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Abstract

Latin America is seen as a highly discriminatory society. However, such a common belief appears not to be based on strong empirical evidence (Chong and Ñopo, 2007). This paper exploits novel experimental data gathered to identify the existence of discrimination in the labor market of Lima, Peru, a fast-growing country where much anecdotal evidence suggests the presence of discriminatory practices at many instances of daily life. Focusing on two dimensions, sex (female/male) and surnames (indigenous/white), we sent 4,820 fictitious and equivalent CVs in response to 1,205 real job vacancies advertised in an important Peruvian newspaper. We randomly allocated indigenous and white surnames across CVs sent in application to professional, technical, and unskilled jobs. Overall, we find that males receive 20 percent more callbacks than females, and whites receive 80 percent more calls than indigenous applicants. Within job categories, we find sexual discrimination only in unskilled jobs, while discrimination against indigenous is verified across all job categories. There are no statistically significant differences in the time to receive a phone call among male/female, and white/indigenous applicants.

Keywords: discrimination, experimental economics, audit studies.

JEL classification codes: C93, J71.

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CONTENT

1. Introduction

There is a wide perception in Latin America that discriminatory practices happen at several levels, although there is no strong statistical evidence to support such common belief (Chong y Ñopo, 2007). With a renewed commitment towards social inclusion in the provision of public services and assistance, the current Peruvian government is designing policies to promote that everyone benefits from the sustained economic progress.

Another factor that makes Peru distinct is the long and complex process of *mestizaje* we experienced from the beginning of the colonial era, in the sixteenth century. This *mestizaje* is reflected in a wide racial spectrum which, unlike other countries, makes it complicated to classify a person in a specific racial category, since the veins of a considerable proportion of the population carry blood from many nationalities. This diversity makes the analysis of potential racial discrimination difficult, an obstacle that we address by using the origin of the surnames as a proxy variable for race, as we explain later on.

A first approximation commonly used to pinpoint different racial groups comes from census data. Unfortunately, the latest census statistics only contain information about the mother tongue learned in childhood, which is used as a rough indicator of indigenous origin. According to the 2007 Peruvian Census of Population and Housing, out of the 24.7 million people older than five years, 83.9 percent learned Spanish in their childhood, while 13.2 percent learned Quechua, 1.8 percent learned Aimara, 0.9 percent learned other native language, and 0.2 percent learned a foreign language.

On the other hand, self-perception statistics obtained from the National Household Survey (ENAHO) 2009 report that 31 percent of the household heads deem to have a Quechua origin[1] 4 percent of them claim to be Aimara, 2 percent to be of Amazonian origin, 2 percent an African descendant, 5 percent to be white, 52 percent claim to be *mestizo*, and 4 percent to belong to other racial group. Similar self-perception data are gathered by the 2011 Americas Barometer (produced by the Latin America Public Opinion Project[2]), which on the basis of self-perception information classifies the Peruvian population as composed of *mestizos* (76 percent), white (6 percent), indigenous (7 percent), and other races (11 percent). Although this type of data is commonly used to distinguish racial groups, it has severe limitations.

In terms of the macroeconomic performance, Peru has attained high growth rates over the last decade. With an annual average Gross Domestic Product (GDP) growth rate of 5.7 percent in 2000-

[1] The question in the survey was: "considering your ancestors and customs, you deem your origin to be?".

[2] www.lapopsurveys.org

2010, Peru ranked second in Latin America. This economic growth has been associated with improvements in several indicators of well-being, including poverty (from 54.8 percent of the population in 2001 to 31.3 percent in 2010), and chronic malnutrition (from 25.4 percent of the child population in 2000 to 17.9 percent in 2010).

In this context of macroeconomic boom, we have seen a reduction in the open unemployment rate in Metropolitan Lima (from 7.2 percent in 2001 to 6.1 percent in 2009), as well as in the underemployment rate (from 39 percent to 34 percent in similar period), one would expect that employers will look primarily at the qualifications of job applicants when making hiring decisions, given the increased competition in labor demand. Besides being the capital city of Peru, Lima explains a bit less than half of its GDP and concentrates 35.2 percent of its total labor force (Census data, 2007).

Despite the outstanding macroeconomic indicators, and some improvements in well-being indicators, there are still many people (especially from rural areas) who do not share the benefits of such progress. In fact, opinion surveys show a perception that is in conflict with the existence of a non-discriminatory, idealistic environment. Thus, the 2011 Report of the Americas Barometer for Peru indicates that 28 percent of the respondents consider to have been discriminated on the grounds of their race (and this rate is eight percentage points higher than the average percent in Latin America). Moreover, 39 percent of the respondents believe that racial discrimination exists.

To which extent does this perception have real foundations? Does it also affect the labor market? And if so, does this perception of discrimination meet up with reality? Those questions can hardly be fully answered with the existing data in Peru, where we do see evidence of wage gaps between male and female workers (Ñopo, 2009), and between predominantly white workers and predominantly indigenous workers (Torero et al., 2003). An experimental study that gets us closer to answering those questions looks at sexual and racial discrimination in Metropolitan Lima (Moreno et al., 2012). In their analysis of three low-skill occupations (salesmen, secretaries, and accounting and administrative assistants), they do not find significant differences in the recruitment rates by sex or race (only in the extremes of the racial spectrum do they find some differences).

This paper investigates the extent to which the smaller share that the indigenous people have in the labor market is due to the employers' discriminatory behavior and not to a lower productivity. We utilize a resume audit methodology to investigate whether companies in Lima, Peru, discriminate against those with an indigenous origin (as captured by their surnames, which unambiguously identify them) and in favor of those with a white origin[3]. We sent fictitious CVs in response to real

[3] Initially, we wanted to include the Afro descendents in our study, but the limited number of surnames that can clearly be identified as Afro-Peruvian prevented us from going further. Estimates of their participation in the labor market indicate that they represent only around 1 percent of the total labor force.

vacancy ads weekly published in an important local newspaper. A set of four equivalent CVs (in terms of education and job experience) were sent for each job ad, grouped into three broad categories of employment: professional, technical, and unskilled jobs. All our CVs included photos in an attempt to capture the effect of physical appearance on the callback rates. While the law in Peru prohibits asking CVs with photos, some employers still continue to request them. In addition to providing novel evidence about the existence and extent of labor discrimination in Lima, to the best of our knowledge, the only other resume audit study that includes photos in the CVs is Ruffle and Shtudiner (2010).

