydnee Caldwell, Odilon Camara, Stefano Caria, Luisa Cefalà, Zoe Cullen, Madeline Duhon, Benjamin Faber, Claudio Ferraz, Frederico Finan, Benjamin Friedrich, Florian Grosset-Touba, Dominik Jurek, Patrick Kline, Louis-Pierre Lepage, Matt Lowe, Jeremy Magruder, Jamie McCasland, Mandy Pallais, Benjamin Roth, Raúl Sánchez de la Sierra, Christopher Stanton, Nicholas Swanson, and multiple participants in UC Berkeley Development Seminar for helpful conversations, comments, and feedback. We especially thank Esayas Ayele Mekonnen for his irreplaceable management of the project implementation. Yimo Huang and Kenza Chaabouni provided excellent research assistance. We gratefully acknowledge funding and support from International Growth Center, Private Enterprise Development in Low-income Countries, the Weiss Fund, and the UC Berkeley Strandberg Fund. The experiment was approved by UC Berkeley Committee for Protection of Human Subjects and is registered at the AEA RCT Registry (AEARCTR-0009224).

†Harvard University, qihangwu@fas.harvard.edu.

‡UC Berkeley, samzwang@berkeley.edu.

1 Introduction

Youth unemployment rates are high in many urban areas of low- and middle-income countries. Highly educated workers also face great challenges when searching for jobs.[1] On the other hand, many private firms complain about the lack of adequately educated workers.[2] This puzzling gap suggests a potentially high level of search frictions between highly educated workers and private firms in these countries. To address this gap, many new hiring channels, such as online job platforms, have emerged to facilitate more interactions between firms and highly educated workers (Kelley et al., 2022; Fernando et al., 2023). Along with the rise in private hiring channels, policymakers have attempted to reduce search costs through active labor market policies (ALMPs), such as subsidizing transportation for job search (Franklin, 2018; Abebe et al., 2021) and organizing job fairs in universities (Abebe et al., 2024). Although these measures tend to induce more job search from job seekers, their impact on employment outcomes is often negligible (McKenzie, 2017). Why?

We provide a new explanation from the perspective of firm hiring. In a simple framework with perfect information, lowering search costs in the labor market would strictly increase the number of successful matches. However, the assumption of perfect information does not reflect the reality in low- and middle-income countries. In a labor market with high search frictions, firms may have very few interactions with highly educated workers to draw inference from (Hensel et al., 2024; Abebe et al., 2024). Among these interactions, workers may send noisy signals about their productivity (Abebe et al., 2021; Bassi and Nansamba, 2022; Carranza et al., 2023). Thus, lowering search costs can trigger firms to update their beliefs about the productivity of highly educated workers, which may have an ambiguous effect on hiring depending on the direction of learning.

We designed a hiring intervention on 799 private formal firms in Addis Ababa, Ethiopia, with the intention to account for such a learning effect. The city of Addis Ababa exemplifies the challenges of firm hiring. Firms in our sample used various channels to seek for job seekers, including formal channels such as notice boards at the city center and personal referrals. Yet, on average, each posted vacancy only received 1.8 applicants, with 65% vacancies receiving zero college-educated applicant. On the other hand, an estimate from Abebe et al. (2021) shows that 33% college graduates were not engaged in any employment activities three years after graduation. These statistics depict a labor market with a high level of search frictions between firms and college-educated workers.

[1]As of 2022, according to the estimates of International Labor Organization (ILO), 25.7% youth population aged between 15 and 24 are not in employment, education, or training. Workers with advanced education do not significantly outperform other demographics. See the discussion in https://ilostat.ilo.org/blog/african-youth-face-pressing-challenges-in-the-transition-from-school-to-work/.

[2]According to the Enterprise Surveys from the World Bank (http://www.enterprisesurveys.org), 19.9% of firms identify an inadequately educated workforce as a major or very severe constraint.

In recent years, we observe a new type of employment agency in Addis Ababa that specializes in the recruitment service for high-skill formal jobs. They manage to form an applicant pool featuring college graduates and match them with firms at a much faster pace. Given that these employment agencies were still new to the majority of firms in Addis Ababa when we conducted the pilot in 2021, we collaborated with 11 employment agencies to help firms find more college-educated applicants. We sampled 799 private formal firms that were actively hiring in Addis Ababa in 2022 and collected detailed hiring records for their posted vacancies. 36% firms are in manufacturing and construction sector, 39% in hospitality sector, with the median number of employees 20. We also observe a relatively high demand for college graduates: 35% firms requested a college graduate for their vacancies at baseline.

We then implemented the following randomized controlled trial (RCT). We randomly matched 41% vacancies in our sample with one of 11 employment agencies at the end of the baseline. Each agency was requested to provide one or two applicants for the matched vacancy within two weeks. Firms could continue to search for applicants through other hiring channels. Among firms that were initially assigned to treatment, 46% received at least one applicant from the matched employment agencies. We further prevented direct communication between firms and employment agencies, so firms could only obtain information of applicants through their résumés or further interactions with the applicants such as conducting interviews. During follow-up surveys, we constructed a list of all applicants for each vacancy and collected (i) firms' perceptions of each applicant's education, experience, and productivity, and (ii) firms' interviewing and hiring decisions for each applicant. For 80% of the applicants, we conducted a phone survey to collect information on education, experience, employment status, and other demographics.

We verify that 80% applicants recommended from the agencies had a college diploma or degree, compared to 44% among non-agency applicants through other channels. Agency applicants were not significantly different in any other dimensions such as experience, gender, age, or employment status at baseline. Compared to control firms, treated firms received 0.39 more college-educated applicants (35% increase), suggesting a credible increase in the access to college-educated applicants. Given that college education is the main selection criterion of employment agencies, we pre-registered a heterogeneity analysis plan regarding firms' baseline request for college graduates.

We first examine whether treated firms were more likely to fill the vacancy by endline, using the initial treatment assignment to obtain intention-to-treat causal effects. Firms initially assigned to treatment were only 9.4 pp. more likely to interview any agency applicant; only seven treated firms hired anyone from the agency. Eventually, treated firms were not more likely to interview any applicant or fill the vacancy, against a simple hiring model where increasing the access to college-educated applicants would have strictly increased the interviewing or hiring of college graduates. This result resonates with recent evidence in low- and middle-income countries where simply lowering search costs for firms does not increase the number of successful matches (Fernando et al., 2023; Abebe et al., 2024; Hensel et al., 2024).

Instead, we discover a general decrease in the perceived average productivity of college graduates. For each firm, we elicit firms' perceptions of all applicants and calculate the percentage of college-educated applicants perceived to be productive. We find that this statistic among treated firms is 24.9 pp. less than that among control firms (p-value 0.038, 32% decrease). Such a decrease in perception did not exist for non-college applicants. One may worry if the treatment effect on perception was driven by the potential selection of firms who would not have had any college-educated applicants absent the treatment. To address this concern, we first show that the decrease in perception is also significant for treated firms that received at least one college-educated applicant from other hiring channels. Second, we asked all firms at endline whether they agreed college graduates are more productive than non-college workers on average; treated firms were 8.7 pp. less likely to agree so (p-value 0.051, 11% decrease). The latter estimate is not subject to the same concern of potential selection induced by treatment.

Consistent with the belief update, we observe a significant change in hiring behavior. Among firms that requested a college graduate at baseline, treated firms were 11.7 pp. less likely to interview (p-value 0.098, 19% decrease) and 19.7 pp. less likely to hire any college graduate (p-value 0.012, 34% decrease). Instead, they were 11.3 pp. more likely to interview (p-value 0.050, 86% increase) and 8.8 pp. more likely to hire at least one non-college worker (p-value 0.106, 80% increase). The treatment effect on the hiring of college graduates cannot be explained through the interactions of the initial treatment assignment and all other baseline characteristics, robust to various statistical inference techniques, and unaffected by the concerns of attrition, matching strategy of employment agencies, demand effect, or negative spillover on the control firms. We also find that among firms that requested a college graduate at baseline, treated firms were less likely to plan to post any jobs in the next three months after endline, suggesting the change in hiring behavior is likely to persist.

To test whether learning explains the shift in hiring behavior, we examine whether treatment effects are stronger among firms with less interaction with college graduates in the past, who were supposed to be more affected by one additional signal. Using the percentage of college-educated workers at baseline (henceforth college share) as a proxy for past interaction, we find that among firms that requested a college graduate at baseline, treated firms with below-median college share were 27.8 pp. less likely to hire a college graduate (p-value 0.047) and 14.9 pp. more likely to hire a non-college worker (p-value 0.079); the treatment effects on firms with above-median college share

are not significant nor robust, consistent with the learning hypothesis.

What triggered learning? From our qualitative interviews with firms at endline, treated firms mentioned that some applicants lacked qualification, most importantly, experience. We first verify whether college-educated applicants were less likely to have qualified experience, using applicants' self-reported information. 67% of all college-educated applicants from the agencies met the minimum requirement for years of experience, which is not significantly different than other college-educated or non-college applicants. To test whether applicants' qualification alone explains the main results, we examine the treatment heterogeneity regarding minimum experience requirement, leveraging the fact that higher requirement for experience is correlated with fewer applicants with qualified experience. Among firms that requested a college graduate at baseline, we still find a salient shift in hiring behavior for treated firms with low experience requirement, suggesting the shift in hiring behavior exists even among firms where it is *objectively* easier for college-educated applicants to have qualified experiences.

However, leveraging the detailed records of firms' perceptions of applicants, we find that of all college-educated applicants whose experiences met the minimum requirement, 33% were perceived as unqualified by the firms *subjectively*. This gap is significantly higher than that of non-college applicants, cannot be explained by other applicants' demographics or whether the applicant's experience matched the job requirement, and is negatively correlated with the perceived productivity. College-educated applicants from agencies were not more likely to be considered qualified. We further provide clues that applicants' résumé writing might be to blame. Although more than 80% college-educated applicants provided a résumé, among college-educated applicants that provided a résumé, 32% were still considered unqualified with respect to experience. Using non-college applicants without résumés as a benchmark, college-educated applicants with a résumé were significantly less likely to be considered qualified. Anecdotes suggest that some college graduates in this context may not know how to effectively communicate their experience and productivity in their résumés, a fact that has been recently more documented in the literature (Abebe et al., 2021; Bassi and Nansamba, 2022; Carranza et al., 2023).[3] The descriptive evidence implies a key information friction: college-educated applicants sent a noisy signal of their productivity through their résumés.

We discuss other potential learning mechanisms that may explain some of the empirical results. First, firms might have learned about college graduates' outside options. We found direct evidence that if anything, firms decreased their beliefs of college graduates' outside options, which would

[3]We were not permitted to conduct more detailed text analysis on applicants' résumés. However, we recently obtained a large sample of résumés from an online job search platform in Ethiopia with more than 11,000 observations. We conducted a preliminary text analysis on a random subset of 488 résumés from college graduates and found that 25% of them did not specify any formal work experience or internships on their résumés.

have encouraged firms to hire more college graduates. We also do not find that college graduates in our sample systematically rejected more interview invitations or offers. Second, when treated firms did not receive applicants from employment agencies, they might interpret it as a signal of high search costs. We still find significant shift in hiring behavior for firms with above-median likelihood of receiving applicants from agencies. Third, treated firms might have hired fewer college graduates because they could afford to make suboptimal hiring decisions and resort to the agencies for future replacement. We do not find evidence suggesting treated firms planned to hire more applicants from the agencies in the future. Fourth, treated firms might update their beliefs about external applicants in general because most agency applicants came from an external pool. Although we find supportive evidence of it, firms only decreased their beliefs about external, college-educated applicants, not for non-college applicants. Our preferred interpretation is that firms learned more about college graduates from external labor pool. Consistent with the interpretation, among firms that requested a college graduate and did not rely on referral at baseline, treated firms became more likely to use referral to hire a college graduate at endline.

What are the implications on matching efficiency? We develop an equilibrium search model with two types of firms (high-type with higher productivity and low-type), two types of workers (college graduates with higher productivity and non-college workers), imperfect information of the productivity of college graduates, and Bayesian update of the productivity when matching with a college-educated applicant. With perfect information and assumption of super-modularity, the unique equilibrium would reach the social optimum where college graduates will only be employed by high-type firms. With imperfect information, there exists a sorting of firms with respect to their priors: on average, overly optimistic firms would post jobs for college graduates and keep learning about their productivity, while overly pessimistic firms would stop hiring college graduates remain overly pessimistic for any future periods. Because overly optimistic, low-type firms would also post jobs for college graduates, the employment value for college graduates decreases, which induces a higher level of unemployment for college graduates than social optimum. If search costs between firms and college graduates decrease, the induced learning among over-optimistic, low-type firms would enhance matching efficiency, but the induced learning among over-optimistic, high-type firms would be potentially efficiency-decreasing if some firms become overly pessimistic as a result.

Guided by the equilibrium search model, we attempt to examine treatment heterogeneity with respect to firms' productivity types. We first construct a skill index by extracting the principal component of four vacancy characteristics: whether the job involved mostly routine tasks, manual tasks, any specific skill requirements, and whether the job required more than two years of previous experience. We then examine the treatment effects among firms with above-median or below-median skill index. Among firms that requested a college graduate, for both types of firms, we find a significant decrease in beliefs of college graduates' productivity, a significant decrease in the hiring of college graduates and an increase in the hiring of non-college workers. Our intervention thus has ambiguous implications on matching efficiency: On one hand, low-type firms hired fewer college graduates and more non-college workers in a shorter amount of time, which would increase the matching efficiency. On the other hand, some high-type firms became less optimistic about college graduates' productivity and hired fewer of them, which would decrease the matching efficiency. However, at endline, both types of firms indicated less willingness to post any jobs in the next three months, suggesting that at least in the short run, our intervention potentially induces a persisting decrease in labor demand for college graduates.

Related Literature and Contributions. This paper provides a new explanation for the high unemployment rates in low- and middle-income countries, especially among highly educated workers, from the perspective of firm hiring. Current literature has documented the existence of prohibitive search costs in low- and middle-income countries and how they prevent job seekers from conducting optimal job search behavior, yet interventions that simply reduce search costs do not often improve job seekers' employment outcomes meaningfully (Abebe et al., 2021; Abel et al., 2019; Bandiera et al., 2023; Banerjee and Sequeira, 2022; Caria et al., 2024; Dammert et al., 2015; Franklin, 2018; Kelley et al., 2022). Some recent evidence from Ethiopia and India shows that simply reducing search costs for firms also do not lead to significant increase in successful matches (Fernando et al., 2023; Hensel et al., 2024). Meanwhile, a growing body of evidence suggests that addressing information asymmetry in the labor market may improve employment outcomes more effectively (Abebe et al., 2024; Abel et al., 2020; Alfonsi et al., 2023; Banerjee and Chiplunkar, 2022; Banerjee and Sequeira, 2022; Bassi and Nansamba, 2022; Beam, 2016; Carranza et al., 2023; Pallais, 2014).[4] Our empirical findings demonstrate how lower search costs for firms can induce a negative learning effect due to existing information frictions, providing an explanation on why addressing information frictions can be more effective in creating successful matches.[5]

[4]Search frictions and information frictions can be intertwined. For example, Banerjee and Sequeira (2022) incentivize job seekers in South Africa to conduct more job searches and find that job seekers adjust their beliefs of the labor market. Abebe et al. (2024) conduct a job fair in Addis Ababa and find that both firms and workers update their beliefs of the labor market through mutual interactions. Our results also show that firms updated their beliefs of the average productivity of college-educated applicants after being exposed to more college-educated applicants.

[5]This implication can be potentially applied to high-income countries because their labor markets also feature a non-negligible level of search costs and information asymmetry (Altmann et al., 2018; Belot et al., 2019; Jäger et al., 2021). Research on ALMPs in high-income countries also finds limited impact of policies that only address search costs (Behaghel et al., 2014; Cottier et al., 2018; Crépon et al., 2013; Dhia et al., 2022). Importantly, Algan et al. (2020) finds more positive results of firm-oriented ALMPs and suggests that the main channel is alleviating the pre-screening and filtering burden of recruitment process.

Second, this paper adds to the emerging literature of firm hiring in low- and middle-income countries, where the study of firms has been limited by the availability of data on private firms. The growing literature on hiring in high-income countries rely on detailed personnel data from large corporations, which is almost non-existent in sub-Saharan African countries with some exceptions (Hjort, 2014; Donald and Grosset-Touba, 2024). Our contributions to this literature are twofold. First, we manage to collect detailed hiring records from a large sample of medium-sized private firms in a low-income country.[6] Second, we are able to describe the search frictions and information frictions faced by firms during the hiring process, which is made possible by having detailed data on applicants and more importantly, firms' perceptions on applicants. Evidence from firms in high-income countries suggests a high level of information frictions before making hiring decisions (Hoffman et al., 2018; Li et al., 2023; Friedrich and Zator, 2024; Benson and Lepage, 2024; Cullen et al., 2022). Such frictions are more severe in low- and middle-income countries where firms have less access to various job platforms and screening technology.

Finally, this paper contributes to a smaller branch of literature on labor market intermediaries. Existing evidence, mainly from high-income countries, documents that labor market intermediaries credibly send a positive signal of workers to firms by inducing a positive selection of workers in the first place (Stanton and Thomas, 2016; Autor, 2008, 2001). In our setting, employment agencies consistently provide college-educated applicants as their main strategy, but with little success in creating more matches, which reveals limitations of positive selection in contexts where information frictions are more severe. The learning mechanism induced by employment agencies resonates recent work by Hunt and Moehling (2024) on the historical role of employment agencies in United States to mitigate discrimination against female job seekers.

Section 2 discusses more context of the labor market and employment agencies in Ethiopia. Section 3 introduces the sampling method, intervention, and data collection. Section 4 discusses the main results on hiring and belief update. Section 5 discusses the factors that may induce learning. Section 6 discusses the implications on matching efficiency with an equilibrium search model. Section 7 concludes.

[6] In low-income countries, researchers usually focus on microbusinesses where the data is more available but the demand for external labor is less relevant (Bassi et al., 2023). Three noticeable exceptions in the literature (Abebe et al., 2024; Fernando et al., 2023; Hensel et al., 2024) provide hiring data from medium-sized private firms in low- and middle-income countries.

2 Context

2.1 Labor Market in Ethiopia

Ethiopia has undergone a significant increase in the number of college-educated population over the last three decades. In the early 1990s, there were only three public universities across the whole country enrolling 1% of all young people aged 18–25. In 2018, the gross attendance rate in tertiary education in Ethiopia jumps to 12% (Ethiopian Socioeconomic Survey).[7] However, the unemployment rate among college graduates has become alarming recently. Abebe et al. (2021) followed 510 young job seekers in Addis Ababa with a college diploma or degree, among whom 33% were not engaged in any employment activities three years after graduation.

This seems at odds with the high labor demand for college graduates we observe from our sample of 799 firms, of which we will discuss the sampling method in the next section. Figure 1, Panel A presents a simple comparison between the demand and supply of college graduates. 35% firms from our sample were looking for college graduates, much higher than the estimated attendance rate in tertiary education by Ethiopian Socioeconomic Survey. Indeed, most firms valued college education. We asked firms at the baseline whether they think college graduates are more productive and have more job opportunities than non-college educated workers. Figure 1, Panel B shows that 70% of the firms agreed that college graduates are more productive than non-college educated workers, and 61% believed there are more job opportunities for college graduates in the current labor market. It is consistent with the common heuristic that higher educational attainment is correlated with higher productivity, either through the value-added to human capital (Becker, 1964) or through the selective procedure of tertiary education (Spence, 1978) .

One explanation to reconcile these two opposing facts is high search frictions. Firms in our sample used multiple ways to search for job seekers, yet the number of applicants for the posted vacancies remained abysmal. Figure 2 shows that 47% of the firms posted their vacancies on the notice boards, the most common job platforms located in the city center of Addis Ababa. 45% of the firms would ask for internal referrals through friends, family, and current employees. 35% would seek for job seekers from informal brokers scattered around the city, mostly for low-skill jobs such as construction work. A smaller proportion of firms would use more costly platforms such as newspapers (11%), online job platforms (13%), and formal employment agencies (8%), to seek for high-skill workers. Figure 3 shows the distribution of the number of applicants received for our

[7]One way to interpret this statistic is that 12% of people aged 18–23 in Ethiopia attended any tertiary institution in 2018. Such a statistic in Sub-Saharan Africa is estimated to be 9.4% in 2018 (UNESCO).

sampled vacancies over the period of five months (excluding those from the employment agencies in our intervention). The median number of applicants was merely one, the average 1.8, with 22% of firms having no applicants at all. Panel B focuses on the distribution of college educated applicants. 65% of these vacancies did not receive any college educated applicant. Figure A1 shows that even among firms that requested a college graduate at baseline, 39% did not receive any college graduate over the course of five months. The descriptive evidence confirms the severity of search frictions in this labor market, under which firms may not be able to obtain enough information of college graduates' productivity and develop accurate beliefs.

2.2 Employment Agencies

Can labor market correct search frictions itself? We observe a new, specialized type of labor market intermediary, employment agency, that might act as a market self-correction. Responding to the increasing gap between unemployed college graduates and firms' demand for skilled workers, some former job brokers in informal sectors register as an employment agency and tailor the recruitment service to highly educated job seekers.[8] By strategically locating at the city center, these employment agencies are able to attract a large group of job seekers with a college diploma or degree as well as firms with higher-paid formal jobs, effectively acting as a new job platform that matches firms and college graduates at a much faster pace. Figure A2 shows a representative employment agency. Figure A3, Panel A shows that the number of new registered employment agencies in Bole sub-city after 2018 increases drastically.[9] Given that only 8% firms in our sample used one of these employment agencies for hiring in the past, we were able to design an RCT to leverage these employment agencies to lower search costs for a random subset of firms.[10]

We interviewed the owners of 25 employment agencies between July and August 2021, in Bole

[8] In 2018, the new Ethiopian government issued an initiative to encourage qualified brokers to register in the government in hope for boosting private and formal employment. To qualify for registration, an employment agency should obtain a business license for taxation purpose, hire at least one expert with professional license in human resources, have at least 4 employees, have a physical office, and deposit 200,000 Ethiopian birr in a security account. The Ministry of Labor and Skills of Addis Ababa appoints local officials to specifically regulate and audit all the registered employment agencies. Upon successful matches, employment agencies usually charge 10–20% first-month salary from firms, although informally they also charge job seekers an entry fee between 100–500 Ethiopian birr.

[9] There is another form of labor market intermediaries, outsourcing companies, that are more prevalent in Addis Ababa prior to 2018. Firms outsource low-skill occupations to these companies such as janitors and security guards, similar to Goldschmidt and Schmieder (2017) and Dorn et al. (2018) in the context of Germany and US. Instead, we see a downward trend of registered outsourcing companies post 2019, which may imply an increase in the demand for high-skill instead of low-skill workers.

[10] The trend of employment agencies is also observed in many other low- and middle-income countries. Figure A3, Panel B shows a time series of newly established employment agencies observed from one of the largest online business-to-business platforms. Despite omitting many employment agencies not able to be observed online, there has been an increasing number of new employment agencies since 2005 across low- and middle-income countries providing recruitment services to private firms.

sub-city where most recruitment services locate, to observe their daily operations and interactions with job seekers. Table B1, Panel A summarizes the qualitative description of the functions of employment agencies. In general, employment agencies do not seem to provide sophisticated recruitment services. Most employment agencies only check applicants' basic documents such as IDs and education certificates. Some may recommend vocational training facilities to job seekers or check previous employers' recommendation. Most do not provide additional training that potentially enhances workers' productivity, or conduct additional grading test that potentially improves the signals of workers' productivity. In addition, we ask 539 job seekers in our sample about their perceived benefits from employment agencies. Table B1, Panel B shows that job seekers mostly agreed that employment agencies provide some advice on which jobs to apply to, but do not help with networking, interview preparation or résumé writing. This corroborates our observation that employment agencies do not increase the human capital or provide better signals of productivity. We thus believe that qualitatively, the main function of employment agencies is to reduce search costs and facilitate matching between firms and college-educated job seekers.

3 Data and Intervention

We first conducted a pilot during early May 2022. We then conducted two rounds of data collection: May–October 2022 (Round 1), November 2022–April 2023 (Round 2).

3.1 Sampling

We conducted a new sampling approach to collect a representative sample of active job vacancies. First, we consulted with local government officials from five sub-cities (Bole, Akaki Kality, Yeka, Nefas Silk-Lafto, Lemi Kura) to understand where most businesses are located within the sub-cities. We then delineated 88 business areas in total where most firms conduct businesses; each business area has about 50–100 formal firms. In each business area, enumerators conducted a census and listed as many formal firms as possible. Enumerators then selected 10 firms from each business area following three criteria: (1) at least 4 employees; (2) currently hiring or planning to hire within 1 month; (3) respondents agreed that hiring is challenging.[11] Figure A4 shows the geographic distribution of 88 sampled business areas and 799 firms selected for the baseline survey.

This sampling method has a few unique advantages. First, we are able to observe currently

[11] We enlisted 3,369 firms in the census. 958 firms had at least four employees and were currently hiring or planning to hire within 1 month. We included the third selection criterion to target firms in need for recruitment service; however, among these 958 firms, 97% agreed that hiring is challenging, and thus this criterion is not as binding.

operating firms in a much faster way. An alternative sampling method is to obtain a firm registry from the Ministry of Trade. Such registry, however, may have outdated information. During our pilot, we obtained a firm registry from Bole sub-city and only succeeded in contacting less than 20% of the listed firms. Table B2, Panel A compares the sampling of firms to that of Hensel et al. (2024), who sampled from the firm registry. Our firm sample includes more firms from hospitality sector and of a larger number of current employees in general. Other existing firm surveys of Ethiopia, such as Large Manufacturing and Electricity Industries Survey, mostly focus on manufacturing firms with at least 10 employees.

Second, we are able to observe firms that did not post jobs on public platforms such as notice boards or online job search platforms. Franklin (2018) discusses potential sampling bias of only sampling from notice boards in the city center. During our pilot, we collected 150 job posts from 3 major notice boards of Addis Ababa; we also collected 2,073 job posts from a major online job search platform of Ethiopia from 2019–22. Table B2, Panel B compares the posted salary distribution between the three different samples. Our vacancy sample is able to capture more lower-paid jobs, particularly those with salary between 2,000–4,000 Ethiopian birr (ETB) per month. Notice boards and online platforms select higher-paid jobs, possibly because these firms are able to afford higher job-posting costs on these platforms.

Third, we specifically target formal firms with at least 4 employees. The median firm size in our sample is 20 employees. Such firms may have a higher labor demand that cannot be met through internal network, hence more likely to hire externally.

3.2 Intervention

During the baseline, enumerators collected basic information of sector, workforce structure, and hiring practices. We then selected one active job vacancy from each firm and collected vacancy details including minimum requirements on education and experience, job descriptions, and highest salaries that firms are willing to pay, or reservation wage. We use "firm" and "vacancy" interchangeably in the main analysis. 80% firms in our sample posted only one vacancy during the baseline survey. For those who posted more than one vacancy, we avoided collecting low-skill positions such as janitors, or positions requiring many years of experience such as executive managers.

At the end of the baseline, we implemented the following intervention. We first selected 11 employment agencies that were actively operating during the survey period and had a large labor pool. Most firms in our sample had not worked with any of the 11 employment agencies before.[12]

[12]In fact, although 25% of the sampled firms had used any external recruitment services in the past, most firms

Among firms with reservation wage at least 2,000 ETB (henceforth eligible firms), we randomly selected 326 firms into treatment group, stratified by business areas. Firms that were not willing to pay more than 2,000 ETB were not considered for the intervention.[13] To examine the extent of spillover effect, in Round 2, we randomly selected 21 business areas, and randomly assigned 75% eligible firms per business areas to the treatment; the other 20 business areas in Round 2 were not selected for the treatment.

The matching process followed three steps. First, enumerators matched each treated firm quasi-randomly with one of the 11 employment agencies.[14] Second, the employment agency was requested to select 1–2 qualified applicants within two weeks for each matched vacancy. We did not interfere with the selection process. Following conventions, we guaranteed 20% first-month salary for employment agencies on behalf of treated firms if the match was successful. No extra costs were incurred to treated firms. We thus preserved the main function of employment agencies, that is, increasing the number of job applicants, without altering monetary incentives for both employment agencies and treated firms.

Third, we deliberately prevented direct communication between the employment agencies and treated firms. We only informed the employment agencies of the job descriptions and vague locations of treated firms; as such, agencies did not know to which firms they were providing the job seekers. Once employment agencies completed the selection process, the survey team collected the résumés of the selected applicants and directly delivered to the treated firms in-person, or directly informed the selected applicants to contact the treated firms. Treated firms only knew whether the applicant was recommended from an employment agency, without knowing exactly which agency. We thus prevented any direct information exchange between firms and employment agencies, and any learning would happen only through interacting with the applicants, such as reading résumés

only hired informal or low-skill workers from informal job brokers and were not aware of the new type of employment agencies that provided educated workers. Only 8% of all firms had worked with the new type of employment agencies observed in the city administration registry. Precisely zero firm reported any of these 11 employment agencies to have been their main recruitment service provider.

[13] We implemented the 2,000 ETB threshold to ensure the cooperation with the employment agencies because some specifically mentioned they would not provide applicants for jobs with too low salary. We used the first two weeks of survey to pilot the treatment. During the pilot, we did not enforce the 2,000 ETB threshold and faced backlash from the employment agencies. As a result, the survey team decided to match some firms initially assigned to control group to the employment agencies. After the pilot, we strictly implemented the initial random assignment and the additional threshold of 2,000 ETB. In the main analysis, we include the pilot sample and use initial random assignment to obtain causal effects.

[14] During the implementation, the initial matching between firms and employment agencies was random. However, when the initially matched agency could not find some specific types of workers (e.g., coffee tasters), very occasionally, the survey team might rematch the vacancy to a different agency to increase the likelihood of finding a qualified worker. We argue that it is less important whether the matching between firms and the 11 employment agencies is strictly random for two reasons. First, all 11 employment agencies function similarly. All agencies check personal identification and educational certificates, some check previous recommendations, and none provide additional grading or training. Second, in reality, firms may consult with multiple agencies at the same time and select the best recruitment service.

or conducting interviews. The survey team did not interfere with any subsequent hiring process.

3.3 Hiring Data

We conducted two follow-up surveys for each firm. One month after the baseline (midline), enumerators visited each firm and asked for a list of all applicants for the sampled vacancy. The survey team collected as many applicants as possible. Enumerators asked firms to go through all printed résumés, applications through online platforms, and personal recommendations, and recorded information of each applicant by enumerators themselves. Our survey protocols potentially omitted some informal applications, for example, workers directly showing up and asking for jobs without any paper records, which were not the majority among applications in the formal sector.

