DISCUSSION PAPER

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Triple penalty in employment access: the role of beauty, race, and sex

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Triple penalty in employment access: the role of beauty, race, and sex

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Abstract

We investigate the role of physical appearance, in addition to race and sex, in the rate of discrimination observed in the labour market of Lima. Our experimental design allows us to disentangle the effect of each of those three variables on the callback rates received by our fictitious job candidates. Since we are controlling for variables that are important in the selection process (mainly, education and job experience), our results provide better indicators of discrimination than the ones we could obtain through the econometric analysis of observational data. We find that discrimination based on looks is greater than that based on race or sex. The first two types of discrimination are in professional and unskilled jobs.

Keywords: Discrimination – Labor Market – Sex – Race – Surnames – Beauty

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Content

1. Introduction

Perhaps as early as in the childhood, we begin to form our perception of human beauty (Langlois and Roggman 1990). While this perception may change over the years, as a result of cultural factors and the influence of the media, the fact is that most people invest some of their time on grooming before starting their daily tasks. In the case of the United States, an average husband spends thirty-two minutes washing, dressing and grooming, while an average wife takes about forty minutes (Hamermesh 2011). While these figures are not necessarily applicable to other societies, it does raise the question of whether beauty pays off.

In the economic sphere, the benefits beautiful persons may get are primarily related to their labor market returns. Again for the U.S., Hamermesh (2011) shows that attractive men (women) earn, on average, wages that are 17% (12%) higher than those who are unattractive, controlling for a variety of factors that can affect earnings (primarily, education and experience). These figures include a "beauty premium" (results for beautiful people, compared to an average-looking people) of 4% and 8%, and an "ugliness penalty" of -13% and -4%, respectively.

In addition to the higher earnings received by attractive people in the US, compared to unattractive people with similar qualifications, studies from Israel and Argentina show that attractive people also receive more callbacks than homely-looking ones, as reported by López et al. (2013) and Ruffle and Shtudiner (2010).

In an increasingly demanding job market, where experience and education play an important role, recruiters have to choose the candidates who would best fit the job requirements. If two job applicants had similar educational background and work experience (i.e., similar human capital), who should be called? In the absence of any particular preference for other attributes unrelated to the candidate's productivity, economic theory predicts that both should have the same chance of receiving a call from the recruiter.

However, such an ideal result this does not always hold in reality, as reported by Galarza and Yamada (2012) for the case of Lima. Using an experimental methodology, the authors found that a white person receives almost twice as many callbacks as a Quechua person with similar human capital, and that male candidates are preferred to females. However, this study does not properly control for the level of physical appearance of the job applicants.

In this paper, we investigate the role of physical appearance, in addition to race and sex, in the observed rate of discrimination in the labor market of Lima, Peru. In that sense, our study builds upon the work by Galarza and Yamada (2012), and expands the analysis by López et al. (2013) and Ruffle and Shtudiner (2010). Our results provide novel information about the extent of discrimination that can be attributed to each of the three dimensions mentioned earlier.

The remainder of the paper is structured as follows. Section 2 reviews the related literature. Section 3 describes our experimental methodology and the procedures we followed. Section 4 discusses the results, and Section 5 concludes.

2. Related studies

Economics defines discrimination in the labor market as a situation in which a person who provides a service, and is similarly productive to another person, in physical or mental, is treated differently and unfairly (for example, with lower earnings or lower callback rates for job interviews); moreover, this differential treatment is related to an observable characteristic, such as race, ethnicity or sex (List and Rasul 2011).

There are two sets of methods to measure discrimination. The first one involves the use of observational data (such as national surveys) to compare the wage gaps of any two groups, so that the part of such a gap that cannot be explained by observables can be, at least partially, attributed to discrimination. The second method uses experimental economics tools for data collection, and is referred to as audit study. The audit studies can be of two types, but both involve the use of fictitious candidates. The first type consists of sending fictitious job applicants, with similar academic background and work experience, trained by the researcher, to actual interviews. A shortcoming of this type of audit study is that many things can happen during interviews that cannot be controlled by the candidate or the experimenter, which may explain the difference in the performance of two otherwise comparable candidates. The second type of audit study, which we used in this paper, is to send fictitious applicants' CVs with similar human capital. Given the equivalence in human capital, the level of discrimination is measured by any statistically significant difference in the average callback rates received by different groups of job candidates.

Since the past decade, a branch of economics has attracted the interest of many economists, the economics of beauty, introduced by Daniel Hamermesh (Hamermesh and Biddle 1994 and 1998, Hamermesh 2006, Hamermesh and Abrevaya 2012). As the name suggests, this nascent branch of economics examines the role played by the individuals' beauty in their daily decisions. In this regard, it is particularly useful the notion that beauty is a scarce and tradable attribute (Hamermesh 2011), so that there are incentives for people to invest money, time, and effort to enhance their beauty. Two additional features emphasized by Hamermesh (2011) are that: while there is no universal standard of beauty ("beauty is in the eye of the beholder"), societies have a similar standard of beauty; furthermore, although beauty involves more characteristics than the physical appearance, the difficulty of measuring all them makes the physiognomy the most widely used indicator of beauty.

Our paper is related to several studies, both in terms of its approach (Hamermesh 2012, Hamermesh and Biddle 1994, Möbius and Rosenblat 2003), and of the methodology used (Banerjee et al., 2009, Bertrand and Mullainathan 2004, Carlsson and Rooth 2006, Kaas and Manger 2010, among others). We review next some of the main related works.

When examining the effects of beauty, the empirical labor literature has focused on the following question: Does workers' physical attractiveness plays a major role in the hiring decisions? As we mentioned in the Introduction, Hamermesh (2011) reports that in the US, homely-looking persons earn lower wages than average-looking persons, who in turn earn lower wages than attractive persons. Moreover, he reports that the "ugliness penalty" is bigger that the "beauty premium", a result that is particularly noticeable for men.

