IZA Institute of Labor Economics

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DISCUSSION PAPER SERIES

IZA DP No. 16993

Soft Skills, Competition, and Hiring Discrimination

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ABSTRACT

Soft Skills, Competition, and Hiring Discrimination*

We conduct a correspondence study to assess demand for soft skills in the context of hiring discrimination in Malaysia. We find no evidence of gender-based discrimination, including in STEM occupations. However, in line with previous studies in the same context, we find evidence of ethnic discrimination. We then test the relevance of two soft skills: leadership and teamwork. We find some evidence that the labor market rewards simple signals of teamwork for the average applicant. Teamwork also plays an important role in the context of labor market discrimination, reducing the discrimination gap by 40%. In contrast, signaling leadership skills has no effect. Last, we consider the role of labor market competition. Companies facing competition in the labor market, measured by the number of competitors advertising similar positions, are 56 to 66% less likely to discriminate. On the supply-side, discrimination increases with the relative quality of the pool of applicants. Our results provide novel evidence that soft skills and labor market competition both play an important role in understanding hiring discrimination. This underlines potential pathways to overcome labor market discrimination and improve job matching.

JEL Classification: J01, J15, J16, J24

Keywords: discrimination, labor market, soft skills, competition

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1 Introduction

Company owners and managers make two decisions with important implications in the labor market: what skills are demanded and who to hire. On the demanded skills, a driver of trends in employment is the changing demand for soft skills (Heckman and Kautz (2012), Weidmann and Deming (2021)). However, we know relatively little about what kind of soft skills employers value in modern entry-level jobs (Heller and Kessler, 2022). On the decision of who to hire, it is in the best interest of companies to hire based on workers productivity. However, several studies have documented the existence of labor market discrimination in a wide range of contexts (Bertrand and Duflo (2017), Neumark (2018)) and it remains unclear how discrimination operates throughout the hiring process and how the existent empirical evidence on discrimination is linked to economic theory (Bertrand and Duflo, 2017).

We conduct a correspondence study in 2023 using a large online job platform to assess demand for soft skills in the context of hiring discrimination in Malaysia. Malaysia is a particularly interesting setting because it is an upper middle income economy, home to multiple ethnicities representing large shares of the population, and previously documented gender gaps in labor force participation and wages. 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 labor market. We also test whether employers respond to signals of two soft skills: teamwork and leadership, both randomly assigned to applications and resumes through the presence of statements that signal each skill (e.g. Demonstrated ability to contribute to teams). Our primary contribution lies in testing how labor market competition and soft skills interact with ethnicity and gender to narrow or widen 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 13 percentage points less likely to contact candidates with Malay-sounding names, and 15 percentage points less likely to contact candidates with Indian-sounding names. These findings are persistent at all stages of the hiring process. Discrimination is more likely to occur in large companies, jobs that offer high wages, and companies that have lower average processing times. We present weak evidence that the labor market rewards simple signals of teamwork for the average applicant. Teamwork also plays an important role in the context of labor market discrimination. While signaling leadership experience has no effect, signaling a teamwork skill reduces the discrimination gap by 40%. Competition also matters. Companies facing competition in the labor market, measured by the number of competitors advertising similar positions, are 56 to 66% less likely to discriminate. On the supply-side, discrimination increases with the relative quality of the pool of applicants. These results provide novel evidence that soft skills and labor market competition both play an important role in understanding hiring discrimination. This underlines a potential pathway to overcome labor market discrimination and improve job matching.

Correspondence studies have been conducted in different contexts, empirically testing the existence of discrimination in race, gender, ethnicity, age, among others (e.g., Bertrand and Mullainathan (2004), Bosch et al. (2010), Bartoš et al. (2016), Deming et al. (2016), Edelman et al. (2017), Kline et al. (2022)). The two known theoretical models of discrimination in the literature are "taste-based discrimination" (Becker, 1971), and "statistical discrimination" (Phelps (1972),Arrow et al. (1973)). Taste-based discrimination occurs when employers derive utility from hiring a candidate based on their ethnicity or gender. In the model of statistical discrimination, employers hire based on their belief that workers of a less favoured group have deficiency in some skills (Lang and Lehmann, 2012). In other words, employers assume an average productivity based on demographics. The existing evidence shows that statistical discrimination does not always explain employers discriminatory behavior. For instance, Bertrand and Mullainathan (2004) do not find differences in callback rates between good quality and bad quality resumes for Black candidates, while for White candidates the difference is 30 percent.[1]

We make three contributions. First, we are among the first to explore how signals of leadership and teamwork soft skills influence hiring decisions at the application stage, particularly in a context of hiring discrimination. A growing literature documents the relevance of soft skills in the labor market. 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 rating of employees positively correlate with communication skills and measures of

[1]Good quality resumes are defined as having more labor market experience and fewer gaps in unemployment.

dependability (Heller and Kessler, 2022). In a recent study, Karpowitz et al. (2023) shows how these soft skills interact with discriminatory practices. They find that assigning leadership roles to women in a classroom setting reduces gender discrimination. Similarly, Kaas and Manger (2012) use a correspondence study to show that presenting soft information, such as reference letters with information on conscientiousness and agreeableness, seems to mitigate discrimination.

Second, unlike most correspondence studies, we exploit data on firm characteristics and decisions at multiple stages of the hiring process to conduct a rich heterogeneity analysis. Most studies are only able to observe if the candidate receives an interview offer. Hangartner et al. (2021) is an interesting exception which tracks online employers actions and collect information that allows them to study hiring decisions. We instead observe five stages in the hiring process: 1) if employers reject an application, 2) if they visit an applicant's profile, 3) the number of visits to each profile, 4) if employers contact the candidate, and 5) if they offer an interview. These five outcomes provide a rich preview into the hiring decision. In addition, we observe several characteristics of the firm and job that are not typically observable to researchers, which we will use to conduct a rich heterogeneity analysis.

Most importantly, we observe the number of applicants applying to a specific job, and the number of similar jobs posted on the platform. This unique data facilitates our third contribution, in which we analyze the role of labor market competition on hiring discrimination, an area which to date has been not been widely explored. de Haan et al. (2017) shows discrimination against disadvantaged groups is more likely in the presence of competition of workers from a non-discriminated group than in a non-competitive scenario. Along these lines, we hypothesize that firms will discriminate less often when there is a low supply of applicants. Unlike de Haan et al. (2017), we uniquely observe quality indicators of the applicant pool, which we use to test our hypothesis that discrimination decreases when the relative quality of applicants in the pool is low. Furthermore, we exploit our unique data to test whether firms discriminate less often when there is high demand for specific job positions. We know of no studies that have previously considered competition on the demand side.

The rest of the document is organized as follows. Section 2 provides background information of Malaysia. Section 3 details the experimental design, section 4 provides summary statistics of the data. Section 5 explores if there is discrimination in the Malaysian labor market, section 6 studies the role of soft-skills, section 7 studies the role of competition. Finally, section 8 concludes.

2 Malaysia's labor market

Malaysia is a multi-ethnic country where Malays represent 57% of the population, Chinese represent 23%, non-Malay Bumiputera (which means "sons of the soil") represent 12%, Indians 7%, and other ethnic groups the remaining 1%.[2] This paper focuses on three of these ethnicities: Malays, Chinese, and Indians. Based on the 2020 census, 63.5% of Malaysians are Muslim, 18.7% are Buddhist, 9.1% are Christian, and 6.1% are Hindu, with the majority of Malays being Muslim.

Malaysia's federal constitution expresses that there shall not be employment discrimination on the basis of race, gender, religion, descent, among others. Despite this constitutional decree, research has previously documented evidence of ethnic-based discrimination (Lee and Khalid (2016); Guan (2005)). Malays are also more likely to be employed in the public sector, as well as in government-linked corporations, while individuals of Chinese and Indian descent are more likely to be employed in the private sector (Lee, 2012). In 2022, Malays made up 77.5% of the public sector, while non-Malay Bumiputera, Chinese, and Indians made up 12.1%, 5.7%, and 3.8% respectively(Lee, 2023). In this way, the labor market in Malaysia seems to be segmented in two: a Malay-dominated public sector and a private sector that tends to be dominated by individuals of Chinese-ethnicity(Lee and Khalid, 2016).

Labor statistics also reveal a wide gender gap in employment . According to Malaysia's 2022 Labour Force Survey (LFS, 2022), 54 percent of women are employed, compared to 79 percent for men. This gap persists across all ethnicities. The main reason given for women not participating in the labor force is housework or family responsibilities, cited by 62.9 percent of women who are out of the labor force (LFS, 2022). Qualitative evidence by Schmillen et al. (2019) suggests that this is due to prevalent social norms that consider most housework, including providing care at home, the responsibility of women. Hence, the lower participation rate in itself does not necessarily reflect discrimination or the relative inability of women to find a job. However, the same study provides evidence of wage discrimination against women, with women earning less compared to men. The

[2]The term "Bumiputera" typically includes Malays. For the purpose of clarity, this paper differentiates between Malays and non-Malay Bumiputera, with the latter being excluded from the correspondence study.

observed difference in earnings found are not explained by ethnicity, age, educational attainment, sector of employment, or employment in a rural (versus urban) area. Against this backdrop of different labor market characteristics between men and women, does discrimination play a role in the relatively low employment among women?

According to the latest report of the Department of Statistics of Malaysia, during the fourth quarter of 2022 there were 204,420 job vacancies posted by 42,592 companies. This number was slightly higher than the third quarter of 2022 when 190,170 job vacancies were posted by 39,472 companies. Of the vacancies posted in the fourth quarter of 2022, 43% were ads for professionals, and close to 50% of the job ads were located in the states of Kuala Lumpur and Selangor (DOSM, 2022). Job vacancies are commonly advertised online in Malaysia. We will exploit this feature by utilizing an online job platform for our study.

Our study focuses on entry level positions, that are particularly important to understand. For instance, using US data Wachter (2020) finds that early career opportunities are an important determinant of future career employment trajectories and earnings. This suggestive evidence likely holds in different contexts. In Malaysia, 35% of fresh graduates in Malaysia work in semi-skilled or low skilled occupations (DOSM, 2021). This fact suggests a mismatch between the demanded and the supplied skills in the labor market for young professionals.

