Can a Soft Skill Signal Mitigate Hiring Discrimination? Evidence from Malaysia*

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September 10, 2026

Abstract

Hiring discrimination remains widespread, raising the question of how disadvantaged workers can improve their labor-market outcomes. Using a correspondence study in Malaysia, we test whether employers value two soft skills, leadership and teamwork, and whether signaling them mitigates discrimination. Applications with Malay and Indian names are 11–14 percentage points less likely to be contacted than those with Chinese names; we find no gender-based discrimination. Signaling teamwork reduces ethnic discrimination by 34–43%, while leadership has no effect. We develop a model using skill signals to distinguish taste-based from statistical discrimination. Our results indicate soft skills can counteract statistical discrimination.

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This RCT was registered as AEARCTR-001 1591. A dated Pre-Analysis Plan, populated Pre-Analysis plan and IRB information are available in the link: https://www.socialscienceregistry.org/trials/11591. We thank Yilan Xu, Catalina Herrera Almanza, Hwok Aun Lee, Marieke Kleemans, Harry Moroz, Apurva Sanghi, Omar Arias, Manuel Salazar, participants at the 2025 Bogota Experimental Economics Conference, and participants at the 2025 Midwest International Economic Development Conference for helpful comments. We also thank Quin Karhoff and Cheng Fang Ling for excellent research assistance.

1 Introduction

Hiring discrimination has been documented in many labor markets (see Bertrand and Duflo (2017) and Neumark (2018) for recent reviews). Affirmative action policies emerged in the 1960s as a formal response to hiring and other forms of discrimination faced by racial and ethnic minorities and women. More recently, diversity, equity and inclusion programs have been widely implemented in many settings with similar objectives. These policies and programs have been controversial, in part due to differing opinions about the role of individuals, organizations, government, and society in addressing historical and ongoing discrimination. Still, access to jobs shapes individual decisions on schooling, work, and fertility, among others (Heath and Mobarak, 2015). Hiring discrimination may thus have lasting consequences for human capital accumulation beyond its immediate labor market effects. In this paper we document hiring discrimination and ask whether affected groups can counteract existing discrimination through signals on a job application. Specifically, we test whether signaling teamwork or leadership skills on a job application can reduce the observed discrimination gap.

To answer this question, we conduct a correspondence study using a large online job platform to assess demand for soft skills in Malaysia.[1] By randomly assigning similar fictitious applicants to advertised entry level jobs, we measure the extent of ethnicity-based (Malay/ Chinese/ Indian) and gender-based (male/female) discrimination in the Malaysian private sector. We then test whether employers respond to randomly assigned signals of two soft skills: teamwork and leadership. Skills are presented through an executive statement on the resume, and through professional, non-professional, and extra-curricular experiences. Our primary empirical contribution lies in testing how a randomly assigned soft skill interacts with a randomly assigned ethnicity to alter the discrimination gap.

We find evidence of ethnicity-based, but not gender-based, discrimination in Malaysia. Relative to individuals with Chinese-sounding names, companies in Malaysia are 11 percentage points less likely to contact candidates with Malay-sounding names, and 14 percentage points less likely to contact candidates with Indian-sounding names. These estimates are in line with earlier evidence of ethnic discrimination in Malaysia. Using a correspondence study approach, Lee and Khalid (2016) found a 18 percentage point difference in callback rates between applications with Malay and Chinese resumes. We observe no differences in callback rates for applications with male-sounding names compared to female-sounding names, despite large differences in labor force participation rates and wages in Malaysia (Department of Statistics Malaysia, 2022).

[1]The RCT was registered as AEARCTR-001 1591. A dated Pre-Analysis Plan, populated Pre-Analysis plan and IRB information are available in the link: https://www.socialscienceregistry.org/trials/11591

Recent employment trends suggest heightened demand for soft skills (Heckman and Kautz, 2012; Weidmann and Deming, 2021) like teamwork, leadership, communication, problem-solving, and emotional intelligence. Yet little is known about what kinds of soft skills employers value in modern entry-level jobs (Heller and Kessler, 2022). Our study compares two soft skills – teamwork and leadership – against a counterfactual candidate. Our results provide no evidence that teamwork or leaderships skills independently improve the likelihood that an employer chooses to contact a candidate *on average*.

Importantly, we show the average effects mask important heterogeneity, highlighting a potential pathway for counteracting discrimination. Our results suggest signaling an aptitude for teamwork narrows the baseline discrimination gap by 6-7 percentage points. This translates to a 34-43% reduction of the observed discrimination gap, consistent with both higher callback rates for Malay and Indian applicants who signal teamwork and a decline in callbacks for Chinese applicants who do so. Together, these results provide novel evidence that an employer's response to a soft skill signal is likely to depend both on the soft skill and the applicant group. This suggests soft skills development and strategic signaling can play an important role in counteracting hiring discrimination.

Our paper makes three primary contributions. First, researchers have long sought to determine the nature of observed discrimination theoretically (Coate and Loury, 1993; Knowles et al., 2001), and empirically (Oreopoulos, 2011; Bosch et al., 2010; Bartoš et al., 2016; Kaas and Manger, 2012; Edelman et al., 2017). Taste-based discrimination occurs when employers derive utility from hiring a candidate based on a specific demographic characteristic (Becker, 1971). In contrast, statistical discrimination (Phelps, 1972; Arrow et al., 1973) arises when employers hire based on their belief that workers of a less favored group have deficiency in some skills (Lang and Lehmann, 2012). Unpacking the nature of discrimination is challenging in part because we rarely observe the employer's expectation of candidate productivity. Instead, we are likely to only observe whether the candidate receives an invitation to interview or other downstream hiring outcomes.[2] To overcome this issue, we build on a theoretical model presented by Ewens et al. (2014). Our model suggests that productivity signals (like leadership or teamwork) will unambiguously increase the discrimination gap under taste-based discrimination, but it may increase or decrease the discrimination gap under statistical discrimination. We generalize the model of statistical discrimination presented in Ewens et al. (2014) in two ways, first by having a concave utility that allows for a discrimination gap shrinkage that goes beyond the linear difference in the signal. Then, by allowing productivity signals to be interpreted by the employer as positive or negative according to the candidate's ethnicity, rather than assuming employers unambiguously interpret signals as positive. Our empirical results show a reduction in the discrimination gap when a teamwork skill is signaled. We argue

[2]Morgan and Várdy (2009) present a theoretical model on statistical discrimination in the interview process.

this finding provides evidence of statistical discrimination.

Second, we add to a burgeoning literature studying the role of soft skills in the job market. Recent evidence suggests employers value specific signals in the labor market (Busso et al., 2025), that more resources are being targeted to have better measurements of skills (Laajaj and Macours, 2021), and soft skills can improve employability (Schlosser and Shanan, 2025). Yet surprisingly little is known about what kinds of soft skills employers value in modern entry-level jobs (Heller and Kessler, 2022). Experimental evidence suggests employers look for teamwork skills (Weidmann and Deming, 2021), and decision-making skills (Deming, 2021). High-paying jobs require social skills (Deming, 2021) and employers' ratings of employees positively correlate with communication skills and measures of dependability (Heller and Kessler, 2022). We provide novel evidence that basic signals of teamwork or leadership skills independently do not improve the likelihood of hiring. However, in our context teamwork skill signals can improve hiring for specific ethnic groups.

Finally, our empirical findings suggest a candidate's decision to signal a specific soft skill on their application can alter the discrimination gap. Many studies have examined the effects of affirmative action policies (Arcidiacono, 2005; Arcidiacono and Lovenheim, 2016; Bleemer, 2022; Guan, 2005). More recently, researchers have sought to examine the impact of diversity, equity and inclusions policies (Bradley et al., 2022; Edmans et al., 2023), and how providing additional information on the ability of an individual can eliminate the discrimination gap (Ayalew et al., 2021). Yet few papers have examined pathways for individual applicants to independently overcome discrimination. In their seminal work, Bertrand and Mullainathan (2004) show the quality of resumes, measured by more labor market experience and fewer gaps in unemployment, does not affect the discrimination gap in the United States.[3] Paul et al. (2023) report no effect of leadership or conscientiousness (as proxied by athletics participation) on the discrimination gap. Veit et al. (2022) vary warmth and competence signals, finding small positive effects of competence signals on callback but no effect on reducing the discrimination gap. These studies suggest information presented on resumes may have a limited effect on the discrimination gap. Recommendation letters may provide a more effective avenue to signal the presence of personal traits or skills, and some studies have provided evidence that credibly signaling soft skills in recommendation letters can reduce or even eliminate discrimination (Kaas and Manger, 2012; Heller and Kessler, 2024). However, recommendation letters remain largely beyond the control of the candidate. Our paper contributes to this literature by providing evidence that basic signals of teamwork skills directly stated in job applications and resumes can shrink the discrimination gap. On

[3]On the other hand, Nunley et al. (2015) vary internship experiences and degree as a proxy for productivity and find that the discrimination gap increases in higher productivity jobs, and Baert et al. (2017) shows that discrimination decreases with more experienced candidates.

the other hand, we also show that not all skills are demanded equally; leadership skills fail to affect the discrimination gap.

The rest of the paper is organized as follows. Section 2 provides a theoretical framework based on a model of taste-based and statistical discrimination. Section 3 details the experimental design, and section 4 explains the empirical approach. Section 5 presents the results. Finally, section 6 concludes.

2 Model of Discrimination with Signals

In this section we present a model of both taste-based and statistical discrimination. Our model builds on Ewens et al. (2014), but departs from it in three ways. First, we cast taste-based and statistical discrimination within a single utility object. Second, we allow employers to have a concave utility function. Third, we allow for the estimated marginal effect of the signals x to be different not only in magnitude but in sign. Our model demonstrates how skill signals will be differentially interpreted under different forms of discrimination, leading to different hiring choices.

2.1 Basic framework

Suppose an employer seeks to hire a new employee. In the first stage of the hiring process, the employer must choose from among many applicants whom to interview. Each applicant i belongs to group $g = \{a, b\}$. The applicant's group represents the visible characteristic that employers may (knowingly or unconsciously) discriminate against. Group a represents the group that has historically been favored in the labor market, while b represents the group that has historically experienced discrimination.