Overall, we register a 12.3 percent response rate, and our findings present evidence of racial discrimination against indigenous job candidates across all job categories considered: in order to get an equal chance of being called back, indigenous applicants need to send 80 percent more applications than whites. The magnitude of racial discrimination in the labor market is greater among professional jobs than unskilled and technical jobs. We further detect sexual discrimination in the entire sample of selected jobs, but this finding is not robust across job categories (and only holds for unskilled jobs, for which males get 30 percent more callbacks than females). The results of the effect of physical appearance in the callback rate are nuanced. Looks seem to matter only for professional jobs.

The remainder of the paper is organized as follows. Section 2 provides background information on discrimination in Peru and highlights the importance of investigating this subject in the current macroeconomic context. Section 3 reviews the main related experimental works and places the contribution of our research in this context. Section 4 presents the experimental design and the procedures we followed. Section 5 discusses the main findings of the paper, and the last section concludes.

2. Discrimination in Peru: Importance and State of the Affairs

Few countries in the world have a population that has not been part of a major process of cultural and genetic *mestizaje*[4] (Kymlicka, 2002). But this process is not homogeneous across societies; on the contrary, each society imagines, measures, and embraces them in a particular way. As a result, identifying a particular racial[5] or ethnic[6] group in any country is far from obvious or easy.

[4] The only mono-national countries would be Iceland, Portugal, South and North Korea (Kymlicka, 2002).

[5] The racial features, or race, are marked by several physical characteristics which may include one or more of the following physical markers: skin color, shape and size of the eyes, hair color and texture, and anthropometric characteristics.

[6] Ethnicity is defined by cultural features that may include religion, history, language, values, customs, and traditions.

To illustrate the complexity of categorizing ethnic or racial groups, Sulmont (2011) surveys several studies on ethnicity and identity conducted in the early 2000s in Peru, and finds that the "indigenous population" may represent between 19.2 and 74.8 percent of the country's population, depending on the criteria used (language, place of birth, race, or a combination of these variables). In accordance with this difficulty to classify racial or ethnic groups in Peru, it is worth to mention that most Peruvians imagine the Amazon native communities as a rather homogeneous population, marked by their original dialects and geographical location. Likewise, the Afro-Peruvian population is classified in racial terms and is identified a minority group, while the Aimara and Quechua population tend to be associated with a combination of poverty and symbolic racism (cultural or linguistic) (Valdivia et al., 2007). On the other hand, the *mestizos* are a vast majority, and whites are part of a racialized category, related to power and wealth.

Most of the social sciences research about race in Peru has taken the form of history studies that traces racism back to our colonial heritage. Few other studies from economics use the official data (typically self-perception) to examine racial wage gaps, and there is even less ethnographic or experimental research. The questions that underlie the empirical works carried out in Peru aim at understanding whether the Peruvian *mestizaje* has gradually blurred the racial discrimination, or whether racism have been displaced by socioeconomic discrimination as the primary form of discrimination. Or whether, ultimately, the various forms of exclusion (political, economic, social, or cultural) are more important than racial discrimination in defining the social relations in the country.

3. Related Literature

Starting with the seminal work of Becker (1957) on segmented markets, the analysis of the existence and implications of labor discrimination has been a recurrent topic in economics[7] and other social sciences, such as sociology and anthropology. Becker analyzed the existence of taste-based discrimination, which arises when the discriminating agent (e.g., a seller or an employer) considers unpleasant that a particular group (from a certain race, age cohort, sex, or religious inclination) enjoys the same conditions as other groups. In this case, the sole interaction with the individuals of the discriminated group increases the disutility of the seller or employer.

An alternative theory of discrimination is statistical discrimination[8], originally examined by Phelps (1972) and Arrow (1973). Applied to the labor market, this type of discrimination occurs when two job applicants with similar qualifications and skills (i.e., similar human capital), suitable for a given occupation, receive different job offers, or earn different wages when they are already

[7] For a well-informed discussion on the subject, consult Altonji and Blank (1999) and Heckman (1998).

[8] Distinguishing statistical discrimination from taste-based discrimination is difficult. See Levitt (2004), List (2004), and Moser (2008) to review examples of how to achieve the identification of one or another theory.

employed. And why could that be the case? Given that employers have limited information about the job applicants' labor productivity, they construct beliefs and expectations (that may reflect stereotypes) based on observable characteristics, such as race, sex, physical appearance, or surnames.

Several studies have emphasized that the sole difference in labor market outcomes, such as wages that is commonly found in developed and developing countries should not be considered as sufficient evidence to claim the existence of discrimination on the part of the employers. It may be just that the survey information that is used to measure those gaps does not contain all the characteristics that are used by employers to make the pay decision (Banerjee et al., 2009). This difficulty to ascertain discrimination using observational data has motivated researchers to rely on experimental methods to detect the presence of discrimination.

There is a growing literature on labor market discrimination in developed countries (see Altonji and Blank, 1999; Bertrand and Mullainathan, 2004, Carlsson and Rooth, 2006; Kaas and Manger, 2012; among others), which, indeed, report evidence of its existence. Altonji and Blank (1999) survey the audit studies conducted in the US until the late nineties. These audit studies could take two forms: sending well-trained auditors who fully meet the requirements for a particular job to perform interviews, or sending resumes that are similar in human capital but differ in the dimension over which discrimination is presumed to exist (e.g., sex or race). Bertrand and Mullainathan (2004), Heckman (1998), and Heckman and Siegelman (1993) have emphasized, for the case of the former type of audit study, two potential problems: the difficulty of ensuring that each pair of mock candidates be observationally equivalent to the interviewer and, perhaps more importantly, that the existence of unobservable (to the researcher) characteristics that determine productivity and may explain differential hiring rates but should not be considered as discrimination.

In an attempt to overcome the aforementioned limitations of audit studies, Moreno et al. (2012) conducted an audit study that utilizes real job applicants, in order to analyze the existence of sexual and racial differences in hiring for three low-skilled occupations in Metropolitan Lima: salespersons, secretaries, and accounting and administrative assistants. This study exploited data from labor suppliers and job applicants who use the intermediation service offered by the Ministry of Labor. The research team selected the job applicants who met the employers' requirements as best as possible, and then sent them to the interviews. The authors do not find significant differences in the hiring rates by sex or race (only for the extreme racial spectrums— extremely white and extremely indigenous--do they find some differences). A possible explanation for this result is that there is selection in the employers that use this public intermediation service in that they tend to be good, non-discriminating employers, either because of their intrinsic preferences or simply because they don't want to run the risk of being caught by the Ministry of Labor.

In another type of audit study, Bertrand and Mullainathan (2004) sent CVs equivalent in all respects but the candidates' names (associated with whites and African Americans) to investigate the presence of racial discrimination in Boston and Chicago. They found evidence of discrimination against African Americans: whites received 50 percent more callbacks for interviews. They further found that this quantitative indicator of discrimination was relatively uniform across different jobs and economic sectors.

