Would you hire a female mechanic? Experimental evidence from motor-mechanics managers in Uganda

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Abstract

Gender segregation in labor markets is a prevalent issue in poor countries, resulting in significant wage gaps and misallocation of talent. Efforts have been made to address this segregation by promoting female labor supply, but the effectiveness of such interventions depends on the level of discrimination faced by women upon entry. Our study tests for gender discrimination within Uganda's motor mechanics industry, a male-dominated sector characterized by severe asymmetric information problems. Partnering with a vocational training center, we conduct an experiment with garage managers to examine the interplay between bias, skills, and trustworthiness in hiring decisions for trainees. At baseline, women and men have comparable hiring outcomes, although women exhibit a trust premium. Improving monitoring induces gender discrimination, revealing the presence of previously hidden discrimination against women. Training interventions improve hiring outcomes for both genders but lead to increased discrimination. While training improves the skills of both genders, it diminishes the comparative advantage that women have in trustworthiness without compensating for it with enhanced skills.

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1 Introduction

Gender segregation in labor markets is prevalent in Sub-Saharan Africa and other poor regions. This phenomenon contributes to gender gaps in earnings (Arbache et al., 2010) and talent misallocation, with substantial implications for development (Hsieh et al., 2019).

Efforts to address gender segregation in labor markets have primarily focused on encouraging women to enter male-dominated fields or increasing their participation in the labor market as a whole (e.g., Dean and Jayachandran, 2019; Bursztyn et al., 2020; Macchiavello et al., 2020; McKelway, 2020; Gassier et al., 2022; Ho, 2022). The effectiveness of these supply-side interventions in reducing gender disparities in the labor markets ultimately depends on whether, upon entry, women face bias and discrimination. While a significant body of research studies gender inequality in labor markets in poor countries (e.g., Jayachandran, 2015, 2021; Dhar et al., 2019) evidence and understanding of gender discrimination in these contexts is scarce.

Labor markets in poor countries have distinct features that can significantly impact the prevalence and nature of discrimination, as compared to richer countries. Traditional gender norms can exacerbate gender-based discrimination stemming from preferences.[1] In addition, the distinct educational paths for men and women in poor countries often result in women lacking the necessary skills to enter male-dominated sectors (Fletcher et al., 2017), thereby increasing the likelihood of statistical discrimination. On the other hand, in highly segregated sectors, self-selection of female candidates suggests that they may possess superior human capital or internal motivation. Internal motivation, which may also be reinforced by women having limited outside options compared to men (Sharma, 2022), likely enhances the reliability and trustworthiness of job candidates. These factors are especially valuable for hiring managers facing significant asymmetric information, as in poor countries (Heath, 2018).

In this paper, we examine gender discrimination within the motor mechanics industry in Uganda, with a specific focus on the interplay between bias, skills, and trustworthiness in hiring decisions. The industry itself exhibits a high level of gender segregation, with less than 10 out of 100 workers being female (Ugandan Census), and is characterized by

[1] Ex-ante, this need not to be negative. Stereotypes associated with women, such as empathy, cooperation, and honesty, can also lead to a more favorable perception of them than men.

severe asymmetric information problems[2]. To investigate this issue, we partner with a vocational training center in Kampala, which has trained female and male mechanics since 2016. Through an experiment involving 40 garage managers, we investigate the hiring outcomes of female and male candidates for trainee positions.

99.5% of the garages in our sample currently exclusively hire male workers, and all managers but one are male. To provide context for our analysis, we asked garage managers to discuss why they currently do not hire women. While some managers attributed the absence of female hires to labor supply-related issues, the majority, 68%, held stereotypical beliefs about women and the nature of the job (Figure 2). Additionally, we asked employers to predict the perceived strengths of male and female trainees in the workplace. The managers' beliefs reflected expected degrees of stereotypes, with female trainees being perceived as better at interacting with clients and colleagues, more trustworthy, easier to manage, and also requiring a lower wage. Conversely, male trainees were regarded as having strengths in physical prowess, experience, and precision (Figure 6).

In our experiment, we provide garage managers with the opportunity to hire trainees from a vocational training center, including female trainees. To be eligible for participation, managers must have hiring decision-making authority and a need for trainees. We employ the Incentivized Resume Rating paradigm (Kessler et al., 2019): managers are tasked with evaluating hypothetical resumes of 24 trainees. The characteristics of these resumes are randomly assigned based on actual trainees' resumes obtained from our partner vocational training center. The experiment is designed to be incentive-compatible, as managers are aware that their choices in the experiment will result in referrals of trainees with desired characteristics. Overall, managers make 936 evaluations.

To examine the influence of bias, skills, and asymmetric information on potential discriminatory outcomes, our experimental design incorporates three levels of variation: candidate gender, training duration (no training, 3-month training, and 2-year training), and the level of support we provide in monitoring the trainees. The gender and training variations are within-subject, meaning that managers evaluate resumes of both female and male candidates with different levels of training. The randomization of the monitoring support is between subjects. Half of the managers are assigned to the treatment group: they are informed that our field officers will conduct check-up visits to monitor trainees, prevent misbehavior, and ensure their welfare once they are hired. The remaining managers are

[2]For example, over 80% of managers note that monitoring trainees is very important.

also told about the visits but are informed that their purpose is solely to ensure the trainees' welfare. This is our active control. By cross-randomizing the three variations, we can assess how bias, skills, and asymmetric information interact to influence hiring decisions and potential discrimination in the context of our study.

We begin our analysis by examining hiring outcomes based on gender in the cell with the most common conditions: candidates with at most 3 months of vocational training and no monitoring support. Within this group, we find no statistically significant gender differences in hiring outcomes based on our experimental results. The probability of female candidates being invited for an in-person meeting stands at 47.37%, comparable to 47.98% for male candidates (p-value 0.905), as is the wage offered. Moreover, male and female candidates are perceived to possess similar and relatively low on-the-job skills (1.6 on a 1-4 scale). This suggests that training and skill development largely occur on the job within the motor-mechanics sector we studied, so that skill-based discrimination may not be the predominant factor influencing hiring decisions. On the other hand, female candidates are consistently rated as more reliable (less likely to require monitoring) than their male counterparts. Additionally, they are perceived as more transparent in reporting transactions, which increases their likelihood of being trusted with cash-handling responsibilities.

Female candidates in our experiment possess a trust premium that does not translate into differences in hiring or wage outcomes, suggesting the presence of hidden discrimination as the average female candidate in the experimental resumes deck is perceived to be of higher quality than the average male candidate. To investigate this further, we compare the hiring outcomes of male and female trainees across two groups of managers: those with and without monitoring support. If hidden discrimination exists, we would expect to observe a preference for male candidates in the group with monitoring support, as the treatment diminishes the importance of trustworthiness in hiring decisions.

Our results confirm this hypothesis. When focusing on baseline candidates with no or short training, the introduction of monitoring support reduces the likelihood of female trainees qualifying for the internship by 34% (a 16.6 percentage point effect). The monitoring treatment does not differentially affect perceived skills by gender (p-value 0.00), but it systematically increases the perceived reliability of male trainees. As a result, female trainees, who are perceived as equally skilled and more reliable than their male counterparts, are less likely to be hired when managers face fewer asymmetric information problems.

Finally, we analyze the impact of higher training levels on hiring outcomes by gender, both with and without monitoring support. This analysis serves two purposes. First, from a policy perspective, we do not have evidence that vocational training affects female employment in poor countries (Fletcher et al., 2017). Second, from a mechanism perspective, it allows us to shed light on the drivers of the observed discrimination. In particular, because the perceived skill level of the candidates at baseline is so low, the lack of difference in skill evaluations does not allow us to discriminate between preference-based or beliefs-based discrimination.

Our results indicate that training systematically improves the hiring outcomes of both women and men. However, increased training does not reduce gender discrimination in hiring when monitoring support is present, while it induces gender discrimination in the absence of monitoring support.[3] These differential effects of training by gender can be attributed to spillover patterns between monitoring and training. On one hand, training enhances perceived skills of candidates, but this effect is more pronounced for men, particularly in the presence of monitoring support. On the other hand, training also increases perceived trustworthiness of candidates, with men benefiting more from this increase, especially in the monitoring support arm. In essence, training diminishes the comparative advantage that women have in trustworthiness, while enhancing the comparative advantage that men possess in terms of skills.

In summary, our findings suggest that women have a comparative advantage in perceived trustworthiness, which partially offsets the discrimination they face, especially in contexts with significant asymmetric information. Allowing women to signal commitment and skills through training improves their job prospects. However, training also increases men's perceived trustworthiness, thereby reducing women's comparative advantage and leading to more discrimination.

Our design does not allow to identify which mental model explains the perceived trustworthiness of women —e.g., selection, (lack of) outside options, increased punishment, or socialization—, nor can we ascertain the accuracy of managers' beliefs. Consequently, our

[3]While the wage offered to candidates increases by 100% from no training to 3 months of training and by an additional 175% from 3 months to 2 years of training, there is no significant difference between the wages of male and female trainees within each level of training. Once again, this confirms that discrimination acts on the extensive rather than intensive margin.

results are consistent with both beliefs-based and taste-based discrimination: it is unclear whether managers genuinely believe that women acquire fewer skills from training or if this belief stems from bias.

Our paper contributes to two main strands of literature. First, it adds to the existing literature on female labor force participation in poor countries. While previous work has primarily focused on supply-side factors, our study highlights the existence of discrimination by managers within a male-dominated sector and demonstrates that the level of discrimination is contingent on the degree of asymmetric information in the labor market. Our work aligns closely with Brown (2023), who studies gender discrimination by managers in a female-dominated sector, and Macchiavello et al. (2020) evaluating an intervention to train women to become managers. While there is evidence that women on average have fewer skills than men in male-dominated sectors Fletcher et al. (2017), we provide the first empirical test of whether training interventions can facilitate women's entry into male-dominated sectors, and we highlight the perverse discrimination effects of offering training opportunities to both men and women alike.

Second, our study contributes to the literature on gender discrimination and its underlying drivers. We demonstrate that women exhibit a comparative advantage in terms of trustworthiness and reliability, a phenomenon likely not specific to a particular culture but plausibly associated with selection processes within male-dominated sectors or a lack of outside options. This suggests that current estimates of gender discrimination and the gender gap are likely underestimations, as they fail to fully account for the positive selection of female candidates. By highlighting the importance of trustworthiness as a valuable attribute in certain industries, our study sheds light on an additional dimension of gender discrimination that has been overlooked in previous research. Incorporating this factor into future analyses can provide a more accurate understanding of the true extent of discrimination against women.

Our results hold relevance for the design of policies to reduce gender inequality in poor countries. Firstly, our results imply that women face discrimination in male-dominated sectors. Although our monitoring support may not be feasible in real-life settings, there are alternative methods that managers can employ to reduce asymmetric information, such as hiring from their networks or utilizing referrals. Secondly, we show that while providing training can help women enter male-dominated sectors, it does not appear to reduce gender discrimination. Finally, the monitoring results suggest that policies to reduce labor market frictions in poor countries may have unintended negative consequences, including the potential for inducing greater gender discrimination.

2 Study Setting

2.1 Motor-Mechanics Sector in Uganda

In Uganda, female labor participation is around 50% (World Bank), and gender segregation is pronounced, with several occupations almost entirely single-gendered (tailoring, transportation services, mechanics, electricians).

The motor mechanics sector studied in this paper is an emerging urban working-class occupation in both formal and informal settings and is heavily male-dominated. Only 9.5% of workers are female (UNHS sample), with managers and owners being almost exclusively male. However, initial focus groups suggest that the female labor supply has been increasing. We collaborate with a Ugandan vocational training center to access over 500 profiles of young job seekers in Kampala. Notably, 80% of these jobseekers are women; the vocational training center specializes in skills typically requested in male-dominated sectors, such as electricians and mechanics.

2.2 Sample Selection

The study population comprises motor mechanics garage managers in Mukono and Wakiso districts, located within the metropolitan area of Kampala, Uganda. Individuals were selected for participation based on the following eligibility criteria: (i) managers of small and medium-size mechanics garages (hereafter referred to as firms), (ii) aged 20 years old or above, (iii) interested in hiring an intern in the subsequent month, and (iv) English or Luganda speakers. Field surveyors approached potential candidates at their workplace, following a random walk in the targeted areas until the desired sample size of 40 firms was reached.

2.3 Descriptive Statistics and Motivating Evidence

Table 1 presents the baseline summary statistics of the sample. Garage managers are 100% male, with more than 16 years of experience in the motor mechanics industry on average. 62% of the managers own the firm. The average number of clients per day is 8.7 of which 65% are recurrent.

The average firm hires 15 workers. On average, 45% of the workers are defined as trainees, while 25% are permanently employed. Managers report an average internship duration of 1.2 years. 45% of current employees at the garages went through a trainee period first, indicating that internships serve as a realistic path toward future employment.

In line with nationally representative data, the motor-mechanics firms we sample are strongly male-dominated. In our sample, only 5% of the firms currently hire female employees. Within the firms that hire women, female employees make up for 10% of the firm size.

Notably, when asked what is their preferred gender composition for their firm, 93% of the managers stated 100% male; the remaining 7% stated 75% male. These skewed gender ratios suggest that women are likely to face discrimination in hiring.

To provide some context on what managers may expect from job candidates, we examine the training and experience patterns of current workers. Among the permanent workers, 12% completed a training certification prior to hiring (Figure 1). On average, 49% of workers had no experience prior to hiring. Of the workers with any training prior to hiring, 87.5% have some hands-on experience with no certification. Only 12.5% have certified training in vocational training centers. The average duration of the certified training is roughly one year.