The utility derived from each applicant i of group g depends on the applicant's productivity, which determines the expected stream of future revenue the employer gets from hiring that employee. An applicant's true productivity is measured by θ_{ig}, but the employer does not observe θ_{ig}. Instead, the employer predicts productivity for each applicant based on one or more signals contained in x_{ig} and provided in the prospective employee's application. Signals may include educational background, technical skills, or soft skills such as teamwork or leadership. In the absence of a signal, the applicant's expected productivity is μ. An employer estimates the applicant's productivity using the following equation:

$$\theta_{ig} = \mu + \gamma x_{ig} \tag{1}$$

Finally, the employer chooses to hire the applicant i that maximizes expected utility as a function of predicted productivity $\hat{\theta}_{ig}$:

$$\max E[U(\hat{\theta_{ig}})] \tag{2}$$

Discrimination exists if an employer prefers an applicant of group a over an equally productive applicant of group b. Consider the choice between applicant r of group a and applicant s of group b, for whom $\theta_{ra} = \theta_{sb}$ holds. For these two equally productive applicants, discrimination exists if $E(U(\hat{\theta_{ra}})) > E(U(\hat{\theta_{sb}}))$.

Although we do not observe an employer's utility function, we can interpret interview requests as a revealed preference for one candidate over another. This leads to our first lemma:

> ***Lemma 1:*** *Conditional on identical signals of productivity, discrimination of either type exists if applicants of group a receive more interview requests than applicants of group b.*

2.2 Taste-based discrimination

Under taste-based discrimination, a prejudice parameter, k, discounts the marginal utility of θ_{ig} gained from an applicant of group b. Under this type of discrimination, the employer prefers to hire the applicant of group a even if the true productivity is revealed to be equal. That is, $U(\theta_{ra}) > U(\theta_{sb})$ for $\theta_{ra} = \theta_{sb}$.

Taste-based discrimination is depicted in figure 1a. For all possible values of θ_{ig}, the employer's utility is always higher for a candidate from group a relative to group b. This difference in utility, conditional on θ_{ig}, reflects the discrimination gap. Let the discrimination gap between applicant r of group a and applicant s of group b be denoted as Γ_d:

$$\Gamma_d(x) = U(\theta_{ra}(x)) - U(\theta_{sb}(x)). \tag{3}$$

A key assumption for taste-based discrimination is that conditional on θ_{ig}, the marginal benefit of an applicant's productivity (the slope of the utility function) is always greater for an applicant of group a relative to an applicant of group b, i.e. $\frac{\partial U_a}{\partial \theta} > \frac{\partial U_b}{\partial \theta}$. This reflects the assumed prejudice parameter k. This simple assumption leads to an important insight, formally captured in Theorem 1:

> ***Theorem 1:*** *Under taste-based discrimination, a productivity-enhancing signal unambiguously increases the discrimination gap. A productivity-reducing signal unambiguously narrows the discrimination gap.*

> ***Proof:*** *Take the derivative of the discrimination gap with respect to x:* $\frac{\partial \Gamma}{\partial x} = \frac{\partial U_a}{\partial \theta}\frac{\partial \theta}{\partial x} - \frac{\partial U_b}{\partial \theta}\frac{\partial \theta}{\partial x}$. *Simplifying, we write:* $\frac{\partial \Gamma}{\partial x} = \frac{\partial \theta}{\partial x}(\frac{\partial U_a}{\partial \theta} - \frac{\partial U_b}{\partial \theta})$. *Under taste-based discrimination,* $\frac{\partial U_a}{\partial \theta} > \frac{\partial U_b}{\partial \theta}$ *always, which means* $\frac{\partial \Gamma}{\partial x} > 0$ *if* $\frac{\partial \theta}{\partial x} > 0$*, and* $\frac{\partial \Gamma}{\partial x} < 0$ *if* $\frac{\partial \theta}{\partial x} < 0$.

To build intuition, consider the case where $x_{ig} = 0$, so that $\theta_{ig} = \mu$. If x_{ig} is productivity-enhancing, then the revised θ_{ig} is greater than the original $\theta_{ig} = \mu$. In figure

1a, the productivity-enhancing signal x_{ig} increases the wedge between the utility function for equally productive candidates of groups a and b. Similarly, a productivity-reducing signal actually reduces the difference in utility between equally productive candidates from groups a and b.

2.3 Statistical discrimination

While taste-based discrimination arises through differential utility, statistical discrimination arises through the prediction of $\hat{\theta}_{ig}$. When $\theta_{ra} = \theta_{sb}$, the statistically discriminating employer inaccurately predicts $\hat{\theta}_{ra} > \hat{\theta}_{sb}$. If the true productivity is revealed to the statistically discriminating employer, equal utility would be derived from two equally productive applicants representing different groups. Mathematically, under statistical discrimination this means $U(\theta_{ra}) = U(\theta_{sb})$ for $\theta_{ra} = \theta_{sb}$.

Following Ewens et al. (2014), we incorporate these differences into our model through equation 1, which becomes:

$$\theta_{ig} = \mu_g + \gamma_g x_{ig} + \varepsilon_{ig} \tag{4}$$

In the revised prediction equation, the intercept and slope terms are group-dependent under statistical discrimination, but not taste-based discrimination. If this assumption holds, then we have Lemma 2:

> ***Lemma 2:*** *Statistical discrimination exists if either the group average predicted productivity varies ($\mu_a \neq \mu_b$), or if the marginal effect of signal x_{ig} on predicted productivity depends on one's group ($\gamma_a \neq \gamma_b$).*

Statistical discrimination is depicted in figure 1b. The employer's utility function is no longer distinguished by group. The discrimination gap instead arises through inaccurate prediction of θ_{ig} as per equation 4. The figure illustrates statistical discrimination when $\hat{\mu}_a > \hat{\mu}_b$, the average productivity of group a is predicted to be higher than average productivity of group b. Statistical discrimination could also arise through $\hat{\gamma}_a$ and $\hat{\gamma}_b$ as stated above.

Let the within group return to the signal x for a worker of type a be denoted as Γ_s^a, and defined as the difference in the employers utility when a worker of type a displays signal x and the utility when there is no signal x:

$$\begin{aligned} \Gamma_s^a(x) &= U(\theta_{ra}(x)) - U(\theta_{ra}(0)) \\ &= U(\mu_a + \gamma_a x) - U(\mu_a) \end{aligned} \tag{5}$$

Defining the analogous $\Gamma_s^b(x)$, and $\Gamma_d(0)$ that displays the discrimination gap in absence of signal x, analogous to the term defined in equation 3, we can regroup terms and get the following identity:

$$\Gamma_s^a(x) - \Gamma_s^b(x) \equiv \Gamma_d(x) - \Gamma_d(0) \tag{6}$$

The identity shows that when the disadvantaged group b extracts more from the signal x, the difference in discrimination gap decreases. The identity leads to theorems 2 and 3:

Theorem 2: *Under statistical discrimination when $\mu_a \geq \mu_b$ and $\gamma_a \leq \gamma_b$, a productivity-enhancing signal for the disadvantaged group b ($\gamma_b > 0$) decreases the discrimination gap relative to the non signal case for every $x > 0$: $\Gamma_d(x) < \Gamma_d(0)$. Symmetrically, a productivity-reducing signal $x < 0$ widens the discrimination gap compared to the non signal case: $\Gamma_d(x) > \Gamma_d(0)$.*

Proof: *Writing $\Gamma_s^g(x)$ where $g = \{a, b\}$, as the integral of a marginal utility : $\Gamma_s^g(x) = U(\mu_g + \gamma_g x) - U(\mu_g) = \int_0^{\gamma_g x} U'(\mu_g + s)ds$.*

Case 1: $0 \leq \gamma_a \leq \gamma_b$: $\Gamma_s^b - \Gamma_s^a = \int_0^{\gamma_b x} U'(\mu_b + s)ds - \int_0^{\gamma_a x} U'(\mu_a + s)ds$. Then, given $0 \leq \gamma_a x \leq \gamma_b x$ we can split the integral as $\Gamma_s^b - \Gamma_s^a = \int_0^{\gamma_a x}[U'(\mu_b + s) - U'(\mu_a + s)]ds + \int_{\gamma_a x}^{\gamma_b x} U'(\mu_b + s)ds$. U exhibits diminishing returns, then the first term is greater or equal than zero as $\mu_a \geq \mu_b$. Second term is greater or equal than zero as $\gamma_a \leq \gamma_b$. Hence, $\Gamma_s^b - \Gamma_s^a \equiv \Gamma_d(x) - \Gamma_d(0) \geq 0$.

Case 2: $\gamma_a < 0 < \gamma_b$: The theorem holds with strict inequality when the signal response for the favored group a is negative. $\Gamma_s^b(x) > 0$ given that $U(\mu_b + \gamma_b x) > U(\mu_b)$ and $\Gamma_s^a(x) < 0$, given that $U(\mu_a < \gamma_a x)$. Here, $\Gamma_s^b - \Gamma_s^a > 0$
.

It is worth noting that we allow for the estimated marginal effect of the signal γ_b to have a different sign than γ_a. That is a key distinction with Ewens et al. (2014), where γ_g are information weighting terms allowed to be different but assumed to be positive. We interpret our model as a generalized version given the additional flexibility that accommodates in the sign of the estimated marginal effect of the signal. Employers can respond in different directions to the same productivity signal x_{ig} according on the individual's group g. These differential responses (in terms of sign) are consistent with statistical discrimination biases.

Theorem 3: *Under statistical discrimination when $\mu_a \geq \mu_b$ and $\gamma_a > \gamma_b$, a productivity-enhancing signal for the disadvantaged group b, $\gamma_b > 0$ has an ambiguous effect on the discrimination gap.*

Proof: *Mathematically, the proof is the same as above. When splitting the term in the two integrals, the first and second integral terms are positive. However, the second term is being subtracted. Hence, the sign of the gap $\Gamma_b^s - \Gamma_a^s$ is ambiguous.*

This leads to our final insight:

Theorem 4: *Observing a productivity enhancing signal $x > 0$ reducing the discrimination gap $\Gamma_d(x) < \Gamma_d(0)$ indicates statistical discrimination, as it is inconsistent with taste-based discrimination.*

Proof: *Follows directly from Theorems 1 and 2.*

We will use this final insight to interpret our empirical findings as evidence of statistical discrimination in the context of our study.

