Learning Before Hiring*

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Abstract

We conducted a hiring intervention with 799 private firms with an active job vacancy in Addis Ababa, Ethiopia, and introduced a subset of the firms to a specialized type of employment agency, which gives them access to a larger number of college-educated applicants. We find two surprising results. First, five months after the intervention, treated firms received 35% more college-educated applicants, but were no more likely to fill the vacancy. Second, among firms that requested a college graduate at baseline, treated firms became 34% less likely to hire any college graduate. We discover a learning mechanism that rationalizes these findings: firms updated their beliefs about college graduates' productivity before making hiring decisions. On average, treated firms became 11% *less* likely to agree that college graduates are more productive than non-college workers. Applicants whose experiences did not meet the job requirement cannot fully explain the results. Among college-educated applicants with qualified experiences, 33% were perceived not qualified, potentially due to applicants' noisy signaling through résumés and firms' costly screening. Our theoretical model shows that in the presence of this learning mechanism, increased exposure to college-educated job seekers can reinforce negative productivity beliefs about them, potentially undermining their employment prospects.

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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, governments and researchers have attempted to reduce search costs in the labor markets 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, lower search costs in the labor market would strictly increase the number of successful matches. The assumption of perfect information, however, 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). Among these interactions, workers may send noisy signals of their productivity (Abebe et al., 2021; Bassi and Nansamba, 2022; Carranza et al., 2023), while firms are constrained to obtain more accurate signals (Algan et al., 2020). Thus, lower search costs can trigger firms to update their beliefs of 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 detect 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

[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.

labor market with a high level of search frictions between firms and college-educated workers.

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 decrease the search costs by increasing firms' access to 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. We then conducted two follow-up surveys one month (midline) and five months (endline) after the baseline, where 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 at midline to collect information on education, experience, employment status, and other demographics.

We first 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 then examine whether treated firms were more likely to interview or hire any applicant recommended by the agency by endline, using the initial treatment assignment to obtain intention-to-treat causal effects. Firms initially assigned to treatment were only 9.4 percentage points more likely to interview any agency applicant; only seven treated firms hired anyone from the agency. Eventually, treated firms were no more likely to fill the vacancy. Instead, we observe a significant change in the 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 supporting correlational evidence: among control firms with at least one college-educated applicant, having more college-educated applicants does not lead to more interviewing or hiring of any college graduate. Both experimental and correlational results reject the simple hiring model where firms had the correct beliefs of college graduates' productivity, and increasing the access to college-educated applicants would have strictly increased the interviewing or hiring of college graduates. We further 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.

Why such a change in hiring behavior? 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 the treatment.

We further conduct the following test: If the learning mechanism drives the main change in hiring behavior, firms with less interaction with college graduates in the past should 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.

We rule out four alternative mechanisms that may explain some of the empirical results. First, firms might have learned about college graduates' reservation wages. We found direct evidence that if anything, firms decreased their beliefs of college graduates' outside options, which would have encouraged firms to hire more college graduates. Second, college graduates were perhaps more likely to reject offers. We do not find that college graduates systematically rejected more interview invitations or offers. Third, we discuss other potential hypotheses about search costs. In particular, when treated firms did not receive applicants from employment agencies, they might interpret it as a signal of high search costs and stop the search earlier. We still find significant shift in hiring behavior for firms with above-median likelihood of receiving applicants from agencies. Last, 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.

What triggered learning? One possibility is that, despite having a college degree, agency applicants were less qualified on other dimensions. Here, we focus on experience, one of the most important hiring criteria for firms. 67% of all college-educated applicants from the agencies met the minimum experience requirement, which is not significantly different than other college-educated or non-college applicants. To formally test whether applicants' qualification explains the main results, we examine the treatment heterogeneity regarding minimum experience requirement, leveraging the fact that higher baseline 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 and thus more qualified applicants, suggesting that applicant qualification alone cannot fully explain our findings.

Why did qualified agency applicants also trigger the shift in hiring behavior? Leveraging our detailed records of firms' perceptions of applicants, we find that many college-educated applicants with qualified experience were not perceived to be qualified by firms. Of all college-educated applicants whose experiences met the minimum requirement for the position, 33% were perceived by the firms as unqualified. 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 applicants' perceived productivity. College-educated applicants from agencies were not more likely to be considered qualified. The descriptive evidence above implies the first type of hiring friction: firms could not observe the experience of college-educated applicants perfectly, allowing a negative signal of their experience to emerge.

We provide clues where this negative signal might have originated. 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. In fact, using non-college applicants without résumés as a benchmark, college-educated applicants who provided 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 convey positive signals about their experience and productivity, a fact that recently gets more documented in the literature (Abebe et al., 2021; Bassi and Nansamba, 2022; Carranza et al., 2023).[3]

Could firms mitigate the noisy signaling by conducting more interviews? We find that on average, treated firms interviewed 0.09 more agency applicants (p-value 0.012) but 0.17 fewer non-agency applicants (p-value 0.129), and were 19.7 pp. less likely to invite all non-agency applicants for interviews (p-value 0.009). Given that our intervention did not directly interfere with firms' interviewing decisions of non-agency applicants, our findings imply a second type of hiring friction: firms face a fixed quota of interviewing, and conducting more interviews can incur higher screening cost for firms. Together with the first type of hiring friction, we present empirical evidence on a new learning mechanism: Firms received noisy productivity signals of college-educated applicants, yet were constrained by screening cost to obtain more accurate information, inducing a negative belief update on college graduates' productivity before they made hiring decisions.

What are the labor market implications of this learning mechanism? We develop an extended hiring model where through the increased access to college-educated applicants, firms received imprecise signals about the productivity of college-educated applicants, updated their beliefs of college graduates' productivity, and made their hiring decisions based on the newly formed beliefs. Firms can also pay a nonnegative screening cost to obtain more accurate signals of applicants' productivity and avoid hiring mistakes. As such, firms would only screen applicants with the observed productivity above certain thresholds so that the benefit of avoiding hiring mistakes outweighs the screening cost. Because some of these screened applicants would be revealed to be less productive, on average, this learning mechanism would induce a negative belief update on college graduates' productivity, even if the productivity noise is unbiased in nature.

[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 370 résumés from college graduates and found that 28% of them did not specify any past experience, similar to the percentage of college-educated applicants that were perceived with zero experience in this paper (33%).

We further simulate this hiring model for 10 rounds and perform three counterfactual exercises to understand what can prevent this endogenous bias formation: (1) Decreasing the standard deviation in the productivity noise, (2) decreasing the screening cost, and (3) increasing the match rate between firms and job seekers. The first is the most effective: Decreasing 50% of the standard deviation in productivity noise can decrease bias by 55%. The second is not as effective: Decreasing 50% of the screening cost can reduce bias by only 18%. This suggests that even a small amount of interviewing cost can contribute substantially to bias formation. The third is counter-effective: Reducing 50% of search frictions *increases* bias by 18%. We thus demonstrate that with the existence of productivity noise and screening cost, simply increasing exposure to job seekers may further exacerbate the negative bias against the productivity of highly educated workers.

Finally, consistent with the theoretical prediction, we find larger treatment effects on firms where the skill requirement was low, suggesting a small college premium for the complier firms. Our complier analysis further suggests that by hiring non-college workers, complier firms paid less salary without significant productivity loss. However, our model shows that the negative bias induced by the two hiring frictions would occur to all firms that interacted with college-educated applicants. Empirically, among those who requested a college graduate at baseline, treated firms with higher skill requirement were also less likely to post a job in the future, suggesting that labor demand could be distorted beyond the scope of complier firms. The learning mechanism may thus further undermine the employment prospects for college graduates.

Related Literature and Contributions. This paper contributes to three strands of literature: firm hiring in developing economies, labor market frictions, and the role of labor market intermediaries. First, we add 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 threefold. First, we manage to collect detailed hiring records from a large sample of medium-sized private firms in a low-income country.[4] Second, we provide empirical evidence on two types of hiring frictions faced by firms, namely, noisy signals of productivity and screening cost; this is made possible by having

[4]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.

detailed data on applicants and more importantly, firms' perceptions on applicants.[5] Third, with a novel theoretical framework inspired by Lepage (2024), we shed light on how these two types of hiring frictions can induce a negative bias formation against certain groups of job seekers.[6]

More broadly speaking, 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).[7] Our empirical findings demonstrate how lower search costs for firms can induce a negative learning effect due to existing information asymmetry, which provides an important insight on what types of active labor market policies (ALMPs) are more effective in creating successful matches in the labor market.[8]

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

[5]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 information frictions can be more severe in low- and middle-income countries where firms have less access to various screening technologies.

[6]A similar paper, Benson and Lepage (2024), describes how firms in the United States develop negative bias on minority workers based on past hiring experiences. Our findings suggest that firms may also draw inferences from applicants, especially in the context where search frictions are high.

[7]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.

[8]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.

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.

The paper proceeds as follows. 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 specification and the two main findings. Section 5 presents evidence on firms' belief update. Section 6 discusses what factors may induce learning. Section 7 discusses the implications of the learning mechanism. Section 8 concludes.

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).[9] 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.

[9] 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).

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 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.[10] 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

[10] 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.

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.[11] 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.[12]

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

[11] 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.

[12] 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.

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.[13] 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 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.

[13] 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.

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.[14] 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.[15] 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.[16] 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

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

[15]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.

[16]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.

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 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 6. We further collected applicants' demographics (age, gender, residential district), current employment status, and salary if employed.[17]

[17]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

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, 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 6.

Figure 4, Panel A presents the number of firms that eventually received extra applicants from the intervention. Among eligible firms, 46% of the treated firms receive at least one extra applicant. Zero eligible control firms receive any extra applicant; almost none of the non-eligible firms receive any extra applicant. For those treated firms that did not receive extra 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 4.4 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

the interview. 80% applicants in our sample participated in the phone survey.

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 extra applicants, Specification 1 obtains an intention-to-treat (ITT) estimate of the effect of receiving extra applicants from the employment agencies.[18]

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

[18] 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.

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}. In Section 4.4, we will provide a series of robustness checks to rule out confounding factors. We will also provide empirical evidence on the mechanism that can explain the estimate of β_1, consistent with our conceptual framework, but difficult to be explained through other mechanisms.

4.2 Effects on Hiring

We first confirm the treatment effect on receiving extra 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-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 percentage points more likely to interview any agency applicants and 1.57 percentage points more likely to hire any agency applicants (p-value 0.172).[19] In fact, 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.

Table 3, Panel A presents the second result on whether firms interviewed or hired any college graduates in general. Even more surprisingly, among firms that requested a college graduate at baseline, treated firms were 11.7 percentage points (p-value 0.098, 19% decrease) or 19.7 percentage points (p-value 0.012, 34% decrease) less likely to interview or hire any college graduates; instead,

[19] 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.

they were 11.3 percentage points (p-value 0.050, 86% increase) and 8.8 percentage points (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.

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, and whether they planned to hire more college graduates to the firm; the latter variable was only collected in Round 2. Table B4 shows that among firms that requested a college graduate at baseline, treated firms were 12.4 percentage points less likely (p-value 0.088, 19% decrease) to plan to post any job in the next three months. Treated firms were also less likely to plan to hire more college graduates to the firm, although the estimate is underpowered and suggestive at best. Combined with Table 3, our results present a significant, and potentially persisting, change in the hiring behavior, particularly among firms that requested a college graduate at baseline.

4.3 A Simple but Incorrect Hiring Model

The surprising results presented above reject 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.[20] 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, when the arrival of college-educated applicants q increases and the search cost $c(q)$

[20] 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.

decreases, this model would only predict a "search effect": 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. The conclusion does not require any assumptions on the productivity distributions of non-college workers or college graduates, as long as firms can observe the applicants' productivity perfectly. This contradicts our empirical findings, where firms credibly received more college-educated applicants yet became less likely to hire any of them.

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. Both correlational and experimental evidence suggest that lower search costs to find college-educated applicants may affect firms' hiring outcomes through a different channel.

4.4 Robustness

We examine the robustness of the main treatment effects in the following six ways. First, following the concern of identification assumption in Section 4.1, Table B6 examine whether the heterogeneous treatment effect regarding baseline request for college graduates can be explained by other baseline characteristics from Table B3. 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 effect 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 effect on hiring a non-college worker is not significant in one of the specifications, but the magnitude remains similar.

Second, we examine the robustness of statistical inference in Table B7. 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.

Third, we examine whether attrition of firms affects the main results systematically. Table B8, 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.

Fourth, 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 B9, 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.

Fifth, 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 B10, 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.

Sixth, 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 B11, 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 A8 further varies the length of radius and replicates this exercise. We do not find heterogeneous treatment effects in any specification.

5 Belief Update

In this section, we formally examine whether firms changed their beliefs of the productivity of college-educated applicants. We then examine whether the belief update rationalizes the two main findings in Section 4 and rule out other alternative mechanisms.

5.1 Direct Measures of Firms' Beliefs

We 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.[21] Table 4, 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 4, 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 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).[22] 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 5 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 the heterogeneous treatment effect regarding baseline request for college graduates. Interestingly, Column 5 and 7 show a lack of heterogeneity: both treated firms that requested a college graduate at baseline or not lowered their beliefs of college graduates' productivity. 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

[21] 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.

[22] 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.

degree, thus undergoing a similar belief update process.

5.2 Explaining the Change in the Hiring Behavior

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 A9, 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 B12 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), and 16.9 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 A10 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 provide two additional robustness tests in Table B13. We first residualize whether the college share is above median on all other baseline characteristics in Panel A. Our results remain unaffected, suggesting that at the very least, treatment heterogeneity captured by other baseline characteristics cannot explain the empirical patterns in Table 5. Second, we 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 A9, Panel B presents the truncated distribution of the imputed number of past interactions. Table B13, Panel B replicates Table 5 with the imputed number of past interactions and finds similar patterns. Thus, our evidence above suggests that learning can explain the shift in hiring behavior.

5.3 Alternative Mechanisms

We discuss four alternative hypotheses that may explain some of the empirical findings. First, firms may update their beliefs about college graduates' outside options. Specifically, through interviewing more college-educated applicants, firms may have realized that college graduates ask for higher salary and chosen not to hire them. We provide direct evidence against this hypothesis in Table B14, using the same specifications as in Table 4. 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.

Second, one may wonder if college graduates were more likely to reject the offers than non-college workers. This hypothesis would not affect the effects on whether firms made any interview invite, but if college graduates were less likely to attend the interview, firms might be less likely to hire college graduates as a result. We are able to observe whether each applicant rejected an interview invite or an offer to test this hypothesis; Table B15 shows the results. On average, only 4.7% applicants rejected the interview invite, 3.0% rejected the offer. We do not find evidence suggesting college graduates were more likely to reject the interview invites or the offers.

Third, we examine whether other hypotheses of search cost may explain the main findings. 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 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 cannot explain why treated firms were less likely to hire college graduates especially when they received more college-educated applicants. We also rule out another possibility that employment agencies might disproportionately lower the search cost of finding non-college educated workers, as we do not find significant effect on the number of non-college applicants in Table 1. One potential alternative mechanism is that when employment agencies were not able to find a match, firms might interpret it as high search costs to find college graduates and stop the search earlier. We show in Table B9 that there is no heterogeneous treatment effect regarding the likelihood of receiving agency applicants. To summarize, we are not able to find a search cost hypothesis to explain our main findings consistently.

Last, firms might resort to agencies in the future to find a replacement for the current position, and as a result they could afford to make a sub-optimal decision now. This hypothesis interprets the decreased hiring of college graduates as a deliberate "error" because making an optimal hiring decision was costly. We find such hypothesis difficult to explain why the treatment effects concentrate among firms that requested a college graduate at baseline as these firms were not inherently more prone to sub-optimal decision making. We further asked firms at endline what hiring channels they plan to search for workers in the future. If the hypothesis of lower future replacement cost holds true, treated firms should prefer to continue using agencies. Table B16 shows that among firms that requested a college graduate at baseline, treated firms did not plan to use agencies more in the future. In fact, treated firms were 12.7 pp. less likely to plan to use other formal hiring channels in the future (p-value 0.015), which we will discuss in Section 7.5. We thus fail to provide evidence that suboptimal decision making drives the main findings.

6 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 two types of hiring frictions: noisy signaling from applicants, and costly screening from firms.

6.1 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. We briefly mentioned earlier that within the same vacancy, agency applicants were not different than non-agency applicants in any dimension except education, as shown in Figure A7. We examine further whether applicants were 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 B17 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 B17.

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 with more qualified applicants, we find a significant and consistent shift in the hiring behavior. Table B18 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 alone cannot explain the shift in hiring behavior.

6.2 Noisy Signaling from Applicants

Leveraging 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 B19, Columns 1–3 further shows that college-educated applicants were significantly less likely to be considered qualified after controlling for years of experience, other baseline applicants' demographics, 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 B19, Column 5 shows a positive correlation between whether an applicant is perceived to be qualified and whether an applicant is perceived to be productive, controlling for actual years of experience and other applicants' demographics, suggesting that the negative noisy signal could translate into negative productivity perception.

Where did this noisy signal originate? We provide one possible explanation: College-educated applicants did not efficiently 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 B20, 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.

6.3 Costly Screening from Firms

So far, all the comparisons conducted in Section 6.2 are without firm fixed effects. Table B19, Column 4 and Table B20, Column 4 both show that the disadvantages of college-educated applicants become insignificant after controlling for firm fixed effects, suggesting that certain firm-level characteristics may also contribute to the noisy signaling of applicants' experiences.

Recall in Table 3, among firms that requested a college graduate at baseline, treated firms become less likely to interview any college-educated applicants, a decrease in extensive margin. However, firms might still interview more college-educated applicants to make sure they hire the best person, an argument of intensive margin, provided that interviewing is not overwhelmingly costly for firms. Table 7 presents the treatment effect on the intensive margin of interviewing. Panel A, Column 1 shows that on average, treated firms did not interview more applicants. Panel B, Column 1 shows the same null result for firms that requested a college graduate at baseline, despite receiving 35% more college-educated applicants. Panel A, Column 2 and 3 break down the total number by agency applicants and non-agency applicants. We find that treated firms invited 0.09 more agency applicants on average (p-value 0.012), but 0.17 fewer non-agency applicants for interview (p-value 0.129). Column 4 shows that treated firms were 19.7 pp. less likely to interview all non-agency applicants (p-value 0.009). We control for the number of non-agency applicants and its interaction with the treatment status in all regressions, so the results cannot be explained simply by the number of non-agency applicants. Our findings thus describe a crowd-out effect: to interview more agency applicants, firms interviewed fewer non-agency applicants. This indicates a fixed quota for interviewing, and conducting more interviews might incur more cost for firms.

Table 7, Panel B examines the intensive margin effect on interviewing by baseline request for college graduates. Among this subset of firms, treated firms interviewed 0.15 more agency applicants (p-value 0.004) but 0.19 fewer non-agency applicants (p-value 0.248); overall, treated firms were 34.6 pp. less likely to interview all non-agency applicants (p-value 0.000). Results suggest that the cost of interviewing mainly affected firms that requested a college graduate at baseline.

With the evidence in Section 6.2, we thus present two key hiring frictions that potentially induced the learning channel: college-educated applicants sent a noisy productivity signal, yet firms were constrained by the interviewing cost and unable to obtain more accurate information. For the rest of the paper, we will discuss the implications of these hiring frictions. We acknowledge that the discussion above does not rule out possibilities where firms might also observe other types of negative signals about college-educated applicants that may also trigger learning, which we will defer to future investigation.

7 Implications

We first outline an extended hiring model to shed light on the general labor market implications. Although our empirical setting is a one-off hiring, in the theoretical framework, we assume firms interact with applicants over time and demonstrate how bias may be formed from recurring interactions. We then discuss potential implications on firms and workers.

7.1 A Revised Hiring Model with Learning Before Hiring

Suppose in a T-period world, firm j opens a vacancy for one worker in each period. Firm j's production function is $\theta_{ij} = \mu_i \theta_j$, θ_j is a firm-specific parameter following a given distribution, and μ_i is the productivity of the matched worker. With probability one, firm j first draws one non-college worker z from the distribution $N(\mu, \sigma_0^2)$, where μ is the mean of non-college workers' productivity and σ_0^2 is the variance their productivity; firm j can observe the productivity z perfectly. Firm j then decides whether to access the pool of college graduates by paying the cost $c(q)$, as discussed in Section 4.3. If firm j accesses the pool, with probability q, firm j draws one college-educated applicant y from the distribution $N(\mu+c, \sigma_c^2)$ where c is the average productivity premium of college graduates and σ_c^2 is the variance their productivity. However, firms can only observe a noisy signal of college-educated applicant's productivity $y^* = y + e$. Assume the productivity noise follows a normal distribution $N(e_0, \sigma_e^2)$, where e_0 is the average bias and σ_e^2 is the variance of noise. Firm j makes the hiring decision, pays w for college graduates or w_0 for non-college workers (both wages are exogenously determined), and enters the next period with a new vacancy.[23]

Suppose in period $K > 1$, firm j have received $N_{jK}(q)$ college-educated applicants in the past. $N_{jK}(q)$ weakly increases in the arrival rate of college-educated applicants q. In the first period, denote firm j's prior of college graduates' productivity as Y_j and then number of past interactions with college graduates N_j. After observing the productivity of $N_{jK}(q)$ college-educated applicants, firm j' forms a new perception of college graduates' productivity in period K:

$$Y_{jK} = \frac{N_j}{N_j + N_{jK}(q)} Y_j + \frac{N_{jK}(q)}{N_j + N_{jK}(q)} \overline{y^*} \tag{3}$$

Where $\overline{y^*}$ is the average observed productivity of the $N_{jK}(q)$ college graduates.