For each applicant, we collected the firm's perception on education, experience, and how productive the applicant would be if hired. We further asked whether the applicant was invited to the interview and whether the applicant passed the interview and got an offer. For firms that successfully hired at least one worker, we recorded the negotiated salary. In addition, enumerators conducted a phone survey of up to 6 job seekers selected from the applicant list and elicited the self-reported education and experience, which will allow us to examine the accuracy of firms' perceptions in Section 5. We further collected applicants' demographics (age, gender, residential district), current employment status, and salary if employed.[15]

Five months after baseline, enumerators visited each firm again (endline). We first collected applicant details for firms that did not make the final decision at midline but had hired anyone for the sampled vacancy since then. We then collected following outcomes of the hired worker: (1) turnover (whether the worker still stayed on the job, quit voluntarily, or had been fired by the firm), (2) performance records (whether firm thought the worker was more productive compared to similar workers, and performance record from the firm), (3) effort (absent days in the last 30 days and overtime hours in the last 7 days). We further collected firms' perceptions of the average productivity of college graduates in the current labor market and future hiring plans.

We cross-validate the firm-reported and applicant-reported data in Figure A5, separately for college-educated and non-college applicants. In general, firms perceived correctly for 98% applicants whether they obtained a college diploma or degree, and 92% perceived correctly the exact level of education. Among the 683 workers who were sampled in the worker survey and hired by firms,

[15]If the firm had no more than 6 applicants, enumerators conducted phone surveys on all applicants. If the firm had more than 6 applicants, enumerators randomly picked 2 job seekers from 3 categories: (i) applicants who passed the interview, (ii) applicants who were invited to the interview but did not show up, (iii) applicants not invited to the interview. 80% applicants in our sample participated in the phone survey.

98% workers confirmed that they were indeed hired, and 96% reported the same job description. These statistics did not differ regarding college education, suggesting no systematic misreporting regarding the employment status of college-educated applicants. We do observe one difference regarding applicants' years of experience: only 75% of the college-educated applicants were correctly perceived regarding the years of experience; this statistic among the non-college applicants is 82%. We will further investigate this discrepancy in Section 5.

Figure 4, Panel A presents the number of firms that eventually received agency applicants from the intervention. Among eligible firms, 46% of the treated firms receive at least one agency applicant. Zero eligible control firms receive any agency applicant; almost none of the non-eligible firms receive any agency applicant. For those treated firms that did not receive agency applicants, many posted their vacancies during the off-season, for example, firms hiring teachers during the school year. We discuss relevant caveats to the estimation in Section 4.6 and alternative mechanisms in Section 5.3.

We then examine what types of applicants were provided by the employment agencies. We first look at whether the applicants are more likely to have a college diploma or degree. Figure 4, Panel B shows that 80% applicants recommended from employment agencies had a college diploma or degree, significantly higher than the average rate 44% observed among other applicants in our sample. Figure A6 further shows that both for firms that requested a college graduate at baseline and firms that did not, employment agencies provided high percentage of college-educated applicants. We further compare agency applicants to non-agency applicants applying to the same job in Figure A7 regarding other characteristics (experience, gender, age, family background, employment status at baseline), controlling for firm fixed effects and clustered at the firm level. Agency applicants did not look significantly different regarding any of these dimensions. This supports our qualitative observation that these employment agencies mainly provided college-educated applicants and did not screen applicants through other criteria.

4 Effect of Employment Agencies on Hiring

4.1 Specification

We use the following specification for the firm-level analysis:

$$Y_{jc} = \alpha_c + \beta T_{jc} + \delta X_{jc} + \epsilon_{jc} \tag{1}$$

T_{jc} is the initial treatment assignment of firm j in business area c. X_{jc} is a vector of baseline characteristics of firms and the posted vacancies. Y_{jc} is the outcome of interest for firm j. β is the parameter of interest, that is, the effect of being matched to an employment agency on outcome Y_{jc}. Since we stratified the treatment by business area, we include business area fixed effects α_c for all regressions to obtain within-cluster comparison. ϵ_{jc} is the idiosyncratic error clustered at the level of the business area. We only include firms with reservation wage at least 2,000 ETB (eligible firms) in the regression because non-eligible firms were not considered for the treatment implementation. Table B3 shows the balance between eligible firms initially assigned to treatment and control groups across all baseline characteristics. Given that not all firms assigned to treatment receive applicants from agency, Specification 1 obtains an intention-to-treat (ITT) estimate of the effect of receiving applicants from the employment agencies.[16]

Given that employment agencies mainly reduced search costs to find college-educated applicants, we pre-registered a heterogeneity analysis regarding firms' baseline request of college graduates with the following specification:

$$Y_{jc} = \alpha'_c + \beta_0 T_{jc} \times (C_{jc} = 0) + \beta_1 T_{jc} \times (C_{jc} = 1) + \delta' X_{jc} + \epsilon'_{jc} \tag{2}$$

C_{jc} is whether firm j in business area c requested a college graduate at baseline for the posted vacancy, which is included in the vector of baseline characteristics X_{jc}. Our main parameter of interest is β_1, the treatment effect among firms that requested a college graduate at baseline, and we will specifically look at whether firm j interviewed or hired any college graduates or non-college workers. One may worry that given the identification assumption is $\mathbb{E}[T_{jc}C_{jc}\epsilon'_{jc}] = 0$, the estimate of β_1 may not be entirely causal because C_{jc} might be correlated with other unobserved characteristics in ϵ'_{jc}. We will provide a series of robustness checks in Section 4.6 to rule out confounding factors and discuss other mechanisms in Section 5.3 that may explain some but not all the findings.

4.2 Effects on Filling Vacancy

We first confirm the treatment effect on receiving applicants from the employment agencies in Table 1. Panel A shows that on average, firms initially assigned to treatment (henceforth treated firms) received 0.37 more agency applicant five months after the intervention. The number of non-

[16] Appendix E replicates all main results using three alternative specifications. (1) Include non-eligible firms in the control group. (2) Use the initial treatment assignment T_{jc} as an instrument to the actual treatment status. This is to address the concern that the actual treatment status is not exactly equal to the initial treatment assignment during the first two weeks of piloting due to logistical constraints. (3) Exclude the pilot sample. All regressions control for all baseline characteristics listed in Table B3.

agency applicants is unaffected. Panel B shows that this increase is mainly driven by the provision of college-educated applicants. Eventually, treated firms received 0.39 more agency applicant by endline (p-value 0.019), a 35% increase compared to control firms. We also try different outcome specifications from Column 4 to 6 (whether the number of applicants was at least 1, 2, or 3), and find that our intervention mainly increased the number of college-educated applicants from one to two, not from zero to one, the pure extensive margin. Panel C further shows the treatment effect on the total number of college-educated applicants is more salient among firms that requested a college graduate at baseline, although among firms that did not request a college graduate at baseline, treated firms also received 0.11 more agency applicant on average.

Table 2 presents the first result on whether firms interviewed or hired any worker to the vacancy. Surprisingly, treated firms were only 9.43 pp. more likely to interview any agency applicants and 1.57 pp. more likely to hire any agency applicants (p-value 0.172).[17] Table B4 further shows that treated firms do not interview a larger number of applicants, a lack of intensive margin treatment effect. Regarding hiring, only seven treated firms in total hired any agency applicants, less than 5% of firms who received at least one agency applicant. Eventually, despite the 35% increase in the number of college-educated applicants, the intervention failed to encourage more firms to fill the vacancy.

This result rejects a simple hiring model where firms have accurate information of the productivity of applicants. Suppose firm j opens a vacancy for one worker and has a labor-complementary production technology. There are two types of workers in the market: Non-college educated workers with productivity following a certain distribution, and college graduates with productivity following a different distribution. We assume zero search cost for firms to find a non-college applicant, but a nonnegative search cost, $c(q)$, for firms who want to find a college-educated applicant; the search cost $c(q)$ decreases in the arrival rate q.[18] Once the search cost is paid, firm j would receive one college-educated applicant with probability q, observe their productivity perfectly, and hire the applicant with the highest productivity. Therefore, as long as firms can observe applicants' productivity perfectly, without any assumptions on the productivity distributions, this model would

[17] The control mean is not exactly zero because some firms assigned to control firms initially were also matched to the employment agencies during the pilot, as discussed in Section 3.2. Appendix E shows that the results are robust to all three alternative specifications.

[18] The search cost can be micro-founded in a simplified Diamond-Mortensen-Pissarides model. Specifically, assume the cost of opening vacancy is k. The Bellman equation of opening a vacancy is $rV = -k + q(J - V)$, where q is the match rate between firms and workers, J is the value of filled position, and V is the value of vacancy. Assuming free entry in the equilibrium and setting $V = 0$, one gets $J = k/q$. One may interpret k/q as the search cost in our model $c(q)$: Firm needs to wait $1/q$ periods to match with a worker, and each period firm needs to pay k to keep the position open. In the equilibrium, the value of filled position equals search cost, although in our simple model we do not require the equilibrium condition.

only predict a "search effect" when the arrival of college-educated applicants q increases: More firms would access the pool of college graduates, and firms who access the pool of college graduates should not decrease hiring of college graduates.

One may wonder if the experimental results reflect some confounding features of the intervention that overshadow the search effect. Table B5, Panel A presents correlational evidence where we restrict the sample to firms with at least one college-educated applicant or at least one non-college applicant. We do not find significant correlation between whether a firm interviewed or hired any college graduates and the number of college-educated applicant. If there only exists the search effect, more college-educated applicants should only increase the likelihood of hiring at least one college graduate, against the correlational evidence. Interestingly, Panel B shows that having more non-college applicants is positively correlated with whether a firm interviewed or hired any non-college applicant, suggesting that search effect is dominant when conducting hiring decisions regarding non-college workers. In addition, recent evidence from other works also suggests that simply lowering search costs for firms does not necessarily lead to more successful matches (Fernando et al., 2023; Abebe et al., 2024; Hensel et al., 2024). We thus believe that lower search costs to find college-educated applicants may affect firms' hiring outcomes through a different channel.

4.3 Belief Update

We now estimate whether our intervention induced a negative update belief about the productivity of college graduates, leveraging the detailed records of firms' perceptions on applicants. For each firm, we compute the percentage of college-educated applicants considered with good productivity.[19] Table 3, Column 1 shows that on average, this statistic is 24.9 pp. lower in treated firms compared to control firms (p-value 0.038, 32% decrease). One way to interpret this result is that firms perceived 32% less applicants with good productivity after the intervention. In Column 2, we calculate the same productivity measure for non-college applicants and do not such a treatment effect, suggesting that the belief update is specific to college-educated applicants.

One may worry that this statistic only exists in firms that had at least one college-educated applicant. Since the intervention increased the number of college-educated applicants by 35%, firms who would not have had any college-educated applicants were also selected into the estimation. To address this concern, first, in Table 3, Column 3, we interact the treatment status with whether or not firms received at least one college-educated non-agency applicant and control for the number

[19] For each applicant, we asked the employer, "How productive do you think this applicant would be if hired on the job, very productive, somewhat productive, somewhat not productive, not productive at all?" In the main analysis, an applicant is considered productive if the employer answers "very productive" or "somewhat productive". We only elicited this perception in Round 2.

of college-educated non-agency applicants. We find that among firms with at least one college-educated non-agency applicant, treated firms still decreased their perception of college graduates' productivity by 21.1 pp. (p-value 0.040).[20] Second, in the endline survey, we asked all firms whether they think college graduates are more productive compared to non-college educated workers in general. Column 4 shows that treated firms are 8.67 pp. less likely to consider college graduates as more productive in general (p-value 0.051, 11% decrease); this statistic is not subject to the selection bias discussed above. Column 6 further shows the treatment effect is stronger for firms with at least one college-educated non-agency applicant. We further employ Equation 2 to look at heterogeneous treatment effect regarding baseline request for college graduates. Interestingly, Column 5 and 7 show a lack of heterogeneity. This is consistent with the fact that treated firms that did not request a college at baseline also received more agency applicants who tend to have a college diploma or degree, thus undergoing a similar belief update process.

Our evidence thus suggests that treated firms became less optimistic about college graduates' productivity. Guided by the simple model, some treated firms might have a different hiring preference and hire different types of workers to the vacancy. We now formally test this prediction.

4.4 Shift in Hiring Behavior

Table 4, Panel A presents the treatment effects on whether firms interviewed or hired any college graduates in general. Among firms that requested a college graduate at baseline, treated firms were 11.7 pp. (p-value 0.098, 19% decrease) or 19.7 pp. (p-value 0.012, 34% decrease) less likely to interview or hire any college graduates; instead, they were 11.3 pp. (p-value 0.050, 86% increase) and 8.8 pp. (p-value 0.106, 80% increase) more likely to interview or hire any noncollege workers, despite the general increase in the number of college-educated applicants. The differences between these two sets of estimates are significant (p-value 0.028 and 0.008), suggesting a significant shift away from interviewing and hiring any college graduates. Panel B focuses on whether firms interviewed or hired any college graduates that were not recommended from the employment agencies and presents similar patterns, suggesting this shift in hiring behavior is not simply driven by firms not interviewing or hiring agency applicant.

Table B6 examines whether the heterogeneous treatment effect regarding baseline request for college graduates can be explained by other firm or vacancy characteristics listed in Table B3.

[20] Compared to control firms with at least one college-educated non-agency applicant, treated firms with zero college-educated non-agency applicant had a much lower belief of college graduates' productivity, possibly because the one negative signal from college applicant would have a higher impact on the belief update process of these firms. Also, although suggestive, the coefficient before the number of college-educated non-agency applicants is negative, also consistent with the direction of learning.

Column 1 and 3 control for the interaction of treatment and all other baseline characteristics; Column 2 and 4 project the baseline request for college graduates on all other baseline characteristics and replace the intermediate variable with the residual. The treatment effects on hiring a college graduate remains significant with larger magnitude, suggesting the decrease in the hiring of college graduates cannot be explained by, at the very least, all other observable characteristics. The treatment effects on hiring a non-college worker are not significant in one of the specifications, but the magnitudes remain similar.

Leveraging the timing of the intervention, we further provide evidence on the dynamics of the treatment effects. All agency applicants were delivered to firms before we conducted midline, but some firms continued to receive applicants afterwards and made hiring decisions between midline and endline. Table B7 shows that treatment effects were already salient by midline: Among firms that requested a college graduate at baseline, treated firms were 12.2 pp. (p-value 0.057, 31% decrease) less likely to hire any college graduates by midline, and 10.0 pp. (p-value 0.050, 120% increase) more likely to hire any non-college workers by midline. After midline, the treatment effect on hiring any college graduates decreases from -12.2 pp. to -19.7 pp., yet the treatment effect on hiring any non-college workers stays around the same magnitude. This potentially reflects (i) that it takes longer for firms to find a college-educated applicant, further confirming higher search costs between firms and college graduates, and (ii) that when firms deemed college graduates to be less productive, the shift from hiring a college graduate to a non-college worker happened in a short amount of time. For other firms, although they perceived college graduates to be more productive compared to non-college workers, they still became less optimistic about the absolute level of college graduates' productivity and decided to either keep waiting for better applicants or stop hiring anyone. We further find suggestive evidence that this treatment effect may not be a one-off phenomenon. At the endline, we asked each firm whether they planned to post more jobs in the next three months. Column 7 shows that among firms that requested a college graduate at baseline, treated firms were 12.4 pp. less likely (p-value 0.088, 19% decrease) to plan to post any job in the next three months. Our results thus present a significant, and potentially persisting, change in the hiring behavior, particularly among firms that requested a college graduate at baseline.

4.5 Explaining the Shift in the Hiring Behavior with Learning

If firms update their beliefs after receiving one signal from college-educated applicants, firms with less exposure to college graduates in the past would experience a more significant belief update, hence larger treatment effects on hiring outcomes. We use the percentage of current employees with a college diploma or degree, or college share, as the main proxy for exposure to college graduates.

One standard deviation increase in baseline college share is correlated with 56% increase in the likelihood of firms requesting a college graduate, with 16% explanatory power. In contrast, one standard deviation increase in the number of current employees is only associated with 15% increase in the likelihood of requesting a college graduate, with 1.3% explanatory power. Figure A8, Panel A shows the distribution of college share across firms.

We first verify that lower college share is correlated with a more significant update on the beliefs of college graduates' productivity. Table B8 examines the heterogeneous treatment effects on the two direct measures of beliefs. At first sight, it seems that both treated firms with above-median and below-median college share experienced a similar level of belief update. We then conduct a robustness check by residualizing whether the college share is above median on all baseline characteristics. Among below-median firms, the treatment effects on beliefs remain significantly negative; among above-median firms, however, the treatment effects become insignificant, possibly because the effects are absorbed by other types of treatment heterogeneity. Although suggestive, the evidence is consistent with the hypothesis that firms with less exposure to college graduates experience a more significant level of belief update.

We now examine the heterogeneous effects on hiring outcomes in Table 5. Among firms that requested a college graduate at baseline, treated firms with below-median college share were 22.1 pp. less likely to interview (p-values 0.086) and 27.8 pp. less likely to hire a college graduate (p-value 0.047), 16.9 pp. more likely to interview (p-value 0.061) and 14.9 pp. more likely to hire a non-college worker (p-value 0.079); the differences between the two sets of estimates are significant (p-values 0.047 and 0.038). No significant treatment effects are found among firms with above-median college share. Figure A9 presents the binscatter plots between the college share and the percentage of firms hiring at least one college graduate or non-college worker, and further shows the treatment effect grows larger as the college share decreases, suggesting our results in Table 5 are not driven by the artificial cutoff of the college share.

We also attempt to impute the number of past interactions with college graduates of each firm in the following way. We first calculate the number of years since the firm was established, multiply it by the number of vacancies posted in the last 12 months (this data only exists in Round 1), assume each vacancy hires one person, and then multiply it by the college share. We then add this number to the number of current employees with a college diploma or degree. Figure A8, Panel B presents the truncated distribution of the imputed number of past interactions. Table B9, Panel B replicates Table 5 with the imputed number of past interactions and finds similar patterns. Thus, despite the noisy estimates on direct measures of beliefs, the treatment heterogeneity on eventual hiring outcomes suggests that learning can explain the shift in hiring behavior.

4.6 Robustness

We further examine the robustness of the main treatment effects in Section 4.4 in the following five ways. First, we examine the robustness of statistical inference in Table B10. Panel A examines the effect on hiring a college graduate. Column 2 does not cluster the standard errors at the level of business area. The standard errors are slightly smaller than the main estimate, which suggests positive correlations within cluster but does not affect the significance. Concerned about statistical inference from a small number of clusters, we use bootstrapping to compute clustered standard errors in Column 3 and conduct a permutation test in Column 4. Standard errors do not vary much. Concerned with the efficiency of the estimates due to heteroskedasticity, in Column 5, we weight the observations with the inverse of the total number of applicants because vacancies with more applicants may conduct interview or hiring decisions faster. To avoid the potential bias induced by the correlation of treatment status and the number of applicants, Column 6 weights the observations with the inverse of the total number of non-agency applicants. Results from both weighting methods remain similar. Panel B examines the effect on hiring a non-college worker with the same specifications; the effect becomes not significant in most specifications. Combined with the first robustness check, this implies that the treatment effect on hiring a non-college worker may not be robustly significant on average, potentially masked by other heterogeneity. For the following discussions, we will mainly focus on the treatment effect on hiring a college graduate.

Second, we examine whether attrition of firms affects the main results systematically. Table B11, Column 1 regresses attrition of firms on the treatment status and finds that treated firms did not have a significantly higher attrition rate on average. In Column 2, we predict attrition likelihood from the entire set of baseline characteristics, and control for the interaction of treatment status and whether the attrition likelihood is above average. The treatment effect on hiring a college graduate remains significantly negative among firms with low attrition likelihood. In addition, we conduct sensitivity analysis in two hypothetical scenarios where no attrited firms hired any college graduate or all attrited firms hired at least one college graduate. The extreme estimates are about only 1–2 percentage points away from the main estimates, suggesting very limited influence of attrition.

Third, we examine whether the main results can be explained by the strategic matching behavior of employment agencies. From qualitative interviews, employment agencies expressed their preferences for higher-paid jobs from which they might get a higher commission fee. We first compare the reduced-form effects of receiving agency applicants to the IV estimates using initial treatment assignment as an instrumental variable; the difference between the two estimates implies the direction of the selection bias. Table B12, Column 1 presents the reduced-form estimates. Among firms that requested a college graduate at baseline, firms receiving agency applicants were 14.8 pp. less likely to hire any college graduate (p-value 0.050), although with a smaller magnitude. Column 2 presents the IV estimate and replicates a significant causal effect of receiving agency applicants. We follow Hausman's test (Hausman, 1978) and confirm the two estimates are different at 10% significant level. This suggests a *positive* selection bias: employment agencies might target firms that were *more* likely to hire a college graduate, not the opposite. In Column 3, we examine whether treatment effect is different for firms with above-average reservation wage. We find negative, although insignificant, heterogeneous treatment effects regarding reservation wage, confirming that the potential strategic matching regarding salary does not drive the main results. We conduct another exercise where we predict the likelihood of receiving applicants from the employment agencies using all baseline characteristics, and examine the treatment effects on firms with below-average likelihood. Column 4 does not find any such heterogeneity at a significant level.

Fourth, we examine whether demand effect explains the main hiring patterns. It is likely that in response to the intervention, treated firms might provide one out of several vacancies that might have a lower chance of hiring a college graduate. Table B13, Column 1 does not show any significant heterogeneous treatment effect regarding whether firms posted more than one vacancy. Another possibility is that treated firms might hope to engage less with the survey team to decrease hassle from employment agencies. From the discussion with the survey team, when the respondent was the owner of the firm, this situation was more likely to happen due to less time availability. Column 2 shows that treatment effect diminishes among firms where respondents were the owners, suggesting that if anything, firms that wished to engage less did not hire fewer college graduates.

Fifth, the interpretation of main result might differ if there is a spillover effect to non-treated firms. To examine potential within-cluster spillover, we leverage the clustered treatment design in Round 2. Table B14, Column 1 examines whether non-treated firms (including non-eligible firms) in intensely treated areas were affected by the treatment, controlling for local district fixed effects. We find no such spillover on non-treated firms. Column 2 shows that the treatment effect does not differ significantly in intensely treated areas. We further look at whether the spillover effect extended beyond clusters. Within each business area, firms in different locations might be subject to different levels of spillover from outside of the cluster. Using the geo-coordinates of firms, we compute the percentage of treated firms within a given radius, excluding firms in the same business area. Column 3 examines whether the treatment effect is stronger among firms with above-average beyond-cluster treatment intensity within 500 meters; we do not find supportive evidence of such spillover. Figure A10 further varies the length of radius and replicates this exercise. We do not find heterogeneous treatment effects in any specification.

5 What Triggers Learning?

We now investigate what potentially induced the learning mechanism. We first show that unqualified applicants can only partially explain the shift in hiring behavior. We then show evidence of noisy productivity signals from applicants, which cannot be mitigated by the use of résumés.

5.1 Applicants' Qualification

One may suspect that although employment agencies provided mostly college-educated applicants, they might not be qualified for the vacancy with respect to other dimensions. Indeed, when we conducted qualitative interviews with some treated firms at the endline, the main reason they did not interview or hire applicants recommended by the agencies is the lack of experience. We now formally examine whether college-educated applicants were less qualified for the vacancy, with a particular focus on past experiences because most firms mentioned experience as one of their most important hiring criteria. For each applicant, we define a qualified applicant if their years of experience meet the minimum requirement of experience set by the firm at baseline. For a subset of applicants, we are able to observe their oral description of past experiences, which we compare to the description of the posted vacancy and determine whether their experiences were a match to the vacancy. In Figure 5, we use blue hollow bars to show the percentages of qualified applicants separately for college-educated and non-college applicants. Panel A uses the first indicator of qualification. On average, 78% of all non-college applicants and 70% of all college-educated applicants meet the experience requirement. Table B15 shows that this negative difference disappears once we control for other applicants' characteristics and whether the experiences were a match to the vacancy. College-educated applicants from employment agencies were slightly less likely to be qualified, but the differences are not robustly significant using various specifications in Table B15.

We now examine to what extent unqualified applicants from employment agencies can explain the belief update and the shift in hiring behavior. A simple heterogeneity test with respect to whether firm received an unqualified agency applicant would be problematic because this itself is an outcome of the intervention. To address this concern, we leverage firms' baseline requirement for applicants' years of experience. Figure A11 shows a negative correlation between baseline experience requirement and the percentage of agency applicants with qualified experience. Specifically, firms that required less than one year of experience saw a significantly higher percentage of qualified applicants from the agencies. Thus, in Table 6, we choose one year as the threshold and examine the treatment heterogeneity regarding whether firm required less than one year of experience. Among firms that requested a college graduate at baseline, although we find suggestive evidence of a shift in hiring behavior for firms with high experience requirement, the estimates are not statistically significant at conventional levels. Instead, for firms with low experience requirement and thus less concerned about applicants' qualification, we find a significant and consistent shift in the hiring behavior. Table B16 shows that this result cannot be explained by treatment heterogeneity through all other baseline characteristics. We thus do not find conclusive evidence that applicant qualification in experience alone cannot explain the shift in hiring behavior.

We acknowledge that firms may also pick up signals of other attributes of college graduates before the interviewing stage that are not captured by years of experience (e.g. trustworthiness). To explain why firms did not have the same perceptions of these attributes as before, one may need to assume that college graduates nowadays were different from those in the past with whom firms interacted, which we are not able to provide evidence for in this setting. However, in the next subsection, we show a discrepancy between applicants' true qualifications and firms' perceptions of their qualifications with respect to experience, which provides a new explanation for belief update without assuming an inherent change in college graduates' attributes.

5.2 Noisy Signaling from Applicants

Using our detailed records of firms' perceptions of each applicant, we now examine whether applicants with qualified experience were actually considered qualified by firms. In Figure 5, we use blue areas to show the percentage of applicants whose *perceived* years of experience meet the minimum requirement. Interestingly, only 53% non-college applicants and 47% college-educated applicants were perceived to be qualified by firms. Among all the qualified applicants, 33% were considered to have insufficient years of experience compared to the minimum requirement. Table B17, Columns 1–3 further show that college-educated applicants were significantly less likely to be considered qualified after controlling for years of experience, other baseline applicants' demographics (e.g. working age), and whether applicants' past experience was a good match for the job description. Agency applicants were not perceived to be significantly less qualified than non-agency college-educated applicants. Evidence above suggests that applicants, especially college-educated, might have sent a noisy signal of their experience to firms. Table B17, Column 5 shows a positive correlation between whether an applicant is perceived to be qualified and whether an applicant is perceived to be productive, after controlling for actual years of experience and other applicants' demographics, suggesting that the negative noisy signal could translate into negative perception of productivity.

Where did this noisy signal originate? We provide one possible explanation: College-educated applicants did not effectively signal their experience through résumés. From our own observations, many résumés from the agency applicants were disorganized and did not highlight their past experiences or provide references. Existing literature has also documented that some college graduates in low- and middle-income countries do not know how to write a good résumé (Carranza et al., 2023; Abebe et al., 2021). Although we were not allowed to collect résumés from applicants and conduct more thorough text analysis during the survey, when elicited perceptions on applicants, many firms simply referred to the applicants' résumés about their education and experience. Our research design also did not allow much room for firms to obtain additional information from applicants except through their résumés or conducting interviews.

We further provide descriptive evidence from our data to support this explanation. Figure 6, Panel A shows that unlike non-college applicants, more than 80% college-educated applicants sent in their résumés when applying for the vacancies. This statistic is 93% for college-educated applicants recommended from the employment agencies. Yet, Panel B shows that college-educated applicants who sent in their résumés were not significantly more likely to be considered qualified with respect to their experience. In fact, Table B18, Column 1–3 show that compared to non-college applicants without résumés across all firms, college-educated applicants with résumés might be even more likely to be considered unqualified. Although suggestive at best, our descriptive evidence shows that college-educated applicants' résumés did not mitigate, if not exacerbate, the noisy signal of their experience, which potentially allows a negative belief about the productivity of college-educated applicants to emerge.

Can firms mitigate the noisy signals of productivity? Our evidence suggests that firms may be constrained to conduct more screening. Recall that in Table B4, treated firms were less likely to interview all non-agency applicants despite interviewing more agency applicants, suggesting that cost of screening may prohibit firms from obtaining more accurate information from applicants.

With the evidence above, we thus provide a likely explanation of firms' belief update as a consequence of noisy productivity signals from college graduates. To generate a negative belief update on average, one may need to assume that firms who requested a college graduate at baseline tended to be over-optimistic. Some existing evidence, such as Abebe et al. (2024), suggests that firms in low-income countries were in fact over-optimistic about the productivity of college graduates. In Section 6, we will use a search model to describe how noisy productivity signals can lead to an equilibrium characterized with over-optimism among firms who post a job for college graduates.

5.3 Alternative Mechanisms

Our evidence above does not exclude other potential learning mechanisms. Here, we discuss whether other mechanisms may explain some of the empirical results.

First, we discuss whether firms updated their beliefs about college graduates' outside options from the intervention. In this hypothesis, by interviewing more college-educated applicants, firms may have realized that college graduates have better outside options and have chosen not to hire them. We provide direct evidence by eliciting firms' perceptions of workers' outside options. Table B19 shows that treated firms became less likely to perceive college-educated applicants with many outside options; no treatment effect is found on whether firms were more likely to agree that college graduates have more outside options. Also, given that treated firms were also less likely to interview college-educated applicants, it is unclear through what channels firms could pick up signals about applicants' reservation wage before interviewing. In addition, we do not find that college graduates were more likely to reject the offers than non-college workers. We observe whether each applicant rejected an interview invite or an offer to test this hypothesis; Table B20 shows that on average, only 2.0% applicants rejected the interview invitation, 2.3% rejected the offer. In summary, it is unlikely that firms stopped hiring college graduates because they perceived college graduates to have more outside options or more likely to reject the offer.[21]

Second, we discuss whether firms updated their beliefs about the search costs of finding college-educated applicants from the intervention. In this hypothesis, when employment agencies were unable to find a match, firms could interpret it as high search costs to find college graduates and stop the search earlier. Table B12 shows that among firms with high reservation wage and with higher likelihood of receiving an agency applicant, we observe similar decrease in the hiring of college graduates. Another possibility is that firms may update their beliefs about the marginal benefit of finding one more college-educated applicant. Suppose firms chose to stop searching when the marginal benefit of having one more applicant was equal to the marginal cost. When employment agencies provided more college-educated applicants to treated firms, the marginal benefit of having one more applicant decreased, thus leading to an earlier stop in the hiring process. This hypothesis can explain why treated firms hired faster, but it cannot explain why treated firms were less likely to hire college graduates especially when they received more college-educated applicants. In summary, it is unlikely that firms stopped hiring college graduates because they perceived higher search costs

[21] Our findings are not inherently against the recent empirical evidence of the high reservation wages of college graduates (Banerjee and Chiplunkar, 2022; Kelley et al., 2022; Alfonsi et al., 2023). The college graduates we observe in the sample, either through firms' own hiring channels or through employment agencies, were potentially already selected to be more willing to take up the jobs in our sample.

or lower marginal benefit of finding college-educated applicants.