3 Experimental Design

We employ a correspondence study, a common method for detecting and quantifying discrimination (Neumark et al., 2019; Guryan and Charles, 2013). The correspondence study attributes differences in callback rates to a randomly assigned characteristic presented on otherwise identical fictional resumes. These differences estimate the level of discrimination against a specific group in a particular setting. Our correspondence study is implemented in Malaysia using an online job platform advertising entry-level jobs in the private sector. Entry-level jobs matter for future labor market outcomes (Wachter, 2020), and are commonly used for correspondence studies to avoid confoundedness from other experiences listed in the job applications.

The RCT was registered as AEARCTR-001 1591. A dated Pre-Analysis Plan, populated Pre-Analysis plan and IRB information are available in the link: https://www.socialscienceregistry.org/trials/11591.

3.1 Study setting: Malaysia

Malaysia is a multi-ethnic country, with a majority Malay (57%), a quarter Chinese (23%), and 7% Indian population. The remaining population is mostly non-Malay Bumiputera (12%).[4] Ethnicity and religion are closely linked: Malays are predominantly Muslim, Chinese are predominantly Buddhist, and Indians are predominantly Hindu (Mahari et al., 2011).

Historically, the labor market in Malaysia has been ethnically segmented. Malays are more likely to be employed in the public sector and government-linked corporations, while individuals of Chinese and Indian descent are more likely to be employed in the private sector (Lee, 2012; Lee and Khalid, 2016). In 2022, approximately four of every five (78%) public sector employees were Malay (Lee, 2023), a much greater share than

[4] The term "Bumiputera" (which means "sons of the soil") is typically included among the population of Malays. We disaggregate the non-Malay Bumiputera sub-population because our study includes only non-Bumiputera Malay names.

would be found in the general population. In contrast, a majority of corporate leaders and shareholders are Chinese (see Appendix C). While selection issues may explain some of these differences, Lee and Khalid (2016) and Guan (2005) provide evidence of ethnic-based discrimination against Malays seeking work in the private sector.

Labor statistics also reveal a wide gender gap in employment. According to Malaysia's 2022 Labour Force Survey, 54 percent of women are employed, compared to 79 percent for men (Department of Statistics Malaysia, 2022). This gap persists across all major ethnicities. The lower participation rate for women does not necessarily reflect discrimination or the relative inability of women to find a job. Social norms likely play an important role as well. Nearly two thirds (63%) of non-working women claim housework or family responsibilities as the primary reason why they aren't active in the labor force (Department of Statistics Malaysia, 2022). Yet, evidence suggests wage gaps also favor of men. The observed difference in earnings is not explained by ethnicity, age, educational attainment, job location (rural/urban), or sector of employment (Schmillen et al., 2019).

3.2 Implementing the correspondence study

To implement our correspondence study, we utilized a common online job platform advertising entry-level positions in Malaysia. We created 90 fictional applicant profiles, and applied to 2,994 jobs. Our sample frame included all non-specialized jobs posted between May 5 and July 21, 2023 that satisfied our basic criteria for full-time, entry-level, bachelor's degree required, and less than one year of experience required. Additional details regarding the sample frame are provided in Appendix A.1.

To apply for a job on the platform, a potential applicant creates a profile which includes a resume. Resumes were generated using a common template. Each resume shows a name, basic contact information, gender, executive summary, technical skills, personal skills, educational background (degree and institution), pre-professional experience, activities and hobbies, language, and a statement that references are available upon request. All resumes have a bachelor's degree conferred by the same university, one of the most prestigious and multi-ethnic institutions in Malaysia.

Each profile was tailored to one of the five most commonly requested bachelor's degrees: accounting, business administration, computer science, electrical engineering, and mechanical engineering. Across degrees, profiles could vary substantially. Within degrees, profiles are identical except for contact information and the randomly assigned characteristics of interest. This means profiles for applicants holding the same degree differ only by ethnicity, gender, and a signal of soft skills.

Each profile has a unique name which reflects an individual's ethnicity and gender. Profiles and resumes also directly specify gender. Names were carefully selected to avoid signals of wealth or other possible correlates (Gaddis, 2017). That said, ethnicity and religion are strongly correlated in this setting, and this is apparent in common naming conventions. In our study, all Malay names are Muslim names. All Indian names are Tamil Hindu names. Chinese names have no religious connotation.

Each applicant projects one of three soft skill signals: leadership, teamwork, or a relatively neutral counterfactual. If anything, the counterfactual could be interpreted as a signal of independence. Soft skills are signaled via an executive statement (on applications and in the resume), a list of personal skills on a resume, and through career-relevant industry-specific experience (an internship experience), non-professional work experience (barista experience), and extracurricular activities (hobbies or clubs). In this way, leadership and experience are linked, just as teamwork and experience are linked. More details on profile creation and characteristics are provided in Appendix A.2.

In total, 90 candidate profiles were created (3 ethnicities x 2 genders x 3 soft skills x 5 degrees = 90 profiles). Each degree has 18 unique candidate profiles allowing for all possible combinations of ethnicity, gender, and emphasized soft skill. For example, 6 of the 18 mechanical engineering applicant profiles are Chinese, 6 are Malay, and 6 are Indian. For a given ethnicity, half are female and half male. Among 3 Chinese female applicants sharing a degree, each is uniquely assigned one of the three soft skills traits to be emphasized (leadership, teamwork, or none), and similarly for Chinese male candidates, and Malay and Indian male and female candidates. Appendix figure A.1 provides a visual representation of the experimental design.

Each week while the study was ongoing, we randomly selected 300 job advertisements from the sample frame. Job advertisements were stratified by company size (greater or less than 50 employees) and company location (located in greater Kuala Lumpur, the capital and largest metropolitan area in Malaysia, or elsewhere) to improve balance in the assignment of job profiles to company characteristics. Each job advertisement was then randomly assigned to a single applicant profile with a relevant degree.[5]

Applications were completed manually during the months of May through July, 2023 (details on the procedure are provided in Appendix A.3). Companies who found a candidate suitable for interview then contacted the candidate using the email address provided. Any follow-up contact was recorded and used as our main outcome of interest. Interview requests were promptly declined using a standardized reply message, typically in less than 48 hours.

3.3 Data

Our data uses information scraped from the initial job postings about both the company and job. Table 1 presents descriptive statistics of job and company characteristics. Col-

[5]A design with a single applicant per profile deals with potential differences in variance introduced in correspondence studies with multiple profiles submitted to the same employer (Neumark, 2012).

umn 1 reports means for all 2,994 observations in the sample. A majority of companies (63%) are located in the greater Kuala Lumpur area. Slightly less than half (45%) have fewer than 50 employees. Companies in the sample operate in many sectors, with the most common being manufacturing (28%), professional services (28%), and retail (13%). On average, 147 applicants applied to a given job advertisement. The average posted monthly salary is 3,283 MYR (755 US dollars).[6] More than half of companies (55%) used a short pre-scan questionnaire to submit the job application, where they ask about specific skills: language spoken, use of software, etc. Answers to pre-scan questionnaire were standardized.

As part of our study design, we filtered every job advertisement by requisite training. A majority of companies in our sample sought applicants with training in business administration (49%) or accounting (24%). The remaining quarter of advertised jobs sought candidates with training in the STEM-related fields of computer science, electrical engineering, or mechanical engineering. Half of the STEM jobs sought computer science training (13% of all jobs), while the other half were recruiting entry-level engineers, either electrical (6%) or mechanical (7%).

Columns 2 and 3 report differential means for STEM and non-STEM advertisements. STEM jobs are advertised by larger companies and less likely to be located in the greater Kuala Lumpur area (this pattern is primarily driven by companies outside Kuala Lumpur seeking candidates specialized in electrical engineering). The expected salary is 14% higher in STEM fields. STEM jobs also appear to be more competitive (185 applicants on average compared to 132 in non-STEM fields). STEM jobs were more commonly advertised by firms in the manufacturing or professional services sectors.

4 Empirical Strategy

Our identification strategy relies on randomly assigning a unique profile to a specific job posting. Each profile conveys a unique combination of ethnicity, gender, and signals of soft skills. In this way, each characteristic was randomly assigned to a specific job posting, and is plausibly exogenous.

Equation 7 estimates the difference in callback rates by ethnicity and gender:

$$y_i = \alpha_0 + \beta_1 F_i + \sum_{j=1}^{2} \delta_j E_{ij} + \sum_{j=1}^{2} \phi_j (\mathrm{F}_i \times E_{ij}) + \varepsilon_i \tag{7}$$

Outcome y_i is a dummy variable that takes the value of one if the company assigned to candidate i contacted the candidate in reference to the candidate's job application

[6] All advertisements post an expected salary range. The position salary is calculated using the mean of the posted salary range for every job. To convert Malaysian ringgit (MYR) to US dollars we use the April 2023 average exchange rate of 0.23 published by the Central Bank of Malaysia https://www.bnm.gov.my/exchange-rates.

(i.e. a callback). F_i is a female indicator variable ($F_i = 1$ for a female profile, and zero otherwise), and E_{ij} is an indicator variable for ethnicity j ($E_{ij} = 1$ for ethnicity j, and zero otherwise). The error term is ε_i.

The parameter β_1 is the mean difference in the outcome attributed to differences in gender. The parameter δ_1 is the mean difference in the outcome between ethnicities E_1 and the omitted ethnicity E_0. Similarly, δ_2 captures the mean difference in contact for interview between ethnicities E_2 and E_0. Statistically significant results for δ_1, δ_2 or $\delta_1 - \delta_2$ provide evidence of ethnic-based discrimination. We also include the interaction between gender and ethnicity ($\mathrm{F}_i \times E_{ij}$), where parameter ϕ_j represents a differential effect for each ethnicity by gender.