Assume firm j knows the variance σ_c^2 and σ_e^2 and has an unbiased prior Y_j. In period K, for each college applicant with observed productivity y^*, firm j would use Bayesian update to determine

[23] For a wage-setting model with endogenously determined wages, see Lepage (2024).

where the true level of productivity is:

$$\hat{y} = \frac{\sigma_e^2}{\sigma_c^2 + \sigma_e^2} Y_{jK} + \frac{\sigma_c^2}{\sigma_c^2 + \sigma_e^2} y^* \triangleq (1-s)Y_{jK} + sy^* \tag{4}$$

Appendix D shows that a new **learning effect** would emerge: for each period $K > 1$, with q increasing and more signals arriving, firm j may update its perception Y_j. The direction of the learning effect becomes negative if college-educated applicants systematically send a negative signal ($e_0 < 0$) or firm j receives a sufficient number of applicants. The magnitude of learning effect exceeds the search effect after a certain rounds of interactions. We can also derive the comparative statics consistent with the mechanism test in Section 5.2: the likelihood of hiring a college graduate increases in the number of past interactions with college graduates N_j as the learning effect diminishes in N_j. Notice that as firm j interacts with more applicants over time, its perception Y_{jK} approaches the truth if the productivity noise is unbiased in nature (*i.e.* $e_0 = 0$).

7.2 Cost of Screening and Endogenous Bias Formation

Now, we allow firm j to decide whether to conduct an interview on the applicant after observing a noisy signal and before conducting the final hiring decision. Firm j needs to pay $c(\theta_j)$ for the interview; after that, firm j can observe applicant's true productivity perfectly. Firm j can also perfectly observe the true productivity of the hired worker.

The incentive of interviewing comes from avoiding hiring mistake. When the observed productivity y^* is less than the non-college benchmark z, firm j would interview the applicant if:

$$\theta_j \int_z (y' - z) g(y^* - y') f(y') dy' \geq c(\theta_j) \tag{5}$$

$g(e')$ is the perceived probability function of the noise, and the $f(y')$ is the perceived probability function of the true productivity of college graduates. The integral describes the expected gains of hiring the college graduate if they are more productive, weighted by the probability density $g(y^* - y')$ given the observed productivity equals y^*. Assume firm j perceives the noise e' to be unbiased and follow $N(0, \sigma_e^2)$, and perceives the true productivity y' to follow $N(Y_{jK}, \sigma_c^2)$, where Y_{jK} is determined by Equation 3. When the observed productivity y^* is above the non-college benchmark z, firm j would always obtain accurate signals through interviewing or directly hiring.[24]

[24] One can write down a similar condition as Equation 5 when firms are concerned about mistakenly hiring the college graduate, from which one can derive an upper bound of observed productivity below which firms would conduct the interview. For those with the observed productivity above the upper bound, however, it is unlikely that their true productivity would fall below the benchmark z, and firms would simply hire them without interviewing.

As such, there exists a threshold $\underline{y_j}(z)$ such that firm j would interview applicants with an observed productivity level above the threshold. If the observed productivity falls below the threshold, the noise will be unfiltered and trigger the learning effect given certain conditions. If the observed productivity is above the threshold, firms would observe the true productivity of college applicants, and the learning effect in Section 7.1 would not be triggered. If the interviewing cost is sufficiently low, increasing the arrival rate q would not perversely decrease the hiring of college graduates.

However, an endogenous bias formation would emerge from this process; Theorem D.6 in Appendix D provides further demonstration. Since firms only have incentive to interview applicants with the observed productivity above a certain threshold, positive noises are more likely to be eliminated, and negative noises are more likely to enter the belief formation as in Equation 3. Therefore, even if the productivity noise is unbiased in nature ($i.e.$ $e_0 = 0$), as long as the interviewing cost is greater than zero, firms would eventually develop biased, negative perceptions of the productivity of college graduates.

7.3 What Could Prevent the Bias Formation?

To further demonstrate the process of the bias formation, we simulate the model for $T = 10$ periods by calibrating the key parameters listed out in Table B22, assuming the productivity noise is unbiased in nature.[25] Figure A14 shows the cross-sectional simulation results for firms at different productivity level, averaging the outcomes in the last five periods. Only around 70% of the college-educated applicants would be interviewed, and firms' beliefs of college graduates' productivity are 8–13% less than the truth, with more productive firms being slightly more biased. Figure A15 shows the time-series simulation for each period and averages the outcomes for all firms. The average belief of college graduates' productivity decreases over time, suggesting a worsening negative bias as the number of interactions between firms and college graduates increases.

Either way, firms would always have incentive to observe the true productivity of college graduates with $y^* > z$. This is the key to the endogenous bias formation discussed below.

[25] We normalize the variance of non-college workers' productivity σ_0 to one, and assume college workers' productivity and the productivity noise have the same variance $\sigma_e = \sigma_c = \sigma_0$. We calibrate the average non-college workers' productivity μ using the moment that equals the percentage of firms hiring a non-college worker when there was no college-educate applicant. We calibrate the average productivity premium of college graduates c using the moment that equals the percentage of firms who agreed college graduates to be more productive than non-college workers. We calibrate the access cost to the pool of college-educated applicants $c(q)$ and arrival rate of college-educated applicants q using our data on whether firms requested a college graduate at baseline and whether firms received any college-educated applicant. We impute the number of college graduates that firms interacted in the past using our data on college share, number of vacancies posted in a year, and firm's age. Last, we calibrate the cost of interviewing by leveraging a linear relationship between the percentage of non-college applicants being interviewed and the imputed skill index in Figure A13. We use the imputed skill index as a proxy of firm-specific productivity. Appendix D shows a one-to-one correspondence between the percentage of non-college applicants being interviewed and the interviewing cost at each level of firm-specific productivity. The linear relationship in Figure A13 further assures that the interviewing cost can be modeled as a convex function in firm-specific productivity.

We now conduct the following three counterfactual exercises in Figure 7. First, we decrease the standard deviation in the productivity noise σ_e by 0–100%. This reflects the scenario where college-educated applicants sent a more accurate signal of their productivity. The simulation result suggests an effective decrease in the bias level: a 50% decrease in the standard deviation in σ_e leads to a six percentage points decrease in the average bias, or a 55% decrease compared to the benchmark level.[26] Second, we decrease the interviewing cost $c(\theta_j)$ by 0–100%. This reflects the scenario where it is easier to obtain more accurate signals. The simulation result suggests this is less effective: a 50% decrease in the screening cost only leads to a two percentage points decrease in the average bias, or a 18% decrease. This implies that even a small amount of interviewing cost may contribute substantially to the bias formation.

Third, we decrease the search frictions by adjusting the match rate of firms and college graduates q from the benchmark level (100% search frictions) to one (where there are no search frictions and firms are guaranteed to receive a college-educated applicant in each period). The simulation result shows that this is counter-effective regarding combating bias: a 50% decrease in the search frictions actually increases the bias level by around two percentage points, or a 18% increase compared to the benchmark level. These counterfactual exercises demonstrate that with the existence of productivity noise and interviewing cost, simply increasing the interaction between firms and college-educated applicants may actually exacerbate the bias formation. This also provides another explanation why treated firms in our sample became less optimistic about the productivity of college graduates without additional assumptions on the nature of the bias. College-educated applicants might have sent an unbiased signal of their productivity, but the interviewing cost prevented firms from filtering out negative productivity noises, allowing negative bias to develop.

7.4 Implications for Firms and Workers

Our hiring model provides an ambiguous prediction for firms' profit. On one hand, 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

[26] Interestingly, when the productivity noise is completely eliminated, our simulation results suggest firms may still develop a certain level of negative bias, around 2% away from the truth. This is consistent with Lepage (2024), where firms may develop negative bias against minority groups if they have some bad hiring experience in the past. The relatively low level of such negative bias, however, suggests that this type of experience-based bias formation may be second-order when firms can update their beliefs before hiring. Our empirical evidence also suggests that unqualified applicants can only partially explain the learning effect.

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.

We further attempt to characterize the complier firms. Our hiring model suggests that the intervention is more likely to affect firms with middle-range productivity where the college premium may not be high enough to withstand a negative belief update. We observe some firms in our sample that might be more subject to the negative belief update. 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, same as in Section 6.3, and examine the treatment heterogeneity regarding skill index in Table B24. Among firms that requested a college graduate at baseline, we observe more salient shift in hiring behavior among treated firms with lower skill index, consistent with the prediction that these positions have lower college premium. Our sample size might thus be underpowered to detect the potential productivity loss when the complier firms shifted to hiring non-college workers.

However, our theoretical model demonstrates that the bias formation is applied to all firms that interacted with college-educated applicants, including firms with high skill index. Table B25, Column 1–2 show that among firms that requested a college graduate, firms with above-average skill index significantly decreased their perceptions of college graduates' productivity. Column 3–4 show that, albeit suggestive, these high-skill firms were also less likely to post any jobs in the future after the intervention, similar to low-skill firms. This suggests that the labor demand might be distorted beyond the scope of complier firms.

To summarize, we do not find evidence suggesting a significant loss in firms' profit induced by the intervention, potentially because the college premium for complier firms is small. The negative bias induced by the learning mechanism, however, would apply to all firms faced with noisy signaling and cost screening and decrease labor demand for college graduates to a larger extent, potentially having a persisting, negative impact on the labor market outcomes of college graduates.

7.5 Referral Hiring

Last, we observe that a subset of firms might resort to referral hiring after the intervention. Table B26 presents the result. Among firms that requested a college graduate at baseline, treated firms became 12.4 pp. less likely to use non-referral channels for hiring (p-value 0.089, 24% decrease), although on average they were not significantly more likely to switch to referral hiring. However, for firms who requested a college graduate and did not plan to use referral at baseline, we observe a 17.6 pp. decrease in using non-referral hiring channel (p-value 0.052) and 16.4 pp. increase in using referral hiring (p-value 0.058), suggesting that this subset of firms might start to resort to referral hiring for more accurate information of the applicants. We also find suggestive evidence that for firms who requested a college graduate at baseline and had higher skill index, the switch towards referral hiring is more salient, suggesting that firms who faced a higher interviewing cost might be more tempted to use referral hiring. This is aligned with an established literature on the informational advantages of referral hiring (Swanson, 2024; Heath, 2018; Beaman and Magruder, 2012). Note that referral hiring would not mitigate the learning effect induced by our intervention as almost all agency applicants were external applicants, but it may impact future hiring behavior and labor demand for workers from external networks, which we defer to future investigation.

8 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, and among firms that requested a college graduate at baseline, treated firms became 34% less likely to hire any college graduate. We rationalize these two main findings with a "learning before hiring" mechanism, where firms updated negatively on the productivity of college graduates. This is not simply triggered by unqualified applicants, but also because firms received noisy signals of the productivity of college-educated applicants and it is costly to conduct more interviews and obtain more accurate information. We simulate a hiring model to demonstrate how this learning mechanism can induce endogenous bias formation which cannot be addressed simply by increasing interactions between firms and job seekers.

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 hiring frictions which may potentially distort the labor demand and disproportionately affect highly educated job seekers.

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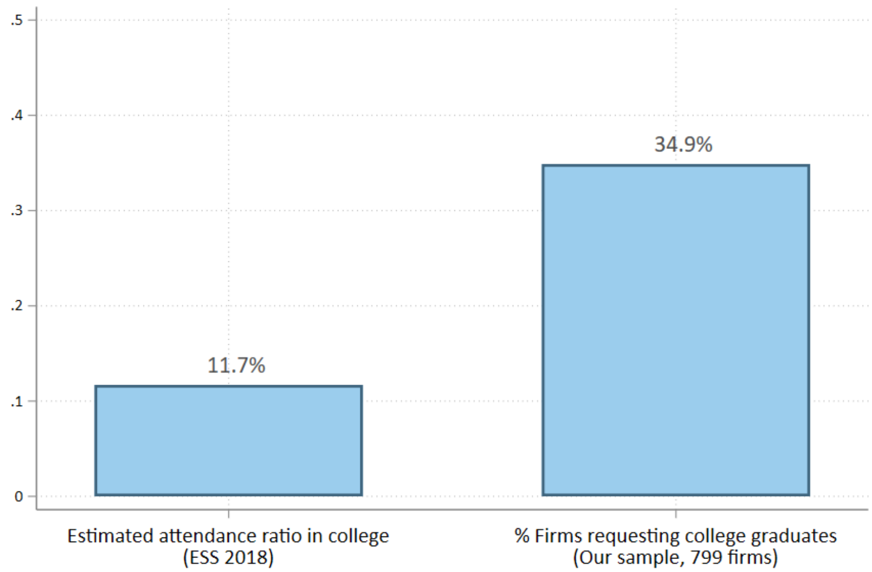
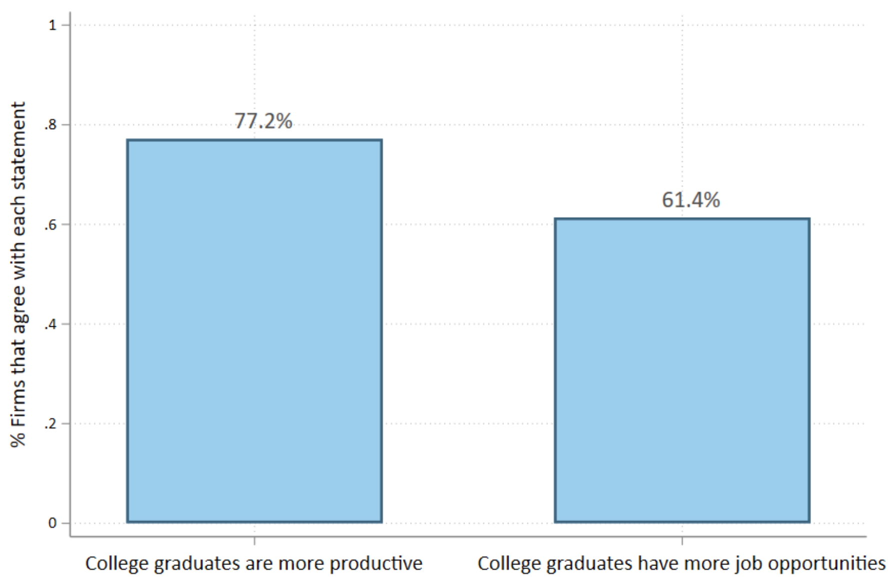
FIGURES

Figure 1: Demand for College Graduates

Panel A. Percentage of firms requesting a college graduate

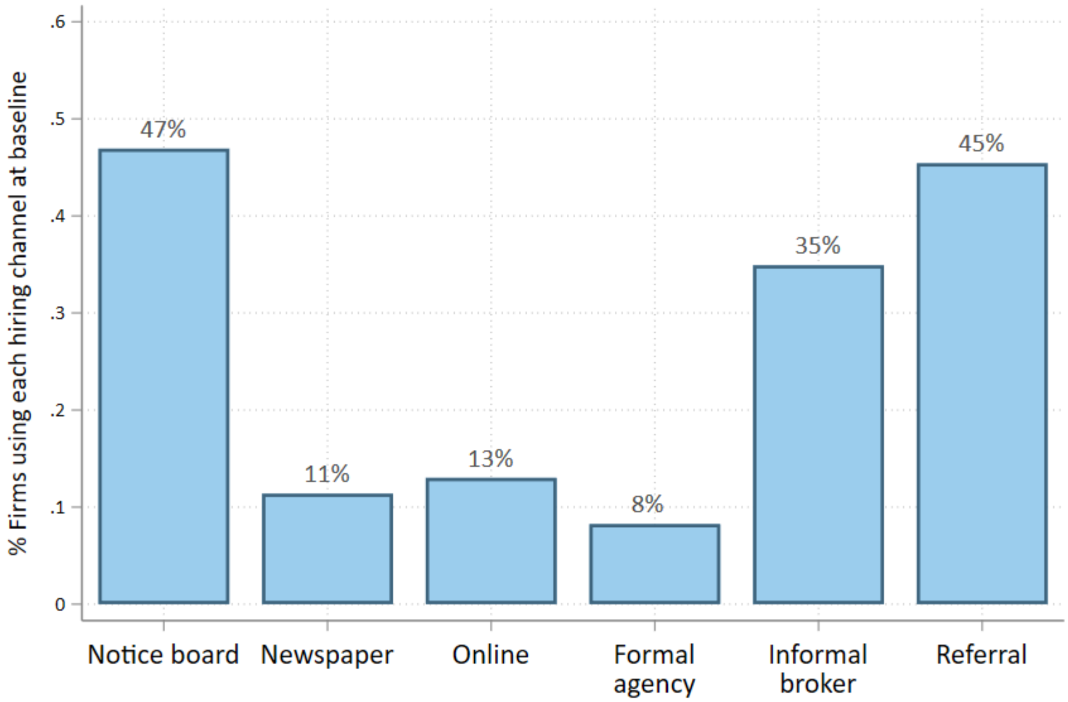


Panel B. Perceptions of college graduates



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.

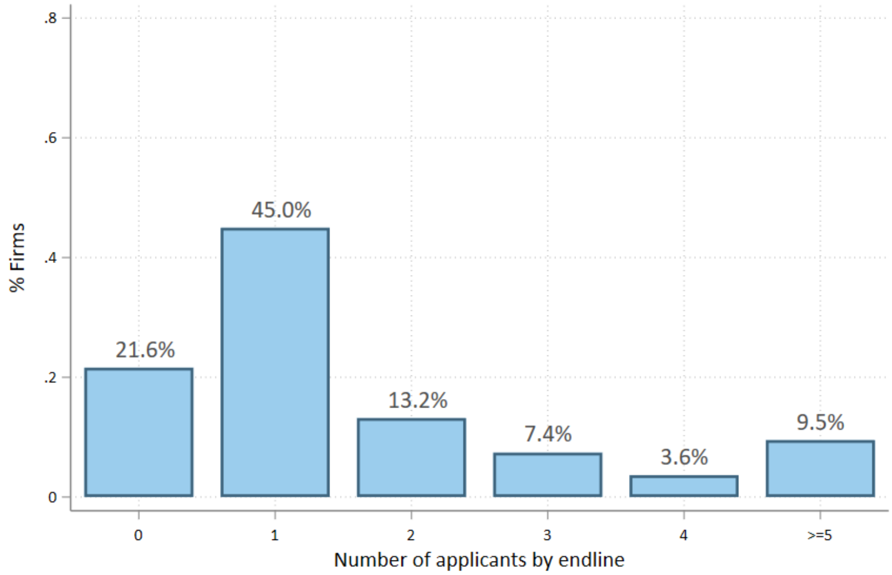
Figure 2: Hiring Channels Used by Firms at Baseline



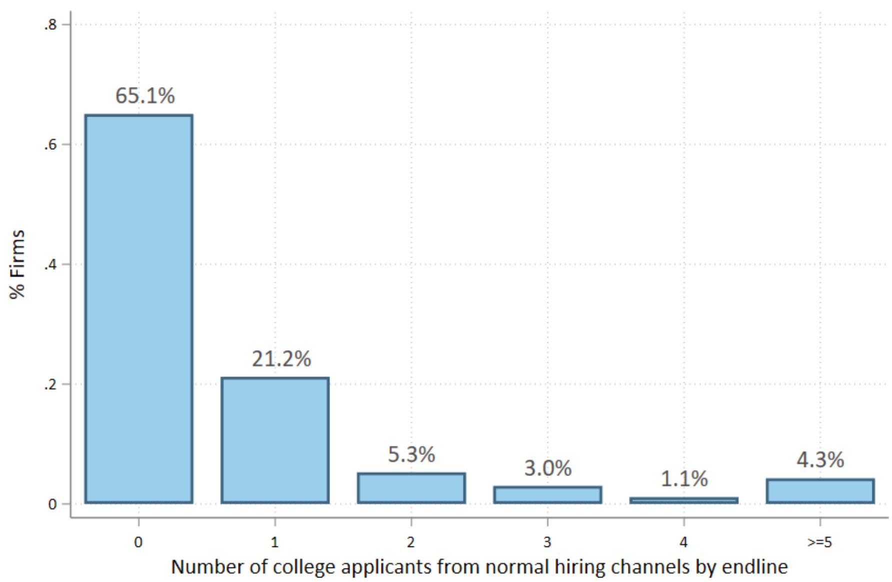
Notes: This figure shows the percentage of firms in our sample using different types of hiring channels, including notice boards, newspapers, online platforms, formal employment agencies, informal job brokers, and personal referrals.