To investigate how managers perceive the characteristics of our job applications, we ask managers to rate the skill training potential of the training programs we include in the resumes. Managers rate the skills associated with a 2-year training certificate comparably to the skills learned from hands-on experience (see Figure 5).

Further, we investigate the hiring process and whether it varies by gender. Survey evidence reveals that candidates are perceived differently based on their gender, with stereotypical expectations being applied to each gender. As summarized in Figure 6, managers report distinct reasons for hiring female candidates compared to male candidates: male job-seekers may be preferred because of physical strength and precision, while female job-seekers may be preferred because of higher trustworthiness, lower wages, capacity to interact with colleagues and easier to manage. 85% of the sample says to be actively looking for workers.

Finally, our survey evidence confirms that both frictions related to finding workers with the right skills and asymmetric information are relevant in our setting. Figure 3 presents the share of respondents considering monitoring a relevant margin for hiring. 85% think that monitoring is very important. Similarly, as shown in Figure 4, the most relevant challenges that managers face in hiring are: (i) the effort allocated to teaching on-the-job skills (40%) and (ii) the lack of trust in the new worker (27%).

3 Experimental Design

Our experiment is designed to examine (1) the presence of gender discrimination in hiring, (2) the interplay between gender discrimination and asymmetric information, (3) the impact of training on hiring outcomes, and (4) the effect of training on discrimination.

Managers: tasks and incentives. In the experiment, we ask managers to evaluate the profiles of 24 candidates during their working time. Managers are informed that the profiles are hypothetical. Following the Incentive Resume Rating exercise developed by Kessler et al. (2019), we inform the respondents that, at the end of the study, referrals will be offered from a pool of real candidates associated with our vocational training center partner. The respondent is carefully guided through the incentive structure before the beginning of the profiles' evaluation: while the rated profiles are hypothetical, the characteristics are linked to the pool of real applicants. The respondent is informed prior to the evaluation that the referred trainee candidates will match the characteristics of preferred profiles during the evaluation.

Jobseekers and hypothetical profiles. On the labor supply side, we collect information on over 500 trainees profiles from a vocational training center we partner with, located in the metropolitan area of Kampala. We combine information from the trainee data to create 24 hypothetical resumes. Each resume is identified by an identification number; for each resume, we cross-randomize baseline information about personal details, motivation, education, skills, and references. Specifically, we include information on name, marital status, age, nationality (all Ugandans), place of birth, motivation, education level, languages spoken, driver's license, institution attended, and references. The resume is shown to the manager as represented in Figure 8.

Design. Our design has three dimensions of randomization: candidate gender, training duration, and monitoring support. All dimensions are cross-randomized.

Managers are randomized into two groups of equal size: monitored and not monitored. In the monitored group, managers are informed that a member of the training center and the research team will conduct unannounced visits to the firm with two objectives: (i) to ensure that the trainees are not being subject to any form of harassment or mistreatment during the internship offered, and (ii) to deter any unwanted behaviors that may undermine the trust in the new employee. In the non-monitored group, managers are subject to active control as they are also provided with two pieces of information: (i) they are told that unannounced visits are meant to ensure the well-being of the trainee, exactly as in the monitored group, and (ii) we explicitly inform the respondent that no support in deterring unwanted behaviors will be provided by the research team during the unannounced visits. Active control information allows us to rule out the possibility that the monitoring treatment includes changes in baseline trust in the pool of candidates. The monitoring dimension is randomly assigned between subjects: a given manager performs the profile evaluation task under the same monitoring condition.

Each manager rates twenty-four job candidate curricula. To compare hiring outcomes by gender, we randomly assign to each manager female and male candidates with equal proportions. To test for statistical discrimination and study the impact of vocational training on female employment, we cross-randomize the gender dimension with the training duration at the profile level. In particular, we create six versions of each profile by cross-randomizing information on gender and the duration of certified training in a 2×3 design.

Along the training dimension, we consider three levels: (i) the No training corresponds to the participation in a one-day Open Day event that provides the trainee with a certificate of attendance; (ii) a three-month certified training program; these programs are nationally recognized and provided by institutions that received governmental approval; (iii) a two-year certified training program, also officially recognized by the national authorities. All training programs are tailored to the industry: informed by initial focus groups and survey evidence, we selected programs that are commonly known among mechanics. On the training dimension, one-fourth of the profiles shown to a respondent holds no training, half holds three-month training, and the remaining fourth holds with two-year training.

Outcomes. We elicit outcomes to capture different margins related to hiring from the hiring manager's perspective: the likelihood of a job offer (extensive margin), the intended wage offered (intensive margin), the perceived level of on-the-job skills, the perceived trustworthiness of the candidate.[4]

For the extensive margin, we elicit two outcomes:

- *Offer*: How likely would you be to offer this applicant a position as a mechanic intern? (1-4 scale)
- *Meet*: Do you want us to refer to you a similar applicant to discuss the option to start an internship or trial period? (Yes/No)
- *Wage*: If you were to hire this applicant, what daily wage would you offer this job applicant during the internship? (UGX)
- *On-job Skills*: How would you rate the job applicant ability to do the service to vehicles your garage handles? (1-4 scale)
- *Trust with Cash*: If you were to hire this applicant, would you trust this applicant to handle cash? (Yes/No)
- *Transparency*: How likely do you think it is that the trainee will accurately report to you the full amount of any direct payments received from clients? To answer this question, think of how many times out of 5 direct payments, the trainee will be transparent. (1-5 scale)

Table 3 reports the survey question corresponding to each outcome. Variables Offer and Meet capture the extensive margin of the job offer. The variable Wage captures the intensive margin of potential job offers: we allow wages to be negative to capture the extent to which managers perceive candidates as already-productive labor input or not. The variable On-job Skills is designed to capture the perceived quality of the potential employee in performing productive work: we tailored the content to relevant skills for

[4]We additionally elicit measures of customer discrimination during piloting phase.

the positions the candidates are most interested in. The two measures of reliability or trustworthiness focus on the applicant behavior with payments which is one of the largest source of moral hazard in the firm.

Balance checks and attrition. Table 2 displays the balance in observable sociodemographic and work characteristics of the hiring manager and the firms' characteristics on the sample between monitored and not-monitored groups. The sample is balanced across all observables.

Overall attrition rates are low as the intervention was implemented within a one-time survey. Only one respondent did not complete the survey and has been replaced by another firm manager in the same neighborhood. We observe no attrition in rating the candidates' profiles with a 100% response rate conditional on concluding the survey.

4 Empirical Strategy

In this section, we describe the empirical strategy to identify (i) the presence of gender discrimination in hiring, (ii) how it interacts with monitoring technologies, and (iii) what is the impact of training on female employment.

We begin by examining how hiring outcomes are impacted by the gender of jobseekers. We first restrict our analysis to the evaluation of candidate profiles that reflect the baseline composition of the labor force of the firms in the sample. Workers typically hold low or no level of certified training as represented in Figure 1; we restrict our baseline sample to firms to which no monitoring support is provided. We are firstly interested in comparing hiring outcomes between female and male candidates to test for gender discrimination. To quantify the causal effect of gender, we first estimate the following regression model:

$$Y_{ij}^{k} = \beta_0 + \beta_1 \text{Female}_{ij} + \delta_i + u_{ij} \tag{1}$$

where Y_{ij}^{k} denotes outcome k for profile i and manager j, and Female_{ij} is a dummy for female candidate. The coefficient β_1 captures the gender bias in the form of the differential effect of female as opposed to male candidates on outcome Y. δ_i are profile fixed effects[5].

[5]We also estimate the model with manager fixed effects: the results are robust to this alternative

In particular, we first test whether the likelihood of offering a job as a trainee to the candidate differs for women and men. To investigate further the mechanisms underlying the possible frictions for a female jobseeker in entering a male-dominated sector, we look at two margins that stroke as first-order in the survey evidence we collected: managers' perception of a candidate's skills and perception of a candidate's trustworthiness. We want to test whether drivers of hiring choices differ by gender as skills and trustworthiness are perceived differentially for female and male workers.

In the second step of the analysis, the focus is on examining the impact of monitoring and training interventions on hiring decisions. This step aims to shed light on the effectiveness of these interventions in addressing the challenges faced by managers. If our monitoring intervention successfully removes a binding constraint, we expect support in monitoring should reduce asymmetric information problems and increase interest in candidates, specifically via an increase in trustworthiness and transparency. If our training intervention is effective at improving candidates' skills, we expect training to improve candidates hiring outcomes, specifically via an increase in perceived skills. We test for these hypotheses through random assignment of monitoring support and training.

To test for the effect of monitoring support, we estimate the following regression on the subset of resumes with no or low training:

$$Y_{ij}^k = \beta_0 + \beta_1 \text{Monitoring}_j + \delta_i + u_{ij} \tag{2}$$

To test for the effect of training, we estimate the following regression focusing on managers which are not offered monitoring support:

$$Y_{ij}^k = \beta_0 + \beta_1 \text{Training}_j + \delta_i + u_{ij} \tag{3}$$

In the third step of the analysis, we investigate the interplay between asymmetric information and gender discrimination. We test this hypothesis through the random assignment of monitoring support and the gender of the candidate. Since we expect women to have a comparative advantage in reliability or trustworthiness, our hypothesis is that improving monitoring may reveal discrimination in hiring. We estimate the following regression

specification. We estimate the model with managers fixed effects also for model (3).

model on the sample of managers with no monitoring support:

$$\begin{aligned} Y_{ij}^{k} = \beta_0 + \beta_1 \text{Female}_{ij} + \beta_2 \text{Monitored}_j + \\ + \beta_3 \text{Female}_{ij} \cdot \text{Monitored}_j + \delta_i + u_{ij} \end{aligned} \tag{4}$$

where Monitored_{ij} is a dummy for receiving the monitoring support. The coefficient β_3 measures the differential effect of monitoring support for female as opposed to male candidates. A negative β_3 coefficient indicates that the changes induced by the introduction of the monitoring technology penalize women relative to men, regardless of the overall effect of monitoring.

Finally, we provide experimental evidence on the impact of a higher level of training on hiring outcomes by gender and by the level of asymmetric information in the labor market.[6] We estimate the fully saturated regression model on the full sample:

$$\begin{aligned} Y_{ij}^{k} = \beta_0 &+ \beta_1 \text{Female}_{ij} + \beta_2 \text{LowTrain}_{ij} + \beta_3 \text{HighTrain}_{ij} + \beta_4 \text{Monitored}_j + \\ &+ \alpha_1 \text{Female}_{ij} \cdot \text{LowTrain}_{ij} + \alpha_2 \text{Female}_{ij} \cdot \text{HighTrain}_{ij} + \alpha_3 \text{Female}_{ij} \cdot \text{Monitored}_j + \\ &+ \alpha_4 \text{LowTrain}_{ij} \cdot \text{Monitored}_j + \alpha_5 \text{HighTrain}_{ij} \cdot \text{Monitored}_j + \\ &+ \eta_1 \text{Female}_{ij} \cdot \text{LowTrain}_{ij} \cdot \text{Monitored}_j \\ &+ \eta_2 \text{Female}_{ij} \cdot \text{HighTrain}_{ij} \cdot \text{Monitored}_j + \delta_i + u_{ij} \end{aligned} \tag{5}$$

where LowTrain_{ij} is a dummy that indicates the 3-month training and HighTrain_{ij} is a dummy that indicates the 2-year training for profile i and manager j. We use the above specifications for all the primary outcomes, controlling for unbalanced characteristics across treatment arms for the monitoring dimensions.

[6]The goal of this treatment is to capture variation in the skills level. In the current experiment, we manipulated the duration of the certified training. In future work, we plan to modify this treatment by hold fix the duration and varying the performance of the trainee in the practical and theory exams associated with the certification.

5 Results

In this section, we discuss the results of the managers' evaluation of 936 resumes through the Incentivized Resume Rating paradigm. First, we explore the raw distribution of all outcomes across treatment cells. We then move to the regression framework to discuss the causal estimates of the treatments over three groups of outcomes: (i) hiring choices, (ii) perceived work skills, and (iii) perceived trustworthiness of jobseekers.

5.1 Is there gender discrimination in hiring?

Figure 9 plots the raw averages of all outcomes by gender: each bar corresponds to a treatment cell for different training levels and monitoring conditions. We first explore our baseline sample of candidates with no or low training and no monitoring support. Managers are interested in meeting candidates in person 48.2% of the time while reporting a relatively low likelihood of offering them the trainee position (scoring on average of 1.7 on a scale from 1 to 4).

Low and no trained candidates score systematically lower on both skills and trustworthiness measures: their skills average rate is 1.06 on a scale from 1 to 4, and candidates are expected to report only 20% of the transactions with clients transparently. Women are also systematically perceived as more trustworthy and transparent than men, suggesting the presence of a trust premium for women.

Figure 10 and Table A.1 illustrate the treatment effects from the regression model (1) for all outcomes. Table 4 also shows the same set of estimates for standardized outcome variables with respect to the mean and variance of profiles with no or low training, absent the monitoring support.

Columns 2 and 3 of Table A.1 show that gender did not alter hiring outcomes at the conventional levels of statistical significance. However, female candidates are perceived by managers as 0.33 standard deviations more transparent than male candidates. Managers believe that women will report transparently 18.6% more transactions held with clients as compared to men. Women thus exhibit a trust premium that does not translate into a difference in hiring or wage outcomes. These patterns are suggestive of hidden discrimination as the average female candidate in the experimental resumes deck is perceived to be of higher quality than the average male candidate.