Equation 7 can be expanded to incorporate heterogeneity analysis. We test for differential discrimination by field (i.e. STEM relative to business jobs). To do this, we estimate equation 8 below, where y_i, F_i, E_{ij}, and ε_i are defined above, and the variable $V_i = 1$ if the job advertisement targeted applicants with training in STEM, and zero otherwise. We estimate:

$$y_i = \alpha_0 + \beta_1 F_i + \sum_{j=1}^{2} \delta_j E_{ij} + \sum_{j=1}^{2} \phi_j (\mathrm{F}_i \times E_{ij}) + \rho_0 V_i + \sum_{j=1}^{2} \rho_j (V_i \times E_{ij}) + \rho_3 (V_i \times F_i) + \varepsilon_i \quad (8)$$

Each estimate ρ_j tests for a differential callback effect by ethnicity and gender for STEM relative to non-STEM jobs.

A primary goal is to test whether signaling soft skills on a job application can reduce an observed discrimination gap. To answer this question we estimate equation 9, which includes an indicator variable S_{is} that takes a value of 1 if soft skill s is a relevant signal for profile i, and zero otherwise. Our three possible soft skills signals include teamwork, leadership or neither. We estimate:

$$y_i = \delta_0 + \beta_1 F_i + \sum_{j=1}^{2} \delta_j E_{ij} + \sum_{s=1}^{2} \gamma_{0s} S_{is} + \sum_{j=1}^{2} \sum_{s=1}^{2} \gamma_{js} (E_{ij} \times S_{is}) + \sum_{s=1}^{2} \gamma_3 s (F_i \times S_{is}) + \varepsilon_i \quad (9)$$

Parameters γ_{0s}, γ_{1s} and γ_{2s} capture the differential effect of the s soft skill by ethnicity, while γ_{3s} captures the differential effect of s by gender. In the analysis that follows we will estimate equation 9 both without and with the interaction terms.

Because profiles were randomly assigned to job advertisements, we can reasonably assume job and company characteristics are uncorrelated with the error term (i.e. $E(\varepsilon_i | x_i) = 0$) in all specifications. Although we cannot explicitly test the exogeneity assumption, we test for balance in job and company characteristics x_i across all three types of randomized profile characteristics. Appendix table B.1 shows the balance test results. In general, job and company characteristics are quite similar across the various assignments of profile characteristics, suggesting treatment assignment is well balanced. Of the 10 characteristics considered using the full sample, we observe a statistically significant small difference at the 5% level in only one variable (use of a pre-scan questionnaire) for only one comparison (male vs. female).

5 Results

Figure 2 presents the mean callback rates by ethnicity. For each ethnicity, we also present the results for female, STEM degree, and soft skills: Teamwork, leadership, and the control skill.[7] The callback rate for candidates with Chinese sounding names is 18%. Comparable candidates with Malay sounding names have callback rates of 5%, and candidates with Indian sounding names have callback rates of 3%. This means Chinese-named candidates receive approximately 3.5 callbacks for each callback received by comparable Malay profiles, and 6 callbacks for each callback received by comparable Indian profiles.

Table 2 reports the difference in callback rates by ethnicity and gender. Column 1 presents estimates using our baseline specification (equation 7). The difference in callback rates are statistically significant: 11 percentage points lower for Malay-sounding names and 14 percentage points lower for Indian-sounding names. The discrimination estimates are also statistically different from one another; discrimination against Indian-sounding names is stronger than discrimination against Malay-sounding names. These effect size estimates are large relative to the broader literature on racial and ethnic discrimination but smaller than earlier evidence from Malaysia, which found an 18 percentage point gap between Malay and Chinese applicants (Lee and Khalid, 2016)[8].

Column 1 also reports differences by gender. We find no evidence of hiring discrimination by gender. Interactions between ethnicity and gender are also insignificant. Malay and Indian women appear to face discrimination at similar rates as their male counterparts. Results are robust to the inclusion of a control for STEM jobs (column 2), and we observe no evidence of differential discrimination across STEM and non-STEM jobs (estimated using equation 8). In a supplemental analysis reported in Appendix C, we provide suggestive evidence that ethnic discrimination is strongly associated with the ethnic composition of the leadership. Companies are more likely to request an interview from candidates that share the same ethnicity as company officers and shareholders.

Can signaling soft skills reduce the observed discrimination gap? To answer this question, columns 3 and 4 of Table 2 present results from estimating equation 9. Column 3 presents the basic effect of soft skills without interactions. We observe no evidence that signaling teamwork or leadership influences company's decision to callback the average candidate. Of course, this does not mean soft skills are generally unimportant to all

[7]Discrimination in STEM fields could be prominent given that women are known to be underrepresented in STEM jobs (Lepage et al., 2025), and there is evidence of majority candidates being favored when evaluated for STEM positions (Kessler et al., 2026).

[8]Lee and Khalid (2016) did not consider discrimination against Indian-sounding names

employers, or even that soft skills do not matter to the employers in this setting.

Despite the null average effect, the results in column 4 demonstrate that soft skills have potential to affect the discrimination gap. Specifically, a signal for teamwork skills significantly improves callback rates for both Malay and Indian candidates. Malay applicants who signaled teamwork skills are 7 percentage points more likely to be contacted than similar Malay applicants signaling a control soft skill ($p < 0.05$). Indian candidates with prominent teamwork skills are 6 percentage points more likely to be contacted than those Indian candidates signaling the control soft skill ($p < 0.1$). These effects represent substantial reductions in the discrimination gap – approximately 43% for Malay and 34% for Indian candidates. Interactions of soft skills with gender are insignificant.[9] It is worth noting that for Chinese candidates the teamwork skill seems to be less valued than the control soft skill (figure 2), which mechanically contributes to the discrimination gap reduction. This result is consistent with the theoretical model of statistical discrimination we present in section 2, where a productivity enhancing signal for the discriminated group could be interpreted negatively for the favored group: $\gamma_a < 0 < \gamma_b$, suggesting that employers may associate different soft skill profiles with different ethnic groups.

Signaling leadership skills may also reduce the discrimination gap (coefficient estimates are positive), but the estimates are smaller than the teamwork interactions and no longer statistically significant. Together, these findings suggest a preference among discriminating employers for minority candidate team players, rather than those with a proclivity to lead.

Our theoretical model suggests a productivity-enhancing signal will reduce the discrimination gap only under statistical discrimination (theorem 4). In our case, it's reasonable to expect both teamwork and leadership skills are viewed favorably, and thus interpreted as productivity-enhancing (rather than a productivity-reducing) signal. Since teamwork reduces the discrimination gap, our results are consistent with a model of statistical discrimination. The observed positive coefficient (albeit insignificant) for leadership skills supports a similar conclusion.

Our results provide novel evidence of statistical discrimination in this setting. It is important to note that both forms of discrimination – statistical and taste-based – can occur simultaneously in a market where heterogeneous companies make hiring decisions under different preferences. While our results confirm that statistical discrimination exists in this setting, we cannot rule out the possibility of taste-based discrimination occurring alongside statistical discrimination. If taste-based discrimination does exist in this setting, it will simply moderate the observed effect. By providing evidence of statistical discrimination, we posit that statistical discrimination dominates any taste-based discrimination that might also exist.

[9] Appendix table B.2 presents q-values accounting for false discovery rates.

6 Discussion and Conclusions

We conducted a correspondence study using an online job platform in Malaysia. We tested for ethnic and gender discrimination. Malay and Indian candidates are 11 and 14 percentage points less likely to receive a callback relative to candidates with a Chinese name. While we interpret our results as evidence of ethnic discrimination, ethinicity and religion are strongly correlated in this setting. Our design cannot distinguish between ethnic and religious discrimination. We do not find evidence of gender discrimination in this setting.

We also tested for the importance of two soft skills in the labor market: leadership and teamwork. Our findings are consistent with Heller and Kessler (2024), in that neither teamwork nor leadership affect average callback rates. Heterogeneous employers may value soft skills in different ways, and the skills we consider may not be the ones of greatest interest to employers in this context. In related work, Heller and Kessler (2022) suggest employers value communication skills and measures of dependability (e.g. taking instructions, showing up on time, being trustworthy and responsible), but teamwork skills are not correlated with employer valuations.

Another potential explanation for the observed null effect is that the signal we employed was relatively weak. Soft skills are usually not certified. (Laajaj and Macours, 2021) studies the importance of properly measuring soft skills, and suggest important implications for employability and other labor market outcomes when measured accurately. Future research should consider which soft skills are most important to employers and how to improve the reliability of a signal. For example, is relevant experience, evidence of training, or certification the most effective approach to signaling?

Despite a null *average* effect for teamwork and leadership, we find signaling an aptitude for teamwork attenuates the discrimination gap by 34-43%. This is a novel finding when compared to other studies that found null or very small effects of presenting information as proxy for personal and soft skills (Veit et al., 2022; Paul et al., 2023; Groh et al., 2012), and is consistent with Kaas and Manger (2012), who consider the role of recommendation letters in discrimination. They find that a letter writer's claims about a candidate's capacity for teamwork, as well as affability, commitment, and conscientiousness can reduce ethnic discrimination. Weidmann and Deming (2021) suggest team players are valued because they improve team performance and might increase the effort teammates exert. The finding has important implications for equity: a disadvantaged candidate can strategically signal soft skills, particularly teamwork, to improve their likelihood of callback and reduce the discrimination gap. Future research can assess whether other soft skills are as important, or even more important than teamwork for achieving reduced discrimination.

We offer several possible policy implications. First, there are opportunities for disadvantaged populations to practice and demonstrate teamwork skills. Kässi and Lehdonvirta (2024) shows that microcredentials are associated to higher earnings. Training programs designed to further develop collaborative soft skills and teamwork may also be relevant. Several experimental studies show training programs designed to develop soft skills can improve entrepreneurial business outcomes in developing countries (Ubfal et al., 2022; Campos et al., 2017; Chioda et al., 2021) and employability (Schlosser and Shanan, 2025). Similarly, Brudevold-Newman and Ubfal (2024) suggests soft skill training can improve labor market outcomes by expediting the time it takes for a new graduate to find a job. That said, not all training programs are created equal. For example, (Groh et al., 2012) report null effects from soft skill trainings on employment in multiple settings. Our findings suggest these types of interventions might be particularly effective in a context of discrimination.