Figure 3: Distribution of the Number of Applicants

Panel A. All applicants



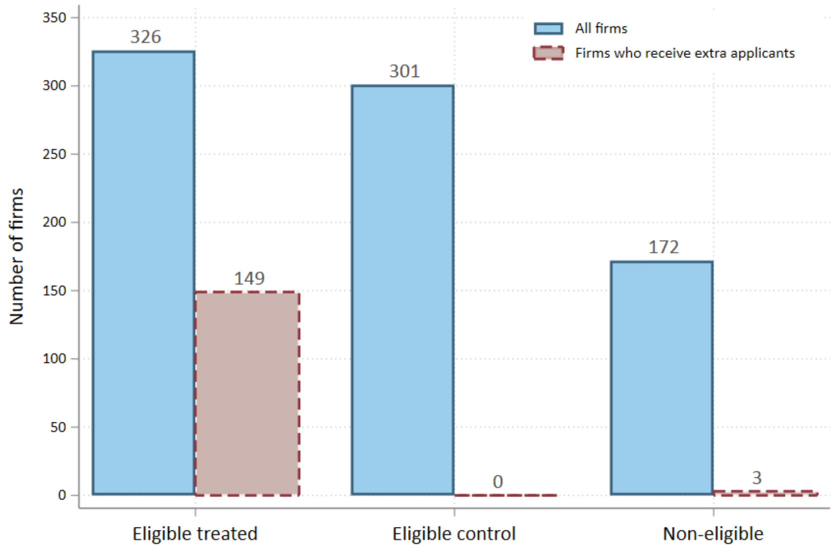
Panel B. College-educated applicants



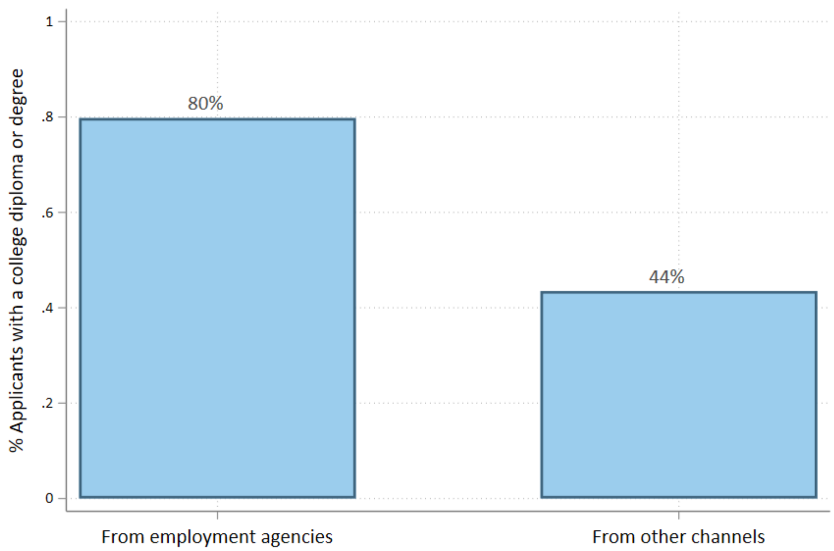
Notes: This figure presents the distribution of the total number of applicants for the posted vacancies by endline, not including applicants from the employment agencies introduced in the intervention. Panel A: Total number of applicants. Panel B: Total number of college educated applicants.

Figure 4: Matching between Employment Agencies and Firms

Panel A. Treatment Implementation



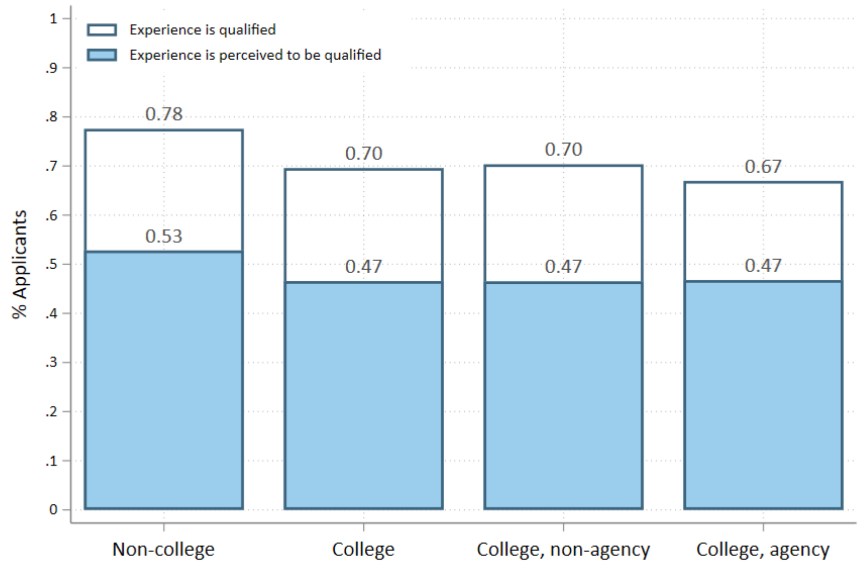
Panel B. Selection of Agency Applicants



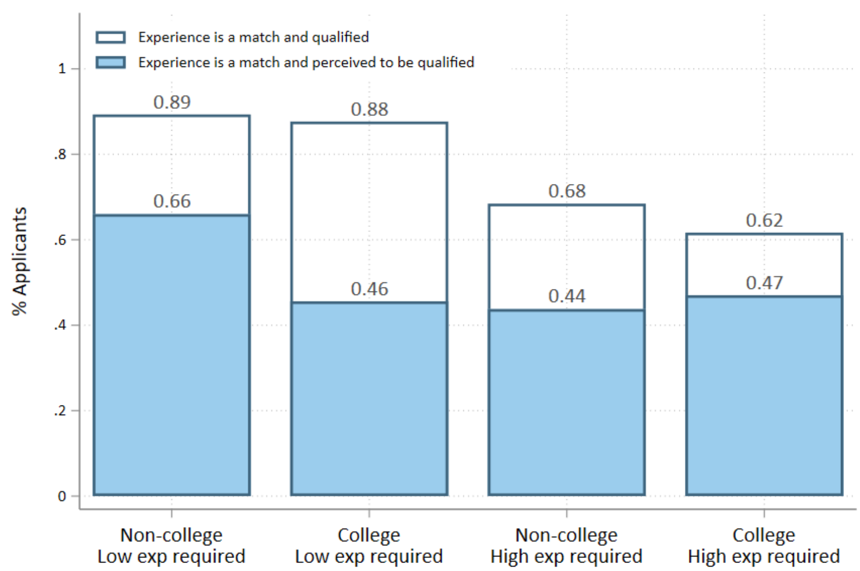
Notes: This figure shows the matching between employment agencies and firms. Panel A shows the number of three groups of firms: (1) Eligible firms (reservation wage at least 2,000 ETB) selected into treatment group, (2) eligible firms selected into control group, (3) non-eligible firms. Panel B shows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

Figure 5: Perceived Qualification of Applicants' Experience

Panel A. By applicants' education and agency status



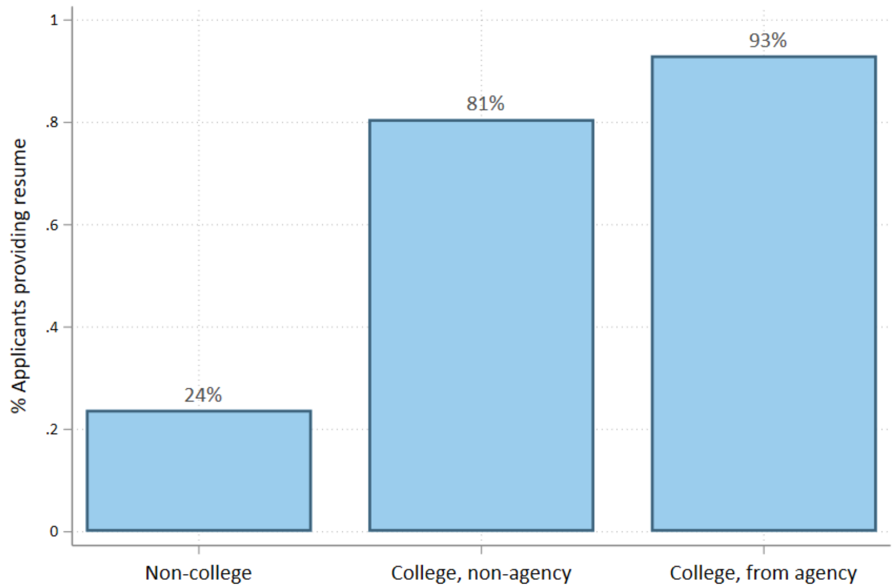
Panel B. By firms' minimum experience requirement



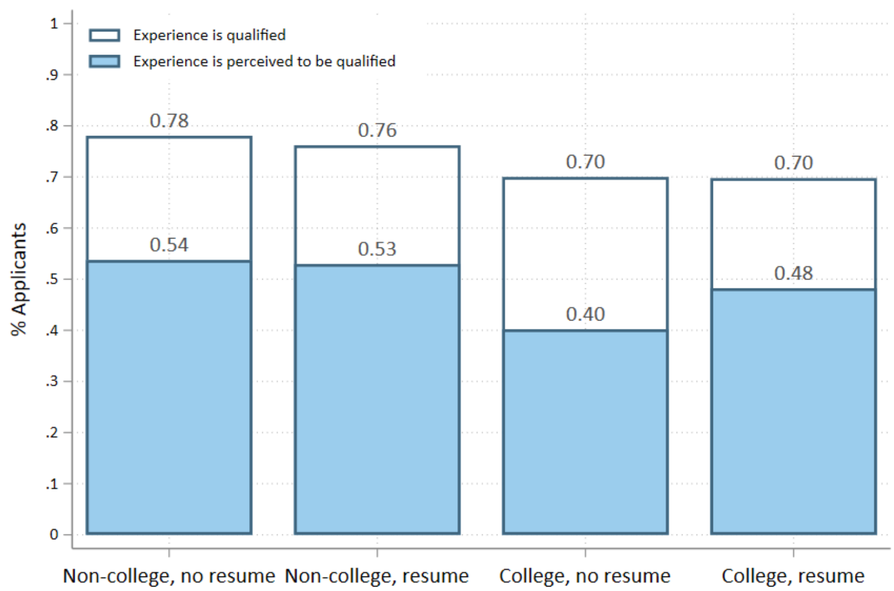
Notes: This figure shows the qualification of applicants' experience for non-college applicants, college-educated applicants not recommended by the employment agencies, and college-educated applicants recommended by the employment agencies. We define an applicant is qualified if their years of experience 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

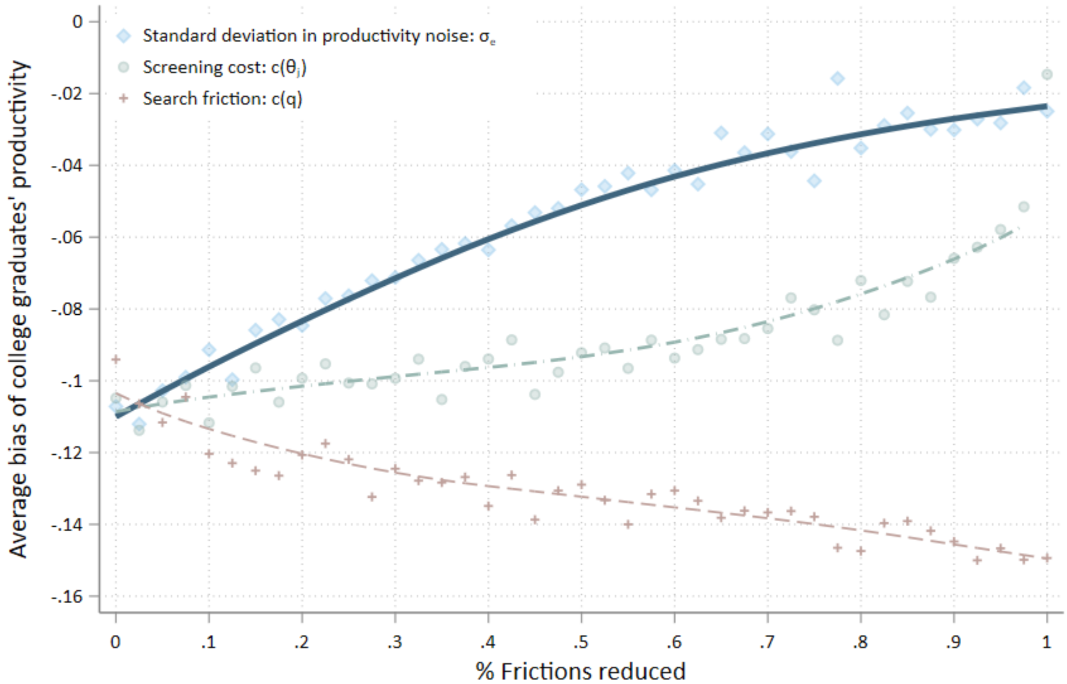


Panel B. Perceived qualification of applicants' experience by résumé usage



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.

Figure 7: Counterfactual Exercises on the Endogenous Bias Formation



Notes: This figure shows the simulation results from our hiring model featuring belief update before making hiring decisions. We run 10 rounds of the simulation where firms observe a noisy but unbiased signal of college-educated applicant's productivity; the noise is randomly drawn from $N(0, \sigma_e^2)$, where we assume σ_e to be equal to the standard deviation of college graduates' true productivity σ_c. College-educated applicants are randomly drawn from the distribution $N(\mu + c, \sigma_c^2)$; μ is the average productivity of non-college workers, c is the college productivity premium. Firms pay a search cost $c(q)$ (a function of arrival rate q) to access college-educated applicants, and interviewing cost $c(\theta_j)$ (a function of firm-level productivity θ_j) to obtain accurate signals of applicants. We conduct three simulation exercises: (1) Decreasing the standard deviation in the productivity noise σ_e (blue diamonds on the top) by 0-100%, (2) decreasing the cost of screening applicants $c(\theta_j)$ (green circles in the middle) by 0-100%, and (3) decreasing the search frictions by increasing the arrival rate of college-educated applicants q (red crosses at the bottom); the arrival rate would reach one when there are no search frictions. The x-axis is the percentage of each type of frictions being reduced in the simulation exercises; the y-axis is firms' average bias of the productivity of college graduates as a proportion of the truth. We report the average of the last five simulations; only firms at the productivity level where they would access the pool of college graduates in the benchmark scenario are included when we calculate the averages.

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: 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 4: 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	-0.249	0.028			-0.087		
	(0.116)	(0.087)			(0.044)		
	[0.038]	[0.755]			[0.051]		
# Non-agency (NA) college app			-0.060			0.000	
			(0.016)			(0.007)	
			[0.001]			[0.968]	
Treated x Zero NA college app			-0.555			-0.058	
			(0.166)			(0.045)	
			[0.002]			[0.200]	
Treated x $\geq$ 1 NA college app			-0.211			-0.135	
			(0.099)			(0.063)	
			[0.040]			[0.034]	
Treated x Not requesting college				-0.392			-0.082
				(0.214)			(0.057)
				[0.076]			[0.150]
Treated x Requesting college				-0.195			-0.093
				(0.122)			(0.054)
				[0.119]			[0.085]
Observations	151	154	151	151	568	568	568
R-squared	0.391	0.505	0.470	0.397	0.329	0.331	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	0.777	0.851			0.782		
Control mean with one NA college app			0.878			0.768	
Control mean with zero NA college app						0.782	
Control mean: Not requesting college				0.767			0.720
Control mean: Requesting college				0.768			0.897

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 1–4, 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 5–7 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. 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 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 3. 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 3. 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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: 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

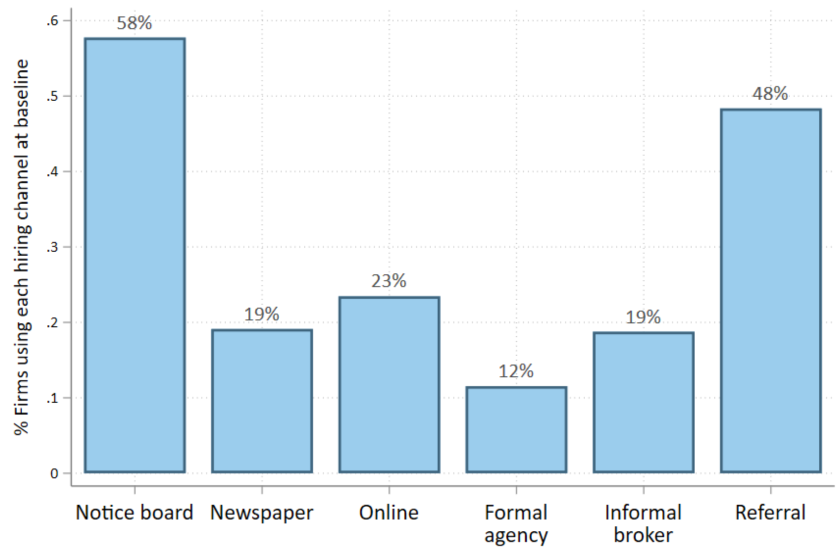
VARIABLES	(1) # Applicants Interviewed	(2) # Agency apps Interviewed	(3) # Non-agency apps Interviewed	(4) All non-agency apps Interviewed
Treated x Not requesting college	-0.108	0.049	-0.157	-0.088
	(0.128)	(0.043)	(0.122)	(0.076)
	[0.401]	[0.262]	[0.202]	[0.249]
Treated x Requesting college	-0.042	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.

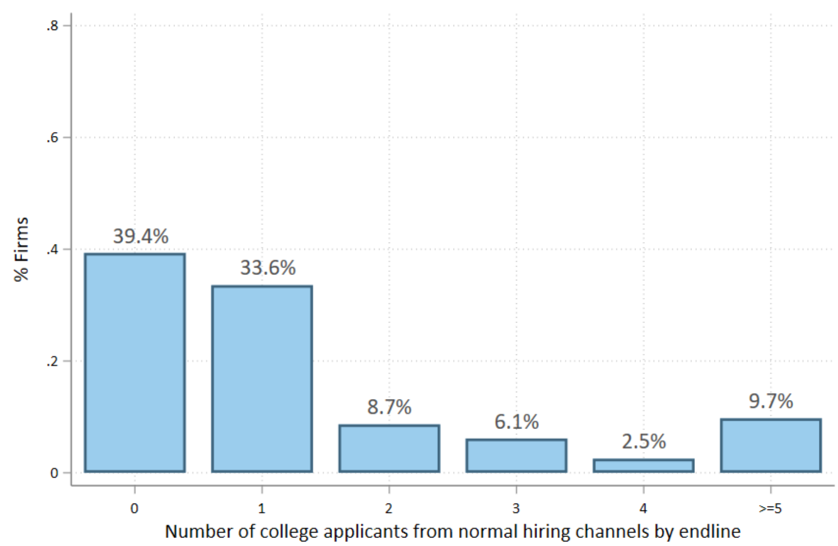
A Appendix Figures

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



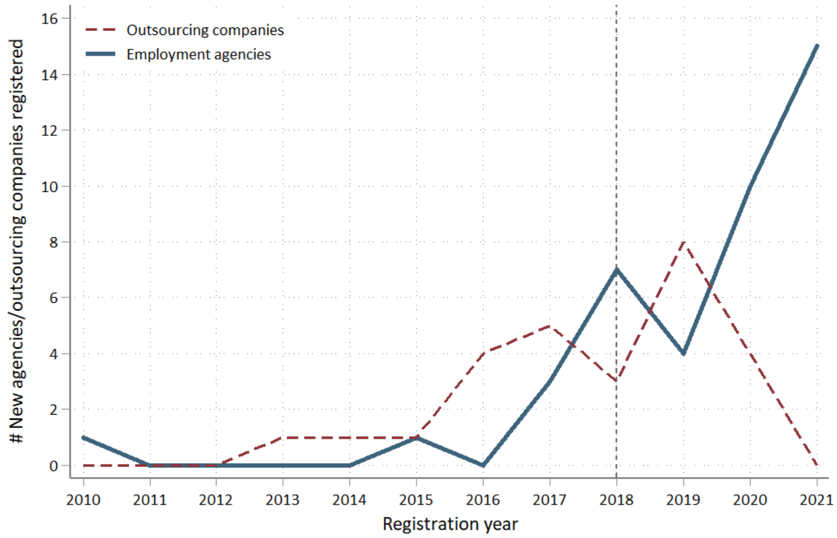
Notes: Panel A shows the percentage of firms that request a college graduate at baseline who use different types of hiring channels. Panel B shows the distribution of the total number of college applicants by endline for firms requesting college graduates, not including applicants from the employment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

Figure A2: A Typical Employment Agency

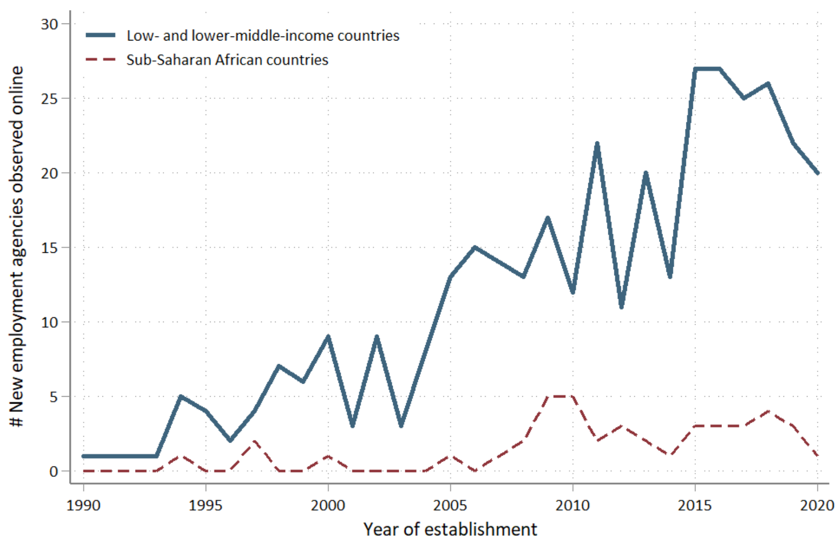
Notes: This figure shows a typical employment agency in our sample located in Bole sub-city, Addis Ababa, Ethiopia.