3 Experimental Design

In this section we describe the research protocol for implementation and data collection, which includes the following steps: profile creation (section 3.1), job search and classification (section 3.2), randomized assignment and job applications (section 3.3), and monitoring applications (section 3.5).

3.1 Profile Creation

We create similar candidate profiles, each including a resume, that differ only by name (signaling both ethnicity and gender), and multiple signals of a particular soft skill.

We focus on two soft skills: leadership and teamwork, which are compared to a relatively neutral counterfactual. Soft skills are signalled 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, soft skills and experience are linked.

Resumes with a teamwork soft skill have the following text added in the resume: a) In the executive statement: "Demonstrated ability to contribute to teams", b) In the internship experience description: "Collaborate as part of a team to prepare relevant internal report", c) In the non-professional experience description: "Work collaboratively with other employees".

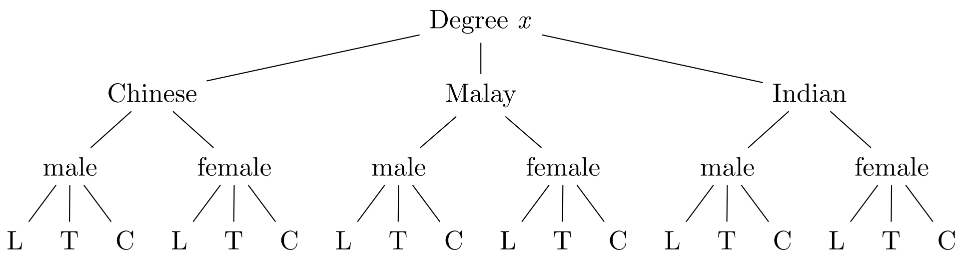
Resumes with a leadership soft skill feature the following text in the resume: a) In the executive statement: "Demonstrated ability to lead teams", b) In the internship experience description: "Lead team in preparation of relevant internal report", c) In the non-professional experience description: "Train and supervise new employees". In addition, leadership resumes are organizers of their hobby/club activity.

Each candidate profile is tailored to one of five degrees: accounting/ accountancy, business administration, computer science, electrical engineering, and mechanical engineering. These degree-based specializations were selected after initially characterizing job advertisements posted between April 11-17, 2022 on the job portal. 671 scraped jobs at that time met the following criteria: full time, entry level, bachelor's degree required, 0-1 years of experience. These jobs were then categorized into the aforementioned degrees. The remaining 15% of total jobs were determined to be too specialized and those kinds of jobs were excluded from the study.

All resumes have a bachelor's degree conferred by the same University, one of the most prestigious and multi-ethnic institutions in Malaysia. In Malaysia, students from a particular ethnicity might attend specific colleges. Hence, the decision of using one institution for all candidates prevents potential associations of perceived quality of an institution to ethnicity.

In total, 90 candidate profiles were created (3 ethnicities x 2 genders x 3 soft skills x 5 industries = 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 the 3 Chinese female applicants within a degree, each is uniquely assigned one of the three soft skills traits to be emphasized (leadership, teamwork, or none), and similarly for

Figure 1: Description of profiles for a given degree



Note: There are five areas of specialization x – accounting/finance, admin/sales/service, technology, mechanical engineering, and electrical engineering. Each specialization has 15 profiles, as described in this figure. The last row depicts soft skills, where L denotes leadership, T denotes teamwork, and C denotes control.

Chinese male candidates, and for the Malay and Indian male and female candidates. This allocation is described for a given degree in figure 1 where L denotes leadership skills, T denotes teamwork skills, and C denotes control.

Each of the 90 profiles has a unique name which reflects an individual's ethnicity and gender (profiles also directly specify the gender), unique phone number, and unique email address corresponding to the name.[3] Names were carefully selected to avoid any signal of wealth or other possible correlates (Gaddis, 2017).[4] Additional profile information takes one of three forms:

1. Information that is consistent across all profiles

2. Information that is consistent across all profiles within a specialization

3. Information that is consistent across all profiles assigned to a specific soft skill

Each profile also has an associated resume. Resumes were generated using a template available online using the same information used to create the profiles. All resumes use the same template. Each resume includes name, basic contact information, gender, executive summary, technical skills, personal skills, educational background, pre-professional experience, activities/hobbies,[5] language, and a statement that references are available upon request.

[3]complete list of names used for profile creation, disaggregated by ethnicity and gender is available upon request

[4]All Malay names are Muslim names. However, ethnicity and religion do not necessarily coincide in Malaysia. All Indian names are Tamil Hindu names.

[5]Hobbies are selected based on observations from the website: https://www.postjobfree.com/l/Malaysia/resumes

3.2 Job Search and Classification

Every Friday from May 12 to July 21, 2023 we scraped all job ads posted within the previous seven days from the job site. Then we filtered and kept job ads that met the criteria: full time, entry level position or requiring at most 1 year of experience. Relevant jobs were then classified into one of the five degree-based specializations. Each job was assigned a degree-based specialization using the area of specialization reported in the ad. For the accounting degree we used job ads classified as "Accounting/Finance". For the business administration degree we used job ads with specializations: 'Admin/Human Resources', 'Sales/Marketing', 'Customer Service' or 'Logistics/Supply Chain'. For the computer science degree we used 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.

We kept one job posting per company in our sample and decided to give priority to jobs in STEM fields. That is, if a company posts two positions in the same week, one for engineering and another for business, we kept the engineering position in our sample. We eliminated all job ads that belong to companies for which applications have been made in previous weeks. The final result of this filtering process results in our sample.

For each job posting that is part of the study, the following information was recorded (from the scraping): 1) Company name 2) Job location 3) Company size 4) Job title 5) Specialization (as categorized on the website) 6) Industry 7) Salary range 8) Average processing time 9) Date of the job posting 10) Text from the job description and company overview.

Our targeted sample is 3,000 job ads. Appendix C provides detailed K-densities information on the power calculations performed to determine the sample size.

3.3 Randomized Assignment and Job Applications

Each week we randomly selected 300 job ads from the sample of ads meeting our inclusion criteria. Among these 300 ads, each job ad was randomly assigned to a single applicant profile. Job ads are stratified to ensure that our treatment and comparison units are balanced on key variables. We use two variables for our strata: company size and company location. Company size is a dummy variable that takes the value of 1 if the company has up to 50 employees, and takes the value of 0 if companies have 51 or more employees. Company location is a dummy variable that takes the value of 1 if the company is located in greater Kuala Lumpur, the capital and largest metropolitan area in Malaysia, and 0 otherwise.[6] Our stratified randomization procedure guarantees balance in the assignment of job profiles to specific characteristics of companies.

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).[7] The order of applications (grouped by profile) each day was also randomized. The application process is straightforward, it consists of submitting the application and complete an optional pitch. However, some jobs have a mandatory pre-scan questionnaire. For these type of ads we standardized answers and recorded the job ads that implemented these questionnaires.

3.4 Monitoring Job Applications

Job applications were monitored using a web scraping algorithm. For each job application, the following data was scraped from the website every Tuesday, Thursday, and Saturday (between 8am-12pm CT):

1. Number of times the profile was viewed by the employer

[6] The locations we classify as Greater Kuala Lumpur are: Kuala Lumpur, Putrajaya, Petaling Jaya, Klang/Port Klang, Kajang/Bangi/Serdang, Subang Jaya, Ampang, Cyberjaya, Seremban, Selangor, Selangor - Others, Selayang, Semenyih, Shah Alam/Subang, Central

[7] If the website is under maintenance, which is common, applications will be delayed until the website is available.

2. Number of applicants to the job posting

3. Number of job applicants ahead of the candidate (Approximate order in the application line)

4. Status of the search (Options include the following: employers are actively processing applications, employers have stopped processing applications, employers declare a candidate not suitable, employers offer an interview or they are not actively processing applications)

5. Number of days between application submission and a candidate is offered an interview (if applicable)

6. Number of days between application submission and a candidate is declared ‘not suitable’ (if applicable)

Companies contacted the candidates directly through email. Any interview request received was manually declined as soon as we observed it. After being contacted, we declined the candidacy within 0-48 hours. However, it is possible that interview requests made on Saturdays was not declined for up to 72 hours. We declined contact using the standard reply message.

3.5 Correspondence study limitations

While correspondence studies are the gold standard for measuring discrimination, there are several common limitations (Lahey and Beasley, 2018). The first important limitation is related to external validity. Would the results hold for different age groups, areas of specialization, or regions? Would the results hold if we had used a different job platform? While we cannot directly address the external validity concerns, we consider five areas of specialization to ensure our results speak beyond a targeted field. We also study entry level discrimination for young professionals, which is important given the consequences for future labor market outcomes (Wachter, 2020). Our findings, at best, are representative of Malaysia’s private sector and do not likely reflect hiring decisions for government jobs. Unfortunately, government jobs are not posted on the online platform we utilized so we were unable to incorporate them in our study. In fact, it’s possible the discrimination we observe here could be reversed in that setting.

A second limitation common in correspondence studies is that researchers are unable to observe any outcomes beyond the initial offer to interview. For example, we cannot observe discrimination that takes place after an interview. This is because we are no longer to hold other variables constant at later stages. Discrimination could be enhanced or reverted in these later stages of the hiring process. Like other studies, this concern is not something we are able to address. However, unlike other studies, we are able to observe earlier stages in the decision-making process. We exploit this information by considering multiple outcomes throughout our analysis.

Finally, there are limitations in regards to how can we interpret the coefficients in the analysis. For instance, the lack of results just displays the outcome at the moment of the experimental implementation. It is possible that employers infer quality of an applicant based on the available information. For example, in a context in which women have difficulties in obtaining an education, a woman participating in the labor market may be extraordinarily qualified relative to a man. Hence, a null result can reflect that the perception of employers compensating based on the prior knowledge of the context.

4 Data

In this section we provide a description of the data we collected. First, we show job and company characteristics of the sample that satisfies our selection criteria. Table 1 present these descriptive statistics. We show the percentage of job postings distributed by location, company size, area of job specialization, industry, company average processing time and salary. All statistics are presented by degree of specialization: Column 1 for Accounting, column 2 for Business Administration, column 3 for Computer Science, column 4 for Electrical Engineering and, column 5 for Mechanical Engineering. Finally, column 6 presents the total sample, for the 2,995 job positions.