Third, we discuss whether firms decrease the hiring of college graduates irrationally. One scenario is a version of "rationalized" irrationality: Because making an optimal hiring decision was costly, our intervention may provide a kind of employment insurance for firms such that they can resort to agencies in the future to find a replacement for the current position. To test this hypothesis, we asked firms at endline what channels they planned to use for hiring in the future. Table B21 shows that among firms that requested a college graduate at baseline, treated firms did not plan to use employment agencies more in the future, suggesting the limitation of "rationalized" irrationality in our setting. However, we remain agnostic about other types of irrationality during the firm hiring process that may potentially contribute to the large decrease in the hiring of college graduates.

Finally, we provide suggestive evidence that firms could also update their beliefs about applicants from external pool, but this only applies to college-educated applicants. Almost all agency applicants were outside of the firms' internal hiring networks. Table B22 first shows that treated firms were less optimistic of the productivity of external applicants in general; no effects were found for the internal recommended applicants. However, the decrease in belief only exists among college-educated applicants, not in non-college ones. In addition, we examine the treatment heterogeneity with respect to whether firms used referral hiring at baseline. On average, there is no detected treatment heterogeneity, but among firms who requested a college graduate and did not plan to use referral at baseline, we observe a 16.3 pp. decrease in using non-referral hiring channel (p-value 0.057) and 16.5 pp. increase in using referral hiring (p-value 0.038), suggesting that the shift in referral hiring is confined to firms that requested a college graduate at baseline. These results potentially help rationalize the magnitudes of our empirical findings: some firms may have had some previous interactions with college graduates, but because of the high search frictions, they met these college graduates mostly through their internal networks, and thus they were not familiar with average college graduates from the external applicant pool. Receiving a college-educated applicant from an external pool may induce a large learning effect despite some limited interactions with college graduates in the past through internal network.[22]

[22] In addition, an established literature discusses the informational advantages of referral hiring (Swanson, 2024; Heath, 2018; Beaman and Magruder, 2012). When firms became less optimistic about the productivity of external college graduates, they may also become more dependent on informal channels to obtain more accurate information from applicants. Table B21 shows that treated firms were less likely to plan to use formal channels to post jobs in the future, suggesting that the shift to referral hiring is potentially persisting.

6 Equilibrium Search Model with Imperfect Information

So far, we show empirical evidence of a negative learning effect, potentially triggered by noisy productivity signals from college-educated applicants. However, there are two remaining questions: (i) Why did some firms have a more optimistic belief of college graduates when search costs are high? (ii) What were the efficiency implications of such learning induced by lowering search costs? In particular, if firms were over-optimistic about college graduates at baseline, they might have waited too long for a college-educated applicant instead of providing jobs to non-college graduates, and the negative learning effect observed in our empirical findings may actually have positive implications on efficiency. In the following, we outline a sketch for an equilibrium search model following Pissarides (2000) and Acemoglu (2001) with two types of firms and two types of workers to guide our discussion of matching efficiency.

6.1 Theoretical framework

Suppose there are two types of workers in the labor market: (1) Non-college workers (subscript n) with worker-specific productivity $\mu_n = 1$ and mass one, and (2) college graduates (subscript c) with worker-specific productivity $\mu_c = \mu > 1$ and mass one. On the other side, there are two types of firms: (1) Low-type firms (subscript l) with firm-specific productivity $\zeta_l = 1$ and mass one, and (2) high-type firms (subscript h) with firm-specific productivity $\zeta_h = \zeta > 1$ and mass one. Assume each firm hires one unit of worker and has a labor-complementary production function to produce an intermediate good $Y_{j,i} = \mu_i \zeta_j, i = n, c$. Low-type firms and high-type firms produce different types of products, and hiring a college graduate would increase production. With super-modularity, the social optimum would be achieved if low-type firms only hire non-college workers and high-skill firms only hire college graduates.

Vacancy posting and matching. Suppose firms live infinitely. In each period, if firm j does not have a worker currently, firm j would pay k to post a vacancy to either non-college workers or college graduates. In each period t, the mass of type-j firms posting a type-i job is $v_{j,i}$; denote $E_{j,i}$ as the mass of type-j firms currently hiring a type-i worker.

Workers and vacancies are randomly matched in essentially two separate labor markets. Define the mass of unemployed workers as u_i, and market tightness $\theta_i = u_i/(v_{hi} + v_{li})$. For each type of vacancy, the likelihood of a vacancy receiving any worker q_i is an increasing function of market tightness θ_i and an increasing function of matching technology a_i: $q_i = q(\theta_i, a_i)$. The matching technology parameter a_i captures search costs holding market tightness constant; search costs are higher when a_i is smaller. The likelihood of a type-i worker matched with any vacancy is $\theta_i q_i$.

Noisy productivity signals. Suppose firms do not have perfect information of college graduates' productivity μ. In each period T, denote firm j's belief of μ as $\mu_j^T = \Xi(S_j^T)$, which can be characterized by the cumulative information set over the last T periods S_j^T. The information set consists of all imperfect observations of college graduates' productivity in the past $S_j^T = \{y_t\}_{t \leq T}$, where $y = \mu + e$ is a noisy observation of college graduates' underlying productivity μ; assume the noise follows a normal distribution $N(0, \sigma_e^2)$. Given a certain level of belief $\mu_j^T = x$, firms perceive the productivity signal distribution to follow a normal distribution $N(x, \sigma_e^2)$; denote the probability density function as f_x, cumulative density function F_x.

We model firm j to perform a Bayesian update on the productivity of college graduates based on the information set S_j^T, assuming the prior for college graduates' productivity follows a normal distribution $h(\cdot) = N(\mu_0, \sigma_h^2)$; we further assume that there is no inherent bias in firms' prior distribution, that is, $\mu_0 = \mu$. Firm j's belief μ_j^T can be described as follows:

$$\mu_j^T = \frac{\int x \Pi_{y \in S_j^T} f_x(y) h(x) dx}{\int \Pi_{y \in S_j^T} f_x(y) h(x) dx} \tag{3}$$

Because we simplify the model so that college graduates inherently are homogeneous, any observed productivity signal is purely driven by noise, and thus according to Bayes' rule, firms would simply update their prior μ_j^T based on any new signals obtained in the new period and make their hiring decisions based on the new prior. Note that if firms do not post a college job, they will not receive a new signal, and thus will not update their beliefs. Denote the distribution of type-j firms' belief in each period T as $G_j^T(\mu')$.

Equilibrium conditions. For type-j firms with a college vacancy with prior μ', denote $V_{j,i}^T$ as the value function of posting a type-i job in period T, $J_{j,i}^T$ as the value function of hiring a type-i worker. Firms pay w_i^T for type-i workers. Workers on the job will exogenously separate from the match with probability δ; r is the discount rate. We can write Bellman equations as follows:

$$rV_{j,c}^T(\mu') = -k + q(\theta_c^T, a_c)(J_{j,c}^T(\mu') - V_{j,c}^T(\mu')) \tag{4}$$

$$rJ_{j,c}^T(\mu') = \mu'\zeta_j - w_c^T + \delta(V_{j,c}^T(\mu') - J_{j,c}^T(\mu')) \tag{5}$$

$$rV_{j,n}^T = -k + q(\theta_n^T, a_n)(J_{j,n}^T - V_{j,n}^T) \tag{6}$$

$$rJ_{j,n}^T = \zeta_j - w_n^T + \delta(V_{j,n}^T - J_{j,n}^T) \tag{7}$$

For type-i workers, denote U_i^T as the value of unemployment in period T, and W_i^T as the value of employment. Unemployed workers receive a benefit b. Bellman equations for workers are:

$$rU_i^T = b + \theta_i^T q(\theta_i^T, a_i)(W_i^T - U_i^T) \tag{8}$$

$$rW_i^T = w_i^T + \delta(U_i^T - W_i^T) \tag{9}$$

Because of Bayesian update, $G_j^T(\mu')$ has full support of $\mathbb{R}$. Thus, for type-j firms, there exists a value M_j^T such that firms would be indifferent between posting a college and a non-college vacancy:

$$V_{j,c}^T(M_j^T) = V_{j,n}^T \tag{10}$$

The proportion of type-j firms posting college jobs is thus:

$$\frac{v_{j,c}^T}{v_{j,c}^T + v_{j,n}^T} = \int_{M_j^T} dG_j^T(\mu') \tag{11}$$

Suppose after the matching, workers and firms engage in Nash bargaining. Workers may face firms with various beliefs and thus with different wage offers:

$$\begin{aligned} \frac{1-\beta}{\beta}(W_c^T - U_c^T) = &\frac{v_{l,c}^T}{v_{l,c}^T + v_{h,c}^T} \int_{M_l^T} [J_{l,c}^T(\mu') - V_{l,c}^T(\mu')] dG_l^T(\mu') \\ &+ \frac{v_{h,c}^T}{v_{l,c}^T + v_{h,c}^T} \int_{M_h^T} [J_{h,c}^T(\mu') - V_{h,c}^T(\mu')] dG_h^T(\mu') \end{aligned} \tag{12}$$

$$\frac{1-\beta}{\beta}(W_n^T - U_n^T) = \frac{v_{l,n}^T}{v_{l,n}^T + v_{h,n}^T}(J_{l,n}^T - V_{l,n}^T) + \frac{v_{h,n}^T}{v_{l,n}^T + v_{h,n}^T}(J_{h,n}^T - V_{h,n}^T) \tag{13}$$

In a stable equilibrium, the in-flow and the out-flow of unemployed workers equals each other:

$$\delta(1 - u_i^T) = \theta_i^T q(\theta_i^T, a_i) u_i^T \tag{14}$$

For market clearing, assuming for the currently employed workers, the proportion of workers working in high-type (low-type) firms equals the proportion of college vacancies opened among high-type (low-type) firms:

$$\frac{v_{j,i}}{v_{j,i} + v_{j,-i}} = \frac{E_{j,i}}{E_{j,i} + E_{j,-i}} \tag{15}$$

Finally, we impose some structure on the distribution $G_j^T(\mu')$. Suppose in the first period, all firms have the correct belief $\mu_j^0 = \mu$ and would enter the pool of college graduates. Appendix D shows that the belief level of the marginal firms M_j^T increases over time. Thus, for each new period T, firms with prior beliefs $\mu_j^{T-1} < M_j^{T-1}$ would not post a college job. For the rest of the firms, some would encounter a college graduate with probability $q(\theta_c^T, a_c)$, develop a pessimistic posterior $\mu_j^T < M_j^T$ and decide not to post a college job eventually. To derive a tractable equation, we use the fact that the Bayesian update equation can be numerically approximated by a simple average of all productivity signals as the number of signals increases. Therefore, the distribution $G_j^T(\cdot)$ can be written as an iterative function:

$$dG_j^T(x) = \begin{cases} dG_j^{T-1}(x) + q(\theta_c^T, a_c) \int_{M_j^{T-1}} f_0(Tx - (T-1)\mu')dG_j^{T-1}(\mu'), & \text{if } x < M_j^{T-1} \\ (1 - q(\theta_c^T, a_c))dG_j^{T-1}(x) + q(\theta_c^T, a_c) \int_{M_j^{T-1}} f_0(Tx - (T-1)\mu')dG_j^{T-1}(\mu'), & \text{if } x \geq M_j^{T-1} \end{cases} \tag{16}$$

Appendix D provides the proof for the existence of a unique equilibrium.

Theorem 6.1. *For each period T, there exists a unique equilibrium characterized by the vector $\Omega^T = \{V_{j,c}^k(M_j^k), V_{j,n}^k, J_{j,c}^k(M_j^k), J_{j,n}^k, M_j^k, U_c^k, U_n^k, W_c^k, W_n^k, w_c^k, w_n^k, u_c^k, u_n^k, v_{j,c}^k, v_{j,n}^k\}_{j=h,l}^{k\leq T}$ determined by Equations 4 - 16.*

6.2 Characterization of the Equilibrium

We discuss three features of the equilibrium with imperfect information. First, there exists a sorting of firms with respect to priors. Only firms with sufficiently optimistic priors would post a college job in each period; on average, firms that post a college job are over-optimistic of college graduates. This is aligned with the evidence from Abebe et al. (2024), where they find firms in low-income countries overestimated how college graduates perform in a cognitive test. However, firms with sufficiently pessimistic priors would not post a college job for any future periods. In fact, one may observe the following:

$$G_j^T(M_j^T) = G_j^{T-1}(M_j^{T-1}) + \int_{M_j^{T-1}} F_\mu(TM_j^T - (T-1)\mu')dG_j^{T-1}(\mu') > G_j^{T-1}(M_j^{T-1})$$

That is, the number of firms that become less optimistic of college graduates increases over time. This is because in every period, a proportion of firms would receive a bad draw from the distribution and overcorrect their beliefs about college graduates' productivity. These firms will never again post a college job because their beliefs will be less than any future belief threshold. This is essentially the same insight as in Lepage (2024).

Second, the number of high-type jobs for college graduates is less than the social optimum. When $T < \infty$, there exists a proportion of low-type firms with overly optimistic beliefs that would post a college job. College graduates would be potentially matched with a lower-paid job, the value of employment decreases, and the unemployment rate among college graduates increases. Such a high unemployment rate can be sustained because enough high-skill firms were pessimistic about college graduates' productivity and did not post a college job even if it is easier for firms to match with an unemployed college graduate. When T approaches infinity, under certain conditions, no low-type firms would post jobs to college graduates, but some high-skill firms would only post jobs to non-college workers because of overly pessimistic beliefs about college graduates' productivity. Thus, imperfect information induces an inefficiently low provision of high-skill jobs to college graduates and a high unemployment rate among college graduates, which cannot be fully corrected over time through learning.

Third, improving matching technology for college graduates has an ambiguous effect on college unemployment and an ambiguous implication on efficiency in the short run. On one hand, improving matching technology increases the chance of firms being matched with and hiring a college graduate. On the other hand, some of these firms would get a bad draw from the distribution, become overly pessimistic, and decide to hire a non-college worker instead; the efficiency implications are different for high-type firms and low-type firms. In the early stage, when there are more optimistic firms in the market, there can be potentially more overly optimistic firms being overcorrected and stop hiring college graduates, potentially overshadowing the positive impact of an improving matching technology and generate an increase in college unemployment.

6.3 Empirical Implications

The equilibrium model above provides an ambiguous prediction for firms' profit in our empirical setting. On one hand, treated firms may suffer from productivity losses because they hire less-productive non-college workers. On the other hand, firms may pay less salary if college graduates are paid higher in the labor market. We attempt a cost-benefit analysis in Table B23 by examining the treatment effects on salary (truncated at the 95% percentile), turnover (whether the new hires quit the job voluntarily, whether firms fired the new hires), productivity (whether the hired workers were perceived with above-average productivity, whether the hired workers had higher performance record than average workers on the similar positions), and effort (whether the new hires had zero days of absence in the last 30 days, whether the new hires work overtime in the last seven days). Panel A shows no significant treatment effects among firms that requested a college graduate on salary or any indicators of match quality. However, given that our intervention has an extensive margin effect on hiring, the treated sample and the control sample may not be balanced. Panel B conducts a simple complier analysis using the technique from Abadie (2003), where the endogenous variables are whether firms hired a college graduate or a non-college worker, instrumented by the interaction of the initial treatment assignment and whether firms request a college graduate at baseline. Among compliers who would have hired a college graduate absent the treatment, firms paid much lower salary for non-college workers while no significant differences are detected in any measure of turnover, productivity, or effort. Although suggestive at best, we do not find evidence indicating a decrease in firm profit.

Our model further suggests different efficiency implications for high-type and low-type firms. To categorize firms with different types, we resort to the task description of each vacancy in our sample. For example, a local car dealership was hiring a receptionist and required applicants to have a Bachelor degree. A local garment company was hiring a tailor with a minimum requirement of college diploma and initially only agreed to pay up to 2,000 ETB per month (about 40 USD, the median monthly salary in our sample is 3,000 ETB). In fact, 39% of the jobs that requested a college graduate involved mostly routine tasks, 29% involved manual tasks, 29% did not require more than two years of previous experience, and 9% did not have specific skill requirement. We thus construct the skill index based on these four indicators, and examine the treatment heterogeneity regarding skill index in Table 7. Among firms that requested a college graduate at baseline, we observe a larger decrease in the belief of college graduates' productivity and a more salient shift in hiring behavior among treated firms with lower skill index. Given that low-type firms benefit less from hiring a college graduate in the model, the shift towards hiring a non-college workers among these firms is potentially efficiency-enhancing.

However, our model also predicts that the learning effect applies to all firms that interacted with college-educated applicants, including high-type firms. Table 7 shows that among firms that requested a college graduate at baseline, treated firms with above-average skill index still significantly decreased their perceptions of college graduates' productivity, were less likely to hire a college graduate and more likely to hire a non-college worker. The shift towards hiring a non-college workers among these firms is potentially efficiency-decreasing. The findings from our intervention thus has ambiguous implications on matching efficiency. In addition, Table 7, Column 6 shows that both high-type and low-type firms are less likely to post any job three months after endline, indicating a possibly persisting decrease in labor demand for college graduates at least in the short run.

7 Conclusion

We conducted a hiring intervention with 799 private firms with an active job vacancy in Addis Ababa, Ethiopia, where we leveraged a specialized type of employment agency to increase the access to college-educated applicants for a subset of firms. We find that treated firms were not more likely to fill the vacancy despite a 35% increase in the number of college-educated applicants. Instead, treated firms were significantly less optimistic of the productivity of college graduates in general. Among firms that requested a college graduate at baseline, treated firms became 34% less likely to hire any college graduate. The learning is not simply triggered by unqualified applicants, but also because firms received noisy signals of the productivity of college-educated applicants. Guided by an equilibrium search model, we find ambiguous implications on matching efficiency but a potentially persisting decrease in labor demand for college graduates.

Our findings reject the simplistic view that firms have perfect information of the labor market, especially in low- and middle-income countries. We discuss the causes for the learning mechanism and its labor market implications. We call for more attention to addressing information frictions which can distort the labor demand and disproportionately affect highly educated job seekers.

Bibliography

Abadie, A. (2003). Semiparametric Instrumental Variable Estimation of Treatment Response Models. *Journal of Econometrics 113*(2), 231–263.

Abebe, G., A. S. Caria, M. Fafchamps, P. Falco, S. Franklin, and S. Quinn (2021). Anonymity or Distance? Job Search and Labour Market Exclusion in a Growing African City. *The Review of Economic Studies 88*(3), 1279–1310.

Abebe, G., S. Caria, M. Fafchamps, P. Falco, S. Franklin, S. Quinn, and F. Shilpi (2024). Matching Frictions and Distorted Beliefs: Evidence from a Job Fair Experiment. *Economic Journal*.

Abel, M., R. Burger, E. Carranza, and P. Piraino (2019). Bridging the intention-behavior gap? the effect of plan-making prompts on job search and employment. *American Economic Journal: Applied Economics 11*(2), 284–301.

Abel, M., R. Burger, and P. Piraino (2020). The Value of Reference Letters: Experimental Evidence from South Africa. *American Economic Journal: Applied Economics 12*(3), 40–71.

Acemoglu, D. (2001). Good jobs versus bad jobs. *Journal of labor Economics 19*(1), 1–21.

Alfonsi, L., M. Namubiru, and S. Spaziani (2023). Meet Your Future: Experimental Evidence on the Labor Market Effects of Mentors. *mimeo, University of California Berkeley*.

Algan, Y., B. Crépon, and D. Glover (2020). Are Active Labor Market Policies Directed at Firms Effective? Evidence from a Randomized Evaluation with Local Employment Agencies. *Working Paper*.

Altmann, S., A. Falk, S. Jäger, and F. Zimmermann (2018). Learning about job search: A field experiment with job seekers in germany. *Journal of Public Economics 164*, 33–49.

Autor, D. (2008). The Economics of Labor Market Tntermediation. *NBER Working Paper No. 14348.*

Autor, D. H. (2001). Why do Temporary Help Firms Provide Free General Skills Training? *The Quarterly Journal of Economics 116*(4), 1409–1448.

Bandiera, O., V. Bassi, R. Burgess, I. Rasul, M. Sulaiman, and A. Vitali (2023). The search for good jobs: evidence from a six-year field experiment in uganda. Technical report, National Bureau of Economic Research.

Banerjee, A. and G. Chiplunkar (2022). How Important are Matching Frictions in the Labour Market? Experimental and Non-experimental Evidence from a Large Indian Firm. *mimeo*.

Banerjee, A. V. and S. Sequeira (2022). Learning by Searching: Spatial Mismatches and Imperfect Information in Southern Labor Markets. *mimeo*.

Bassi, V., J. H. Lee, A. Peter, T. Porzio, R. Sen, and E. Tugume (2023). Self-employment within the firm. Technical report, National Bureau of Economic Research.

Bassi, V. and A. Nansamba (2022). Screening and Signalling Non-Cognitive Skills: Experimental Evidence from Uganda. *The Economic Journal 132*(642), 471–511.

Beam, E. A. (2016). Do job fairs matter? experimental evidence on the impact of job-fair attendance. *Journal of Development Economics 120*, 32–40.

Beaman, L. and J. Magruder (2012). Who Gets the Job Referral? Evidence from a Social Networks Experiment. *American Economic Review 102*(7), 3574–3593.

Becker, G. S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. University of Chicago press.

Behaghel, L., B. Crépon, and M. Gurgand (2014). Private and public provision of counseling to job seekers: Evidence from a large controlled experiment. *American economic journal: applied economics 6*(4), 142–174.

Belot, M., P. Kircher, and P. Muller (2019). Providing advice to jobseekers at low cost: An experimental study on online advice. *The review of economic studies 86*(4), 1411–1447.

Benson, A. and L. P. Lepage (2024). Learning to discriminate on the job. *Available at SSRN 4155065*.

Caria, A. S., G. Gordon, M. Kasy, S. Quinn, S. O. Shami, and A. Teytelboym (2024). An adaptive targeted field experiment: Job search assistance for refugees in jordan. *Journal of the European Economic Association 22*(2), 781–836.

Carranza, E., R. Garlick, K. Orkin, and N. Rankin (2023). Job Search and Hiring with Limited Information about Workseekers' Skills. *American Economic Review*.

Cottier, L., Y. Fluckiger, P. Kempeneers, and R. Lalive (2018). Does job search assistance really raise employment? *IZA Discussion Paper*.

Crépon, B., E. Duflo, M. Gurgand, R. Rathelot, and P. Zamora (2013). Do labor market policies have displacement effects? evidence from a clustered randomized experiment. *The quarterly journal of economics 128*(2), 531–580.

Cullen, Z. B., S. Li, and R. Perez-Truglia (2022). What's my employee worth? the effects of salary benchmarking. Technical report, National Bureau of Economic Research.

Dammert, A. C., J. Galdo, and V. Galdo (2015). Integrating mobile phone technologies into labor-market intermediation: a multi-treatment experimental design. *IZA Journal of Labor & Development 4*(1), 11.

Dhia, A. B., B. Crépon, E. Mbih, L. Paul-Delvaux, B. Picard, and V. Pons (2022). Can a website bring unemployment down? experimental evidence from france. Technical report, National Bureau of Economic Research.

Donald, A. and F. Grosset-Touba (2024). Complementarities in labor supply: How joint commuting shapes work decisions. *Working paper*.

Dorn, D., J. F. Schmieder, and J. R. Spletzer (2018). Domestic Outsourcing in the United States. *US Department of Labor Technical Report*.

Fernando, A. N., N. Singh, and G. Tourek (2023). Hiring frictions and the promise of online job portals: Evidence from india. *American Economic Review: Insights 5*(4), 546–562.

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

Friedrich, B. U. and M. Zator (2024). Price discovery in labor markets: Why do firms say they cannot find workers? *Working paper*.

Goldschmidt, D. and J. F. Schmieder (2017). The Rise of Domestic Outsourcing and the Evolution of the German Wage Structure. *The Quarterly Journal of Economics 132*(3), 1165–1217.

Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica: Journal of the Econometric Society*, 1251–1271.

Heath, R. (2018). Why do Firms Hire Using Referrals? Evidence from Bangladeshi Garment Factories. *Journal of Political Economy 126*(4), 1691–1746.

Hensel, L., T. Tekleselassie, and M. Witte (2024). Formalized Employee Search and Labor Demand. *Working Paper*.

Hjort, J. (2014). Ethnic divisions and production in firms. *The Quarterly Journal of Economics 129*(4), 1899–1946.

Hoffman, M., L. B. Kahn, and D. Li (2018). Discretion in hiring. *The Quarterly Journal of Economics 133*(2), 765–800.

Hunt, J. and C. Moehling (2024). Do Female–Owned Employment Agencies Mitigate Discrimination and Expand Opportunity for Women? *Working Paper* (32383).

Jäger, S., C. Roth, U. Cologne, N. Roussille, and B. Schoefer (2021). Worker Beliefs About Outside Options. *mimeo, UC Berkeley*.

Kelley, E. M., C. Ksoll, and J. Magruder (2022). How do Online Job Portals Affect Employment and Job Search? Evidence from India.

Lepage, L.-P. (2024). Experience-based discrimination. *American Economic Journal: Applied Economics 16*(4), 288–321.

Li, D., L. R. Raymond, and P. Bergman (2023). Hiring as Exploration. *National Bureau of Economic Research*.

McKenzie, D. (2017). How effective are active labor market policies in developing countries? a critical review of recent evidence. *The World Bank Research Observer 32*(2), 127–154.

Pallais, A. (2014). Inefficient hiring in entry-level labor markets. *American Economic Review 104*(11), 3565–3599.

Pissarides, C. A. (2000). *Equilibrium unemployment theory.* MIT press.

Spence, M. (1978). Job Market Signaling. In *Uncertainty in economics*, pp. 281–306. Elsevier.

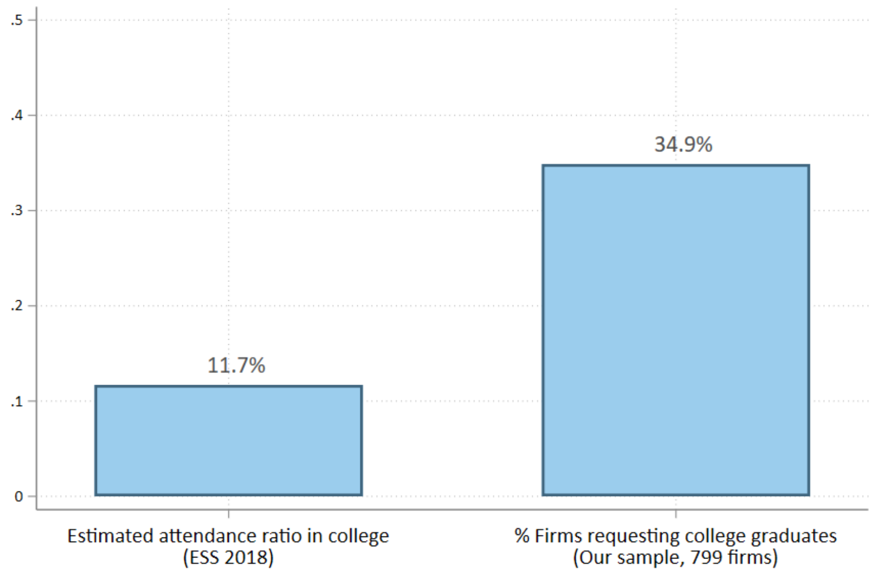
Stanton, C. T. and C. Thomas (2016). Landing the First Job: The Value of Intermediaries in Online Hiring. *The Review of Economic Studies 83*(2), 810–854.

Swanson, N. (2024). All in the family: Kinship pressure and firm-worker matching. *Working paper*.

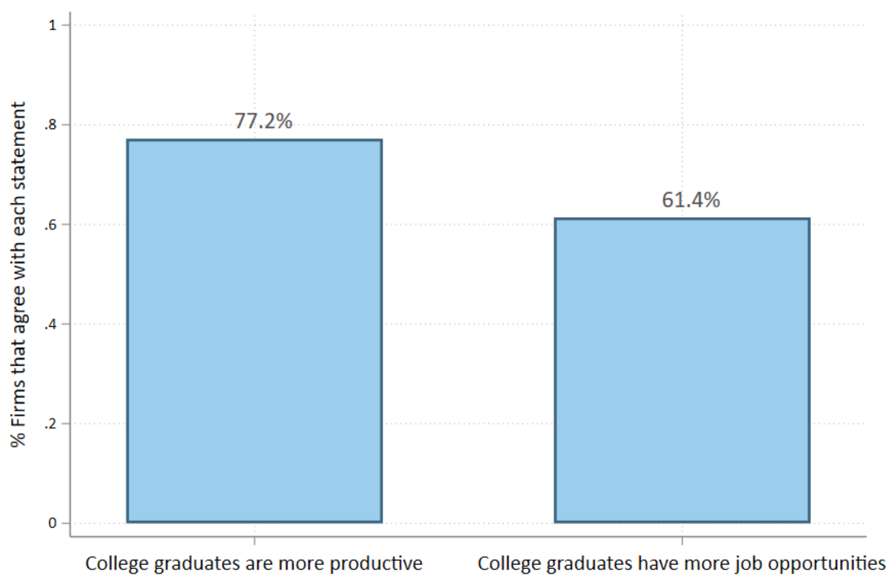
FIGURES

Figure 1: Demand for College Graduates

Panel A. Percentage of firms requesting a college graduate

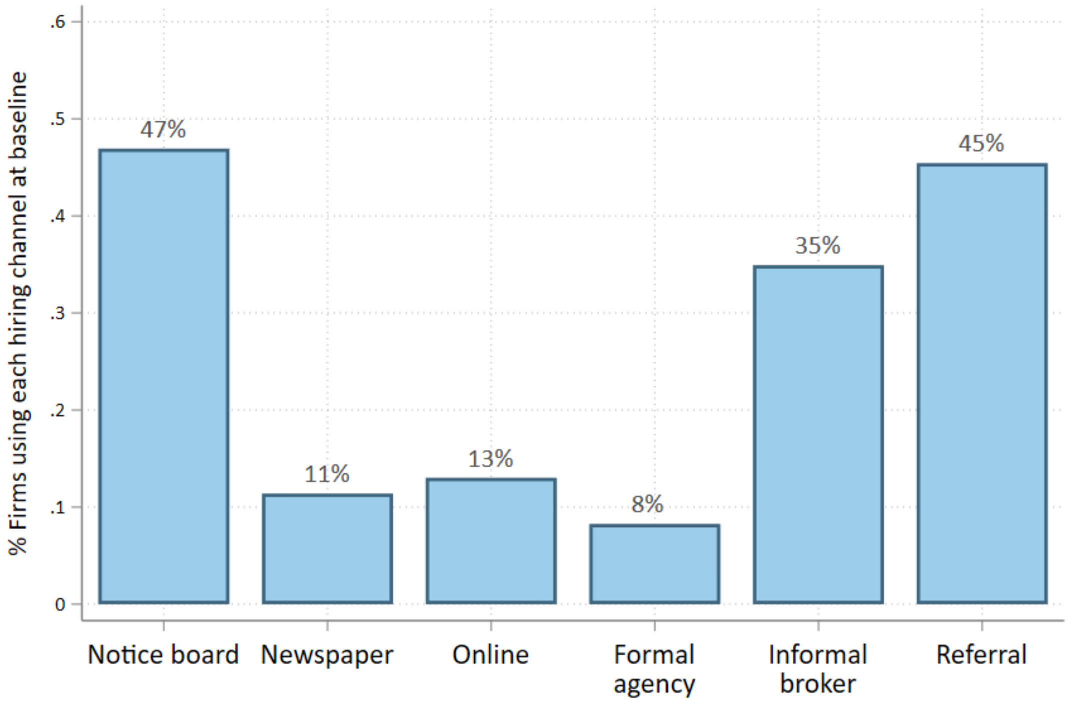


Panel B. Perceptions of college graduates



Notes: Panel A shows the estimated attendance ratio of tertiary education from Ethiopian Socioeconomic Survey in 2018, as a proxy for the percentage of labor force with a college degree, and the percentage of firms that request a college graduate at baseline in our sample. Panel B shows the percentage of firms that agreed at baseline that college graduates have better productivity than non-college educated workers, and that college graduates have more job opportunities than non-college educated workers.

