Gender Stereotypes in Job Advertisements:

What Do They Imply for the Gender Salary Gap?

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This draft: March 2020

Abstract

Gender stereotypes, the assumptions concerning appropriate social roles for men and women, permeate the labor market. Analyzing information from over 2.5 million job advertisements on three different employment search websites in Mexico, we find evidence that advertisements seeking "communal" characteristics, stereotypically associated with women, specify lower salaries than those seeking "agentic" characteristics, stereotypically associated with men. Given the continued widespread use of gender-targeted advertisements in Mexico, we use a random forest algorithm to predict whether non-targeted ads are in fact directed toward men or women, based on the language they use. We find that the non-targeted ads for which we predict gender show larger salary gaps (8-35 percent) than explicitly gender-targeted ads (0-13 percent). If women are segregated into occupations deemed appropriate for their gender, this pay gap between jobs requiring communal versus agentic characteristics translates into a gender pay gap in the labor market.

Keywords: Gender stereotypes; Salary gap; Discrimination; Big data; Machine learning; Mexico

JEL Codes: C52; C53; E24; J64; O54.

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1. Introduction

Although it has declined somewhat over time, the global gender salary gap has proven to be very persistent. According to the *Global Gender Gap Report* (World Economic Forum, 2019), the salary gap between men and women doing similar work around the world has stalled at approximately 65 percent. Olivetti and Petrongolo (2016) explain that increasing gender convergence in human capital coupled with more stringent anti-discrimination measures leaves gender norms as the remaining explanation for the gap. Salary decompositions in various countries show that this portion of the gap is now much more important than the part explained by gender differences in education and experience.[1] The economics literature has responded with increased interest in gender stereotypes and their corresponding norms and roles. The most recent literature on economic penalties to motherhood in various countries also sheds light on gender stereotyping as an important source of disparities in the labor market.[2]

This paper analyzes how gender stereotypes affect the salary gap through a different mechanism. We propose that the gender stereotyping of job positions in the labor market opens salary gaps, given that firms assign different values to abilities associated with men and women. These associations are, of course, rooted in stereotypical views of how people should behave based on their gender. Ellemers (2018) explains that "assertiveness and performance are seen as indicators of greater agency in men, and

[1] For the U.S., see Blau and Kahn (2017); for Mexico, see Arceo-Gómez and Campos-Vázquez (2014); for several countries in Latin America, see Hoyos and Nopo (2010); for a world-wide study, see Ñopo, Daza, and Ramos (2012).

[2] See, for instance, for Chile, Berniell et al. (2019); for Denmark, Kleven, Landais, and Søgaard (2018); for Denmark, Sweden, Germany, Austria, the U.S. and the U.K., Kleven et al. (2019); for Mexico, Aguilar-Gomez, Arceo-Gomez, and De la Cruz Toledo (2019); for a comparison of heterosexual and lesbian couples in Norway, Eckhoff Andresen and Nix (2019); for Sweden, Angelov, Johansson, and Lindahl (2016); for the U.S. and the U.K., Kuziemko et al. (2018).

warmth and care for others are viewed as signs of greater communality in women" (p. 277). The stereotyped language used to describe job positions in employment search websites may induce women to apply for jobs described with stereotypically feminine ("communal") characteristics and men to apply for jobs with stereotypically masculine ("agentic") characteristics (as shown, for example, in Born and Taris 2010; Gaucher, Friesen, and Kay 2011, and Flory, Leibbrandt, and List 2015). If stereotypically feminine and masculine characteristics are not valued equally in the labor market, this self-selection produces a salary gap.

Employment search websites provide a particularly rich set of big data regarding job descriptions, and this data has increasingly been used to study labor markets. The growing use of online job searches has provided a better understanding of the job search process (Faberman & Kudlyak, 2016) and the matching process between vacancies and job seekers (Banfi, Choi, & Villena-Roldan, 2019; Kuhn & Shen, 2013a). Other studies have used employment websites to study how job seekers respond to vacancies from distressed firms (Brown & Matsa, 2016) and how changes in the demand for skills relate to tightness in labor markets (Hershbein & Kahn, 2018; Modestino, Shoag, & Ballance, 2019). There are also studies on the hiring preferences of firms (Kuhn & Shen, 2015) and the effects of workers' job location preferences on unemployment rates (Marinescu and Rathelot 2018).

Studies have also focused on the salaries offered in job advertisements. Brenčič (2012) finds that the specification of salaries is strategic: ads for skilled jobs in the U.K. and Slovenia are less likely to specify compensation, possibly because firms want to be more selective for these jobs. Other researchers have studied how salaries vary either with the job title or with the qualifications specified in the ad. Marinescu and Wolthoff (2019) find that the job title explains up to 90 percent of the variation in advertised salaries in the U.S., but that only 20 percent of advertisements specify salary. They also observe that job titles explain more than 80 percent of the variation in applicants' education and experience. Thus, job titles convey significant information about the jobs they advertise. Finally, Deming and Kahn (2018) study the relationship between demand for skills and salaries specified. They find that ten specific skills explain about 12 percent of the variance in salaries across firms in the U.S., and that cognitive and social skills account for 5 percent of that variation. They also find a positive correlation between demand for skills and firm performance, even after controlling for required qualifications.

The present study focuses on salaries and gender discrimination, which previous studies have examined in a number of ways. Kuhn and Shen (2013b) analyze explicit discrimination in the Chinese labor market through the use of ads directed specifically at men or women. They find that ads directed at women also tend to specify young applicants and criteria for height and attractiveness, whereas ads directed at men have older age requirements and rarely any for physical appearance. They also find that jobs with higher skill levels tend to be gender neutral (which, they argue, implies a negative targeting of skills to women) and attribute this phenomenon to the tight labor market for high-skilled workers. They do not, however, find any evidence of a salary gap in gender-targeted ads. Chowdhury et al. (2018) perform a similar analysis in India, and also find a negative targeting of skills to women. As they dig deeper into the data, they find high occupational gender segregation, with women favored for low-status, low-salary jobs, while ads targeted to men specify higher salaries within the same occupations. They thus provide evidence of a gender salary gap.