5.2 What is the impact of monitoring support and training on hiring?

Table 5 and Figure 11 show the treatment effect of informing managers about the monitoring support before they take hiring decisions in the regression model (2). In the presence of monitoring, the likelihood of receiving a job offer increases by 0.48 standard deviation (column 1). Monitoring also increases the level of perceived skills by roughly the same amount (0.44 std, column 4); finally, perceived transparency also increases: managers report that, on average, they expect to report 46% more transaction with clients transparently compared to the scenario with no monitoring support (see column 6 of Table A.4 for non-standardized outcomes). Overall, results are consistent with the hypothesis that monitoring support reduces asymmetric information both on skills and trustworthiness of jobseekers.

Table 6 and Figure 12 reports the treatment effects of different levels of training proposed in Equation (3). While the 3-month training does not substantially affect hiring outcomes, perceived skills or perceived trust, the 2-year training increases drastically all three dimensions. Column 1 shows that the 2-year training increases the likelihood of a job offer by 1.6 std. Candidates with high level of training are 28.5 pp more likely to meet the manager compared to no training (equivalent to a 86% increase). The 2-year training also increases the likelihood to meet by 23.2% pp compared to the 3-month training (p-value 0.00). On average, the expected daily wage offer increases by roughly 4000 UGX, 260% of the expected wage absent training (see Table A.3 for treatment effects on non-standardized outcomes). Perceived skills and trust also dramatically increase. Transparency increases by 30% with high training levels. All effects are statistically different both compared to no training and low training at the conventional levels of statistical significance (p-value 0.00).

5.3 Does improving monitoring lead to gender discrimination?

To investigate the hypothesis of hidden discrimination against women, we compare the hiring outcomes of male and female trainees when we offer managers support in monitoring and when we do not. If hidden discrimination exists, we would expect to observe a stronger preference for male candidates relative to female candidates in the group with monitoring support, as the monitoring treatment diminishes the importance of trustworthiness in hiring decisions.

In the presence of monitoring support, managers' interest in meeting drops to 39%: this reduction is mostly driven by female candidates. Managers are substantially less interested in meeting women candidates, with the probability dropping from 48% to 32%. Monitoring does not affect the average likelihood of a job offer for no training but increases it by 0.7 points on the 1-4 scale (from a score of 1.78 under no monitoring) for candidates with 3-months training. Similarly, managers to whom we offer monitoring support rate men as significantly more likely to be offered the job (2.43 female vs 2.05 male, p-value = 0.008) as compared to women with the same characteristics. Thus, the introduction of monitoring support induces gender discrimination.

To quantify the extent of discrimination, when monitoring support is present, we estimate the regression model (4). To put results into perspective, a male candidate with a 3-month certified training is as likely to get a job offer as a female candidate with a 2-year certified training and roughly 40% more likely than a male with 3-month training but no monitoring support. The interest of the manager to meet the candidate in person follow the same patterns: in the presence of monitoring, men with 3-month training have a probability of 56% to meet the hiring manager in person while a women with 2-years training has 51% probability of meeting. Perceived skills marginally increase under monitoring for low levels of training, while perceived transparency increases systematically both with no or low levels of training: managers believe that candidates will correctly report 75% of the transaction with clients when monitoring is present, while candidates will correctly report roughly 50% of the transactions if no monitoring support is provided.

Table 7 and A.4 show the treatment effect of the regression model 4 for standardized and not standardized outcomes. Column 1 of 7 demonstrates that the presence of monitoring support increases the likelihood of receiving a job offer by 0.552 standard deviations for men. The effect for women is also positive but significantly smaller in magnitude: monitoring reduces both the likelihood of receiving a job offer (0.225 std) and of meeting the manager in person (0.335 std). Monitoring widens the gender gap in the likelihood of receiving a job offer at all levels of training: in the presence of monitoring support, women are on average 14.2% less likely to meet the managers than men. The difference is statistically significant at the conventional level of 5%. We detect no effects on wages, as reported in column 3. Column 4 presents the results for the perception of on-the-job skills. Monitoring increases the perceived skills of male candidates by 0.564 standard deviations (p-value 0.027) while no women, on average also benefit from monitoring but less. Columns 5 and 6 show how monitoring benefits all candidates equally: on average, managers expect trainees to report roughly 20% more transactions with clients correctly. Absent monitoring, women are perceived as more trustworthy (0.299 sd, p-value 0.012). Overall, the benefits from monitoring for men are larger than for women, reducing the comparative advantage of women with respect to trustworthiness.

5.4 What is the impact of training on hiring outcomes and gender discrimination?

We analyze patterns in Figure 9 to explore further the distribution of hiring outcomes, perceived skills, and trustworthiness when candidates have higher levels of training (2-year certified program). Finally, we also investigate the spillover patterns between monitoring and training. Candidates with 2-year training are 64% more likely to be hired compared to lower levels of training; absent monitoring, profiles with high training are 54% more likely to be considered by managers for in-person meetings compared to lower levels of training (26 pp increase). The likelihood of receiving a job offer follows similar patterns. These statistics hide heterogeneity across gender. Regardless of monitoring, the likelihood of receiving a job offer increases by 76% for men and 51% for women when training is high. Absent monitoring support increased training reflects a wide gap in hiring: women are 24.7% less likely to meet the manager (16.4 pp decrease, men having 84% probability of meeting). There is no evidence that training closes the gender gap in hiring choices when monitoring support is present. The daily wage increased from ugx 2450 absent monitoring for the level of training to ugx 6020 when highly trained and ugx 11800 when highly trained and monitored. We observe no wage gap across training levels or monitoring conditions.

An increase in training enhances perceived skills dramatically. The effect is more pronounced for men, suggesting that training increases the comparative advantage in skills. Training also increases the perceived trustworthiness of jobseekers: managers report that they expect trainees with high training to transparently report transactions with clients

67% of the time as opposed to 50% for no or low levels of training. The relative gains in perceived trust induced by training are larger for men, particularly when monitoring support is present. The share of transactions with clients expected to be correctly reported increases by 35.1% for men and 33.7% for women due to training and absent monitoring. When monitoring is present, the increase is 11.5pp larger for men than women.

Figure 14 and Table A.5 show the treatment effects estimated in the regression model 5. Table 8 reports the same estimates for standardized outcomes. The 2-year training increases the likelihood of meeting the manager for both men and women; however, the effects are more pronounced for male candidates: absent monitoring support, men with 2-year training are more likely to meet the manager by 0.85 standard deviations compared to no training, while women's increase is 0.291 standard deviation. The difference across gender is statistically significant at 5% level. We observe a similar pattern for the likelihood of a job offer: men are more likely to receive an offer by 1.9 standard deviations than those without training, while women are more likely to receive an offer by 1.22 (p-value 0.04). In the presence of monitoring similar effect persists, suggesting that training does not offset the gender bias induced by the introduction of monitoring support. While the interaction of training and monitoring move the extensive margin in hiring choices significantly, the 2-year training systematically increases wages. Column 3 shows the positive causal impact of high training on wages offered. On average, absent monitoring, high training increases wages by ugx 4000, roughly doubling the pay compared to no training levels. All estimates of the causal effect of high training on hiring outcomes are statistically different from the effect of the 3-month training (p-values 0.00). When monitoring support is introduced, the effect of high training on wages increases: managers expect to pay a trainee with 2-year certified training approximately ugx 6600 more when monitoring is present. Overall, we find no evidence that training can deter gender discrimination in hiring when monitoring costs are low, while training induces gender discrimination when monitoring costs are high.

Column 4 of Table A.5 and Table 8 describes the treatment effects on job skills in our regression framework. We do find stark evidence that high training alters upwards managers' perception of candidates' skills. The increase in perceived skills is systematically higher for men than women: women's skills are on average perceived 0.92 standard deviations lower than men's skills (p-value 0.005). Columns 5 and 6 of Table A.5 and Table 8 describe the impact on our two measures of trustworthiness. The 2-year training increases perceived trust with cash by 1 standard deviation, on average. Candidates with high training are expected to report 40% transactions with clients correctly (17.25 pp, p-value 0.00). The relative increase in our trust measures is higher for men than for women, the difference averaging 0.34 standard deviation. Overall, training diminishes the comparative advantage that women have in trustworthiness and boosts the comparative advantage that men hold in terms of perceived skills.

In summary, our experimental evidence suggests that women have a comparative advantage in perceived trustworthiness, which partially offsets the discrimination they face with regard to job skills. The trust premium does not translate into better hiring outcomes. Certified training increases labor market prospects for both men and women. However, training also accentuates gender discrimination against women: training increases relatively more the perceived trustworthiness and skills of male candidates, thus reducing women's comparative advantage in trustworthiness and increasing men's comparative advantage in skills.

6 Conclusions and Implications for Policy

This paper examines gender discrimination in hiring within a male-dominated sector in a poor country. Our context is the motor mechanics sector in Kampala, Uganda. The study identifies two challenges that are particularly prominent in low-income countries and are encountered by managers: the need to effectively screen for skills and prevent moral hazard. The goal of the study is to understand how these goals interact with biases, and to what extent they determine discrimination in hiring.

Our first set of results shows that, despite managers holding stereotypical views of female candidates, managers show similar interest in male and female candidates. However, through the randomization of monitoring technology, the data reveals that gender discrimination in hiring is present but "hidden": women, all-else-equal, are perceived as higher-quality candidates. At baseline, we observe that female candidates are rated as systematically more trustworthy and reliable. The introduction of support in monitoring leads to an increase in gender discrimination because the removal of asymmetric information diminishes women's comparative advantage.

Our second set of results examines the effectiveness of training as a potential solution to address female labor force participation and discrimination. While training improves women's outcomes, we find evidence of systematically lower returns to training for women with respect to men. Our analysis identifies the mechanism: we find evidence of spillovers from training onto perceived reliability. Thus, training, as monitoring, also reduces women's comparative advantage.

Highlighting the interconnection between discrimination and asymmetric information in the context of labor markets has important policy implications, particularly considering extensive efforts to address asymmetric information problems in poor countries. In addition, previous research shows that employers take actions to reduce monitoring costs (e.g., via in-network hiring or referrals). Our findings show that the adoption of strategies to minimize monitoring costs by managers leads to gender discrimination in hiring.

Our analysis of the impact of training programs is also directly policy relevant. Previous work investigates the impact of training on workers' outcomes, and, as discussed in Fletcher et al. (2017), policymakers are currently exploring the use of training programs to enhance female labor force participation in impoverished nations. Our findings point at a fairness trade-off in the design of training programs. While these programs can be beneficial for both men and women, offering training opportunities to both genders may have a negative impact on women's outcomes.

Our experimental results provide novel insights on the relevant issue of gender discrimination in male-dominated sectors in poor countries. Further research is needed to identify the determinants of women's trustworthiness premium and to provide insights into the dynamics of discrimination over time and beyond the marginal job candidate.

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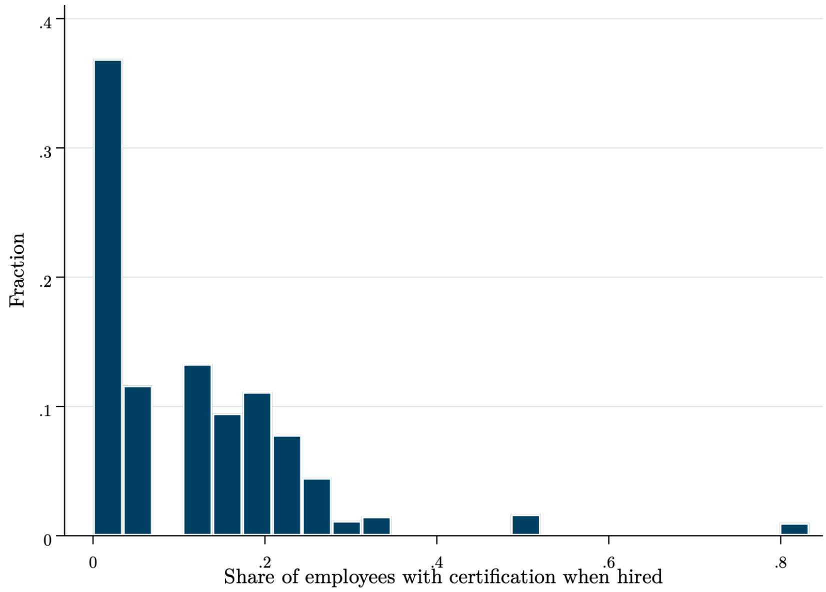
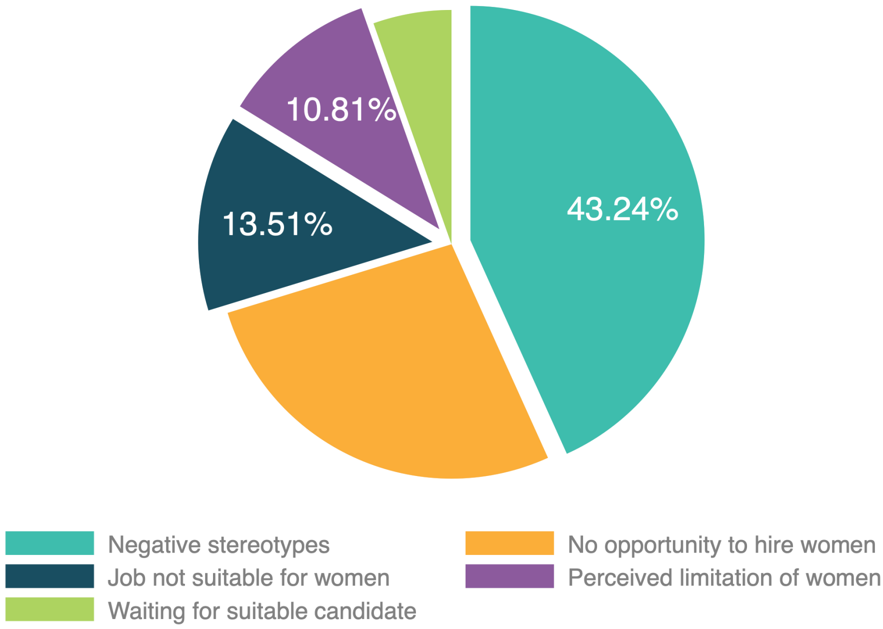
Figures