Most of the companies (63%) are located in the greater Kuala Lumpur area. This distribution is consistent within degree of specialization except for electric engineering jobs that are mostly located outside of greater Kuala Lumpur. Most of the jobs, about 55%, are posted by companies with more than 50 employees.[8] The area of job specialization described in the job platform matches with

[8]In the data we observe brackets of company size by number of employees: 1-50, 51-200, 201-500, 501-1000, 1001-2000, 2001-5000, and more than 5000.

our degrees of specialization and each degree-based specialization is represented by jobs in several industries. On average a company takes 17 days to process job applications, 50% of them take more than 20 days.The offered monthly salary posted in the job ad is 3,283 MYR (755 US dollars).[9] More than 50% of the jobs offer up to MYR 4,348 (1,000 US dollars) per month. For the degrees of computer science, electrical engineering and mechanical engineering almost 50% of the jobs ads offer more than MYR 6,522 (1,500 US dollars). In our final sample, the Business Administration degree makes up almost 50% of the positions. There were far fewer job ads posted in the Technology and Engineering specializations.

Tables 2, 3 and 4 provide evidence of the balance in our sample for the three dimensions of randomization we conducted: ethnicity, gender and soft skills. For each of these tables we present the means, standard errors across a set of company and job characteristics. In addition, we present the differences between the treatment arms and the standard errors of these differences. The job and company characteristics we observe are: companies located in the Greater Kuala Lumpur area, small firms (with less than 50 workers), offered salary, average days a company takes to process applications, if the job application included a pre-scan questionnaire, the average number of questions for the questionnaire, proportion of applications with a business degree, proportion of job applications with engineering degree, number of applicants for the job position, applicants with more education, applicants asking for a higher salary, and number of foreign applicants. There are minor differences among treatment arms. We only find statistically significant differences for the pre-scan questionnaire in the gender randomization, 53% of male applicants face a pre-scan questionnaire, while this number is 57% for female. In the soft skill randomization, the number of foreign job applicants for the leadership skills is slightly higher than the control group. We believe these differences are spurious. We observe balance across all other job and company characteristics.

The outcome variables we observe represent 5 stages of the hiring process performed by the employer: 1) Application is rejected (declared not suitable), 2) Profile is viewed by employer, 3) number of profile views, 4) candidate is contacted and 5) an interview is offered. These stages reflect actions taken by the employer in the hiring process ranging from candidate screening to job interview

[9]The monthly salary is obtained by taking the average of the salary range advertised on the the ad. To convert Malaysian ringgit (MYR) to US dollars we use the April average exchange rate of 0.23 published by the Central Bank of Malaysia https://www.bnm.gov.my/exchange-rates.

offers.

Table 5 show the summary statistics in job applications and outcomes by each of our three randomized variations: ethnicity, gender, and soft skills. By ethnicity, we observe that 24.9% of the Chinese applications are rejected, while rejection rate is 34.7% for Malay and 38.4% for Indian applications. Roughly 51% of the Chinese profiles get views while Malay and Indian ones get 26 and 21%, respectively. The contact rate for Chinese is 17.5%, for Malay is 5% and for Indian 2.5%. Roughly 11% of the Chinese candidates are offered an interview, while this number is 3.4% for Malay and 2.2% for Indian.

Overall by gender, male and female have similar rates for all outcome variables. We observe that 32.9% of male and 32.3% of female candidates are rejected. About 33% of profiles are viewed for both genders. The contact rate for male is 7.8%, while for female is 8.9%. Similarly, the interview rate difference is minimal, 5.3 % of male candidates receive an interview offer and for female this number is 5.5%.

Finally, we analyze the summary statistics by soft skill. For profiles with leadership soft skill and the control group 'neither', 34% of applications are rejected. While only 30% of candidates with a teamwork soft skill are rejected. The number of profile views for candidates with leadership skill is lower than the other two groups. That is, 31.5% compared to 33.4% for teamwork and the control group. The percentage of contacted candidates is 8% for the 3 groups of soft skill and the percentage of interview requests is 5% for leadership and the control group, and 6% for the teamwork candidates.

Table 1: Company and Job Descriptive Statistics (Percentage)

	Degree					
	(1) Account.	(2) Business	(3) Comp. Sci.	(4) Elec. Eng.	(5) Mec. Eng.	(6) Total
Location						
Kuala Lumpur	66.4	65.3	72.2	39.4	39.1	63.1
Rest of Malaysia	33.6	34.7	27.8	60.6	60.9	36.9
Company Size						
Up to 50 employees	43.8	46.7	46.1	38.3	34.7	44.6
51 employees or more	56.2	53.3	53.9	61.7	65.3	55.4
Area of Job Specialization						
Accounting/Finance	100.0	0.0	0.0	0.0	0.0	24.4
Admin/Human Res.	0.0	29.3	0.0	0.0	0.0	14.5
Information Tech.	0.0	0.0	89.7	0.0	0.0	11.6
Construc./Manufact.	0.0	0.0	0.0	2.7	12.9	1.0
Engineering	0.0	0.0	0.0	97.3	87.1	12.0
Sales/Marketing	0.0	54.5	0.0	0.0	0.0	27.0
Services	0.0	16.3	10.3	0.0	0.0	9.4
Industry						
Primary sector	1.8	2.3	0.0	1.7	6.1	2.1
Manufact./Industry	25.3	24.9	15.1	66.9	72.4	29.6
Healthcare	3.4	7.6	1.1	2.2	3.6	5.1
Real Estate, legal	8.1	5.4	2.2	0.6	0.0	4.9
Professional services	37.3	20.0	61.7	12.7	10.7	28.6
Retail	8.6	20.6	7.0	5.5	2.0	13.7
Transp./Telecomm.	3.7	3.7	5.4	2.8	0.0	3.6
Services	5.5	8.0	3.8	3.3	3.1	6.2
Others	6.2	7.7	3.8	4.4	2.0	6.2
Processing Time						
1-5 days	15.2	15.9	18.6	6.9	9.9	15.1
6-10 days	10.5	12.4	12.4	13.3	11.9	12.0
11-15 days	9.6	10.2	10.1	8.5	10.4	9.9
16-20 days	13.2	12.0	13.7	15.4	11.9	12.7
More than 20 days	51.5	49.6	45.4	55.9	55.9	50.4
Salary						
Less than 500	8.2	11.1	3.9	9.6	6.9	9.1
500-700	24.7	24.7	10.1	18.1	15.8	21.8
700-1000	21.5	25.2	23.2	21.8	25.2	23.8
1000-1500	3.0	6.3	15.5	3.7	2.5	6.2
More than 1500	42.6	32.8	47.4	46.8	49.5	39.1
Total	24.4	49.6	13.0	6.3	6.7	100.0

Note: Descriptive statistics for the final sample for a total of 2,995 job ads that satisfy our inclusion criteria. All statistics are presented by degree of specialization. Column 1 is for Accounting, column 2 for Business Administration, column 3 for Computer Science, column 4 for Electrical Engineering, column 5 for Mechanical Engineering and, column 6 for all of them. Descriptive statistics for location, company size, area of job specialization, industry, average time to process applications, average monthly salary offered per job in US dollars. To convert Malaysian Ringgit to US dollars we use the April 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: Balance for Ethnicity

	(1)	(2)	(3)	(4)	(5)
	Chinese	Malay	Indian	Differences	
				(1)-(2)	(1)-(3)
Greater Kuala Lumpur	0.65	0.62	0.62	0.02	0.03
	(0.48)	(0.48)	(0.48)	(0.02)	(0.02)
Small Firms	0.44	0.44	0.45	-0.00	-0.01
	(0.50)	(0.50)	(0.50)	(0.02)	(0.02)
Salary (USD)	744.54	756.94	765.15	-12.40	-20.61
	(253.32)	(315.34)	(300.69)	(16.15)	(15.76)
Days to Process	16.73	16.64	16.85	0.09	-0.12
	(9.34)	(9.45)	(9.44)	(0.46)	(0.46)
Pre-scan Questionnaire	0.53	0.56	0.56	-0.02	-0.03
	(0.50)	(0.50)	(0.50)	(0.02)	(0.02)
Number of questions	1.83	1.86	1.89	-0.04	-0.07
	(2.20)	(2.24)	(2.23)	(0.10)	(0.10)
Business degree	0.50	0.49	0.50	0.00	-0.00
	(0.50)	(0.50)	(0.50)	(0.02)	(0.02)
Engineering degree	0.25	0.26	0.27	-0.01	-0.01
	(0.44)	(0.44)	(0.44)	(0.02)	(0.02)
Number of job applicants	150.82	141.21	147.22	9.60	3.60
	(284.81)	(235.54)	(211.37)	(11.71)	(11.29)
Applicants with more education	7.36	6.56	6.96	0.80	0.40
	(15.57)	(12.06)	(11.01)	(0.62)	(0.61)
Applicants with higher exp. salary	67.53	67.73	69.62	-0.19	-2.08
	(127.44)	(131.83)	(124.44)	(5.81)	(5.68)
Number of foreign job applicants	6.02	5.57	6.52	0.46	-0.50
	(11.00)	(13.47)	(18.21)	(0.65)	(0.78)
Observations	1006	1008	981		

Note: This table reports descriptive statistics for the sample by ethnicity and balance tests. Columns 1 to 3 report the mean and standard deviation for each ethnicity across different set of job and company characteristics. Columns 4 and 5 present the difference between column 1 and 2, and 1 and 3 respectively.