Other characteristics of job advertisements might help or harm a firm's attempt to attract workers. For instance, Leibbrandt and List (2018) analyze the impact of having an equal employment opportunity (EEO) statement in a job advertisement. In an experiment using random assignment of the EEO statement, they find that minorities are less willing to apply to jobs with such statements, which survey evidence suggests could be the result of an unwillingness by jobseekers to be token hires. In a similar experiment, Flory, Leibbrandt, and List (2015) randomly vary the compensation scheme in job advertisements in order to gauge the effect of specifying a competitive compensation scheme on an advertisement's ability to attract female applicants. Corroborating the results of previous studies,[3] they find that women are less willing to apply for jobs with individual relative performance compensation schemes. To distinguish the effect of a competitive-compensation job from one stereotypically associated with men, they include jobs stereotypically associated with women, with variation in the wording of the ad to appeal to men. These jobs attract more women, as expected, and when language is added to appeal to men, the applicant pool almost balances. Although some studies examine salary gaps in advertisements, and some analyze the effect of their wording, we find no studies investigating both the relationship between the stereotypical wording of the ad and the salaries related to the stereotypes. Our paper aims to fill this gap in the literature.

We focus on Mexico, a developing country with more traditional gender norms than those in developed countries. Mexico's female labor force participation rate is 46 percent, lower than that of other countries in Latin America. Economic penalties for motherhood are quite large (Aguilar-Gomez, Arceo-Gomez, and De la Cruz Toledo 2019),

[3] See, for instance, Gneezy, Leonard, and List (2009), Niederle and Vesterlund (2007), and Niederle and Vesterlund (2011) for reviews of the literature on gender and competition.

and women still carry over 70 percent of the burden of household work.[4] The gender salary gap is not very large, however (about 14 percent in 2018).[5] It is mostly unexplained across income percentiles, but particularly at the top and the bottom of the salary distribution (Arceo-Gómez and Campos-Vázquez 2014). Our working hypothesis is that gender stereotypes unrelated to childbearing may help to explain part of the remaining gender salary gap.

Recent studies have begun to exploit online job data to explore gender discrimination in Mexico. Using advertisements from CompuTrabajo.com, Helleseter, Kuhn, and Shen (2018) find that even though gender-specific advertisements are evenly balanced between men and women, there is an age twist: ads targeted to women specify young women, and those targeted to men specify middle-aged men. There is also negative targeting of skill in Mexico, as Kuhn & Shen (2013b) found in China. Arceo-Gomez and Campos-Vazquez (2019a) combine explicit discrimination with a correspondence study to examine whether explicitly discriminatory ads are more biased with regard to marital status or race, as measured by callback rates. They find evidence of double discrimination against married women in ads targeted at women, and some discrimination towards dark-skinned women in explicitly discriminatory ads. However, there are no studies of the salaries specified or on gender salary gaps, or of stereotypes in the wording of job advertisements and their relationship with salary.

There is ample evidence that gender stereotypes are also reflected in the labor market, particularly in the types of jobs associated either with men or women. The main contribution of the current study is its relating of stereotyped language in job

ADOECD Time Use Database. Retrieved on March 5, 2020 from https://stats.oecd.org/index.aspx?queryid=54757.

[5] OECD Gender Data. Retrieved on March 5, 2020 from http://www.oecd.org/gender/data/employment/.

advertisements to the gender gap in the salaries specified in those advertisements. This stereotyped language leads to gender segregation in the labor market, since women and men both tend to apply to jobs stereotypically associated with their sex. Evidence for gender salary gaps in advertisements could thus translate into gender salary gaps in the labor market.

Our study tests whether advertisements whose language expresses stereotypes about women are associated with lower salaries than those expressing stereotypes about men. To do this, we first exploit the still-frequent use of gender-targeted employment advertisements in Mexico. Using over 2.5 million job ads from three different employment search websites (OCC Mundial, Bumeran, and CompuTrabajo), we first analyze the frequency of the words used to describe jobs targeted to men and to women. Since only a small percentage of ads are explicitly discriminatory, we use a random forest algorithm to classify implicitly discriminatory ads according to associations with the language used. Finally, we estimate the gender salary gap for both explicitly and implicitly discriminatory ads.

Our findings show that ads with "communal" words specify salaries that are 10 percent less than those with no such words, and ads with "agentic" words offer 3 percent more than those without such words. Explicitly discriminatory ads show a gender salary gap of 13 percent in OCC Mundial; there is no substantial gap in Bumeran or CompuTrabajo. However, implicitly discriminating ads have a gap of 35 percent in Bumeran, 21 percent in OCC Mundial and 9 percent in CompuTrabajo. That is, ads that convey gender only indirectly, through stereotyped language, have greater gender salary gaps than ads that are explicitly gendered.

The rest of this paper is organized as follows. Section 2 describes our data collection and cleaning process. Section 3 presents our three main results. Finally, Section 4 discusses the results and offers some concluding remarks.

2. Data

The data was gathered by “scraping” job advertisements from three different employment search websites in Mexico: OCC Mundial, Bumeran, and CompuTrabajo. These three private-sector platforms have become an essential tool for Mexican job seekers and companies recruiting workers, and also have an important presence in other Latin American countries. Such websites have the advantage of describing the skills and characteristics required for certain jobs with great precision. They are not, however, a random sample of all vacancies in the country, so our results are not representative of the entire Mexican labor market.