Figure A3: Trends of Employment Agencies

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

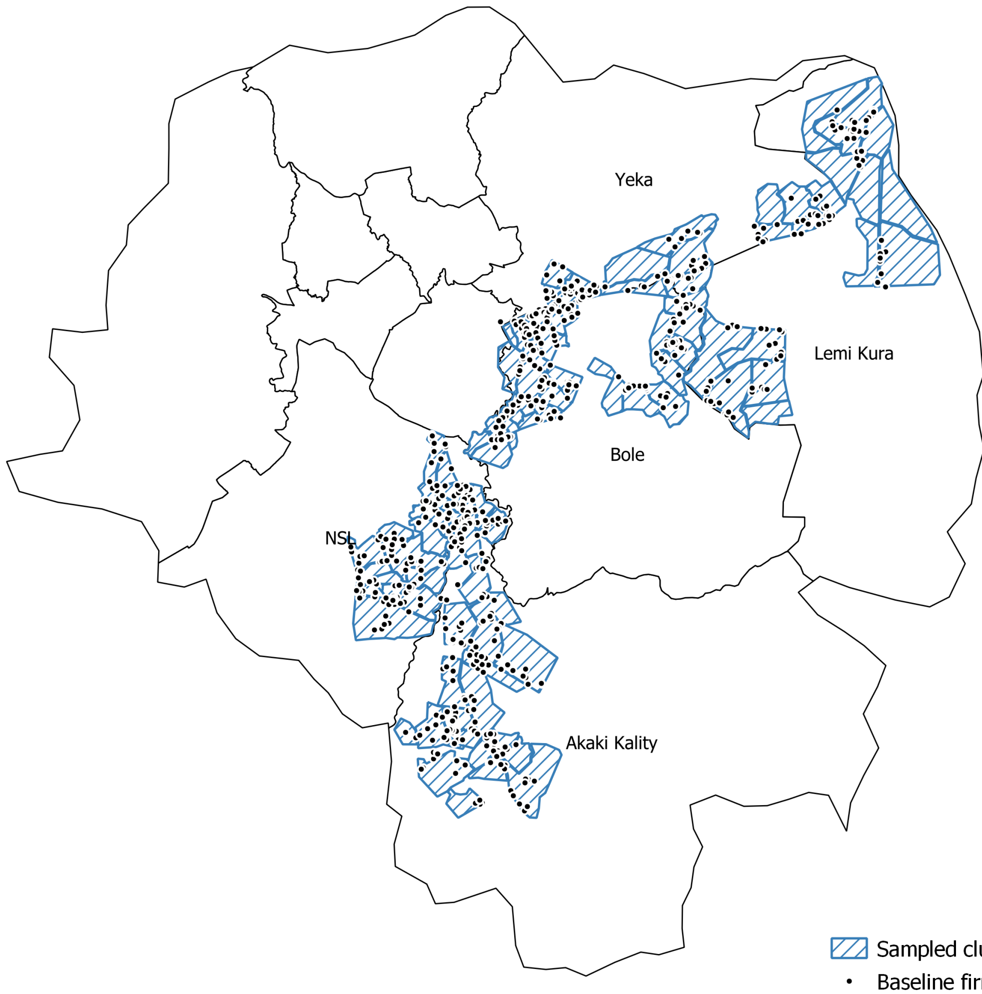


Panel B. Number of employment agencies in low- and middle-income countries, 1990–2020



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.

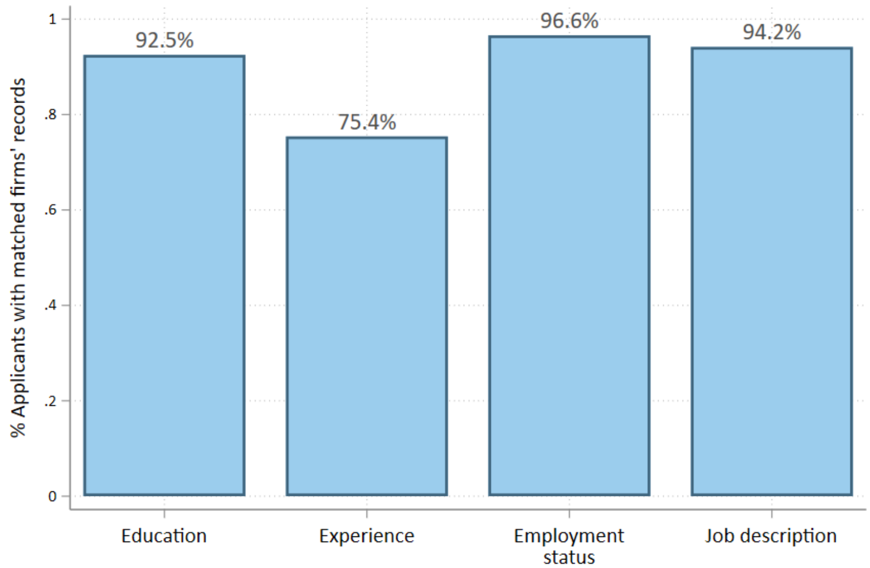
Figure A4: Sampling Map



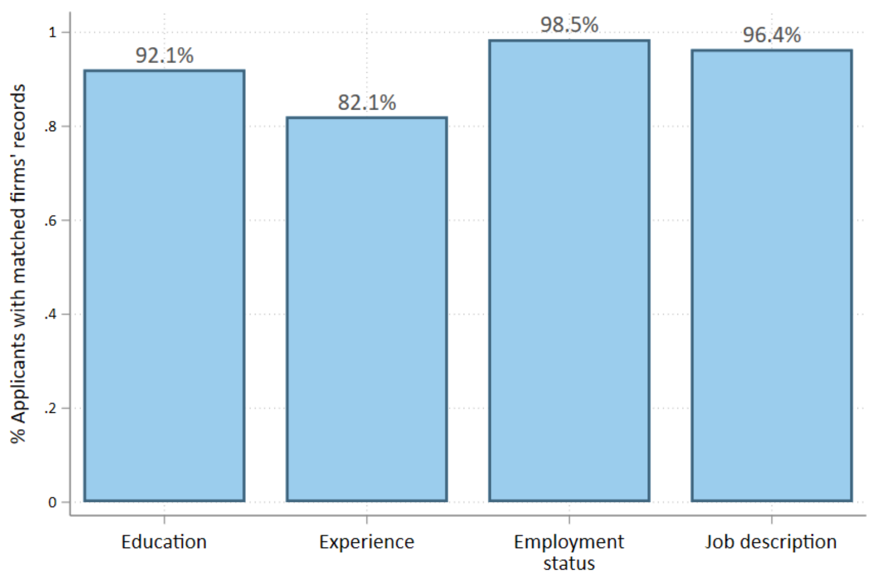
Notes: This figure shows the geographical distribution of 88 business areas from five sub-cities and 799 firms selected in the baseline survey.

Figure A5: Data Validation

Panel A. College-educated applicants

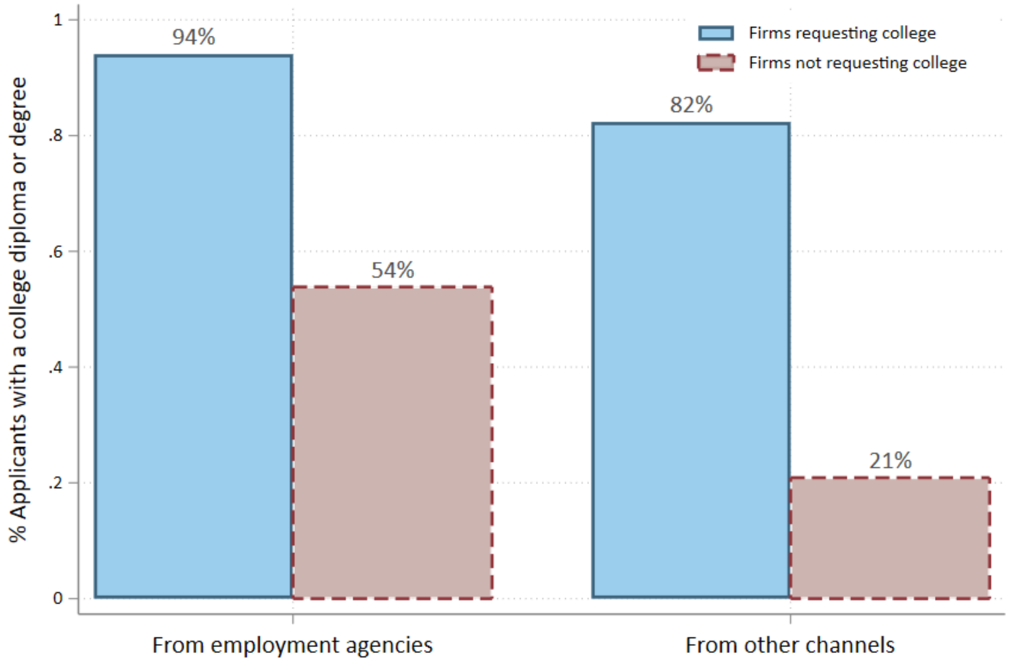


Panel B. Non-college applicants



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.

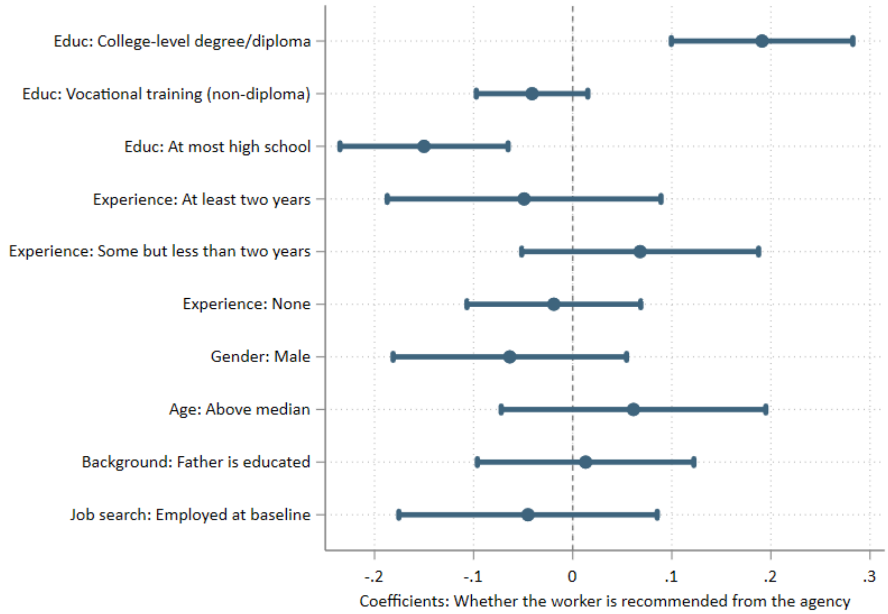
Figure A6: Selection of Agency Applicants by Baseline Request for College Graduates



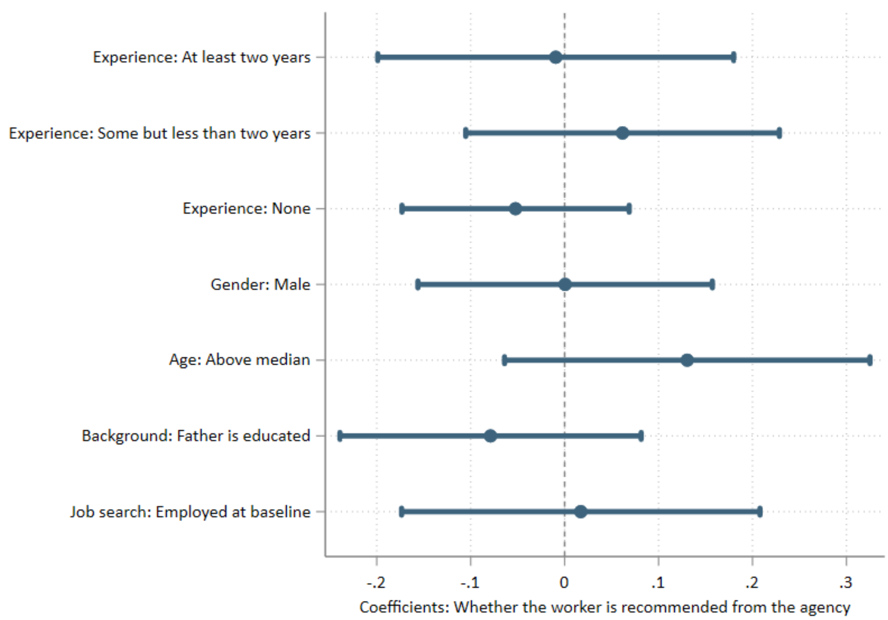
Notes: This figure shows the selection patter of applicants. The blue bars show the percentages of college graduates among the applicants provided by the employment agencies or other hiring channels for the vacancies that request a college graduate at baseline. The red bars with dashed contour show the 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



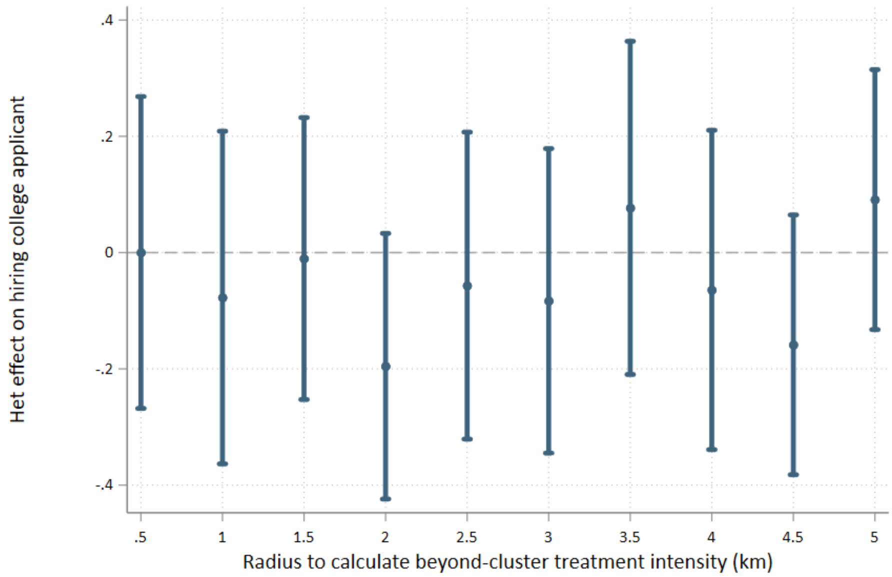
Panel B. College-educated applicants



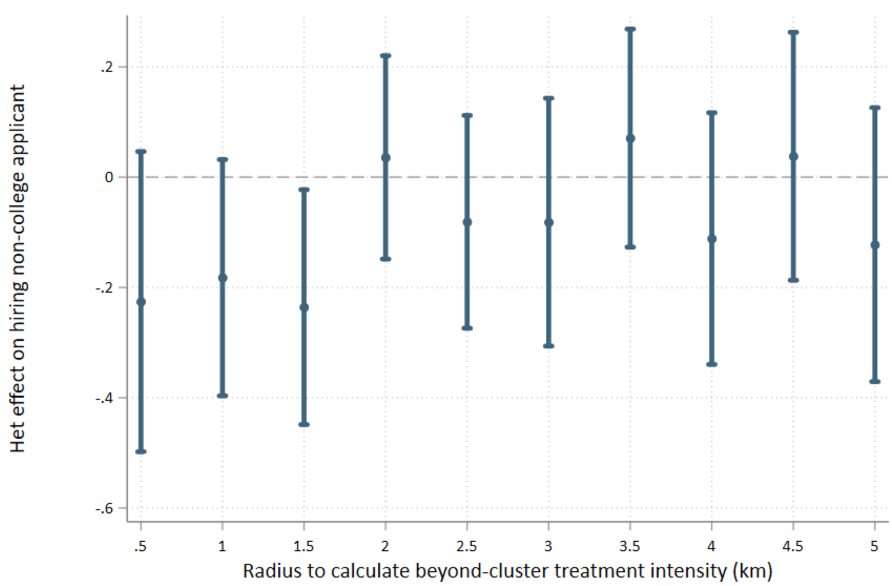
Notes: This figure shows the selection of applicants from the employment agencies in terms of observable characteristics. Panel A includes all applicants; Panel B only includes college-educated applicants. For each characteristics, we compare agency applicants to non-agency applicants, controlling for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

Figure A8: Heterogeneous Effects by Treatment Intensity

Panel A. Hiring any college graduate



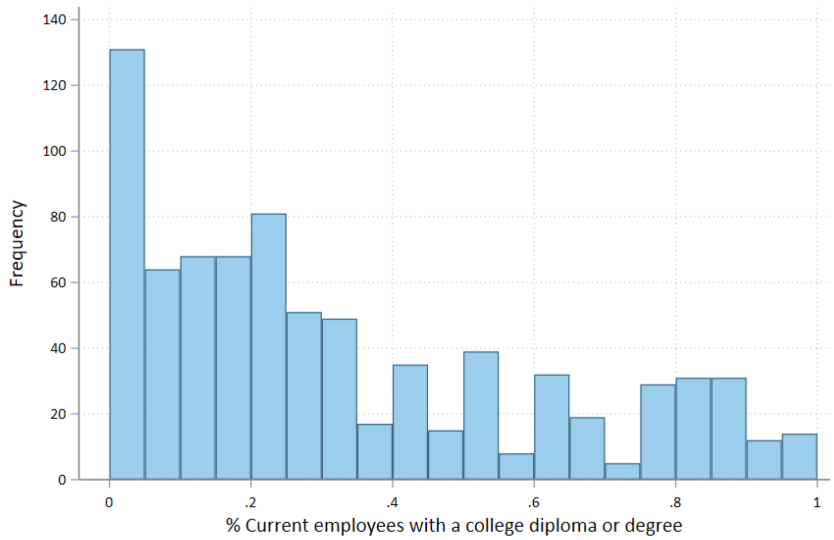
Panel B. Hiring any non-college worker



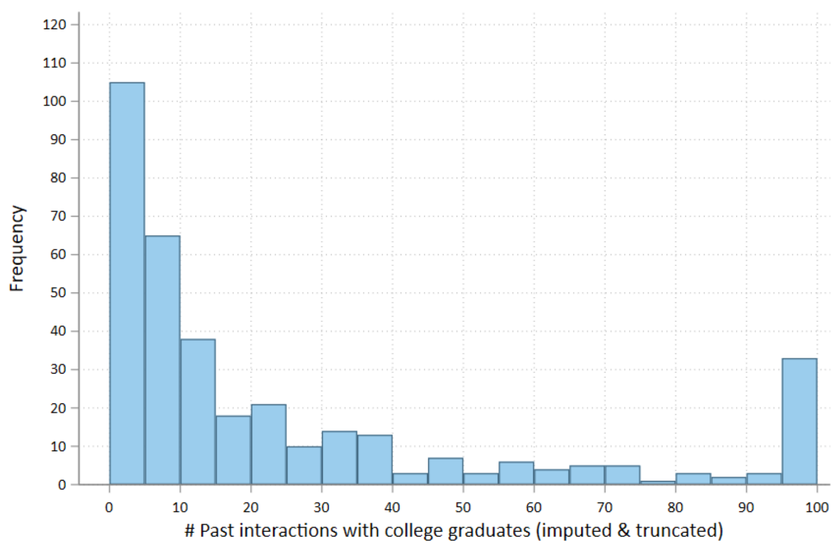
Notes: This figure shows the heterogeneous treatment effects by beyond-cluster treatment intensity in the nearby regions. Only firms with reservation wage at least 2,000 ETB (eligible firms) are included. In each regression, we regress whether firm hires any college or non-college workers on (i) initial 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 A9: Firms' Past Interaction with College Graduates

Panel A. College share as proxy



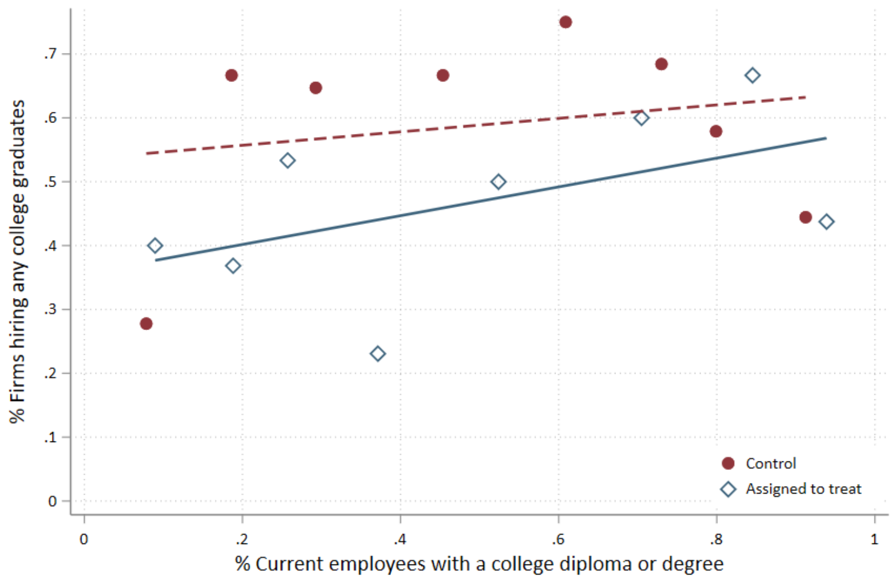
Panel B. Imputed number of past interactions