Table 3: Balance for Gender

	(1) Male	(2) Female	(3) (1)-(2)
Greater Kuala Lumpur	0.63	0.64	0.01
	(0.48)	(0.48)	(0.02)
Small Firms	0.45	0.44	-0.02
	(0.50)	(0.50)	(0.02)
Salary (USD)	748.22	762.60	14.38
	(293.76)	(287.83)	(13.44)
Days to Process	16.82	16.65	-0.17
	(9.55)	(9.26)	(0.37)
Pre-scan Questionnaire	0.53	0.57	0.04**
	(0.50)	(0.50)	(0.02)
Number of questions	1.84	1.89	0.05
	(2.23)	(2.22)	(0.08)
Business degree	0.49	0.50	0.00
	(0.50)	(0.50)	(0.02)
Engineering degree	0.26	0.26	0.00
	(0.44)	(0.44)	(0.02)
Number of job applicants	144.20	148.69	4.50
	(251.38)	(240.67)	(9.05)
Applicants with more education	6.64	7.30	0.66
	(12.62)	(13.47)	(0.48)
Applicants with higher exp. salary	66.24	70.38	4.14
	(122.53)	(133.26)	(4.71)
Number of foreign job applicants	5.94	6.16	0.22
	(15.27)	(13.84)	(0.63)
Observations	1508	1487	

Note: This table reports descriptive statistics for the sample by gender and balance tests. Columns 1 and 2 report the mean and standard deviation for each gender across different set of job and company characteristics. Columns 3 presents the difference between column 1 and 2.

Table 4: Balance for Soft Skills

	(1)	(2)	(3)	(4)	(5)
	Leadership	Teamwork	Neither	Differences	
				(1)-(3)	(2)-(3)
Greater Kuala Lumpur	0.63	0.65	0.62	-0.01	-0.03
	(0.48)	(0.48)	(0.49)	(0.02)	(0.02)
Small Firms	0.45	0.45	0.43	-0.02	-0.02
	(0.50)	(0.50)	(0.50)	(0.02)	(0.02)
Salary (USD)	751.22	763.36	751.99	0.77	-11.37
	(269.54)	(326.23)	(274.43)	(15.33)	(17.06)
Days to Process	16.22	17.19	16.79	0.57	-0.40
	(9.51)	(9.32)	(9.37)	(0.46)	(0.45)
Pre-scan Questionnaire	0.54	0.55	0.56	0.02	0.01
	(0.50)	(0.50)	(0.50)	(0.02)	(0.02)
Number of questions	1.88	1.86	1.85	-0.03	-0.01
	(2.25)	(2.22)	(2.20)	(0.10)	(0.10)
Business degree	0.49	0.49	0.50	0.01	0.00
	(0.50)	(0.50)	(0.50)	(0.02)	(0.02)
Engineering degree	0.26	0.26	0.25	-0.01	-0.01
	(0.44)	(0.44)	(0.44)	(0.02)	(0.02)
Number of job applicants	140.58	152.95	145.64	5.06	-7.32
	(222.81)	(286.54)	(223.20)	(10.06)	(11.55)
Applicants with more education	6.68	7.33	6.87	0.18	-0.47
	(11.87)	(15.64)	(11.16)	(0.52)	(0.61)
Applicants with higher exp. salary	67.52	69.72	67.58	0.06	-2.13
	(127.89)	(137.63)	(117.52)	(5.54)	(5.75)
Number of foreign job applicants	6.91	6.11	5.16	-1.75**	-0.95
	(18.61)	(13.64)	(10.55)	(0.81)	(0.64)
Observations	993	1004	998		

Note: This table reports descriptive statistics for the sample by soft skill and balance tests. Columns 1 to 3 report the mean and standard deviation for each soft skills across different set of job and company characteristics. Columns 4 and 5 present the difference between column 1 and 3, and 2 and 3 respectively.

Table 5: Summary Statistics of the Outcomes

	Rejected		Profile viewed		Contacted		Interview requested		Total job applications	
	No.	%	No.	%	No.	%	No.	%	No.	%
Ethnicity										
Chinese	250	24.9	507	50.4	176	17.5	109	10.8	1,006	100.0
Malay	350	34.7	265	26.3	49	4.9	34	3.4	1,008	100.0
Indian	377	38.4	209	21.3	25	2.5	19	1.9	981	100.0
Gender										
Male	496	32.9	492	32.6	117	7.8	80	5.3	1,508	100.0
Female	481	32.3	489	32.9	133	8.9	82	5.5	1,487	100.0
Soft Skill										
Leadership	336	33.8	313	31.5	83	8.4	51	5.1	993	100.0
Teamwork	299	29.8	335	33.4	84	8.4	61	6.1	1,004	100.0
Neither	342	34.3	333	33.4	83	8.3	50	5.0	998	100.0

Note: This table displays the summary statistics of the outcome variables by ethnicity, gender and soft skill. The outcome variable 'Rejected' occurs when the employer disregards the application on the website. 'Profile viewed' occurs when the employer visits the profile of the candidate at least once. 'Contacted' occurs when the employer contacts the candidate through email, and 'Interview requested' occurs when the email of the employer contains either of the following words: Interview, shortlisted, invite, available, call. The last two columns present the total number of job applications in the sample.

5 Understanding Hiring Discrimination

In this section we explore if there is hiring discrimination in the labor market of Malaysia. First we explore ethnicity-based discrimination and gender-based discrimination. Then, we explore if ethnic discrimination is enhanced or muted by gender. Finally, we present how discrimination varies by job and company characteristics.

5.1 Ethnicity-based Discrimination

The first research question we want to address is, "Is there ethnicity-based discrimination (Malay/ Chinese/ Indian) in the Malaysian labor market?" If yes, to what extent? To answer these questions, we estimate specification 1:

$$\mathrm{y}_i = \delta_0 + \sum_{j=1}^{2} \delta_j E_{ij} + \varepsilon_i \tag{1}$$

Where y_i is the outcome of interest. In our main analysis y_i is a dummy variable that takes the value of 1 if the company (employer) i contacted the candidate (Contacted). As stated above, we observe 5 different outcomes: y_i is a dummy variable that takes the value of 1 if the employer i rejected the application (Rejected), viewed the profile of the candidate (Profile viewed), the number of times employer i viewed the profile of the candidate (N of profile views), and finally, for those profiles contacted, we observe if the company offered an interview (Interview requested).[10] E_j is the ethnicity variable, where $j = \{0, 1, 2\}$. That is, E_j is a dummy variable that takes the value of 1 for ethnicity j and 0 for other ethnicities. ε_i is the error term. The parameter δ_1 is the mean difference in y_i, contact for interview in our main analysis, between ethnicities E_1 and 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 and/or δ_2 provide evidence of ethnic-based discrimination.

Table 6 presents the results of specification 1. We find evidence of ethnic discrimination against Malay and Indian sounding name profiles at all observable levels of the hiring decision process. Job candidates with Malay and Indian sounding names are 9.9 and 13.6 percentage points more likely to have a rejected application in comparison to a Chinese sounding name candidate. Usually, these

[10] For contacted profiles, we can compare the average number of days between application submission and contact by ethnicity and gender. We can perform a similar analysis for profiles that were initially rejected.

applications are rejected without having a profile examination. In the same fashion, profiles with Malay and Indian names are 24 and 29 percentage points less likely to be viewed by employers and the number of views is significantly smaller. Chinese applications receive 1.3 profile views on average, while Malay and Indian have 0.8 and 0.9 fewer views, respectively. When we assess the variables that are usually observable to the researcher in correspondence studies (contact and interview requests), we find that Malay and Indian applications are respectively 13 and 15 percentage points less likely to be contacted by employers and 7.5 and 8.9 percentage points less likely to be offered an interview compared to Chinese candidates. The contact gap for Malay (13 percentage points) is comparable to the findings of Lee and Khalid (2016) who find a contact gap of 18 percentage points. We test if the coefficients for Malay and Indian are equal for each of the outcomes. The coefficients for Malay and Indian are statistically different in 4 out of the 5 outcomes.[11]

Table 6: Ethnic Discrimination

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Malay	0.099***	-0.241***	-0.802***	-0.126***	-0.075***
	(0.020)	(0.021)	(0.069)	(0.014)	(0.011)
Indian	0.136***	-0.291***	-0.913***	-0.149***	-0.089***
	(0.021)	(0.020)	(0.067)	(0.013)	(0.011)
Constant	0.249***	0.504***	1.275***	0.175***	0.108***
	(0.014)	(0.016)	(0.060)	(0.012)	(0.010)
R^2	0.015	0.073	0.080	0.056	0.030
N	2,995	2,995	2,995	2,995	2,995
Malay = Indian					
p-value	0.086	0.009	0.014	0.006	0.046
F-statistic	2.947	6.836	6.074	7.505	3.986

Note: This table presents the results of specification 1. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.01

[11] Results for the five outcomes of interest are presented using the full sample. We do not estimate conditional results (e.g. the probability of being contacted given that the profile was visited) because the sample that visited a profile is not random anymore and produce biased estimates in the discrimination coefficient. This choice applies to the rest of the analysis.

5.2 Gender-based Discrimination

Our second research question is, "Is there gender-based discrimination (male/ female) in the Malaysian labor market? If so, what is the extent of the discrimination?" To answer these questions, we estimate specification 2:

$$y_i = \beta_0 + \beta_1 F_i + \varepsilon_i \tag{2}$$

The outcome y_i and error term ε_i are defined as in specification 1. F_i is a dummy variable that takes the value of 1 if company i received an application of a female candidate, and 0 if they received an application of a male candidate. The parameter β_1 is the mean difference in y_i, between male and female. A statistically significant value for β_1 suggests there is gender-based discrimination.

Table 7 present the results of specification 2. We do not find evidence of the presence of gender discrimination in any dimension of the hiring process. The magnitude of the coefficients is close to zero and all coefficients are statistically zero. These results hold when we add a dummy for engineering degrees and the interactions with gender. These results indicate that there is no gender discrimination at the entry-level in the Malaysian labor market. Hence, discrimination might not explain the observed employment gender gap in the youth population of Malaysia.