As mentioned earlier, few other studies analyze labor discrimination in a developing country from an experimental perspective. Bravo et al. (2009) for Chile; and Bradley and Shtudiner (2010) for Israel conduct resume audit studies. Bravo et al. (2009) examine the existence of discrimination in three dimensions: gender, social class (that is captured by the place of residence in Santiago, the capital of Chile), and (indigenous) origin of the surnames. Their results indicate that among the professional jobs, those CV with indigenous surnames are discriminated (i.e., receive fewer calls from potential employers); also, people living in slums and women are discriminated in unskilled jobs, and women receive more calls and more quickly than men in jobs for technicians.

Bradley and Shtudiner (2010) examine the role of physical appearance in labor discrimination in Israel. They sent two CVs for each selected job ad (for banking, budgeting, accountancy, finance, industrial engineer, PCs' programming, and sales and customer service), one containing a picture and one without a picture. In turn, half of the pictures attached to the CVs were from a handsome person and the other half from a plain-looking one. While, they find a beauty premium for males (the handsome applicants' callback rate was 19.7 percent versus a 9.2 percent for plain-looking ones), they find a small but negative beauty premium for females (respective rates are 12.8 percent and 13.6 percent), which the authors attribute to jealousy (hiring persons, which are mostly females, do not like attractive competitors in the workplace).

Summing up, for the case of Peru, Torero et al. (2003) and Ñopo (2009) report differential wages for whites and indigenous people, and men and women, respectively, after controlling for a series of observable characteristics. As is usual in those studies, these wage gaps could be explained by unobservable characteristics related to productivity, and not necessarily by a discriminatory behavior on the part of the employer. Moreover, the only experimental study thus far designed to detect labor discrimination, Moreno et al. (2012), did not find strong evidence of sexual and racial discrimination in hiring for three types of low-skill employments in Lima. This paper is related to Bertrand and Mullainathan (2004), with the additional feature that we included photographs in the CVs, in order to capture the effect that physical appearance may have on the response rates. To the best of our knowledge, the only study similar to ours is Ruffle and Shtudiner (2010)[9]. We thus analyze labor market discrimination in a booming developing country, where one could expect that employers would care significantly more about the qualifications of the potential employees (which are crucial to sustain growth) rather than any other observable characteristic in the hiring process.

[9] A thought-provoking paper for the US and Canada is Hamermesh and Biddle (1994), who use survey data and find a positive effect of looks on earnings.

4. Experimental Design and Procedures

4.1 Selection of Jobs

In Peru, a substantial proportion of job seekers search for vacancies in the job ads published every Sunday in the newspapers. Many positions in the public sector are even required to publicly announce their vacancies. To make easier our analysis, we classified the job vacancies in three categories: professional (requiring at least a University degree, which takes no less than five years in Peru), technical (requiring the completion of a degree at a technical college, which takes between two and four years), and unskilled (requiring secondary school or lower). This classification was instrumental for the data analysis.

Job vacancies for the experiment were selected from one of the largest labor networks in Lima, *Aptitus*. This network publishes job ads from thousands of companies on its Website and releases a printed version of every Sunday on a well-known newspaper of national circulation. In a typical week, most of the job ads are for unskilled jobs (roughly between 40 and 50 percent), followed by technical jobs (around one third of the total), and the rest is for professional jobs. Given that publishing job ads in *Aptitus* has a cost (which goes from the equivalent of US$ 120 for an ad of 3.77 cm by 1.97 cm to US$ 6,530 for a job ad of 24.7 cm by 27.6 cm), it is very likely that our sample includes companies that have certain level of income (and/or some urgency for hire), different from those companies that use other means to select employees.

We used the following criteria in the selection of job offers.

i. The job experience requested should not exceed 5 years (in fact, only 27.5 percent of the selected job ads required some job experience, as shown in Annex 1). This means that we focus on entry-level jobs,
ii. Vacancies should not ask for salary expectations,
iii. Nor should they ask the candidate to deliver the CV in person,
iv. The vacancies should not be biased towards any particular sex; we excluded job ads requesting only women,
v. The email address of the contact person (employer) should show the company's domain. We thus made every effort to exclude employment agencies, since these are in charge of recruiting employees for several companies at the same time, and would make us vulnerable to their discovery of our fictitious candidates (at some point, we used the same cell number for several job candidates). A more profound reason for doing so is that employment agencies may not necessarily share the preferences of the employers.

We thus did not restrict our sample of companies to any particular economic activity.

4.2 Constructing the CVs

We created a database of CVs for the three job categories we applied for using real existing CVs available on two employment Web sites, *Laborum* and *Computrabajo*[10]. We used intensively *Laborum* to construct the job experiences for professional and technical occupations, and *Computrabajo* for unskilled and technical occupations. In the pilot stage, we identified the most common job vacancies for the three job categories, and constructed templates for those jobs. This allowed us to more quickly tailor the CVs to the specific requirements of the selected job ads during the field work.

The CVs were constructed in such a way that, in addition to showing similar qualifications and experience for all candidates applying for the same position, the credentials included made our candidates very competitive ones for the positions they applied for (for example, a request for someone with "technical or college education", was responded by sending applicants with college education). The format of every set of CVs sent in response to each job ad was similar. In particular, the education levels of our candidates are as follows:

Professional Jobs: Applicants for any given professional job earned the same undergraduate degree from the largest and arguably the most prestigious public university[11]. We opted for this single university for two reasons: it offers most of the careers (unlike any other university, public or private) and, among the rest of large public universities, all of them have a strong negative perception about the quality of at least one career. Moreover, choosing a prestigious and large private university would certainly bias upwards the credentials of our job applicants, thus making harder to detect discrimination.

Technical Jobs: Our applicants graduated from the most prestigious technical institutes/colleges. While no ranking for these organizations is available, we guided our selection by the demand that their graduates have in the labor market in their respective specialties.

Moreover, our applicants for professional and technical jobs have a fine knowledge of English (depending on the requirement of the jobs, they could have either an advanced- level knowledge or be fluent in English). Similarly, they all have computer training at the user level, acquired at the same information technology institute.

Unskilled Jobs: In selecting the secondary schools for all our applicants (the only education information included in the CVs for unskilled jobs), we used the list of the major Large School District Units (*Grandes Unidades Escolares*) in Lima. More specifically, all of our applicants obtained their secondary school diploma from public schools which were given the category of *emblematic schools* by the Ministry

[10] www.laborum.pe and www.computrabajo.com.pe

[11] According to a ranking of the best universities in Peru, based on the opinions of a sample of readers and head hunters, as well as indicators of quality and prestige, this public university ranks fourth in the overall ranking, and first among the public universities. This ranking was conducted by the magazine América Economía in 2010.

of Education, on the basis of a series of indicators signaling prestige[12].