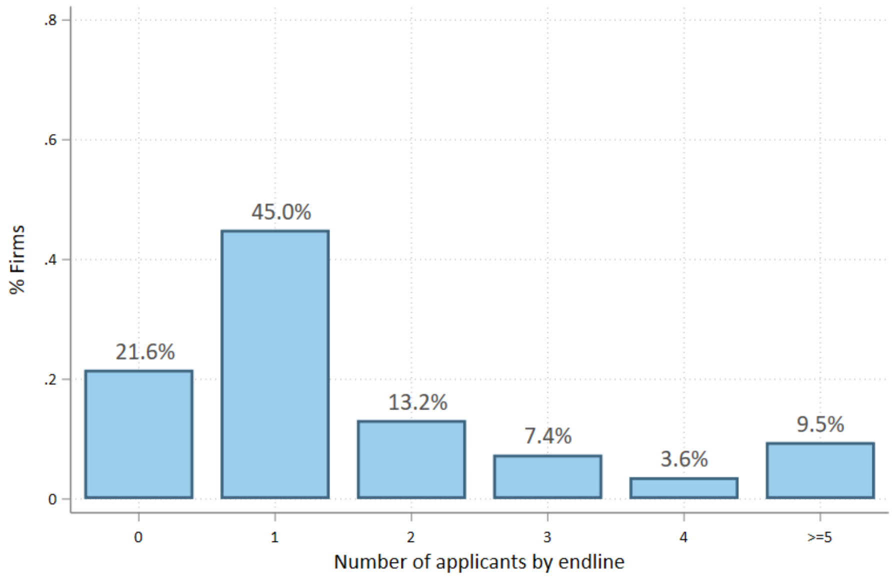
Figure 2: Hiring Channels Used by Firms at Baseline



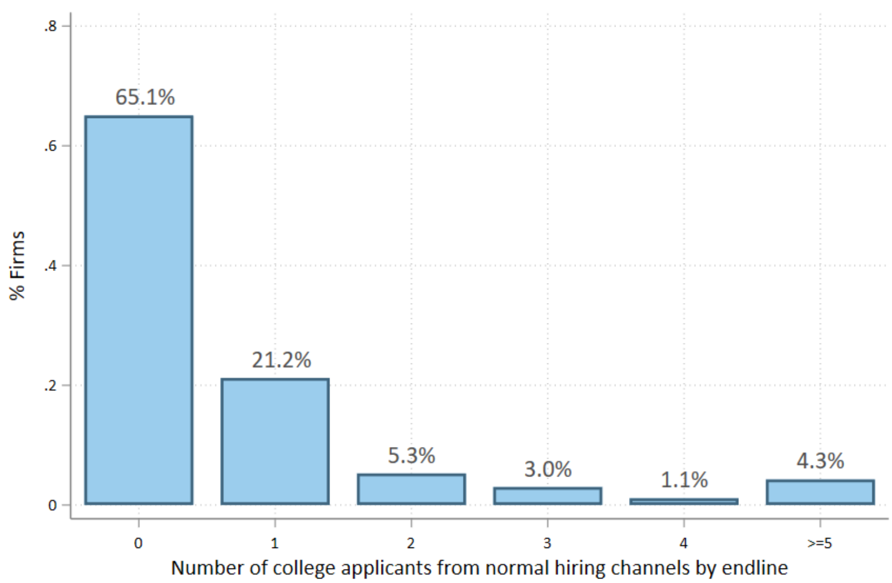
Notes: This figure shows the percentage of firms in our sample using different types of hiring channels, including notice boards, newspapers, online platforms, formal employment agencies, informal job brokers, and personal referrals.

Figure 3: Distribution of the Number of Applicants

Panel A. All applicants



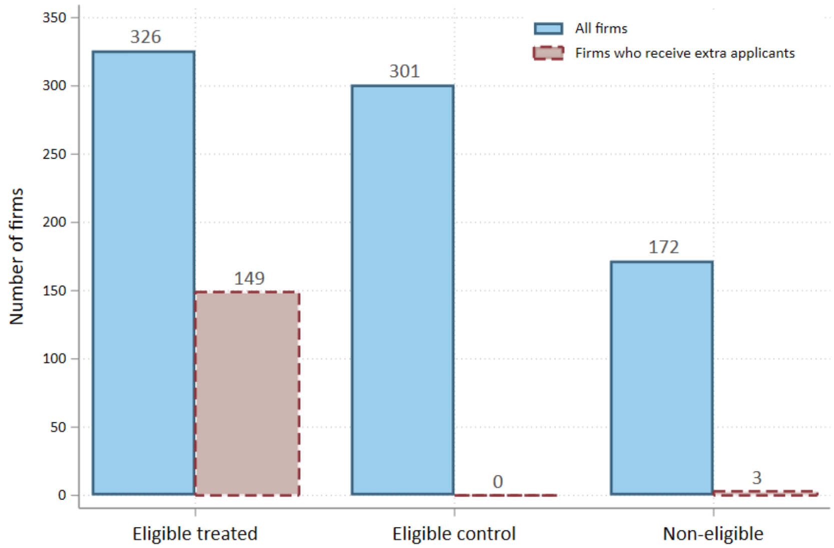
Panel B. College-educated applicants



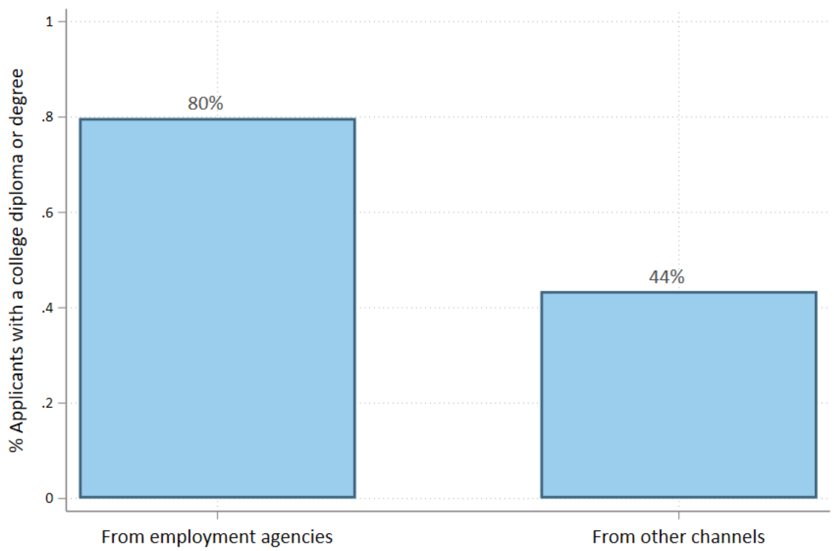
Notes: This figure presents the distribution of the total number of applicants for the posted vacancies by endline, not including applicants from the employment agencies introduced in the intervention. Panel A: Total number of applicants. Panel B: Total number of college educated applicants.

Figure 4: Matching between Employment Agencies and Firms

Panel A. Treatment Implementation



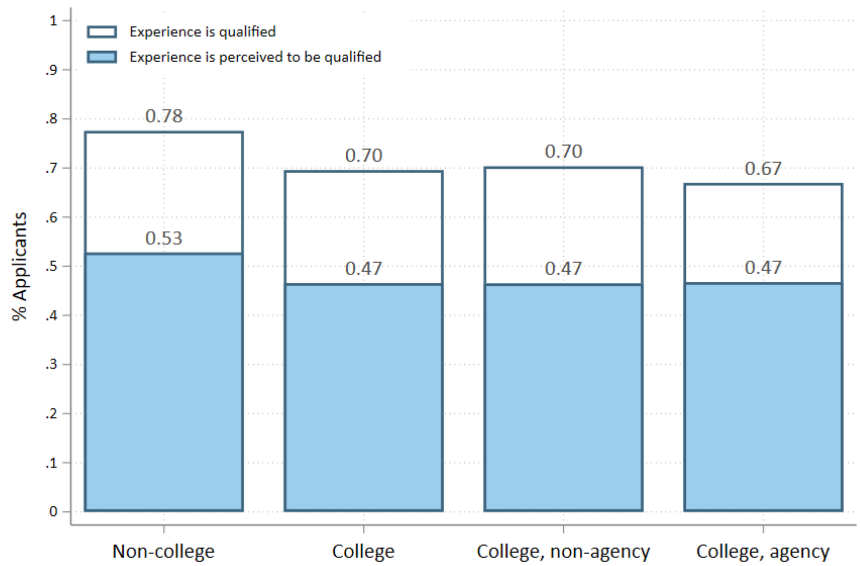
Panel B. Selection of Agency Applicants



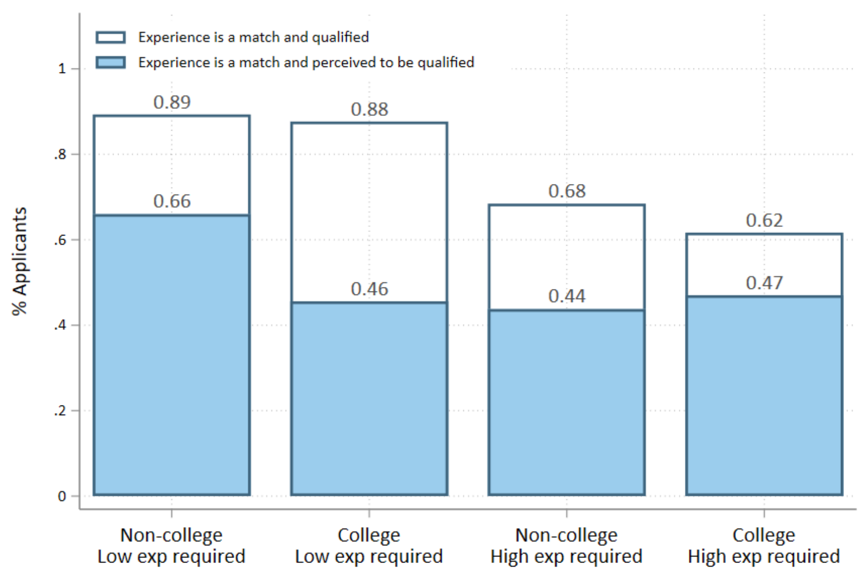
Notes: This figure shows the matching between employment agencies and firms. Panel A shows the number of three groups of firms: (1) Eligible firms (reservation wage at least 2,000 ETB) selected into treatment group, (2) eligible firms selected into control group, (3) non-eligible firms. Panel B shows the percentages of college graduates among the applicants provided by the employment agencies and applicants from other hiring channels.

Figure 5: Actual and Perceived Qualification of Applicants' Experience

Panel A. By applicants' education and agency status



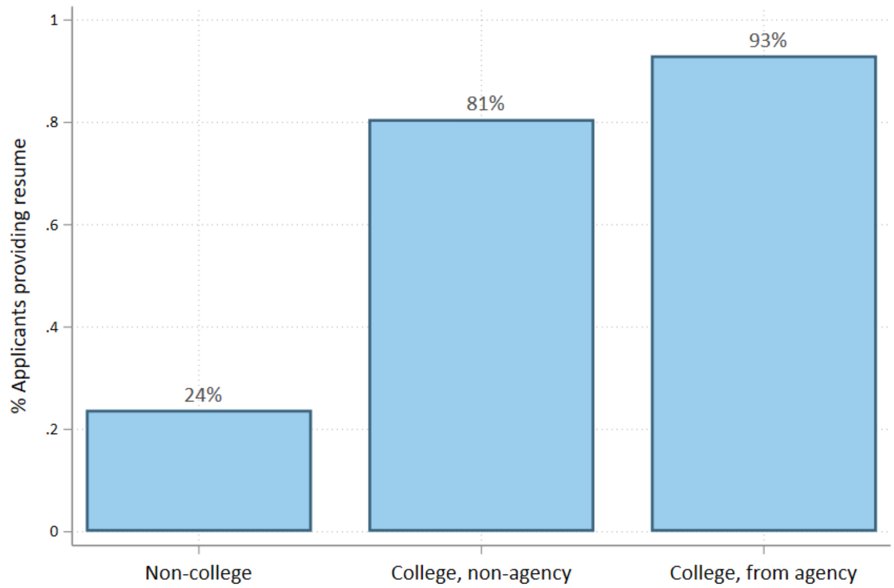
Panel B. By firms' minimum experience requirement



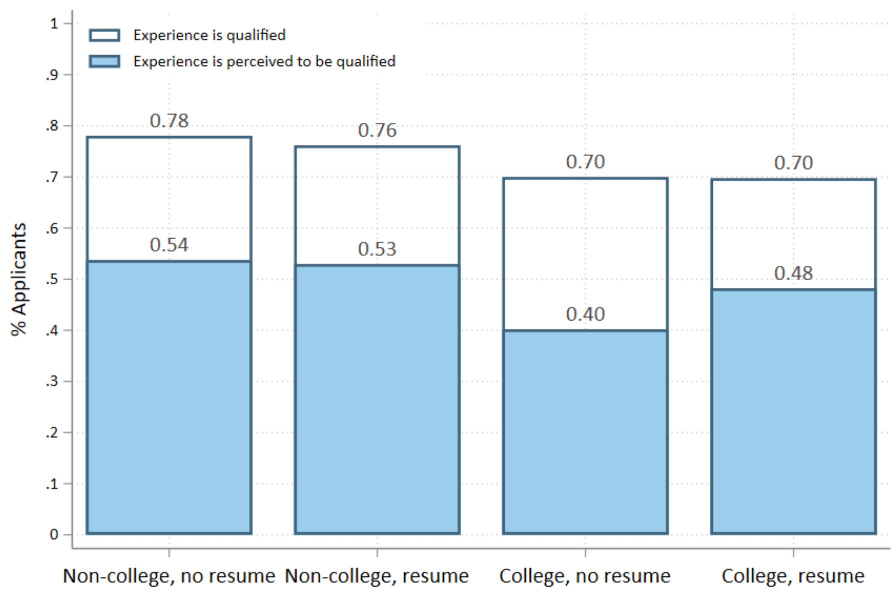
Notes: This figure shows the qualification of applicants' experience for non-college applicants, college-educated applicants not recommended by the employment agencies, and college-educated applicants recommended by the employment agencies. We define an applicant is qualified if their years of experience meet the minimum requirement of the posted vacancy. Panel A shows the percentage of applicants that were qualified among non-college applicants, college applicants on average, college agency applicants, and college non-agency applicants. Panel B shows the percentage of applicants that were qualified among non-college applicants in firms that required less than one year of experience, college applicants in firms that required less than one year of experience, non-college applicants in firms that required at least one year of experience, and college applicants in firms that required at least one year of experience. The blue contour uses applicants' self-reported years of experience to construct the qualification indicator. The solid area uses firms' perceived years of experience for each applicant to construct the qualification indicator.

Figure 6: Résumé and Applicants' Qualification

Panel A. Usage of résumé



Panel B. Perceived qualification of applicants' experience by résumé usage



Notes: Panel A shows the percentage of applicants providing résumé, among non-college workers, college graduates not recommended from the employment agency, and college graduates recommended from the employment agency. Panel B shows the qualification of applicants experience for non-college applicants with no résumé, non-college applicants with résumé, college-educated applicants with no résumé, and college-educated applicants with résumé. A qualified applicant is defined as whether their years of experience meet the minimum requirement of the posted vacancy. The blue contour uses applicants' self-reported years of experience to construct the qualification indicator. The solid area uses firms' perceived years of experience for each applicant to construct the qualification indicator.

TABLES

Table 1: First-stage Treatment Effects on the Number of Applicants

Panel A. All applicants

VARIABLES	(1) # Agency	(2) # Non-agency	(3) # All	(4) # App ≥1	(5) # App ≥2	(6) # App ≥3
Assigned to treat	0.373	-0.023	0.345	0.098	0.125	0.046
	(0.078)	(0.191)	(0.203)	(0.050)	(0.063)	(0.046)
	[0.000]	[0.903]	[0.093]	[0.052]	[0.049]	[0.324]
Observations	583	583	583	583	583	589
R-squared	0.420	0.339	0.340	0.256	0.309	0.317
Control mean	0.137	2.069	2.203	0.800	0.400	0.266

Panel B. College-educated applicants

VARIABLES	(1) # Agency	(2) # Non-agency	(3) # All	(4) # App ≥1	(5) # App ≥2	(6) # App ≥3
Assigned to treat	0.317	0.0772	0.390	0.0524	0.129	0.0371
	(0.065)	(0.153)	(0.163)	(0.049)	(0.041)	(0.033)
	[0.000]	[0.615]	[0.019]	[0.285]	[0.002]	[0.261]
Observations	586	586	586	586	589	586
R-squared	0.448	0.350	0.393	0.443	0.363	0.329
Control mean	0.096	1.024	1.116	0.448	0.209	0.137

Panel C. College-educated applicants by baseline request for college graduates

VARIABLES	(1) # Agency	(2) # Non-agency	(3) # All	(4) # App ≥1	(5) # App ≥2	(6) # App ≥3
Treated x Not requesting college	0.113	0.103	0.211	0.068	0.051	0.016
	(0.053)	(0.161)	(0.169)	(0.065)	(0.043)	(0.032)
	[0.035]	[0.522]	[0.217]	[0.296]	[0.244]	[0.613]
Treated x Requesting college	0.621	0.038	0.657	0.029	0.248	0.068
	(0.101)	(0.273)	(0.293)	(0.060)	(0.076)	(0.063)
	[0.000]	[0.890]	[0.028]	[0.631]	[0.001]	[0.278]
Observations	586	586	586	586	589	586
R-squared	0.492	0.350	0.396	0.443	0.373	0.330
Control mean: Firms not requesting college	0.038	0.481	0.519	0.243	0.103	0.060
Control mean: Firms requesting college	0.168	1.685	1.846	0.698	0.336	0.228

Notes: This table examines the treatment effects on the number of applicants. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. Observation with above 99.5 percentile are truncated (number of applicants above 13). Dependent variables: Column 1, number of applicants (all or college-educated) recommended from the employment agencies. Column 2, number of applicants (all or college-educated) not recommended from the employment agencies. Column 3, total number of applicants (all or college-educated). Column 4–6, whether the number of applicants (all or college-educated) is at least one, two, or three. In Panel C, we interact the initial treatment assignment with whether firms request a college graduate at baseline. All regressions include a full set of baseline characteristics from Table B3, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table 2: Treatment Effects on Vacancy Filling

VARIABLES	(1) Interview Agency	(2) Interview Non-agency	(3) Interview Any	(4) Hire Agency	(5) Hire Non-agency	(6) Hire Any
Assigned to treat	0.094	0.004	0.052	0.016	-0.004	0.000
	(0.032)	(0.053)	(0.048)	(0.011)	(0.052)	(0.051)
	[0.004]	[0.937]	[0.281]	[0.172]	[0.937]	[0.996]
Observations	580	580	580	580	580	580
R-squared	0.229	0.270	0.268	0.206	0.268	0.264
Control baseline char.	Yes	Yes	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.024	0.756	0.762	0.003	0.744	0.747

Notes: This table presents whether treated firms interviewed or hired the applicants recommended from the matched employment agencies. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. Dependent variables: Column 1 and 4, whether the firm interviewed or hired any applicant recommended by the employment agency. Column 2 and 5, whether the firm interviewed or hired any applicant not recommended by the employment agency. Column 3 and 6, whether the firm interviewed or hired any applicant at endline. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table 3: Belief Update in the Productivity of College Graduates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	% Applicants perceived productive by firm				Whether firm agrees		
	College	Non-college	College	College	College grads are more productive		
Assigned to treat	-0.262	0.027			-0.087		
	(0.108)	(0.087)			(0.044)		
	[0.021]	[0.755]			[0.050]		
# Non-agency (NA) college applicants			-0.045			0.001	
			(0.012)			(0.006)	
			[0.001]			[0.854]	
Treated x Zero NA college applicants			-0.559			-0.057	
			(0.160)			(0.045)	
			[0.001]			[0.205]	
Treated x $\geq$ 1 NA college applicants			-0.246			-0.135	
			(0.088)			(0.062)	
			[0.008]			[0.032]	
Treated x Not requesting college				-0.398			-0.082
				(0.212)			(0.057)
				[0.069]			[0.150]
Treated x Requesting college				-0.210			-0.093
				(0.113)			(0.053)
				[0.070]			[0.085]
Observations	151	154	151	151	568	568	568
R-squared	0.393	0.505	0.463	0.399	0.329	0.332	0.329
Control firm/vacancy char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.779	0.851			0.782		
Control mean: Not requesting college				0.767			0.720
Control mean: Requesting college				0.772			0.897
Control mean with one NA college app			0.878			0.772	
Control mean with zero NA college app						0.782	

Notes: This table presents whether treated firms updated beliefs of the average productivity of college graduates. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. In column 1–3, for each firm, we compute the percentage of applicants perceived with good productivity in each category (college graduates, non-college workers); this data only exists in Round 2. Column 4 and 5 look at whether firm agreed that college graduates are more productive than non-college workers. In Column 3 and 5, we interact the initial treatment assignment with whether or not firm received at least one non-agency (NA) college-educated applicants, and control for the number of college-educated non-agency applicants. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table 4: Shift in Hiring Behavior

Panel A. All applicants

VARIABLES	(1) Interview College	(2) Interview Non-college	(3) (2)-(1)	(4) Hire College	(5) Hire Non-college	(6) (5)-(4)
Treated x Not requesting college	0.057	0.001	-0.055	0.033	-0.002	-0.036
	(0.059)	(0.049)	(0.072)	(0.063)	(0.048)	(0.077)
	[0.342]	[0.976]	[0.443]	[0.595]	[0.964]	[0.643]
Treated x Requesting college	-0.117	0.113	0.230	-0.197	0.088	0.285
	(0.070)	(0.057)	(0.103)	(0.076)	(0.053)	(0.105)
	[0.098]	[0.050]	[0.028]	[0.012]	[0.106]	[0.008]
Observations	580	580		580	580	
R-squared	0.348	0.493		0.327	0.502	
Control baseline char.	Yes	Yes		Yes	Yes	
Business area FE	Yes	Yes		Yes	Yes	
Cluster at business area	Yes	Yes		Yes	Yes	
Control mean: Not requesting college	0.231	0.714		0.198	0.692	
Control mean: Requesting college	0.614	0.131		0.586	0.110	

Panel B. Non-agency applicants

VARIABLES	(1) Interview College	(2) Interview Non-college	(3) (2)-(1)	(4) Hire College	(5) Hire Non-college	(6) (5)-(4)
Treated x Not requesting college	0.019	-0.018	-0.038	0.022	-0.004	-0.025
	(0.060)	(0.050)	(0.070)	(0.063)	(0.048)	(0.076)
	[0.747]	[0.712]	[0.593]	[0.730]	[0.941]	[0.741]
Treated x Requesting college	-0.152	0.091	0.243	-0.196	0.080	0.276
	(0.081)	(0.056)	(0.110)	(0.077)	(0.053)	(0.103)
	[0.065]	[0.106]	[0.030]	[0.012]	[0.133]	[0.009]
Observations	580	580		580	580	
R-squared	0.333	0.495		0.330	0.507	
Control baseline char.	Yes	Yes		Yes	Yes	
Business area FE	Yes	Yes		Yes	Yes	
Cluster at business area	Yes	Yes		Yes	Yes	
Control mean: Not requesting college	0.231	0.714		0.192	0.692	
Control mean: Requesting college	0.600	0.131		0.586	0.110	

Notes: This table presents the treatment effects on whether firms hired a college graduate or a non-college worker. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. We interact initial treatment assignment and whether or not firm requested a college graduate at baseline. Dependent variables: Column 1 and 4, whether the firm interviewed any college-educated or non-college applicant at endline. Column 2 and 5, whether the firm hired any college graduate or non-college worker at endline. Column 3 computes the differences between the estimates in Column 1 and 2. Column 6 computes the differences between the estimates in Column 4 and 5. Panel B excludes agency applicants from constructing the outcome variables. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table 5: Explaining the Shift in Hiring Behavior with College Share

VARIABLES	(1) Interview College	(2) Interview Non-college	(3) (2)-(1)	(4) Hire College	(5) Hire Non-college	(6) (5)-(4)
Treated x Not requesting college	0.050	-0.028	-0.078	0.023	-0.024	-0.047
	(0.065)	(0.064)	(0.092)	(0.071)	(0.065)	(0.097)
	[0.446]	[0.664]	[0.400]	[0.747]	[0.719]	[0.632]
Treated x Requesting college	-0.091	0.020	0.111	-0.189	0.011	0.200
x Above-median college share	(0.127)	(0.114)	(0.199)	(0.127)	(0.115)	(0.194)
	[0.476]	[0.864]	[0.580]	[0.142]	[0.926]	[0.306]
Treated x Requesting college	-0.221	0.169	0.389	-0.278	0.149	0.427
x Below-median college share	(0.127)	(0.089)	(0.193)	(0.138)	(0.084)	(0.202)
	[0.086]	[0.061]	[0.047]	[0.047]	[0.079]	[0.038]
Observations	580	580		580	580	
R-squared	0.351	0.495		0.328	0.504	
Control baseline char.	Yes	Yes		Yes	Yes	
Business area FE	Yes	Yes		Yes	Yes	
Cluster at business area	Yes	Yes		Yes	Yes	
Control mean: Not requesting college	0.231	0.714		0.198	0.692	
Control mean: Requesting college	0.614	0.131		0.586	0.110	

Notes: This table examines whether learning can explain the shift in hiring behavior in Table 4. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. We interact the initial treatment assignment, whether or not firm requested a college graduate at baseline, and whether the percentage of college-educated workers in the firm at baseline (henceforth college share) was above median. We also control for the treatment status with whether college share was above median to guarantee full saturation. Dependent variables: Column 1 and 4, whether the firm interviews and hires any college-educated worker at endline. Column 2 and 5, whether the firm interviews and hires any non-college worker at endline. Column 3 computes the differences between the estimates in Column 1 and 2. Column 6 computes the differences between the estimates in Column 4 and 5. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table 6: Explaining the Shift in Hiring Behavior with Experience Requirement

VARIABLES	(1) Interview College	(2) Interview Non-college	(3) (2)-(1)	(4) Hire College	(5) Hire Non-college	(6) (5)-(4)
Treated x Not requesting college	0.111	-0.016	-0.127	0.086	-0.035	-0.121
	(0.072)	(0.065)	(0.101)	(0.072)	(0.064)	(0.100)
	[0.129]	[0.805]	[0.212]	[0.235]	[0.591]	[0.232]
Treated x Requesting college	-0.215	0.135	0.350	-0.363	0.078	0.441
x Low experience requirement	(0.138)	(0.116)	(0.196)	(0.139)	(0.121)	(0.196)
	[0.124]	[0.247]	[0.078]	[0.011]	[0.520]	[0.027]
Treated x Requesting college	-0.056	0.092	0.148	-0.110	0.063	0.172
x High experience requirement	(0.078)	(0.066)	(0.113)	(0.078)	(0.060)	(0.109)
	[0.469]	[0.169]	[0.193]	[0.162]	[0.302]	[0.118]
Observations	580	580		580	580	
R-squared	0.357	0.493		0.338	0.503	
Control baseline char.	Yes	Yes		Yes	Yes	
Business area FE	Yes	Yes		Yes	Yes	
Cluster at business area	Yes	Yes		Yes	Yes	
Control mean: Not requesting college	0.231	0.714		0.198	0.692	
Control mean: Requesting college	0.614	0.131		0.586	0.110	

Notes: This table examines whether college graduates' qualifications can explain the shift in hiring behavior in Table 4. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. We interact the initial treatment assignment, whether or not firm requested a college graduate at baseline, and whether firm required less than one year of experience (low experience requirement). We control for the interaction of treatment status and whether firm has low experience requirement to guarantee full saturation. Dependent variables: Column 1 and 4, whether the firm interviews and hires any college-educated worker at endline. Column 2 and 5, whether the firm interviews and hires any non-college worker at endline. Column 3 computes the differences between the estimates in Column 1 and 2. Column 6 computes the differences between the estimates in Column 4 and 5. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table 7: Treatment Effects by Skill Requirement

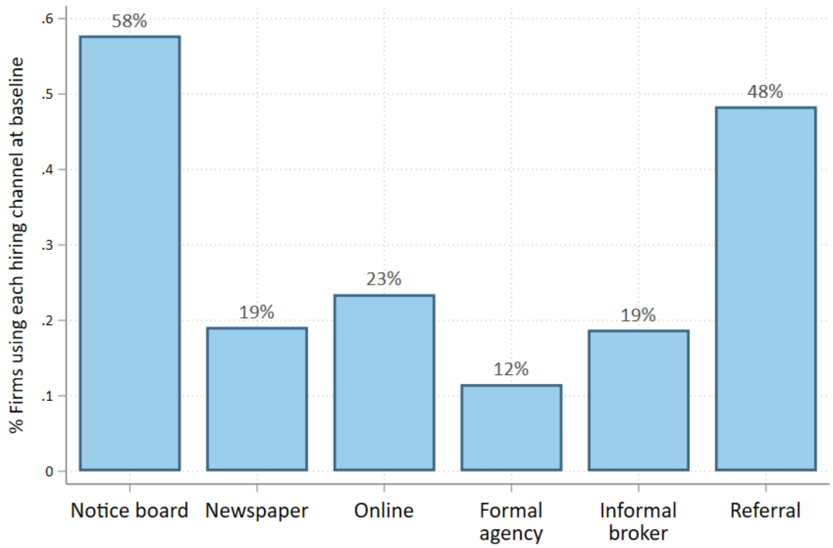
VARIABLES	(1) % Perceived prod. College	(2) Agreed college more productive	(3) Hire College	(4) Hire Non-college	(5) (5)-(4)	(6) Hire Any, planned
Treated x Not requesting college	-0.384	-0.026	0.083	-0.033	-0.116	-0.022
	(0.222)	(0.058)	(0.076)	(0.070)	(0.115)	(0.079)
	[0.092]	[0.653]	[0.276]	[0.640]	[0.314]	[0.785]
Treated x Requesting college	-0.322	-0.122	-0.334	0.241	0.575	-0.163
x Skill index < 0	(0.200)	(0.105)	(0.090)	(0.085)	(0.149)	(0.106)
	[0.117]	[0.247]	[0.000]	[0.006]	[0.000]	[0.126]
Treated x Requesting college	-0.225	-0.091	-0.201	0.093	0.295	-0.128
x Skill index > 0	(0.116)	(0.054)	(0.077)	(0.053)	(0.105)	(0.072)
	[0.059]	[0.098]	[0.010]	[0.079]	[0.006]	[0.079]
Observations	151	568	580	580		568
R-squared	0.402	0.333	0.332	0.508		0.326
Sample	All	All				All
Control baseline char.	Yes	Yes	Yes	Yes		Yes
Business area FE	Yes	Yes	Yes	Yes		Yes
Cluster at business area	Yes	Yes	Yes	Yes		Yes
Control mean: Not requesting college	0.787	0.736	0.198	0.692		0.652
Control mean: Requesting college	0.785	0.896	0.586	0.110		0.653