Table 7: Gender Discrimination

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Female	-0.005	0.003	0.013	0.012	0.002
	(0.017)	(0.017)	(0.053)	(0.010)	(0.008)
Constant	0.329***	0.326***	0.700***	0.078***	0.053***
	(0.012)	(0.012)	(0.037)	(0.007)	(0.006)
R^2	0.000	0.000	0.000	0.000	0.000
N	2,995	2,995	2,995	2,995	2,995

Note: This table presents the results of specification 2. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.01

5.3 Ethnicity and Gender

Does ethnicity-based discrimination vary by gender? If so, what is the extent? To understand the interaction between gender and ethnicity, we use specification 3 that adds to specification 1 a gender dummy and its interaction with the ethnicity variable:

$$\mathrm{y}_i = \alpha_0 + \beta_1 F_i + \sum_{j=1}^{2} \delta_j E_{ij} + \sum_{j=1}^{2} \gamma_j (E_{ij} \times F_i) + \varepsilon_i \tag{3}$$

We would like to know if ethnic discrimination is enhanced or muted by gender. A statistically significant coefficient on either of the interaction terms γ_j would suggest that gender heterogeneity matters for ethnic discrimination. Table 8 present the results of specification 3. The interaction terms of ethnicity and female are zero for all the hiring stages we observe. Gender does not seem to be relevant enhancing or attenuating ethnic discrimination against Indian and Malay sounding names.

Table 8: Ethnicity and Gender

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Malay	0.132***	-0.268***	-0.847***	-0.113***	-0.081***
	(0.028)	(0.029)	(0.096)	(0.019)	(0.016)
Indian	0.156***	-0.308***	-0.928***	-0.134***	-0.094***
	(0.029)	(0.029)	(0.095)	(0.018)	(0.015)
Female	0.029	-0.024	-0.016	0.033	-0.004
	(0.027)	(0.032)	(0.120)	(0.024)	(0.020)
Female × Malay	-0.067*	0.054	0.091	-0.027	0.012
	(0.041)	(0.042)	(0.139)	(0.028)	(0.023)
Female × Indian	-0.040	0.035	0.029	-0.031	0.010
	(0.041)	(0.041)	(0.134)	(0.026)	(0.021)
Constant	0.234***	0.516***	1.283***	0.159***	0.110***
	(0.019)	(0.022)	(0.085)	(0.016)	(0.014)
R^2	0.016	0.074	0.081	0.058	0.030
N	2,995	2,995	2,995	2,995	2,995

Note: This table presents the results of specification 3. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.01

5.4 Heterogeneity: Job and Company Characteristics

Does discrimination vary by job and company characteristics? Kline et al. (2022) find that in the United States contact gaps are highly concentrated in particular companies. We explore characteristics of companies to approximate this result. Again, we use specifications 1 and 2 as the basis for ethnicity and gender-based discrimination, respectively. We add to both specifications a variable x_{il} that reflects one of six job or company characteristics that we observe: company location, job salary, company size, company average processing time, if companies pre-scan candidates on the platform, and if the job specialization is in engineering. For all these variables we construct dummies to conduct the heterogeneity analysis.

We interact this job or company characteristic with the ethnicity and gender variable in specifications 7 and 8 respectively.[12]

$$\mathrm{y}_i = \delta_0 + \sum_{j=1}^{2} \delta_j E_{ij} + \psi_l x_{il} + \sum_{j=1}^{2} \psi_{jl}(E_{ij} \times x_{il}) + \varepsilon_i \tag{4}$$

$$\mathrm{y}_i = \beta_0 + \beta_1 \mathrm{F}_i + \psi_l x_{il} + \psi_{il}(\mathrm{F}_i \times x_{il}) + \varepsilon_i \tag{5}$$

Results of the heterogeneity analysis by job and company characteristics for ethnic discrimination are presented in tables 15 to 20. We find that discrimination heterogeneity is manifested in different stages of the hiring process. We find that companies that offer high salaries are more likely to discriminate against both Malay and Indian sounding name candidates in terms of profile views. However, this result does not hold for contact or interview offers. Concordantly, small companies are less likely to discriminate in terms of profile views against the two aforementioned ethnic groups. Companies that have a low average processing time of applications (less than 10 days) discriminate more in the initial process of hiring. That is, they are more likely to reject applications before viewing the profile when they observe the name of a specific ethnicity. When the company process applications quickly, Malay-sounding name applicants are 12 percentage points more likely to be rejected compared to Chinese-sounding name applicants, for Indian-sounding name applicants the coefficient is 20 percentage points. Time is also a relevant dimension when companies decide to contact candidates. The median number of days companies take to contact candidates differs by

[12] A similar specification can be used to analyze if response to soft skills vary with job and company characteristics.

ethnicity: For Chinese name candidates is 4 days, for Malay name candidates 5 days and for Indian name candidates 7 days. We find this evidence consistent with a hypothesis of the existence of statistical discrimination since employers can be taking more time to collect information of discriminated groups, or sorting applications. Companies that conduct pre-scan questionnaires in the application process are less likely to discriminate against Indian-sounding name candidates in the profile visit outcome. We do not find heterogeneous effect for location or for engineering jobs.

Heterogeneity results for gender discrimination are presented in tables 21 to 26. Companies located in Kuala Lumpur and small companies are less likely to visit female profiles than male profiles. There is no effect in any of the other outcomes of the hiring process. We do not find heterogeneous effect for for high paying jobs, for companies with low processing time, for companies with pre-scan questionnaires or jobs in engineering.

6 Do Soft Skills Matter?

In this section we explore if soft skills are relevant in the labor market and how soft skill signals affect ethnic and gender discrimination. The role of soft information has been previously raised by Kaas and Manger (2012) that find that soft information on conscientiousness and agreeableness mitigate the discrimination practices.

6.1 Response to Soft Skills

Does the labor market respond to signals of soft skills (leadership/ teamwork/ neither)? If so, what is the extent of the response? To answer these questions, we use the soft skill signal that we randomly assigned to each profile. We can test if soft skills are differentially relevant in the labor market using specification 6:

$$\mathrm{y}_i = \theta_0 + \sum_{k=1}^{2} \theta_k S_{ik} + \varepsilon_i \tag{6}$$

Again, the outcome y_i and error term ε_i are defined as in specification 1. The soft skills we want to test are leadership and teamwork, in comparison to a control soft skill that we call 'neither'. S_k is the soft skills variable, where $k = \{0, 1, 2\}$. That is, S_k is a dummy variable that takes the value of 1 for soft skill k (e.g. leadership) and 0 for other soft skills (e.g. teamwork and our counterfactual soft skill). The parameter θ_1 is the mean difference in y_i for candidates with soft skills S_1 and S_0. That is, the mean difference between candidates with leadership soft skill signal and our counterfactual soft skill. Likewise, θ_2 captures the mean difference in the outcome between teamwork soft skill and our counterfactual soft skill. A statistically significant result for θ_1 and/or θ_2 suggest that employers value the soft skills we included in the application (leadership and teamwork, respectively) during the hiring process.

Table 9 present the results of specification 6. Signaling a teamwork soft skill reduces the probability of having a profile rejected in 4.5 percentage points. This is the only outcome in the hiring process statistically significant at the 5% level. The teamwork soft skill does not affect any of the other outcomes of the hiring process. Overall the leadership soft skill is not relevant in the hiring decision process of Malaysian companies. All coefficients are not statistically significant and nearly zero for all outcomes. We test the equality of the coefficients for teamwork and leadership. They are only statistically different for the outcome of rejected applications.The coefficients are statistically equal for the rest of the outcomes. We argue that there is weak evidence on the relevance of teamwork soft skill in the labor market. Overall, signaling a soft skill does not have a effect on the average outcome for candidates along the hiring process.

6.2 Soft skills, Ethnicity and Gender

We want to know if signalling a soft skill narrows or widens the discrimination gap? To this end we use specifications 7 and 8. Specification 7 builds on specification 1, adding the soft skill variables and interactions with ethnicity variables. A statistically significant coefficient on either of the interaction terms ν_{kj} would suggest a soft skill signal matters in the context of ethnic discrimination.

$$\mathrm{y}_i = \delta_0 + \sum_{j=1}^{2} \delta_j E_{ij} + \sum_{k=1}^{2} \theta_k S_{ik} + \sum_{k=1}^{2}\sum_{j=1}^{2} \nu_{kj}(E_{ij} \times S_{ik}) + \varepsilon_i \tag{7}$$

Specification 8 builds on specification 2, adding the soft skill variables and interactions with gender variables. Again, a statistically significant coefficient on either of the interaction terms ν_k would suggest a soft skill is relevant for gender discrimination.

$$\mathrm{y}_i = \beta_0 + \beta_1 \mathrm{F}_i + \sum_{k=1}^{2} \theta_k S_{ik} + \sum_{k=1}^{2} \nu_k(\mathrm{F}_i \times S_{ik}) + \varepsilon_i \tag{8}$$

Table 9: Response to Soft Skills

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Teamwork	-0.045**	-0.000	-0.013	0.000	0.011
	(0.021)	(0.021)	(0.063)	(0.012)	(0.010)
Leadership	-0.004	-0.018	-0.012	0.000	0.001
	(0.021)	(0.021)	(0.065)	(0.012)	(0.010)
Constant	0.343***	0.334***	0.714***	0.083***	0.050***
	(0.015)	(0.015)	(0.045)	(0.009)	(0.007)
R^2	0.002	0.000	0.000	0.000	0.000
N	2,995	2,995	2,995	2,995	2,995
Teamwork = Leadership					
p-value	0.052	0.379	0.979	0.995	0.361
F-statistic	3.789	0.776	0.001	0.000	0.833

Note: This table presents the results of specification 6. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors.
* p<0.1, ** p<0.05, *** p<0.01

Table 10 presents the result of specification 7. In this specification we assess the differential effects of ethnic discrimination when candidates signal soft skills. We find that signaling teamwork skills improve the hiring chances of both Malay and Indian candidates in the hiring process. Having a signal of teamwork increases the likelihood of being contacted in 7 percentage points in comparison to the baseline category. In other words, signaling a collaborative soft skill attenuates the discrimination against Malay by 43%. For Indian-sounding names the teamwork soft skill attenuates the discrimination gap in 34%, but this result is only significant at the 10% level. Interestingly, the number of rejections decrease and the number of profile views increases for both ethnicities. However, these results are not statistically significant at the conventional levels. These results have important implications, hiring opportunities improve when candidates signal teamwork skills. We cannot reject the hypothesis of equality of these effects across Malay and Indian candidates.

Our results are interesting given that the signal is not endorsed by any certificate or institution. The soft skill signal is subtly displayed in three parts of the resume: 1) a sentence in the description of each of the previous job positions stating a collaborative role in a single task, 2) a bullet point stating teamwork and collaboration in a section describing personal skills, and 3) A sentence in the executive summary of the resume stating,“Demonstrated ability to contribute to teams”.