As mentioned earlier, since we are aiming at entry-level jobs, our typical job applicant is in his/her mid twenties. They are all single, with no children. Also, each CV included a cellular phone number of contact (we used a set of two cell numbers per each job category). Unlike other studies, we found out that providing traditional wired telephones or setting up answering machines would not work in Peru, because employers call cell numbers and do not usually leave any message over the phone. Given the increasing labor supply, they would simply take the next CV in the pile if the previous job applicant did not answer the cell phone.

The CVs were sent electronically before the deadline (if specified in the job ad), and every set of four CVs for a given job ad usually shipped away the same day but at different hours, to avoid any effect associated with the day of receipt by employers. In terms of the optimal timing to send the CV (if candidates thought about that strategically), which might affect the response rate, especially in the cases where no many qualified candidates applied for the same position, one might think that, after sending the job ads every Sunday, employers expect to collect a number of CV before starting the screening process at the beginning of the next week. If that is the case, candidate should send their CVs as soon as possible. However, it is not clear that all employers will follow that procedure, because incidentally, when we kept sending CVs until the end of a week, the response rates in the case of low-skilled positions were higher than when we sent CVs at the beginning of the week (although for different companies).

4.3 The Applicants' Identities and Photos

We required a vast database of indigenous and white surnames for our crowd of applicants, both of which were obtained from a public Website[13] that lists and classifies names by their origins. The selected white surnames have a predominant foreign origin (Spanish, Italian, and French) to emphasize the idea of the skin color, while the indigenous (or *Quechuas*) surnames are clearly distinctive of their origin. Sample surnames used include Bresciani, Camogliano, De la Puente, Visconti (for white applicants), and Ccolque, Chanca, Orcco (for indigenous candidates). After getting a long list of the two types of surnames, we obtained random combinations of those to come up with a database of around 500 full names (first name + paternal surname + maternal surname) for each type of applicant (indigenous and white). We then created more than one thousand e-mail accounts, one for each job applicant. Thus, every job applicant from our database applied for almost 5 jobs along the length of the study.

The photos of our candidates were collected from the Internet, and subsequently modified by a

[12] These indicators include having distinguished alumni. These schools have a contribution from the national government for improvements in infrastructure and equipment, aimed at reducing the gap with the education offered by private schools.

[13] http://apellidosperuanos.wordpress.com/

professional using Photoshop, in order to standardize the style (all men wear suits and women generally wear formal dress or a blouse). After eliminating blurred, lenses-wearing and smiley photos[14], we asked a panel of seven judges to rate the physical attractiveness of the remaining 149 pictures (74 indigenous-looking subjects and 75 white subjects, 70 females and 79 males) in a 1-to-7 scale (from homely to strikingly handsome). Judges have various professional backgrounds, including lawyer, anthropologist, economist, mathematician, human resource specialists, psychologist, and sociologist ranging in age from early thirties to late fifties. For the ranking, we showed the headshots in color for a few seconds and judges had to rate them one after another. We first showed females (whites then indigenous).

The racial difference between our pool of indigenous and white applicants results apparent in terms of the thicker nose and lips, the more pronounced cheekbones, and the darker skins of the former. Our judges' ratings indicate that, on average, whites (especially females) are physically more attractive than indigenous candidates[15]. We should mention, however, that while we included headshots in color on the CVs, they were most likely printed in black and white (if printed at all) by the recruiting persons. If this is the case, any difference in physical appearance among our four applicants for any given job position should narrow to the eyes of the recruiting persons.

4.4 Sending the CVs

Our sample design consists of four treatments that correspond to variations in terms of sex and surname of origin (which had a corresponding headshot on the CV), as shown in table 1. The inclusion of the photographs is an innovation of our experiment (only shared with Ruffle and Shtudiner, 2010), and responds to our interest in looking at the extent to which physical appearance strengthens or weakens the extent of discrimination. We sent 1,205 CVs for each treatment, for a total of 4,820 CVs sent, 2,410 for females and 2,410 for males.

In this design, we can measure the discrimination by surnames for female and male applicants by examining the differences in the callback rates in treatments T1 versus T3, and T2 versus T4, respectively. Similar analysis of the extent of sexual discrimination for indigenous and whites can be done by comparing the callback rates in T1 versus T2, and T3 versus T4. Since we are sending out equivalent CVs in terms of qualifications and job experience, there should not be any statistical difference between the callback rates for any of these treatments, had not there been any statistical discrimination. We will further split the statistical and econometric analysis by category of

[14] Our research team created a previous ranking in order to have a more homogenous set of photos across types of surnames. We then found out that whites were rated as being physically more attractive than indigenous photos, and this gap was larger for females. We then excluded photographs that were rated very low (especially indigenous ones) and very high (this applies to the case of female whites).

[15] The Spearman correlation coefficient between the dummy variable for white surnames and our physical appearance index is 0.874.

employment (professional, technical, and unskilled) in section 5.

In a given week, we selected around 20 job ads per category of employment, and we thus sent an average of 212 CVs every week. The field work lasted for 22 weeks, starting from mid-June 2011 and ending in mid-November 2011, with a one-week break on Independence Day the last week of July. Our research team selected job ads every Sunday and the CVs were constructed and submitted starting the following Tuesday. If we had to choose between any two given job ads, we chose the one for which we had some CV models (experience and education) ready.

At the beginning of the fieldwork, we sent only one CV for each company, but when we found out that this procedure constrained our expected number of submissions per week, we chose up to two job ads from the same company, and we also selected ads from the *Aptitus* Web site (only 2 percent of the total number of ads came from this source), which had a number of additional postings to the printed version (98 percent of ads were selected from this source). One of the difficulties encountered when we tried to increase the number of CVs sent each week had to do with the existence of employment agencies that are in charge of the employees' selection on behalf of several companies at the same time. We decided not to send CVs to these agencies, for the reasons explained in section 4.1. When our assistants were in doubt about the source of the job ads, they verified the existence of the company (checking whether it had a Web page, for instance).

4.5 Answering the Calls and Information Registered from Companies

The vast majority of responses for interviews from the employers were phone calls (81 percent). Considering that we only used up to eight mobile phones in the study, and that we sent four CVs for every job position, we typically had an assistant answering two cell phones at all times. In the remaining 19 percent of the responses, our job candidates received e-mails. For either callbacks or e-mails, our fictitious job applicants politely declined to go further with the job application, mentioning that they had already accepted another job offer. We registered the number of hours after the CVs were sent out until a response was received (if the case).