Figure 1: Distribution of employees with training certification



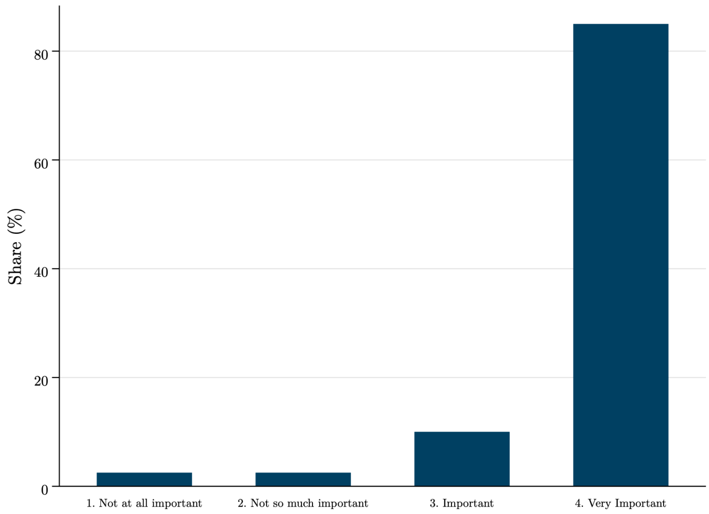
Note: This figure plots a histogram of managers' responses to the question "Of the employees currently working at your garage, how many had certified training when hired?" divided by the number of employees currently working at their garage.

Figure 2: Reasons for not hiring women



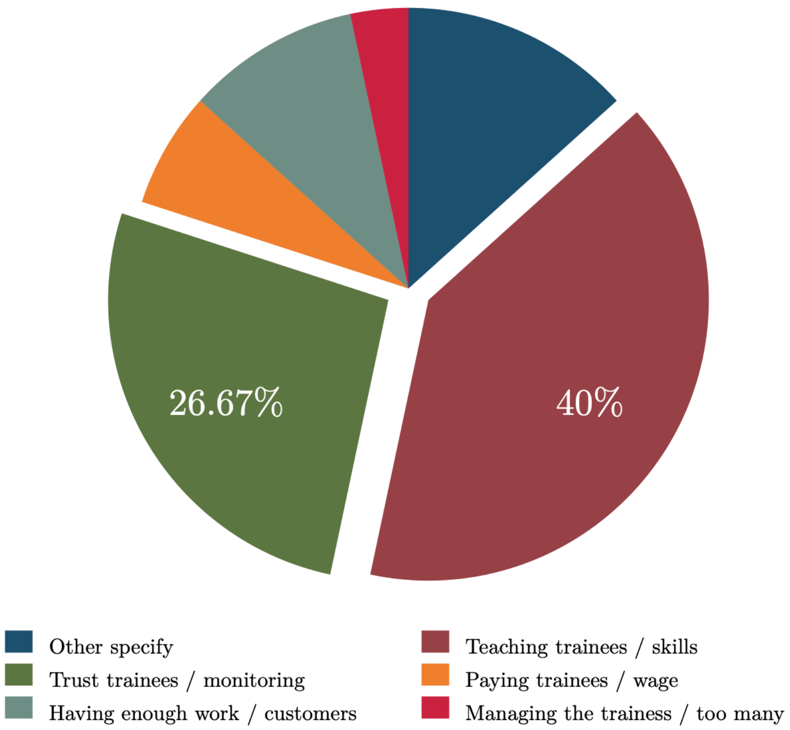
Note: This figure plots the share of managers listing a specific type of reason in response to being asked whether they can explain why they do not currently have any female employees or trainees.

Figure 3: Beliefs about importance of monitoring



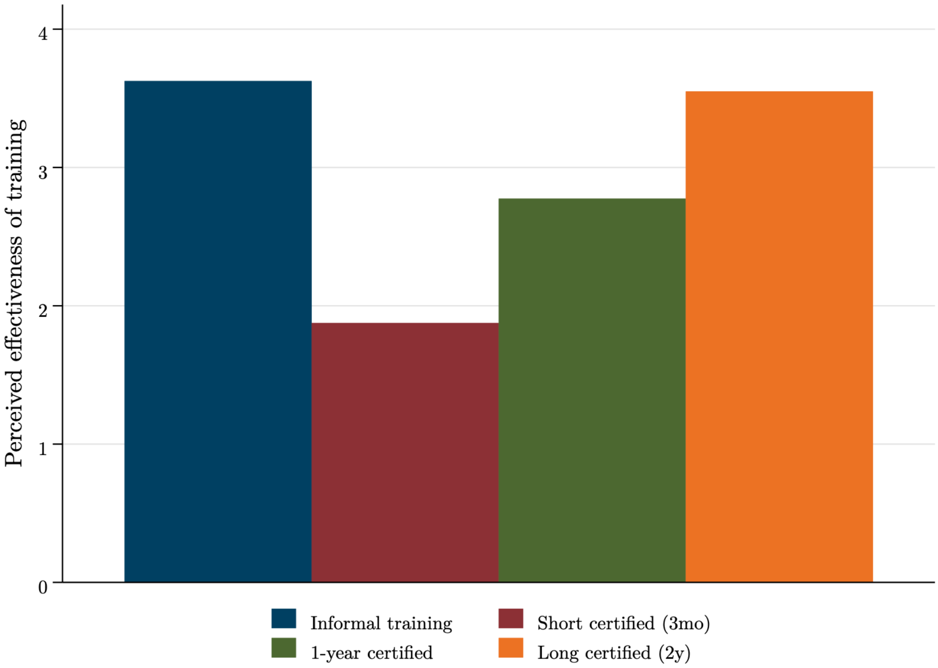
Note: This figure plots the share of managers who chose a specific degree of importance in response to the question "To which extent do you consider monitoring or supervising your new trainees important?".

Figure 4: Managers' biggest challenges in hiring trainees



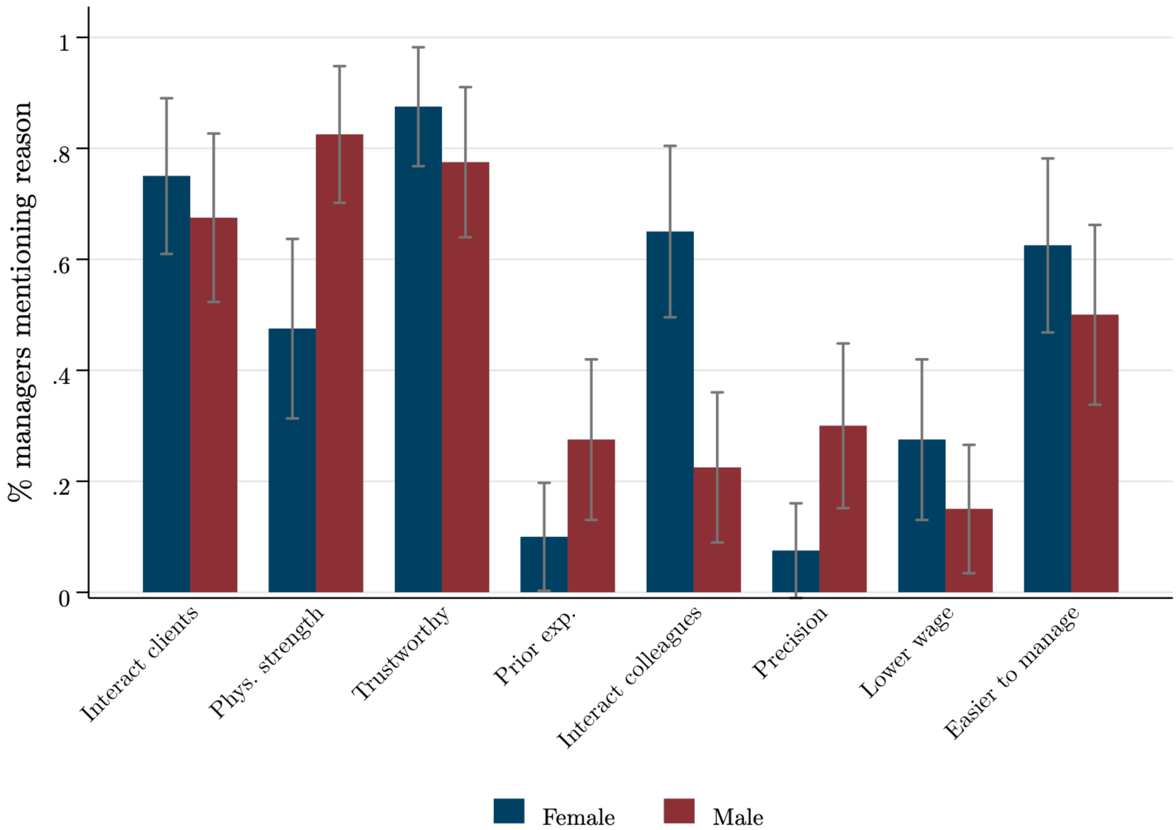
Note: This figure plots the share of managers who chose a specific challenge in response to the question "What is the biggest challenge you face when hiring trainees?".

Figure 5: Perceived effectiveness of training



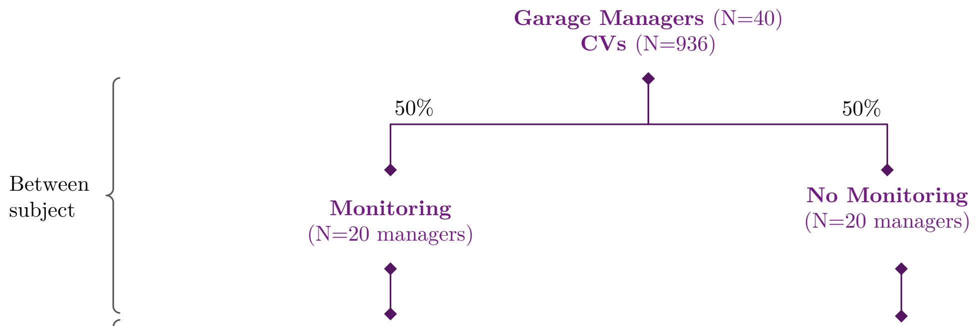
Note: This figure plots managers effectiveness ratings for each skill training.

Figure 6: Managers' beliefs of strengths of male and female job candidates



Note: This figure plots the share of managers who mention a particular strength in response to the question "Think of a [male/female] job applicant for a trainee mechanics job. What are the strengths of a [male/female] candidate?".

Figure 7: Design Chart



Within subject

Monitoring:

	CVs	Female (50%)	Male (50%)
25%	No training	59	59
50%	3-month training	119	119
25%	2-year training	58	59

No Monitoring:

	CVs	Female (50 %)	Male (50 %)
25%	No training	60	59
50%	3-month training	117	114
25%	2-year training	56	57

Figure 8: Example of trainee resume

Job Application as Mechanic Trainee

Application ID Number 5

Personal Details

A [redacted] N [redacted]

female, Married

26 years old

Ugandan nationality

Originally from Mpererwe Mugalu Zone

Motivation

It is a good job.