As with any correspondence study, there are limitations to the interpretation of our empirical findings (Lahey and Beasley, 2018). First, we are unable to observe outcomes following the initial offer to interview. Theoretically, discrimination could increase or retreat in later stages of the hiring process, but we won't observe later stage discrimination. The second limitation is with respect to external validity. Our approach allows us to analyze discrimination by companies operating in Malaysia's private sector and advertising entry-level positions in business and STEM fields. Entry-level jobs are important – one third of new graduates in Malaysia work in semi-skilled or low skilled entry-level jobs (Department of Statistics Malaysia, 2021)) – especially given the consequences for future labor market outcomes (Wachter, 2020). Our findings do not reflect hiring decisions for government jobs, where a higher share of the Malay population has historically been employed. Government jobs are not posted on the online platform we utilized, and we were unable to incorporate them in our study. It's plausible that the discrimination we observe could be reversed in that setting. Our findings are also limited by the specific jobs we considered. For example, our estimates do not directly correspond to what we might expect for senior positions, informal jobs that are not typically posted online, or positions in other fields. This caveat includes fields in which gender discrimination might be more important.

Finally, a major contribution of our paper is our theoretical model that builds on Ewens et al. (2014). The model allows us to distinguish statistical and taste-based discrimination under certain conditions. The main insight of the model (from theorem 2) is summarized as follows: statistical discrimination exists if the discrimination gap reduces with a productivity-enhancing signal, or expands with a productivity-reducing signal. Using the theory as our guide, we interpret our empirical findings as evidence of statistical discrimination. We provide direct empirical evidence of statistical discrimination as the discrimination gap decreases with the presence of a soft skill signal.

Future research could apply our model to test for the presence of statistical or taste-based discrimination in other settings. Other signals, beyond the two soft skills we considered in this study, can be assessed. The theoretical model is general enough to apply to any signal. For example, signals related to education, experience, technical skills, or other soft skills like communication. Future research in this area would be immensely beneficial in two important ways. First, it will improve our understanding of what enhances or dampens hiring discrimination in labor markets. Second, knowing the type of hiring discrimination – statistical or taste-based discrimination – allows policymakers to design better solutions for more equitable labor markets.

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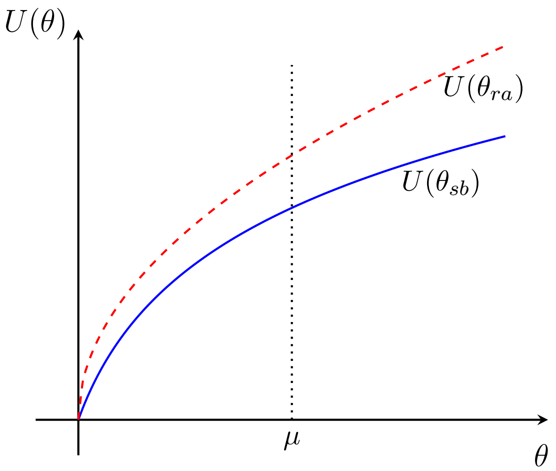
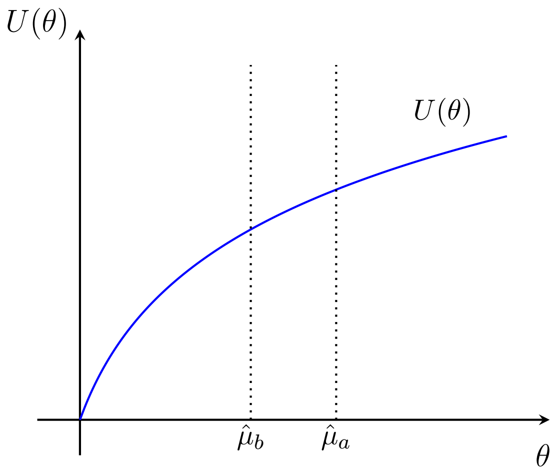
Figures and Tables

Figure 1: Utility functions under discrimination



(a) Taste-based



(b) Statistical

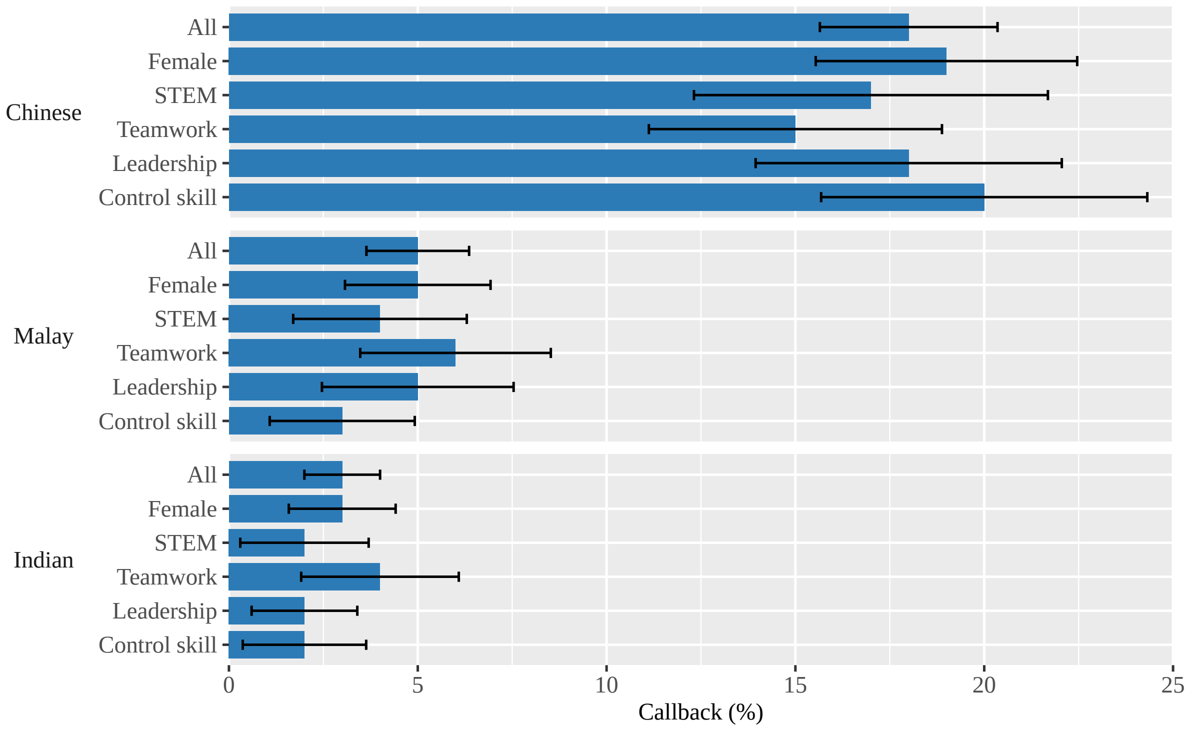
* *Note:* The figure illustrates the utility function of the employer as a function of its productivity. Panel a displays the utility functions in the presence of taste-based discrimination, there are different utility functions depending on the group of the candidate. Panel b illustrates the utility function under statistical discrimination, that is one utility function but with different predictions of θ for each group of candidates.

Table 1: Company and Job Descriptive Statistics

	(1) Full sample	(2) STEM	(3) Non-STEM
Panel A. Company characteristics			
Greater Kuala Lumpur	0.63	0.55	0.66
	(0.48)	(0.50)	(0.47)
Company size $\leq$ 50 employees	0.45	0.41	0.46
	(0.50)	(0.49)	(0.50)
Industry-Manufacturing	0.28	0.41	0.24
	(0.45)	(0.49)	(0.43)
Industry-Professional services	0.28	0.35	0.25
	(0.45)	(0.48)	(0.43)
Industry-Retail	0.13	0.05	0.16
	(0.34)	(0.22)	(0.37)
Industry-Other	0.31	0.19	0.35
	(0.46)	(0.39)	(0.48)
Panel B. Posted job characteristics			
Position posted salary (USD)	755.63	836.92	732.10
	(290.78)	(360.15)	(262.86)
Position number of applicants	146.46	185.75	132.45
	(246.15)	(240.21)	(246.78)
Use of pre-scan questionnaire	0.55	0.52	0.56
	(0.50)	(0.50)	(0.50)
Accounting	0.24	0.00	0.33
	(0.43)	(0.00)	(0.47)
Business Administration	0.49	0.00	0.67
	(0.50)	(0.00)	(0.47)
Computer Science	0.13	0.50	0.00
	(0.34)	(0.50)	(0.00)
Electrical Engineering	0.06	0.24	0.00
	(0.24)	(0.43)	(0.00)
Mechanical Engineering	0.07	0.26	0.00
	(0.25)	(0.44)	(0.00)
Observations	2,994	783	2,211

Note: Descriptive statistics for the final sample for a total of 2,994 job ads that satisfy our inclusion criteria. The table presents means and standard deviations. Column 1 presents statistics for the full sample, column 2 for STEM advertisements (Computer Science, Electrical Engineering or Mechanical Engineering), and column 3 for non-STEM advertisements (Accounting and Business Administration). To convert Malaysian Ringgit to US dollars we use the April 2023 average exchange rate published by the Central Bank of Malaysia https://www.bnm.gov.my/exchange-rates. That is, a exchange rate of 0.23.

Figure 2: Callback Rates by Ethnicity and Other Individual Characteristics



[*] *Note:* The figure presents average callback rates for each ethnicity: Chinese, Malay and Indian, disaggregated by individual characteristics. Bars present the mean callback rates, confidence intervals are presented around the mean.

