Soft Skills and Hiring Discrimination

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Abstract

Hiring discrimination remains widespread, raising questions about how disadvantaged workers can improve labor market outcomes. We examine if employers value soft skills and whether such skills mitigate discrimination. Using a correspondence study in Malaysia, we test the effects of two soft skill signals: leadership and teamwork. We find Malay and Indian names are 11-14 percentage points less likely to be contacted, compared to Chinese names. Signaling teamwork skills reduces discrimination by 34-43%. We present a model that uses signals to distinguish statistical from taste-based discrimination. Our results are consistent with statistical discrimination, and suggest soft skills can counteract hiring discrimination.

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. 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 strong 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. 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).

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. In contrast, a leadership signal has no effect on the discrimination gap. 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 type. 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 (Galarza and Yamada, 2014; 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. To overcome this issue, we use a theoretical model similar to Ewens et al. (2014). Our model suggests a productivity-enhancing signal (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. Our empirical results shows a reduction in the discrimination gap when a teamwork skill is signaled. We argue this finding provides evidence of statistical discrimination.

Second, we add to a burgeoning literature studying the role of soft skills in the job market. While it is known that employers value specific signals in the labor market (Busso et al., 2025). 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.

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). 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. More recently, Paul et al. (2023) report no effect of leadership or conscientiousness (as proxied by athletics participation) on 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, letters remain largely beyond the control of the candidate. Our paper contributes to this literature by providing evidence that basic signals of teamwork skills in job applications can shrink the discrimination gap. On 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, building on Ewens et al. (2014). Our model demonstrates how signals will be differentially interpreted under different forms of discrimination, leading to different hiring decisions.

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 $\hat{\theta}_{ig}$:

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

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 quality, discrimination 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 (i.e. $\Gamma = U(\theta_{ra}(x)) - U(\theta_{sb}(x))$).

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, this means $U(\theta_{ra}) = U(\theta_{sb})$ for $\theta_{ra} = \theta_{sb}$ under statistical discrimination.

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

$$\theta_{ig} = \mu_g + \gamma_g x_{ig} + \varepsilon_{ig} \tag{3}$$

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 3. The figure shows $\mu_a > \mu_b$ since group a has historically been favored in the marketplace.

The parameter θ_{ig} is generally unobserved, which makes it difficult to discern whether observed discrimination is taste-based or statistical. However, the signal's effect on the discrimination gap depends on the relative magnitude of γ_a to γ_b. This insight is formalized in 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 decreases the discrimination gap. A productivity-reducing signal expands the discrimination gap.*

Proof: *Take the derivative of the discrimination gap with respect to x: $\frac{\partial \Gamma}{\partial x} = \frac{\partial U_a}{\partial \theta_a}\frac{\partial \theta_a}{\partial x} - \frac{\partial U_b}{\partial \theta_b}\frac{\partial \theta_b}{\partial x}$. Noting that $\frac{\partial \theta_g}{\partial x} = \gamma_g$, we can write: $\frac{\partial \Gamma}{\partial x} = \frac{\partial U_a}{\partial \theta_a}\gamma_a - \frac{\partial U_b}{\partial \theta_b}\gamma_b$. Equation 3 assumes $\theta_g = \mu_g$ when $x = 0$. If the function U exhibits diminishing returns to θ and $\mu_a \geq \mu_b$, then $\frac{\partial U_a}{\partial \theta}|_{x=0} < \frac{\partial U_b}{\partial \theta}|_{x=0}$. As a result, $\frac{\partial U_a}{\partial \theta}|_{x=0}\gamma_a < \frac{\partial U_b}{\partial \theta}|_{x=0}\gamma_b$ and $\frac{\partial \Gamma}{\partial x} < 0$ when $\gamma_a \leq \gamma_b$. An increase in x decreases the discrimination gap while a reduction in x expands the discrimination gap.*

Theorem 3: *Under statistical discrimination when $\mu_a \geq \mu_b$ and $\gamma_a > \gamma_b$, a signal's effect on the discrimination gap is ambiguous.*

Proof: *Mathematically, the proof is the same as above, but now the sign of $\frac{\partial \Gamma}{\partial x} = \frac{\partial U_a}{\partial \theta_a}\gamma_a - \frac{\partial U_b}{\partial \theta_b}\gamma_b$ is ambiguous.*

This leads to our final insight:

Theorem 4: *Statistical discrimination exists if the discrimination gap reduces with a productivity-enhancing signal or expands with a productivity-reducing signal.*

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.

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%).[1] 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 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. While we will interpret our results as evidence of ethnic discrimination, we cannot distinguish between ethnic and religious discrimination.

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.

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. Column 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).[2] More than half of companies (55%) used a pre-scan questionnaire.