In addition to basic information from companies whose job ads were selected (company name, specific position advertised, category of job offered, and economic sector of activity), we recorded the size of the job ads when those were obtained from the printed version of *Aptitus* (98 percent of the cases). This variable will be used as a proxy for the size of the companies in our analysis (we thus classified the selected job ads into five categories/sizes). We further registered whether the job involves a direct contact with the public. This is particularly useful information for analyzing the role of physical appearance in the callback rates (the analysis is deferred until section 5).

Annex 1 summarizes the candidates', jobs', and companies' main characteristics. As for the job characteristics, we see that for almost 75 percent of jobs our candidates applied for, the vacancies did not request any job experience, and a similar proportion of job ads (around 9 percent) required up to one year, between one and two years, and three or more years of experience. Using the job ad size as a proxy variable for the company size, we see that most of the jobs we applied for came from medium and micro enterprises.

5. Results

This section analyzes the descriptive results of the investigation in terms of the callback rates and the physical appearance index (sections 5.1 and 5.2) and discusses the regressions results of running the callback dummy on several variables of interest (section 5.3)

5.1. Mean Callback Rates by Surname and Sex

Overall, out of the 4820 CVs we sent, 595 were answered via cell phone or e-mail, representing a response rate of 12.34 percent, which is slightly smaller than the response rates of similar experiments conducted in Chile (Bravo et al., 2009) [16.76 percent], Israel (Ruffle and Shtudiner, 2010) [14.50 percent], and the United States (Bertrand and Mullainathan, 2004) [14.65 percent].

Table 2 shows the overall response rates by surnames and sex. The highest response rates were received by unskilled job applicants (17.0 percent) while the lowest ones were received by technical job candidates (8.8 percent). The callback rate for professional applicants was 11.5 percent. Moreover, we find a sexual gap in favor of males in professional and unskilled jobs (panel A), and an even larger gap in favor of whites in all job categories (panel B).

Tables 3 and 4 provide the mean tests for the overall differential callback rates by sex and surname and for professional, technical, and unskilled jobs. As seen in table 3, the sexual gaps in callback rates among indigenous job applicants range between 4 and 6.5 percentage points across job categories, meaning that callback rates for indigenous male job applicants are between 40 percent and 180 percent higher than that for indigenous female applicants. Moreover, we also see sexual discrimination against white females in unskilled jobs (males receive 29 percent more callback rates). Interestingly enough, white female job applicants for technical jobs receive 97 percent *more* callback rates than their male counterparts. As shown in Annex 2 (main technical occupations) it is hard to argue that this positive discrimination could be explained by the type of selected jobs, since only 20 percent of jobs were for sales and marketing occupations, perhaps the only occupations in which employers would strongly prefer a female rather than a male employee.

In terms of the callback rates by surname (shown in table 4), the pattern looks more clear in favor of whites, who receive statistically significant higher callback rates than indigenous job applicants, overall (by 7.1 percentage points) and for professional and unskilled jobs (by 8.8 percentage points in both cases). These gaps imply that white job applicants receive between 70 and 120 percent more often callback rates than indigenous applicants. In turn, while these gaps exist for both male and female whites, they are mostly explained by the difference for female white applicants, who are between 80 and 210 percent more likely be called back than female indigenous applicants.

Furthermore, similarly to the positive sexual discrimination in the case of technical jobs (females received more callbacks than males), we observe positive discrimination in favor of indigenous males among our technician applicants, who receive 40 percent more often callback rates than similarly-qualified white males (a gap that is barely statistically significant, however).

Summing up, we find evidence of sexual discrimination against females in unskilled jobs. The magnitude of the statistical discrimination is larger in the case of indigenous applicants, who are discriminated in all job categories considered in this study. Moreover, when sexual discrimination against females occurs, this is more striking for indigenous than for white candidates. Finally, we seem to find positive discrimination in technical jobs, for which female and indigenous applicants are more likely to be called back. Regression analysis in section 5.3 is required to confirm the robustness of some of these results.

5.2. The Physical Appearance Index: Differences by Sex and Surname

The previously discussed results do not consider the role that our job applicants' physical appearance may be playing in the employers' decision to call them for interviews. As mentioned in the previous section, each photo used in the experiment has a physical appearance rate that goes from 1 (homely) to 7 (strikingly beautiful). The overall average rate assigned by our judges was 3.98 for the entire set of applicants, which coincides with the midpoint between 'homely' and 'strikingly beautiful'. The rates range from 2.5 to 5.75 (averages). We then normalized these ratings for ease of interpretation of the econometric results examined in section 5.3.

Table 5 shows the differences in the physical appearance indicator for all of our 4,820 applicants (columns 2 and 3), and for those who were called back (or successful, columns 4 and 5). We should mention that the physical appearance indicator for the successful applicants is higher, on average, than that for the unsuccessful ones (4.23 versus 3.95). A means test for such difference reports a p-value of 0.000, thus showing that we cannot accept the null that the physical appearance indices are equal. As shown in panel A, for all candidates (column 2), we do not see statistically significant differences in physical appearance between our male and female applicants for unskilled jobs (for the entire sample and for those who were called back). However, female applicants for technical and professional jobs are perceived significantly prettier than male candidates. Further, as seen in panel B, our white applicants (the total number and those who were called back) are statistically significantly more beautiful than our indigenous applicants for all job categories (p-values of 0.000 in all cases).

In the next section, we analyze the effect of physical appearance on the response rate in an econometric context, using the normalized physical appearance index. There are two ways we could normalize these ratings, each one corresponding to a different way employers may look at pictures when screening CVs. On the one hand, if recruiters have *different* standards to judge physical appearance of distinct racial groups, we should normalize the physical appearance index for *each* one of them (we will call this case "Story 1"). On the other hand, if recruiters have a *common* pattern to judge the physical appearance of all racial groups, then we should normalize the physical appearance rating for the *entire* sample of job applicants (we will call this case "Story 2"). It is important to mention that the physical appearance index density of whites appear to be statistically different from that of indigenous (the Kolmogorov-Smirnov test of equality of probability distributions between the physical appearance indices of those groups rejects the null hypothesis).

5.3. Regression Analysis

5.3.1 Main Results

Tables 6, 7, and 8 present the main econometric findings from the linear probability models, where the dependent variable takes the value of 1 if the job candidate was called back and 0 if that was not the case. We control for the company-level heterogeneity using a proxy variable for the company size and dummies for the economic sector of activity.