Data collection from all three websites began in February 2018, and continued through January 2020, with a break in data collection from CompuTrabajo from May to December 2018 (see Table 1). The dataset includes a total of 2,638,754 job advertisements, with two restricted samples including explicitly gender-targeted ads: 113,081 seeking women and 122,205 seeking men.

To download and process the job advertisement data, we use different algorithms for each website, but the information in all three is alike, allowing us to build a unified database. Generally, each job advertisement has some defined fields (salary, age, company) and some text. To generate our variables of interest, we use text analysis to find keywords related to sociodemographic characteristics (gender, salary, age, location, experience, marital status, and required education), skills, and explicit discrimination. We identify a set of keywords for specific traits and skills required for the job: educational requirements, age, work experience, driver's license, and language requirements, as well as personal traits like responsibility, teamwork, and commitment. For a list of the Spanish terms with English translations, see Table S1 in the Supplementary Materials.

Descriptive statistics for data from the three websites and the samples are shown in Table 1.[6] Only about 10 percent of all job advertisements explicitly specify male or female applicants; CompuTrabajo has the highest proportion of gender-targeted ads (14.2 percent). Almost all job advertisements in OCC Mundial specify a salary (99 percent), while only about half of the ads in Bumeran (59 percent) and CompuTrabajo (38 percent) do so. Among those that include salary, the average monthly salary for all three websites is around $8000 MXN (approximately $400 USD). Gender-targeted ads specify lower salaries. The greatest gender salary gap is close to 10.6 percent, or $1350 MXN ($67.50 USD) monthly, on OCC Mundial.

Some characteristics are more frequent in gender-targeted ads than in the ads as a whole. The most striking fact is that gender-targeted ads also discriminate by age. For example, in OCC Mundial, although only a quarter of the ads specify age, the proportion increases to 70 percent in gender-targeted ads, and the difference is similar in Bumeran and CompuTrabajo. Moreover, when gender is specified, women are usually required to be younger than men (the maximum age specified in ads in OCC Mundial is 36.7 for women vs. 40 for men, in Bumeran the figures are 38.1 vs. 39.9, and in CompuTrabajo they are 38.3 vs. 40.6). In general, job ads are restricted to relatively young applicants (approximately 32 years old), confirming the "age-twist" found by Helleseter, Kuhn, and Shen (2018).

[6] We also perform a classification by occupation using specific keywords in the job titles. However, only 80 percent of the ads could be classified. See Table S2 in the Supplementary Materials.

Other common specifications in gender-targeted ads are experience and marital status. For instance, in OCC Mundial, 73 percent of the ads require experience, but the figure is 84 percent for gender-targeted ads, evenly balanced by gender. In the sample as a whole, specification of marital status is not common, but it appears more often in gender-targeted ads. Interestingly, in gender-targeted ads, it is more common to specify married men (4 percent) and single women (2 percent).

Some educational requirements are more common in ads specifying men than in those specifying women, including technical school and junior high school diplomas: in OCC Mundial these were requested in 14 percent of the ads directed at men, as compared with only 3 percent of those directed at women. Engineering degrees were specified in 26 percent of ads targeted at men, but only 8 percent of those targeted at women. Advertisements requiring only some college or bachelor's degrees are more frequent in ads for women than in those for men.

In addition to these sociodemographic data, we also search for specific skill requirements associated with gender stereotypes. We follow the classifications of Heckman and Kautz (2012), as shown in the first column of Table 1. The first two specifications are "communal" and "agentic" characteristics. Here, we follow a vast literature on non-cognitive skills that discusses returns to personal traits (Heckman & Kautz, 2012) as well as a literature on the categorization of personality traits (Asch, 1946; Saucier, 2009; Spence, Helmreich, & Stapp, 1975). The classification distinguishes between communal content, which refers to relationships and social functioning, and agentic content, which refers to goal achievement and task functioning. These characteristics have been related to stereotypes in women and men (see, for example, Rudman and Phelan 2010, and Spence et al. 1975). In general, traits such as independence, leadership, and decision-making are stereotypically associated with men, while those like understanding, warmth, and gentleness are associated with women (Abele and Wojciszke, 2014)

We classify the traits specified in job ads as communal if they apply to enhancing group work and as agentic if they apply to individual work or goal-achievement. Examples of words referring to communal characteristics are *commitment*, *punctual*, *honest*, *attentive*, *teamwork*, *helpful*, and *courteous*. All of these qualities enhance social interaction and relationships. Examples of words referring to agentic characteristics are *control*, *initiative*, *motivation*, *pressure*, *proactive*, *responsible*, and *enthusiasm*.

Table 1 shows descriptive statistics for traits related to communal and agentic characteristics. On the one hand, some communal characteristics, such as commitment, are used equally in ads directed at both genders. Others, such as honesty and teamwork, are mainly found in ads targeted to men. Ads directed at women are twice as likely to specify attentiveness and courtesy than those directed at men. The vast majority of agentic characteristics (for example, initiative, motivation, proactivity, and pressure) are specified equally in ads directed at men and at women. Control, pressure, and responsibility are more frequent in those directed at men. Enthusiasm is the only agentic characteristic that is more frequent in ads directed at women.

We also analyze the requirement of appearance in job advertisements, following Kuhn and Shen (2013b), who find that Chinese employment search websites require attractiveness in job advertisements. This category includes use of the words *photograph* or *appearance*. Table 1 shows that on all three websites these characteristics are specified twice as often in ads targeted to women.

We classify other important skill requirements that are common in our dataset, following Deming and Kahn (2018).These categories include use of the words *language*, *software*, *customer service*, *availability*, *driver's license*, *career development*, and *benefits*. Ads on all three websites ask for specific abilities from women, for example, knowledge of English or of software like Word, Excel, or Windows. Customer service terms like *client*, *follow-up*, and *sales* are also more frequent in ads directed at women. Terms referring to travel and time availability are more common in ads directed at men.