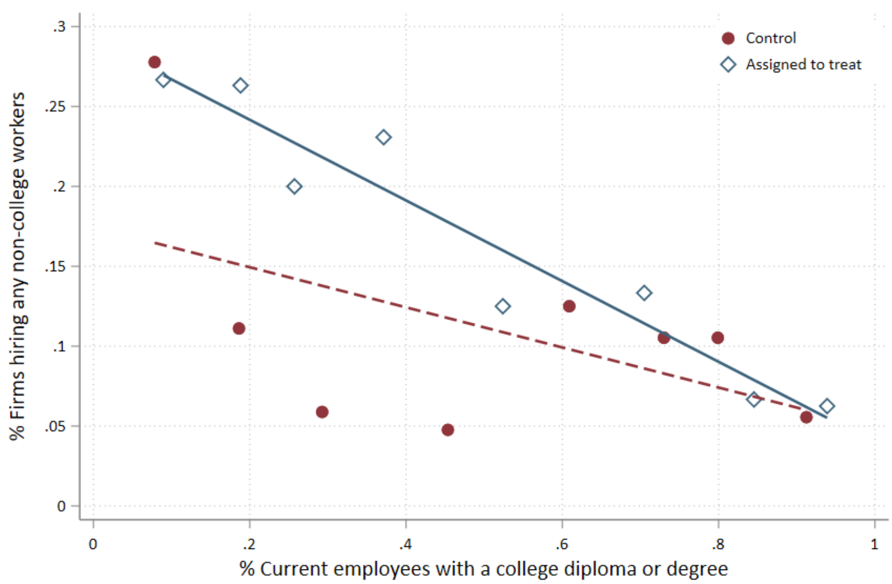
Notes: Panel A shows the distribution of the college share over the whole sample, defined as the percentage of current employees with a college diploma or degree. Panel B shows the distribution of the imputed number of past interactions with college graduates. Only Round 1 sample is included in Panel 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 A10: Hiring of College Graduates and Non-College Workers By College Share

Panel A. Hiring of college graduates

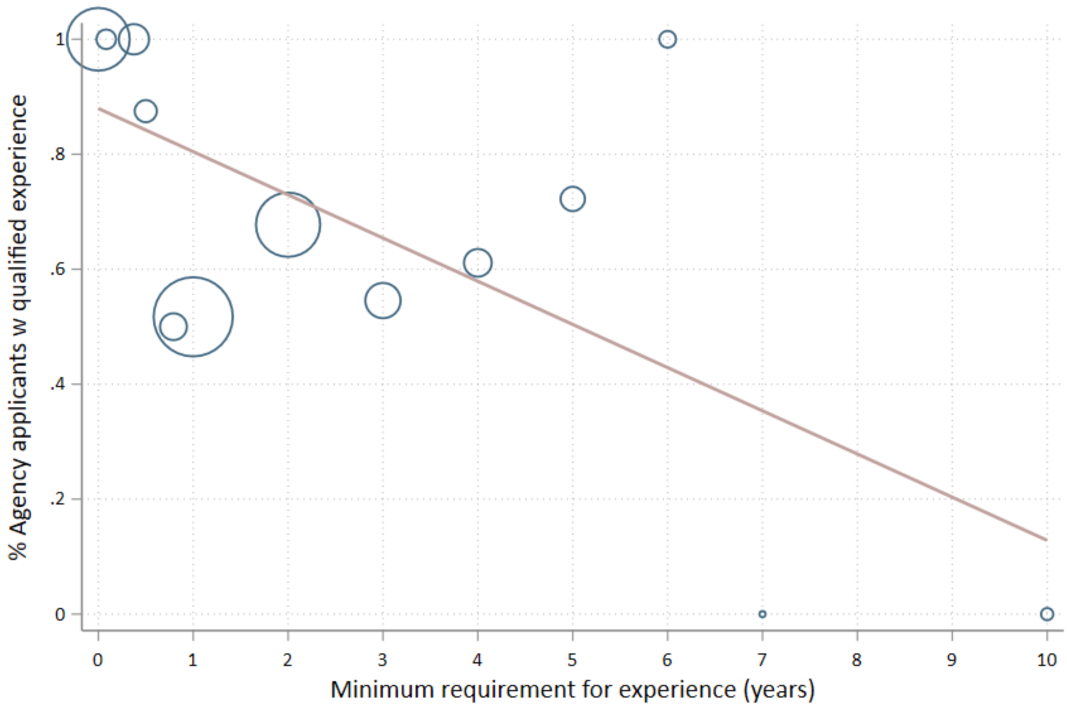


Panel B. Hiring of non-college workers



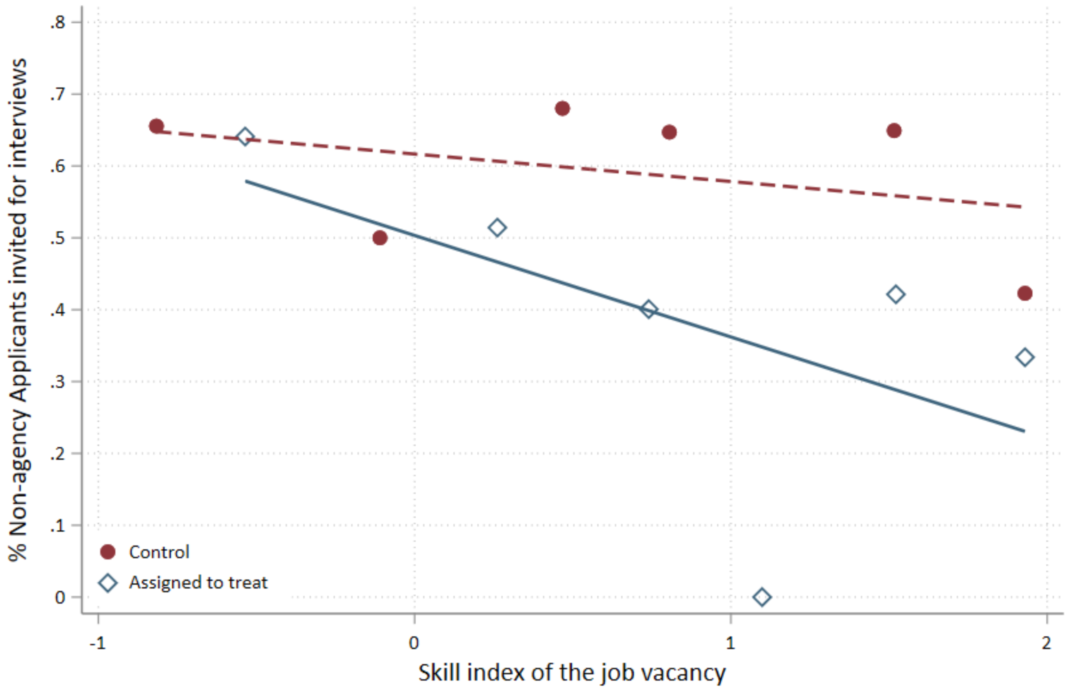
Notes: This figure presents the bin-scatter plots of the hiring of college graduates and non-college educated workers. Only firms with reservation wage at least 2,000 ETB (eligible firms) and requesting a college graduate at baseline are included. The horizontal axis is the percen tage of current employees 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 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.

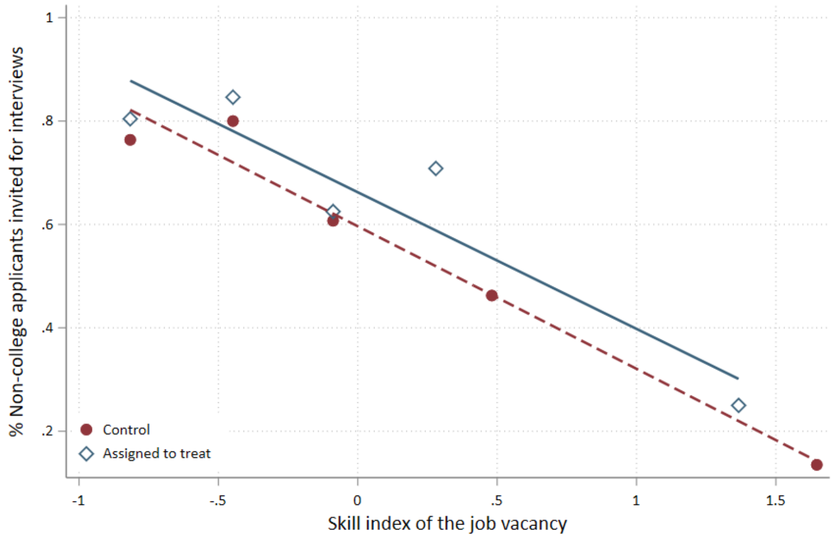
Figure A12: Firms with a Higher Skill Requirement Were Less Likely to Invite All Applicants for Interviews



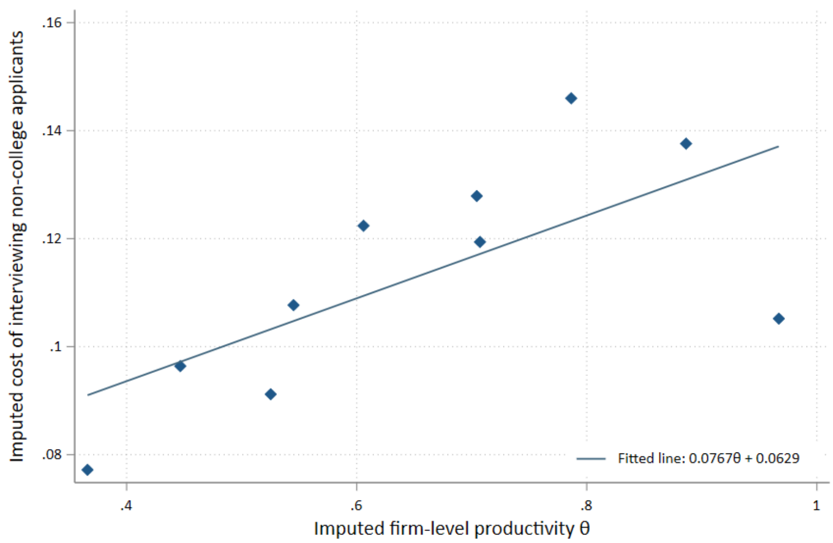
Notes: This figure shows the binscatter plot of the percentage of non-agency applicants invited for interviews against the imputed skill index for the job vacancy, separately for treated and control firms. Only firms that request a college graduate at baseline are included. The skill index for each vacancy is imputed by extracting the principal component for the following four vacancy characteristics: Whether the vacancy requires specific skills, whether it involves manual labor, whether it involves routine work, whether it requires at least two years of experience. The skill index is positively correlated with whether the vacancy requires specific skills.

Figure A13: Simulation: Calibration of the Interviewing Cost

Panel A. Interviewing non-agency applicants and skill index

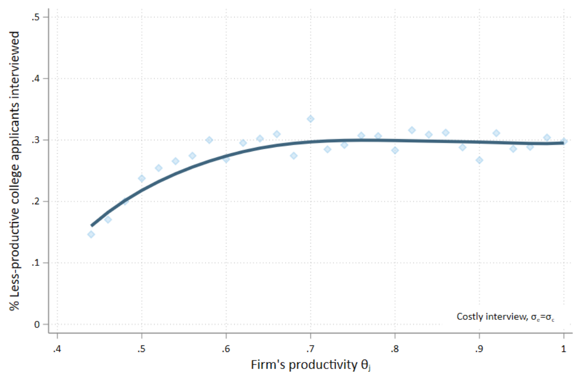


Panel B. Imputed cost of interviews and firm-level productivity

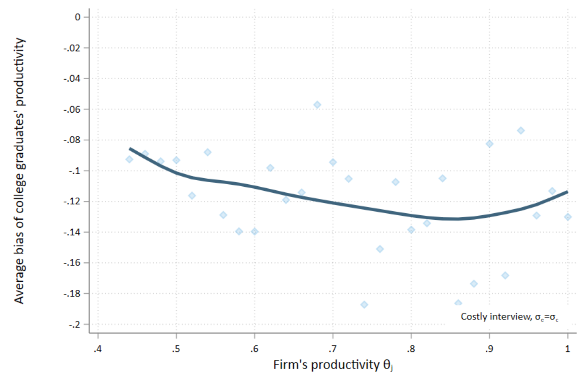


Notes: Panel A shows the binscatter plot of the percentage of non-college applicants invited for interviews against the imputed skill index for the job vacancy, separately for treated and control firms. Only firms with zero college applicants are included. The skill index for each vacancy is imputed by extracting the principal component for the following four vacancy characteristics: Whether the vacancy requires specific skills, whether it involves manual labor, whether it involves routine work, whether it requires at least two years of experience. The skill index is positively correlated with whether the vacancy requires specific skills. Panel B shows the scatter plot of the imputed cost of interviewing non-college applicants against the imputed firm-level productivity. For the cost of interviewing, we first calculate the threshold of being interviewed z_s^* at each value of skill index, assuming non-college productivity follows $N(\mu, \sigma_0^2)$ (see Table B22 for calibration). We then back out the cost of interviewing, $c(\theta_j)/\theta_j$, following $\int_0 z\phi(\frac{z_s^* - z}{\sigma_e})\phi(\frac{z-\mu}{\sigma_0})dz = \frac{c(\theta_j)}{\theta_j}$ (see Appendix D for more details). To impute firm-level productivity, we rescale the skill index such that the minimum (maximum) of the skill index equals the percentile of average posted salary with respect to the posted salary distribution.

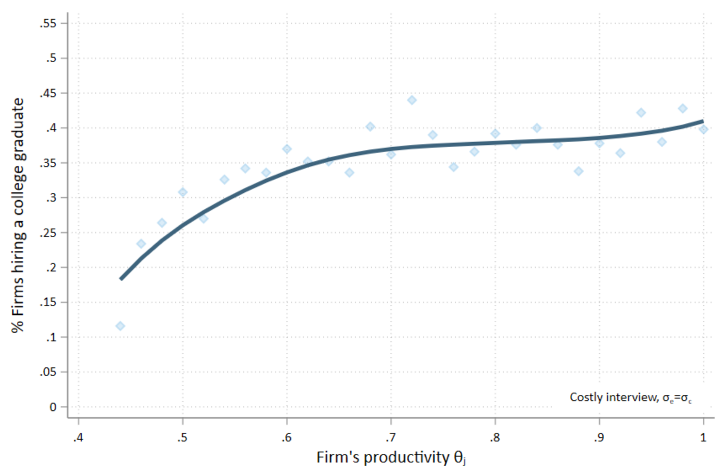
Figure A14: Simulation Results: Cross Section



(a) % College-educated applicants interviewed



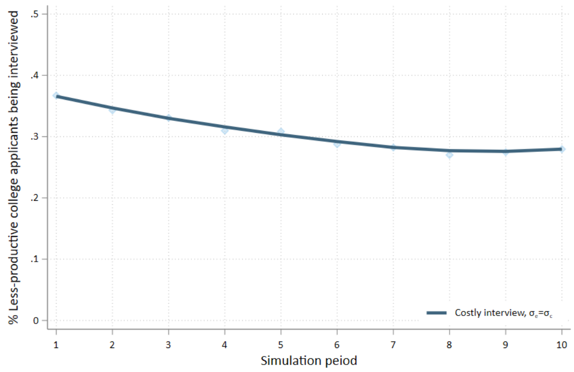
(b) Belief of college graduates' productivity



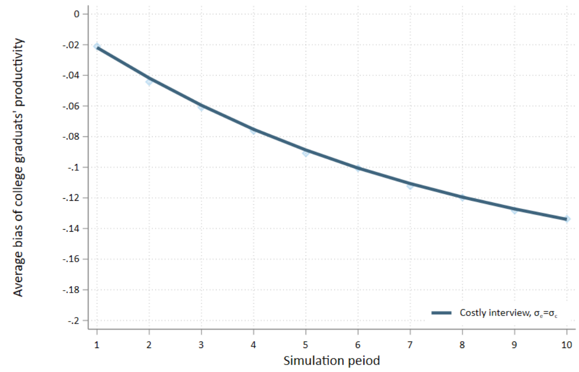
(c) Percentage of firms hiring a college graduate

Notes: This figure shows the cross-sectional simulation of firm's interviewing and hiring decisions and beliefs of college graduates' productivity. We run 10 rounds of the simulation where firms update their beliefs of college graduates' productivity based on the college-educated applicants randomly drawn from the distribution $N(\mu + c, \sigma_c^2)$; μ is the average productivity of non-college workers, c is the college productivity premium, and σ_c is the variance of college graduates' productivity. Firms observe a noisy but unbiased signal of college-educated applicant's productivity; the noise is randomly drawn from $N(0, \sigma_e^2)$, where σ_e is the variance of noise; we further assume σ_e to be the same level as σ_c. We assume nonnegative interviewing cost, where we calibrate the interviewing cost from Figure A13. We report the average of the last five simulations for each level of firm's productivity θ_j; only firms at the productivity level where they would access the pool of college graduates are included. Panel A reports the simulated percentage of college-educated applicants invited to the interviews. Panel B reports the simulated average bias of college productivity premium c as a percentage compared to the truth. Panel C reports the simulated percentage of firms that would hire a college graduate.

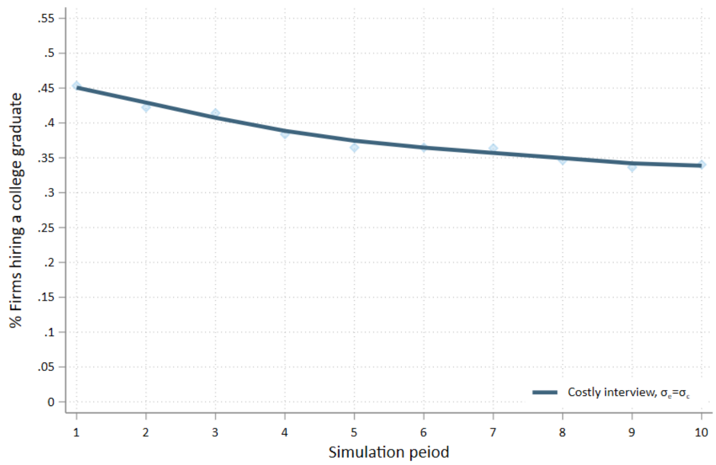
Figure A15: Simulation Results: Time Series



(a) % College-educated applicants interviewed



(b) Belief of college graduates' productivity



(c) Percentage of firms hiring a college graduate

Notes: This figure shows the time-series results from the simulation. We run 10 rounds of the simulation where firms update their beliefs of college graduates' productivity based on the college-educated applicants randomly drawn from the distribution $N(\mu + c, \sigma_c^2)$, where μ is the average productivity of μ, c college productivity premium, and σ_c the variance of college graduates' productivity. Firms observe a noisy but unbiased signal of college-educated applicant's productivity; the noise is randomly drawn from $N(0, \sigma_e^2)$, where σ_e is the variance of the noise; we further assume σ_e to be the same level as σ_c. We assume nonnegative interviewing cost, where we calibrate the interviewing cost from Figure A13. Only firms that access the pool of college graduates are included. Panel A reports the simulated percentage of college-educated applicants invited to the interviews. Panel B reports the simulated average bias of college productivity premium c as a percentage compared to the truth. Panel C reports the simulated percentage of firms that would hire a college graduate.