Notes: This table presents the treatment effects on interviewing and hiring outcomes by skill requirement. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. We interact the initial treatment assignment with whether or not firm requested a college graduate at baseline for all regression, and whether the constructed skill index is greater than zero. The skill index is constructed by extracting principal components of four vacancy characteristics: whether the vacancy required specific skill requirement, whether the vacancy involved manual task, whether the vacancy involved routine task, whether the vacancy required at least two years of experience. We also control for the interaction between the initial treatment assignment and whether the constructed skill index is greater than zero to guarantee full saturation. Dependent variables: Column 1, percentage of college-educated applicants perceived with good productivity. Column 2, whether firm agreed that college graduates are more productive than non-college workers. Column 3 and 4, whether the firm hired a college graduate or a non-college worker. Column 5 computes the difference between the estimates in Column 3 and 4. Column 6, whether the firm planned to post any jobs in the next three months after endline. All regressions include a full set of baseline characteristics, control for business area fixed effects, and cluster at business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

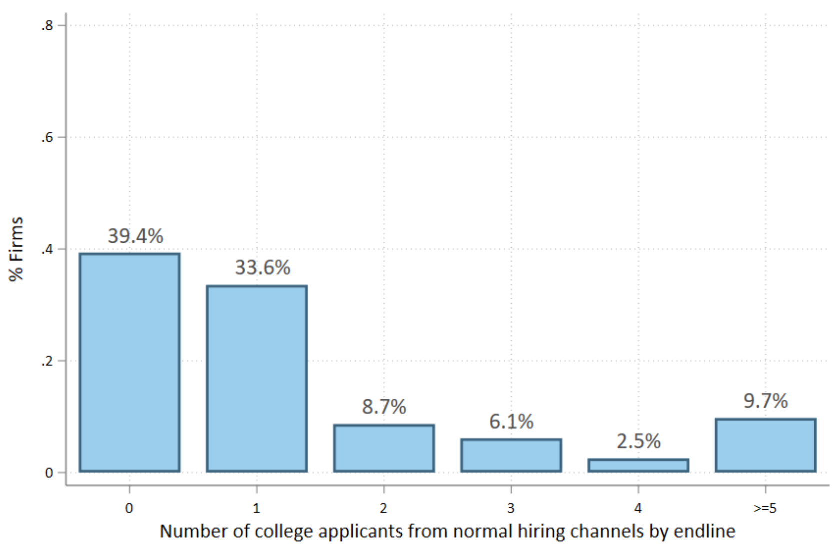
A Appendix Figures

Figure A1: Hiring Channels and Access to College-educated Applicants Among Firms Requesting College Graduates

Panel A. Hiring Channel



Panel B. Access to college-educated applicants



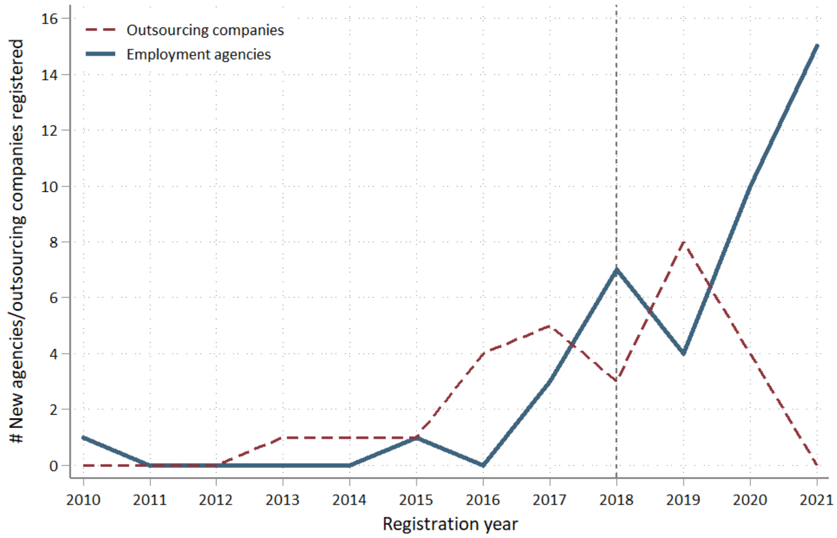
Notes: Panel A shows the percentage of firms that request a college graduate at baseline who use different types of hiring channels. Panel B shows the distribution of the total number of college applicants by endline for firms requesting college graduates, not including applicants from the employment agencies in the intervention.

Figure A2: A Typical Employment Agency

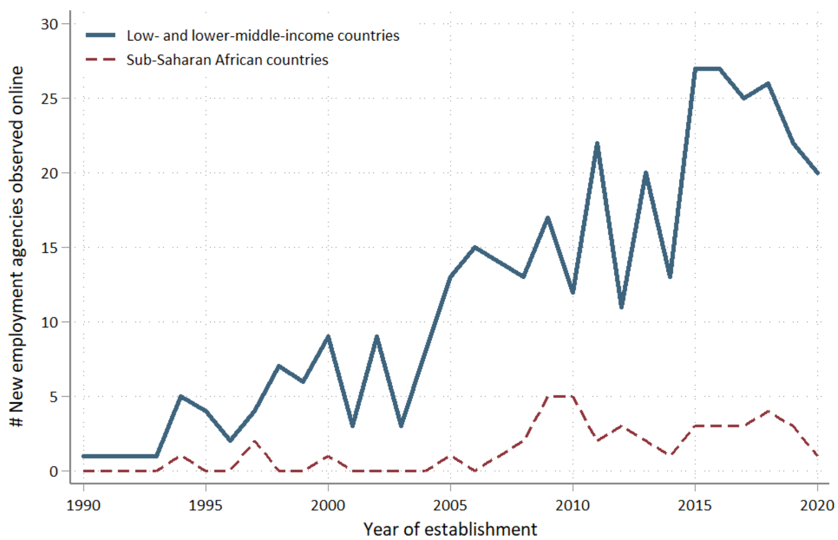
Notes: This figure shows a typical employment agency in our sample located in Bole sub-city, Addis Ababa, Ethiopia.

Figure A3: Trends of Employment Agencies

Panel A. Number of employment agencies in Bole sub-city, 2010–21

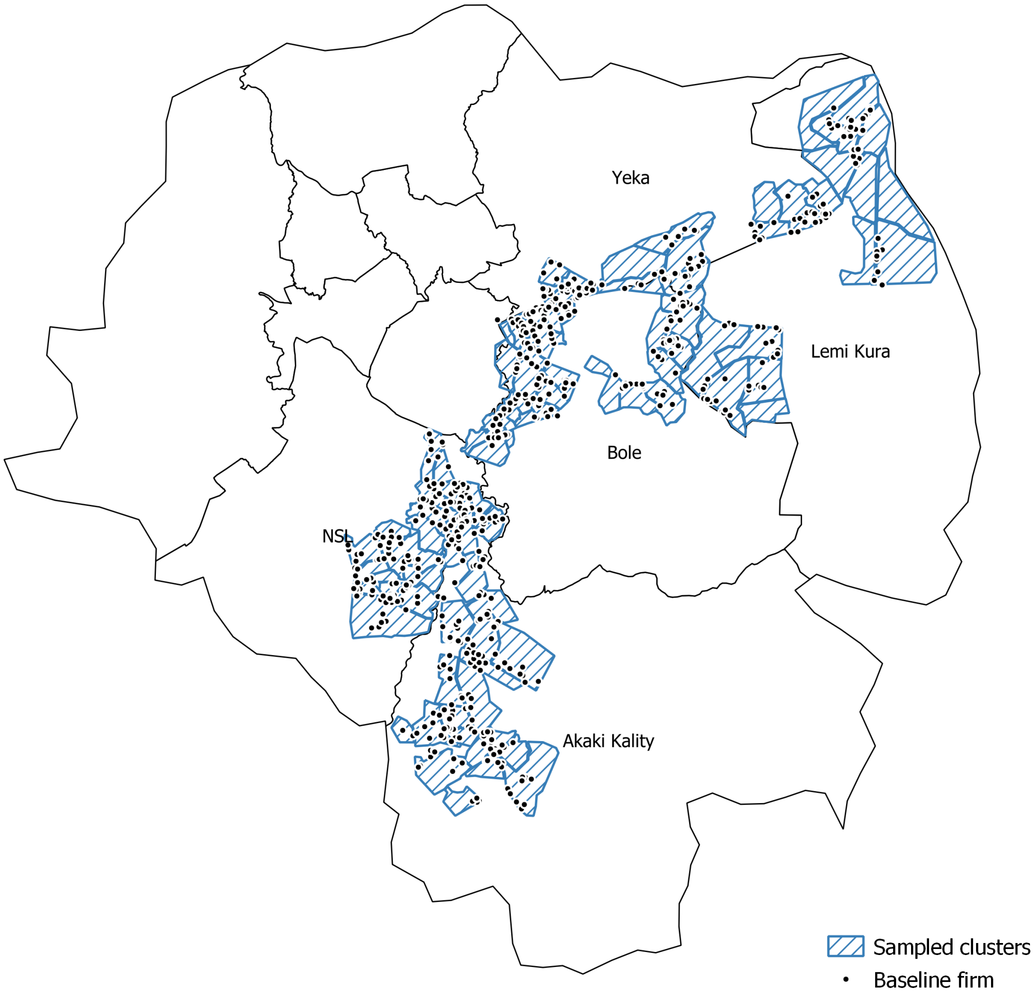


Panel B. Number of employment agencies in low- and middle-income countries, 1990–2020



Notes: This figure shows the trend of employment agencies in the recent decades. Panel A shows the number of registered labor market intermediaries in Bole sub-city during 2010–21. The data come from the registry of employment agencies from Bole sub-city. Blue solid line shows the trend of employment agencies. Red dashed line shows the trend of outsourcing companies, another form of labor market intermediaries that focus exclusively on low-skill occupations such as construction, security guards, and janitors. Panel B shows the number of new employment agencies observed online from 1990–2020. The data comes from one of the largest business-to-business service platforms where we search for all existing records of employment agencies of each country. Blue solid line shows the time series for low- and lower-middle-income countries according to World Bank definition. Red dashed line shows the time series only for sub-Saharan African countries.

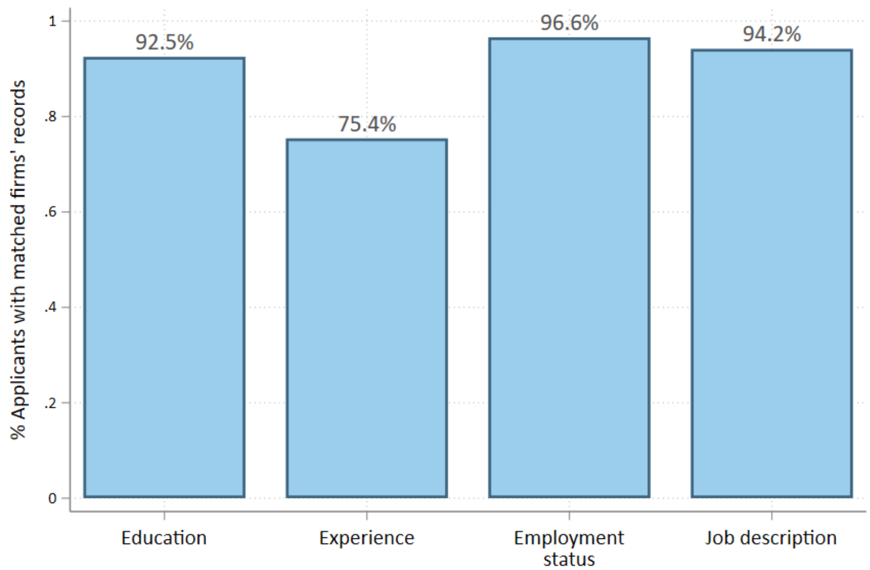
Figure A4: Sampling Map



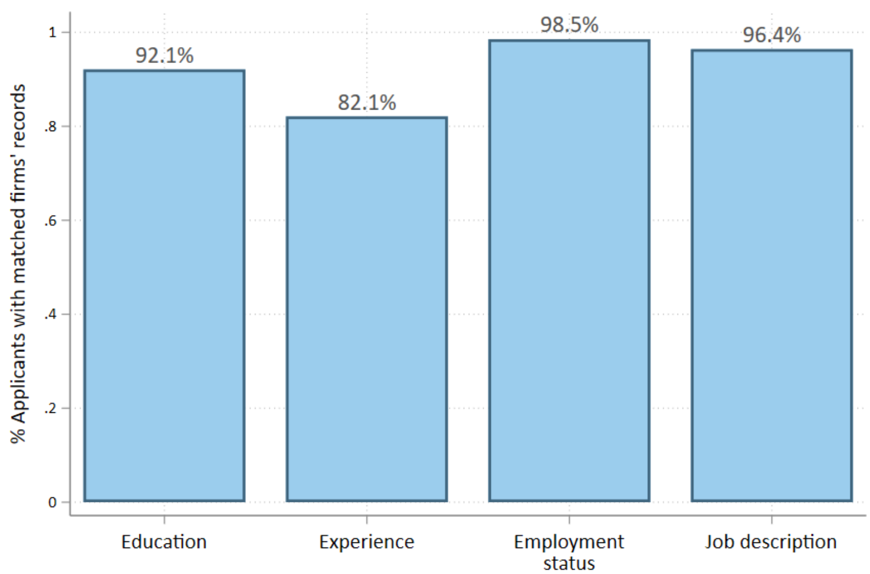
Notes: This figure shows the geographical distribution of 88 business areas from five sub-cities and 799 firms selected in the baseline survey.

Figure A5: Data Validation

Panel A. College-educated applicants

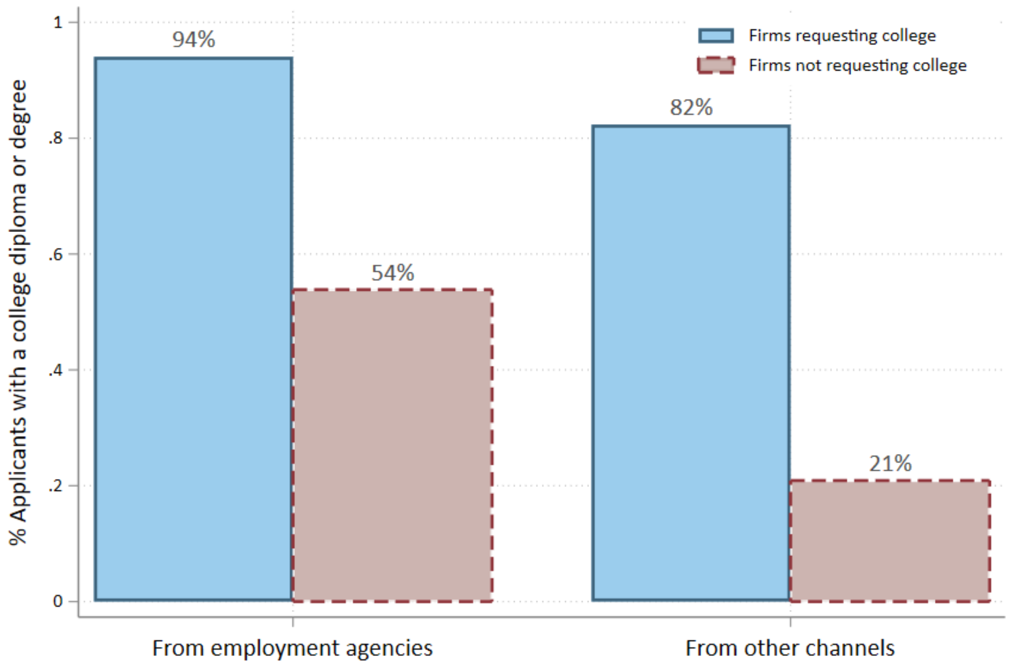


Panel B. Non-college applicants



Notes: This figure shows the results from a data validation exercise, separately for college-educated and non-college workers. For education and experience, we focus on 1,050 workers who were sampled in the worker survey at midline. For employment status and job description, we focus on 683 workers who were sampled in the worker survey and hired by firms for the sampled vacancies according to firms' reports. We calculate the percentage of records with the same education level, the same years of experience, and among those who were hired by firms according to firms' report, the same employment status, and the same job description.

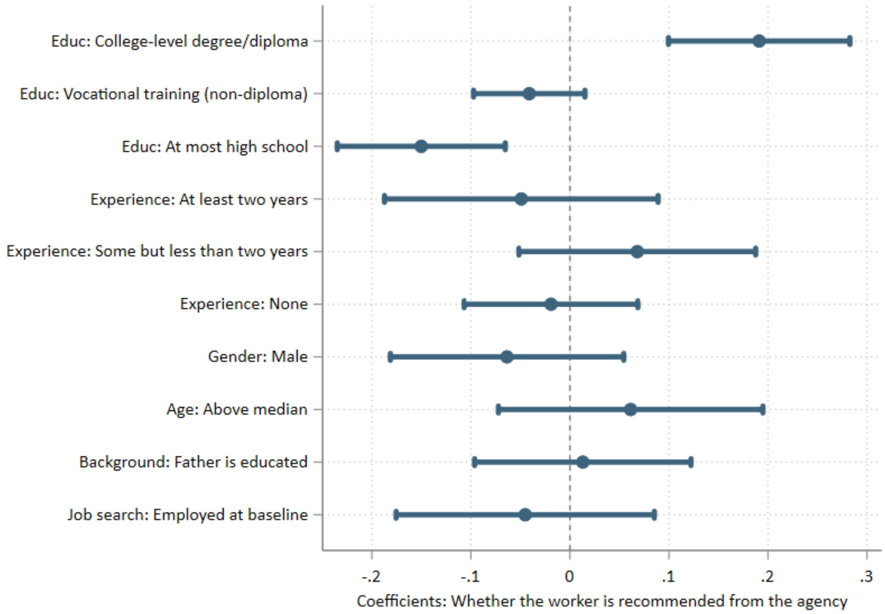
Figure A6: Selection of Agency Applicants by Baseline Request for College Graduates



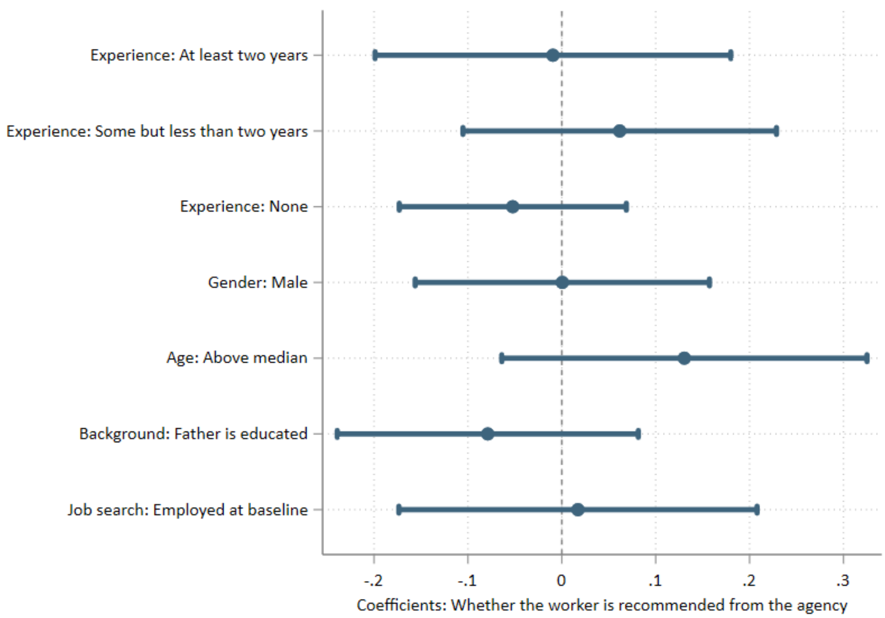
Notes: This figure shows the selection patter of applicants. The blue bars show the percentages of college graduates among the applicants provided by the employment agencies or other hiring channels for the vacancies that request a college graduate at baseline. The red bars with dashed contour show the percentages of college graduates among the applicants provided by the employment agencies or other hiring channels for the vacancies that do not request a college graduate at baseline.

Figure A7: Selection of Applicants from Employment Agencies

Panel A. All applicants



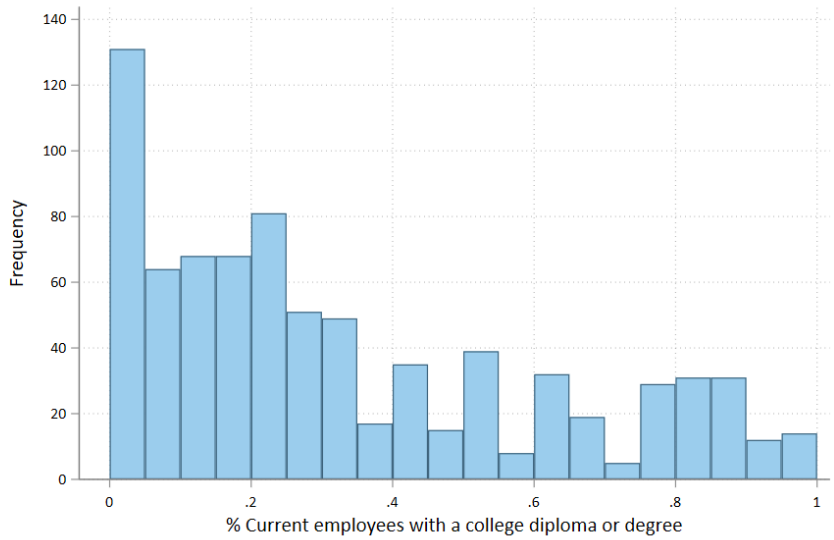
Panel B. College-educated applicants



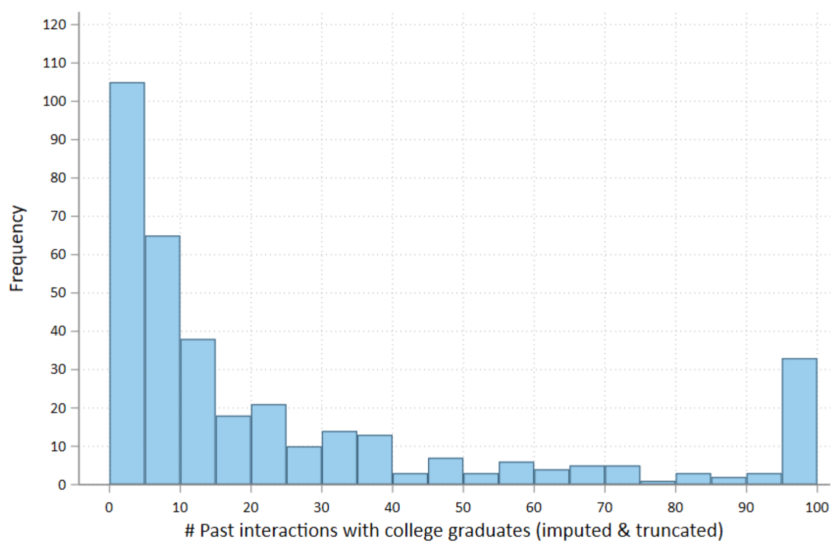
Notes: This figure shows the selection of applicants from the employment agencies in terms of observable characteristics. Panel A includes all applicants; Panel B only includes college-educated applicants. For each characteristics, we compare agency applicants to non-agency applicants, controlling for firm fixed effects and cluster at the firm level. 95% confidence intervals are shown for each estimate.

Figure A8: Firms' Past Interaction with College Graduates

Panel A. College share as proxy



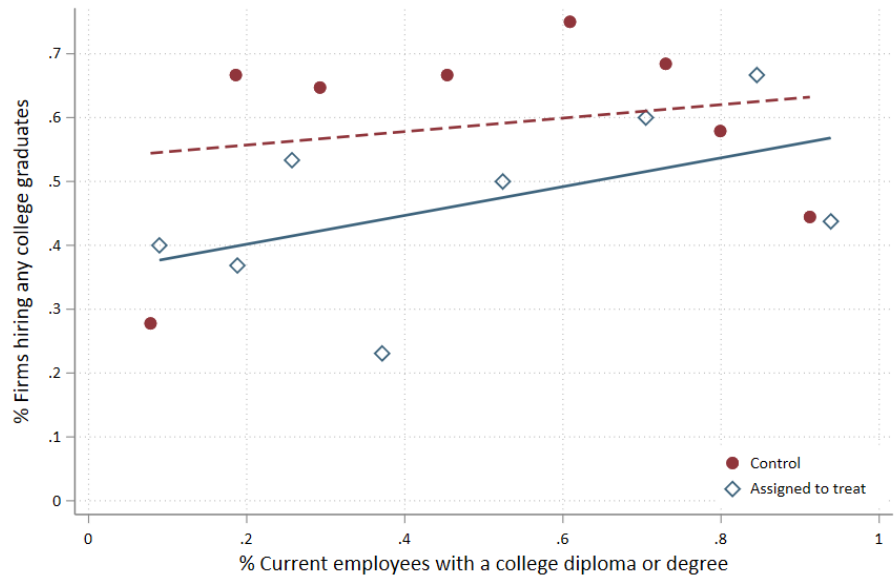
Panel B. Imputed number of past interactions



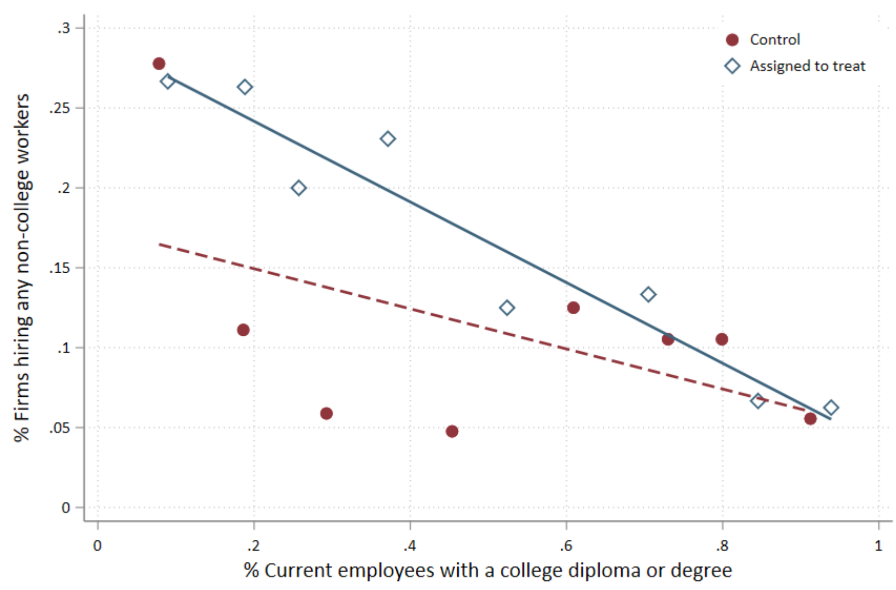
Notes: Panel A shows the distribution of the college share over the whole sample, defined as the percentage of current employees with a college diploma or degree. Panel B shows the distribution of the imputed number of past interactions with college graduates. Only Round 1 sample is included in Panel B, and we winsorize the right tail at 100. To impute the past interactions, for each firm, we first calculate the number of years since the firm was established, multiply it by the number of vacancies posted in the last 12 months (this data only exists in Round 1), and then multiply it by the college share, assuming each vacancy hires one person. We further add this imputed number with the number of current employees with a college diploma or degree.

Figure A9: Hiring of College Graduates and Non-College Workers By College Share

Panel A. Hiring of college graduates



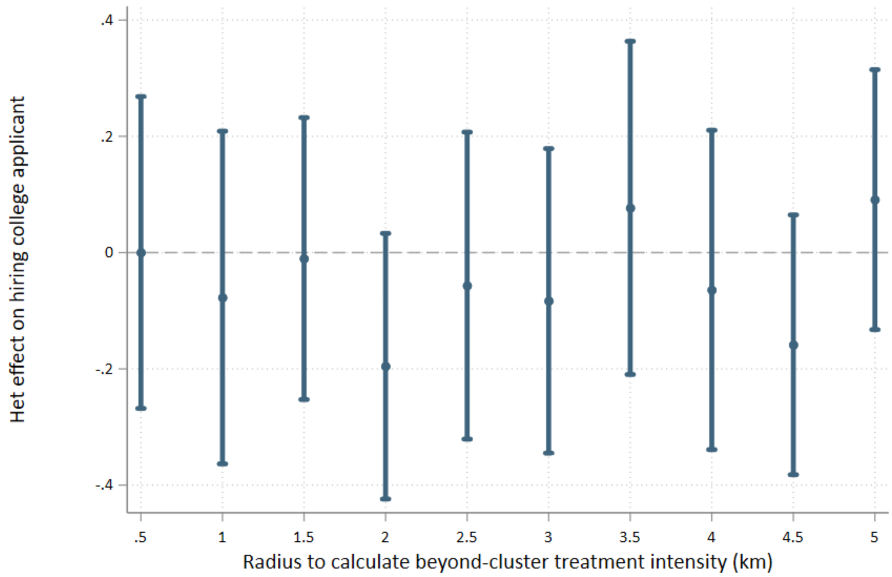
Panel B. Hiring of non-college workers



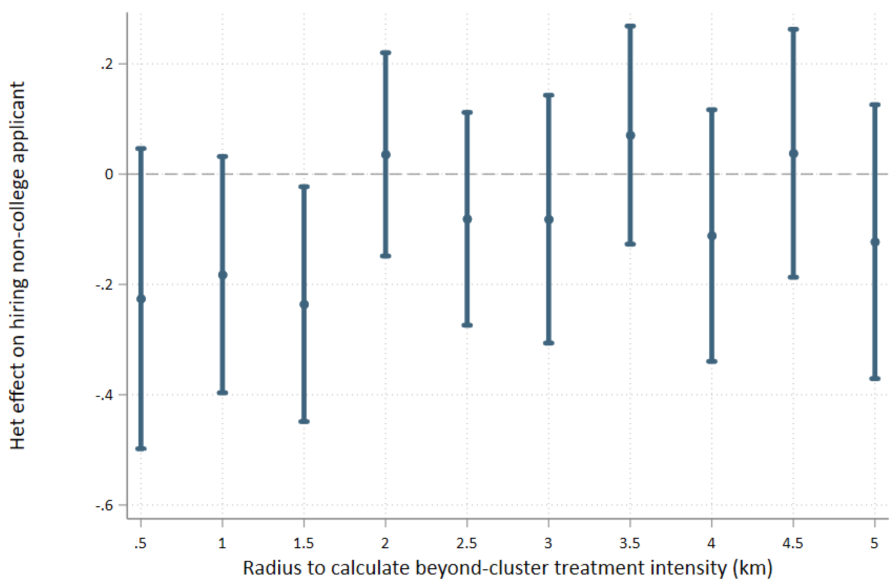
Notes: This figure presents the bin-scatter plots of the hiring of college graduates and non-college educated workers. Only firms with reservation wage at least 2,000 ETB (eligible firms) and requesting a college graduate at baseline are included. The horizontal axis is the percen tage of current employees with a college diploma or degree, a proxy for the exposure to college graduates. The vertical axis in Panel A is the percentage of firms hiring at least one college graduate; In Panel B, the percentage of firms hiring at least one non-college worker. Blue diamonds are firms initially assigned to treatment. Red dots are firms initially assigned to control group.