We also find substantial differences in what employers offer apart from salary. Companies are described as good places to work, with opportunities for training and advancement slightly more frequent in ads targeted to women. Benefits such as bonus payments, commissions, and private medical insurance are described roughly equally for both genders. One striking difference is that ads targeted to women are twice as likely to specify compensation by commission.

Table 1: Descriptive Statistics

		OCC Mundial			Bumeran (Bum)			CompuTrabajo (CT)			*p*-value Ho: Male=Female		
Category		Total	Male	Female	Total	Male	Female	Total	Male	Female	**OCC**	**Bum**	**CT**
	Number of observations	1,560,716	58,489	55,760	555,592	22,386	24,364	522,446	41,330	32,957	-	-	-
	Start and end date	February 2018 to January 2020			February 2018 to January 2020			February 2018 to May 19, 2018 and December 2018 to January 2020					
Demographic Characteristics Specified	Specifies woman	0.04	0	1	0.04	0	1	0.06	0	1	-	-	-
	Specifies man	0.04	1	0	0.04	1	0	0.08	1	0	-	-	-
	Includes salary	0.99	1.00	1.00	0.59	0.68	0.65	0.38	0.47	0.45	0.05	0.00	0.00
	Mean real salary (MXN/mo.)	$12,597	$11,709	$10,362	$13,571	$8,866	$8,913	$8,439	$7,925	$7,859	0.00	0.62	0.23
	Specifies age	0.23	0.69	0.64	0.38	0.79	0.71	0.83	0.91	0.91	0.00	0.00	0.92
	Minimum age	24.67	25.46	24.18	22.66	23.81	23.62	22.81	23.52	22.99	0.00	0.00	0.00
	Maximum age	39.63	40.10	36.75	41.99	40.13	38.52	42.07	40.69	38.33	0.00	0.00	0.00
	Specifies location	0.99	1.00	0.99	0.93	0.95	0.95	0.87	0.90	0.86	0.00	0.10	0.00
	Specifies experience	0.72	0.84	0.83	0.79	0.87	0.83	0.79	0.84	0.83	0.00	0.00	0.00
	Specifies married	0.00	0.04	0.01	0.00	0.03	0.01	0.01	0.03	0.00	0.00	0.00	0.00
	Specifies single	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.00
	Specifies student	0.03	0.02	0.03	0.04	0.01	0.02	0.02	0.02	0.02	0.00	0.00	0.00
	Jr. High Diploma	0.11	0.14	0.03	0.10	0.24	0.06	0.14	0.30	0.08	0.00	0.00	0.00
	High school diploma	0.22	0.24	0.29	0.33	0.30	0.42	0.33	0.30	0.39	0.00	0.00	0.00
	Some school	0.08	0.09	0.16	0.11	0.11	0.15	0.10	0.09	0.14	0.00	0.00	0.00
	Tech. Cert.	0.02	0.06	0.03	0.02	0.06	0.02	0.03	0.07	0.03	0.00	0.00	0.00
	Bachelor’s degree	0.36	0.29	0.48	0.39	0.29	0.44	0.36	0.28	0.44	0.00	0.00	0.00
	Engineering degree	0.17	0.26	0.08	0.13	0.12	0.05	0.10	0.14	0.05	0.00	0.00	0.00

Communal	Commitment	0.10	0.04	0.04	0.03	0.03	0.02	0.02	0.02	0.03	0.12	0.00	0.00
	Punctual	0.07	0.10	0.11	0.09	0.14	0.12	0.08	0.11	0.09	0.00	0.00	0.00
	Honest	0.02	0.07	0.05	0.03	0.05	0.04	0.03	0.07	0.05	0.00	0.00	0.00
	Attentive	0.24	0.17	0.39	0.32	0.24	0.40	0.31	0.21	0.41	0.00	0.00	0.00
	Teamwork	0.22	0.17	0.15	0.11	0.12	0.10	0.09	0.09	0.09	0.00	0.00	0.43
	Helpful	0.07	0.09	0.13	0.08	0.08	0.11	0.08	0.09	0.11	0.00	0.00	0.00
	Courteous	0.01	0.01	0.02	0.01	0.02	0.02	0.01	0.01	0.03	0.00	0.00	0.00
Agentic	Control	0.17	0.25	0.22	0.13	0.21	0.20	0.14	0.18	0.17	0.00	0.04	0.00
	Initiative	0.03	0.04	0.04	0.03	0.04	0.04	0.02	0.03	0.04	0.00	0.46	0.00
	Motivation	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.02	0.02	0.00
	Pressure	0.08	0.14	0.13	0.09	0.12	0.09	0.09	0.11	0.10	0.00	0.00	0.00
	Proactive	0.07	0.11	0.13	0.09	0.12	0.10	0.08	0.08	0.10	0.00	0.00	0.00
	Responsible	0.09	0.15	0.14	0.11	0.14	0.10	0.29	0.30	0.28	0.01	0.00	0.00
	Enthusiasm	0.02	0.01	0.03	0.04	0.01	0.03	0.03	0.02	0.02	0.00	0.00	1.00
Appearance	Requests photograph	0.04	0.07	0.12	0.03	0.03	0.06	0.04	0.04	0.08	0.00	0.00	0.00
	Specifies good appearance	0.11	0.11	0.31	0.13	0.14	0.32	0.13	0.09	0.30	0.00	0.00	0.00
Language	English	0.17	0.11	0.15	0.18	0.07	0.10	0.11	0.06	0.11	0.00	0.00	0.00
	Common computer software	0.10	0.11	0.15	0.09	0.07	0.11	0.11	0.10	0.14	0.00	0.00	0.00
Customer service	Sales	0.33	0.32	0.39	0.43	0.30	0.47	0.42	0.30	0.44	0.00	0.00	0.00
	Customer	0.42	0.29	0.50	0.48	0.29	0.54	0.42	0.28	0.51	0.00	0.00	0.00
	Follow-up	0.16	0.15	0.23	0.17	0.12	0.21	0.15	0.10	0.20	0.00	0.00	0.00
Availability	Availability	0.03	0.04	0.04	0.03	0.04	0.03	0.04	0.05	0.04	0.60	0.00	0.00
	Travel	0.07	0.13	0.05	0.04	0.08	0.04	0.28	0.28	0.22	0.00	0.00	0.00
	Driver’s license	0.02	0.09	0.02	0.02	0.07	0.01	0.03	0.08	0.01	0.00	0.00	0.00
Career	Growth	0.16	0.17	0.20	0.28	0.15	0.17	0.25	0.21	0.20	0.00	0.00	0.04
	Development	0.03	0.02	0.05	0.04	0.01	0.08	0.03	0.02	0.05	0.00	0.00	0.00
	Training	0.18	0.14	0.18	0.26	0.12	0.20	0.25	0.14	0.19	0.00	0.00	0.00
Benefits	Bonus	0.19	0.17	0.19	0.30	0.22	0.25	0.25	0.20	0.22	0.00	0.00	0.00
	Benefits	0.68	0.72	0.72	0.58	0.78	0.74	0.66	0.76	0.74	0.06	0.00	0.00
	Insurance	0.04	0.03	0.04	0.03	0.03	0.02	0.04	0.03	0.02	0.00	0.00	0.00