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: Treatment Effects on Future Hiring Plans

VARIABLES	(1) Plan to post Any job	(2) Plan to post Any job	(3) Plan to hire More college	(4) Plan to hire More non-college
Treated x Not requesting college	0.00452	-0.0433	-0.0222	0.0817
	(0.0706)	(0.114)	(0.0776)	(0.0582)
	[0.949]	[0.706]	[0.776]	[0.168]
Treated x Requesting college	-0.124*	-0.165	-0.0800	-0.0429
	(0.0719)	(0.144)	(0.0769)	(0.0631)
	[0.0876]	[0.259]	[0.305]	[0.501]
Observations	568	298	298	298
R-squared	0.324	0.374	0.480	0.410
Sample	All	Round 2	Round 2	Round 2
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	0.652	0.598	0.517	0.218
Control mean: Requesting college	0.653	0.519	0.835	0.0253

Notes: This table presents the treatment effects on firms' future hiring plans. 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 2, whether the firm planned to post any jobs in the next three months after endline. Column 3, whether the firm planned to hire more college graduates in the next three months after endline. Column 4, whether the firm planned to post any jobs but not to hire more college graduate in the next three months after endline. Column 2–4 restrict the sample to Round 2 because we only have information on whether the firm planned to hire any college graduate in Round 2. 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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Correlational Evidence of the Shift in Hiring Behavior

Panel A. Number of college-educated applicants

	(1)	(2)	(3)	(4)	(5)	(6)
	Interview	Interview	Interview	Hire	Hire	Hire
VARIABLES	Any	College	Non-college	Any	College	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

	(1)	(2)	(3)	(4)	(5)	(6)
	Interview	Interview	Interview	Hire	Hire	Hire
VARIABLES	Any	College	Non-college	Any	College	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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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	0.0296	-0.0612	-0.00797	0.0351
	(0.219)	(0.0536)	(0.183)	(0.0364)
	[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)
	[0.0857]	[0.000307]	[0.238]	[0.0270]
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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B7: 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	0.0335	0.0335	0.0335	0.0335	-0.0279	-0.0274
	(0.0628)	(0.0607)	(0.0633)	(0.0751)	(0.0805)	(0.0818)
	[0.595]	[0.582]	[0.597]	[0.657]	[0.730]	[0.739]
Treated x Requesting college	-0.197**	-0.197***	-0.197***	-0.197**	-0.230**	-0.192**
	(0.0764)	(0.0715)	(0.0751)	(0.0786)	(0.0888)	(0.0862)
	[0.0116]	[0.00595]	[0.00854]	[0.0140]	[0.0116]	[0.0287]
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	-0.00219	-0.00219	-0.00219	-0.00219	0.0297	0.0592
	(0.0481)	(0.0544)	(0.0498)	(0.0547)	(0.0606)	(0.0587)
	[0.964]	[0.968]	[0.965]	[0.968]	[0.625]	[0.316]
Treated x Requesting college	0.0875	0.0875	0.0875	0.0875	0.0776	0.0579
	(0.0535)	(0.0640)	(0.0593)	(0.0844)	(0.0610)	(0.0618)
	[0.106]	[0.172]	[0.140]	[0.303]	[0.207]	[0.352]
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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B8: 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	0.0259	0.0539	0.0309	0.0572	-0.00808	-0.0180	0.00829
	(0.0235)	(0.0789)	(0.0627)	(0.0642)	(0.0633)	(0.0490)	(0.0511)
	[0.273]	[0.497]	[0.623]	[0.376]	[0.899]	[0.715]	[0.872]
Treated x Requesting college	0.0215	-0.168**	-0.197**	-0.177**	0.0578	0.0828	0.103*
	(0.0137)	(0.0723)	(0.0761)	(0.0780)	(0.0598)	(0.0535)	(0.0538)
	[0.123]	[0.0227]	[0.0116]	[0.0264]	[0.337]	[0.125]	[0.0593]
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	0.0149	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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B9: 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	0.0336	0.175			-0.150*	-0.000464		
	(0.0753)	(0.385)			(0.0870)	(0.296)		
	[0.657]	[0.650]			[0.0896]	[0.999]		
Delivered x Requesting college	-0.148**	-0.358**			0.00724	0.164		
	(0.0743)	(0.148)			(0.0565)	(0.106)		
	[0.0495]	[0.0180]			[0.898]	[0.126]		
Treated x Not requesting college			0.0149	0.0301			0.0213	-0.0206
			(0.0667)	(0.115)			(0.0492)	(0.0890)
			[0.824]	[0.795]			[0.666]	[0.818]
Treated x Requesting college			-0.199*	-0.192**			0.0579	0.0845
			(0.103)	(0.0876)			(0.0748)	(0.0535)
			[0.0580]	[0.0312]			[0.441]	[0.118]
Treated x Requesting college			-0.121				0.206	
x High reservation wage			(0.131)				(0.149)	
			[0.359]				[0.171]	
Treated x Requesting college				-0.0271				-0.0136
x Unlikely delivered				(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	0.0964				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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B10: Robustness: Demand Effect

VARIABLES	(1) Hire College	(2) Hire College	(3) Hire Non-college	(4) Hire Non-college
Treated x Not requesting college	0.0241	0.0389	0.0105	0.0131
	(0.0798)	(0.0715)	(0.0710)	(0.0596)
	[0.763]	[0.588]	[0.883]	[0.827]
Treated x Requesting college	-0.213**	-0.221***	0.152*	0.0699
	(0.0914)	(0.0801)	(0.0790)	(0.0548)
	[0.0228]	[0.00724]	[0.0578]	[0.206]
Treated x Requesting college	-0.0113		-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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B11: 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	0.0446			0.0131		
x Not requesting college	(0.1000)			(0.109)		
	[0.657]			[0.905]		
Intensely treated area	0.0158			-0.0368		
x Requesting college	(0.158)			(0.0959)		
	[0.921]			[0.702]		
Treated x Not requesting college		0.0305	-0.0575		0.0132	0.0520
		(0.0748)	(0.0973)		(0.0557)	(0.0762)
		[0.684]	[0.556]		[0.813]	[0.497]
Treated x Requesting college		-0.272***	-0.204*		0.100	0.225**
		(0.102)	(0.107)		(0.0647)	(0.0895)
		[0.00951]	[0.0595]		[0.124]	[0.0141]
Treated x Requesting college		0.148			0.00777	
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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B12: Explaining the Belief Update with College Share

	(1)	(2)	(3)	(4)
	% Perceived productive		Agreed college grads	
VARIABLES	College applicants		are more productive	
Treated x Above-median college share	-0.285**		-0.0766	
	(0.133)		(0.0476)	
	[0.0381]		[0.112]	
Treated x (Residualized) above-median college share		-0.347		-0.0909
		(0.391)		(0.0937)
		[0.380]		[0.335]
Treated x Below-median college share	-0.237*		-0.0997*	
	(0.129)		(0.0567)	
	[0.0756]		[0.0825]	
Treated x (Residualized) below-median college share		-0.273**		-0.0868*
		(0.120)		(0.0438)
		[0.0287]		[0.0509]
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 4 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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B13: Robustness: Explaining the Shift in Hiring Behavior with College Share

Panel A. Residualized 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	0.0577	0.00389	-0.0538	0.0334	0.000253	-0.0332
	(0.0604)	(0.0499)	(0.0729)	(0.0634)	(0.0483)	(0.0772)
	[0.342]	[0.938]	[0.462]	[0.600]	[0.996]	[0.669]
Treated x Requesting college	0.113	-0.0756	-0.189	0.0252	-0.171	-0.197
x (Residualized) above-median college share	(0.206)	(0.176)	(0.315)	(0.203)	(0.182)	(0.294)
	[0.585]	[0.668]	[0.551]	[0.902]	[0.348]	[0.506]
Treated x Requesting college	-0.114	0.113*	0.227**	-0.195**	0.0863	0.282***
x (Residualized) below-median college share	(0.0700)	(0.0575)	(0.103)	(0.0771)	(0.0542)	(0.106)
	[0.107]	[0.0533]	[0.0305]	[0.0133]	[0.115]	[0.00967]
Observations	580	580	580	580	580	580
R-squared	0.352	0.494	0.498	0.329	0.505	0.487
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. Imputed number of past interactions (only Round 1)

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	-0.0783	-0.0840	-0.00576	-0.0187	-0.0356	-0.0168
	(0.102)	(0.0903)	(0.136)	(0.102)	(0.0962)	(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	0.0514
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)
	[0.0667]	[0.0826]	[0.0245]	[0.0372]	[0.288]	[0.0465]
Observations	247	247	247	247	247	247
R-squared	0.321	0.517	0.438	0.316	0.500	0.430
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. In Panel A, we regress whether the percentage of college-educated workers in the firm at baseline (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. In Panel B, we 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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B14: 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*	-0.0522			-0.0417		
	(0.127)	(0.110)			(0.0441)		
	[0.0501]	[0.637]			[0.347]		
# Non-agency (NA) college app			-0.0285*			0.00390	
			(0.0155)			(0.0115)	
			[0.0739]			[0.736]	
Treated x Zero NA college app			-0.485***			-0.0574	
			(0.177)			(0.0579)	
			[0.00953]			[0.325]	
Treated x ≥ 1 NA college app			-0.227*			-0.0141	
			(0.117)			(0.0564)	
			[0.0601]			[0.804]	
Treated x Not requesting college				-0.295			-0.0715
				(0.236)			(0.0559)
				[0.218]			[0.205]
Treated x Requesting college				-0.244*			0.00190
				(0.122)			(0.0642)
				[0.0534]			[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			1			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 B15: Applicants' Rejection of Interview Invites or Offers

VARIABLES	(1) Reject interview	(2) Reject interview	(3) Reject offer	(4) Reject offer
College graduate	0.0339	0.0457	-0.0539	-0.0557
	(0.0597)	(0.0823)	(0.0696)	(0.0764)
	[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	0.0198	0.0198	0.0225	0.0225

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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B16: 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	0.00342	-0.00186	0.0466
	(0.0377)	(0.0495)	(0.0499)
	[0.928]	[0.970]	[0.353]
Treated x Requesting college	0.0554	-0.127**	0.0801
	(0.0564)	(0.0513)	(0.0737)
	[0.329]	[0.0151]	[0.280]
Observations	568	568	568
R-squared	0.347	0.473	0.465
Control mean	0.0935	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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B17: 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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B18: 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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B19: 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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B20: Perceived Qualifications 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	1.79e-08	5.88e-06	0.0108	0.689	0.0183	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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B21: Intensive Margin of the Effect on Conducting Interviews by Skill Requirement

VARIABLES	(1) # Applicants Interviewed	(2) # Agency apps Interviewed	(3) # Non-agency apps Interviewed	(4) All non-agency apps Interviewed
Treated x Not requesting college	-0.155	0.0170	-0.172	-0.0594
	(0.135)	(0.0435)	(0.125)	(0.0764)
	[0.256]	[0.696]	[0.174]	[0.439]
Treated x Requesting college	0.0102	0.0821	-0.0720	-0.00822
x Skill index < 0	(0.214)	(0.0500)	(0.210)	(0.132)
	[0.962]	[0.104]	[0.732]	[0.951]
Treated x Requesting college	-0.302	-0.0237	-0.278	-0.184
x Skill index > 0	(0.222)	(0.121)	(0.195)	(0.135)
	[0.177]	[0.845]	[0.157]	[0.178]
Treated x Skill index > 0	0.255	0.184	0.0715	-0.212*
	(0.195)	(0.112)	(0.146)	(0.120)
	[0.195]	[0.105]	[0.626]	[0.0816]
Observations	589	589	589	580
R-squared	0.809	0.252	0.822	0.368
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	0.0162	1.741	0.709
Control mean: Requesting college	1.470	0.0403	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. 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 further interact the initial treatment assignment with whether the constructed skill index is greater than zero to guarantee full saturation. We 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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B22: Calibration for the Simulation Exercise

Parameter	Interpretation	Value	Moment	Data
σ_0	Standard deviation of non-college workers' productivity	1	Assumption (benchmark)	
σ_c	Standard deviation of college graduates' productivity	1	Assumption ($=\sigma_0$)	
θ_j	Firm productivity	$U[0,1]$	Assumption	
μ	Mean of non-college workers' productivity	1.063	$\mathbb{E}[H_j^n = 1 \mid N_j^c = 0] = 1 - \Phi(-\frac{\mu}{\sigma_0})^{N_j^n}$	H_j^n: Whether firm j hires a non-college worker N_j^c: # of firm j's college applicants N_j^n: # of firm j's non-college applicants
c	Productivity premium of college graduates	0.927	$\mathbb{E}[D_j = 1 \mid N_j^c = 0] = 1 - \Phi(-\frac{c}{\sqrt{\sigma_0^2+\sigma_c^2}})$	D_j: Whether firm j agrees that college graduates are more productive
q	Arrival rate of college applicants	0.607	$\mathbb{E}[N_j^c \geq 1 \mid C_j = 1]$	C_j: Whether firm j requests college graduates
$c(q)$	Access cost to the pool of college applicants	0.396	$\mathbb{E}[A_j = 0] = c(q)/c$	A_j: Whether firm j accesses the pool of college graduates (see Note (a))
$c(\theta_j)$	Interviewing cost	$0.0767\theta_j^2 + 0.0629\theta_j$ (see Note (b))	$\int_0 z\Phi(\frac{z_s^*-z}{\sigma_e})\phi(\frac{z-\mu}{\sigma_0})dz = c(\theta_j)/\theta_j$	I_j^n: % Non-college workers interviewed by firm j
			$\mathbb{E}[I_j^n \mid s_j = s, N_j^c = 0] = 1 - \Phi(\frac{z_s^*-\mu}{\sigma_0})$	s_j: Skill index of firm j (see Note (c))
N_j	Initial # of past college graduates	see Note (d)	$Pr(M_j^c = m)$	M_j^c: Imputed number of past college graduates (see Note (e))

Notes: This table shows the parameters calibrated for the simulation exercise.
(a) First, 35% firms request a college graduate at baseline; we assume all these firms access the pool of college graduates. Among these firms, 60.7% get at least one college applicant. Then, among the firms that do not specifically request a college graduate (65%), 20.8% get at least one college applicants. We thus assume that 34.3% (=20.8%/60.7%) of these firms also access the pool of college graduates. In total, we impute that $35\% + 65\% \times 34.3\% = 57.3\%$ of all firms access the pool of college graduates.
(b) We calibrate the cost of interviewing using Figure A13.
(c) To impute skill index, we first extract principal components from four vacancy characteristics: whether it requires specific skills, whether it involves routine task, whether it involves manual tasks, whether it requires at least two years of experience. We make sure each value of skill index has at least 10 observations.
(d) We assume the probability density function of the number of past college graduates to follow an inverse function $p(m) = 0.2617/(m+1)$, $m \leq 70$. The coefficient is calculated from the best fitted line of regressing $Pr(M_j^c = m)$ on $1/(m+1)$. The upper bound 70 is to ensure the cumulative distribution does not exceed 1.
(e) We impute the number of past college graduates by multiplying (i) the number of vacancies opened last year, (ii) the number of years the firm is established, and (iii) the percentage of current employees with a college degree or diploma, plus the number of current employees with a college degree or diploma. This variable only exists in Round 1.

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	0.0847	0.0355	0.108	-0.00522	-0.0201
	(10.09)	(0.160)	(0.0756)	(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	0.0202	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
$E[Y_n \mid H_n(1) > H_n(0)]$	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]
$E[Y_c \mid H_c(1) < H_c(0)]$	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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B24: Treatment Effects on Hiring College Graduates by Skill Index

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	0.112	-0.0344	-0.147	0.0833	-0.0331	-0.116
	(0.0726)	(0.0725)	(0.109)	(0.0759)	(0.0704)	(0.115)
	[0.126]	[0.636]	[0.183]	[0.276]	[0.640]	[0.314]
Treated x Requesting college	-0.250***	0.280***	0.529***	-0.334***	0.241***	0.575***
x Skill index < 0	(0.0897)	(0.0830)	(0.146)	(0.0900)	(0.0852)	(0.149)
	[0.00678]	[0.00116]	[0.000527]	[0.000389]	[0.00584]	[0.000224]
Treated x Requesting college	-0.120*	0.120**	0.240**	-0.201**	0.0933*	0.295***
x Skill index > 0	(0.0700)	(0.0561)	(0.102)	(0.0768)	(0.0525)	(0.105)
	[0.0898]	[0.0361]	[0.0213]	[0.0105]	[0.0793]	[0.00625]
Observations	580	580		580	580	
R-squared	0.354	0.499		0.332	0.508	
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 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. 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. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B25: Treatment Effects on Hiring Plan by Skill Index

VARIABLES	(1) % Perceived prod. College apps	(2) Agreed college more productive	(3) Plan to hire Any	(4) Plan to hire Any	(5) Plan to hire College	(6) Plan to hire Non-college
Treated x Not requesting college	-0.384*	-0.0260	-0.0217	-0.0454	-0.0278	0.0770
	(0.222)	(0.0576)	(0.0792)	(0.130)	(0.0805)	(0.0651)
	[0.0923]	[0.653]	[0.785]	[0.728]	[0.732]	[0.244]
Treated x Requesting college	-0.322	-0.122	-0.163	-0.164	0.143	-0.133
x Skill index < 0	(0.200)	(0.105)	(0.106)	(0.181)	(0.110)	(0.0859)
	[0.117]	[0.247]	[0.126]	[0.372]	[0.199]	[0.129]
Treated x Requesting college	-0.225*	-0.0910*	-0.128*	-0.165	-0.0774	-0.0441
x Skill index > 0	(0.116)	(0.0543)	(0.0720)	(0.145)	(0.0722)	(0.0651)
	[0.0593]	[0.0981]	[0.0795]	[0.261]	[0.290]	[0.502]
Observations	151	568	568	298	298	298
R-squared	0.402	0.333	0.326	0.374	0.495	0.415
Sample	All	All	All	Round 2	Round 2	Round 2
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: Not requesting college	0.787	0.736	0.652	0.598	0.517	0.218
Control mean: Requesting college	0.785	0.896	0.653	0.519	0.835	0.0253

Notes: This table presents the treatment effects on firms' future hiring plans 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 planned to post any jobs in the next three months after endline. Column 5, whether the firm planned to hire more college graduates in the next three months after endline. Column 6, whether the firm planned to post any jobs but not to hire more college graduate in the next three months after endline. Column 1, 4–6 restrict the sample to Round 2 because we only have information on whether the firm planned to hire any college graduate in Round 2. 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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B26: Treatment Effect on Referral Hiring

VARIABLES	(1) Hire Non-referral	(2) Hire Referral	(3) Hire Non-referral	(4) Hire Referral	(5) Hire Non-referral	(6) Hire Referral
Treated x Not requesting college	0.0339	-0.00891	0.0665	-0.0224	0.0283	0.0133
	(0.0584)	(0.0496)	(0.0846)	(0.0655)	(0.0591)	(0.0503)
	[0.564]	[0.858]	[0.435]	[0.733]	[0.634]	[0.792]
Treated x Requesting college	-0.124*	0.0827				
	(0.0717)	(0.0737)				
	[0.0889]	[0.265]				
Treated x Requesting college			-0.176*	0.164*		
x Not Using referral			(0.0895)	(0.0852)		
			[0.0524]	[0.0576]		
Treated x Requesting college			-0.00448	-0.0290		
x Using referral			(0.127)	(0.117)		
			[0.972]	[0.806]		
Treated x Requesting college					-0.0664	0.147
x Skill score < 0					(0.123)	(0.126)
					[0.592]	[0.248]
Treated x Requesting college					-0.162	0.224*
x Skill score > 0					(0.159)	(0.120)
					[0.309]	[0.0645]
Observations	578	578	578	578	578	578
R-squared	0.290	0.264	0.293	0.270	0.291	0.268
Control mean: Not requesting college	0.516	0.286	0.516	0.286	0.516	0.286
Control mean: Requesting college	0.497	0.179	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. We interact the initial treatment assignment with whether firm requests a college graduate at baseline for all regression. For Column 3 and 4, we further interact the initial treatment assignment with whether firm requests a college graduate at baseline and whether firm uses referrals at baseline. We control for the interaction between the initial treatment assignment and whether firm uses referrals at baseline to guarantee full saturation. For Column 5 and 6, we further interact the initial treatment assignment with whether firm requests a college graduate at baseline and whether the imputed skill score for the vacancy is above or below zero. The skill score for each vacancy is imputed by extracting the principal component for the following four vacancy characteristics: Whether the vacancy requires specific skills, whether it involves manual labor, whether it involves routine work, whether it requires at least two years of experience. We control for the interaction between the initial treatment assignment and whether the imputed skill score for the vacancy is above zero to guarantee full saturation. 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. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

General framework. Suppose in a T-period model, firm j opens a vacancy for one worker in each period. Firm j's production function is $\theta_{ij} = \mu_i\theta_j$, θ_j is a firm-specific parameter following a given distribution, and μ_i is the productivity of the matched worker. There are two types of workers in the market: Non-college educated workers with productivity z_i following a normal distribution $N(\mu, \sigma_0^2)$, and college graduates with productivity y_i following a normal distribution $N(\mu + c, \sigma_c^2)$, where c is the true productivity premium of college education. For each period, firm j decides to hire one worker for the vacancy.

- Step 0: Firm j draws a non-college applicant $z \sim N(\mu, \sigma_0^2)$ with probability one.
- Step 1: Firm j decides whether to access the pool of college graduates at the cost of $c(q)$; q is the arrival rate of college graduates.[27] For simplicity, once firm j gains the access, firm j will receive one college-educated applicants with probability q, drawn from the distribution $y \sim N(\mu + c, \sigma_c^2)$.

[27] 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 $V = 0$, then $J = k/q$. 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.

- Step 2: Firm j decides to hire the applicant with the higher productivity or not hire any applicant. If a worker is hired, firm j would pay w to college graduates and w_0 to non-college workers; both wages are exogenously determined. If no one is hired, the vacancy absolves.

- Step 3: Firm j enters the next period and opens another vacancy.

Scenario 0: No information asymmetry. Suppose firms observe z and y perfectly. Assume the distributions of non-college workers and college graduates are orthogonal. Among those who already accessed the pool of college graduates, without loss of generality, suppose firm j only considers whether to hire the college applicant or the non-college applicant. In period K, the probability of firm j hiring a college graduate is:[28]

$$\Pi_0(q) = q[1 - Pr(y \leq z)] = q[1 - \Phi\big(-\frac{c}{\sqrt{\sigma_0^2 + \sigma_c^2}}\big)] \tag{6}$$

The hiring probability of each college-educated applicants remains unchanged in all periods. Therefore, if the access to college-educated applicants q increases, firms should access to more college-educated applicants and are more likely to hire a college graduate. We call this a **search effect**.

Scenario 1: Noisy signal, no screening. Suppose firms can observe the productivity of non-college worker z perfectly, but can only observe a noisy signal of college-educated applicant's productivity $y^* = y + e$. Assume the noise follows a normal distribution $N(e_0, \sigma_e^2)$.

To solve for firm j's hiring decision making in period K, we assume firm j conducts a Bayesian learning on the college applicant's true productivity, but firm j's belief is formed based on previous interactions with college applicants. Denote firm j's prior of college graduates' productivity as $Y_{j1} \triangleq Y_j$. Denote $N_{jK}(q)$ as the number of college-educated applicants that firm j receives before period K. Define $N_{j1} \triangleq N_j$ as the number of college graduates that firm j interacts in the past. Assume firm j knows the variance σ_c and σ_e. For period $K > 1$, firm j' forms a new perception of college graduates' productivity as follows:

$$Y_{jK} = \frac{N_j}{N_j + N_{jK}(q)} Y_j + \frac{N_{jK}(q)}{N_j + N_{jK}(q)} \overline{y^*} \tag{7}$$

[28] More generally, if firm j also considers whether or not they hire at all, the probability of firm j hiring a college graduate becomes:

$$\Pi_0(q) = q[1 - Pr(y \leq z \mid y < 0)] = q[1 - \int^0 Pr(y < 0) f(z) dz - \int_0 Pr(y \leq z) f(z) dz]$$

All the discussions and predictions below follow through; similar for Scenario 1 and 2.