Education, Skills, and Training

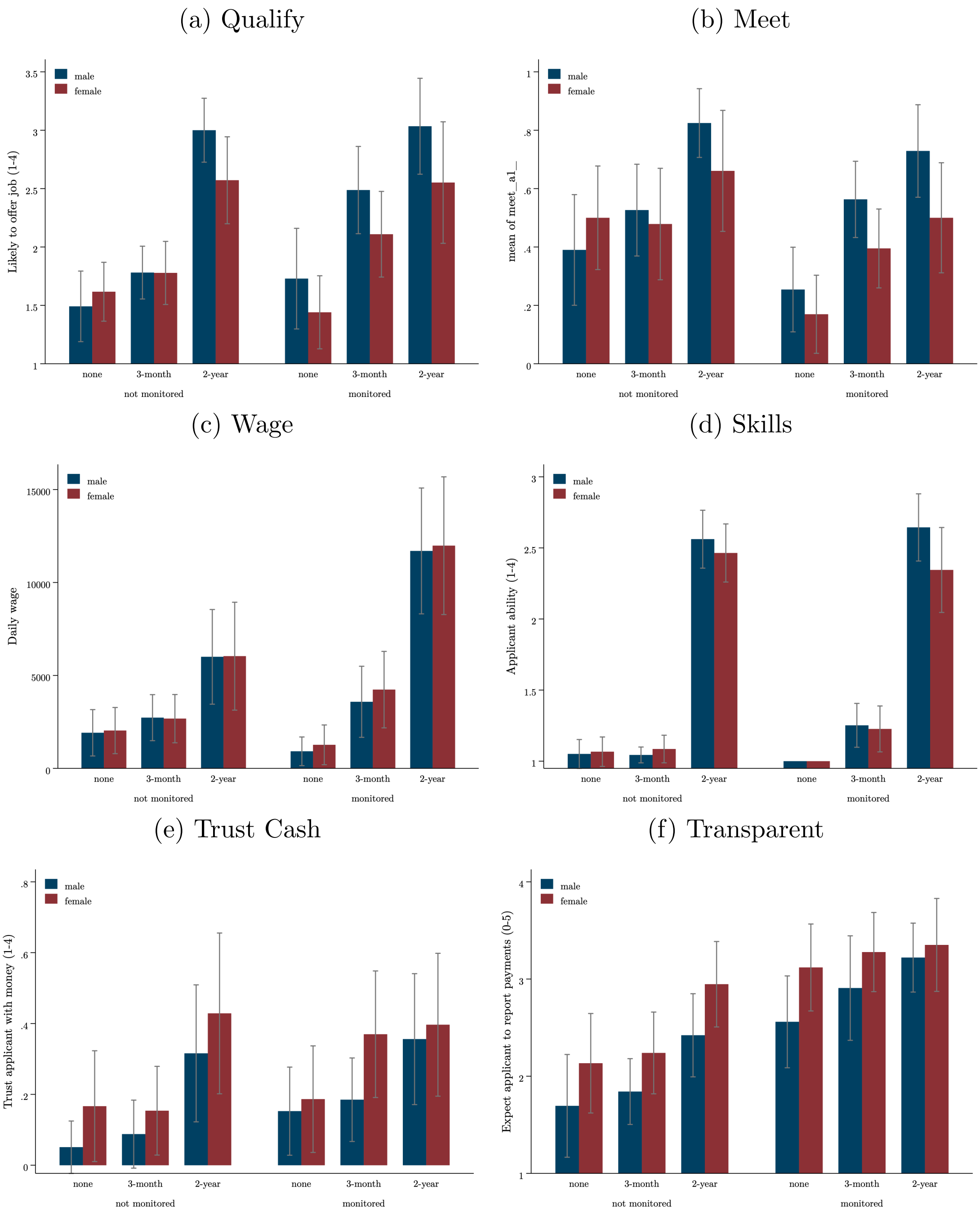
Educational achievement	Primary School (P7)
Spoken Language(s)	Luganda and Rukiga
Drivers Licence	No
Qualification	Motor vehicle mechanics (MODULAR) certificate
Training Characteristics	3 MONTHS; Practical training
Institution Attended	Kyeyunga Vocational and Technical School in Kawempe Ttula

Training Center References

Please, call the training center managers J[redacted] N [redacted] 077 [redacted] or J [redacted] M [redacted] at 774 [redacted]

Note: This figure displays an example of a CV profile shown to managers.

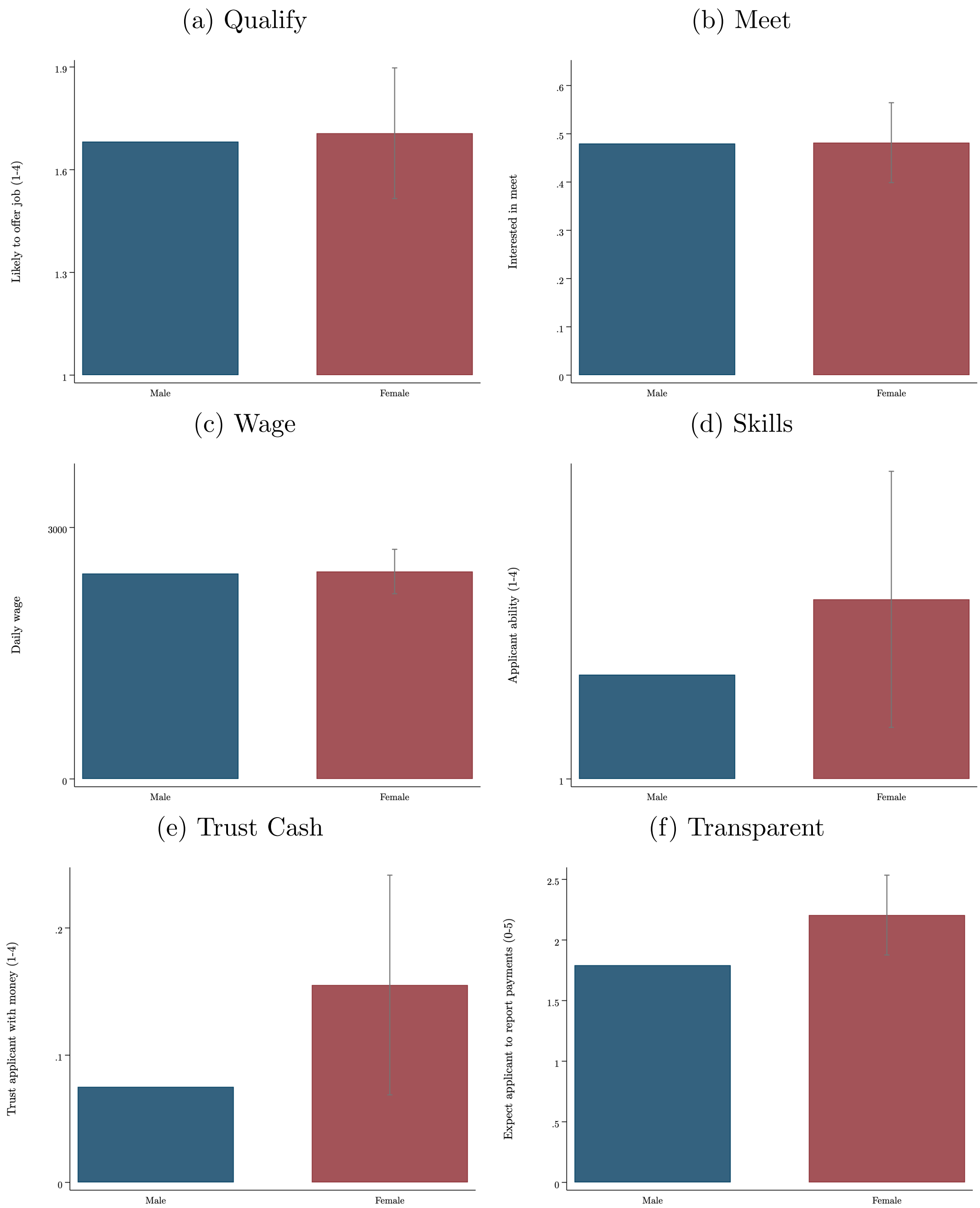
Figure 9: Managers' evaluations - Raw data



Note: This figure shows the means of various outcome variables by treatment group. Each panel shows a different outcome variable, and the confidence interval bars use standard errors clustered by manager.

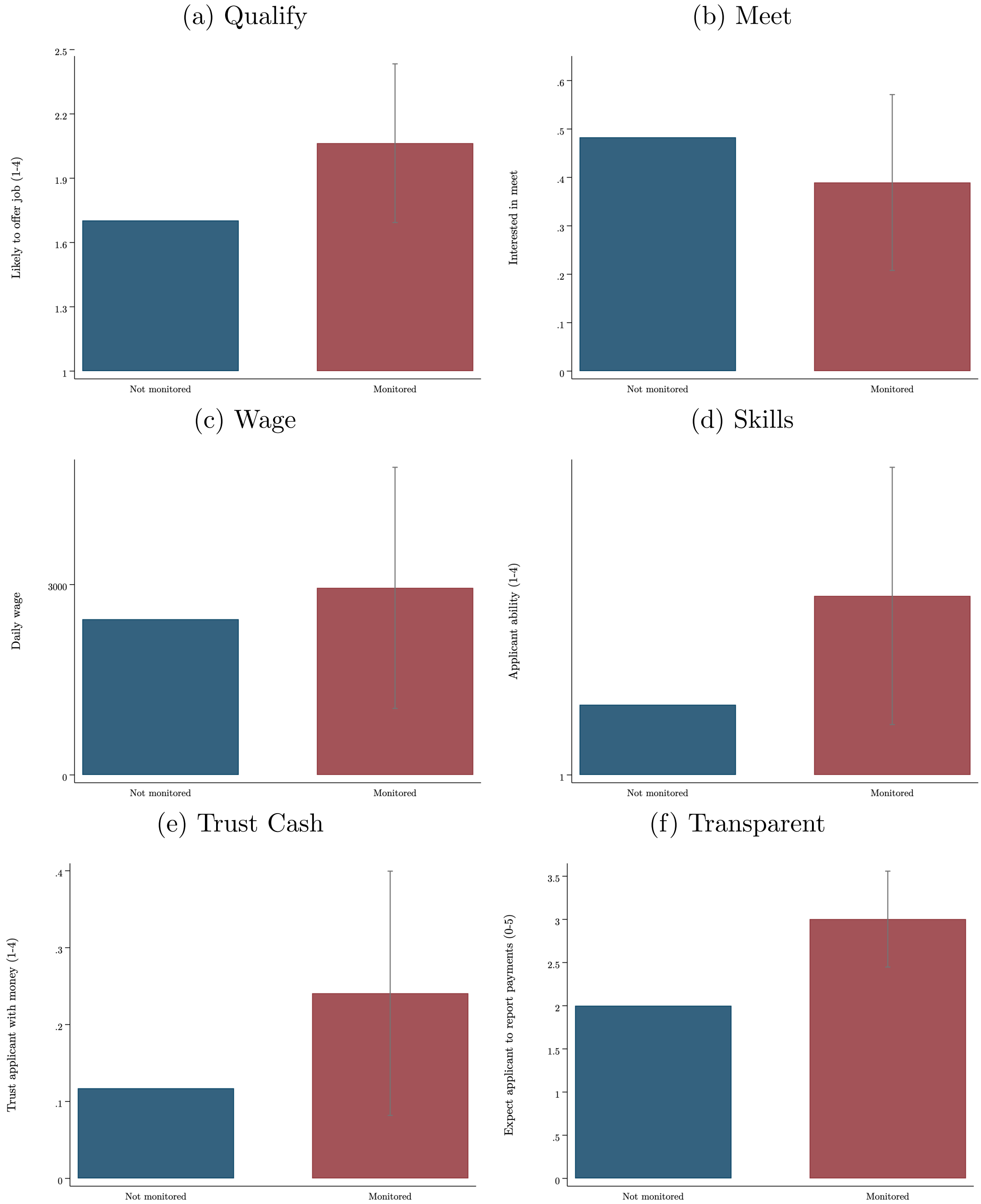
Figure 10: Experimental Results: female

(a) Qualify (b) Meet (c) Wage (d) Skills (e) Trust Cash (f) Transparent



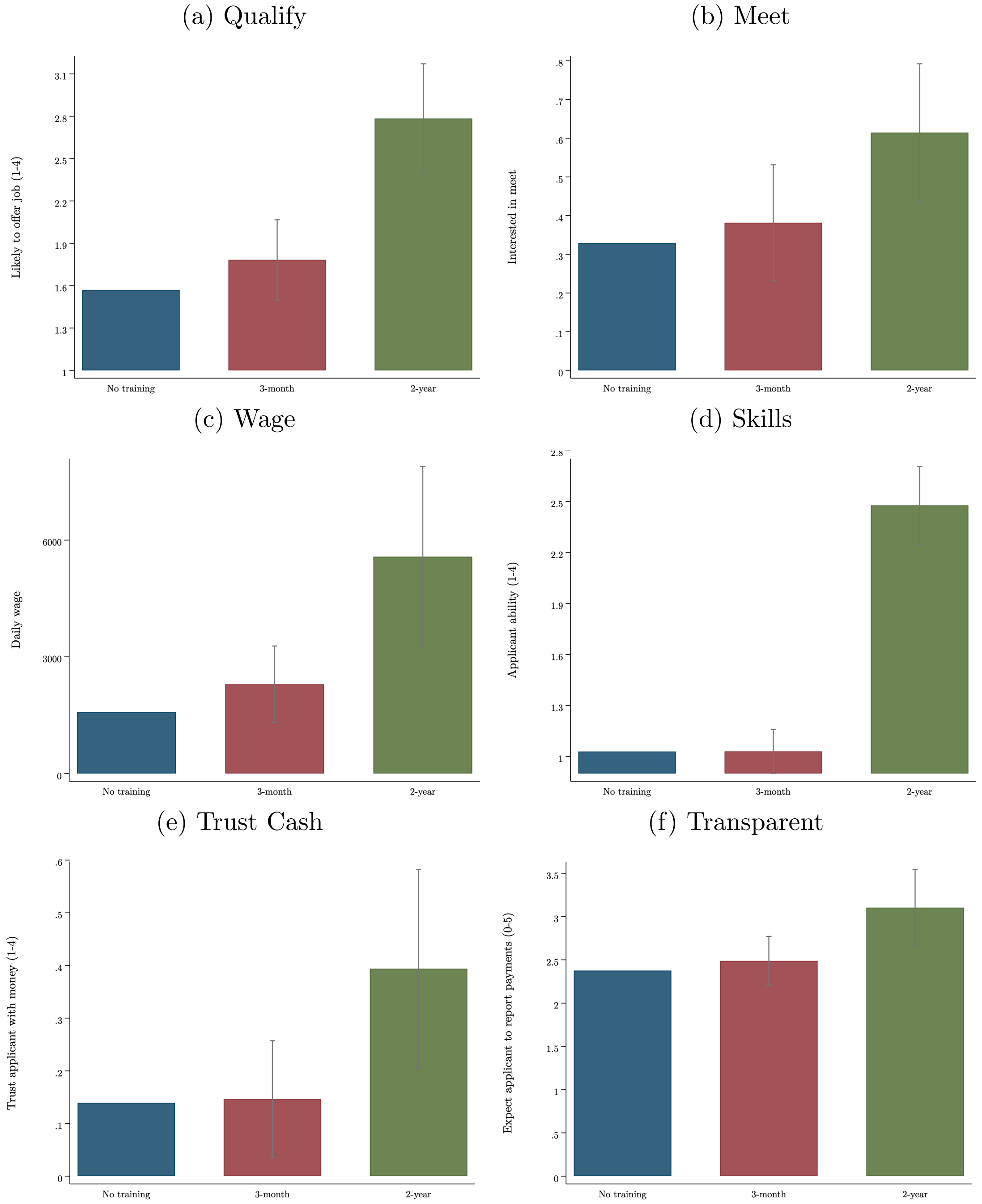
Note: This figure shows the predicted mean of the Qualify, Meet, Wage, Skills, Trust Cash, and Transparent outcomes for men and women separately. The estimates are from the fully saturated OLS model described in Equation (1). The control group mean is plotted without confidence interval. The remaining bars are based on the linear combination of coefficients for each treatment combination. The bars report 95 percent confidence intervals from a regression of each outcome on dummies for the treatment groups.