Commissions	0.13	0.09	0.19	0.25	0.10	0.29	0.24	0.10	0.22	0.00	0.00	0.00
Base salary	0.25	0.23	0.30	0.36	0.23	0.34	0.36	0.29	0.33	0.00	0.00	0.00

Note: Data collection from CompuTrabajo was interrupted from May to December 2018 because of a technical issue. Statistics were calculated by the authors using data from OCC Mundial, Bumeran, CompuTrabajo. Each word is a dummy variable that is 1 if the word appears in the job description; 0 otherwise. See Table S1 for the Spanish words used.

3. Results

3.1 Job Advertisements Use Gender Stereotypes

The main aim of this section is to analyze the most frequent words in job advertisements for each website, using single-word analysis, bigram analysis, and category analysis. We analyze advertisements that explicitly specify men or women. First, stop words (highly common words like *on*, *a*, *some*, *like*, *the*) and diacritical marks were removed from the dataset. A count was made of unique words for each gender, using the root of the word and disregarding the gender inflection. For example, *honest* was counted as a unique word regardless of whether it appeared in the masculine form *honesto* or the feminine form *honesta*.

Because the total number of unique words is different for each gender (as in Arceo-Gomez & Campos-Vazquez, 2019b),[7] we calculate a ratio for database b as shown in equation (1): the number of mentions of word i as a proportion of the total number of unique words in ads directed at women, over the same proportion in ads directed at men. If the specifications of worker characteristics are the same for both genders, this ratio equals one. If it is larger than one, then word i is more common in ads directed at women than in those directed at men.

$$Ratio_{i,b} = \frac{\frac{\sum_{ad} \mathbf{1}(word=i)_{ad,b,female}}{\sum_{ad} Number\ of\ words_{ad,b,female}}}{\frac{\sum_{ad} \mathbf{1}(word=i)_{ad,b,male}}{\sum_{ad} Number\ of\ words_{ad,b,male}}} \tag{1}$$

$$i \in \{words\}$$

$$ad \in \{individual\ advertisements\}$$

[7] This difference is not large. The mean word count of an ad directed at women is 130.75 words; for men it is 132.59 words (women: 128.83 in OCC Mundial, 117.68 in Bumeran, and 145.73 in CompuTrabajo; men: 129.43 in OCC Mundial, 120.32 in Bumeran, and 147.85 in CompuTrabajo.)

$$b \in \{OCC\ Mundial, Bumeran, CompuTrabajo\}$$

To obtain a ranking of the most frequent words overall, we count the number of unique words in the total set of advertisements directed at both genders. We then calculate the ratio of the frequency of each word with respect to the total sample. The frequency of the 50 words with the highest ratio represents 28.2-29.2 percent of the total frequency of words.[8]