Where $\overline{y^*}$ is the average observed productivity of the $N_{jK}(q)$ college graduates that firm j receives before period K.

In period K, for each college applicant with observed productivity y^*, firm j would conduct Bayesian update with the newly formed perception Y_{jK}:

$$\hat{y}_j = \frac{\sigma_e^2}{\sigma_c^2 + \sigma_e^2} Y_{jK} + \frac{\sigma_c^2}{\sigma_c^2 + \sigma_e^2} y^* \triangleq (1-s) Y_{jK} + s y^* \tag{8}$$

Assume firm j's prior Y_j is unbiased and follows the same distribution $N(\mu + c, \sigma_c^2)$. For simplicity, assume firm j decides whether to hire the college applicant or the non-college applicant after accessing the pool of college graduates, the probability of firm j hiring a college graduate in period K is thus:

$$\Pi_{jK}(q) = q[1 - Pr(\hat{y}_j \leq z)] = q[1 - \Phi\big(-\frac{c + [s + (1-s)\frac{N_{jK}(q)}{N_j + N_{jK}(q)}]e_0}{\sqrt{\sigma_0^2 + s^2(\sigma_e^2 + \sigma_c^2) + (1-s)^2 Var(Y_{jK})}}\big)] \tag{9}$$

The following theorem describes that $\Pi_{jK}(q)$ may decrease in q under certain conditions. Denote $\mu_j(q) = c + [s + (1-s)\frac{N_{jK}(q)}{N_j + N_{jK}(q)}]e_0$, $\sigma_j^2(q) = \sigma_0^2 + s^2(\sigma_e^2 + \sigma_c^2) + (1-s)^2 Var(Y_{jK})$, and $\lambda(q) = \frac{1 - \Phi(-\mu_j(q)/\sigma_j(q))}{\phi(-\mu_j(q)/\sigma_j(q))}$, where s and Y_{jK} are defined in Equations 7 and 8.

Theorem D.1. $\Pi_{jK}(q)$ *decreases in q if the following three conditions are both satisfied:*

1. $e_0 < 0$,
2. $N_{jK}(q) > sN_j$, *and*
3. $\frac{dN_{jK}(q)}{dq} > \overline{K}$, *where* $\overline{K} = \frac{\lambda(q)\sigma_j^3(q)[N_j + N_{jK}(q)]^3}{qN_j(1-s)[-(N_j + N_{jK}(q))\sigma_j(q)^2 e_0 + (1-s)^3(\sigma_c^2 + \sigma_e^2)(N_{jK}(q) - sN_j)\mu_j(q)]} > 0$.

Proof. Take partial derivative regarding q following Equation 9,

$$\frac{\partial \Pi_{jK}(q)}{\partial q} = \underbrace{1 - \Phi(\cdot)}_{\text{Search effect}} + \underbrace{\frac{q\phi(\cdot)}{\sigma_j^2(q)}\big[\frac{\partial \mu_j(q)}{\partial q}\sigma_j(q) - \frac{(1-s)^2}{2\sigma_j(q)}\frac{\partial Var(Y_{jK})}{\partial q}\mu_j(q)\big]}_{\text{Learning effect } \Lambda}. \tag{10}$$

Take partial derivative of $\mu_j(q)$ regarding q,

$$\frac{\partial \mu_j(q)}{\partial q} = \frac{N_j(1-s)e_0}{(N_j + N_{jK}(q))^2}\frac{dN_{jK}(q)}{dq}. \tag{11}$$

$N_{jK}(q)$ increases in q by assumption, thus $\frac{\partial \mu_j(q)}{\partial q} < 0$ if $e_0 < 0$.

Write down $Var(Y_{jK})$ according to Equation 7,

$$Var(Y_{jK}) = \big(\frac{N_j}{N_j + N_{jK}(q)}\big)^2 \sigma_c^2 + \big(\frac{N_{jK}(q)}{N_j + N_{jK}(q)}\big)^2 (\sigma_c^2 + \sigma_e^2)$$

Take partial derivative regarding q,

$$\frac{\partial Var(Y_{jK})}{\partial q} = (1-s)^2 \frac{dN_{jK}(q)}{dq} \frac{2N_j}{(N_j + N_{jK}(q))^3} [-N_j \sigma_c^2 + N_{jK}(q)(\sigma_c^2 + \sigma_e^2)] \tag{12}$$

This term would be positive if $N_{jK}(q) > sN_j = \frac{\sigma_c^2}{\sigma_c^2 + \sigma_e^2} N_j$.

Replace the two terms in Equation 10 with Equations 11 and 12, and extract the common term $\frac{dN_{jK}(q)}{dq}$. The learning effect can be expressed as follows:

$$\Lambda = \frac{q\phi(\cdot)}{\sigma_j^3(q)} \frac{N_j(1-s)}{(N_j + N_{jK}(q))^2} \big[\sigma_j(q) e_0 - (1-s)^3 (\sigma_c^2 + \sigma_e^2) \frac{N_{jK}(q) - sN_j}{N_j + N_{jK}(q)} \mu_j(q)\big] \cdot \frac{dN_{jK}(q)}{dq} \tag{13}$$

The first two conditions guarantee that Λ decreases in $\frac{dN_{jK}(q)}{dq}$. The third condition guarantees that the learning effect is dominant. $\square$

Theorem D.1 describes a new **learning effect**: with more signals arriving, firm j may update its perception Y_j depending on the direction of learning. The first two conditions describe the direction of learning: (i) The average perception of $\hat{y}_j$ can decrease if the productivity noise is negative in nature, *i.e.* $e_0 < 0$. (ii) The variation of $\hat{y}_j$ can increase when firm j receives a sufficient number of productivity noises, *i.e.* $N_{jK}(q) > sN_j$. The third condition illustrates that the magnitude of learning effect depends on the increment of the interaction. Note that if we approximate $N_{jK}(q)$ with qK, then this condition is deduced to $K > \overline{K}$. As long as firms conduct enough rounds of hiring, with the first two conditions, the learning effect will eventually exceed the search effect. Notice that these three conditions are not necessary conditions. From the proof, we can see the first two conditions do not have to be always satisfied as long as one of them is sufficiently strong.

The following lemma develops useful comparative statics to test the mechanism.

Lemma D.2. *$\Pi_{jK}(q)$ increases in e_0.*

Proof. $\frac{\partial \Pi_{jK}(q)}{\partial e_0} = q\phi(\cdot) \frac{1}{\sigma_j(q)} \frac{\partial \mu_j(q)}{\partial e_0}$, $\frac{\partial \mu_j(q)}{\partial e_0} = s + (1-s) \frac{N_{jK}(q)}{N_j + N_{jK}(q)} > 0$. $\square$

Lemma D.3. *Suppose $e_0 < 0$, $N_{jK}(q) > sN_j$, and $\mu_j(q) > 0$. Then $\Pi_{jK}(q)$ increases in N_j.*

Proof. $\frac{\partial \Pi_{jK}(q)}{\partial N_j} = q\phi(\cdot) \frac{1}{\sigma_j^2(q)} \big[\frac{\partial \mu_j(q)}{\partial N_j} \sigma_j(q) - \frac{(1-s)^2}{2\sigma_j(q)} \frac{\partial Var(Y_{jK})}{\partial N_j} \mu_j(q)\big]$. With $e_0 < 0$, we have $\frac{\partial \mu_j(q)}{\partial N_j} =$

$-(1-s)\frac{N_{jK}(q)}{(N_j+N_{jK}(q))^2}e_0 > 0$. With $N_{jK}(q) > sN_j$, we have $\frac{\partial Var(Y_{jK})}{\partial N_j} = \frac{2N_{jK}(q)(\sigma_c^2+\sigma_e^2)[sN_j - N_{jK}(q)]}{[N_j+N_{jK}(q)]^3} <$ 0. Hence $\frac{\partial \Pi_{jK}(q)}{\partial N_j} > 0$. $\square$

Notice when N_j approaches infinity, this scenario does not converge to Scenario 0 because firms still receive noisy signals of the productivity of college graduates. One can prove the following if $e_0 < 0$ and $\sigma_e > \sigma_c$:

$$\Pi_{jK}(q|N_j \to \infty) = q[1 - \Phi\big(-\frac{c+se_0}{\sqrt{\sigma_0^2 + s^2(\sigma_e^2+\sigma_c^2) + (1-s)^2\sigma_c^2}}\big)] < \Pi_0(q) \tag{14}$$

However, $\Pi_{jK}(q|N_j \to \infty)$ is strictly increasing in q now, because when firm j conducts Bayesian learning as in Equation 8, the prior Y_{jK} is no longer affected by new signals, and thus the learning effect disappears.

A useful observation is that, as firms interact with more college graduates over time, if the productivity noise is unbiased in nature (*i.e.* $e_0 = 0$), the perception Y_{jK} would approach the truth $\mu + c$. This may not hold true in the next scenario when firms have incentive to obtain more accurate productivity signals of college applicants.

Scenario 2: Noisy signal with screening. Suppose after firms observe a noisy signal, firm j can decide whether to conduct an interview on the applicant. Firm j needs to pay a positive cost $c(\theta_j)$ for the interview, but after the interviewing, firm j can observe applicant's productivity perfectly. Firm j can perfectly observe the productivity after hiring the worker.

The benefit of interviewing is to avoid hiring mistake. When the applicant's observed productivity y^* is below the non-college benchmark z, firms may worry they may mistakenly hire the non-college applicant but the college applicant is actually more productive.[29] Firm j would thus interview the college applicant with the observed productivity y^* if the expected productivity premium of hiring the college applicant is sufficiently high:

$$\theta_j \int_z (y'-z)g(y^*-y')f(y')dy' \triangleq \theta_j H(y^*|z) \geq c(\theta_j) \tag{15}$$

Where $g(\cdot)$ is the perceived probability function of the noise, and the $f(y')$ is the perceived probability function of the true productivity of college applicants. The integral term summarizes the following: given the non-applicant productivity z, firm j would calculate the gain from hiring a college applicant assuming the true productivity is y', factoring the likelihood that the observed

[29]More generally, firms also worry they may mistakenly hire no one to the position. The algebra becomes more complicated, but all the following theorems and predictions are followed.

productivity is y^*, *i.e.* $g(y^* - y')$. We assume that firm j considers noise to be unbiased, *i.e.* $e' \sim N(0, \sigma_e^2)$, but firm j will factor in its newly formed perception of college applicants in each period K, that is, $y' \sim N(Y_{jK}, \sigma_c^2)$, Y_{jK} defined as in Scenario 1.

Lemma D.4. *Suppose $\theta_j H(z) > c(\theta_j)$. There exists a unique value $\underline{y_j}(z) < z$ such that $\theta_j H(\underline{y_j}(z)) = c(\theta_j)$.*

Proof. We first prove that $H(y^* \mid z)$ increases in y^* when $y^* < z$:

$$\frac{\partial H}{\partial y^*} = \theta_j \int_z (y' - z) g'(y^* - y') f(y') dy' = \theta_j \int_z (y' - z) \phi'(\frac{y^* - y'}{\sigma_e}) f(y') dy'$$

Using the fact $\phi'(x) = -x\phi(x)$,

$$\begin{aligned} \frac{\partial H}{\partial y^*} &= \theta_j \int_z (y' - z) \frac{y' - y^*}{\sigma_e} \phi(\frac{y^* - y'}{\sigma_e}) f(y') dy' \\ &= \theta_j \frac{z - y^*}{\sigma_e} \int_z (y' - z)^2 \phi(\frac{y^* - y'}{\sigma_e}) f(y') dy' \end{aligned}$$

Given the integral is strictly positive, the inequality is greater than zero if $y^* < z$.

The assumption of $H(z)$ guarantees that $\theta_j H(z) > c(\theta_j)$. If y^* approaches $-\infty$, $g(y^* - y')$ would approach zero, thus $H(-\infty) = 0 < c(\theta_j)$. Hence, there exists a unique value $\underline{y_j}(z) < z$ such that $\theta_j H(\underline{y_j}(z)) = c(\theta_j)$. $\square$

When the observed productivity y^* is above the benchmark z, firms may also worry about mistakenly hiring the college applicant when in fact the non-college worker is more productive. One can write down a similar condition as Equation 15 and derive an upper bound $\overline{y_j}(z)$, beyond which it is less profitable for firms to conduct interviews. However, once the observed productivity y^* is above $\overline{y_j}(z)$, firm j would simply hire the college applicant because its true productivity is unlikely to be below the non-college benchmark z. As such, firms would always be able to observe the true productivity of college applicant if $y^* > z$, either through conducting interviewing or simply hiring the applicants.

Therefore, Lemma D.4 depicts a threshold for each firm j: If the observed productivity of the college applicant is above such a threshold, firm j would obtain the perfect productivity signal and the productivity noise will be eliminated. If $c(\theta_j)$ is convex, firm j would have a higher threshold if the productivity level θ_j is higher. If the observed productivity falls below the threshold, the productivity noise will be unfiltered as in Scenario 1, which may trigger the learning effect. Suppose $\Pi'_{jK}(q)$ is the new probability of firm j hiring a college graduate with the interviewing cost. The following theorem provides sufficient conditions when the learning effect becomes dominant in this scenario; notice the conditions are stricter than that in Theorem D.1 because the learning effect is weaker.

Theorem D.5. $\Pi'_{jK}(q)$ *decreases in* q *if the following three conditions are both satisfied:*

1. $e_0 < 0$,
2. $N_{jK}(q) > sN_j$, *and*
3. $\frac{dN_{jK}(q)}{dq} > \overline{K}'$, *where* $\overline{K}' = \frac{\sigma_j^3(q)[N_j+N_{jK}(q)]^3\left(\lambda(q)+\frac{1-Pr(y^*<\underline{y_j}(z))}{Pr(y^*<\underline{y_j}(z))}[1-\Phi(-\frac{c}{\sqrt{\sigma_c^2+\sigma_0^2}})]\phi(-\frac{\mu_j(q)}{\sigma_j(q)})\right)}{qN_j(1-s)[-(N_j+N_{jK}(q))\sigma_j(q)^2e_0+(1-s)^3(\sigma_c^2+\sigma_e^2)(N_{jK}(q)-sN_j)\mu_j(q)]} > \overline{K}$.

Proof. Firm j would only trigger learning effect when $y^* < \underline{y_j}(z)$ as in Scenario 1, and would not trigger the learning effect when $y^* \geq \underline{y_j}(z)$ as in Scenario 0. Using Equations 6 and 9,

$$\Pi'_{jK}(q) = Pr(y^* < \underline{y_j}(z))\Pi_{jK}(q) + Pr(y^* \geq \underline{y_j}(z))\Pi_0(q) \tag{16}$$

Take the derivative regarding q and notice that $\underline{y_j}(z)$ is independent of q,

$$\frac{\partial \Pi'_{jK}(q)}{\partial q} = Pr(y^* < \underline{y_j}(z))\frac{d\Pi_{jK}(q)}{dq} + (1 - Pr(y^* < \underline{y_j}(z)))\frac{d\Pi_0(q)}{dq}$$

The rest of the proof is similar to that of Theorem D.1 with a different constant $\overline{K}'$. □

Since firms only have incentive to interview applicants with the observed productivity above a certain threshold, positive productivity noises are more likely to be filtered. Therefore, even if the productivity noise is unbiased in nature (*i.e.* $e_0 = 0$), firms may develop biased, negative perceptions of the productivity of college graduates. The following theorem formalizes this intuition.

Theorem D.6. *Suppose* $e_0 \leq 0$, *then* $\mathbb{E}[Y_{jK}] < \mu + c$.

Proof. Suppose firm j interacted with a college applicant before period K whose true productivity is y. Given the non-college benchmark productivity z, if the productivity noise $e > \underline{y_j}(z) - y$, firm j would interview this applicant and observe the true productivity; otherwise, firm j would observe $y + e$. Define $\gamma_j(y)$ as firm j' expectation of a college applicant's productivity with underlying productivity y, which can be derived as follows:

$$\gamma_j(y) = \int^{\underline{y_j}(z)-y}(y+e)g(e)de + \int_{\underline{y_j}(z)-y} yg(e)de = y + \int^{\underline{y_j}(z)-y} eg(e)de$$

Define γ_j as firm j's expectation of a college applicant in general. We have:

$$\gamma_j = \int \gamma_j(y) f(y) dy = \int \big(y + \int^{\underline{y_j}(z)-y} eg(e)de\big) f(y)dy$$
$$= \mu + c + \int \int^{\underline{y_j}(z)-y} eg(e)def(y)dy$$

Because the productivity noise follows normal distribution $e \sim N(e_0, \sigma_e^2)$, for any value a, let $e' = e - e_0$, then $\int^{a+e_0} eg(e)de = \int^{a}(e_0 + e')g(e')de' < e_0 + \int^{a} e'g(e')de'$. Let $G(a) = \int^{a} e'g(e')de'$. Because $G'(a) = ag(a)$, $G(a)$ is a decreasing function when $a < 0$ and increasing when $a > 0$. Because $g(e')$ is symmetric, $G(-\infty) = G(+\infty) = 0$. Hence, $G(a) < 0$ for any value a. With this, we can prove the following:

$$\gamma_j = \mu + c + \int \int^{\underline{y_j}(z)-y} eg(e)def(y)dy < \mu + c + e_0$$

Using Equation 7 and that $e_0 \leq 0$,

$$\mathbb{E}[Y_{jK}] = \frac{N_j}{N_j + N_{jK}(q)}(\mu + c) + \frac{N_{jK}(q)}{N_j + N_{jK}(q)} \frac{\gamma_j}{N_{jK}(q)}$$
$$< \mu + c + \frac{1}{N_j + N_{jK}(q)} e_0 \leq \mu + c$$

□

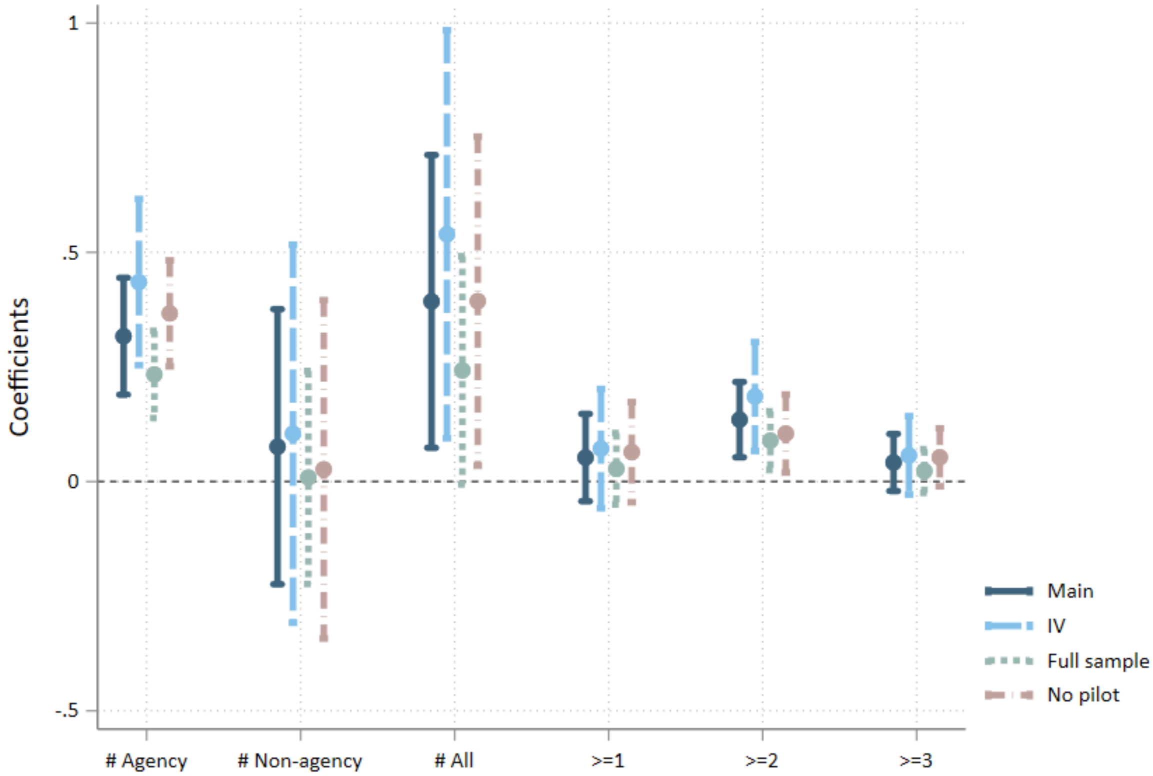
Calibration. To estimate the interviewing cost function, we assume that firms have the same interviewing cost for non-college workers. Firm j would interview a non-college worker with productivity z^* to avoid the mistake of not hiring anyone:

$$\theta_j \int_0 (z - 0)g(z^* - z)f(z)dz \geq c(\theta_j) \tag{17}$$

For each productivity level θ_j, define $\underline{z}(\theta_j)$ as the threshold above which firms would interview the non-college workers. We can estimate $c(\theta_j)$ with the following steps: (1) Calculate the percentage of non-college workers being interviewed for firms at different level of θ_j, which is proxied by the skill index constructed from the empirical data. This corresponds to the moment $Pr(z \geq \underline{z}(\theta_j))$. (2) Estimate $\underline{z}(\theta_j)$ using the moments $Pr(z \geq \underline{z}(\theta_j))$ and assuming $z \sim N(\mu, \sigma_0^2)$. (3) Estimate the interviewing cost $c(\theta_j)$ from Equation 17, using the estimated $\underline{z}(\theta_j)$ and the distributional assumptions of $f(z)$ and $g(e')$.