Table 2: Effects of Ethnicity, Gender and Soft Skills on Callback Rates

	(1)	(2)	(3)	(4)
Malay	-0.114***	-0.112***	-0.127***	-0.164***
	(0.019)	(0.020)	(0.014)	(0.024)
Indian	-0.135***	-0.135***	-0.150***	-0.175***
	(0.018)	(0.019)	(0.013)	(0.023)
Female	0.033	0.037	0.014	0.017
	(0.024)	(0.025)	(0.010)	(0.017)
Teamwork			0.000	-0.038
			(0.012)	(0.031)
Leadership			-0.001	-0.018
			(0.012)	(0.031)
Female × Malay	-0.026	-0.026		
	(0.028)	(0.028)		
Female × Indian	-0.031	-0.030		
	(0.026)	(0.026)		
STEM degree		0.001		
		(0.029)		
Malay × STEM		-0.006		
		(0.031)		
Indian × STEM		-0.000		
		(0.029)		
Female × STEM		-0.019		
		(0.022)		
Teamwork × Malay				0.070**
				(0.033)
Teamwork × Indian				0.059*
				(0.032)
Leadership × Malay				0.041
				(0.034)
Leadership × Indian				0.016
				(0.032)
Teamwork × Female				-0.009
				(0.024)
Leadership × Female				-0.002
				(0.024)
Constant	0.159***	0.159***	0.169***	0.187***
	(0.016)	(0.018)	(0.015)	(0.023)
R^2	0.058	0.058	0.057	0.059
Observations	2,994	2,994	2,994	2,994
Malay = Indian				
p-value	0.073	0.074	0.006	0.376
F-statistic	3.220	3.202	7.484	0.784

Note: This table presents the results of specifications 7, 8, and 9. The outcome for all columns takes the value of 1 if the company contacted the candidate through email. Robust Standard errors are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01

A Supplemental information on the correspondence study

This appendix includes additional details regarding the implementation of the correspondence study. The first section describes the sample frame. The second subsection provides more details on profile creation. The third subsection describes the manual application process. The last subsection displays generic examples of the job application process.

A.1 Sample frame

Our sample frame included all jobs posted online between May 5 and July 21, 2023 that satisfied our basic criteria for full-time, entry-level, bachelor's degree required, and less than one year of experience required. In an initial screening of job postings over a seven day period in April, 2023, 85% of job postings meeting our criteria were filtered into one of five bachelor degree categories: accounting, business administration, computer science, electrical engineering, and mechanical engineering. The remaining 15% of jobs were determined as too specialized. Any job advertisements that fell outside the five targeted bachelor degree categories were excluded from the study.

Each job was assigned a degree-based specialization using the area of specialization reported in the ad. Job ads classified as "Accounting/Finance" were assigned an accounting degree. For the business administration degree, we used job ads with specializations: 'Admin/Human Resources', 'Sales/Marketing', 'Customer Service' or 'Logistics/Supply Chain'. The computer science degree was assigned to the specializations: 'Tech & Helpdesk Support' or 'Computer/Information Technology'. For electrical engineering, we used specializations that are related to 'Electronical', 'Electronics' or 'Other engineering'. If the position had the word 'engineer' and the industry of the company was related to Electronical or Electronics, we also classified the ad into the electrical engineering degree. Finally, for mechanical engineering we used specializations related to mechanical, industrial or chemical engineering and specializations related to oil and gas. In addition, we classified a job into the mechanical engineering degree if the position had the word 'engineer' and the industry of the company was related to heavy industrial machinery or manufacturing production. All job ads that were not relevant for the degree-based specializations were removed from the sample.

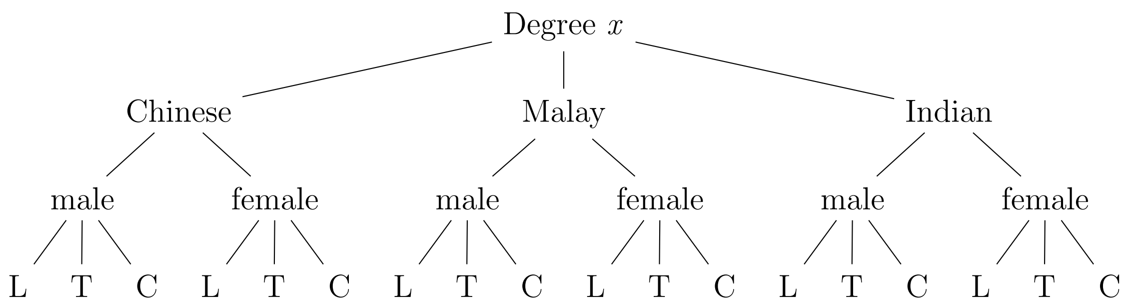
Each company is included in our sample only once. If a company posted more than one position in the same week, we randomly selected one job for inclusion in the study, with priority given to engineering and computer science jobs. All subsequent job postings (by the same company in later weeks) were excluded from the sample. In total, approximately 9% of all job postings during this period were included in the sample frame.

A.2 Profile characteristics

A competitive entry-level engineer's experience cannot mirror that of an accounting graduate. Similarly, a recent computer science graduate will highlight different kinds of experiences than a recent business graduate. We use five degree-based specialization x – accounting/finance, admin/sales/service, technology, mechanical engineering, and electrical engineering. All candidates for jobs within an area of specialization were assigned the same degree: accounting, business administration, computer science, electrical engineering, and mechanical engineering. Within degrees, profiles are identical except for contact information and the randomly assigned characteristics of interest.

Figure A.1 provides an illustration of how characteristics were assigned to candidates of a given degree. Each specialization has 18 profiles, as described in this figure.

Figure A.1: Description of profiles for a given degree



Note: The last row depicts soft skills, where L denotes leadership, T denotes teamwork, and C denotes control.

Each profile has a unique name which reflects an individual's ethnicity and gender. A complete list of names used for profile creation, disaggregated by ethnicity and gender, is available upon request. Contact information is unique to each profile since a unique phone number and email were requisites of profile creation. Email addresses correspond to the name, as is customary.

When creating the profiles we uploaded their corresponding resume to it. Table A.1 summarizes how soft skills were signaled in the resumes. Differences are highlighted in boldface in the table (regular font was used in resumes). Soft skill signals were identical across all five degrees of specialization. A sample resume is presented in figure A.2.

A.3 Application process

The application process was carried out manually from May 17 to July 28, 2023. At the beginning of each week, a research assistant was given a list of randomly assigned jobs for each applicant profile. Applications were completed on Mondays, Wednesdays, and Fridays of every week, with day of the week randomly assigned. Applications were submitted during the same time span each of these days (8am-12pm CT or as soon as

Table A.1: Text used for soft skills signals on resumes

Soft skill: Teamwork	
Executive Summary	Demonstrated ability to **contribute to teams**.
Personal Skills	**Teamwork, Collaboration**, Communication
Pre-Professional Experience	**Collaborate as part of a team** to prepare relevant internal report.
	Work collaboratively with other employees
Activities/Hobbies	Book Club
	Photography Club
Soft skill: Leadership	
Executive Summary	Demonstrated ability to **lead teams**.
Personal Skills	**Leadership, Management**, Communication
Pre-Professional Experience	**Lead team** in preparation of relevant internal report.
	Train and supervise new employees
Activities/Hobbies	Book Club, **Organizer**
	Photography Club, **Social Media Director**
Soft skill: Counterfactual	
Executive Summary	Demonstrated ability to **work independently**.
Personal Skills	**Independence, Motivation**, Communication
Pre-Professional Experience	**Work autonomously** to prepare relevant internal report.
	Complete assigned tasks independently.
Activities/Hobbies	Book Club
	Photography Club

possible thereafter if the website was under maintenance.) The order of applications (grouped by profile) each day was also randomized. To apply for a job, the research assistant logged in to a candidate profile, accessed the URL of the randomly assigned job, filled out a "pitch" using the unique executive summary (tailored to degree and soft skill) listed on the resume associated with the assigned profile, and clicked to submit. In addition, 55% of the jobs required a mandatory pre-scan questionnaire. Answers to pre-screen questions were standardized. Figure A.3 shows a generic example of a pre-scan questionnaire in the application process. All the applications were performed through the profiles, the corresponding resumes were already posted within the profile. Figure A.4 shows a generic example of the application interface in the job site.

A.4 Sample materials

Figure A.2: Sample Resume

Kamil Mustapha

Phone: +60 12 7877 1795 **Gender:** Male

Email: kamil.mustapha@outlook.com

EXECUTIVE SUMMARY
Fresh Bachelor of Accounting graduate with previous internship experience in PwC Malaysia. Currently pursuing Chartered Financial Analyst (CFA) Level I Certification. Demonstrated ability to contribute to teams.

TECHNICAL SKILLS
- Microsoft Visual Basic
- QuickBooks
- SQL

PERSONAL SKILLS
- Teamwork
- Collaboration
- Communication

EDUCATION
Bachelor of Accounting (2022)
University of Malaya
Kuala Lumpur

PRE-PROFESSIONAL EXPERIENCE
Intern
PwC Malaysia (Jul 2022 – Sep 2022)
Compile and analyze financial statements. Create a budget aligned with company financial goals. Collaborate as part of a team to prepare relevant internal report.

Barista
Starbucks Malaysia (Oct 2021 – Jul 2022)
Serve customer with variety of beverages and meals. Greet customers, take orders, and complete customer transactions on the cash register. Work collaboratively with other employees.

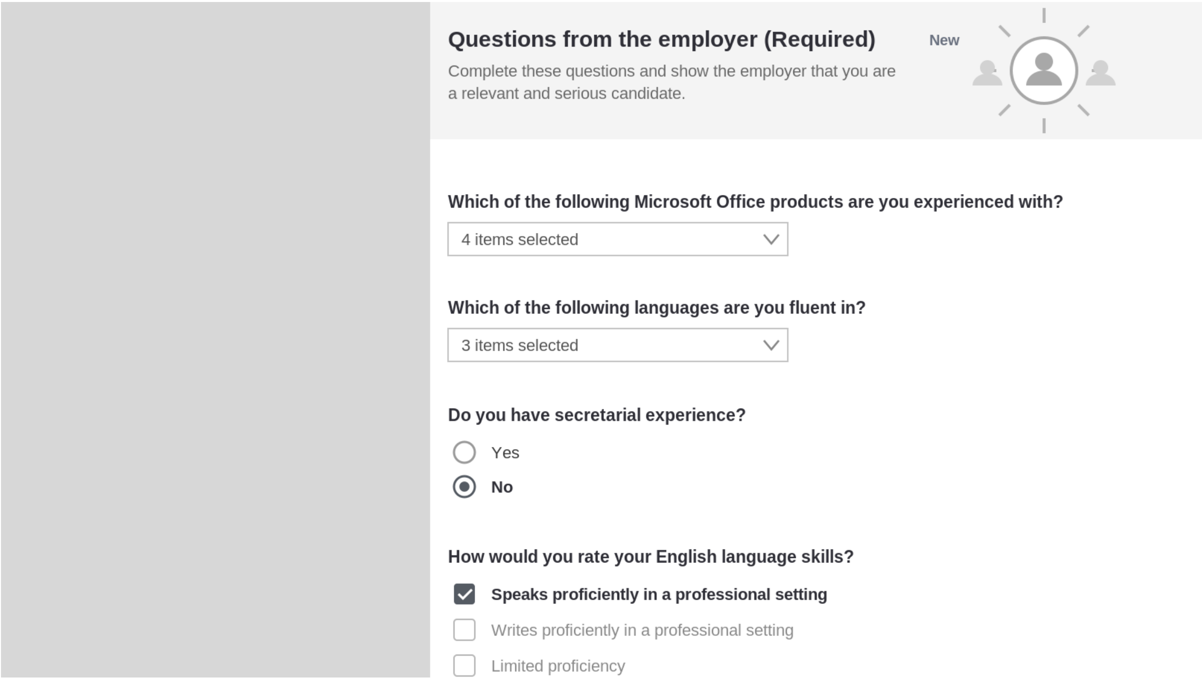
ACTIVITIES / HOBBIES
- Book Club
- Photography Club
- Running
- Baking

LANGUAGES English, Bahasa Melayu, Mandarin

REFERENCES Available upon request.