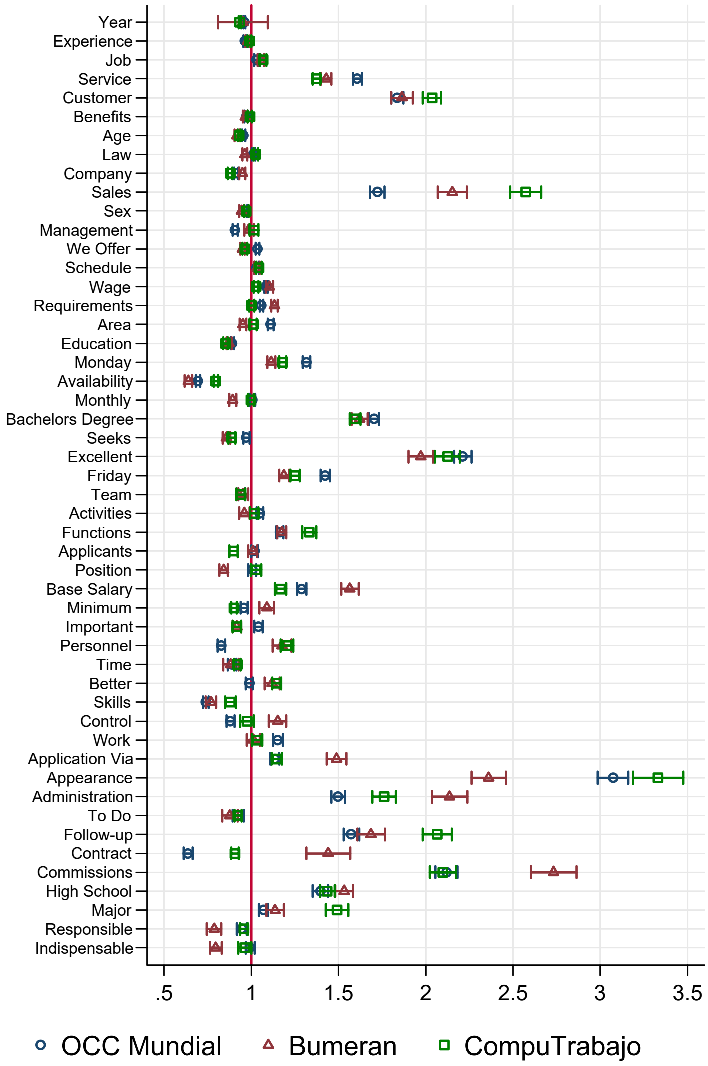
Figure 1 shows these ratios for the top 50 words for each website. The words are presented in descending order of ratios: the most frequent word in the three websites is *year*, at the top; the least frequent is *indispensable*. These words can be divided into two categories: the first expressing basic characteristics of the job, such as location and desired sociodemographic characteristics of the applicant, and the second related to the specific skills sought. The most frequent words expressing basic characteristics are *year*, *experience*, *job*, *benefits*, *age*, *law*,[9] *company*, *sex*, *schedule*, *salary*, *requirements*, *education*, *Monday*, *monthly*, *Bachelor's degree*, *area*, *seeks*, *Friday*, *activities*, *functions*, *position*, *minimum*, *base salary*, *personnel*, *time*, *better*, *work*, *to do*, *contract*, *high school*, *major*, *we offer*, *applicants*, *indispensable*, and *commissions*. The most frequent words describing desired skills are *service*, *customer*, *availability*, *excellent*, *sales*, *management*, *team*, *follow-up*, *skills*, *control*, *appearance*, *administration*, and *responsible*.

[8] In OCC, these words represent 28.23 percent of the total; in Bumeran, 29.56 percent and in CompuTrabajo, 29.20 percent.

[9] The word *ley* ("law") appears frequently in Mexican job advertisements in the phrase *prestaciones de ley* ("benefits as provided by law") or *prestaciones superiores a la ley* ("benefits superior to those required by law")

The first set of these most frequent words describes the basic characteristics of the job opportunity. Some of them are about the hours, location, and contact information (e.g., *Monday*, *Friday*, *schedule*, *time*, *area*, *applicants*, *company*), some are about the nature of the work (e.g., *position*, *work*, *job*, *to do*, *functions*, *activities*, *requirement*, *request*, *personnel*, *indispensable*). Other words are about the applicant's characteristics and qualifications (e.g., *high school*, *bachelor's degree*, *education*, *age*, *year*, *sex*, *major*, and *experience*). Finally, there are words referring to the conditions of the employment. such as type and frequency of payment (*monthly*, *commissions*, *base salary*, *contract*, *salary*, *law*, *responsible*, and *benefits*).

Figure 1. Ratios of frequencies of most commonly used words



Note: Lines represent 95 percent confidence intervals calculated with 200 random bootstrap samples. Adjacent points indicate similar word roots with different endings. Each point represents the ratio between the proportions of word occurrence for each website. Stop words and punctuation are omitted.

The following words describing the nature of the work are generally balanced between genders, with ratios close to one: *year*, *experience*, *work*, *benefits*, *age*, *law*, *company*, *sex*, *requirements*, *offer*, *salary*, *monthly*, *zone*, *seeks*, *applicant*, *position*, *area*, *job*. However, advertisements are more specific regarding women's schedule; the word *hours* appears 1.1 times more often in ads directed at women, and the words

Monday and *Friday* also appear more often (1.2-1.35 and 1.3-1.4 times). Advertisements also tend to be more explicit about women's education, *bachelor's degree* and *high school* are repeated nearly 1.5-1.7 more times in ads directed at women. These ads also tend to mention more details about salary: *base salary* and *commissions* are almost twice as frequent as in ads directed at men. *Contract* is only 0.6-0.8 times as frequent in ads directed at men in OCC Mundial and CompuTrabajo, but in Bumeran.

Words about characteristics that appear in ads directed at both genders are *team* and *management*. Those mentioned in ads targeted to women include *appearance*, which is 2.2-3.4 times more frequent than in ads directed at men. Women are also asked to have more interaction with customers and perform more administrative tasks, as seen in the following words found more frequently in ads directed at them: *sales* (with a ratio of 1.6-2.6), *follow-up* (1.7-2.3), *service* (2.3-2.6), *customer* (1.7-2.1) and *administration* (1.4-2.2). Men are asked for other *skills* (.75-.9), *responsibility* (.75-.9), *time* (.7-.8) and *availability* (.6-.8).

In general, advertisements tend to use nearly the same words to describe the basic characteristics of the job. However, some words related to education, hours, and salary are more frequent in ads directed at women. Words related to applicant characteristics and skills more frequently specify good appearance for women, and ads directed at them include more customer service-related terms like *sales*, *follow-up*, *service*, and *customer*. Words in this category directed at men include *availability*, *time*, *responsibility*, and *skills*.

In order to provide more context for the analysis, we calculate the same ratios for bigrams. Punctuation and stop words are removed and unique pairs of words are counted, independent of word order. The ratio between the proportions of bigrams are then calculated for each website. The results are shown in Figure 2. Standard errors are larger here than in the single-word analysis. The bigrams are classified into three categories: description of general characteristics of the job, description of sociodemographic characteristics and skills sought in applicants, and description of salary and benefits.

Many of the bigrams are related to the basic job description, with some related to job conditions such as hours, contact information, and location. Some of these bigrams are *Monday-Friday*, *schedule-Monday*, *work-location*, *contract-time*, *full-time*, *apply here*,[10] and *a.m.-p.m*. Words related to days and hours appear more often in advertisements direct at women. *Monday-Friday* has a ratio of 1.2-1.4, and the ratio for *schedule-Monday* is similar.