On the other hand, Payet (2007), who surveyed clients of five restaurants. Payet found that attractive waitresses (but not waiters) received higher tips, controlling for the productivity at work (a control question was about the quality of the service received), this difference was clearly tip discriminatory conduct on the part of customers.

It is interesting to add that beauty not only does can generate a significant and direct impact on the labor market, but also on other markets, such as marriage. In fact, Hamermesh and Abrevaya (2012) found a relationship between physical attractiveness and happiness, using data from three countries (United States, Canada and the UK): the higher salaries of beautiful people contribute to the happiness of the couple.

As for the experimental studies on labor discrimination, the reader is referred to review Galarza and Yamada (2012). For our purposes, it suffices to mention that Bertrand and Mullainathan (2004) is the most cited article in the economics literature. These authors analyzed racial discrimination in the United States (Chicago and Boston), by examining the callback rates of candidates with African American and white names. They found a 50% higher callback rate for whites.

Moreover, to the best our knowledge, the only experimental works that examined the role of physical appearance in labor discrimination are Ruffle and Shtudiner (2010) and Lopez et al. (2013), and both used a resume audit study in the same fashion as Bertrand and Mullainathan (2004) did. Ruffle and Shtudiner (2010) sent CV with photo (beautiful or homely-looking) and without photo in Israel. They find a beauty premium for men (the average callback rate for attractive men was higher than that for homely-looking men and that for candidates with no photo attached to their CVs), but interestingly, the beauty premium is negative for women (the callback rate for CVs without photographs was higher than that for CVs with beautiful or homely-looking photos). The authors try to explain this finding by the alleged female jealousy when recruiting (recruiting people, mostly women in Israel, do not want competition, they claim). This argument is, however, unconvincing.

Lopez et al. (2013) also sent CVs in pairs (a CV with a beautiful photo and another one with a homely-looking photo) to analyze the effect of beauty in the labor market of Buenos Aires, Argentina. The results indicate that beautiful job applicants received 36% more callbacks than homely-looking ones. Moreover, beautiful people are called more quickly. It is important to remark that, unlike Ruffle and Shtudiner (2010), Lopez et al. used an objective measure of beauty: a ratio that measures the symmetry of the eyes and nose. The ugly photos were obtained by altering this symmetry (some pictures even look artificially ugly).

Finally, the study by Galarza and Yamada (2012) pioneered the analysis of racial and sexual discrimination in the labor market of Lima, using an experimental methodology similar to that of Bertrand and Mullainathan (2004). They sent four CV (two white candidates and two Quechua candidates) with the same level of human capital for every single selected job opening, and found that there was significant discrimination against Quechua candidates and to a lesser extent, against women. An important point to mention about this study is that white applicants had a higher score of subjective beauty (determined by a panel of judges) than Quechua applicants. This is an important limitation of this work.

In the context described earlier, the contribution of this paper is to disentangle the effect of beauty from that of race in the observed labor discrimination, for both females and males. The analysis of this subject is particularly important in the current booming macroeconomic context, where one would expect that the candidates' qualifications will prevail in the hiring decisions, while in times of recession, we would expect the discriminatory stereotypes to strengthen.

3. Experimental Design and Implementation

3.1. Selecting the Job Vacancies

The job vacancies used in the experiment were selected from one of the largest job networks in Lima, *Aptitus*, which weekly publishes online hundreds of job ads from multiple companies. A printed version of such vacancies is published every Sunday in the newspaper *El Comercio*.

We used the following criteria for the selection of job offers:

i) The job experience requested should not exceed 5 years (in fact, only 18 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,
vi) Vacancies should not request to attach the photo to the CV.

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

3.2. Constructing the CVs

We created a database of CVs for the three job categories we applied for (described below) using real existing CVs available on two large employment Web sites, http://www.bumeran.com.pe and http://www.computrabajo.com.pe. 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 format of every set of 4 CVs sent in response to each job ad was similar. In particular, the education levels of our candidates for each job category are as follows:

(i) *Professional Jobs*.- Applicants for professional jobs earned the same undergraduate degree from the largest and arguably the most prestigious public university in Peru.[2] We chose this 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

[2] 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.

upwards the credentials of our job applicants, thus making harder to detect discrimination.

(ii) *Technical Jobs*.- Our applicants graduated from the most prestigious technical institutes/colleges. While no ranking for these organizations is available, we based our selection on the demand that their alumnae have in the labor market in their respective specialties.

(iii) *Unskilled Jobs*.- In selecting the secondary schools for all our applicants (this is 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 of Education, on the basis of a series of indicators signaling prestige.[3]

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 call.

All 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.

3.3. Selecting Surnames and Photos

We used a vast database of indigenous and white surnames for our crowd of job applicants, both of which were gathered from a public Website[4] that classifies names by their origins. The selected white surnames have a predominant foreign origin (Spanish, Italian, and French), while the indigenous (*Quechuas*) surnames are clearly distinctive of their origin. Sample surnames used include Anderson, Bresciani, Camogliano, Goicochea, Koechlin (for white applicants), and Aylas, Huamancuri, Sullca and Waylla (for indigenous candidates). After getting a long list of the two types of surnames, we got random combinations of those to come up with

[3] 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.

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

a database of 720 full names (first name + paternal surname + maternal surname) for each type of applicant (indigenous and white). We then created personal e-mail accounts.