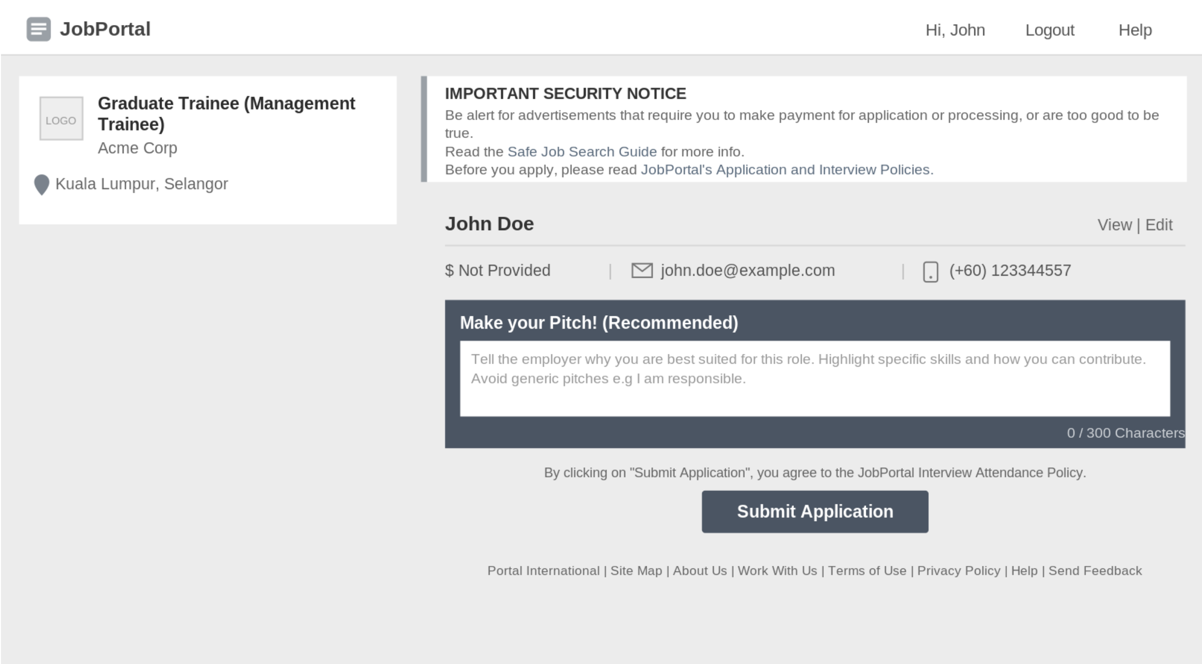
[*] *Note:* This a sample resume of an individual with teamwork skills.

Figure A.3: Job Site Interface: Pre-scan questionnaire



* *Note:* The figure presents a generic example of the job site interface when the application requires pre-scan questions to be completed.

Figure A.4: Application Interface: Submission



* *Note:* The figure presents a generic example of the job site interface when submiting a job application.

B Supplementary tables

Table B.1: Mean Differences by Randomly Assigned Profile Characteristic

	Ethnicity			Gender	Soft Skill		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Chinese - Malay	Chinese - Indian	Malay - Indian	Male - Female	Team - Control	Lead - Control	Team - Lead
Greater Kuala Lumpur	0.02	0.02	0.00	0.01	-0.01	-0.03	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Company size $\leq$ 50 employees	-0.00	-0.01	-0.00	-0.02	-0.02	-0.02	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Industry-Manufacturing	-0.02	-0.03	-0.01	-0.00	-0.01	0.00	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Industry-Professional services	0.00	-0.01	-0.01	0.03	0.02	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Industry-Retail	0.02	0.01	-0.01	-0.00	-0.03*	-0.01	-0.02
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Industry-Other	-0.00	0.04*	0.04*	-0.02	0.02	-0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Position posted salary (USD)	-11.91	-20.13	-8.21	14.05	0.27	-11.37	11.63
	(16.15)	(15.77)	(17.49)	(13.45)	(15.34)	(17.06)	(17.07)
Position number of applicants	9.74	3.73	-6.01	4.41	4.93	-7.32	12.25
	(11.72)	(11.30)	(10.11)	(9.05)	(10.07)	(11.55)	(11.55)
Pre-scan questionnaire	-0.02	-0.03	-0.01	0.04**	0.02	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
STEM degree	-0.01	-0.01	-0.01	0.00	-0.01	-0.01	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)

Note: This table presents mean differences by randomized profile characteristic. Standard errors are reported in parenthesis. The number of observations for the sample is 2,994. Columns 1, 2 and 3 report differences by ethnicity: column 1 shows the difference for the outcome between Chinese and Malay, column 2 shows the difference between Chinese and Indian, and column 3 shows the difference between Malay and Indian. Column 4 reports differences by gender. Columns 5, 6, and 7 report differences by soft skill: column 6 reports the difference of teamwork to the control, column 7 reports the difference of leadership skill to the control, and column 8 reports the difference between teamwork and leadership.

Table B.2: Effect of Soft Skills on Callback Rates accounting for False Discovery Rates

	(1)	(2)	(3)	(4)
Malay	-0.164***	-0.164***	-0.164***	-0.164***
	(0.024)	(0.024)	(0.024)	(0.024)
			[0.000]	[0.000]
Indian	-0.175***	-0.175***	-0.175***	-0.175***
	(0.023)	(0.023)	(0.023)	(0.023)
			[0.000]	[0.000]
Female	0.017	0.017	0.017	0.017
	(0.017)	(0.017)	(0.017)	(0.017)
				[0.354]
Teamwork	-0.038	-0.038	-0.038	-0.038
	(0.031)	(0.031)	(0.031)	(0.031)
Leadership	-0.018	-0.018	-0.018	-0.018
	(0.031)	(0.031)	(0.031)	(0.031)
Teamwork × Malay	0.070**	0.070**	0.070**	0.070**
	(0.033)	(0.033)	(0.033)	(0.033)
	[0.069]	[0.139]	[0.072]	[0.084]
Teamwork × Indian	0.059*	0.059*	0.059*	0.059*
	(0.032)	(0.032)	(0.032)	(0.032)
	[0.069]	[0.139]	[0.104]	[0.122]
Leadership × Malay	0.041	0.041	0.041	0.041
	(0.034)	(0.034)	(0.034)	(0.034)
		[0.311]	[0.280]	[0.327]
Leadership × Indian	0.016	0.016	0.016	0.016
	(0.032)	(0.032)	(0.032)	(0.032)
		[0.616]	[0.616]	[0.616]
Teamwork × Female	-0.009	-0.009	-0.009	-0.009
	(0.024)	(0.024)	(0.024)	(0.024)
Leadership × Female	-0.002	-0.002	-0.002	-0.002
	(0.024)	(0.024)	(0.024)	(0.024)
Constant	0.187***	0.187***	0.187***	0.187***
	(0.023)	(0.023)	(0.023)	(0.023)
R^2	0.059	0.059	0.059	0.059
Observations	2,994	2,994	2,994	2,994

Note: This table presents the results of specification 9 replicating column 4 of table 2 accounting for false discovery rates. The outcome for all columns takes the value of 1 if the company contacted the candidate through email. Robust Standard errors are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Estimated q-values using the Benjamini and Hochberg 1995 step-up method to control for the false discovery rate are reported in brackets for four different families: Column 1 reports the q-values for the predefined family of: Malay team players and Indian team players, column 2 adds Malay leaders and Indian leaders, column 3 adds Malay and Indian dummies, and column 4 adds Female.

C Supplemental analysis using SSM data

To better understand the nature of the discrimination gap, we obtained company-level data that allow us to classify the ethnicity of company officers (individuals holding statutory positions such as directors) and shareholders (owners). Specifically, we merged our primary dataset with data from the Companies Commission of Malaysia (SSM, for its acronym in Bahasa Melayu). Slightly less than half (49%) of companies in our sample were successfully merged with the SSM data, and table C.1 shows companies in the SSM data are not representative of the full sample. Companies in the SSM data are on average larger, are more likely to be in the manufacturing industry (as opposed to professional services), and they are slightly more likely to advertise STEM jobs. Companies in the SSM data receive more applicants for their positions, 164 applicants compared to 130 in companies that are not in the SSM data.

Importantly, the SSM data includes the names of each company's officers and shareholders. We use these names to estimate the ratio of stakeholder ethnicity (separately for officers and shareholders) for each company in the SSM subsample. We used a four step procedure to assign names to a corresponding ethnicity: 1) We matched the SSM list to readily available lists of first and last names, patronymics and n-grams that are characteristic of one of the three ethnicities included in the study. Whenever two names perfectly matched, we assigned the corresponding ethnicity. Some of the n-grams and names have leading or trailing spaces (or both). The spaces were added to ensure that longer names would not be misclassified for containing 2 letter n-grams embedded in them. 2) For the names that remained unclassified, we used OpenAI to assign a likely ethnicity from among the three ethnicities of interest in the study (Chinese, Malaysian, Indian). We made suggestions to update inconsistencies. 3) We manually verified the name assignment and corrected assignments based on our best understanding of ordinary naming conventions in this context. 4) We used information on the identification national document format, available in our dataset, to classify non-Malaysian ethnicities as international.