The second set of bigrams is related to applicants' sociodemographic characteristics (e.g., *years-age*, *years-experience*, *years-sex*, *age-requirements*, *sex-requirements*, *technical-degree*, *high school-education*, *junior high school-education*, *education-years*, *similar-position*, *years-minimum*, *any marital-status*, *and bachelor's-degree*). Almost all of these sociodemographic bigrams are equally balanced between men and women, including *years-age*, *years-experience*, *minimum experience*, *age-requirements*, and *sex-requirements*. *Bachelor's- degree* is more frequent in ads targeted to women, with a ratio of 1.5-2. Finally, *Any Marital-Status* is slightly dominant in advertisements targeted to men (with a ratio of .7-.95), as is *Junior High School* (.2-.4).

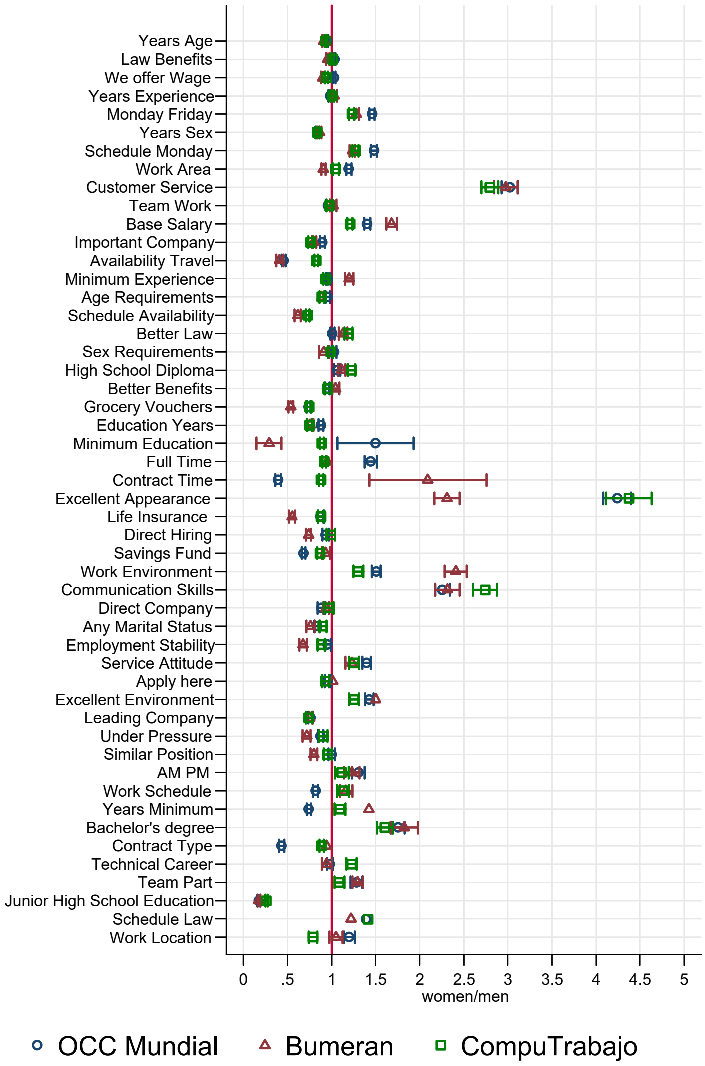
Bigrams that describe applicants' skills and characteristics, such as *team-work*, show similar frequency for both genders. Those that appear more often in ads targeted at women are *service-attitude* (1.2-1.5), *customer-service* (2.6-3.0), *speaking-skills* (2.2-

2.9), and *excellent-appearance* (2.2-4.7); those more frequent in ads targeted to men are *schedule-availability* (.6-.75), *availability-travel* (.4-.9), and *under-pressure* (.7-.95). These findings are similar to those of the single-word analysis.

Many bigrams are related to salary and benefits, such as *law-benefits*, *we offer-salary*, *base-salary*, *better-law*, *better-benefits*, *grocery-vouchers*, and *savings-fund* are equally frequent in ads targeted to men and women. An exception is *life-insurance*, which is more frequent in ads targeted to men (.5-.9). Another set of bigrams refers to work environment. This category includes *work-environment*, *excellent-environment*, *leading-company*, and *direct-company*. Words related to work environment are more frequent in ads directed at women.

The analysis of bigrams shows the same tendencies as the single-word analysis. However, it also offers new insight into the most specified characteristics in advertisements directed at men. One example is the explicitly-stated irrelevance of their marital status; another is the specification of workers with only a junior high school education. Bigrams also offer robustness to some results, including the finding that sales and customer service jobs are more often directed at women, and they confirm that women are discriminated against based on their physical appearance. Finally, the bigram analysis confirms that advertisements directed at men are more likely to specify time availability. The frequency of words could be related to the type of job advertised.

Figure 2: Ratios of frequencies of most commonly used bigrams



Note: Lines represent 95 percent confidence intervals calculated with 200 random bootstrap samples. Adjacent points indicate similar word roots with different endings. Each point represents the ratio between the proportions of bigram occurrence for each website. Stop words and punctuation are omitted.