The photos of our candidates were also collected from the Internet, and were subsequently modified by a Photoshop professional, in order to standardize the style (all men wear suits and women wear formal dress). Every candidate from a particular race was assigned a corresponding full name. The subjective beauty indicator was gathered from a panel of more than 50 judges, including students and professionals with different backgrounds who took a hiring decision at some point of their careers (human resource specialists, psychologists, anthropologists, business administrators, economists, mathematicians, and sociologists). Judges rated headshots using a 1-to-7 scale (from homely-looking to strikingly handsome). After establishing the ranking, we classified the photos as "beautiful" if their scores were between 4 and 6, and "homely" if such scores were between 1.6 and 3.

As shown in Table 1, the group of beautiful applicants is statistically more beautiful than the homely-looking job applicants.

Table 1: Average rating of physical appearance

	Male		**Female**	
	White	Quechua	White	Quechua
Beautiful	4.68	4.92	4.78	4.79
Homely	2.57	2.48	2.61	2.21

Given the difficulty to get job candidates from both sexes and races with the same level of subjective beauty, we control for any difference in this variable in the regressions presented in section 4.

3.4. Treatments and sample size

Our sample design consists of twelve treatments that correspond to variations in terms of physical appearance (3), race or surname (2), and sex (2), as shown in table 2. The inclusion of the photographs is an innovation of our experiment (only shared with López et al. (2013) and Ruffle and Shtudiner (2010), and responds to our interest in looking at the extent to which physical appearance strengthens or weakens the level of discrimination. We selected 1,247 jobs ads for which we sent out 4,988 fictitious CVs, 1,576 for professional jobs, 1,692 for technical jobs, and 1,720 for unskilled jobs. Also, roughly in one third of the CVs we did not attach a photo (1,628), in one third (1,676) we attached a beautiful photo and in the remaining third (1,684) we attached a homely-looking photo.

Each set of 4 CVs sent for a given vacancy denoted a similar human capital (education and job experience). Two included a white surname (for female and male) and two included a Quechua surname. We sent every set of 4 CVs with the same level of beauty, if the case: with no photo attached, with a beautiful photo, and with a homely-looking photo. Thus, in the absence of labor discrimination, one would observe a similar average callback rate for every group of candidates or treatment (beautiful/homely/with no photo, white/Quechua, and females/males). Any statistically significant difference in callback rates (comparing groups with different physical appearance, race, or sex) will indicate discrimination.

Table 2: Treatments, sample size, and callback rates

		Quechua		**White**	
		Male	Female	Male	Female
Quechua	Beautiful	**T1** [419] 18.14%	**T2** [419] 13.84%		
	Homely	**T3** [421] 10.69%	**T4** [421] 6.41%		
	No Photo	**T5** [407] 12.04%	**T6** [407] 6.39%		
White	Beautiful			**T7** [419] 25.78%	**T8** [419] 22.67%
	Homely			**T9** [421] 16.86%	**T10** [421] 10.21%
	No Photo			**T11** [407] 14.00%	**T12** [407] 10.07%

Note: Number of observations are indicated in square brackets.

4. Results

4.1. Descriptive Statistics

In this section, we analyze the descriptive results, in terms of the callback rate received by different groups of our fictitious candidates. Annex 1 presents the main characteristics of the sample (job experience, company size, economic sector, and proportion of jobs that involve direct contact with the client). Annex 2 shows the main occupations CVs were sent to within each job category (professional, technical and unskilled).

696 out of the 4,988 CVs sent had a callback, resulting in an overall response rate of 13.95%, which is slightly smaller than the callback rate reported in Chile (Bravo et al. 2009) [16.76%] and Israel (Ruffle and Shtudiner 2010) [14.50%], but higher than the rate found in the United States (Bertrand and Mullainathan 2004) [8.05%].

Table 3 shows the overall callback rates by sex, race, and degree of beauty. As we can see, the greatest response rate was received by unskilled candidates (15.41%), while the lowest one was received by technicians (12.65%). The response rate for professional candidates was 13.77%. We also find a gender gap in favor of male applicants in all job categories (Panel A) and a racial gap in favor of white applicants for professional and unskilled jobs, but not for technical jobs (Panel B).

Regarding the effect of physical appearance (Panel C), the response rate of the CVs sent with a photo (whether beautiful or homely-looking) was 15.57%, which implies that the CV without photo had a lower response rate (10.63%). In that sense, including the photo in the CVs seems to be providing useful information for the recruiters in their selection decisions. Within the set of CVs with photos we found a gap between the candidates deemed as homely-looking and those deemed as beautiful, in favor of the latter, for all job categories.

Table 3: Average Callback Rates by gender, race and beauty

Job Category	Nº of CVs Sent			Callback Rate (%)			
	A. By Sex						
	Female	**Male**	**Total**	**Female**	**Male**	**Total**	
Professional	788	788	1,576	11.55	15.99	13.77	[217]
Technical	846	846	1,692	10.05	15.25	12.65	[214]
Unskilled	860	860	1,720	13.26	17.56	15.41	[265]
Total	2,494	2,494	4,988	11.63	16.28	13.95	[696]
Job Category	**B. By Race**						
	Quechua	**White**	**Total**	**Quechua**	**White**	**Total**	
Professional	788	788	1,576	8.63	18.91	13.77	[217]
Technical	846	846	1,692	12.88	12.41	12.65	[214]
Unskilled	860	860	1,720	12.09	18.72	15.41	[265]
Total	2,494	2,494	4,988	11.27	16.64	13.95	[696]
Job Category	**C. By Physical Appearance (With Photo)**						
	Homely	**Beautiful**	**Total**	**Homely**	**Beautiful**	**Total**	
Professional	540	520	1,060	10.56	21.92	16.13	[171]
Technical	568	572	1,140	9.68	16.08	12.89	[147]
Unskilled	576	584	1,160	12.85	22.43	17.67	[205]
Total	1,684	1,676	3,360	11.05	20.11	15.57	[523]

Note: Number of observations in the most right column shown in square brackets.