The results for the leadership soft skill are not as strong. However, signaling leadership increases the interview requests for Malay but only at the 10% level of significance. Having different results for each soft skill might reflect a differential demand for each skill in the labor market. The leadership soft skills is not statistically significant for any of the three ethnicities. It is possible that employers expect a particular soft skill to be useful at entry-level positions to contribute to the working environment. For instance, workers from a different ethnicity that have the capacity to collaborate or “blend in” may be perceived by employers as more valuable workers.

Interestingly, signaling soft skills does not change the outcomes of Chinese candidates, but it does so for otherwise more-likely-to-be-discriminated groups. That teamwork soft skills can mitigate the effects of extant discrimination, without necessarily increasing the outcomes on their own implies that some types of soft skills can help marginalized groups in the labor market overcome discrimination.

Table 11 present the results for specification 8, the interaction of gender and soft skills. None of the coefficients is statistically significant. This finding is reasonable given that previously we did not find evidence of gender discrimination.

Table 10: Ethnicity and Soft Skills

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Malay	0.112***	-0.239***	-0.903***	-0.163***	-0.103***
	(0.035)	(0.037)	(0.118)	(0.024)	(0.019)
Indian	0.167***	-0.325***	-1.030***	-0.174***	-0.099***
	(0.036)	(0.035)	(0.118)	(0.023)	(0.019)
Teamwork	-0.022	-0.017	-0.193	-0.043	-0.006
	(0.033)	(0.039)	(0.145)	(0.029)	(0.025)
Leadership	0.017	-0.034	-0.056	-0.020	-0.021
	(0.034)	(0.039)	(0.151)	(0.030)	(0.024)
Indian × Lead	-0.063	0.060	0.066	0.016	0.017
	(0.051)	(0.050)	(0.165)	(0.032)	(0.026)
Malay × Lead	0.002	-0.019	0.044	0.041	0.047*
	(0.051)	(0.051)	(0.174)	(0.034)	(0.027)
Indian × Team	-0.031	0.041	0.286*	0.059*	0.013
	(0.051)	(0.050)	(0.165)	(0.032)	(0.027)
Malay × Team	-0.037	0.009	0.255	0.070**	0.037
	(0.049)	(0.052)	(0.165)	(0.033)	(0.028)
Constant	0.250***	0.521***	1.358***	0.196***	0.117***
	(0.024)	(0.027)	(0.107)	(0.022)	(0.018)
R^2	0.018	0.075	0.082	0.059	0.032
N	2,995	2,995	2,995	2,995	2,995
Malay × Lead = Indian × Lead					
p-value	0.228	0.093	0.835	0.201	0.070
F-statistic	1.455	2.820	0.043	1.639	3.292
Malay × Team = Indian × Team					
p-value	0.906	0.482	0.776	0.572	0.157
F-statistic	0.014	0.495	0.081	0.320	2.004

Note: This table presents the results of specification 7. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.01

Table 11: Gender and Soft Skills

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Female	0.005	-0.017	-0.067	0.015	0.009
	(0.030)	(0.030)	(0.090)	(0.018)	(0.014)
Team	-0.038	-0.026	-0.085	0.005	0.015
	(0.029)	(0.030)	(0.090)	(0.017)	(0.014)
Lead	0.005	-0.021	-0.059	0.001	0.006
	(0.030)	(0.030)	(0.092)	(0.017)	(0.014)
Female × Lead	-0.020	0.005	0.095	-0.001	-0.011
	(0.043)	(0.042)	(0.131)	(0.025)	(0.020)
Female × Team	-0.014	0.053	0.144	-0.010	-0.010
	(0.042)	(0.042)	(0.126)	(0.025)	(0.020)
Constant	0.340***	0.342***	0.748***	0.076***	0.046***
	(0.021)	(0.021)	(0.065)	(0.012)	(0.009)
R^2	0.002	0.001	0.000	0.001	0.001
N	2,995	2,995	2,995	2,995	2,995

Note: This table presents the results of specification 8. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

7 Competition in the Labor Market

In this section we assess whether labor market competition has a role to play in determining discrimination. On the demand side, competition arises through the number of companies looking for similar jobs. On the supply side, competition arises through the number of applicants for each job position and the quality of these applicants.

To measure competition on the demand side, we sum all the job ads advertised in the job site by specialization and week. Within the distribution of jobs by specialization, we classify them as "High Demand" jobs if they are above the median in the distribution. To measure competition on the supply side, we use information on the number of applicants for each job position. We classify "High Supply" positions as those that have a number of applicants above the median of the number of applicants in our sample distribution.

We test if companies discriminate more or less when there is High Competition $HC_i \in \{HD_i, HS_i\}$. That is, either High Demand HD_i or High Supply HS_i following the specification:

$$\begin{aligned} \mathrm{y}_i = \delta_0 + \sum_{j=1}^{2} \delta_j E_{ij} + \psi_{d,s} HC_i + \omega(HD_i \times HS_i) \\ + \sum_{j=1}^{2} \psi_{jd,js}(E_{ij} \times HC_i) + \sum_{j=1}^{2} \omega_j (E_{ij} \times HD_i \times HS_i) + \varepsilon_i \end{aligned} \tag{9}$$

Table 12 present the results when we take into account high competition jobs in our specification and interact them with the ethnicity variables. We find that when there is high demand for workers, contact rates for Malay and Indian sounding name candidates increase in 14 and 13 percentage points and interview requests significantly increase in 9 and 10 percentage points, respectively. These results are sizeable and represent a reduction of the contact discrimination gap of 56 and 66% and a reduction of the discrimination gap for interview requests of 74 and 69%. The number of job openings is relevant for companies to know how easy or hard is for them to find workers (Abraham et al., 2020). We do not find statistically significant results for the interaction of ethnicity with a high supply of applicants. This finding is not consistent with de Haan et al. (2017) since discrimination against disadvantaged groups is more likely in the presence of competition of workers from a non-discriminated group than in a non-competitive scenario.

Table 12: Ethnic Discrimination: Supply and Demand

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Malay	0.066	-0.204***	-0.824***	-0.207***	-0.126***
	(0.043)	(0.045)	(0.164)	(0.033)	(0.029)
Indian	0.137***	-0.242***	-0.962***	-0.233***	-0.144***
	(0.044)	(0.045)	(0.149)	(0.032)	(0.028)
High Demand	-0.045	0.060	-0.004	-0.135***	-0.102***
	(0.039)	(0.044)	(0.178)	(0.036)	(0.029)
High Supply	-0.068*	-0.053	-0.264	-0.085**	-0.063**
	(0.038)	(0.044)	(0.174)	(0.037)	(0.031)
Malay × HD	0.057	-0.018	0.017	0.137***	0.094***
	(0.058)	(0.061)	(0.213)	(0.042)	(0.035)
Malay × HS	0.026	-0.061	0.027	0.061	0.045
	(0.057)	(0.059)	(0.205)	(0.042)	(0.036)
Indian × HD	0.031	-0.090	-0.009	0.130***	0.099***
	(0.060)	(0.060)	(0.204)	(0.039)	(0.033)
Indian × HS	-0.016	-0.068	0.049	0.064	0.039
	(0.058)	(0.058)	(0.190)	(0.040)	(0.034)
HD × HS	0.122**	-0.115*	-0.167	0.064	0.068*
	(0.055)	(0.063)	(0.241)	(0.048)	(0.039)
Malay × HD × HS	-0.032	-0.002	-0.023	-0.080	-0.081*
	(0.082)	(0.083)	(0.277)	(0.055)	(0.045)
Indian × HD × HS	-0.037	0.142*	0.159	-0.054	-0.059
	(0.083)	(0.082)	(0.268)	(0.052)	(0.043)
Constant	0.278***	0.526***	1.444***	0.269***	0.175***
	(0.029)	(0.033)	(0.135)	(0.029)	(0.025)
R^2	0.020	0.096	0.092	0.073	0.042
N	2,995	2,995	2,995	2,995	2,995

Note: This table presents the results of specification 9. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Competition on the supply side can also arise through the quality of the pool of applicants. Are employers less likely to discriminate when the quality of the pool of applicants is low? In the data, we observe quality indicators of the applicant pool, which we use to test our hypothesis that discrimination decreases when the relative quality of applicants in the pool is low. We test two dimensions of perceived relative quality: 1) when the majority of the candidates applying for a position have lower level of education than our candidate 2) when the majority of candidates applying for the position have a lower expected salary than our candidate (a below median salary). In our specification we interact the ethnicity dummies with: 1) a dummy if the job has a low education supply and, 2) a dummy if the job has a low salary supply. We expect to observe an attenuation in the discrimination gap when the majority of applicants in the pool have either low education supply or low quality based on their expected salary.

Table 13 present the results of the interaction of ethnic variables with low education in the supply of applicants. Our results show that with a pool of applicants with low education, Malay-sounding names are 11 percentage points more likely to be contacted and Indian-sounding names are 12 percentage points more likely to be contacted. This represents a reduction in the contact discrimination gap above 60%. For interview offers, discrimination against Malay-sounding names reduces in 55% and for Indian-sounding names in 65%.

Table 13: Ethnic Discrimination: Majority of Supply with Low Education

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Malay	0.109***	-0.262***	-0.857***	-0.169***	-0.096***
	(0.026)	(0.027)	(0.089)	(0.019)	(0.016)
Indian	0.133***	-0.315***	-0.982***	-0.197***	-0.121***
	(0.027)	(0.027)	(0.084)	(0.018)	(0.015)
Low Educ Supply	0.024	-0.068**	-0.168	-0.115***	-0.072***
	(0.028)	(0.032)	(0.125)	(0.023)	(0.019)
Malay × LES	-0.034	0.056	0.137	0.108***	0.053**
	(0.042)	(0.043)	(0.143)	(0.027)	(0.022)
Indian × LES	0.005	0.063	0.171	0.120***	0.079***
	(0.043)	(0.042)	(0.139)	(0.025)	(0.021)
Constant	0.241***	0.530***	1.342***	0.221***	0.138***
	(0.017)	(0.020)	(0.076)	(0.017)	(0.014)
R^2	0.015	0.075	0.081	0.070	0.039
N	2,957	2,957	2,957	2,957	2,957

Note: This table presents the results of specification 1 adding a dummy for majority of job positions with low quality education and its interaction with ethnicity variables. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. The number of observations is smaller than the rest of the specifications because there are jobs for which we cannot observe information of the pool of applicants. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Table 14 present the results when the pool of candidates have low perceived quality in terms of their expected salary. Discrimination decreases when the majority of applicants have a low expected salary. Malay and Indian sounding names discrimination gap for the rejection outcome decreases in 58 and 49%, respectively. Profile views discrimination gap for Malay names drops by 43% and for Indian names by 34%. Finally, contact discrimination gap for Malay-names drops by 45% and 33% for Indian-sounding names. Interestingly, results are stronger for Malay-sounding name candidates.