Table 6 shows the main results for the entire sample (columns I and II). We find that indigenous applicants have lower callback rates (by 7.1 percentage points) than white candidates. Such difference means that white applicants receive around 80 percent more callbacks than similarly qualified indigenous applicants. Moreover, females are less often called (by roughly two percentage points) than males, which means that males receive roughly 20 percent more callbacks than females.

The qualitative results for each of the three job categories in terms of the discrimination against indigenous job candidates are similar to the ones just described for the entire sample. In particular, the magnitude of the discrimination against indigenous is the largest in the case of professional jobs (white applicants receive almost 120 percent more callbacks than indigenous applicants) (table 7), as compared to technical jobs (for which white applicants receive roughly 60 percent more callbacks than indigenous applicants) (table 8), and unskilled jobs (white applicants receive almost 70 percent more callbacks than their indigenous counterparts) (table 9). These results suggest a U-shaped relationship between the education levels (implicit in the job categories: undergraduates-professional jobs, technical college-technical jobs, and high school- unskilled jobs) and the magnitude of discrimination against indigenous, which deserves further exploration.

In terms of sexual discrimination, in professional and technical jobs, females and males receive statistically similar callback rates, while in unskilled jobs males receive 32 percent more callbacks than females. We run auxiliary regressions to examine the role of sex within the main occupations ('selling and marketing', 'driver'[16], and 'telemarketing/customer service', as shown in Annex 2). In particular, splitting the samples accordingly, we do not find sexual discrimination within the 'selling and marketing' job category, but we do find such discrimination outside this job category (being female reduces the callback rates by 5.6 percentage points, significant at 5 percent level). Moreover, there is a clear sexual discrimination within the 'driver' category (being female reduces the callback rates by 8.8 percentage points, significant at 5 percent level), but also outside this job category (being female reduces the callback rate by 4.0 percentage points, significant at 10 percent level). Furthermore, while no sexual discrimination is found within the 'telemarketing/customer service' occupation, the situation is different outside that occupation (being female reduces the callback rates by 5.3 percentage points, significant at 1 percent level).

5.3.2 The Role of Physical Appearance

The results discussed thus far from including our normalized physical appearance index in the regressions are reported in columns III, IV, V, and VI of tables 6, 7, 8, and 9. Recall that we have two stories about how employers may judge job applicants' physical appearance. The first one, which we call story 1, is consistent with employers having different standards for different groups (one way to put it is to say that employers may judge physical appearance, conditional on a job candidate belonging to a certain group (e.g., whites or indigenous). The second story, story 2, is consistent with employers judging physical appearance, unconditionally (same standard for judging all job applicants). An interesting topic for research would be to examine which of these stories is prevalent in the labor market of Lima.

Under the story 1, including the physical appearance index in the regressions does not alter the main results discussed above (if any, there are little changes in the magnitudes reported earlier), which is an artifact of making the physical appearance index for whites uncorrelated with the one for indigenous. Physical appearance only appears to be marginally significant in the regressions for the entire sample (columns III and IV, table 6) and in those for professional jobs (columns III and IV, table 7). These results imply that, besides being male and having a white surname, good looks increase the likelihood of a call for an interview only in professional jobs. To give an idea of the magnitude of discrimination based on looks in professional jobs (and without controlling for any variables), while candidates in the top quartile of physical appearance had a callback rate of 5 percent, the callback rate for those in the lowest quartile was 7 percent, and such difference is only marginally significant (p-value = 0.103). However, in the case of white candidates, the callback rates for those in the top and those in the bottom quartiles of physical appearance were 20 percent and 15 percent, respectively; and such difference was statistically significant (p-value = 0.006).

On the other hand, if we consider the story 2 (see columns V and VI of tables 6, 7, 8, and 9), we do

[16] This occupation refers mostly to cab driving, not trucks.

see changes in the role of surnames and physical appearance in the callback rates. (As a result of the random assignment of sex to the CVs sent, the magnitude of discrimination against females does not change much when we consider different specifications). In particular, we continue to see discrimination against indigenous but only for the entire sample (table 6). Moreover, a significant part of such discrimination (roughly around half of it) seems to be due to physical appearance itself. As shown in tables 7, 8, and 9, when we introduce the physical appearance index, normalized according to story 2, we fail to see statistically significant discrimination against indigenous, and the magnitude of such discrimination drops to less than half. Furthermore, similarly to the results we saw considering story 1, physical appearance significantly affects the callback rates for professional jobs, unlike what happens for technical and unskilled jobs.

6. Concluding Remarks

This is the first study testing racial and sexual discrimination using a resume audit study in Lima, Peru. Our findings present a clear picture of racial discrimination in the Lima's booming economy. Candidates with an indigenous surname face a disadvantage at the callback stage, when white job candidates receive 80 percent more callbacks than similarly qualified indigenous candidates. While this result is robust across job categories (unskilled, technical, and professional), the magnitude of the racial gap (callback rates for whites minus that for indigenous) has a U-shaped relationship with the education levels; we thus find larger gaps in the extremes of the education distribution (professional and unskilled jobs) and a medium-size gap in the middle (technical jobs). This result may be consistent with aspects such as the ability for social interactions and the existence of social connections, being important for professional jobs. Employers may thus believe that those desired aspects are more strongly correlated with being whites. In the other extreme, the reasons for discrimination in unskilled jobs may be different, since such abilities do not seem to be necessary to have a better performance at work.

We further find evidence of sexual discrimination against women, but this finding is not robust across job categories (and is only verified in unskilled jobs, for which males get 30 percent more callbacks than females). The disadvantage that females have in the workplace seems thus to reduce when jobs require higher qualifications, a result that is consistent with the increased women's participation in the labor force observed in the last decade.

With the intent to capture the effect of physical appearance on the callback rates, we attached headshots to the CVs. We have two stories to tell about such effect, depending on how employers judge individuals' physical appearance when recruiting their employees. If they judge different racial groups differently, then we find a beauty premium, but this result is not robust across job categories (and only holds for professional occupations). If, on the contrary, employers have the same pattern in their minds when judging the individuals' physical appearance from any racial group, then physical appearance explains about half of the racial callback gap for the entire sample (and this finding is only verified for professional jobs). Taken together with the presence of racial discrimination in all job categories, these findings suggest that racial discrimination may persist regardless of the looks.

One of the factors not considered in our analysis is the magnitude of the labor supply for every position selected in the experiment. If existed, such information could be used as a control in our callback rate regressions. However, as long as we selected jobs with no systematic pattern in the odds of being called, we should not expect the labor supply intensity to bias our callback rate indicator.