Let's see now if the differences observed in the above table are statistically significant. Tables 4, 5 and 6 present evidence of the differences in the average callback rates by sex, race and beauty, for the three job categories, respectively. As seen in Table 4, the sex gap in the response rates for the Quechua candidates lies between 2.0 percentage points (professional jobs, although this difference is not significant) and 8.3 percentage points (technical jobs); thus implying that the response rates for male Quechua candidates are between 27% and 95% higher than those for female Quechua candidates. As for the white candidates, the most pronounced gap is found in professional jobs for which males receive 44% more callbacks than females. We also see a smaller gap against female white applicants (30%) for unskilled jobs exists a smaller, and no such statistically significant gap for technical jobs.

Table 4: Callback Rates By Sex and Job Category

Race	Sex				Ratio M/F	Difference (M-F)	
	Female	n	Male	n		Value (p.p)	(*p-value*)
A. TOTAL							
Total	11.63	290	16.28	406	1.400	4.65	0.000***
Quechua	8.90	111	13.63	170	1.532	4.73	0.000***
White	14.35	179	18.93	236	1.318	4.57	0.002***
B. Professional Jobs							
Total	11.55	91	15.99	126	1.385	4.44	0.010**
Quechua	7.61	30	9.64	38	1.267	2.03	0.310
White	15.48	61	22.34	88	1.443	6.85	0.014**
C. Technical Jobs							
Total	10.05	85	15.25	129	1.518	5.20	0.001***
Quechua	8.75	37	17.02	72	1.946	8.27	0.000***
White	11.35	48	13.48	57	1.188	2.13	0.348
D. Unskilled Jobs							
Total	13.26	114	17.56	151	1.325	4.30	0.013**
Quechua	10.23	44	13.95	60	1.364	3.72	0.094*
White	16.28	70	21.16	91	1.300	4.88	0.066*

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

In terms of response rate by race (shown in Table 5), the overall rate for white applicants is 48% higher than that for Quechua candidates. While we do not observe racial gaps for men and women who applied for technical jobs, such a gap is large for professional jobs: white (female + male) applicants received 120% more callbacks than Quechua applicants, while for the racial gap for males is 131%. Moreover, for unskilled jobs, the gap is substantially lower: white applicants receive 55% more callbacks than Quechua applicants. A curious result from our research is that for technical jobs, both Quechuas and whites received a statistically similar response rate, which suggests that there is no racial gap for this job category. We will later on discuss this and other results using regression analysis.

Table 5: Callback Rates By Race and Job Category

	Race				Ratio W/Q	Difference (W-Q)	
Sex	**Quechua**	**n**	**White**	**n**		**Value (p.p)**	**(*p-value*)**
			A. TOTAL				
Total	11.27	281	16.64	415	1.477	5.37	0.000***
Male	13.63	170	18.93	236	1.388	5.29	0.000***
Female	8.90	111	14.35	179	1.613	5.45	0.000***
			B. Professional Jobs				
Total	8.63	68	18.91	149	2.191	10.28	0.000***
Male	9.64467	38	22.34	88	2.316	12.69	0.000***
Female	7.61421	30	15.48	61	2.033	7.87	0.000***
			C. Technical Jobs				
Total	12.88	109	12.41	105	0.963	-0.47	0.769
Male	17.02128	72	13.48	57	0.792	-3.55	0.151
Female	8.74704	37	11.35	48	1.297	2.60	0.208
			D. Unskilled Jobs				
Total	12.09	104	18.72	161	1.548	6.63	0.000***
Male	13.95	60	21.16	91	1.517	7.21	0.005***
Female	10.23	44	16.28	70	1.591	6.05	0.008***

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

Table 6 shows that there is a "beauty gap", in the sense that the response rate for beautiful applicants is significantly higher than that for homely-looking applicants, and this happens in all three job categories analyzed. As for the magnitude of the beauty gap, this is 82% for all CVs sent with photographs, and this figure reaches 108% for professional jobs. A simple way to better understand these figures is as follows: in order to have the same success in getting a callback for an interview as the beautiful candidates who send 100 CVs (20 CVs receive calls), homely-looking candidates must send 182 CVs. This figure increases to 208 CVs in the case of professional jobs.

Table 6: Callback Rates by Physical Appearance

	Physical Appearance				Ratio B/H	Difference (B-H)	
Job Category	**Homely**	**n**	**Beautiful**	**n**		**Value (p.p)**	**(*p-value*)**
Total	11.05	186	20.11	337	1.820	9.06	0.000***
Professional	10.56	57	21.92	114	2.077	11.37	0.000***
Technical	9.68	55	16.08	92	1.661	6.40	0.001***
Unskilled	12.85	74	22.43	131	1.746	9.58	0.000***

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

Now let's see how much of the beauty gaps is due to what we might call "beauty premium" and how much is due to a "penalty for ugliness." For the former case, we compare the response rate for beautiful applicants with that received by candidates who did not attach photos to their CVs, and for the latter case, we compare the response rates for homely-looking applicants with those received by candidates who did not attach photos to their CVs. Using the figures reported in Table 7, we find that there is a beauty premium (beautiful candidates receive a response rate that is 89% higher than that received by candidates who did not attach photos to their CV), which is particularly marked for females (such rate reaches 122%) and whites (100%), while the beauty premium for males and Quechuas reached 69% and 73%, respectively. Furthermore, we do not observe a penalty for ugliness.

Table 7 also allows us to identify sex gaps within each group of candidates who whether attached photos (beautiful or homely-looking) to their CVs or not. Interestingly, we find that these gaps are much larger among those who did not attach photos to their CVs (between 39% for whites, and 88% for Quechuas) than among those who did attach photos (between 30% for whites, and 42% for Quechuas). And those gaps are mainly explained by those observed for homely-looking candidates (about 65% for both races). Furthermore, we observe greater sex gaps for Quechuas than for whites, except for homely-looking candidates, as we saw earlier.