Figure A10: Heterogeneous Effects by Treatment Intensity

Panel A. Hiring any college graduate

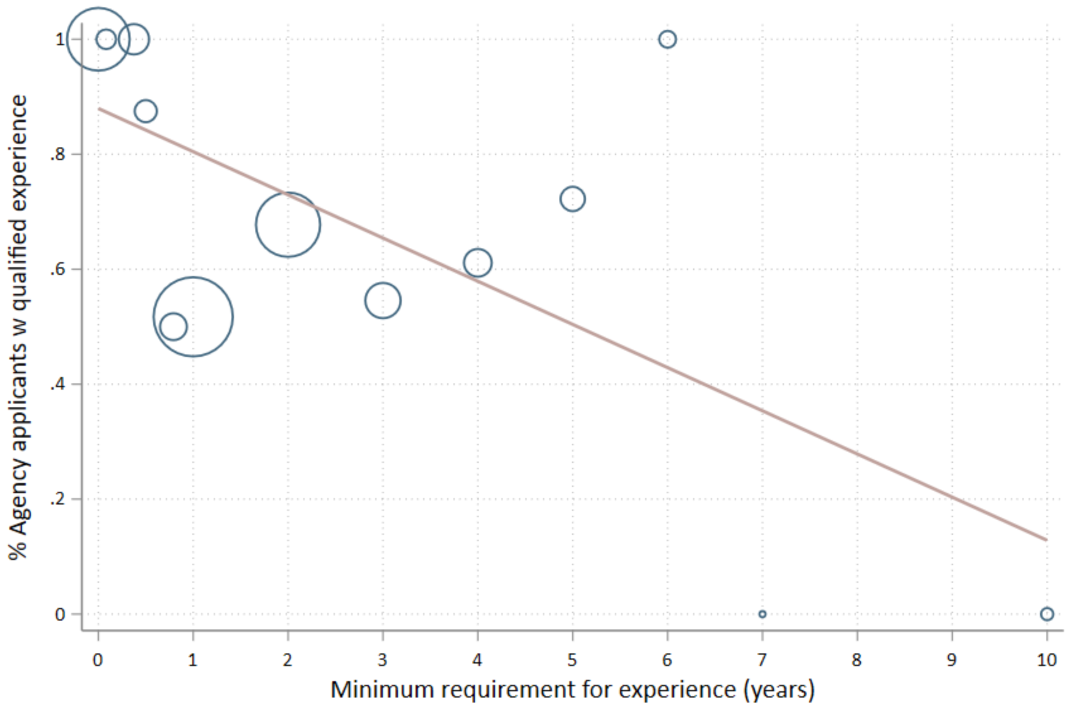


Panel B. Hiring any non-college worker



Notes: This figure shows the heterogeneous treatment effects by beyond-cluster treatment intensity in the nearby regions. Only firms with reservation wage at least 2,000 ETB (eligible firms) are included. In each regression, we regress whether firm hires any college or non-college workers on (i) initial treatment assignment, (ii) interaction of treatment assignment and whether the firm requested a college graduate at baseline, and (iii) triple interaction of treatment assignment, whether the firm requested a college graduate at baseline, and whether the treatment intensity is above average. Treatment intensity is calculated by the percentage of firms within the radius of $x - 0.5$ and x kilometers (excluding own business area) selected for treatment. We only report coefficients of the triple interaction terms. 95% confidence intervals are shown.

Figure A11: Correlation Between Applicant Qualification and Minimum Experience Requirement



Notes: This figure shows the binscatter plot of the percentage of agency applicants whose years of experience met firms' minimum requirement for experience. The size of the plots indicates the number of firms at each value of the experience requirement.

B Appendix Tables

Table B1: Qualitative Survey: Functions of Employment Agencies

Panel A. Self report from 25 agencies

Functions of employment agencies	% all agencies
Check applicants' ID	91.3
Check applicants' education certificates	82.6
Recommend vocational training to workers	52.2
Check previous employers' recommendation	39.1
Provide additional training	13.0
Conduct additional grading test	4.3

Panel B. Report from 539 job seekers

Functions of employment agencies	% of 539 workers
Offer advice on job search or which job to apply to	51.9
Provide connections with employers/workers	12.1
Coach me on job interviews	5.8
Help me revise my CV	1.7

Notes: This table presents qualitative reports of the functions of employment agencies. Panel A shows the percentage of the 25 employment agencies during pilot survey who agree with each statement. Panel B shows the percentage of the 539 job seekers during worker survey who agree with with each statement.

Table B2: Sample Selection Across Different Data

Panel A. Sampling of Firms

	This paper	Hensel et al. 2022	LMMIS 2014
Sector: Manufacturing	0.36	0.51	1.00
Sector: Hospitality	0.39	0.27	0.00
Sector: Others	0.25	0.22	0.00
Number of employees: Average	58	14	99
Number of employees: Median	20	10	32

Panel B. Sampling of Vacancies

Salary (birr)	This paper	Notice board pilot	Major online platform
25 percentile	2,000	3,500	4,609
50 percentile	3,000	4,020	8,017
75 percentile	4,800	5,208	13,926
Average	3,878	4,737	12,429

Notes: This table compares sampling of firms of vacancies between this paper and other data sources. Panel A compares the sampling of firms between this paper, Hensel et al. (2024), and Large and Medium Manufacturing and Electricity Industries Survey (LMMIS, the latest available year is 2014). Panel B compares the sampling of vacancies between this paper, vacancies collected from three major notice boards of Addis Ababa during our pilot in November 2020, and job posts from a major online job search platform in Ethiopia.

Table B3: Balance Table

	(1)	(2)	(3)	(4)	(5)	(6)
		Mean outcomes				P-value
	All	Eligible control		Eligible treated		T−C
Observations	627	335		292		
Sector						
Manufacturing and construction	0.42	0.41	(0.49)	0.43	(0.50)	0.71
Hospitality (hotels, restaurants)	0.27	0.28	(0.45)	0.26	(0.44)	0.58
Education	0.11	0.12	(0.32)	0.11	(0.32)	0.91
Health	0.05	0.07	(0.25)	0.03	(0.18)	0.10
Current employees						
Number of current employees	66.30	57.84	(87.18)	76.00	(152.09)	0.16
Pct of female employees	0.53	0.54	(0.27)	0.52	(0.26)	0.26
Pct of employees with college diploma/degree	0.37	0.38	(0.29)	0.37	(0.29)	0.62
Pct of employees with zero exp	0.20	0.19	(0.23)	0.20	(0.24)	0.70
Pct of temporary employees	0.16	0.15	(0.27)	0.17	(0.28)	0.70
Pct of employees hired through rec	0.15	0.16	(0.22)	0.14	(0.22)	0.38
Hiring practices						
The firm has a HR department	0.51	0.50	(0.50)	0.51	(0.50)	0.77
Posting jobs on notice board	0.54	0.55	(0.50)	0.53	(0.50)	0.70
Posting jobs on newspaper	0.14	0.15	(0.35)	0.14	(0.34)	0.79
Posting jobs on online platforms	0.16	0.14	(0.35)	0.17	(0.38)	0.30
Hiring from formal employment agencies	0.08	0.07	(0.25)	0.10	(0.30)	0.19
Hiring from informal brokers	0.25	0.28	(0.45)	0.22	(0.42)	0.17
Hiring through recommendation	0.50	0.50	(0.50)	0.49	(0.50)	0.83
Posted vacancy						
Reservation wage (USD)	91.49	87.83	(61.29)	95.78	(91.71)	0.26
Requiring college diploma or degree	0.44	0.45	(0.50)	0.44	(0.50)	0.92
Requiring vocational certificate	0.08	0.07	(0.25)	0.09	(0.28)	0.32
Requiring high school degree	0.14	0.15	(0.35)	0.14	(0.34)	0.70
Requiring no experience	0.20	0.21	(0.41)	0.19	(0.39)	0.45
Requiring more than 2y experience	0.19	0.16	(0.37)	0.21	(0.41)	0.23
Skilled task	0.55	0.55	(0.50)	0.55	(0.50)	0.99
Manual task	0.64	0.65	(0.48)	0.63	(0.48)	0.55
Routine task	0.69	0.70	(0.46)	0.69	(0.46)	0.76

Notes: This table shows the balance between 292 eligible firms initially assigned to treatment and 335 eligible firms initially assigned to control group. Standard deviations are shown in parentheses. Column (6) shows the p-value of a simple comparison of each characteristics between eligible treated and eligible control firms, clustered at the level of business area.

Table B4: Intensive Margin Effects on Interviewing

Panel A. All firms

VARIABLES	(1) # Applicants Interviewed	(2) # Agency apps Interviewed	(3) # Non-agency apps Interviewed	(4) All non-agency apps Interviewed
Assigned to treatment	-0.080	0.092	-0.171	-0.197
	(0.114)	(0.036)	(0.112)	(0.074)
	[0.485]	[0.012]	[0.129]	[0.009]
Observations	589	589	589	580
R-squared	0.808	0.238	0.822	0.345
Control baseline char.	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes
Control mean	1.633	0.027	1.606	0.631

Panel B. By baseline requests for college graduates

VARIABLES	(1) # Applicants Interviewed	(2) # Agency apps Interviewed	(3) # Non-agency apps Interviewed	(4) All non-agency apps Interviewed
Treated x Not requesting college	-0.108	0.049	-0.157	-0.088
	(0.128)	(0.043)	(0.122)	(0.076)
	[0.401]	[0.262]	[0.202]	[0.249]
Treated x Requesting college	-0.042	0.150	-0.191	-0.346
	(0.166)	(0.050)	(0.164)	(0.092)
	[0.803]	[0.004]	[0.248]	[0.000]
Observations	589	589	589	580
R-squared	0.809	0.243	0.822	0.357
Control baseline char.	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes
Control mean: Not requesting college	1.757	0.016	1.741	0.709
Control mean: Requesting college	1.470	0.040	1.430	0.531

Notes: This table examines whether treated firms conducted more interviews. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. In Panel B, we interact the initial treatment assignment with whether or not firm requested a college graduate at baseline. We also control for the number of non-agency applicants and the interaction with treatment status to control for the mechanical effect through the number of applicants. Dependent variables: Column 1, the number of applicants that were invited for interviews, including agency and non-agency. Column 2, the number of agency applicants invited for interviews. Column 3, the number of non-agency applicants invited for interviews. Column 4, whether firm invited all non-agency applicants for interviews. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B5: Correlational Evidence of the Search Effect

Panel A. Number of college-educated applicants

VARIABLES	(1) Interview Any	(2) Interview College	(3) Interview Non-college	(4) Hire Any	(5) Hire College	(6) Hire Non-college
# College applicants	-0.003	0.000	-0.027	-0.005	-0.001	-0.018
	(0.014)	(0.014)	(0.006)	(0.016)	(0.013)	(0.006)
	[0.855]	[0.999]	[0.000]	[0.746]	[0.909]	[0.005]
Observations	135	135	135	135	135	135
R-squared	0.641	0.666	0.827	0.612	0.609	0.828
Mean baseline char.	Yes	Yes	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.781	0.336	0.536	0.759	0.303	0.515

Panel B. Number of non-college applicants

VARIABLES	(1) Interview Any	(2) Interview College	(3) Interview Non-college	(4) Hire Any	(5) Hire College	(6) Hire Non-college
# Non-college applicants	0.019	0.009	0.022	0.019	0.000	0.019
	(0.009)	(0.022)	(0.011)	(0.009)	(0.022)	(0.011)
	[0.041]	[0.674]	[0.039]	[0.041]	[0.992]	[0.105]
Observations	206	206	206	206	206	206
R-squared	0.621	0.607	0.658	0.621	0.612	0.712
Mean baseline char.	Yes	Yes	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.781	0.336	0.536	0.759	0.303	0.515

Notes: This table presents the correlation between the number of college-educated or non-college applicants and the interviewing and hiring outcomes. In Panel A, the sample is restricted to firms with at least one college-educated applicant, controlling for the number of non-college applicants. In Panel B, the sample is restricted to firms with at least one non-college applicant, controlling for the number of college-educated applicants. Dependent variables: Column 1 and 4, whether the firm interviewed or hired any applicant at endline. Column 2 and 5, whether the firm interviewed or hired any college graduate at endline. Column 3 and 6, whether the firm interviewed or hired any non-college worker at endline. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B6: Robustness: Identification Assumption

VARIABLES	(1) Hire College	(2) Hire College	(3) Hire Non-college	(4) Hire Non-college
Treated x Not requesting college	0.030	-0.061	-0.008	0.035
	(0.219)	(0.054)	(0.183)	(0.036)
	[0.893]	[0.258]	[0.965]	[0.338]
Treated x Requesting college	-0.417	-0.494	0.223	0.291
	(0.239)	(0.131)	(0.188)	(0.129)
	[0.086]	[0.000]	[0.238]	[0.027]
Observations	580	580	580	580
R-squared	0.366	0.332	0.522	0.506
Business area Fixed effects	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes
Specification	All interactions	Residual	All interactions	Residual
Control mean	0.311	0.311	0.505	0.505

Notes: This table examines the robustness of the effects on hiring college graduates or non-college workers regarding the identification assumption. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. All regressions include a full set of baseline characteristics from Table B3, control for business area fixed effects, and cluster at business area level. Specifications: Column 1 and 3, controlling for the interaction between the initial treatment assignment and a full set of baseline characteristics from Table B3 (excluding whether the firm is in education or health sectors, and whether the firm uses notice board for hiring at baseline). Column 2 and 4, we first regress whether the firm requested a college graduate at baseline on all other baseline characteristics from Table B3, extract the residual, and interact the initial treatment assignment with the residual. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B7: Dynamics of Treatment Effects

VARIABLES	(1) Hire College Midline	(2) Hire Non-college Midline	(3) (2)-(1)	(4) Hire College Endline	(5) Hire Non-college Endline	(6) (5)-(4)	(7) Hire Any Planned
Treated x Not requesting college	0.007	0.066	0.059	0.033	-0.002	-0.036	0.005
	(0.049)	(0.054)	(0.074)	(0.063)	(0.048)	(0.077)	(0.071)
	[0.887]	[0.226]	[0.429]	[0.595]	[0.964]	[0.643]	[0.949]
Treated x Requesting college	-0.122	0.100	0.222	-0.197	0.088	0.285	-0.124
	(0.063)	(0.050)	(0.084)	(0.076)	(0.053)	(0.105)	(0.072)
	[0.057]	[0.050]	[0.010]	[0.012]	[0.106]	[0.008]	[0.088]
Observations	580	580		580	580		568
R-squared	0.279	0.442		0.327	0.502		0.324
Control baseline char.	Yes	Yes		Yes	Yes		Yes
Business area FE	Yes	Yes		Yes	Yes		Yes
Cluster at business area	Yes	Yes		Yes	Yes		Yes
Control mean: Not requesting college	0.154	0.571		0.198	0.692		0.652
Control mean: Requesting college	0.393	0.0828		0.586	0.110		0.653

Notes: This table presents the dynamics of the treatment effects on hiring. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. We interact initial treatment assignment and whether or not firm requested a college graduate at baseline. Dependent variables: Column 1 and 4, whether the firm hired any college-educated at midline or at endline. Column 2 and 5, whether the firm hired any non-college worker at midline or at endline. Column 3 computes the differences between the estimates in Column 1 and 2. Column 6 computes the differences between the estimates in Column 4 and 5. Column 7, whether the firm planned to hire any workers in the next three months following endline. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B8: Explaining the Belief Update with College Share

VARIABLES	(1)	(2)	(3)	(4)
	% Perceived productive College applicants		Agreed college grads are more productive	
Treated x Above-median college share	-0.285		-0.077	
	(0.133)		(0.0476)	
	[0.038]		[0.112]	
Treated x (Resid.) above-median college share		-0.347		-0.091
		(0.391)		(0.094)
		[0.380]		[0.335]
Treated x Below-median college share	-0.237		-0.010	
	(0.129)		(0.0567)	
	[0.076]		[0.083]	
Treated x (Resid.) below-median college share		-0.273		-0.087
		(0.120)		(0.044)
		[0.029]		[0.051]
Observations	151	151	568	568
R-squared	0.394	0.394	0.329	0.329
Control baseline char.	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes
Control mean	0.785	0.785	0.808	0.808

Notes: This table examines whether the belief update in Table 3 is more significant among firms whose percentage of college-educated workers in the firm at baseline (college share) is below median. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. In Column 1 and 3, We interact initial treatment assignment, whether firm requests a college graduate at baseline, and whether the college share is above median. We further interact the treatment status with whether the college share is above median to guarantee full saturation. In Column 2 and 4, we regress whether the college share is above median on other baseline firm and vacancy characteristics and extract the residual. We then interact initial treatment assignment, whether firm requests a college graduate at baseline, and the residual. We further interact the treatment status with the residual to guarantee full saturation. Dependent variables: Column 1 and 2, percentage of college-educated applicants perceived with good productivity. Column 3 and 4, whether firm agreed that college graduates are more productive than non-college workers. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B9: Explaining the Shift in Hiring Behavior with College Share with a Different Proxy

VARIABLES	(1) Interview College	(2) Interview Non-college	(3) (5)-(4)	(4) Hire College	(5) Hire Non-college	(6) (5)-(4)
Treated x Not requesting college	-0.078	-0.084	-0.006	-0.019	-0.036	-0.017
	(0.102)	(0.090)	(0.136)	(0.102)	(0.096)	(0.146)
	[0.450]	[0.359]	[0.966]	[0.855]	[0.714]	[0.909]
Treated x Requesting college	-0.246	-0.117	0.129	-0.211	-0.159	0.051
x Above-median interaction	(0.167)	(0.155)	(0.239)	(0.155)	(0.151)	(0.226)
	[0.150]	[0.455]	[0.593]	[0.182]	[0.297]	[0.821]
Treated x Requesting college	-0.295	0.236	0.531	-0.367	0.139	0.506
x Below-median interaction	(0.156)	(0.132)	(0.226)	(0.170)	(0.129)	(0.245)
	[0.067]	[0.083]	[0.025]	[0.037]	[0.288]	[0.046]
Observations	247	247		247	247	
R-squared	0.321	0.517		0.316	0.500	
Control baseline char.	Yes	Yes		Yes	Yes	
Business area FE	Yes	Yes		Yes	Yes	
Cluster at business area	Yes	Yes		Yes	Yes	
Control mean: Not requesting college	0.231	0.714		0.198	0.692	
Control mean: Requesting college	0.614	0.131		0.586	0.110	

Notes: This table examines the robustness of the results from Table 5. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. We first impute the number of past interactions with college graduates. We then interact initial treatment assignment, whether firm requests a college graduate at baseline, and whether the imputed past interaction is above median. We further interact the treatment status with whether the imputed past interaction is above median to guarantee full saturation. Dependent variables: Column 1 and 4, whether the firm interviews or hires any college-educated worker at endline. Column 2 and 5, whether the firm interviews or hires any non-college worker at endline. Column 3 computes the differences between the estimates in Column 1 and 2. Column 6 computes the differences between the estimates in Column 4 and 5. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B10: Robustness: Statistical Inference

Panel A. Hiring college graduates

VARIABLES	(1) Hire College	(2) Hire College	(3) Hire College	(4) Hire College	(5) Hire College	(6) Hire College
Treated x Not requesting college	0.033	0.033	0.033	0.033	-0.030	-0.033
	(0.063)	(0.061)	(0.059)	(0.075)	(0.082)	(0.083)
	[0.595]	[0.582]	[0.570]	[0.657]	[0.713]	[0.694]
Treated x Requesting college	-0.197	-0.197	-0.197	-0.197	-0.226	-0.187
	(0.076)	(0.071)	(0.075)	(0.079)	(0.088)	(0.086)
	[0.012]	[0.006]	[0.008]	[0.014]	[0.012]	[0.033]
Observations	580	580	580	580	489	455
R-squared	0.327	0.327	0.327	0.327	0.445	0.496
Control baseline char.	Yes	Yes	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Main	Robust sd	Bootstrap	Permutation test	Weighted by # apps	Weighted by # non-agency app
Control mean	0.372	0.372	0.372	0.372	0.460	0.472

Panel B. Hiring non-college workers

VARIABLES	(1) Hire Non-college	(2) Hire Non-college	(3) Hire Non-college	(4) Hire Non-college	(5) Hire Non-college	(6) Hire Non-college
Treated x Not requesting college	-0.002	-0.002	-0.002	-0.002	0.028	0.060
	(0.048)	(0.054)	(0.050)	(0.055)	(0.061)	(0.059)
	[0.964]	[0.968]	[0.965]	[0.968]	[0.645]	[0.313]
Treated x Requesting college	0.088	0.088	0.088	0.088	0.070	0.052
	(0.053)	(0.064)	(0.059)	(0.084)	(0.061)	(0.062)
	[0.106]	[0.172]	[0.140]	[0.303]	[0.261]	[0.405]
Observations	580	580	580	580	489	455
R-squared	0.502	0.502	0.502	0.502	0.719	0.748
Control baseline char.	Yes	Yes	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Main	Robust sd	Bootstrap	Permutation test	Weighted by # apps	Weighted by # non-agency app
Control mean	0.433	0.433	0.433	0.433	0.544	0.557

Notes: This table examines the robustness of the treatment effects on hiring college graduates or non-college workers regarding statistical inference. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. We interact initial treatment assignment and whether firm requests a college graduate at baseline. Panel A examines the effect on the hiring of college graduates; Panel B examines the effect on the hiring of non-college workers. Specifications: Column 1, main. Column 2, only robust standard errors. Column 3, bootstrapping standard errors. Column 4, permutation test. Column 5, observations weighted by the total number of applicants. Column 6, observations weighted by the total number of non-agency applicants. All regressions include a full set of baseline characteristics from Table B3, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B11: Robustness: Attrition

VARIABLES	(1) Attrition	(2) Hire College	(3) Hire College	(4) Hire College	(5) Hire Non-college	(6) Hire Non-college	(7) Hire Non-college
Treated x Not requesting college	0.026	0.054	0.031	0.057	-0.008	-0.018	0.008
	(0.023)	(0.079)	(0.063)	(0.064)	(0.063)	(0.049)	(0.051)
	[0.273]	[0.497]	[0.623]	[0.376]	[0.899]	[0.715]	[0.872]
Treated x Requesting college	0.021	-0.168	-0.197	-0.177	0.058	0.083	0.103
	(0.014)	(0.072)	(0.076)	(0.078)	(0.060)	(0.053)	(0.054)
	[0.123]	[0.023]	[0.012]	[0.026]	[0.337]	[0.125]	[0.059]
Treated x Requesting college x Attrition likelihood		-0.126			0.167		
		(0.166)			(0.144)		
		[0.448]			[0.250]		
Observations	589	580	581	581	580	581	581
R-squared	0.224	0.330	0.327	0.308	0.506	0.497	0.507
Control baseline char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Main	Interaction	All attrited firms hired	No attrited firms hired	Interaction	All attrited firms hired	No attrited firms hired
Control mean	0.015	0.372	0.371	0.386	0.433	0.432	0.447

Notes: This table examines the robustness of the effects on hiring college graduates or non-college workers regarding attrition. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. All regressions include a full set of baseline characteristics from Table B3, control for business area fixed effects, and cluster at business area level. Specifications: Column 1, regressing treatment status on attrition; Column 2 and 5, including an interaction of treatment status, whether the firm requested a college graduate at baseline, and whether the predicted attrition likelihood is above average. The predicted attrition likelihood is constructed by regressing attrition on the entire set of baseline characteristics. Column 3 and 6, assuming all attrited firms interviewed or hired within one month; Column 4 and 7, assuming no attrited firms interviewed or hired within one month. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B12: Robustness: Matching Strategy of Employment Agencies

VARIABLES	(1) Hire College	(2) Hire College	(3) Hire College	(4) Hire College	(5) Hire Non-college	(6) Hire Non-college	(7) Hire Non-college	(8) Hire Non-college
Delivered x Not requesting college	0.034	0.175			-0.150	-0.000		
	(0.075)	(0.385)			(0.087)	(0.296)		
	[0.657]	[0.650]			[0.090]	[0.999]		
Delivered x Requesting college	-0.148	-0.358			0.007	0.164		
	(0.074)	(0.148)			(0.057)	(0.106)		
	[0.049]	[0.018]			[0.898]	[0.126]		
Treated x Not requesting college			0.015	0.030			0.021	-0.021
			(0.067)	(0.115)			(0.049)	(0.089)
			[0.824]	[0.795]			[0.666]	[0.818]
Treated x Requesting college			-0.199	-0.192			0.058	0.085
			(0.103)	(0.088)			(0.075)	(0.053)
			[0.058]	[0.031]			[0.441]	[0.118]
Treated x Requesting college x High reservation wage			-0.121				0.206	
			(0.131)				(0.149)	
			[0.359]				[0.171]	
Treated x Requesting college x Unlikely delivered				-0.027				-0.014
				(0.131)				(0.112)
				[0.837]				[0.904]
Observations	580	580	580	580	580	580	580	580
R-squared	0.321	0.178	0.328	0.327	0.504	0.377	0.505	0.502
Control baseline char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	OLS	IV	OLS	OLS	OLS	IV	OLS	OLS
Control mean	0.372	0.372	0.372	0.372	0.433	0.433	0.433	0.433
F-statistic		5.984				5.984		
Hausman test:								
Not requesting college	0.663				0.640			
Requesting college	0.096				0.144			

Notes: This table examines the robustness of the effects on hiring college graduates or non-college workers regarding strategic matching of employment agencies. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. All regressions include a full set of baseline characteristics from Table B3, control for business area fixed effects, and cluster at business area level. The independent variable for Column 1, 2, 5, and 6 is whether the firm receives extra applicants. Specifications: Column 1 and 5, OLS regression; Column 2 and 6, using initial random assignment as an instrument; Column 3 and 7, OLS regression with initial treatment assignment as the main independent variable and interacting with whether the firm requested a college graduate at baseline and whether the reservation wage is above average; Column 4 and 8, OLS regression with initial treatment assignment as the main independent variable and interacting with whether the firm requested a college graduate at baseline and whether the predicted likelihood of receiving extra applicants is below average. The predicted likelihood is constructed by regressing whether the firms receive any extra applicant on the entire set of baseline characteristics. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B13: Robustness: Demand Effect

VARIABLES	(1) Hire College	(2) Hire College	(3) Hire Non-college	(4) Hire Non-college
Treated x Not requesting college	0.024	0.039	0.010	0.013
	(0.080)	(0.072)	(0.071)	(0.060)
	[0.763]	[0.588]	[0.883]	[0.827]
Treated x Requesting college	-0.213	-0.221	0.152	0.070
	(0.091)	(0.080)	(0.079)	(0.055)
	[0.023]	[0.007]	[0.058]	[0.206]
Treated x Requesting college	-0.011		-0.140	
x Many vacancies	(0.148)		(0.124)	
	[0.939]		[0.263]	
Treated x Requesting college		0.156		0.157
x Less engaging		(0.159)		(0.137)
		[0.330]		[0.257]
Observations	485	580	485	580
R-squared	0.356	0.329	0.496	0.504
Control baseline char.	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes
Control mean	0.393	0.372	0.464	0.433

Notes: This table examines the robustness of the effects on hiring college graduates or non-college workers regarding demand effects. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. All regressions include a full set of baseline characteristics from Table B3, control for business area fixed effects, and cluster at business area level. Specifications: Column 1 and 3, interacting treatment assignment, whether the firm requested a college graduate at baseline, and whether there is more than one vacancy during baseline (Round 2) or whether the firm usually posts more than one job vacancy per year (Round 1). Column 2 and 4, interacting treatment status, whether the firm requested a college graduate at baseline, and whether the respondents are the owners themselves, a proxy for less engagement. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B14: Robustness: Spillover

VARIABLES	(1) Hire College	(2) Hire College	(3) Hire College	(4) Hire Non-college	(5) Hire Non-college	(6) Hire Non-college
Intensely treated area	0.045			0.013		
x Not requesting college	(0.100)			(0.109)		
	[0.657]			[0.905]		
Intensely treated area	0.016			-0.037		
x Requesting college	(0.158)			(0.096)		
	[0.921]			[0.702]		
Treated x Not requesting college		0.031	-0.057		0.013	0.052
		(0.075)	(0.097)		(0.056)	(0.076)
		[0.684]	[0.556]		[0.813]	[0.497]
Treated x Requesting college		-0.272	-0.204		0.100	0.225
		(0.102)	(0.107)		(0.065)	(0.090)
		[0.010]	[0.059]		[0.124]	[0.014]
Treated x Requesting college		0.148			0.008	
x Intensely treated area		(0.130)			(0.107)	
		[0.259]			[0.942]	
Treated x Requesting college			-0.142			-0.102
x High intensity w/n 500m			(0.121)			(0.118)
			[0.246]			[0.391]
Observations	315	580	563	315	580	563
R-squared	0.341	0.330	0.334	0.493	0.502	0.502
Only non-treated firms	Yes			Yes		
Local district FE	Yes			Yes		
Business area FE		Yes	Yes		Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.311	0.372	0.372	0.505	0.433	0.433

Notes: This table examines the robustness of the effects on hiring college graduates or non-college workers regarding spillover on control firms. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. All regressions include a full set of baseline characteristics from Table B3 and cluster at business area level. The independent variable in Column 1 and 4 is whether the business area is selected for the intense treatment arm. Specification: Column 1 and 4, only control firms are included, controlling for local district fixed effects. Column 2 and 5, interacting the treatment assignment, whether the firm requested a college graduate at baseline, and whether the business area is selected for the intense treatment arm, controlling for business area fixed effects. Column 3 and 6, interacting the treatment assignment, whether the firm requested a college graduate at baseline, and whether the treatment intensity within 500-meter radius is above average, controlling for business area fixed effects. Treatment intensity is calculated by the percentage of firms in nearby 500 meters (excluding own business area) selected for treatment. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B15: Qualification of College Graduates' Experience