The ratio of stakeholder ethnicity (separately for officers and shareholders) for each company in the SSM subsample are reported in column 1 of table C.1. In the SSM data subset, 37% of companies have at least one non Chinese officer, and 9% at least one non Chinese shareholder. The majority of officers and shareholders are Chinese, only 13% of officers and 5% of shareholders are non Chinese. Table C.2 shows the balance test results using the SSM subsample. Job and company characteristics are quite similar across the various assignments of profile characteristics, suggesting treatment assignment is well balanced. A greater number of applications signaling teamwork or leaderships skills (relative to the control) were submitted to jobs in the professional services industry. Relative to a leadership signal, slightly fewer applications signaling teamwork were sent to retail positions.

Equation 8 can be modified to incorporate heterogeneity by the ethnicity of either the officers or the shareholders. When testing for heterogeneity by the ethnicity of company leaders, V_i simply represents the percentage of either non Chinese officers or shareholders (estimated separately).

Table C.3 reports heterogeneity analysis using the restricted sample for which we observe information on the ethnicity of officers and shareholders. Column 1 reports the result of estimating equation 8 by officer and shareholder representation respectively. These specifications allow us to examine whether ethnic discrimination is concentrated in Chinese-managed or Chinese-owned firms. Column 1 controls for and interacts the candidate ethnicity with the share of non Chinese officers (i.e., Malay or Indian) in the company. When the board of officers is 100% non Chinese, the average callback rates drop 15 percentage points. In this specification, the difference for Malay candidates relative to Chinese candidates disappears entirely (from 0.13 to 0). For Indian candidates, the gap falls from 0.14 to 0.03. A similar pattern emerges when examining shareholder composition in Column 2. When shareholders are all non Chinese, the callback difference narrows from 0.11 to -0.03 for Malay and from 0.13 to 0 for Indian candidates. Column 3 reports the results of an estimation that simultaneously considers the share of officer and shareholder controls and interactions. Results are qualitatively similar, but somewhat weaker, likely due to multicollinearity.

Overall, our results suggest discrimination against candidates with Malay and Indian-sounding names is concentrated in Chinese-managed and Chinese-owned firms. These results should be interpreted cautiously. Table C.1 shows that 63% of companies have only Chinese officers and 91% of companies have only Chinese shareholders. The interaction effect is driven by a small number of companies with a high share of non Chinese officers and shareholders, rather than companies with a small number of non Chinese officers and shareholders. To show this, we re-estimate equation 8 replacing the share of non Chinese officers and shareholders with a binary indicator for presence of non Chinese officers and shareholders. Results are shown in columns 4 to 6 of table C.3. Although the signs remain the same, the interactions are no longer statistically significant. Column 4 controls for and interacts the candidate ethnicity with the binary indicator on the company having non Chinese officer representation. Column 5 controls for and interacts the candidate ethnicity with a binary variable on the company having any presence of non Chinese shareholders. Column 6 reports the results of an estimation that simultaneously considers the officer and shareholder binary controls and interactions. The results show that there are no statistically significant heterogeneous effects on the presence of officers or shareholders on callback rates.

These results are suggestive of majorities having preference or more information over candidates of their own ethnicity. Columns 1 to 3 of table C.3 show that discrimination against Malay and Indian-sounding names disappears (an even reverses) when companies go from zero representation in these groups to full control of management or ownership. On the other hand, columns 4 to 6 show that having presence of at least of one individual that is Malay or Indian does not affect the discrimination gap.

Table C.1: Comparison of Company and Job Characteristics included or excluded from the SSM dataset

	(1) In the SSM data	(2) Not in the SSM data
Panel A. Company characteristics		
Greater Kuala Lumpur	0.64	0.63
	(0.48)	(0.48)
Company size $\leq$ 50 employees	0.38	0.51
	(0.49)	(0.50)
Industry-Manufacturing	0.32	0.25
	(0.47)	(0.43)
Industry-Professional services	0.24	0.31
	(0.43)	(0.46)
Industry-Retail	0.12	0.14
	(0.33)	(0.35)
Industry-Other	0.31	0.30
	(0.46)	(0.46)
Non Chinese Officers	0.37	
	(0.48)	
Non Chinese Officers (%)	0.13	
	(0.23)	
Non Chinese Shareholders	0.09	
	(0.29)	
Non Chinese Shareholders (%)	0.05	
	(0.18)	
Panel B. Posted job characteristics		
Position posted salary (USD)	754.80	756.30
	(275.09)	(303.18)
Position number of applicants	163.88	129.92
	(244.12)	(247.01)
Use of pre-scan questionnaire	0.55	0.56
	(0.50)	(0.50)
Accounting	0.24	0.25
	(0.42)	(0.43)
Business Administration	0.47	0.52
	(0.50)	(0.50)
Computer Science	0.15	0.11
	(0.36)	(0.31)
Electrical Engineering	0.07	0.06
	(0.25)	(0.24)
Mechanical Engineering	0.08	0.06
	(0.27)	(0.24)
Observations	1,453	1,541

Note: Descriptive statistics for the final sample split for those in the SSM data or not in that data. We classify companies to be in the SSM data when they have information on both officers and shareholders. The table presents means and standard deviations. Column 1 presents statistics for the companies in the SSM data sample, column 2 for companies not in the SSM data. To convert Malaysian Ringgit to US dollars we use the April 2023 average exchange rate published by the Central Bank of Malaysia https://www.bnm.gov.my/exchange-rates. That is, a exchange rate of 0.23.

Table C.2: Mean Differences by Randomly Assigned Profile Characteristic: SSM Subset

	Ethnicity			Gender	Soft Skill		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Chinese - Malay	Chinese - Indian	Malay - Indian	Male - Female	Team - Control	Lead - Control	Team - Lead
Greater Kuala Lumpur	0.03	0.00	-0.02	0.01	-0.01	-0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Company size $\leq$ 50 employees	-0.00	0.00	0.00	-0.01	0.02	0.00	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Industry-Manufacturing	-0.04	-0.02	0.02	-0.01	-0.04	-0.03	-0.01
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Industry-Professional services	-0.01	-0.04	-0.02	0.03	0.09***	0.05**	0.03
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Industry-Retail	0.00	0.01	0.00	-0.01	-0.04	0.00	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Industry-Other	0.05	0.05	-0.00	-0.02	-0.01	-0.03	0.02
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Position posted salary (USD)	7.19	-23.28	-30.47	7.59	9.44	2.41	7.03
	(21.29)	(24.95)	(22.94)	(19.02)	(23.21)	(22.39)	(24.23)
Position number of applicants	14.42	4.39	-10.03	12.33	-2.10	0.46	-2.56
	(16.45)	(16.50)	(14.47)	(12.89)	(16.04)	(15.04)	(16.32)
Pre-scan questionnaire	-0.00	-0.03	-0.03	0.04	0.04	0.03	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
STEM degree	-0.03	-0.02	0.01	0.01	-0.03	-0.03	-0.00
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)

Note: This table presents mean differences by randomized profile characteristic in the SSM subset. Standard errors are reported in parenthesis. The number of observations for the sample is 1,453. Columns 1, 2 and 3 report differences by ethnicity: column 1 shows the difference for the outcome between Chinese and Malay, column 2 shows the difference between Chinese and Indian, and column 3 shows the difference between Malay and Indian. Column 4 reports differences by gender. Columns 5, 6, and 7 report differences by soft skill: column 6 reports the difference of teamwork to the control, column 7 reports the difference of leadership skill to the control, and column 8 reports the difference between teamwork and leadership.

Table C.3: Heterogeneous Callback Rates by Stakeholder Ethnicity

	(1)	(2)	(3)	(4)	(5)	(6)
Malay	-0.128***	-0.113***	-0.127***	-0.129***	-0.109***	-0.128***
	(0.029)	(0.027)	(0.029)	(0.031)	(0.027)	(0.031)
Indian	-0.140***	-0.131***	-0.138***	-0.139***	-0.129***	-0.140***
	(0.027)	(0.026)	(0.028)	(0.029)	(0.026)	(0.029)
Female	0.026	0.027	0.026	0.025	0.027	0.025
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Female × Malay	-0.036	-0.038	-0.036	-0.035	-0.039	-0.036
	(0.038)	(0.039)	(0.038)	(0.038)	(0.039)	(0.038)
Female × Indian	-0.029	-0.030	-0.028	-0.028	-0.031	-0.028
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Non Chinese Officers (%)	-0.152***		-0.127*			
	(0.057)		(0.076)			
Non Chinese Officers (%) × Malay	0.131**		0.135			
	(0.063)		(0.088)			
Non Chinese Officers (%) × Indian	0.106*		0.058			
	(0.059)		(0.080)			
Non Chinese Shareholders (%)		-0.141***	-0.056			
		(0.045)	(0.069)			
Non Chinese Shareholders (%) × Malay		0.085*	-0.006			
		(0.047)	(0.077)			
Non Chinese Shareholders (%) × Indian		0.134**	0.103			
		(0.055)	(0.080)			
Non Chinese Officers				-0.052		-0.047
				(0.034)		(0.036)
Non Chinese Officers × Malay				0.048		0.053
				(0.039)		(0.042)
Non Chinese Officers × Indian				0.035		0.029
				(0.037)		(0.039)
Non Chinese Shareholders					-0.051	-0.026
					(0.054)	(0.057)
Non Chinese Shareholders × Malay					0.008	-0.022
					(0.055)	(0.059)
Non Chinese Shareholders × Indian					0.046	0.030
					(0.058)	(0.062)
Constant	0.174***	0.159***	0.173***	0.174***	0.157***	0.174***
	(0.025)	(0.024)	(0.025)	(0.027)	(0.024)	(0.027)
R^2	0.063	0.061	0.064	0.061	0.059	0.062
Observations	1,453	1,453	1,453	1,453	1,453	1,453

Note: This table presents the results of specification 7 using the SSM subset. Columns 1 uses the share of non Chinese officers, column 2 uses the share of non Chinese shareholders, column 3 adds both in the specification. Columns 4 to 6 use a binary variable for at least one non Chinese officers and shareholders instead. The outcome for all columns is callback and takes the value of 1 if the Company contacted the candidate through email. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.01