Table 7: Callback Rates By Sex and Physical Appearance

	Sex				Ratio M/F	Difference (M-F)	
Race	Female	n	Male	n		Value (p.p)	(p-value)
A. TOTAL							
Total	11.63	290	16.28	406	1.400	4.65	0.000***
Quechua	8.90	111	13.63	170	1.532	4.73	0.000***
White	14.35	179	18.93	236	1.318	4.57	0.002***
B. WITH PHOTO							
Total	13.27	223	17.86	300	1.35	4.58	0.000***
Quechua	10.12	85	14.40	121	1.42	4.29	0.007***
White	16.43	138	21.31	179	1.30	4.88	0.010**
B1. Beautiful							
Total	18.26	153	21.96	184	1.20	3.70	0.059*
Quechua	13.84	58	18.14	76	1.31	4.30	0.090*
White	22.67	95	25.78	108	1.14	3.10	0.294
B.2. Homely							
Total	8.31	70	13.78	116	1.66	5.46	0.000***
Quechua	6.41	27	10.69	45	1.67	4.28	0.027**
White	10.21	43	16.86	71	1.65	6.65	0.005***
C. NO PHOTO							
Total	8.23	67	13.02	106	1.58	4.79	0.002***
Quechua	6.39	26	12.04	49	1.88	5.65	0.005***
White	10.07	41	14.00	57	1.39	3.93	0.085*

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

Table 8 shows the racial gaps by level of physical appearance and whether the candidates attached a photo to the CVs or not. Similarly to the sex gap seen in Table 7, the racial gap is uniform for homely-looking candidates (about 60%, in favor of the whites). The callback rates for male candidates from both races with no photo attached to their CVs are not statistically different, in contrast to what happens for females (the racial gap is almost 60% in this case). In general, the racial gaps are similar in magnitude regardless of their physical appearance, especially for females.

Table 8: Callback Rates By Race and Physical Appearance

Sex	Race: Quechua	n	Race: White	n	Ratio W/Q	Difference (W-Q): Value (p.p)	Difference (W-Q): (p-value)
A. TOTAL							
Total	11.27	281	16.64	415	1.477	5.37	0.000***
Male	13.63	170	18.93	236	1.388	5.29	0.000***
Female	8.90	111	14.35	179	1.613	5.45	0.000***
B. WITH PHOTO							
Total	12.26	206	18.87	317	1.54	6.61	0.000***
Male	14.40	121	21.31	179	1.48	6.90	0.000***
Female	10.12	85	16.43	138	1.62	6.31	0.000***
B1. Beautiful							
Total	15.99	134	24.22	203	1.51	8.23	0.000***
Male	18.14	76	25.78	108	1.42	7.64	0.008***
Female	13.84	58	22.67	95	1.64	8.83	0.001***
B.2. Homely							
Total	8.55	72	13.54	114	1.58	4.99	0.001***
Male	10.69	45	16.86	71	1.58	6.18	0.009***
Female	6.41	27	10.21	43	1.59	3.80	0.046**
C. NO PHOTO							
Total	9.21	75	12.04	98	1.31	2.83	0.064*
Male	12.04	49	14.00	57	1.16	1.97	0.405
Female	6.39	26	10.07	41	1.58	3.69	0.056*

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

Let us examine now if these results remain in an econometric regression context, in which we will control for the heterogeneity that may exist among the companies the CVs were sent to.

4.2. Econometric Results

The general equation to estimate using OLS is as follows:

$$\text{Callback Rate}_i = \alpha_0 + \alpha_1 \text{Male}_i + \alpha_2 \text{White}_i + \alpha_3 \text{Beautiful}_i + \alpha_4 \text{Beauty level}_i + \alpha_5 \text{With Photo}_i + \varepsilon_i,$$

where we want to explain the *callback rate*, variable that takes the value of 1 if the candidate "i" has received a callback from the employer for an interview, and the value of 0, if no response has been received. The right-hand-side variables are also binary ones (and take the value of 1 if the candidate has the respective characteristic, and 0, otherwise), except for the *Beauty level*, which is a continuous variable that reports the level of subjective physical appearance corresponding to candidate "i", provided that he/she is deemed as beautiful, and takes the value of zero if candidate "i" is not beautiful. Thus, α_4 gives the incremental benefit from being beautiful in terms of receiving a callback. Given the difficulty of its interpretation, we will only look at the statistical significance, and sign of this coefficient. This coefficient is reported in the fourth row of the following four tables.

The other coefficients of interest, α_1, α_2, α_3, α_5, measure the extent of discrimination due to sex, race, beauty, and to the sole fact of including a photo in the CV, respectively. A coefficient with a positive sign that is statistically significant would provide evidence of discrimination in favor of the related characteristic (being male, white, beautiful, or having attached a photo to their CVs).

Tables 9, 10, 11, and 12 report the main regression results.[5] In all the cases, we will look at the results from columns III, IV and V, as they include the three variables of interest (sex, race and beauty). In all regressions, the main results remain unaltered when we control for the companies' economic sector.

Table 9 shows the results for the entire sample of observations. As indicated in column III, white candidates have a larger response rate (by 6.6 percentage points) than Quechua candidates. This difference implies that white candidates receive 55% more callbacks than similarly qualified Quechua candidates. Males also receive more callbacks than females (by 4.6 percentage points), which means that the former receive 34% more callbacks than the latter. On the other hand, if the candidate is a beautiful person, the response rate increases by 9.1 percentage points, that is, a beautiful job applicant receives a callback rate that is 83% bigger that that received by a homely-looking applicant (column III). Moreover, for each additional point on the level of beauty that a beautiful candidate has (variable "beauty level"), the probability of being called back for an interview increases by 1.8 percentage points (column IV). On the other hand, attaching a photo to the CV increases the likelihood of being called back by 4.9 percentage points (or in 47%) (column V).