VARIABLES	(1) Qualified	(2) Qualified	(3) Qualified	(4) Qualified
College	-0.072	0.036	0.075	0.093
	(0.036)	(0.036)	(0.045)	(0.051)
	[0.047]	[0.309]	[0.097]	[0.071]
From agency (i)	0.032	0.003	-0.105	-0.065
	(0.081)	(0.083)	(0.139)	(0.121)
	[0.692]	[0.971]	[0.451]	[0.593]
College x From agency (ii)	-0.066	-0.042	0.037	0.066
	(0.097)	(0.096)	(0.159)	(0.130)
	[0.500]	[0.661]	[0.818]	[0.610]
Observations	1,050	1,013	436	741
R-squared	0.009	0.117	0.075	0.647
Control applicant char.	No	Yes	Yes	Yes
Only matched experience	No	No	Yes	No
Firm FE	No	No	No	Yes
Cluster at firm	Yes	Yes	Yes	Yes
Mean: Non-college	0.758	0.758	0.758	0.758
P-value: (i) + (ii) = 0	0.548	0.462	0.382	0.986

Notes: This table examines whether college applicants are more qualified for the job regarding their experiences. An applicant was qualified for the job if their years of experience met the job requirement. We regress whether the applicant was qualified on whether the applicant had a college diploma or degree, whether the applicant was recommended from the employment agency, the interaction of the college indicator and the agency indicator. All regressions cluster at the firm level. We report the average mean of non-college applicants, and the p-value of the t-test whether the summation of the agency indicator and its interaction with the college indicator equals zero. Specifications: Column 2–4, controlling for a series of applicant characteristics (age, age squared, gender, whether the applicant's father has at least eight years of schooling, whether the applicant was employed at baseline). Column 3, sample restricted to applicants whose description of their past experiences suited the job description of the vacancy; the description of applicants' past experiences only exists in Round 2. Column 4–6, controlling for firm fixed effects. All regressions cluster at the firm level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B16: Robustness: Explaining the Shift in Hiring Behavior with Experience Requirement

VARIABLES	(1) Interview College	(2) Interview Non-college	(3) (2)-(1)	(4) Hire College	(5) Hire Non-college	(6) (5)-(4)
Treated x Not requesting college	0.059	-0.001	-0.060	0.037	-0.005	-0.042
	(0.059)	(0.050)	(0.070)	(0.062)	(0.048)	(0.076)
	[0.326]	[0.978]	[0.396]	[0.549]	[0.923]	[0.578]
Treated x Requesting college	-0.194	0.199	0.394	-0.358	0.173	0.531
x (Resid.) low experience requirement	(0.167)	(0.129)	(0.222)	(0.164)	(0.135)	(0.225)
	[0.249]	[0.126]	[0.081]	[0.032]	[0.205]	[0.021]
Treated x Requesting college	-0.108	0.108	0.216	-0.180	0.080	0.260
x (Resid.) high experience requirement	(0.069)	(0.059)	(0.102)	(0.074)	(0.055)	(0.103)
	[0.120]	[0.070]	[0.038]	[0.018]	[0.146]	[0.014]
Observations	580	580		580	580	
R-squared	0.350	0.493		0.333	0.503	
Control baseline char.	Yes	Yes		Yes	Yes	
Business area FE	Yes	Yes		Yes	Yes	
Cluster at business area	Yes	Yes		Yes	Yes	
Control mean: Not requesting college	0.231	0.714		0.198	0.692	
Control mean: Requesting college	0.614	0.131		0.586	0.110	

Notes: This table examines the robustness of the results from Table 6. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. We regress whether firm required less than one year of experience on other baseline firm and vacancy characteristics and extract the residual. We then interact initial treatment assignment, whether firm requests a college graduate at baseline, and the residual. We control for the interaction of treatment status and the residual to guarantee full saturation. Dependent variables: Column 1 and 4, whether the firm interviews or hires any college-educated worker at endline. Column 2 and 5, whether the firm interviews or hires any non-college worker at endline. Column 3 computes the differences between the estimates in Column 1 and 2. Column 6 computes the differences between the estimates in Column 4 and 5. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B17: Perceived Qualification of College Graduates' Experience

VARIABLES	(1) Perceived Qualified	(2) Perceived Qualified	(3) Perceived Qualified	(4) Perceived Qualified	(5) Perceived Productive	(6) Perceived Productive
College	-0.149	-0.135	-0.116	-0.053	-0.065	-0.031
	(0.031)	(0.035)	(0.052)	(0.049)	(0.048)	(0.086)
	[0.000]	[0.000]	[0.027]	[0.279]	[0.171]	[0.722]
From agency (i)	-0.018	-0.003	-0.011	-0.052	-0.193	-0.317
	(0.080)	(0.083)	(0.137)	(0.109)	(0.137)	(0.143)
	[0.825]	[0.970]	[0.934]	[0.636]	[0.162]	[0.028]
College x From agency (ii)	0.013	-0.000	-0.101	0.042	0.117	0.263
	(0.090)	(0.091)	(0.152)	(0.115)	(0.161)	(0.180)
	[0.886]	[0.999]	[0.510]	[0.716]	[0.468]	[0.147]
Years of experience	0.070	0.079	0.061	0.085	0.003	0.003
	(0.004)	(0.005)	(0.007)	(0.008)	(0.007)	(0.011)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.704]	[0.779]
Perceived qualified					0.085	0.043
					(0.047)	(0.057)
					[0.068]	[0.455]
Observations	1,050	1,013	436	741	592	427
R-squared	0.292	0.334	0.238	0.685	0.086	0.558
Control applicant char.	No	Yes	Yes	Yes	Yes	Yes
Only matched experience	No	No	Yes	No	No	No
Firm FE	No	No	No	Yes	No	Yes
Cluster at firm	Yes	Yes	Yes	Yes	Yes	Yes
Mean: Non-college	0.508	0.508	0.508	0.267	0.787	0.787
P-value: (i) + (ii) = 0	0.916	0.938	0.115	0.853	0.363	0.623

Notes: This table examines whether college applicants are more likely to be considered qualified for the job regarding their experiences. An applicant was considered qualified for the job if firms' perception of the applicant's years of experience met the job requirement. In Column 1–4, we regress whether the applicant was considered qualified on whether the applicant had a college diploma or degree, whether the applicant was recommended from the employment agency, the interaction of the college indicator and the agency indicator, and the actual years of experience. The dependent variable in Column 5 and 6 is whether the applicant was perceived with good productivity; we further control for whether the applicant was considered qualified. All regressions cluster at the firm level. We report the average mean of non-college applicants, and the p-value of the t-test whether the summation of the agency indicator and its interaction with the college indicator equals zero. Specifications: Column 2–6, controlling for a series of applicant characteristics (age, age squared, gender, whether the applicant's father has at least eight years of schooling, whether the applicant was employed at baseline). Column 3, sample restricted to applicants whose description of their past experiences suited the job description of the vacancy; the description of applicants' past experiences only exists in Round 2. Column 4 and 6, controlling for firm fixed effects. All regressions cluster at the firm level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B18: Perceived Qualification And College Graduates' Résumé

VARIABLES	(1) Perceived Qualified	(2) Perceived Qualified	(3) Perceived Qualified	(4) Perceived Qualified	(5) Perceived Productive	(6) Perceived Productive
College (i)	-0.109	-0.071	-0.121	-0.029	0.052	0.029
	(0.049)	(0.054)	(0.092)	(0.055)	(0.078)	(0.080)
	[0.028]	[0.187]	[0.189]	[0.600]	[0.509]	[0.720]
Résumé (ii)	-0.109	-0.082	-0.063	0.048	-0.128	-0.039
	(0.054)	(0.054)	(0.101)	(0.090)	(0.064)	(0.130)
	[0.045]	[0.130]	[0.531]	[0.595]	[0.046]	[0.764]
College x Résumé (iii)	0.032	-0.016	0.041	-0.053	-0.042	-0.113
	(0.073)	(0.073)	(0.138)	(0.088)	(0.102)	(0.168)
	[0.659]	[0.822]	[0.764]	[0.547]	[0.680]	[0.504]
Years of experience	0.071	0.079	0.060	0.085	0.002	0.004
	(0.004)	(0.005)	(0.007)	(0.008)	(0.007)	(0.011)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.790]	[0.698]
Perceived qualified					0.078	0.040
					(0.046)	(0.058)
					[0.092]	[0.491]
Observations	1,045	1,008	435	737	592	427
R-squared	0.296	0.337	0.237	0.684	0.098	0.551
Control applicant char.	No	Yes	Yes	Yes	Yes	Yes
Only matched experience	No	No	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Cluster at firm	Yes	Yes	Yes	Yes	Yes	Yes
Mean: Non-college	0.519	0.519	0.519	0.258	0.779	0.779
P-value: (i) + (ii) + (iii) = 0	0.000	0.000	0.011	0.689	0.018	0.505

Notes: This table examines whether college applicants are more likely to be considered qualified for the job regarding their experiences if they provided a résumé. An applicant was considered qualified for the job if firms' perception of the applicant's years of experience met the job requirement. In Column 1–4, we regress whether the applicant was considered qualified on whether the applicant had a college diploma or degree, whether the applicant provided a résumé, the interaction of the college indicator and the résumé indicator, and the actual years of experience. The dependent variable in Column 5 and 6 is whether the applicant was perceived with good productivity; we further control for whether the applicant was considered qualified. All regressions cluster at the firm level. We report the average mean of non-college applicants, and the p-value of the t-test whether the summation of the college indicator, the résumé indicator, and its interaction with the college indicator equals zero. Specifications: Column 2–6, controlling for a series of applicant characteristics (age, age squared, gender, whether the applicant's father has at least eight years of schooling, whether the applicant was employed at baseline). Column 3, sample restricted to applicants whose description of their past experiences suited the job description of the vacancy; the description of applicants' past experiences only exists in Round 2. Column 4 and 6, controlling for firm fixed effects. All regressions cluster at the firm level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B19: Belief Update in the Outside Options of College Graduates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	% Apps perceived w high outside options				Whether firm agrees		
	College	Non-college	College	College	College grads have more outside options		
Assigned to treat	-0.258	-0.052			-0.042		
	(0.127)	(0.110)			(0.044)		
	[0.050]	[0.637]			[0.347]		
# Non-agency (NA) college applicants			-0.028			0.004	
			(0.015)			(0.012)	
			[0.074]			[0.736]	
Treated x Zero NA college applicants			-0.485			-0.057	
			(0.177)			(0.058)	
			[0.010]			[0.325]	
Treated x $\geq$ 1 NA college applicants			-0.227			-0.014	
			(0.117)			(0.056)	
			[0.060]			[0.804]	
Treated x Not requesting college				-0.295			-0.071
				(0.236)			(0.056)
				[0.218]			[0.205]
Treated x Requesting college				-0.244			0.002
				(0.122)			(0.064)
				[0.053]			[0.976]
Observations	152	154	152	152	568	568	568
R-squared	0.455	0.491	0.488	0.455	0.344	0.345	0.345
Control firm/vacancy char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.687	0.703			0.588		
Control mean: Not requesting college				0.630			0.535
Control mean: Requesting college				0.712			0.683
Control mean with one NA college app			0.767			0.713	
Control mean with zero NA college app						0.528	

Notes: This table presents whether treated firms updated beliefs of the outside options of college graduates. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. In column 1–4, for each firm, we compute the percentage of applicants perceived with high outside options in each category (college graduates, non-college workers); this data only exists in Round 2. Column 5–7 look at whether firm agreed that college graduates have more outside options than non-college workers. In Column 3 and 5, we interact the initial treatment assignment with whether or not firm received at least one non-agency (NA) college-educated applicants, and control for the number of college-educated non-agency applicants. In Column 4 and 6, we interact the initial treatment assignment with whether or not firm requested a college graduate at baseline. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B20: Applicants' Rejection of Interview Invites or Offers

VARIABLES	(1) Reject interview	(2) Reject interview	(3) Reject offer	(4) Reject offer
College graduate	0.034	0.046	-0.054	-0.056
	(0.060)	(0.082)	(0.070)	(0.076)
	[0.570]	[0.578]	[0.438]	[0.466]
Observations	1,007	851	754	681
R-squared	0.470	0.458	0.714	0.748
Control worker char.	No	Yes	No	Yes
Control mean	0.020	0.020	0.023	0.023

Notes: This table presents whether college graduates are more likely to reject interview invites or offers compared to non-college workers. All regressions control for firm fixed effects and cluster at firm level. Column 1 and 2 only include applicants who receive the interview invite. Column 3 and 4 only include applicants who receive an offer. Column 2 and 4 also control for workers' experience, gender, and age. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B21: Effects on Future Hiring Channels

VARIABLES	(1) Hire from agencies	(2) Hire form other formal channels	(3) Hire from informal rec
Treated x Not requesting college	0.003	-0.002	0.047
	(0.038)	(0.049)	(0.050)
	[0.928]	[0.970]	[0.353]
Treated x Requesting college	0.055	-0.127	0.080
	(0.056)	(0.051)	(0.074)
	[0.329]	[0.015]	[0.280]
Observations	568	568	568
R-squared	0.347	0.473	0.465
Control mean	0.094	0.480	0.480

Notes: This table presents the treatment effects on what hiring channels firms plan to use in the future. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. We interact the initial treatment assignment with whether the firm requested a college graduate at baseline. All regressions include a full set of baseline characteristics from Table B3, control for business area fixed effects, and cluster at business area level. Dependent variables: Column 1, whether firms plan to hire from employment agencies. Column 2, whether firms plan to hire from other formal channels (notice boards, newspaper, online job search platforms). Column 3, whether firms plan to hire from informal recommendations (including informal brokers). Standard errors are shown in parentheses; p-values are shown in brackets.

Table B22: Treatment Effect on Referral Hiring

Panel A. Belief update

	(1)	(2)	(3)	(4)
	% Perceived productive			
VARIABLES	External	Internal	External, college	External, non-college
Assigned to treat	-0.186	0.205	-0.304	0.091
	(0.111)	(0.208)	(0.132)	(0.087)
	[0.101]	[0.336]	[0.028]	[0.299]
Observations	226	52	131	121
R-squared	0.322	0.891	0.432	0.541
Control firm/vacancy char.	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes
Control mean	0.774	0.886	0.774	0.774

Panel B. Effect on hiring

	(1)	(2)	(3)	(4)
	Hire	Hire	Hire	Hire
VARIABLES	Non-referral	Referral	Non-referral	Referral
Treated x Using referral	-0.024	0.000	-0.023	-0.000
	(0.068)	(0.074)	(0.068)	(0.073)
	[0.727]	[0.995]	[0.736]	[0.995]
Treated x Not using referral	-0.033	0.054		
	(0.070)	(0.059)		
	[0.641]	[0.363]		
Treated x Not using referral			0.058	-0.023
x Not requesting college			(0.084)	(0.067)
			[0.495]	[0.729]
Treated x Not Using referral			-0.163	0.165
x Requesting college			(0.085)	(0.079)
			[0.057]	[0.038]
Observations	578	578	578	578
R-squared	0.285	0.263	0.292	0.269
Control mean: Not requesting college	0.516	0.286	0.516	0.286
Control mean: Requesting college	0.497	0.179	0.497	0.179

Notes: This table examines whether firms hire through referrals after receiving a negative signal induced from the treatment. The sample is restricted to firms eligible for treatment with reservation wage at least 2,000 ETB. Panel A shows the treatment effect on the percentage of applicants being perceived as productive by firms, in four categories, respectively: (1) External applicants, (2) internal applicants, (3) external college-educated applicants, (4) external non-college applicants. Panel B shows the heterogeneous treatment effect on hiring. Dependent variables: Column 1 and 3, whether the firm hires from a non-referral channel. Column 2 and 4, whether the firm hires from internal referrals. Column 1 and 2 interact the initial treatment assignment with whether the firm relied on referral at baseline; Column 3 and 4 further interact the initial treatment assignment, whether the firm relied on referral at baseline, and whether the firm requested a college graduate at baseline. All regressions control for all baseline firm and vacancy characteristics, include business area fixed effects, and cluster at the business area level. Standard errors are shown in parentheses; p-values are shown in brackets.

Table B23: Treatment Effects on Salary and Match Quality

Panel A. Simple ATE

VARIABLES	(1) Salary (USD)	(2) Voluntary quit	(3) Fired by firm	(4) Above-avg prod (surveyed)	(5) Above-avg prod (measured)	(6) No absent days	(7) Overtime work
Assigned to treat	0.731	-0.138	0.085	0.036	0.108	-0.005	-0.020
	(10.09)	(0.160)	(0.076)	(0.186)	(0.261)	(0.163)	(0.211)
	[0.943]	[0.392]	[0.268]	[0.850]	[0.683]	[0.975]	[0.924]
Observations	116	142	142	142	82	142	142
R-squared	0.702	0.487	0.429	0.601	0.787	0.511	0.517
Control baseline char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at business area	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.111	0.111	0.020	0.535	0.476	0.636	0.333

Panel B. Complier analysis

VARIABLES	(1) Salary (USD)	(2) Voluntary quit	(3) Fired by firm	(4) Above-avg prod (surveyed)	(5) Above-avg prod (measured)	(6) No absent days	(7) Overtime work
$E[Y_n \vert H_n(1) > H_n(0)]$	55.5	.305	.0603	.53	.31	.544	.531
	(7.15)	(.103)	(.0437)	(.122)	(.152)	(.122)	(.122)
	[0.000]	[0.003]	[0.168]	[0.000]	[0.041]	[0.000]	[0.000]
$E[Y_c \vert H_c(1) < H_c(0)]$	121	.153	.0246	.622	.647	.577	.302
	(15.8)	(.103)	(.0593)	(.149)	(.232)	(.147)	(.143)
	[0.000]	[0.135]	[0.678]	[0.000]	[0.005]	[0.000]	[0.035]
Diff	-65.8	.151	.0357	-.0926	-.337	-.0324	.229
	(17)	(.144)	(.0712)	(.199)	(.295)	(.2)	(.194)
	[0.000]	[0.294]	[0.616]	[0.642]	[0.252]	[0.871]	[0.240]

Notes: This table presents the treatment effects of employment agencies on salary and match quality at endline. Panel A presents the average treatment effects among firms requesting a college graduate at baseline and eligible for treatment with reservation wage at least 2,000 ETB are included in the regressions. All regressions include a full set of baseline characteristics from Table B3, control for business area fixed effects, and cluster at business area level. Panel B presents the complier analysis following Abadie (2003). Endogeneous variables: Whether firms hire any college graduates (H_c), and whether firms hire any non-college workers (H_n). Instrument: Interaction of initial treatment assignment and baseline request for college graduates. No other controls are included in the complier analysis. Dependent variables: Column 1, monthly salary in US dollars. Column 2, whether the hired worker voluntarily quits. Column 3, whether the hired worker is fired by firms. Column 4, whether the hired worker is considered to be more productive than average workers on the similar positions. Column 5, whether the efficiency measure of the hired worker is above that of similar workers (only in Round 2). Column 6, whether the hired worker has zero absent day in the last 30 days. Column 7, whether the hired worker works overtime in the last 7 days. Standard errors are shown in parentheses; p-values are shown in brackets.

C Main Variable Descriptions

C.1 Firm-level variables

Module	Survey questions	Variables	Use in paper
Baseline sector	What is the main business of this company?	Manufacturing and construction	Baseline control
		Hospitality (Hotels, restaurants)	Baseline control
		Education	Baseline control
		Health	Baseline control
Baseline workforce	How many employees are currently in your company? (including both permanent and temporary)	Number of current employees	Baseline control
	What's the percentage/number of female workers currently hired in the company?	Pct of female employees	Baseline control
	What's the percentage/number of well-educated workers (at least diploma) currently hired in the company?	Pct of employees with college degree	Baseline control, mechanism test
	What's the percentage/number of workers with zero year of experience currently hired in the company?	Pct of employees with zero experience	Baseline control
	What's the percentage/number of temporary workers currently hired in the company?	Pct of temporary employees	Baseline control
	What's the percentage/number of workers currently hired through referrals or recommendations?	Pct of employees hired through recommendation	Baseline control
Baseline hiring	What's the respondent's position in the firm?	The firm has a HR department (the respondent is a human resource manager or expert)	Baseline control
		The respondent is less engaging (the respondent is the owner)	Robustness
	Have you tried to hire labor from notice boards, newspaper, or online platforms before?	Hiring only from formal channels	Baseline control
	Have you tried to hire labor from agencies or informal brokers before?	Hiring from agencies or brokers	Baseline control
	Which agency did you go to most often before?	Experience with emp agencies	Footnote
	Have you tried to hire labor through personal recommendation?	Hiring through recommendation	Baseline control
Baseline vacancy	What will be the highest salary you would pay for this position?	Reservation wage	Eligibility, baseline control, robustness
	How many vacancies are you posting?	Posting more than one vacancy (only in Round 2)	Robustness
	What is the minimal requirement on education?	Required college-level diploma or degree (incl. TVET Level 3–4)	Baseline control, mechanism test
		Required vocational certificate (excl. TVET Level 3–4)	Baseline control
		Required high school degree	Baseline control
	What is the minimal requirement on experience?	Required no experience	Baseline control
		Required $\geq$2y experience	Baseline control
	What will be the brief job description for this new position?	Skilled task, manual task, routine task	Baseline control, mechanism test
Endline outcome	What is the agreed monthly salary when you first hire this person?	Monthly salary	Cost-benefit
	Did the hired worker quit voluntary?	Voluntary quit	Cost-benefit
	Did you fire this hired worker?	Fired by firm	Cost-benefit
	Compare this worker to the average 1-3 workers in the similar positions. How productive do you think this worker is on the job?	Above-average prod. (surveyed)	Cost-benefit
	What's the performance measure of this worker in the last month?	Above-average prod. (estimated)	Cost-benefit
	How many days is this worker absent in the last 30 days?	Zero absent days	Cost-benefit
	How many overtime hours does this worker work in the last week?	Overtime work	Cost-benefit
	What channels are you planning to use to post vacancies?	Plan to hire from agencies, other formal channels, or informal recommendation	Alt mechanism
	Do you think it is easier for a college graduate to get a job in Addis Ababa, compared to someone who didn't go to college?	Perception: College graduates have more job opportunities	Descriptives
	Imagine two workers. They came from the same subcity, went to the same secondary school, and have the same work experience. The only difference is that one went to college and the other one didn't. For the vacancy you posted, which one do you think will be more productive?	Perception: College graduates are more productive	Mechanism test

C.2 Applicant-level variables

Module	Survey questions	Variables	Use in paper
Firm applicant form	What's the education level of the applicant?	Educ: College-level diploma or degree (incl. TVET Level 3–4)	Main outcome
		Educ: Vocational (non-diploma, excl. TVET Level 3–4)	Balance
		Educ: At most high school	Balance
	Years of work experience	Experience: ≥2y	Information asymmetry
		Experience: Some but <2y	Balance
		Experience: None	Data validation
	Was this worker sent by one of our employment agencies?	Agency/non-agency applicants	Main outcome
	Did you invite this applicant to interview?	Invited to interview	Main outcome
	Did the applicant reject the interview invite?	Reject interview	Alt mechanism
	Did you offer a job to this applicant?	Hired	Main outcome
	Did the applicant reject the offer?	Reject offer	Alt mechanism
	If this worker is to be hired on the job, how productive would this worker be?	Perceived to be productive (only Round 2)	Mechanism test
Worker survey	Gender	Gender	Balance
	What is your age?	Age: Above median	Balance
	Are you currently employed?	Currently employed	Balance, data validation
	What is your current job?		Data validation
	What is your monthly salary?	Current salary	Data validation

D Model

D.1 Theoretical framework

Suppose there are two types of workers in the labor market: (1) Non-college workers (subscript n) with worker-specific productivity $\mu_n = 1$ and mass one, and (2) college graduates (subscript c) with worker-specific productivity $\mu_c = \mu > 1$ and mass one. On the other side, there are two types of firms: (1) Low-type firms (subscript l) with firm-specific productivity $\zeta_l = 1$ and mass one, and (2) high-type firms (subscript h) with firm-specific productivity $\zeta_h = \zeta > 1$ and mass one. Assume each firm hires one unit of worker and has a labor-complementary production function to produce an intermediate good $Y_{j,i} = \mu_i \zeta_j, i = n, c$. Low-type firms and high-type firms produce different types of products, and hiring a college graduate would increase production: $Y_j = Y_{j,h} + Y_{j,l}$. engage in perfect competition in both product market and labor market. The final total output is an aggregate of the two types of intermediates with constant elasticity of substitution: $Y = (\alpha_h Y_h^\rho + \alpha_l Y_l^\rho)^{1/\rho}$, $\alpha_h + \alpha_l = 1$.

Suppose firms live infinitely. In each period, if firm j does not have a worker currently, firm j would pay k to post a vacancy to either non-college workers or college graduates. In each period t, the mass of low-type (high-type) firms posting a non-college job is v_{ln} (v_{hn}), the mass of low-type (high-type) firms posting a college job is v_{lc} (v_{hc}); the total mass of jobs for non-college (college) workers is $v_n = v_{ln} + v_{hn}$ ($v_c = v_{lc} + v_{hc}$). Workers and vacancies are randomly matched in essentially two separate labor markets. Define the mass of unemployed workers as $u_i, i = n, c$.

Define market tightness $\theta_i = u_i/v_i, i = n, c$. For each type of vacancy, the likelihood of a vacancy receiving any worker q_i is an increasing function of the market tightness θ_i, as well as an increasing function of matching technology a_i: $q_i = q(\theta_i, a_i)$. Similarly, for each type of worker, the likelihood of a worker matched with any vacancy is $\theta_i q_i$.

Scenario 0: Perfect information. Suppose firms know perfectly the college productivity μ. Firms' discount rate of future return is $1/(1+r)$. Since there is no uncertainty, firms would hire the matched worker as long as there is a successful match. For the current matches, suppose workers would separate from the job randomly with probability δ. The Bellman equations for a type-j firm are:

$$rV_{j,i} = -k + q(\theta_i, a_i)(J_{j,i} - V_{j,i}) \tag{17}$$

$$rJ_{j,i} = \mu_i \zeta_j - w_i + \delta(V_{j,i} - J_{j,i}) \tag{18}$$

For a type-i worker, suppose if the worker can claim benefit b if unemployed and get paid w_i if hired on a job. The Bellman equations for a type-i workers are:

$$rU_i = b + \theta_i q(\theta_i, a_i)(W_i - U_i) \tag{19}$$

$$rW_i = w_i + \delta(U_i - W_i) \tag{20}$$

Workers engage in Nash bargaining with their employers. If both types of firms post jobs for type-i workers, workers would negotiate based on their expected return from working in both firms. The Nash bargaining equation is as follows:

$$\frac{1-\beta}{\beta}(W_i - U_i) = \frac{v_{l,i}}{v_i}(J_{l,i} - V_{l,i}) + \frac{v_{h,i}}{v_i}(J_{h,i} - V_{h,i}) \tag{21}$$

Suppose the in-flow of unemployed workers equals the out-flow of unemployed workers:

$$\delta(1 - u_i) = \theta_i q(\theta_i, a_i) u_i \tag{22}$$

The mass of vacancies for type-i workers are (denote the other type as $-i$):

$$v_{j,i} = 0 \text{ if } \; V_{j,i} < V_{j,-i}, \text{ or } \; V_{j,i} = V_{j,-i} \text{ if } \; v_{j,i} > 0 \text{ and } \; v_{j,-i} > 0 \tag{23}$$

Finally, for market clearing, note the following parity:

$$v_{h,c} + v_{l,c} + v_{h,n} + v_{h,n} = u_c + u_n \tag{24}$$

In a separating equilibrium (more discussion below), we simply have $v_{h,i} = u_i$ or $v_{l,i} = u_i$, and the market is clear. In a pooling equilibrium where both types of firms hire type-i workers, because firms engage in perfect competition both in labor market with a linear production function, if firm j hires a type-i worker, the market price $P_{j,i}$ would equal the same wage w_i. Given the aggregate CES output function, for high-type workers the market price is derived as follows:

$$P_{j,i} = \alpha_{j,i} Y^{1-\rho} Y_{j,i}^{\rho-1} = \alpha_{j,i} Y^{1-\rho} (\zeta_j \mu_i (1 - v_{j,i}))^{\rho-1} = w_i$$

Take the ratio $P_{h,i}/P_{l,i}$, we have

$$\zeta(1 - v_{h,i}) = (\frac{1-\alpha_h}{\alpha_h})^{\frac{1}{\rho-1}} (1 - v_{l,i}) \tag{25}$$

Theorem D.1. *Given college graduates' productivity μ, high-type firms' productivity ζ, matching technology a_i, separation rate δ, unemployment benefit b, the cost of posting the vacancy k, the discount rate r and the bargaining power β, there exists a unique equilibrium characterized by the vector $\Omega = \{V_{j,i}, J_{j,i}, U_i, W_i, w_i, u_i, v_{j,i}\}_{i=c,n,j=h,l}$ determined by Equations 17 - 25.*

Proof. Given the definitions of matching function, $q_i \leq 1$, $\theta_i q_i \leq 1$. Given that $v_i, u_i \in [0, 1]$, vector Ω is a compact set in $\mathbb{R}^{20}$. Equations 17 - 15 defines a set-valued function $\Omega \to \omega(\Omega)$, where $\omega(\Omega)$ is non-empty, convex, and has closed graph. Thus, $\Omega = \omega(\Omega)$ has a unique fixed point. ☐

Given that $\mu > 1$, $\zeta > 1$, and that college graduates are perfect substitute for non-college workers, the benchmark model may reach a separating equilibrium if all high-type firms post jobs for college graduates and all low-type firms post jobs for non-college workers. The labor market tightness for each market in the social optimum would be $\theta_c = \theta_n = 1$. One can write down the value functions for vacancy opening:

$$V_{h,c} = \frac{\frac{(1-\beta)\zeta\mu-(1-\beta)b-\beta k}{\delta+r} - \frac{k}{q(1,a_c)}}{\frac{r+q(1,a_c)}{q(1,a_c)} - \frac{\delta}{\delta+r}} > V_{h,n} = \frac{\frac{\zeta-\beta-(1-\beta)b-\beta k}{\delta+r} - \frac{k}{q(1,a_n)}}{\frac{r+q(1,a_n)}{q(1,a_n)} - \frac{\delta}{\delta+r}}$$

$$V_{l,c} = \frac{\frac{(1-\beta\zeta)\mu-(1-\beta)b-\beta k}{\delta+r} - \frac{k}{q(1,a_c)}}{\frac{r+q(1,a_c)}{q(1,a_c)} - \frac{\delta}{\delta+r}} < V_{l,n} = \frac{\frac{(1-\beta)(1-b)-(1-\beta)b-\beta k}{\delta+r} - \frac{k}{q(1,a_n)}}{\frac{r+q(1,a_n)}{q(1,a_n)} - \frac{\delta}{\delta+r}}$$

If $\beta\zeta < 1$, one can derive a range of $\mu \in [\overline{\mu}, \underline{\mu}]$ to satisfy the incentive compatibility conditions above. This is also the social optimum scenario because $\zeta\mu + 1 > \zeta + \mu$. If μ is outside this range, one can prove that this leads to a pooling equilibrium where both types of firms would post two types of jobs in the following logic: Suppose no firms post college jobs, then the matching rate q_c for college graduates would be one because all college graduates are unemployed yet no other vacancies, while the matching q_n for non-college workers equal zero because there is no unemployed workers. Under certain regulatory condition $\frac{k(\beta+\delta+r)}{1-\beta} + b < 1$, it is strictly more profitable for both types of firms to deviate and post college jobs until $V_{j,c} = V_{j,n}, j = h, l$.