Another variable that is not accurately capturing the effect that physical appearance may have on the response rate is our indicator of physical appearance, since there is a high correlation between perceived physical appearance and having a white surname. This issue could be solved by using similarly attractive photos across indigenous and white applicants, and females and males. Another criticism to our design is the subjective physical appearance ranking we used, which is based on a panel of judges, whose perceptions do not necessarily match those of the recruiters.

Lastly, we should stress that our results are not necessarily representative of the entire labor market in Metropolitan Lima, since we are not considering the universe of existing firms in that market. Paying for advertising job vacancies in the newspaper may induce a form of employers selection. By the same token, there are other forms of advertising job vacancies that are used in the market (online, social networks, among others), which are not considered in the analysis.

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Tables

Table 1: Treatments and sample size

		Physical appearance (photo)			
		Indigenous		White	
		Female	Male	Female	Male
Surname	Indigenous	**T1 (1205)**	**T2 (1205)**		
	White			**T3 (1205)**	**T4 (1205)**

Table 2: Callback Rates by Sex and Surname

Category of Employment	Nº of CVs Sent			Callback Rate (%)		
	A. By Sex					
	Female	Male	Total	Female	Male	Total
Professional	810	810	1,620	10.6	12.5	11.5 [187]
Technical	828	828	1,656	8.9	8.7	8.8 [146]
Unskilled	772	772	1,544	14.5	19.4	17.0 [262]
Total	2,410	2,410	4,820	11.3	13.4	12.3 [595]
	B. By Surname					
	Indigenous	White	Total	Indigenous	White	Total
Professional	810	810	1,620	7.2	15.9	11.5 [187]
Technical	828	828	1,656	6.9	10.7	8.8 [146]
Unskilled	772	772	1,544	12.6	21.4	17.0 [262]
Total	2,410	2,410	4,820	8.8	15.9	12.3 [595]

Note: Number of observations appears in square brackets.

Table 3: Callback Rates by Sex and Category of Jobs

	Sex				Ratio	Difference (M - F)	
Surname	Female	N	Male	N	M : F	Percnt. pts.	P-value
A. TOTAL							
Total	11.3%	272	13.4%	323	1.2	2.1	0.013**
Indigenous	6.3%	76	11.3%	136	1.8	5.0	0.000***
White	16.3%	196	15.5%	187	1.0	-0.7	0.692
B. Professional jobs							
Total	10.6%	86	12.5%	101	1.2	1.9	0.122
Indigenous	5.2%	21	9.1%	37	1.8	4.0	0.015**
White	16.0%	65	15.8%	64	1.0	-0.2	0.538
C. Technical jobs							
Total	8.9%	74	8.7%	72	1.0	-0.2	0.569
Indigenous	3.6%	15	10.1%	42	2.8	6.5	0.000***
White	14.3%	59	7.2%	30	0.5	-7.0	0.001***
D. Unskilled jobs							
Total	14.5%	112	19.4%	150	1.3	4.9	0.005***
Indigenous	10.4%	40	14.8%	57	1.4	4.4	0.032**
White	18.7%	72	24.1%	93	1.3	5.4	0.033**

* (**) [***] Statistical significance at 10 (5) [1] percent.

Table 4: Callback Rates by Surname and Category of Jobs

	Surname				Ratio W : I	Difference (W - I)	
Sex	Indigenous	N	White	N		Percnt. pts.	P-value
A. TOTAL							
Total	8.8%	212	15.9%	383	1.8	7.1	0.000***
Male	11.3%	136	15.5%	187	1.4	4.2	0.001***
Female	6.3%	76	16.3%	196	2.6	10.0	0.000***
B. Professional jobs							
Total	7.2%	58	15.9%	129	2.2	8.8	0.000***
Male	9.1%	37	15.8%	64	1.7	6.7	0.002***
Female	5.2%	21	16.0%	65	3.1	10.9	0.000***
C. Technical jobs							
Total	6.9%	57	10.7%	89	1.6	3.9	0.003***
Male	10.1%	42	7.2%	30	0.7	-2.9	0.069*
Female	3.6%	15	14.3%	59	3.9	10.6	0.000***
D. Unskilled jobs							
Total	12.6%	97	21.4%	165	1.7	8.8	0.000***
Male	14.7%	57	24.1%	93	1.6	9.3	0.000***
Female	10.4%	40	18.7%	72	1.8	8.3	0.000***

* (**) [***] Statistical significance at 10 (5) [1] percent level.

Table 5: Physical Appearance Index: Mean Differences by Sex and Surname

Job Category	Job Applicants			
	Total	P-value	Successful	P-value
	A. By Sex (Male vs Female)			
Total	Yes (Female)	0.010**	Yes (Female)	0.000***
Professional	No	0.105	Yes (Female)	0.005***
Technical	Yes (Female)	0.058*	Yes (Female)	0.000***
Unskilled	No	0.012	No	0.241
	B. By Surname (White vs Indigenous)			

Total	Yes (White)	0.000***	Yes (White)	0.000***
Professional	Yes (White)	0.000***	Yes (White)	0.000***
Technical	Yes (White)	0.000***	Yes (White)	0.000***
Unskilled	Yes (White)	0.000***	Yes (White)	0.000***

Variable in parentheses is the one showing a higher physical appearance index.
* (**) [***] Statistical significance at 10 (5) [1] percent level.

Table 6: OLS Regression Results for the Entire Sample
Dependent variable: Callback Dummy

Variable	I	II	Story 1		Story 2	
			III	IV	V	VI
Indigenous Surname	**-0.071*** **	**-0.071*** **	**-0.071*** **	**-0.071*** **	**-0.034***	**-0.032***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.019)	(0.019)
Female		**-0.021** **	**-0.022** **	**-0.022** **	**-0.022** **	**-0.022** **
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Physical Appearance Index [a]			**0.008***	**0.009***	**0.021** **	**0.022** **
			(0.005)	(0.005)	(0.010)	(0.010)
Constant	**0.143*** **	**0.154*** **	**0.154*** **	-0.001	**0.136*** **	-0.021
	(0.026)	(0.026)	(0.026)	(0.032)	(0.027)	(0.033)
Company Size FEs	Y	Y	Y	Y	Y	Y
Economic Activity FEs	N	N	N	Y	N	Y
Dependent var. mean	0.123	0.123	0.123	0.123	0.123	0.123
N	4724	4724	4724	4724	4724	4724
R-Squared	0.0139	0.0149	0.0156	0.0272	0.0159	0.0275

Notes. Robust standard errors in parentheses
[a] Columns III & IV use the normalized physical appearance index for each subsample (whites & indigenous) (story 1), while columns IV & V use the normalized physical appearance index for the entire sample (story 2).
* (**) [***] Significance at 10 (5) [1] percent level.