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 4 estimates the difference in callback rates by ethnicity and gender:

$$y_i = \alpha_0 + \beta_1 F_i + \sum_{j=1}^{2} \delta_j E_{ij} + \sum_{j=1}^{2} \phi_j (\mathrm{F}_i \times E_{ij}) + \varepsilon_i \tag{4}$$

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 (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 4 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 5 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:

$$y_i = \alpha_0 + \beta_1 F_i + \sum_{j=1}^{2} \delta_j E_{ij} + \sum_{j=1}^{2} \phi_j (\mathrm{F}_i \times E_{ij}) + \rho_0 V_i + \sum_{j=1}^{2} \rho_j (V_i \times E_{ij}) + \rho_3 (V_i \times F_i) + \varepsilon_i \tag{5}$$

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 6, 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:

$$y_i = \delta_0 + \beta_1 F_i + \sum_{j=1}^{2} \delta_j E_{ij} + \sum_{s=1}^{2} \gamma_{0s} S_{is} + \sum_{j=1}^{2} \sum_{s=1}^{2} \gamma_{js}(E_{ij} \times S_{is}) + \sum_{s=1}^{2} \gamma_3 s(F_i \times S_{is}) + \varepsilon_i \tag{6}$$

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 6 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 disaggregate by gender, degree, and soft skills. The callback rate for candidates with Chinese sounding names is 18%. Comparable candidates with Malay sounding names have callback rates of 5%, and 3% of all applications for Indian sounding names.

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 4). 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)[3].

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 5). In a supplemental analysis reported in Appendix C, we provide evidence that ethnic discrimination is strongly associated with the ethnicity of company 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 6. Column 3 presents the basic effect of soft skills without interactions. We observe no evidence that signaling teamwork or leadership influences the company's decision to callback the average candidate in this context. Of course, this does not mean soft skills are generally unimportant to all employers, or even that soft skills do not matter to the employers in this setting. It is possible that the signals we used were relatively weak. As such, the observed null coefficient should only be interpreted as the effect of the signals used.

Despite the null average effect, the results in column 4 demonstrate a potential role for soft skills 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. Indian candidates with prominent teamwork skills are 6 percentage points more likely to be contacted than those Indian candidates signaling the control soft skill. 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.

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.

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. 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. Future research should consider which soft skills are most important to employers, and whether a stronger signal through even more relevant experience or certification could be more effective.

Despite a null *average* effect for teamwork and leadership, we find signaling an aptitude for teamwork attenuates the discrimination gap by 34-43%. This novel finding 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, opportunities for disadvantaged populations to practice and demonstrate teamwork are important. 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). 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. Our findings suggest these types of interventions might be particularly effective in a context of discrimination.

As with any correspondence study, there are several 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 main 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, which allows us to distinguish statistical and taste-based discrimination under certain conditions. The main insight of the model (from theorem 4) 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.

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 positive or negative 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 and whether this occurs in a context of statistical or taste-based discrimination. Second, knowing the type of hiring discrimination allows policymakers to design better solutions for more equitable labor markets.

Notes

[1]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.

[2]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.

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

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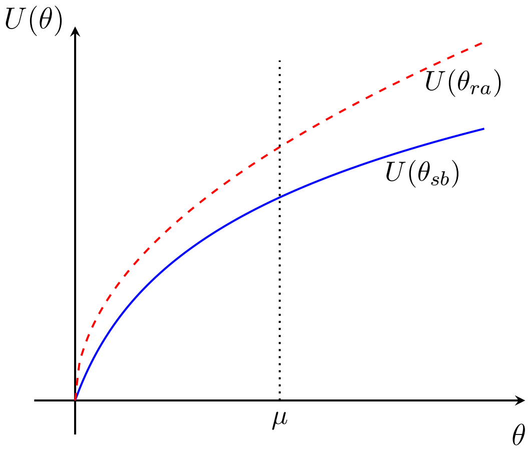
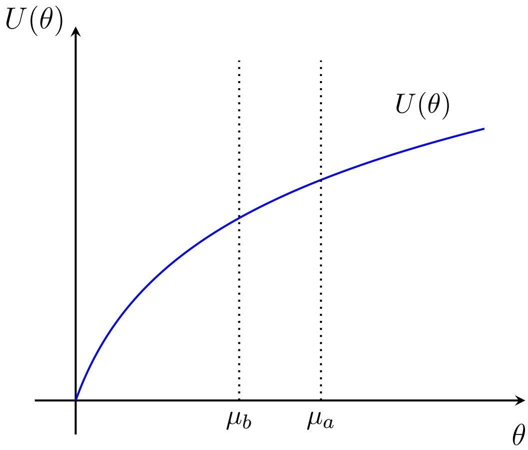
Figures and Tables