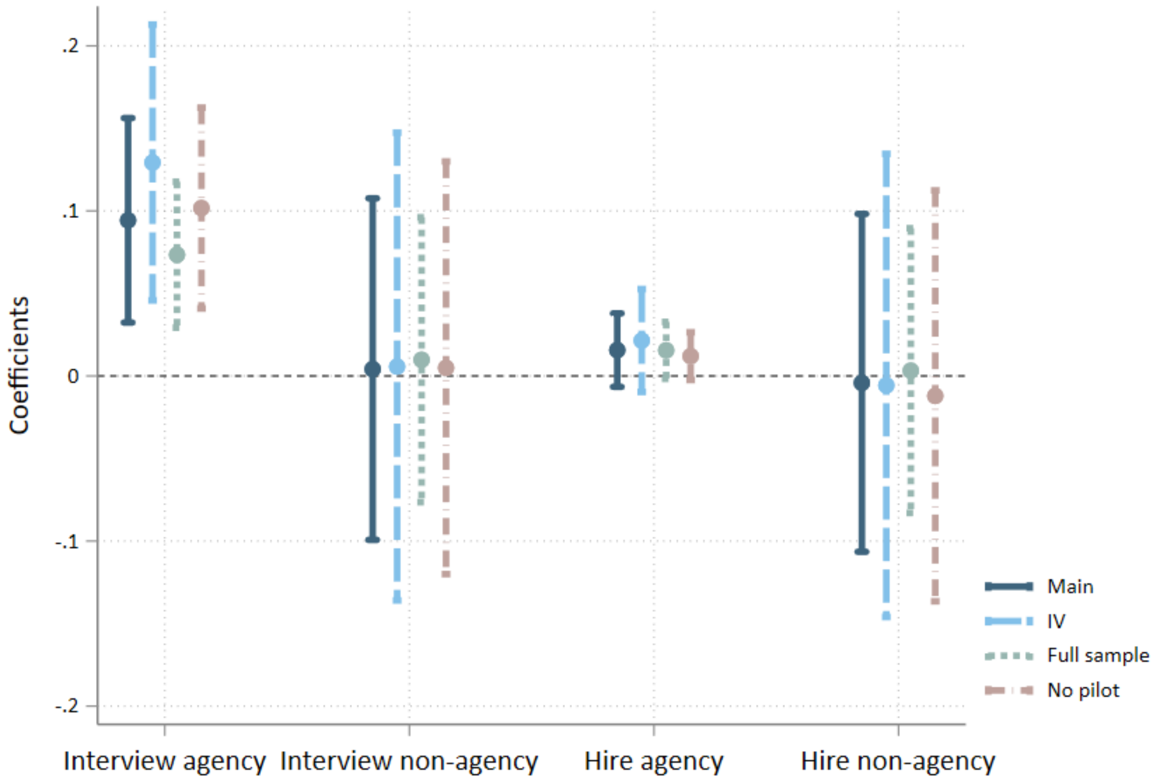
E Replications

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.

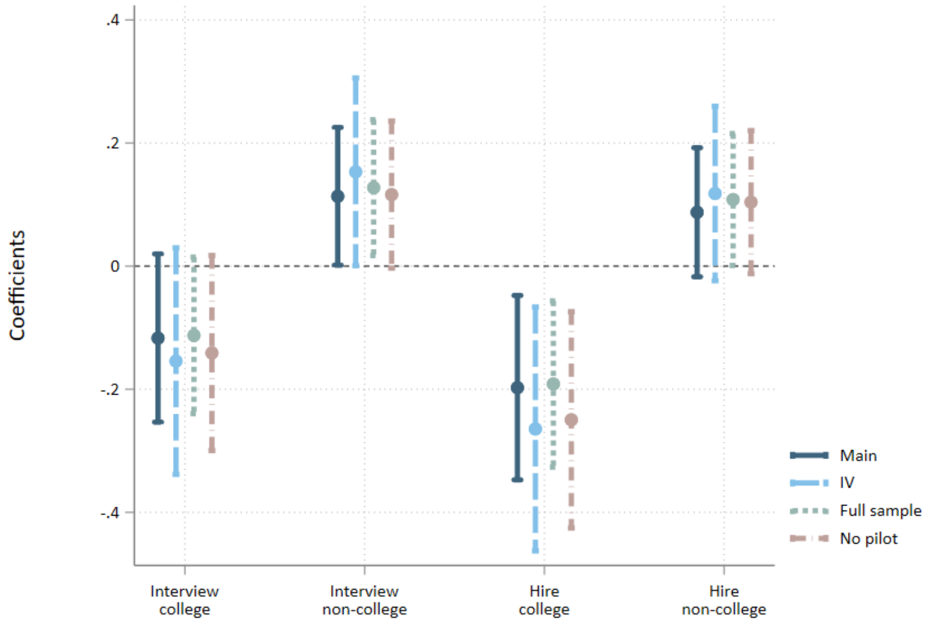
Figure E2: Replication of the Effects on Take-up of Employment Agencies



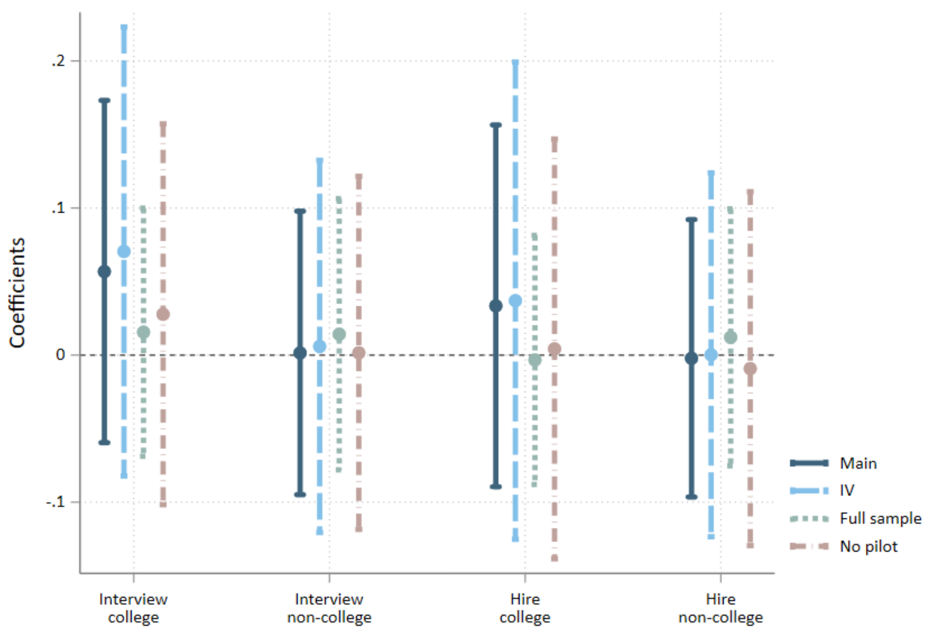
Notes: This figure replicates the main results in Table 2. All regressions include a full set of baseline characteristics, control for business area fixed effects, and cluster at business area level. For each dependent variable, we show (1) reduced-form estimate from the main specification, (2) IV estimate 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

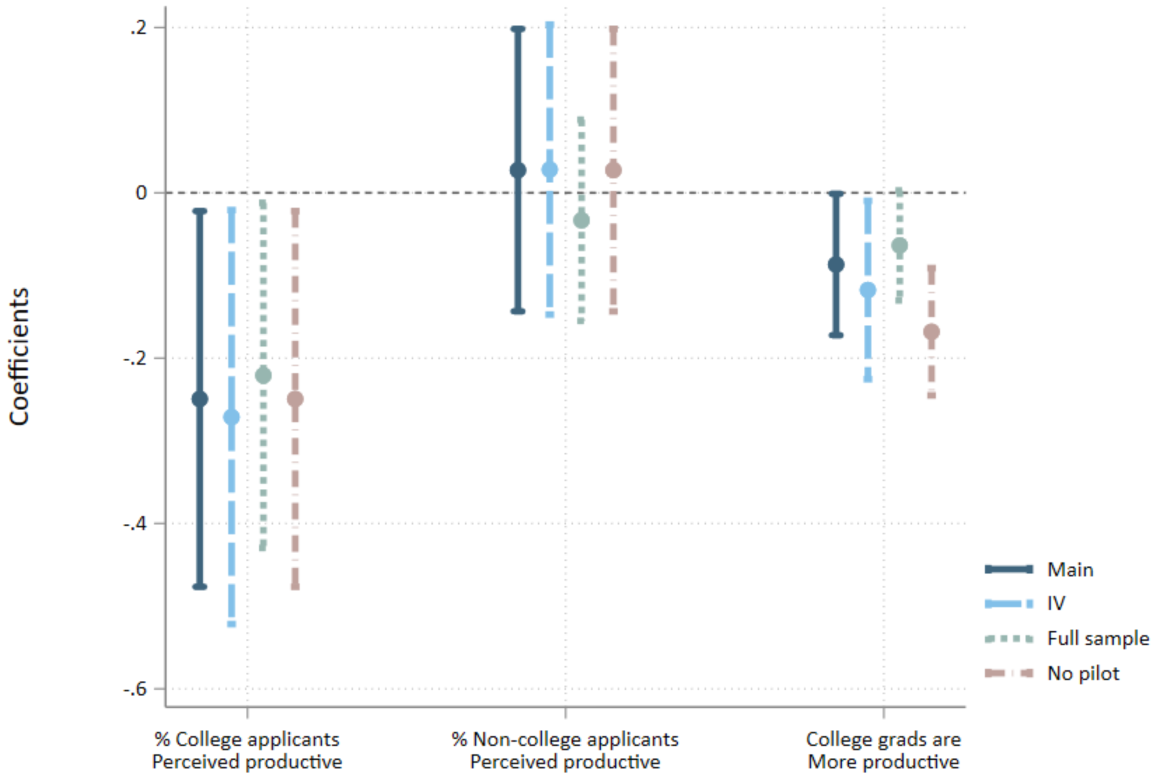


Panel B. Heterogeneous effect on firms not requesting college graduates



Notes: This figure replicates the main results in Table 3, 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.

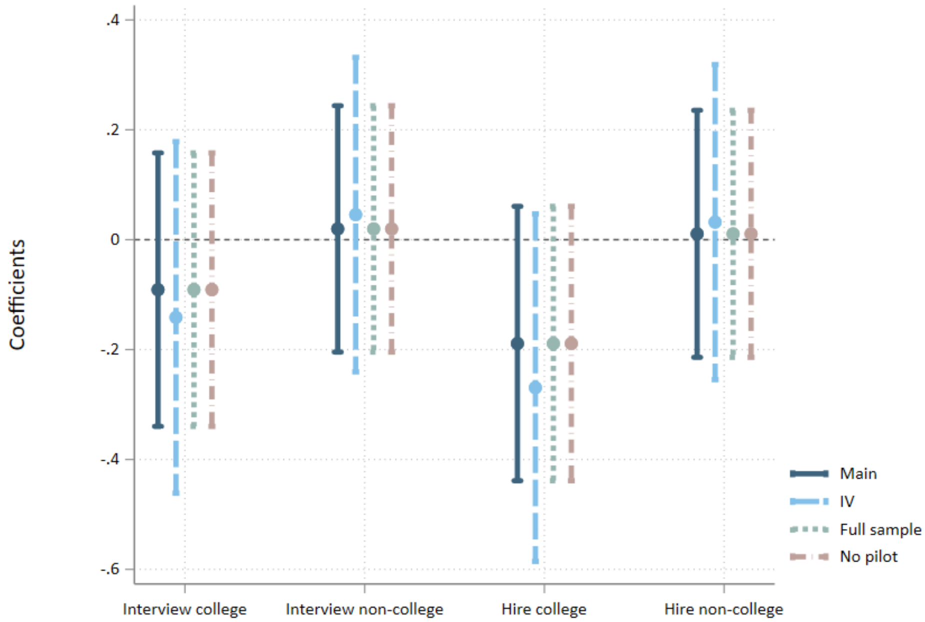
Figure E4: Replication of the Effects on Perceptions



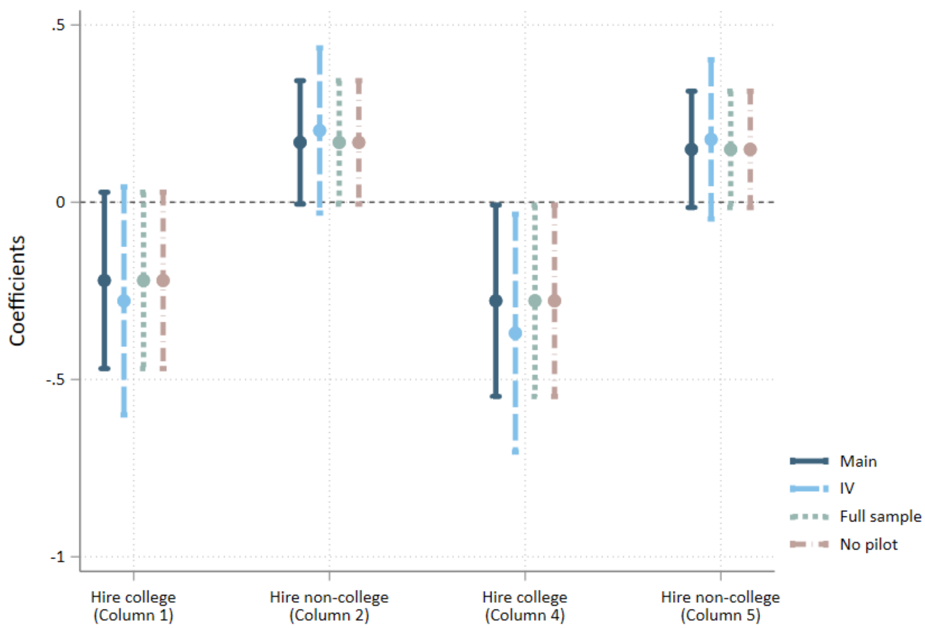
Notes: This figure replicates the main results in Table 4, Column 1, 2, and 5. All regressions include a full set of baseline characteristics, control for business area fixed effects, and cluster at business area level. For each dependent variable, we show (1) reduced-form estimate from the main specification, (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



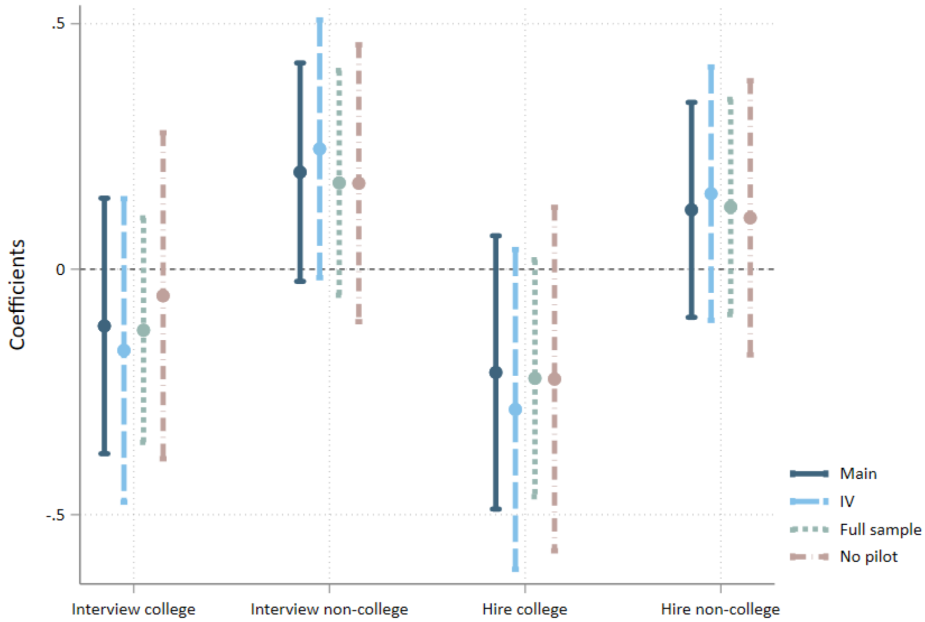
Panel A. Firms requesting a college graduate at baseline and with above-median college share



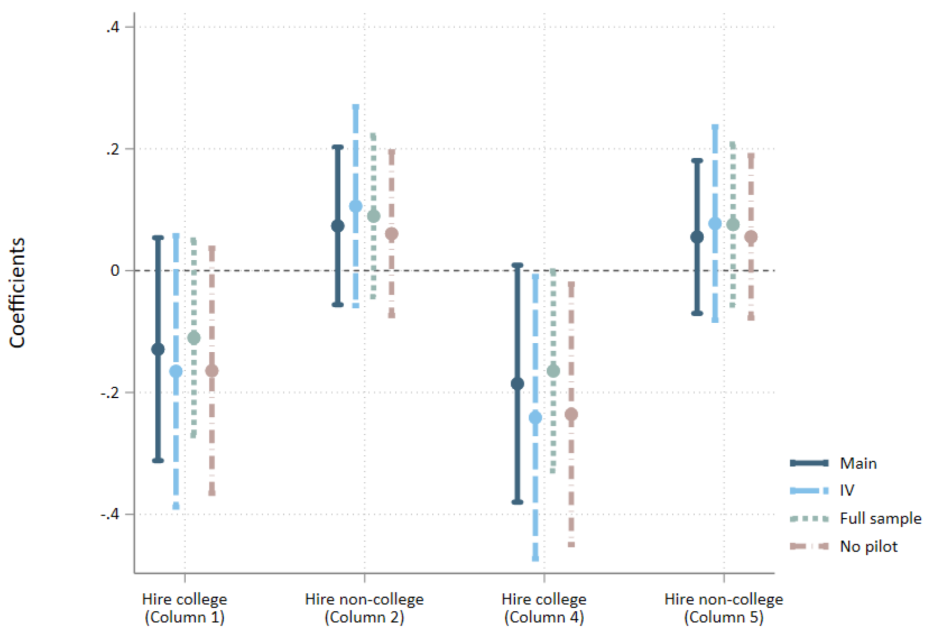
Notes: This figure replicates the main results in Table 5. All regressions include a full set of baseline characteristics, control for business area fixed effects, and cluster at business area level. For each dependent variable, we show (1) reduced-form estimate from the main specification, (2) IV estimate 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 Applicants' Qualification

Panel A. Firms requesting a college graduate and more exposed to qualified workers

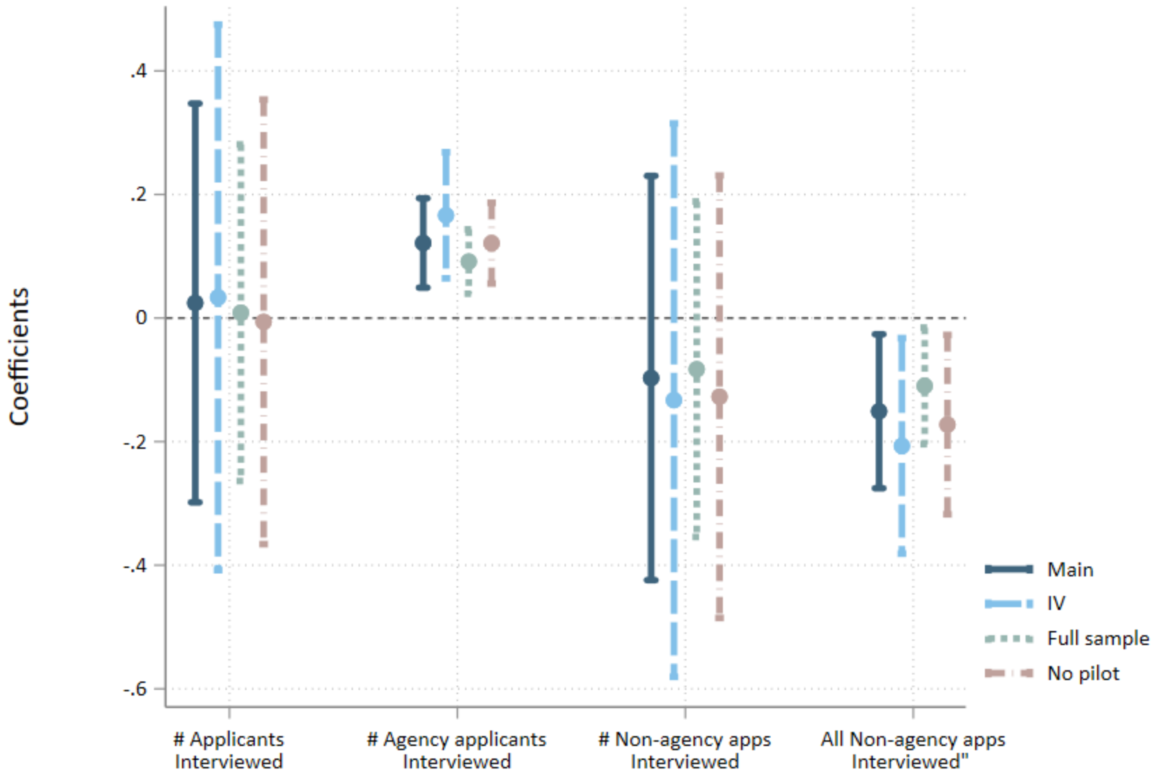


Panel A. Firms requesting a college graduate and less exposed to qualified workers



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.

Figure E7: Replication of the Intensive Margin Effects on Interviewing



Notes: This figure replicates the main results in Table 7. 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.