Figure 11: Experimental Results: monitoring



Note: This figure shows the predicted mean of the Qualify, Meet, Wage, Skills, Trust Cash, and Transparent outcomes for monitored and not-monitored candidates separately. The estimates are from the fully saturated OLS model described in Equation (2). The control group mean is plotted without confidence interval. The remaining bars are based on the linear combination of coefficients for each treatment combination. The bars report 95 percent confidence intervals from a regression of each outcome on dummies for the treatment groups.

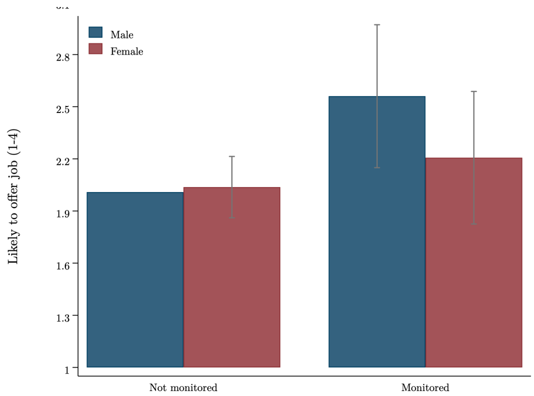
Figure 12: Experimental Results: training



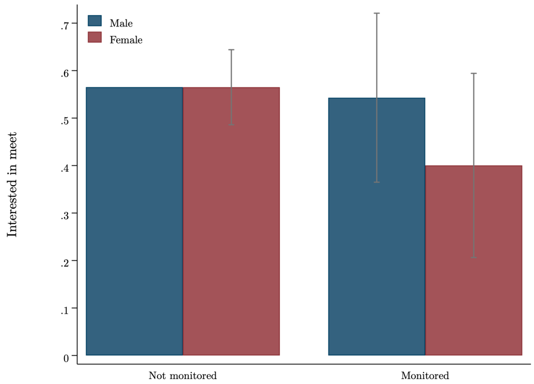
Note: This figure shows the predicted mean of the Qualify, Meet, Wage, Skills, Trust Cash, and Transparent outcomes for candidates based on their level of training (none, 3 months or 2 years). The estimates are from the fully saturated OLS model described in Equation (3). The control group mean is plotted without confidence interval. The remaining bars are based on the linear combination of coefficients for each treatment combination. The bars report 95 percent confidence intervals from a regression of each outcome on dummies for the treatment groups.

Figure 13: Experimental Results: female x monitoring

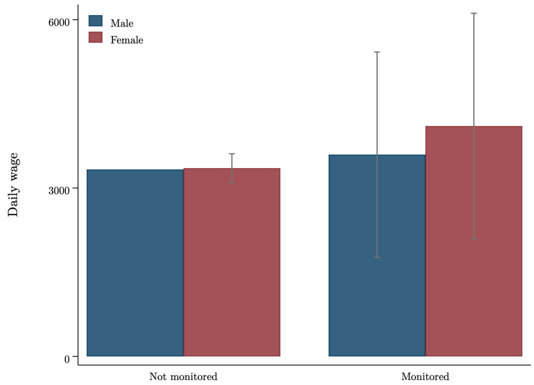
(a) Qualify



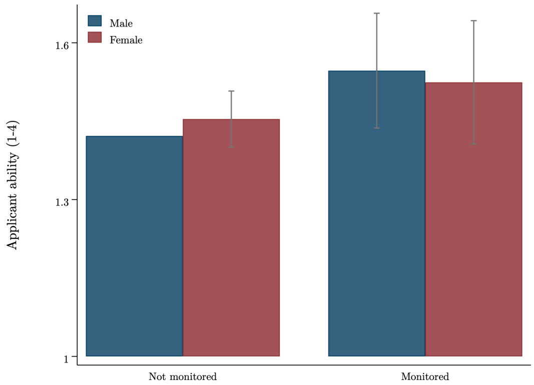
(b) Meet



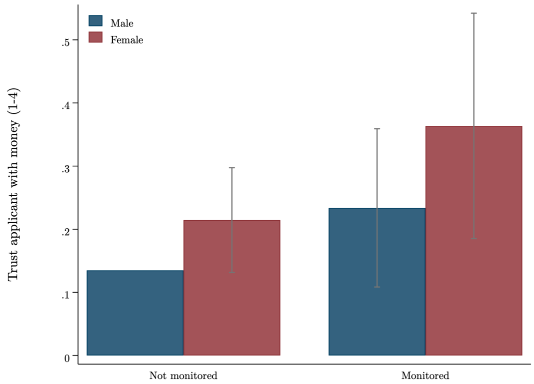
(c) Wage



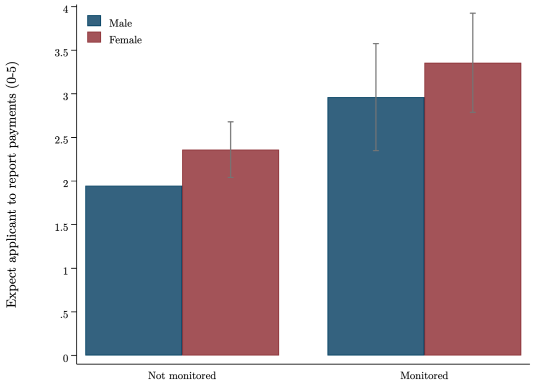
(d) Skills



(e) Trust Cash



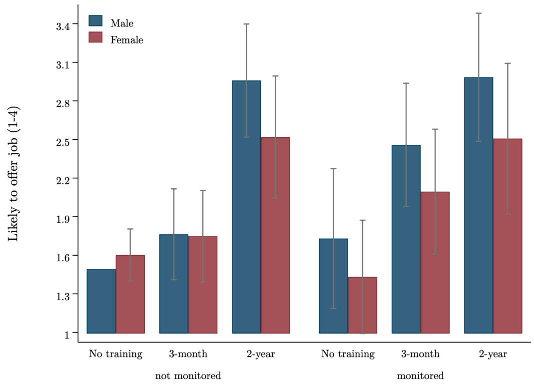
(f) Transparent



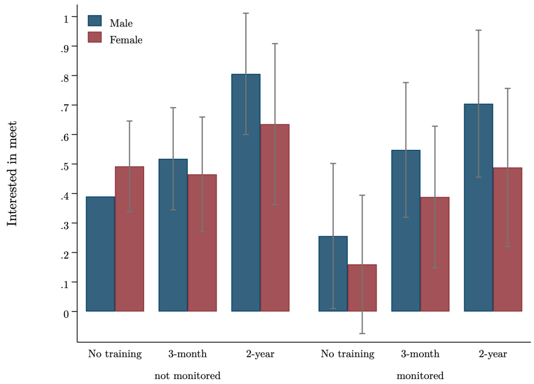
Note: This figure shows the predicted mean of the Qualify, Meet, Wage, Skills, Trust Cash, and Transparent outcomes the combination of the treatment dimensions: monitoring and gender. The estimates are from the fully saturated OLS model described in Equation (4). The control group mean is plotted without confidence interval. The remaining bars are based on the linear combination of coefficients for each treatment combination. The bars report 95 percent confidence intervals from a regression of each outcome on dummies for the treatment groups.

Figure 14: Experimental Results: full specification

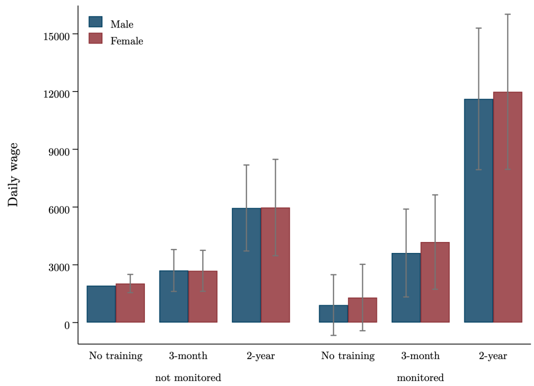
(a) Qualify



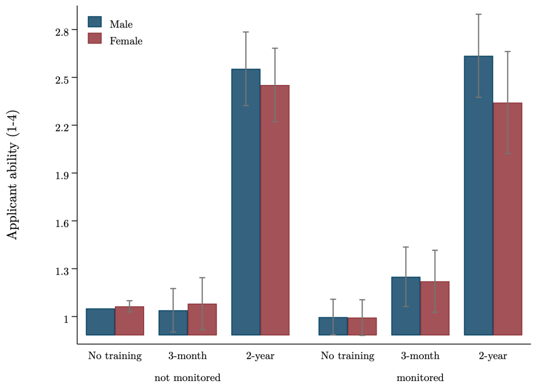
(b) Meet



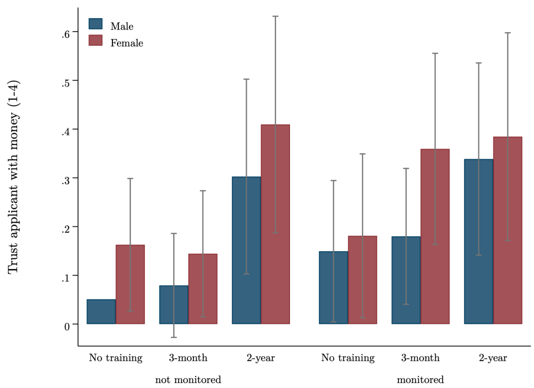
(c) Wage



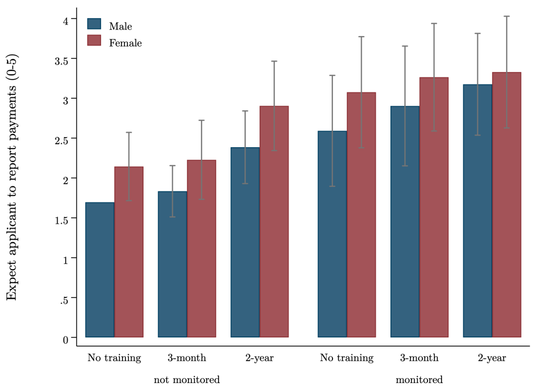
(d) Skills



(e) Trust Cash



(f) Transparent



Note: This figure shows the predicted mean of the Qualify, Meet, Wage, Skills, Trust Cash, and Transparent outcomes under various treatment combinations. The estimates are from the fully saturated OLS model described in (5). The control group mean is plotted without confidence interval. The remaining bars are based on the linear combination of coefficients for each treatment combination (e.g., $\beta_0 + \beta_1 + \beta_2 + \alpha_1$ for the female, low-training, no monitoring bar). The bars report 95 percent confidence intervals from a regression of each outcome on dummies for the treatment groups.

Tables

Table 1: Descriptive statistics

	Mean	SD	Min	Max	N
Firm					
firm size	16.05	12.32	1.00	66.00	40
firm age	11.75	9.09	1.00	52.00	40
employees w train (%)	0.51	0.31	0.00	1.00	39
trainees (%)	0.45	0.23	0.05	1.00	39
fully employed (%)	0.25	0.29	0.00	0.95	39
employees prior certif (%)	0.12	0.17	0.00	0.83	39
trainee wage (ugx)	6,800	6,552	0.00	25,000	40
time trainee (weeks)	58.70	45.96	4.00	208	40
customers per day	8.68	4.39	3.00	20.00	40
recurrent customers (%)	0.64	0.20	0.20	1.00	40
empl experience at entry (m)	28.02	51.63	0.00	288	40
job retention	0.49	0.27	0.00	0.90	40
any female employee	0.05	0.22	0.00	1.00	40
female employees (%)	0.00	0.02	0.00	0.10	39
m-f composition pref: 100-0	0.93	0.27	0.00	1.00	40
m-f composition pref: 75-25	0.07	0.27	0.00	1.00	40
job applicants (weekly)	2.17	1.75	0.00	7.00	40
Manager					
age	36.35	12.12	21.00	76.00	40
owner	0.62	0.49	0.00	1.00	40
experience (years)	16.38	12.10	4.00	55.00	40
monthly income (ugx)	384,750	273,195	100,000	1,200,000	40

Note: This table provides summary statistics of various characteristics of the garages/managers in our sample. N is 39 instead of 40 for variables about employees as one firm does not have any employees.