Figure 1: Utility functions under discrimination

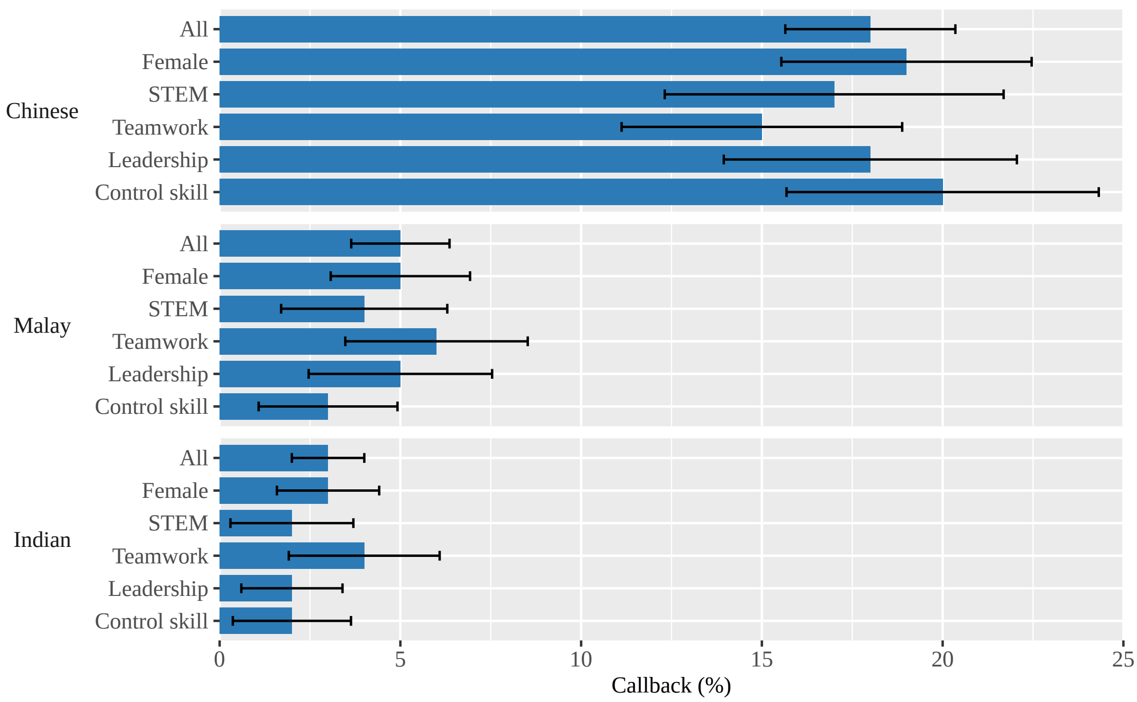


(a) Taste-based



(b) Statistical

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 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.

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 4, 5, and 6. 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.

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.

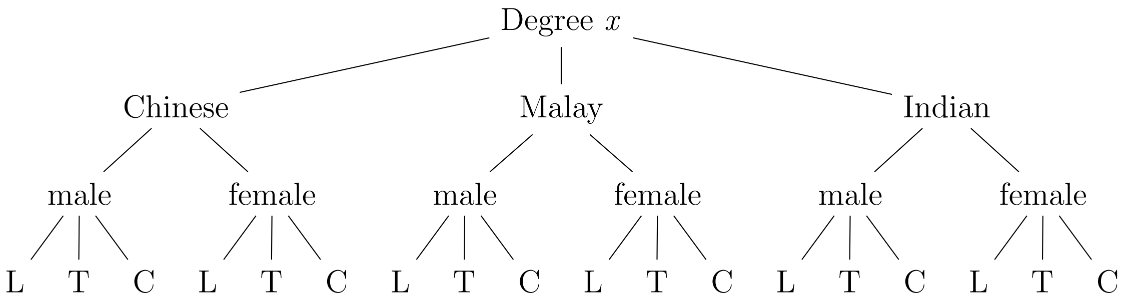
Each job was assigned a degree-based specialization using the area of specialization reported in the ad. Job ads classified as "Accounting/Finance" were assigned an accounting degree. For the business administration degree, we used job ads with specializations: 'Admin/Human Resources', 'Sales/Marketing', '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

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.

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.

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.

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.

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 repo
	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

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 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-screen questionnaire. Answers to pre-screen questions were standardized.

B Supplementary tables

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

	Ethnicity			Gender	Soft Skill		
	(1) Chinese - Malay	(2) Chinese - Indian	(3) Malay - Indian	(4) Male - Female	(5) Team - Control	(6) Lead - Control	(7) 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.

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 shareholders and officers. 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 and are more likely to be in the manufacturing industry (as opposed to professional services). 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. Companies in the SSM data are slightly more likely to advertise STEM jobs.

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 5 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 5 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 zero). 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 5 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 1 controls for and interacts the candidate ethnicity with the binary indicator on the company having non Chinese officer representation.

Column 2 controls for and interacts the candidate ethnicity with a binary variable on the company having any presence of non Chinese shareholders. Column 3 reports the results of an estimation that simultaneously considers the officer and shareholder controls and interactions. The results show that there are no statistically significant heterogeneous effects on the presence of officers or shareholders on callback rates.

Table C.1: Company and Job Descriptive Statistics: SSM and out of SSM data

	(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 ex-

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 ≤ 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 4 using the SSM subset and a binary variable for non Chinese officers and non Chinese shareholders. 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