The model of statistical discrimination predicts that companies would discriminate and rely on stereotypes when facing an overload of applications. Our analysis shows that there is not a differential effect with a high number of applicants. A potential explanation of our results is that companies that receive more applications have a greater capacity to process them. Importantly, we find that when the pool of applicants has a low perceived quality, measured either by education level or expected salary in the pool of applicants, narrows the discrimination gap against Malay and Indian profiles.

Table 14: Ethnic Discrimination: Majority of Supply with Low Expected Salary

	(1)	(2)	(3)	(4)	(5)
	Rejected	Profile viewed	N of profile views	Contacted	Interview requested
Malay	0.153***	-0.334***	-0.952***	-0.178***	-0.097***
	(0.033)	(0.035)	(0.117)	(0.024)	(0.021)
Indian	0.196***	-0.370***	-1.026***	-0.191***	-0.115***
	(0.033)	(0.034)	(0.112)	(0.023)	(0.019)
Low Salary Supply	0.084***	-0.113***	-0.205*	-0.064**	-0.035*
	(0.028)	(0.033)	(0.124)	(0.026)	(0.021)
Malay × LSS	-0.089**	0.145***	0.232	0.081***	0.034
	(0.042)	(0.044)	(0.146)	(0.029)	(0.025)
Indian × LSS	-0.096**	0.124***	0.173	0.064**	0.040*
	(0.043)	(0.043)	(0.140)	(0.028)	(0.023)
Constant	0.197***	0.576***	1.407***	0.216***	0.132***
	(0.021)	(0.026)	(0.098)	(0.022)	(0.018)
R^2	0.017	0.078	0.082	0.060	0.032
N	2,957	2,957	2,957	2,957	2,957

Note: This table presents the results of specification 1 adding a dummy for majority of job positions with low expected salary and its interaction with ethnicity variables. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. The number of observations is smaller than the rest of the specifications because there are jobs for which we cannot observe information of the pool of applicants. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

8 Conclusions

We conducted a correspondence study using an online job platform in Malaysia. We tested for ethnic discrimination, gender discrimination and the value of signaling soft skills in the labor market. Unlike many correspondence studies, the data allow us to observe different stages in the hiring process. We observe if the employer rejects an application, visits the profile of a candidate, times the profile is visited, if they contact them and if they offer an interview. Uniquely, we observe competition in the labor market on both the demand and supply side.

We do not find evidence of gender discrimination in the hiring process. Malaysia's observed differential wages and labor force participation rates by gender do not seem to be associated with discrimination or human capital accumulation. More research is needed to determine why women in the Malaysian labor market have lower employment rates and wages.

We find that Indian and Malay sounding name profiles are discriminated against in comparison to Chinese-sounding name profiles. There is discrimination along all the hiring process variables we observe. Malay and Indian candidates are 8 and 9 percentage points less likely to receive an interview offer relative to a Chinese candidate. Discrimination for both ethnicites is also present in other outcomes. They are at least 10 percentage points more likely to be rejected for the position they apply for, even when the profile was not thoroughly examined. Their profiles are visited less often and are less likely to be contacted by the employer. Ethnic discrimination varies by company characteristics. Small companies seem to examine job applications of Malay and Indian sounding names more carefully measured by profile visits. However, this does not translate into higher contact rates or interview offers. Jobs that offer high salaries have fewer visits to the profiles of the discriminated groups. Companies with low average processing time reject more applications of Indian and Malay sounding names.

The results of this paper are consistent with the model proposed by Bartoš et al. (2016) where employers decide to put differential levels of effort to collect information of candidates according to their ethnicity. Companies in Malaysia reject applications at different rates based on ethnicity of the applicant, companies also visit profiles differentially according to ethnicity, and they take more days to contact applicants that have names of a discriminated ethnicity, when they do so. Bertrand

and Duflo (2017) suggests that some employers use quick heuristics in the hiring process. In line with this hypothesis, we observe that companies that spend less time processing applications are more likely to disregard applications of the discriminated groups.

We find that in general soft skill signals are weakly associated with hiring decisions in the labor market. However, signaling a teamwork skill in the job application and resume attenuates the contact discrimination gap by 40% for both Malay and Indian sounding names. These findings have important policy implications. In the practice, it would be desirable for disadvantage groups to invest more in soft skills through relevant experience but also highlight such experience when applying for jobs to improve their likelihood of being hired. These findings are consistent with Weidmann and Deming (2021) that find that team players improve team performance and might increase the effort teammates exert.

Previous literature documented that employers value soft skills differently in the labor market. Heller and Kessler (2022) find that 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. On the contrary, our findings show that teamwork skills narrow discrimination and are consistent with Kaas and Manger (2012) who find that providing information of affability, commitment, capacity for teamwork, and conscientiousness in recommendation letters reduce ethnic discrimination. The divergence in preference for soft skills could be attributed to the context, our findings occur in a context of discrimination and where soft skills are only signaled in a job application, while Heller and Kessler (2022) findings are ex-post evaluation of soft skills of an in-person internship program. It is quite possible that employers weight differently on skills in the presence of hiring discrimination or informational frictions. Employers might get marginal value from candidates with collaborative skills but no value from candidates with leadership skills at entry-level positions.

We also present unique evidence that competition in the labor market affects discrimination practices. When there is competition on the demand side, that is, more companies looking for candidates in similar jobs, the contact discrimination gap drops by more than 50%. On the supply side, we do not observe differential discrimination in the presence of more candidates, as the model of statistical discrimination would suggest. However, when we account for the perceived quality of the pool of applicants measured by educational level or expected salary, we find that a lower perceived quality in the pool of applicants decreases the likelihood of discrimination in different stages of the hiring process. These results have important policy implications. Firm competition can be promoted as a measure to alleviate discrimination in the labor market. On the supply side, a better matching of workers quality to job positions can improve hiring opportunities of discriminated groups.

Our findings are novel evidence that fostering certain soft skills, like teamwork, can improve the opportunities in the labor market for groups of population facing barriers to participation. Similarly, understanding the labor market structure and promoting competition on the demand side can have positive spillovers on discriminated groups.

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A Heterogeneous effects for ethnicity

Table 15: Ethnicity heterogeneous effect: Location

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Malay	0.101***	-0.229***	-0.825***	-0.152***	-0.078***
	(0.034)	(0.035)	(0.122)	(0.023)	(0.018)
Kuala Lumpur	-0.022	0.045	-0.046	-0.018	0.006
	(0.029)	(0.033)	(0.129)	(0.025)	(0.020)
Malay×KL	-0.005	-0.017	0.035	0.041	0.006
	(0.042)	(0.044)	(0.148)	(0.029)	(0.023)
Indian	0.121***	-0.280***	-0.994***	-0.173***	-0.094***
	(0.034)	(0.034)	(0.117)	(0.022)	(0.017)
Indian× KL	0.023	-0.016	0.128	0.037	0.008
	(0.043)	(0.042)	(0.142)	(0.027)	(0.022)
Constant	0.263***	0.475***	1.305***	0.186***	0.105***
	(0.023)	(0.027)	(0.107)	(0.021)	(0.016)
R^2	0.015	0.075	0.081	0.058	0.030
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 7. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Table 16: Ethnicity heterogeneous effect: High salaries

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Malay	0.083**	-0.161***	-0.638***	-0.125***	-0.090***
	(0.037)	(0.038)	(0.114)	(0.024)	(0.021)
High Salary	-0.039	0.075**	0.220*	0.005	-0.020
	(0.030)	(0.034)	(0.125)	(0.026)	(0.022)
Malay × HS	0.022	-0.118***	-0.241*	-0.002	0.023
	(0.044)	(0.045)	(0.143)	(0.029)	(0.025)
Indian	0.114***	-0.221***	-0.752***	-0.159***	-0.109***
	(0.037)	(0.037)	(0.111)	(0.022)	(0.019)
Indian× HS	0.032	-0.102**	-0.236*	0.014	0.029
	(0.045)	(0.044)	(0.139)	(0.027)	(0.023)
Constant	0.275***	0.453***	1.125***	0.172***	0.122***
	(0.025)	(0.028)	(0.101)	(0.021)	(0.018)
R^2	0.016	0.076	0.082	0.057	0.030
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 7. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Table 17: Ethnicity heterogeneous effect: Small companies

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Malay	0.125***	-0.274***	-0.775***	-0.125***	-0.084***
	(0.026)	(0.028)	(0.089)	(0.018)	(0.015)
Small Firm	0.119***	-0.017	0.171	0.029	0.003
	(0.028)	(0.032)	(0.123)	(0.024)	(0.020)
Malay × Small	-0.060	0.074*	-0.063	-0.004	0.021
	(0.041)	(0.042)	(0.141)	(0.028)	(0.023)
Indian	0.168***	-0.329***	-0.926***	-0.142***	-0.096***
	(0.027)	(0.027)	(0.081)	(0.017)	(0.014)
Indian × Small	-0.074*	0.084**	0.026	-0.017	0.015
	(0.042)	(0.041)	(0.137)	(0.026)	(0.022)
Constant	0.196***	0.512***	1.200***	0.162***	0.107***
	(0.017)	(0.021)	(0.076)	(0.016)	(0.013)
R^2	0.022	0.076	0.084	0.058	0.031
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 7. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Table 18: Ethnicity heterogeneous effect: Low processing time