Table 2: Balance

Variable	(1) not monitored N	(1) not monitored Mean/(SE)	(2) monitored N	(2) monitored Mean/(SE)	(1)-(2) Pairwise t-test Mean difference
firm size	20	17.3	20	14.8	2.5
		(2.0)		(3.4)	
firm age	20	14.8	20	8.7	6.1**
		(2.5)		(1.2)	
employees w train (%)	20	0.4	19	0.6	-0.2*
		(0.1)		(0.1)	
trainees (%)	20	0.4	19	0.5	-0.0
		(0.0)		(0.1)	
fully employed (%)	20	0.4	19	0.1	0.3***
		(0.1)		(0.0)	
employees prior certif (%)	20	0.2	19	0.0	0.1***
		(0.0)		(0.0)	
trainee wage (ugx)	20	8850.0	20	4750.0	4100.0**
		(1837.2)		(767.3)	
time trainee (weeks)	20	79.8	20	37.6	42.2***
		(11.1)		(6.9)	
customers per day	20	6.7	20	10.7	-4.0***
		(0.7)		(1.1)	
recurrent customers (%)	20	0.6	20	0.7	-0.1
		(0.0)		(0.0)	
empl experience at entry (m)	20	35.1	20	20.9	14.2
		(14.9)		(6.7)	
job retention	20	0.4	20	0.5	-0.1
		(0.1)		(0.1)	
any female employee	20	0.1	20	0.1	0.0
		(0.1)		(0.1)	
female employees (%)	20	0.0	19	0.0	0.0
		(0.0)		(0.0)	
m-f composition pref: 100-0	20	0.9	20	0.9	0.0
		(0.1)		(0.1)	
m-f composition pref: 75-25	20	0.1	20	0.1	-0.1
		(0.1)		(0.1)	
job applicants (daily)	20	1.8	20	2.6	-0.9
		(0.4)		(0.4)	
manager age	20	40.5	20	32.2	8.3**
		(2.9)		(2.2)	
manager is owner	20	0.7	20	0.6	0.1
		(0.1)		(0.1)	
manager experience (years)	20	21.1	20	11.6	9.5**
		(3.0)		(1.9)	
manager monthly income (ugx)	20	434500.0	20	335000.0	99500.0
		(75937.9)		(40409.1)	

Note: This table provides a baseline balance check. Column 6 lists the mean differences and indicates the significance level of a t-test of that difference using robust standard errors. Significance: ***=.01, **=.05, *=.1.

Table 3: Outcomes

Question Wording	**Outcome**
Based on your first impression, how likely would you be to offer this job applicant a position as a mechanic (trainee)? Please respond on a scale from 1 to 4, where 1 is not likely at all and 4 is very likely.	Offer Job
Based on your first impression, How would you rate the job applicant ability to do the service to vehicles your garage handles (e.g., cars or bodas)? Please respond on a scale from 1 to 4, where 1 is not skilled at all and 4 is very skilled.	Job Skills
Based on your first impression, would you trust this trainee with business money?	Trust w Cash
If you were to hire this applicant, what daily wage would you offer this job applicant during the trainee period?	Wage
Do you want us to refer to you a similar applicant to start a trainee period at your garage?	Meet
Imagine you hire this trainee. How likely do you think it is that the trainee will accurately report to you the full amount of any direct payments received from clients? To answer this question, think of how many times out of 5 direct payments, the trainee will be transparent. Please indicate your estimate on a scale of 0 to 5, with 0 being never transparent at all and 5 being always transparent.	Transparent

Note: This table describes the survey questions corresponding to the six outcome variables used in the empirical strategy.

Table 4: OLS gender - baseline sample, standardized outcomes

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	0.0325	0.00373	0.00839	0.151	0.361*	0.300**
	[0.121]	[0.0804]	[0.0445]	[0.122]	[0.186]	[0.114]
Observations	350	350	350	350	350	350
R-squared	0.120	0.119	0.018	0.068	0.067	0.155
control mean	0.158	-0.138	-0.159	-0.115	0.229	0.313

Note: This table summarizes the analysis of the effect of the gender on hiring outcomes. The outcome variables are standardised with respect to the control mean and variance. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The sample are managers who evaluate CVs with low or no training. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect of monitoring on hiring outcomes - baseline sample, standardized outcomes

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
monitored	0.480*	-0.190	0.174	0.440*	0.558	0.727***
	[0.244]	[0.182]	[0.330]	[0.257]	[0.354]	[0.199]
Observations	706	706	631	706	706	705
R-squared	0.106	0.105	0.019	0.060	0.078	0.229
control mean	0.634	0.318	0.496	1.652	0.580	0.342

Note: This table summarizes the analysis of the effect of the monitoring support treatment on hiring outcomes. The outcome variables are standardised with respect to the control mean and variance. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The sample are managers who evaluate CVs with low or no training. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effect of training on hiring outcomes - baseline sample, standardized outcomes

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
3-month	0.284	0.106	0.250	0.00281	0.0333	0.0813
	[0.180]	[0.146]	[0.165]	[0.280]	[0.239]	[0.0979]
2-year	1.616***	0.580***	1.405***	6.534***	1.150**	0.527***
	[0.247]	[0.173]	[0.390]	[0.493]	[0.406]	[0.153]
Observations	463	463	463	463	463	463
R-squared	0.307	0.142	0.148	0.786	0.106	0.144
control mean	0.104	-0.123	-0.117	-0.096	0.399	0.493

Note: This table summarizes the analysis of the effect of training on hiring outcomes. The outcome variables are standardised with respect to the control mean and variance. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The sample are managers who receive no monitoring support. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: OLS gender x monitoring - baseline sample, standardized outcomes

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	0.0381	-0.000474	0.00807	0.146	0.360*	0.299**
	[0.116]	[0.0795]	[0.0447]	[0.120]	[0.185]	[0.114]
monitored	0.734***	-0.0453	0.0927	0.564**	0.447	0.735***
	[0.271]	[0.179]	[0.318]	[0.245]	[0.280]	[0.220]
female × monitored	-0.509**	-0.290**	0.171	-0.246	0.226	-0.0130
	[0.200]	[0.123]	[0.129]	[0.189]	[0.252]	[0.161]
Observations	706	706	631	706	706	705
R-squared	0.121	0.115	0.021	0.062	0.097	0.251
control mean	0.688	0.357	0.498	1.674	0.379	0.183

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on indicators for the gender and monitoring treatments and their interaction. The outcome variables are standardised with respect to the control mean and variance. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. The sample are managers who evaluate CVs with no monitoring. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: OLS gender x train x monitoring - full sample, standardized outcomes

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	0.147	0.208	0.0395	0.0584	0.505	0.325**
	[0.133]	[0.155]	[0.0823]	[0.0789]	[0.303]	[0.153]
3-month	0.361	0.260	0.278	-0.0526	0.128	0.100
	[0.232]	[0.174]	[0.189]	[0.304]	[0.238]	[0.115]
2-year	1.952***	0.845***	1.420***	6.782***	1.136**	0.500***
	[0.289]	[0.207]	[0.388]	[0.515]	[0.446]	[0.163]
female × 3-month	-0.167	-0.315	-0.0456	0.129	-0.211	-0.0394
	[0.196]	[0.189]	[0.0984]	[0.118]	[0.327]	[0.142]
female × 2-year	-0.732**	-0.554***	-0.0313	-0.516	-0.0221	0.0509
	[0.284]	[0.141]	[0.0913]	[0.379]	[0.472]	[0.160]
monitored	0.317	-0.272	-0.354	-0.246	0.445	0.649**
	[0.358]	[0.247]	[0.274]	[0.250]	[0.324]	[0.249]
female × monitored	-0.544*	-0.404**	0.0980	-0.0718	-0.362	0.0258
	[0.283]	[0.190]	[0.145]	[0.0919]	[0.401]	[0.201]
3-month × monitored	0.609*	0.333	0.673*	1.194***	0.0101	0.126
	[0.332]	[0.260]	[0.354]	[0.437]	[0.372]	[0.169]
2-year × monitored	-0.283	0.0669	2.348***	0.614	-0.282	-0.0771
	[0.470]	[0.302]	[0.731]	[0.725]	[0.534]	[0.217]
female × 3-month × monitored	0.0793	0.186	0.109	-0.242	0.878*	-0.0503
	[0.316]	[0.245]	[0.162]	[0.240]	[0.468]	[0.193]
female × 2-year × monitored	0.493	0.310	0.0235	-0.795	0.0867	-0.291
	[0.460]	[0.269]	[0.270]	[0.561]	[0.583]	[0.223]
Observations	936	936	848	936	936	934
R-squared	0.261	0.173	0.343	0.708	0.117	0.255
control mean	0.000	-0.000	-0.000	0.000	0.000	0.000
p-value (3-month = 2-year)	0.000	0.000	0.000	0.000	0.011	0.002

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on indicators for the gender, training, and training treatment levels and their interactions. The outcome variables are standardized with respect to the control mean and variance. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. The bottom row reports the p-value of a hypothesis test that the 3-month coefficient is equal to the 2-year coefficient. The sample are all evaluations done by all managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A Appendix

A.1 Appendix Tables

Table A.1: OLS gender - baseline sample

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	0.0244	0.00183	23.86	0.0334	0.0800*	0.414**
	[0.0912]	[0.0395]	[126.6]	[0.0271]	[0.0413]	[0.157]
Observations	350	350	350	350	350	350
R-squared	0.120	0.119	0.018	0.068	0.067	0.155
control mean	2.225	0.546	4144.186	1.480	0.178	2.429

Note: This table summarizes the analysis of the effect of the gender on hiring outcomes. The outcome variables are not standardised. Outcomes measures are reported in Table 3. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The sample are managers who evaluate CVs with low or no training. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: OLS monitor - no or low training sample

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
monitored	0.361*	-0.0934	494.3	0.0975*	0.124	1.003***
	[0.183]	[0.0898]	[938.1]	[0.0570]	[0.0785]	[0.275]
Observations	706	706	631	706	706	705
R-squared	0.106	0.105	0.019	0.060	0.078	0.229
control mean	1.968	0.546	3323.974	1.417	0.179	2.166

Note: This table summarizes the analysis of the effect of monitoring on hiring outcomes. The outcome variables are not standardised. Outcomes measures are reported in Table 3. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The sample are managers who evaluate CVs with low or no training. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: OLS training - no monitoring sample

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
3-month	0.214	0.0524	710.8	0.000622	0.00737	0.112
	[0.136]	[0.0716]	[470.4]	[0.0621]	[0.0529]	[0.135]
2-year	1.215***	0.285***	3993.0***	1.448***	0.255**	0.727***
	[0.185]	[0.0851]	[1107.9]	[0.109]	[0.0899]	[0.211]
Observations	463	463	463	463	463	463
R-squared	0.307	0.142	0.148	0.786	0.106	0.144
control mean	1.570	0.329	1582.164	1.030	0.139	2.376

Note: This table summarizes the analysis of the effect of training on hiring outcomes. The outcome variables are not standardised. Outcomes measures are reported in Table 3. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The sample are managers who evaluate CVs with low or no training. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: OLS gender x monitoring - baseline sample

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	0.0286	-0.000233	22.95	0.0323	0.0797*	0.412**
	[0.0873]	[0.0391]	[127.0]	[0.0265]	[0.0410]	[0.157]
monitored	0.552***	-0.0223	263.4	0.125**	0.0990	1.014***
	[0.203]	[0.0880]	[903.5]	[0.0543]	[0.0620]	[0.304]
female × monitored	-0.383**	-0.142**	486.6	-0.0546	0.0501	-0.0179
	[0.150]	[0.0607]	[365.4]	[0.0419]	[0.0559]	[0.222]
Observations	706	706	631	706	706	705
R-squared	0.121	0.115	0.021	0.062	0.097	0.251
control mean	2.009	0.565	3330.435	1.422	0.135	1.948

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on indicators for the gender and monitoring treatments and their interaction. The outcome variables are not standardised. Outcomes measures are reported in Table 3. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. The sample are managers who evaluate CVs with no monitoring. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: OLS gender x train x monitoring

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	0.111	0.102	112.4	0.0129	0.112	0.449**
	[0.0999]	[0.0760]	[234.0]	[0.0175]	[0.0672]	[0.212]
3-month	0.271	0.128	789.8	-0.0117	0.0284	0.138
	[0.175]	[0.0857]	[537.3]	[0.0674]	[0.0527]	[0.159]
2-year	1.467***	0.416***	4036.2***	1.503***	0.252**	0.690***
	[0.217]	[0.102]	[1103.4]	[0.114]	[0.0988]	[0.225]
female × 3-month	-0.126	-0.155	-129.6	0.0285	-0.0468	-0.0543
	[0.148]	[0.0932]	[279.8]	[0.0262]	[0.0724]	[0.197]
female × 2-year	-0.550**	-0.273***	-89.01	-0.114	-0.00490	0.0702
	[0.214]	[0.0693]	[259.5]	[0.0840]	[0.105]	[0.221]
monitored	0.238	-0.134	-1006.6	-0.0545	0.0985	0.896**
	[0.269]	[0.122]	[778.8]	[0.0553]	[0.0717]	[0.344]
female × monitored	-0.409*	-0.199**	278.6	-0.0159	-0.0802	0.0356
	[0.213]	[0.0936]	[413.4]	[0.0204]	[0.0888]	[0.277]
3-month × monitored	0.457*	0.164	1913.0*	0.264***	0.00224	0.174
	[0.249]	[0.128]	[1006.0]	[0.0969]	[0.0824]	[0.234]
2-year × monitored	-0.212	0.0329	6673.9***	0.136	-0.0625	-0.106
	[0.353]	[0.149]	[2077.2]	[0.161]	[0.118]	[0.299]
female × 3-month × monitored	0.0596	0.0917	309.0	-0.0535	0.195*	-0.0694
	[0.238]	[0.121]	[459.5]	[0.0532]	[0.104]	[0.267]
female × 2-year × monitored	0.370	0.152	66.87	-0.176	0.0192	-0.401
	[0.346]	[0.132]	[766.5]	[0.124]	[0.129]	[0.307]
Observations	936	936	848	936	936	934
R-squared	0.261	0.173	0.343	0.708	0.117	0.255
control mean	1.492	0.390	1915.254	1.051	0.051	1.695
p-value (3-month = 2-year)	0.000	0.000	0.000	0.000	0.011	0.002