Scenario 1: Imperfect information. Suppose not firms do not have perfect information of college graduates' productivity μ. In each period T, denote firm j's belief of μ as $\mu_j^T = \Xi(S_j^T)$, which can be characterized by the cumulative information set over the last T periods S_j^T. The information set consists of all imperfect observations of college graduates' productivity in the past $S_j^T = \{y_t\}_{t \leq T}$, where $y = \mu + e$ is a noisy observation of college graduates' underlying productivity μ; assume the noise follows a normal distribution $N(0, \sigma_e^2)$. Given a certain level of belief $\mu_j^T = x$, firm's belief of the productivity signal distribution to follow a normal distribution $N(x, \sigma_e^2)$; denote the probability density function as f_x, cumulative density function F_x.

We model firm j to perform a Bayesian update on the productivity of college graduates based on the information set S_j^T, assuming the prior for college graduates' productivity follows a normal distribution $h(\cdot) = N(\mu_0, \sigma_h^2)$; we further assume that there is no inherent bias in firms' prior distribution, that is, $\mu_0 = \mu$. Firm j's belief μ_j^T can be described as follows:

$$\mu_j^T = \frac{\int x \Pi_{y \in S_j^T} f_x(y) h(x) dx}{\int \Pi_{y \in S_j^T} f_x(y) h(x) dx} \tag{26}$$

We first discuss firm's hiring behavior when randomly matched with a college graduate. Because we simplify the model so that college graduates inherently are homogeneous, any observed productivity signal is purely driven by noise, and thus according to Bayes' rule, firms would simply update their prior μ_j^T based on any new signals obtained in the new period and make their hiring decisions based on the new prior. Essentially, the Bellman equations for firms remain the same after replacing the college graduates' productivity with firm j's belief μ_j^T. Note that if firms do not post a college job, they will not receive a new signal and thus will not update their beliefs. In the following, we will characterize the new equilibrium for college vacancies; the equilibrium for non-college vacancies remains the same as in Scenario 0.

Suppose in each period T, the distribution of type-j firms' belief follows a distribution $G_j^T(\mu')$.

The Bellman equations for type-j firms with a college vacancy with prior μ' are as follows:

$$rV_{j,c}^T(\mu') = -k + q(\theta_c^T, a_c)(J_{j,c}^T(\mu') - V_{j,c}^T(\mu')) \tag{27}$$

$$rJ_{j,c}^T(\mu') = \mu'\zeta_j - w_c^T + \delta(V_{j,c}^T(\mu') - J_{j,c}^T(\mu')) \tag{28}$$

$$rV_{j,n}^T = -k + q(\theta_n^T, a_n)(J_{j,n}^T - V_{j,n}^T) \tag{29}$$

$$rJ_{j,n}^T = \zeta_j - w_n^T + \delta(V_{j,n}^T - J_{j,n}^T) \tag{30}$$

The Bellman equations for type-i workers remain the same:

$$rU_i^T = b + \theta_i^T q(\theta_i^T, a_i)(W_i^T - U_i^T) \tag{31}$$

$$rW_i^T = w_i^T + \delta(U_i^T - W_i^T) \tag{32}$$

Because of Bayesian update, $G_j^T(\mu')$ has full support of $\mathbb{R}$. Thus, for type-j firms, there exists a value M_j^T such that firms would be indifferent between posting a college and a non-college vacancy:

$$V_{j,c}^T(M_j^T) = V_{j,n}^T \tag{33}$$

The proportion of type-j firms posting college jobs is thus:

$$\frac{v_{j,c}^T}{v_{j,c}^T + v_{j,n}^T} = \int_{M_j^T} dG_j^T(\mu') \tag{34}$$

For Nash bargaining, now college graduates may face firms with various beliefs and thus with different wage offers. The Nash bargaining equation becomes the following:

$$\begin{aligned} \frac{1-\beta}{\beta}(W_c^T - U_c^T) &= \frac{v_{l,c}^T}{v_{l,c}^T + v_{h,c}^T}\int_{M_l^T}[J_{l,c}^T(\mu') - V_{l,c}^T(\mu')]dG_l^T(\mu') \\ &\quad + \frac{v_{h,c}^T}{v_{l,c}^T + v_{h,c}^T}\int_{M_h^T}[J_{h,c}^T(\mu') - V_{h,c}^T(\mu')]dG_h^T(\mu') \end{aligned} \tag{35}$$

$$\frac{1-\beta}{\beta}(W_n^T - U_n^T) = \frac{v_{l,n}^T}{v_{l,n}^T + v_{h,n}^T}(J_{l,n}^T - V_{l,n}^T) + \frac{v_{h,n}^T}{v_{l,n}^T + v_{h,n}^T}(J_{h,n}^T - V_{h,n}^T) \tag{36}$$

Suppose the in-flow of unemployed workers equals the out-flow of unemployed workers:

$$\delta(1 - u_i^T) = \theta_i^T q(\theta_i^T, a_i)u_i^T \tag{37}$$

For market clearing, assuming for the currently employed workers, the proportion of workers working in high-type (low-type) firms equals the proportion of college vacancies opened among high-type (low-type) firms:

$$1 - u_i^T = \frac{v_{h,i}^T}{v_{h,i}^T + v_{h,-i}^T}(1 - v_{h,i}^T - v_{h,-i}^T) + \frac{v_{l,i}^T}{v_{l,i}^T + v_{l,-i}^T}(1 - v_{l,i}^T - v_{l,-i}^T) \tag{38}$$

Finally, we impose some structure on the distribution $G_j^T(\mu')$. Suppose in the first period, all firms have the correct belief $\mu_j^0 = \mu$ and would enter the pool of college graduates. A simple observation is that in each period, only firms with sufficiently optimistic posterior beliefs derived from Equation 26 would eventually post a college job, and some previously marginal firms where $\mu' = M_j^{T-1}$ would get a negative productivity signal and decide not to post a college job, thus $V_{j,c}^T(M_j^{T-1}) < V_{j,n}^T$. We thus prove that $M_j^T > M_j^{T-1}$ for all T.

For each new period T, firms with prior beliefs $\mu_j^{T-1} < M_j^{T-1}$ would not post a college job. For the rest of the firms, some would encounter a college graduate with probability $q(\theta_c^T, a_c)$, develop a pessimistic posterior $\mu_j^T < M_j^T$ and decide not to post a college job eventually. To derive a tractable equation, we use the fact that the Bayesian update equation 26 can be numerically approximated by a simple average of all productivity signals as the number of signals increases. Therefore, the distribution $G_j^T(\cdot)$ can be written as an iterative function:

$$dG_j^T(x) = \begin{cases} dG_j^{T-1}(x) + q(\theta_c^T, a_c)\int_{M_j^{T-1}} f_0(Tx - (T-1)\mu')dG_j^{T-1}(\mu'), & \text{if } x < M_j^{T-1} \\ (1 - q(\theta_c^T, a_c))dG_j^{T-1}(x) + q(\theta_c^T, a_c)\int_{M_j^{T-1}} f_0(Tx - (T-1)\mu')dG_j^{T-1}(\mu'), & \text{if } x \geq M_j^{T-1} \end{cases} \tag{39}$$

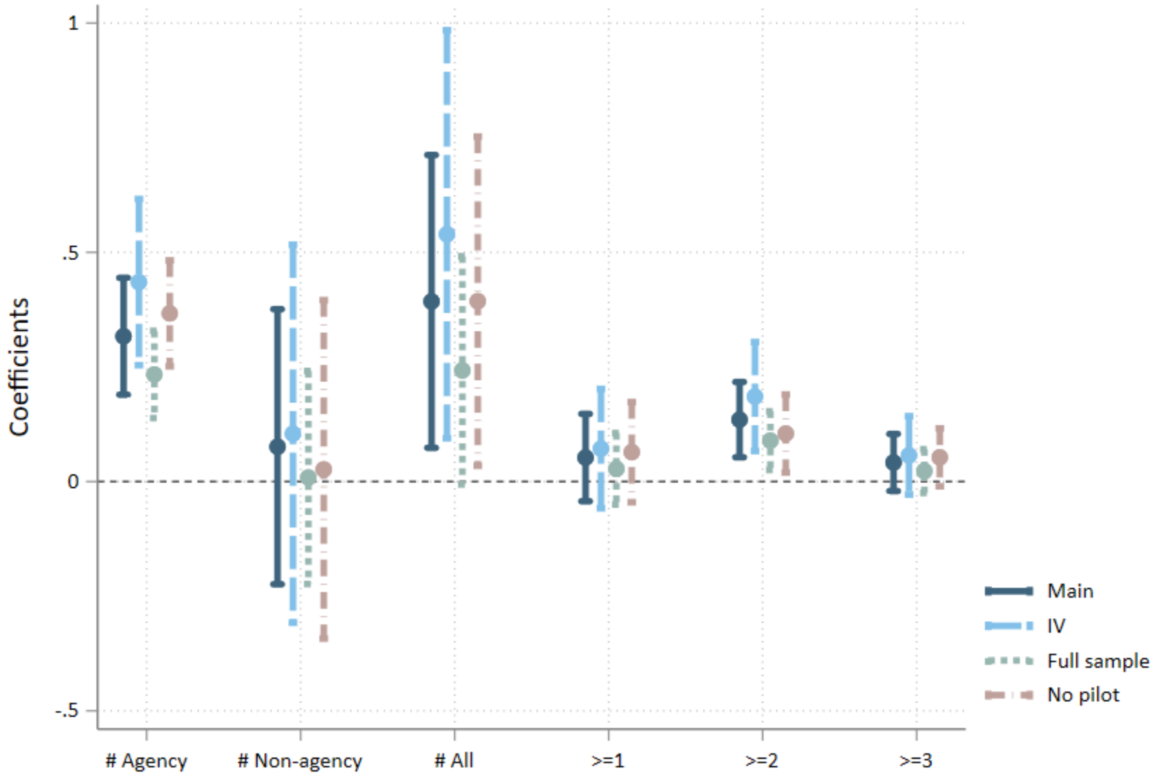
We now have the following theorem to prove the existence of a unique equilibrium.

Theorem D.2. *For each period T, there exists a unique equilibrium characterized by the vector $\Omega^T = \{V_{j,c}^k(M_j^k), V_{j,n}^k, J_{j,c}^k(M_j^k), J_{j,n}^k, M_j^k, U_c^k, U_n^k, W_c^k, W_n^k, w_c^k, w_n^k, u_c^k, u_n^k, v_{j,c}^k, v_{j,n}^k\}_{j=h,l}^{k\leq T}$ determined by Equations 27 - 39.*

Proof. Similar to the proof of Theorem D.1, Ω^T is a compact set in $\mathbb{R}^{22T}$. Equations 27 - 38 define a set-valued, convex function $\omega^T(\Omega^T)$ with closed graph projecting to the same compact set in $\mathbb{R}^{22T}$. By induction, Equation 39 uniquely determined $G_j^k(\cdot)$ for all $k \leq T$. Thus, $\Omega^T = \omega^T(\Omega^T)$ has a unique fixed point. □

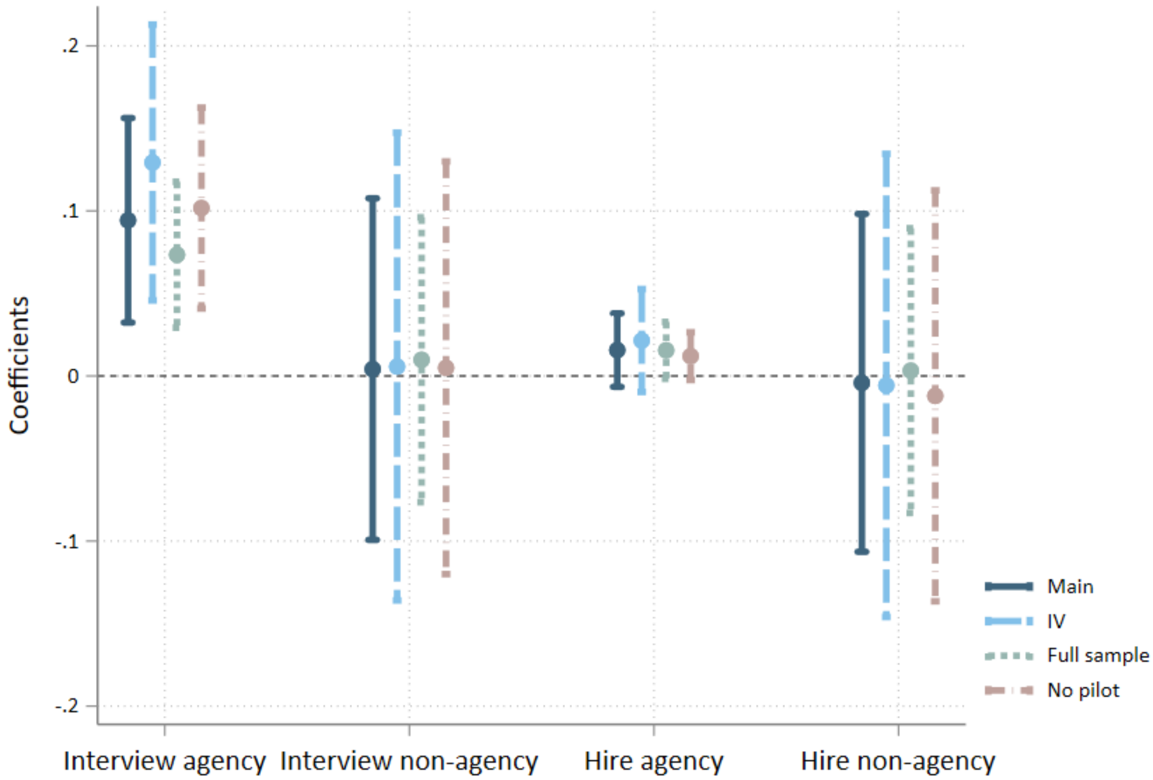
E Replications

Figure E1: Replication of the First-Stage Effects on the Number of College-Educated Applicants



Notes: This figure replicates the main results in Table 1, Panel B. All regressions include a full set of baseline characteristics, control for business area fixed effects, and cluster at business area level. For each dependent variable, we show (1) reduced-form estimate from the main specification, (2) IV estimate on the actual treatment status, (3) reduced-form estimate using full sample, and (4) reduced-form estimate excluding pilot sample. 95% confidence intervals are shown.

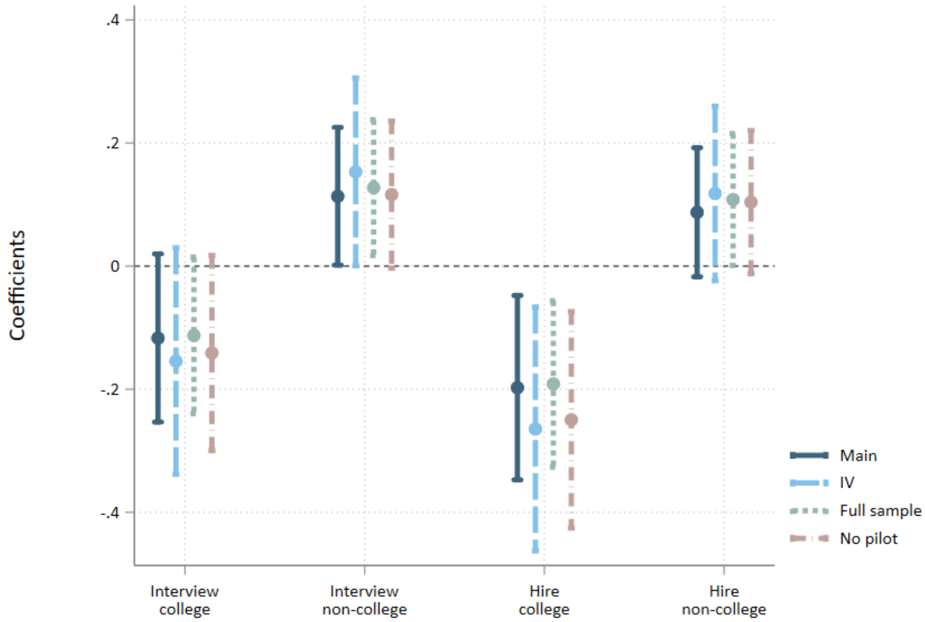
Figure E2: Replication of the Effects on Take-up of Employment Agencies



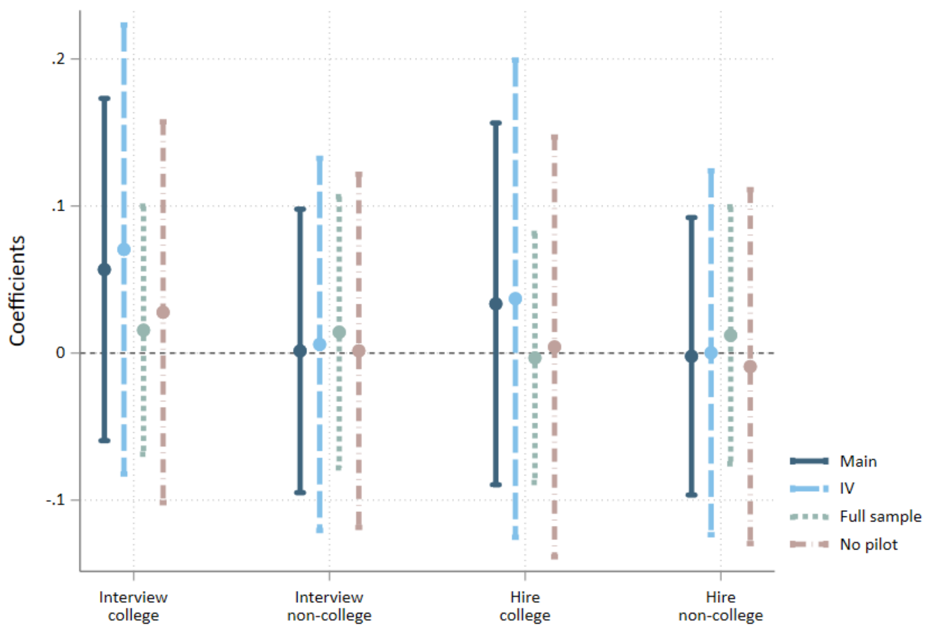
Notes: This figure replicates the main results in Table 2. All regressions include a full set of baseline characteristics, control for business area fixed effects, and cluster at business area level. For each dependent variable, we show (1) reduced-form estimate from the main specification, (2) IV estimate on the actual treatment status, (3) reduced-form estimate using full sample, and (4) reduced-form estimate excluding pilot sample. 95% confidence intervals are shown.

Figure E3: Replication of the Effects on Hiring by Baseline Request

Panel A. Heterogeneous effect on firms requesting college graduates

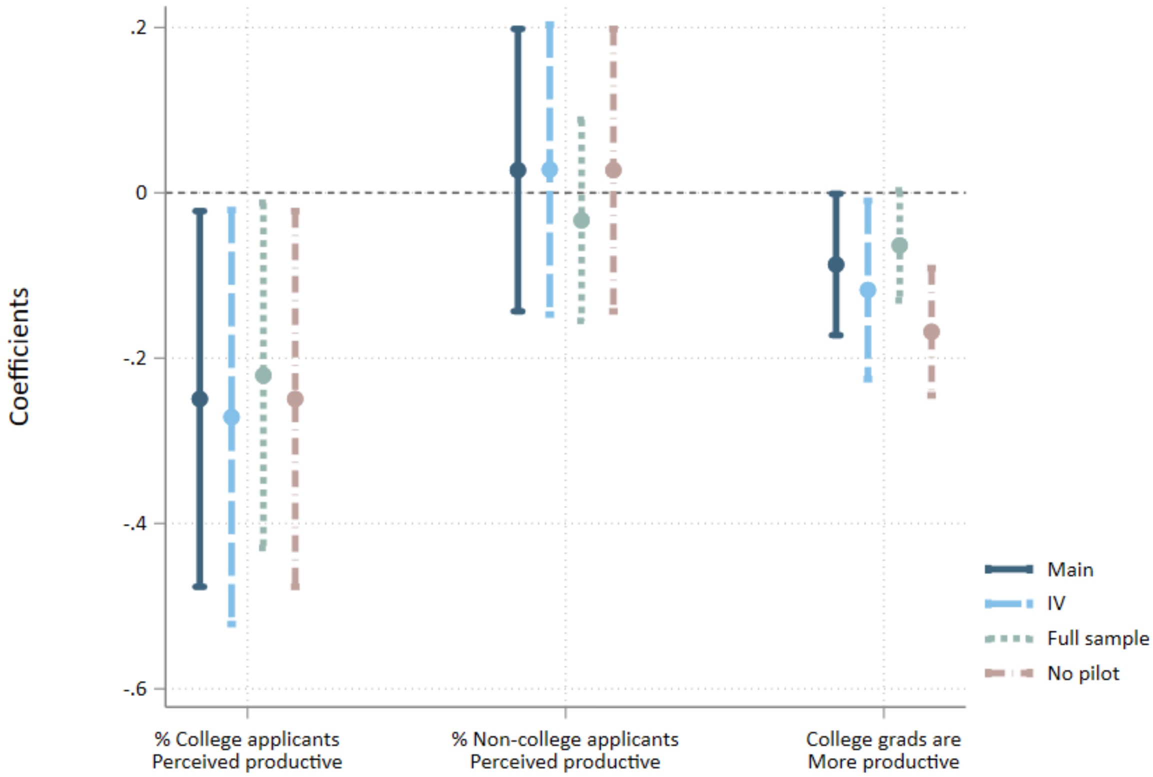


Panel B. Heterogeneous effect on firms not requesting college graduates



Notes: This figure replicates the main results in Table 4, Panel A. All regressions include a full set of baseline characteristics, control for business area fixed effects, and cluster at business area level. For each dependent variable, we show (1) reduced-form estimate from the main specification, (2) IV estimate on the actual treatment status, (3) reduced-form estimate using full sample, and (4) reduced-form estimate excluding pilot sample. 95% confidence intervals are shown.

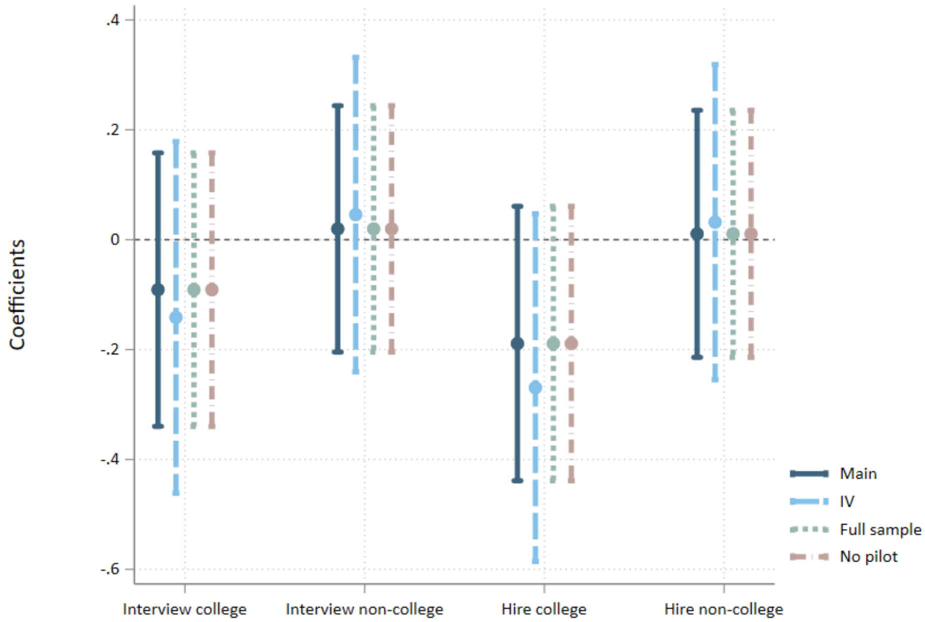
Figure E4: Replication of the Effects on Perceptions



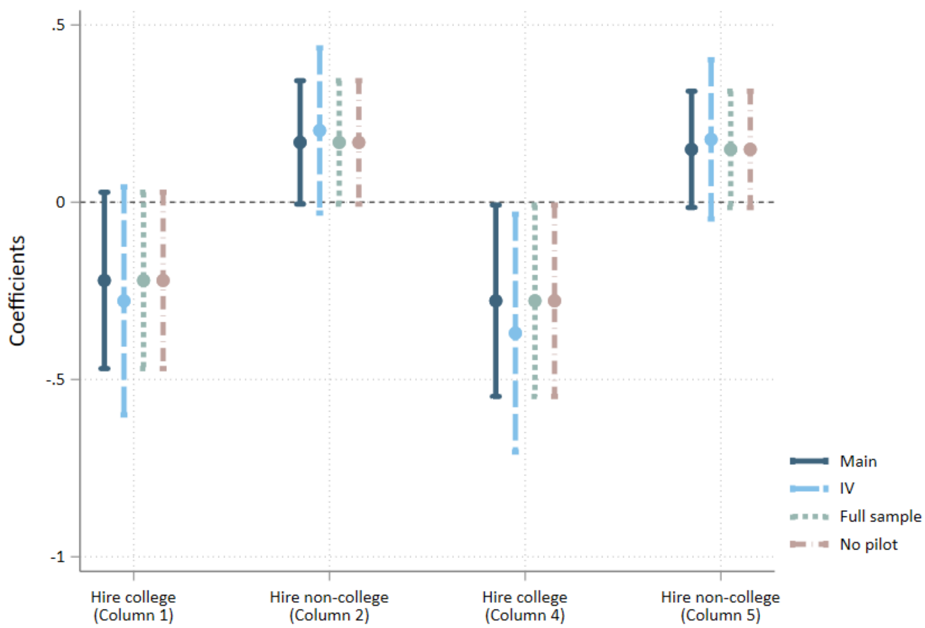
Notes: This figure replicates the main results in Table 3, Column 1, 2, and 5. All regressions include a full set of baseline characteristics, control for business area fixed effects, and cluster at business area level. For each dependent variable, we show (1) reduced-form estimate from the main specification, (2) IV estimate on the actual treatment status, (3) reduced-form estimate using full sample, and (4) reduced-form estimate excluding pilot sample. 95% confidence intervals are shown.

Figure E5: Replication of the Heterogeneous Effects By College Share

Panel A. Firms requesting a college graduate at baseline and with above-median college share



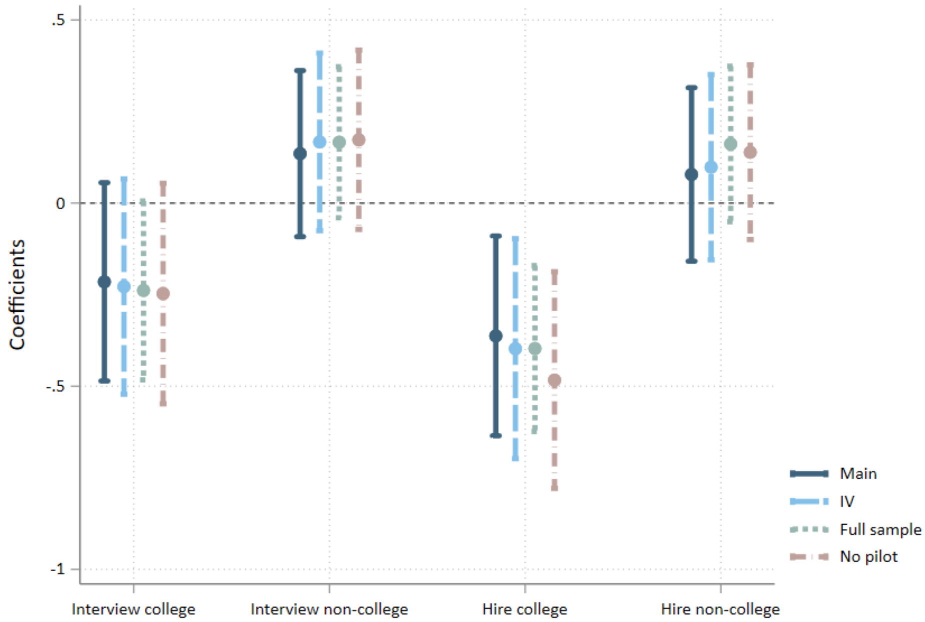
Panel A. Firms requesting a college graduate at baseline and with above-median college share



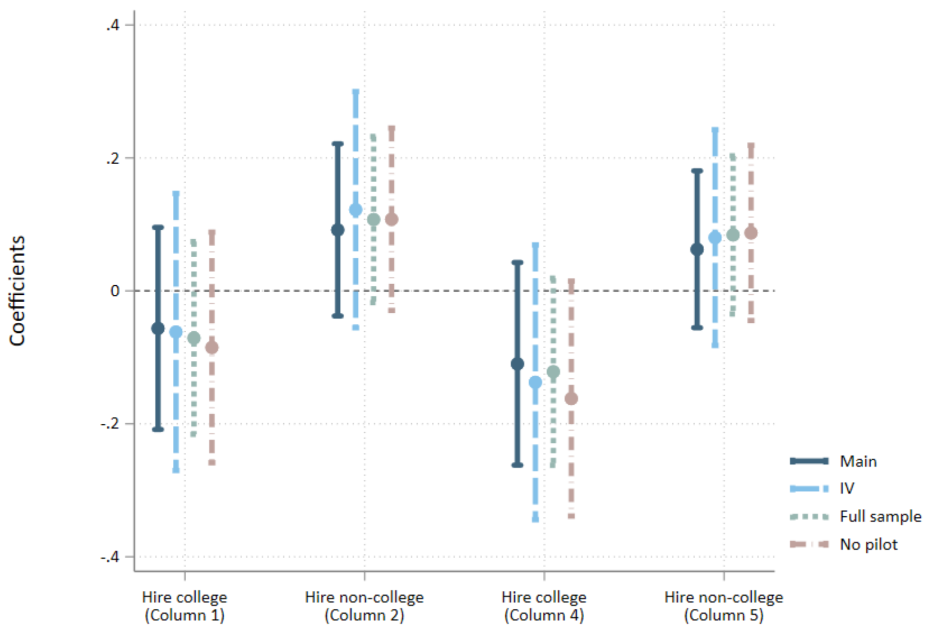
Notes: This figure replicates the main results in Table 5. All regressions include a full set of baseline characteristics, control for business area fixed effects, and cluster at business area level. For each dependent variable, we show (1) reduced-form estimate from the main specification, (2) IV estimate on the actual treatment status, (3) reduced-form estimate using full sample, and (4) reduced-form estimate excluding pilot sample. 95% confidence intervals are shown.

Figure E6: Replication of the Heterogeneous Effects By Experience Requirement

Panel A. Firms requesting a college graduate and with low experience requirement



Panel A. Firms requesting a college graduate and with high experience requirement



Notes: This figure replicates the main results in Table 6. All regressions include a full set of baseline characteristics, control for business area fixed effects, and cluster at business area level. For each dependent variable, we show (1) reduced-form estimate from the main specification, (2) IV estimate on the actual treatment status, (3) reduced-form estimate using full sample, and (4) reduced-form estimate excluding pilot sample. 95% confidence intervals are shown.