[5] Results are similar when we run probabilistic models (e.g., probit) instead of a linear probability model.

Table 9: OLS Results on the Callback Dummy: Entire Sample

Variable	I	II	III	IV	V
Male	**0.0465*** **	**0.0465*** **	**0.0458*** **	**0.0457*** **	**0.0465*** **
	(0.0098)	(0.0976)	(0.0123)	(0.0123)	(0.0974)
White		**0.0537*** **	**0.0661*** **	**0.0673*** **	**0.0537*** **
		(0.0976)	(0.0123)	(0.0123)	(0.0974)
Beautiful			**0.0906*** **		
			(0.0123)		
Beauty level (dummy*ranking)				**0.0182*** **	
				(0.0025)	
With Photo					**0.0494*** **
					(0.0098)
Constant	**0.1162*** **	**0.0894*** **	**0.0545*** **	**0.05555*** **	**0.0561*** **
	(0.0639)	(0.0751)	(0.0148)	(0.1049)	(0.0096)
Average Callback Rate	0.1395	0.1395	0.1395	0.1395	0.1395
N	4988	4988	3360	3360	4988
R-Squared	0.0045	0.0105	0.0279	0.0273	0.015

Note: Robust Standard Errors in parentheses.

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

Tables 10, 11 and 12 display the results for each job category examined: professional, technical, and unskilled, respectively. As shown in Table 10, column III, for professional jobs, race and beauty are the two most important factors correlated with discrimination. In particular, while being male increases the likelihood of being called back for an interview by 5.8 percentage points, being white increase it by 10.8 percentage points, and being a beautiful candidate increase it by 11.4 percentage points. These percentages imply gaps of 44% (sexual), 99% (racial), and 108% (by physical appearance), respectively, which show that a white (Quechua) professional job applicant who is beautiful (homely-looking) has enormous payoff (penalty), in terms of calls for interviews, in the Lima labor market. Companies also prefer the candidates to attach a photo to their CVs: a candidate who does so has a higher probability, by 7.2 percentage points (a 81% higher chance), of being called back compared to another one who does not attach a photo to his/her CV (column V).

Table 10: OLS Results on the Callback Dummy: Professional Jobs

Variable	I	II	III	IV	V
Male	**0.0444****	**0.0444****	**0.0585*****	**0.0577*****	**0.0444*****
	(0.0173)	(0.0171)	(0.0220)	(0.0221)	(0.0171)
White		**0.1028*****	**0.1075*****	**0.1093*****	**0.1028*****
		(0.0171)	(0.0220)	(0.0221)	(0.0171)
Beautiful			**0.1137*****		
			(0.0221)		
Beauty level (dummy*ranking)				**0.0230*****	
				(0.0045)	
With Photo					**0.0722*****
					(0.0166)
Constant	**0.1155*****	**0.0641*****	**0.0225**	**0.0236**	**0.0155*****
	(0.0114)	(0.0127)	(0.0183)	(0.0184)	(0.0158)
Average Callback Rate	0.1377	0.1377	0.1377	0.1377	0.1377
N	1576	1576	1060	1060	1576
R-Squared	0.0047	0.0264	0.0516	0.0510	0.0361

Note: Robust Standard Errors in parentheses.
*(**)[***] Statistical significance at 10 (5) [1] percent level.

Moreover, for technical jobs (Table 11), the sexual and beauty gaps are smaller, in absolute value, than those observed for professional jobs. We also see that there is no racial gap, and that the beauty gap is still higher than the gender gap (66% versus 41%, as seen in column III). Even if we include only those jobs where there is a direct contact with the public (mainly, sales), race continues to have no effect on the response rate in these types of jobs. We did not observe any "photo effect" in this case, either.

Table 11: OLS Results on the Callback Dummy: Technical Jobs

Variable	I	II	III	IV	V
Male	**0.0520*** **	**0.0520*** **	**0.0439*** **	**0.0436*** **	**0.0520*** **
	(0.0161)	(0.0161)	(0.0198)	(0.0197)	(0.0161)
White		**-0.0047**	**0.0052**	**0.0062**	**-0.0047**
		(0.0161)	(0.0198)	(0.0198)	(0.0161)
Beautiful			**0.0640*** **		
			(0.0197)		
Beauty level (dummy*ranking)				**0.0135*** **	
				(0.0041)	
With Photo					**0.0076**
					(0.0170)
Constant	**0.1004*** **	**0.1028*** **	**0.0723*** **	**0.0717*** **	**0.0977*** **
	(0.0103)	(0.1264)	(0.0166)	(0.0166)	(0.0169)
Average Callback Rate	0.1265	0.1265	0.1265	0.1265	0.1265
N	1692	1692	1140	1140	1692
R-Squared	0.0061	0.0062	0.0135	0.0138	0.0063

Note: Robust Standard Errors in parentheses.

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

Finally, for the case of unskilled jobs, we find that the role of sex is marginal, while beauty and race are still the main sources of discrimination, with gaps of 75% and 66%, respectively (Table 12, column III). In turn, including a picture to the CVs increases the probability of being called in 65% (7 percentage points, as shown in column V). Why would an employer prefer to hire a beautiful female candidate instead of a homely-looking, but equally qualified candidate? One possible reason may be that this employer's customers will be more interested in demanding his services or buying his products if they are delivered by an attractive employee. If this were the case, the effect of beauty on callback rates should be higher in jobs where there is a direct contact with the public, which is not the case in our data. Another possibility is that the employer has a special taste for working with beautiful employees, in which case we would be observing a preference-based discrimination (Becker, 1957).