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on indicators for the gender, training, and training treatment levels and their interactions. The outcome variables are not standardised. Outcomes measures are reported in Table 3. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. The bottom row reports the p-value of a hypothesis test that the 3-month coefficient is equal to the 2-year coefficient. The sample are all evaluations done by all managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: OLS gender - full sample, standardized outcomes

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	-0.318***	-0.206***	0.0696	-0.241**	0.437***	0.276***
	[0.105]	[0.0633]	[0.0565]	[0.117]	[0.114]	[0.0757]
Observations	936	936	848	936	936	934
R-squared	0.085	0.092	0.016	0.024	0.055	0.107
control mean	0.976	0.318	0.784	1.935	0.573	0.532

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on an indicator for the gender treatment. The outcome variables are standardised with respect to the control mean and variance. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: OLS gender - full sample

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	-0.239***	-0.101***	198.0	-0.0535**	0.0969***	0.382***
	[0.0792]	[0.0311]	[160.5]	[0.0259]	[0.0251]	[0.104]
Observations	936	936	848	936	936	934
R-squared	0.085	0.092	0.016	0.024	0.055	0.107
control mean	2.225	0.546	4144.186	1.480	0.178	2.429

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on an indicator for the gender treatment. The outcome variables are not standardised. Outcomes measures are reported in Table 3. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: OLS monitor - full sample, standardized outcomes

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
monitored	0.370	-0.201	0.714*	0.337	0.434	0.659***
	[0.224]	[0.170]	[0.354]	[0.291]	[0.387]	[0.185]
Observations	936	936	848	936	936	934
R-squared	0.089	0.091	0.050	0.025	0.054	0.203
control mean	0.634	0.318	0.496	1.652	0.580	0.342

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on an indicator for the monitoring treatment. The outcome variables are standardised with respect to the control mean and variance. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: OLS monitor - full sample

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
monitored	0.278	-0.0991	2029.7*	0.0746	0.0961	0.909***
	[0.168]	[0.0835]	[1006.1]	[0.0644]	[0.0856]	[0.255]
Observations	936	936	848	936	936	934
R-squared	0.089	0.091	0.050	0.025	0.054	0.203
control mean	1.968	0.546	3323.974	1.417	0.179	2.166

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on an indicator for the monitoring treatment. The outcome variables are not standardised. Outcomes measures are reported in Table 3. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: OLS training - full sample, standardized outcomes

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
3-month	0.607***	0.313***	0.578***	0.555**	0.254	0.138**
	[0.140]	[0.109]	[0.160]	[0.238]	[0.161]	[0.0590]
2-year	1.572***	0.677***	2.525***	6.636***	1.004***	0.417***
	[0.187]	[0.128]	[0.418]	[0.376]	[0.246]	[0.0893]
Observations	936	936	848	936	936	934
R-squared	0.214	0.136	0.262	0.694	0.080	0.111
control mean	0.104	-0.123	-0.117	-0.096	0.399	0.493

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on an indicator for the training treatment. The outcome variables are standardised with respect to the control mean and variance. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: OLS training - full sample

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
3-month	0.456***	0.154***	1642.9***	0.123**	0.0562	0.191**
	[0.105]	[0.0538]	[456.0]	[0.0526]	[0.0357]	[0.0814]
2-year	1.181***	0.333***	7176.4***	1.470***	0.223***	0.576***
	[0.140]	[0.0632]	[1189.2]	[0.0832]	[0.0546]	[0.123]
Observations	936	936	848	936	936	934
R-squared	0.214	0.136	0.262	0.694	0.080	0.111
control mean	1.570	0.329	1582.164	1.030	0.139	2.376

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on an indicator for the gender treatment. The outcome variables are not standardised. Outcomes measures are reported in Table 3. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: OLS gender x monitoring - full sample, standardized outcomes

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	-0.125	-0.0881	-0.00157	-0.0527	0.386**	0.314***
	[0.111]	[0.0826]	[0.0453]	[0.143]	[0.181]	[0.107]
monitored	0.558**	-0.0851	0.621*	0.521*	0.382	0.695***
	[0.242]	[0.162]	[0.334]	[0.283]	[0.327]	[0.198]
female × monitored	-0.379*	-0.234*	0.195	-0.371	0.107	-0.0692
	[0.203]	[0.122]	[0.130]	[0.229]	[0.228]	[0.150]
Observations	936	936	848	936	936	934
R-squared	0.105	0.105	0.051	0.027	0.068	0.225
control mean	0.688	0.357	0.498	1.674	0.379	0.183

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on indicators for the gender and monitoring treatments and their interaction. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: OLS gender x monitoring - full sample

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	-0.0939	-0.0433	-4.454	-0.0117	0.0854**	0.434***
	[0.0835]	[0.0406]	[128.7]	[0.0317]	[0.0401]	[0.147]
monitored	0.419**	-0.0419	1763.7*	0.116*	0.0847	0.959***
	[0.182]	[0.0796]	[948.3]	[0.0627]	[0.0724]	[0.274]
female × monitored	-0.285*	-0.115*	554.4	-0.0822	0.0236	-0.0955
	[0.152]	[0.0600]	[369.8]	[0.0507]	[0.0505]	[0.207]
Observations	936	936	848	936	936	934
R-squared	0.105	0.105	0.051	0.027	0.068	0.225
control mean	2.009	0.565	3330.435	1.422	0.135	1.948

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on indicators for the gender and monitoring treatments and their interaction. The outcome variables are not standardised. Outcomes measures are reported in Table 3. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.14: OLS gender x train - full sample, standardized outcomes

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	-0.123	0.00983	0.0893	0.0229	0.324	0.335***
	[0.147]	[0.101]	[0.0708]	[0.0403]	[0.197]	[0.102]
3-month	0.676***	0.427***	0.587***	0.555**	0.140	0.171**
	[0.173]	[0.134]	[0.175]	[0.239]	[0.184]	[0.0838]
2-year	1.813***	0.877***	2.541***	7.092***	0.997***	0.467***
	[0.236]	[0.154]	[0.408]	[0.370]	[0.249]	[0.106]
female × 3-month	-0.136	-0.226*	-0.0175	-0.000461	0.226	-0.0653
	[0.159]	[0.127]	[0.0776]	[0.119]	[0.246]	[0.0978]
female × 2-year	-0.488**	-0.404***	-0.0330	-0.920***	0.0210	-0.0938
	[0.236]	[0.135]	[0.113]	[0.288]	[0.283]	[0.116]
Observations	936	936	848	936	936	934
R-squared	0.229	0.151	0.263	0.698	0.094	0.132
control mean	0.158	-0.138	-0.159	-0.115	0.229	0.313
p-value (3-month = 2-year)	0.000	0.000	0.000	0.000	0.002	0.004

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on indicators for the gender and training treatment levels and their interactions. The outcome variables are standardised with respect to the control mean and variance. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. The bottom row reports the p-value of a hypothesis test that the 3-month coefficient is equal to the 2-year coefficient. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.15: OLS gender x train - full sample

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
female	-0.0923	0.00483	253.7	0.00508	0.0718	0.462***
	[0.111]	[0.0497]	[201.4]	[0.00893]	[0.0436]	[0.141]
3-month	0.508***	0.210***	1667.6***	0.123**	0.0310	0.235**
	[0.130]	[0.0661]	[496.4]	[0.0530]	[0.0409]	[0.116]
2-year	1.362***	0.431***	7223.0***	1.571***	0.221***	0.644***
	[0.178]	[0.0756]	[1161.0]	[0.0820]	[0.0552]	[0.147]
female × 3-month	-0.103	-0.111*	-49.70	-0.000102	0.0500	-0.0902
	[0.119]	[0.0623]	[220.6]	[0.0265]	[0.0544]	[0.135]
female × 2-year	-0.367**	-0.199***	-93.86	-0.204***	0.00465	-0.130
	[0.177]	[0.0663]	[319.8]	[0.0639]	[0.0626]	[0.160]
Observations	936	936	848	936	936	934
R-squared	0.229	0.151	0.263	0.698	0.094	0.132
control mean	1.610	0.322	1462.963	1.025	0.102	2.127
p-value (3-month = 2-year)	0.000	0.000	0.000	0.000	0.002	0.004

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on indicators for the gender and training treatment levels and their interactions. Outcomes measures are reported in Table 3. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. The bottom row reports the p-value of a hypothesis test that the 3-month coefficient is equal to the 2-year coefficient. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16: OLS train x monitoring - full sample, standardized outcomes

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
3-month	0.277	0.101	0.255	0.0131	0.0222	0.0809
	[0.185]	[0.143]	[0.164]	[0.312]	[0.234]	[0.0935]
2-year	1.589***	0.569***	1.404***	6.526***	1.120***	0.522***
	[0.248]	[0.172]	[0.389]	[0.486]	[0.400]	[0.149]
monitored	0.0450	-0.475**	-0.308	-0.282	0.261	0.660***
	[0.281]	[0.217]	[0.275]	[0.243]	[0.368]	[0.225]
3-month × monitored	0.648**	0.428**	0.725**	1.071**	0.450	0.101
	[0.259]	[0.206]	[0.324]	[0.440]	[0.318]	[0.117]
2-year × monitored	-0.0356	0.223	2.361***	0.221	-0.235	-0.220
	[0.378]	[0.252]	[0.752]	[0.740]	[0.510]	[0.176]
Observations	936	936	848	936	936	934
R-squared	0.242	0.154	0.342	0.702	0.099	0.232
control mean	0.084	0.113	0.021	0.036	0.264	0.160

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on indicators for the monitoring and training treatment levels and their interactions. The outcome variables are standardised with respect to the control mean and variance. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. The bottom row reports the p-value of a hypothesis test that the 3-month coefficient is equal to the 2-year coefficient. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17: OLS train x monitoring - full sample

	(1) offer job	(2) meet	(3) wage	(4) job skills	(5) trust w cash	(6) transparent
3-month	0.208	0.0497	724.6	0.00290	0.00491	0.112
	[0.139]	[0.0702]	[465.0]	[0.0692]	[0.0519]	[0.129]
2-year	1.194***	0.280***	3990.5***	1.446***	0.248***	0.721***
	[0.186]	[0.0847]	[1105.8]	[0.108]	[0.0886]	[0.206]
monitored	0.0338	-0.233**	-875.6	-0.0624	0.0578	0.912***
	[0.211]	[0.107]	[782.8]	[0.0538]	[0.0815]	[0.310]
3-month × monitored	0.487**	0.210**	2061.2**	0.237**	0.0997	0.140
	[0.195]	[0.101]	[919.5]	[0.0976]	[0.0705]	[0.161]
2-year × monitored	-0.0267	0.110	6711.8***	0.0491	-0.0521	-0.303
	[0.284]	[0.124]	[2137.7]	[0.164]	[0.113]	[0.243]
Observations	936	936	848	936	936	934
R-squared	0.242	0.154	0.342	0.702	0.099	0.232
control mean	1.555	0.445	1974.790	1.059	0.109	1.916

Note: This table reports the results of a multivariate OLS regression of various outcomes variables on indicators for the monitoring and training treatment levels and their interactions. Outcomes measures are reported in Table 3. Resume fixed effects are included but not reported in the table. Standard errors are clustered by respondent. The control group is the male, no monitoring, no training group. The bottom row reports the p-value of a hypothesis test that the 3-month coefficient is equal to the 2-year coefficient. We use the full sample of managers. Standard errors in brackets * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.2 Vocational Training programs - Mechanics

Motor Vehicle mechanics is one of the occupations/courses offered by government and private Vocational institutions.

All trainees/students are assessed under the guidelines and offered certificates from the Uganda Directorate of Industrial Training.

After training, a trainee/student is awarded a certificate or transcript by DIT according to the law.

Certificate These are nationally recognized certificates awarded in levels 1-4.

- Level 1:
  - Accomplished 3 years of post P.7 full-time Technical/Vocational schooling in the occupation evidenced by coverage of Assessment and Training Package (ATP).
  - On-the-job apprenticeship training program from registered enterprises or training centers (coverage of ATP).
  - Accumulated industrial experience and routine practice of specific tasks of the occupation under the guidance of a skilled supervisor/master.
  - Upgrading through accumulated modular assessments and certification.
- Level II:
  - Accomplished 2 years of post S.IV full-time Technical/Vocational institute training in the occupation evidenced by coverage of ATP.
  - Upgrading from UVQF level I award.
- Level III:
  - Upgrading from UVQF level II award.
  - Graduates of higher education with direct S.VI entry and whose practical skills are to be validated for the job market.
  - An entrepreneur of SME's recognized by UMA, PSFU, and USSIA.

  - BTVET instructor having accomplished at least 9 months of in-service instructor training program at an approved center.

- Level IV:
  - BTVET instructor with a minimum of Diploma technical qualification and having accomplished at least 9 months of in-service instructor training program at an approved center.
  - Upgrading from UVQF level III award.

Modular

- Modules are part(s) of a whole curriculum. They can be considered as "self-contained" partial qualifications described by learning outcomes or competencies and can be assessed and certified individually.
- A person who completes a module and takes an assessment for it is awarded a modular transcript.
- A single module can be completed in a period of 3 months.
- Once all the modules of an occupation have been fully completed and assessed, the trainee is awarded a Certificate.