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Malay	0.067***	-0.223***	-0.782***	-0.113***	-0.063***
	(0.022)	(0.025)	(0.078)	(0.016)	(0.013)
Low Proc Time	0.195***	-0.028	0.022	0.053*	0.034
	(0.033)	(0.036)	(0.138)	(0.028)	(0.023)
Malay× LPT	0.117**	-0.069	-0.074	-0.049	-0.044*
	(0.048)	(0.046)	(0.166)	(0.032)	(0.026)
Indian	0.083***	-0.284***	-0.894***	-0.137***	-0.081***
	(0.022)	(0.024)	(0.078)	(0.015)	(0.012)
Indian × LPT	0.203***	-0.026	-0.075	-0.046	-0.028
	(0.047)	(0.045)	(0.152)	(0.031)	(0.026)
Constant	0.196***	0.512***	1.269***	0.161***	0.099***
	(0.015)	(0.018)	(0.070)	(0.014)	(0.011)
R^2	0.102	0.077	0.081	0.059	0.031
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 7. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Table 19: Ethnicity heterogeneous effect: Pre-scan questions

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Malay	0.084***	-0.254***	-0.868***	-0.141***	-0.075***
	(0.028)	(0.031)	(0.108)	(0.020)	(0.016)
Pre-scan	0.082***	-0.038	-0.155	-0.004	0.011
	(0.027)	(0.032)	(0.121)	(0.024)	(0.020)
Malay$\times$ Pre-scan	0.023	0.024	0.125	0.027	0.001
	(0.040)	(0.042)	(0.141)	(0.027)	(0.023)
Indian	0.158***	-0.340***	-1.049***	-0.154***	-0.086***
	(0.030)	(0.030)	(0.102)	(0.019)	(0.015)
Indian $\times$ Pre-scan	-0.044	0.088**	0.249*	0.007	-0.006
	(0.041)	(0.041)	(0.135)	(0.026)	(0.021)
Constant	0.205***	0.525***	1.358***	0.177***	0.102***
	(0.019)	(0.023)	(0.093)	(0.018)	(0.014)
R^2	0.022	0.075	0.082	0.057	0.030
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 7. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Table 20: Ethnicity heterogeneous effect: Engineering

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Malay	0.113***	-0.261***	-0.880***	-0.122***	-0.075***
	(0.024)	(0.024)	(0.079)	(0.016)	(0.013)
Engineering	0.035	-0.091**	-0.298**	0.004	-0.006
	(0.032)	(0.036)	(0.136)	(0.028)	(0.022)
Malay × Eng	-0.055	0.077	0.301*	-0.018	0.001
	(0.046)	(0.048)	(0.162)	(0.031)	(0.025)
Indian	0.133***	-0.293***	-0.943***	-0.146***	-0.089***
	(0.024)	(0.024)	(0.079)	(0.015)	(0.013)
Indian × Eng	0.010	0.012	0.121	-0.012	0.000
	(0.048)	(0.045)	(0.147)	(0.029)	(0.024)
Constant	0.240***	0.527***	1.352***	0.174***	0.110***
	(0.016)	(0.018)	(0.070)	(0.014)	(0.011)
R^2	0.016	0.078	0.084	0.057	0.030
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 7. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * $p<0.1$, ** $p<0.05$, *** $p<0.1$

B Heterogeneous effects for gender

Table 21: Gender heterogeneous effect: Location

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Female	-0.030	0.048*	0.116	0.003	-0.004
	(0.028)	(0.028)	(0.089)	(0.016)	(0.013)
Kuala Lumpur	-0.038	0.077***	0.109	0.004	0.008
	(0.025)	(0.025)	(0.077)	(0.014)	(0.012)
Female×KL	0.039	-0.073**	-0.163	0.014	0.009
	(0.036)	(0.035)	(0.110)	(0.021)	(0.017)
Constant	0.353***	0.278***	0.631***	0.075***	0.048***
	(0.020)	(0.019)	(0.061)	(0.011)	(0.009)
R^2	0.001	0.003	0.001	0.001	0.001
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 8. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Table 22: Gender heterogeneous effect: High salaries

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Female	-0.045	0.007	-0.036	0.011	-0.004
	(0.031)	(0.031)	(0.085)	(0.017)	(0.015)
High Salary	-0.049*	0.003	0.022	0.007	-0.007
	(0.027)	(0.026)	(0.078)	(0.015)	(0.013)
Female×HS	0.057	-0.006	0.073	0.002	0.008
	(0.037)	(0.037)	(0.108)	(0.021)	(0.018)
Constant	0.363***	0.324***	0.685***	0.073***	0.058***
	(0.022)	(0.022)	(0.064)	(0.012)	(0.011)
R^2	0.001	0.000	0.001	0.001	0.000
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 8. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Table 23: Gender heterogeneous effect: Small companies

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Female	-0.015	0.038*	0.084	0.019	0.010
	(0.022)	(0.023)	(0.066)	(0.013)	(0.010)
Small Firm	0.062**	0.073***	0.230***	0.029**	0.023*
	(0.024)	(0.024)	(0.075)	(0.014)	(0.012)
Female×Small	0.024	-0.078**	-0.151	-0.015	-0.017
	(0.035)	(0.035)	(0.107)	(0.021)	(0.017)
Constant	0.300***	0.293***	0.595***	0.064***	0.043***
	(0.016)	(0.016)	(0.046)	(0.009)	(0.007)
R^2	0.006	0.003	0.004	0.002	0.001
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 8. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Table 24: Gender heterogeneous effect: Low processing time

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Female	0.007	-0.005	-0.024	0.011	0.002
	(0.018)	(0.020)	(0.060)	(0.011)	(0.009)
Low Proc Time	0.330***	-0.074***	-0.095	0.021	0.010
	(0.028)	(0.027)	(0.084)	(0.017)	(0.014)
Female × LPT	-0.058	0.029	0.140	0.002	-0.001
	(0.040)	(0.038)	(0.124)	(0.024)	(0.019)
Constant	0.242***	0.346***	0.725***	0.072***	0.050***
	(0.013)	(0.014)	(0.043)	(0.008)	(0.007)
R^2	0.081	0.003	0.001	0.002	0.000
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 8. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Table 25: Gender heterogeneous effect: Pre-scan questions

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Female	0.012	-0.002	-0.026	0.003	-0.003
	(0.025)	(0.026)	(0.083)	(0.015)	(0.012)
Pre-scan	0.097***	-0.012	-0.091	-0.004	0.003
	(0.024)	(0.024)	(0.075)	(0.014)	(0.012)
Female× Pre-scan	-0.036	0.008	0.075	0.016	0.008
	(0.034)	(0.035)	(0.107)	(0.020)	(0.017)
Constant	0.277***	0.333***	0.748***	0.080***	0.051***
	(0.017)	(0.018)	(0.058)	(0.010)	(0.008)
R^2	0.007	0.000	0.001	0.001	0.000
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 8. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

Table 26: Gender heterogeneous effect: Engineering

	(1) Rejected	(2) Profile viewed	(3) N of profile views	(4) Contacted	(5) Interview requested
Female	-0.009	0.017	0.033	0.016	0.003
	(0.020)	(0.020)	(0.061)	(0.012)	(0.010)
Engineering	0.013	-0.035	-0.123	0.001	-0.003
	(0.028)	(0.027)	(0.082)	(0.016)	(0.013)
Female × Eng	0.014	-0.057	-0.079	-0.017	-0.005
	(0.039)	(0.038)	(0.118)	(0.023)	(0.018)
Constant	0.326***	0.335***	0.732***	0.077***	0.054***
	(0.014)	(0.014)	(0.043)	(0.008)	(0.007)
R^2	0.000	0.004	0.003	0.001	0.000
N	2995	2995	2995	2995	2995

Note: This table presents the results of specification 8. The outcomes are: In column 1 Rejected takes the value of 1 if the company disregarded the application as not-suitable. Column 2 Profile viewed takes the value of 1 if the profile was visited by the company at least once. Column 3 is the number of visits to the website profile. In column 4 Contacted takes the value of 1 if the Company contacted the candidate through email. Finally, column 5 Interview requested takes the value of 1 if the Company contacted the candidate requesting an interview. Robust Standard errors. * p<0.1, ** p<0.05, *** p<0.1

C Power Calculations

We perform a power calculation analysis to determine the proper sample size in our experimental setting. To this end, we need to fix the parameters: Type-I error (α) and type-II error (β). As it is standard in the literature, α is set to a level of 0.05. The power is defined as (1-β), that is the probability of rejecting the null hypothesis when it is false, usually set to be 0.8. Figure 2 plots the relation between the required sample size on the y-axis and the expected effect, in our case, difference in contact rate on the x-axis. The solid line uses the stated parameters, while the dashed-line uses a more conservative power of 0.9. For instance, if we expect to find a difference in contact rates between two groups (e.g. Chinese and Malay) of 10 percentage points, we will need a sample of 1,000 observations for a power of 0.8 and around 1,300 observations for a power of 0.9. It is important to note that as the expected difference in the effect (contact rates) increases the sample size requirement decreases.

To put the sample size calculation in context we add the sample size and difference in contact rates of related studies (in red). In Malaysia, Lee and Khalid (2016) find a difference of 18 percentage points in contact rates with a sample of 3,012 resumes. This study finds particularly high rates of discrimination in relation to others and provides a close approximation to the expected difference in contact rates in our study. If we expect to find a similar differential effect, a sample of roughly 500 observations would be sufficient. However, we allow for the possibility of a lower differential effect, which would be consistent with Kaas and Manger (2012) that estimate 9 percentage point differences in contact rates between German and Turkish sounding names in German labor market with a sample of 1,056 resumes (under power), Galarza and Yamada (2014) that find 7 percentage point differences in contact between white and indigenous in Peru using a sample of 4,820 resumes, and Bertrand and Mullainathan (2004) that document a 4 percentage point difference in contact rates between white and black sounding names, with a sample of 4,890 resumes. Our targeted sample size will be 3,000 observations and should be sufficient to detect a 7 percentage point difference in contact rates, which is more conservative than the 18 percentage point difference found in the most closely related study.

Figure 2: Power calculations