Table 12: OLS Results on the Callback Dummy: Unskilled Jobs

Variable	I	II	III	IV	V
Male	**0.0430*** **	**0.0430*** **	**0.0362Δ**	**0.0367***	**0.0430** **
	(0.0174)	(0.0173)	(0.0221)	(0.0221)	(0.0172)
White		**0.0663*** **	**0.0879*** **	**0.0890*** **	**0.0663*** **
		(0.0173)	(0.0221)	(0.0221)	(0.0172)
Beautiful			**0.0958*** **		
			(0.0221)		
Beauty level (dummy*ranking)				**0.0184*** **	
				(0.0045)	
With Photo					**0.0696*** **
					(0.0172)
Constant	**0.1325*** **	**0.0994*** **	**0.0664*** **	**0.0694*** **	**0.0525*** **
	(0.0115)	(0.1349)	(0.0192)	(0.0192)	(0.0168)
Average Callback Rate	0.1541	0.1541	0.1541	0.1541	0.1541
N	1720	1720	1160	1160	1720
R-Squared	0.0036	0.0120	0.0313	0.0295	0.0201

Note: Robust Standard Errors in parentheses.

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

Δ p-value = 0.101.

An interesting result drawn from the three previous tables in regards to the magnitude of the racial gap according to the educational level of the candidates (secondary for unskilled jobs, technical for technical jobs, and university for professional jobs) is that there is a U-shape relationship between the magnitude of the racial gap and the educational level, where the smallest racial gap occurs in technical jobs and higher ones are observed at the two ends of the educational levels considered (secondary and university). This is a result that deserves further exploration in future studies.

The size of the company, the customer contact and service companies

In order to make a richer analysis of the information collected, we examine below the econometric results splitting the sample by company size (we use the job ad size as a proxy), by whether jobs involve a direct contact with the, and by some specific economic sector of activity. Table 13 reports these results. Firstly, with respect to firm size (columns I and II), we found that, while large and medium companies strongly prefer males and, secondly, whites, for small and micro enterprises beauty seems to be the most important factor, followed by race and sex. We should remark that we are only using a proxy variable for the firm size, but it is nevertheless interesting to find that in smaller firms physical appearance plays a greater role than in large companies when it comes to overcoming the first hurdle in the employment selection process.

Secondly (see columns III and IV), and to our surprise, we found that for jobs that does not involve contact with the customer, beauty is the most important variable, followed by sex and race. In contrast with this result, for jobs involving contact with the customers, there is no preference for male or female candidates, while race and beauty are similarly important. Furthermore, race for jobs involving contact with the customers is similarly important than beauty for office jobs.

Table 13: Size of the company, customer contact, and trade and services

	Company Size		**Contact with Customer?**		**Sectors**
Variable	Large / Medium (I)	Small / Micro (II)	Yes (III)	No (IV)	Commerce, consultancies / services (V)
Male	**0.1000*** **	**0.0404*** **	**0.0318^{∇}**	**0.0536*** **	**0.0385***
	(0.0371)	(0.0131)	(0.0209)	(0.0152)	(0.0197)
White	**0.0905** **	**0.0623*** **	**0.0953*** **	**0.0499*** **	**0.0799*** **
	(0.0371)	(0.0131)	(0.0209)	(0.0152)	(0.0197)
Beautiful	**0.0775** **	**0.0952*** **	**0.0857*** **	**0.0931*** **	**0.1223*** **
	(0.0371)	(0.0131)	(0.0208)	(0.0153)	(0.0197)
Constant	**0.0490^{Δ}**	**0.0520*** **	**0.0537*** **	**0.0551*** **	**0.0420*** **
	(0.0322)	(0.0109)	(0.0182)	(0.0128)	(0.0161)
Average Callback Rate	0.1379	0.1390	0.1453	0.1362	0.1471
N	420	2920	1196	2164	1352
R-Squared	0.0404	0.0284	0.0322	0.0271	0.0419

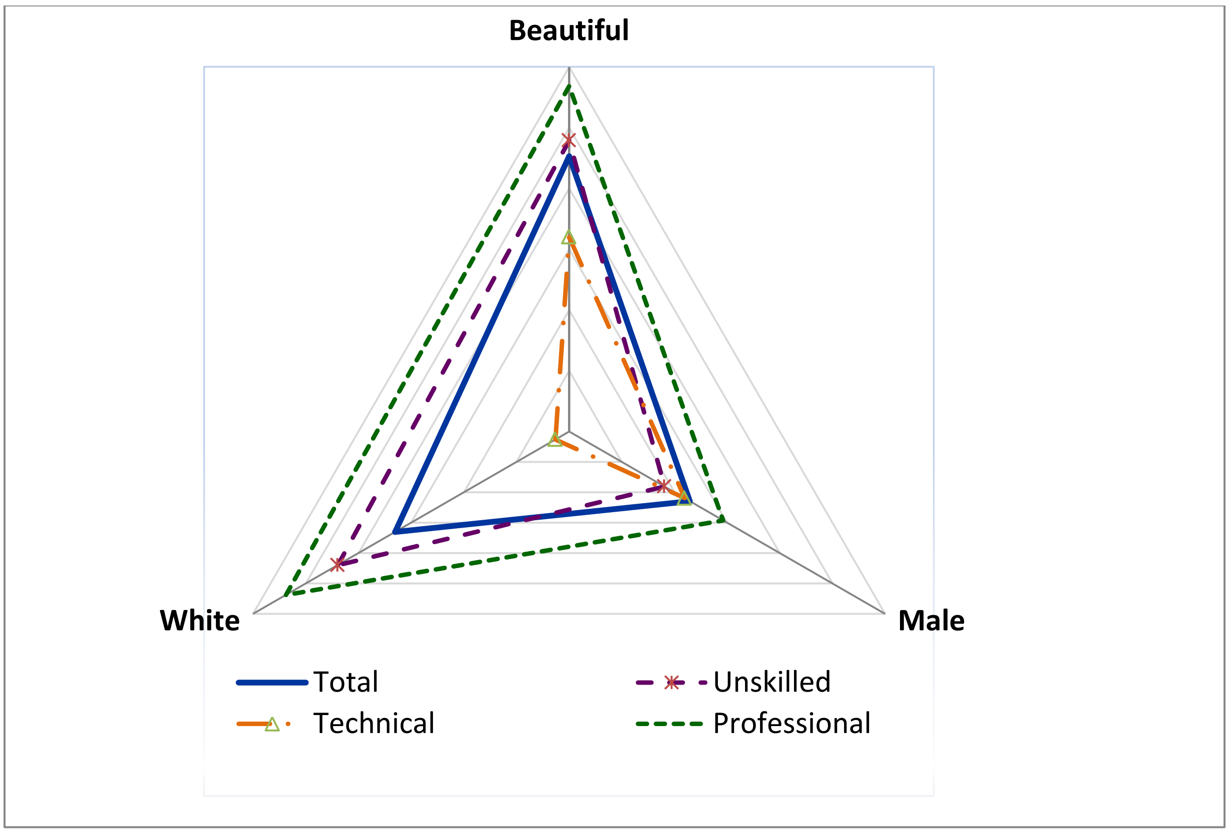
Note: Robust Standard Errors in parentheses.
*(**)[***] Statistical significance at 10 (5) [1] percent level.
∇ p-value= 0.125.
Δ p-value = 0.131.