Table 7: OLS Regression Results for Professional Jobs
Dependent variable: Callback Dummy

Variable	I	II	Story 1		Story 2	
			III	IV	V	VI
Indigenous Surname	**-0.085*** **	**-0.085*** **	**-0.085*** **	**-0.085*** **	-0.033	-0.028
	(0.016)	(0.016)	(0.016)	(0.016)	(0.032)	(0.032)
Female		-0.019	-0.020	-0.021	-0.021	-0.021
		(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Physical Appearance Index [a]			**0.012‡**	**0.014***	**0.030***	**0.033***
			(0.008)	(0.008)	(0.017)	(0.017)
Constant	0.126	**0.136†**	**0.132♠**	0.014	0.104	-0.019
	(0.084)	(0.127)	(0.026)	(0.092)	(0.084)	(0.095)
Company Size FEs	Y	Y	Y	Y	Y	Y
Economic Activity FEs	N	N	N	Y	N	Y
Dependent var. mean	0.115	0.115	0.115	0.115	0.115	0.115
N	1572	1572	1572	1572	1572	1572
R-Squared	0.0203	0.0213	0.0227	0.0296	0.0233	0.0302

Notes. Robust standard errors in parentheses.
† P-value of 0.109. ‡ P-value of 0.121. ♠ P-value of 0.115.
[a] Columns III & IV use the normalized physical appearance index for each subsample (whites & indigenous) (story 1), while columns IV & V use the normalized physical appearance index for the entire sample (story 2).
* (**) [***] Significance at 10 (5) [1] percent level.

Table 8: OLS Regression Results for Technical Jobs
Dependent variable: Callback Dummy

Variable	I	II	Story 1		Story 2	
			III	IV	V	VI
Indigenous Surname	**-0.039*** **	**-0.039*** **	**-0.039*** **	**-0.039*** **	-0.013	-0.014
	(0.014)	(0.014)	(0.014)	(0.014)	(0.026)	(0.027)
Female		0.002	0.002	0.002	0.001	0.001
		(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Physical Appearance			0.005	0.004	0.014	0.014
Index [a]			(0.007)	(0.007)	(0.014)	(0.015)
Constant	**0.020** **	**0.018***	**0.019***	**-0.129*** **	0.006	**-0.141*** **
	(0.010)	(0.011)	(0.011)	(0.037)	(0.011)	(0.039)
Company Size FEs	Y	Y	Y	Y	Y	Y
Economic Activity FEs	N	N	N	Y	N	Y
Dependent var. mean	0.088	0.088	0.088	0.088	0.088	0.088
N	1632	1632	1632	1632	1632	1632
R-Squared	0.0113	0.0113	0.0115	0.0296	0.0119	0.0299

Notes. Robust standard errors in parentheses.
[a] Columns III & IV use the normalized physical appearance index for each subsample (whites & indigenous) (story 1), while columns IV & V use the normalized physical appearance index for the entire sample (story 2).
* (**) [***] Significance at 10 (5) [1] percent level.

Table 9: OLS Regression Results for Unskilled Jobs
Dependent variable: Callback Dummy

Variable	I	II	Story 1		Story 2	
			III	IV	V	VI
Indigenous Surname	**-0.089*** **	**-0.089*** **	**-0.090*** **	**-0.090*** **	-0.038	-0.041
	(0.019)	(0.018)	(0.019)	(0.019)	(0.036)	(0.036)
Female		**-0.047*** **	**-0.049*** **	**-0.049*** **	**-0.049*** **	**-0.049*** **
		(0.018)	(0.019)	(0.019)	(0.019)	(0.019)
Physical Appearance Index [a]			**0.013†**	0.013	**0.029†**	0.028
			(0.005)	(0.009)	(0.019)	(0.018)
Constant	**0.545*** **	**0.568*** **	**0.573*** **	**0.688*** **	**0.548*** **	**0.664*** **
	(0.127)	(0.127)	(0.126)	(0.164)	(0.127)	(0.165)
Company Size FEs	Y	Y	Y	Y	Y	Y
Economic Activity FEs	N	N	N	Y	N	Y
Dependent var. mean	0.170	0.170	0.170	0.170	0.170	0.170
N	1520	1520	1520	1520	1520	1520
R-Squared	0.0430	0.0470	0.0483	0.0796	0.0485	0.0798

Notes. Robust standard errors in parentheses.
† P-value of 0.116.
[a] Columns III & IV use the normalized physical appearance index for each subsample (whites & indigenous) (story 1), while columns IV & V use the normalized physical appearance index for the entire sample (story 2).
* (**) [***] Significance at 10 (5) [1] percent level.

Annexes

Annex 1: Summary Statistics

Applicant Characteristics	Surname	Indigenous	1205	50.0%
		White	1205	50.0%
	Sex	Female	1205	50.0%
		Male	1205	50.0%
Job Characteristics	Job Category	Professional	1544	32.0%
		Technical	1656	34.4%
		Unskilled	1620	33.6%
	Experience Requested	None	3496	72.5%
		Up to One Year	436	9.1%
		Btw One and Two Years	456	9.5%
		Three to More Years	432	9.0%
	Public/Office	Job Dealing with Public	1624	33.7%
		Office	3196	66.3%
Company Characteristics	Company Size[1]	1: Micro	2430	51.4%
		2	1250	26.5%
		3: Medium	876	18.5%
		4	148	3.1%
		5: Large	20	0.4%

[1] Proxied by the job ad size published in the newspapers. 96 job ads were obtained from *Aptitus* Web site.

Annex 2: Main Jobs/Occupations by Category of Employment

Professional Careers	Business Administration	35.1
	Accountancy	13.3
	Civil Engineering	12.1
	Mechanic Engineering	8.9
	Others[1]	30.6
	Total	100.0
Technical Jobs	Sales and Marketing	20.5
	Accounting Assistant	14.5
	Mechanical Technician	11.1
	Computer Technician/Programming	9.9
	Business Administration Assistant	8.7
	Graphical Design	6.3
	Electronic Technician	6.3
	Others[2]	22.7
	Total	100.0
Unskilled Jobs	Sales and Marketing	33.7
	Driver (not truck!)	18.9
	Call Centers / Customer Service	9.3
	Restaurants	7.3
	Others[3]	30.8
	Total	100.0

[1] Includes architecture, law, economics, agronomy, several other engineering careers (electric, electronic, geological, industrial, textile, mining, telecommunications), medicine, nutritionist, psychology and veterinary.

[2] Includes fashion design, secretary, and several technical occupations (pharmaceutical, electrical, electro mechanic, auto motor mechanic, textile, construction) and chef.

[3] Includes security, warehouse, office assistant, cleaning, messenger and manufacturing assistants.