Thirdly, given that 40% of the companies we sent the CVs to (see Annex 1) belong to the sectors of retail and wholesale, consultancy, and manufacture, we examined the regression results for these sectors. As shown in column V of table 13, beauty is the most significantly correlated variable with the callback rates. Its importance is similar in magnitude to that of the combined effect of being male and white.

5. Conclusion

This paper has shown statistical evidence about the existence -and magnitude- of discrimination based on physical appearance, race, and sex (which we call gaps) in the labor market of Lima. Figure 1 summarizes the main findings regarding the magnitude of those gaps, shown in each of the three axes. In reading the graph, if the resulting shape is an equilateral triangle, this would mean that there are equal-sized gaps. Also, smaller triangles indicate smaller gaps in magnitude.

Figure 1: Impact of beauty, race and sex on the callback rate



As we can see, then, for the entire sample (blue solid line), the beauty gap more than doubles the sexual gap, and is 1.5 times the racial gap. This result is in turn mainly explained by the discrimination observed in professional jobs (green, dashed line) and unskilled jobs (purple, dashed line with a star), which show larger triangles, and exhibit higher discrimination rates by beauty and race.

Our results provide quite unprecedented indicators on labor market discrimination in Peru. Although we are only examining the first stage of the selection process, we believe that the results are extremely important for labor market analysis Lima, because we suspect that in the second phase of the selection (the interviews) there is an even bigger room for discrimination.

While all forms of discrimination are reprehensible, the magnitude of that based on looks it strikingly large in professional and unskilled jobs. As discussed herein, this discrimination based on looks happens not only in jobs where there is a direct contact with the customer, but also in office jobs.

We hope that the results of this study will contribute to discuss this complex subject, and to design solutions to mitigate the problem.

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Annexes

Annex 1: Summary Indicators

Job Applicants Characteristics	Race	White	2494	50.00%
		Quechua	2494	50.00%
	Sex	Male	2494	50.00%
		Female	2494	50.00%
	Treatment	No Photo	1628	32.64%
		Homely	1684	33.76%
		Beautiful	1676	33.60%
Jobs Characteristics	Job Category	Professional	1576	31.60%
		Technical	1692	33.92%
		Unskilled	1720	34.48%
	Job Experience	None	4084	81.88%
		Up to 1 year	428	8.58%
		Between 1 & 2 years	436	8.74%
		3 or more years	40	0.80%
	Public / Office	Contact with the Public	3164	63.43%
		Office	1824	36.57%
Company's Characteristics	Size of Company *	1: Micro	3037	60.89%
		2	1035	20.75%
		3: Medium	496	9.94%
		4	224	4.49%
		5: Large	172	3.45%
	Economic Sector	Wholesale and retail	804	16.12%
		Consultancy (professional, technical or scientific)	628	12.59%
		Manufacturing	572	11.47%
		Others	2984	59.82%

* Based on size of job ads. 24 Job ads were gathered from Aptitus online.

Annex 2: Main Occupations by Job Category

Professional	Business Administration	216	13.71%
	Arquitecture	48	3.05%
	Accountancy	524	33.25%
	Economics and Finance	48	3.05%
	Civil Engineering	224	14.21%
	Industrial Engineering	128	8.12%
	Mechanic Engineering	60	3.81%
	Sales and Marketing	144	9.14%
	Others	184	11.68%
	Total	1576	100.00%
Technical	Assistant in Business Administration	144	8.51%
	Assistant in Accountancy	412	24.35%
	Asisstant in Logistics	56	3.31%
	Graphic Design	84	4.96%
	Mechanic	84	4.96%
	Technician in Computers	148	8.75%
	Technician in Electricity	124	7.33%
	Technician in Electronics	124	7.33%
	Technician in Pharmaceuticals	40	2.36%
	Technician in Mechanics	36	2.13%
	Sales and Marketing	280	16.55%
	Others	160	9.46%
	Total	1692	100.00%
Unskilled	Services Helper	76	4.42%
	Warehouse Helper	72	4.09%
	Cook Helper	76	4.42%
	Call Center / Customer Service	140	8.14%
	Driver	276	16.05%
	Waiter/Waitress	88	5.12%
	Security	48	2.79%
	Sales and Marketing	700	40.70%
	Others	244	14.19%
	Total	1720	100.00%