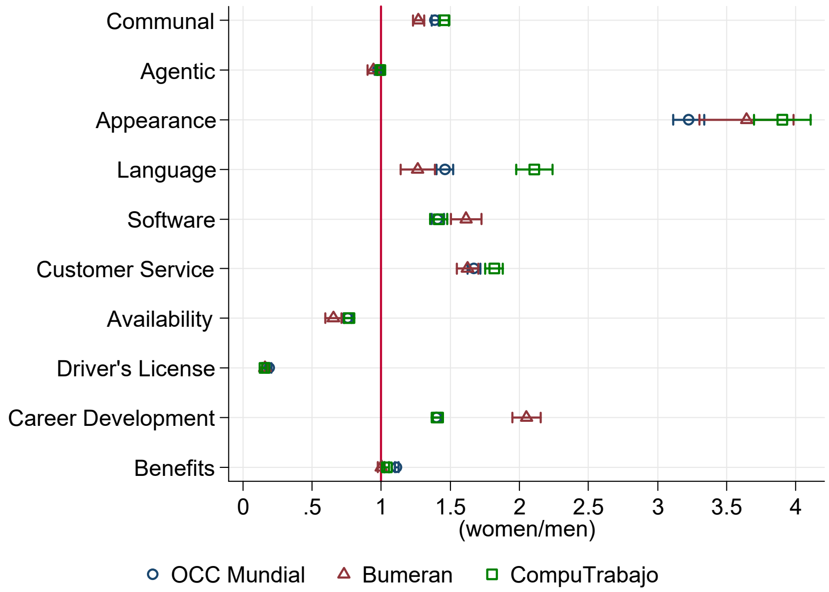
The third part of this descriptive analysis is a study of categories of words. Most of the repeated words and bigrams are grouped into different categories, including communal or agentic characteristics, appearance, language, software, customer service, availability, driver's license, career development, and benefits. Table 1 shows the specific arrangement of these categories of words; in addition to the most frequent words, other descriptive words are also included.

Figure 3 shows the gender ratios of the frequency of these categories of words. The presentation is similar to that of Figures 1 and 2. Characteristics are categorized as communal if they refer to group work and as agentic if they refer to individual work or achievement of individual goals (Abele and Wojciszke, 2014). Words associated with communal characteristics include *commitment*, *motivation*, *punctual*, *honest*, *attentive*, *helpful*, *teamwork*, and *courteous*; those considered agentic include *pressure*, *control*, *proactive*, and *stress*. Communal characteristics are more frequent in ads targeted to women, with a ratio of 1.25-1.5 for the three websites. Agentic characteristics are evenly balanced in OCC Mundial and CompuTrabajo, but in Bumeran are more frequent in ads directed at men.

Words in a number of categories are used more often in ads directed at women. Words in the Appearance category, which includes *appearance* and *photograph*, are used nearly 3.2 times as often, and words in the Language category, which includes the word *English*, *are* repeated 1.3-2.3 as often. Customer Service words such as *sales*, *customer*, and *follow-up* are used 1.6-1.8 times as often, and words in the Career development category are used 1.4-2.1 times as often. However, consistent with the findings of the single-word and bigram analyses, ads directed at men use words in the Availability category, which refer to time availability, travel, and having a driver's license, more often than those directed at women: the ratio for this category is .6-.9.

Overall, the analysis of categories indicates that ads directed at women specify more communal characteristics as well as those related to appearance, language, software, and customer interaction, while those directed at men more frequently specify time and travel availability (as measured by the requirement of a driver's license). Agentic characteristics are specified equally for both genders.

Figure 3: Ratio of frequencies of most commonly used categories



Note: Lines represent 95 percent confidence intervals calculated with 200 random bootstrap samples. Adjacent points indicate similar word roots with different endings. Each point represents the ratio between the proportions of category occurrence for each website. Stop words and punctuation were omitted. Communal category includes the words *commitment*, *punctual*, *honest*, *attentive*, *teamwork*, *helpful*, and *courteous*; Agentic category includes the words *control*, *initiative*, *motivation*, *pressure*, *proactive*, *responsible*, *stress*, and *enthusiasm*; Appearance category includes the words *photograph* and *appearance*. The Language category includes the word *English*; Software category includes the words Excel, Word, and Windows; Customer Service category includes the words *sales*, *customer* and *follow-up*. Availability category includes the words *time* and *travel*; Career category includes the words *growth*, *development*, and *training*; Benefits category includes the words *bonus*, *benefits*, *insurance*, *commissions* and *base salary*.

3.2 Specific Words Are Related to Salary

In this section, we analyze the relationship between words and the salary specified in job advertisements using three different estimations. The first calculates the effect of a word on the salary specified and its asymmetric effect in gender-targeted and non-targeted ads. The second method is a LASSO estimation to analyze the extent to which different words explain the salary variation in ads directed at women and at men. The final estimation is an analysis of adjusted R-squared to determine which word or characteristic explains more of the variation.

The analysis of the asymmetric salary effect consists of a regression with (log) specified salary as a dependent variable and an interaction of each category with a gender-targeted dummy controlled by the presence of the word and the dummy.[11] We are interested in two effects of this regression. The first is the effect of a skill or characteristic on the salary specified. The second is the coefficient of the interaction, which can be interpreted as the differentiated effect of a skill or characteristic on the gender-targeted salary compared to the non-gender-targeted salary. If there are no salary differences between targeted and non-targeted ads, we expect the coefficient to equal zero. A positive coefficient implies an association between the word and a higher salary in gender-targeted ads; a negative coefficient implies an association with a higher salary in non-targeted ads.

Figure 4 shows the effects of each category on salary and the asymmetric effects. The Communal category has a negative effect on the salary specified, reducing it by 7-20 percent. However, almost half of this effect is offset in gender-targeted ads, where the presence of these words increases the salary by 2.5-10 percent. This characteristic is more frequent in ads targeted to women, so they are most affected by its presence.

---

[11] $\ln(salary)_{ad,base} =$

$$= \alpha_0 + \alpha_1 d.GenderTargeted_{ad} + \sum_j (\delta_j skill_{j,ad}) + \sum_j \beta_j (skill_{j,ad} * d.GenderTargeted_{ad}) + \sum_i \gamma_i (X_{i,ad} + d.X_{i,ad}) + u_{ad}$$

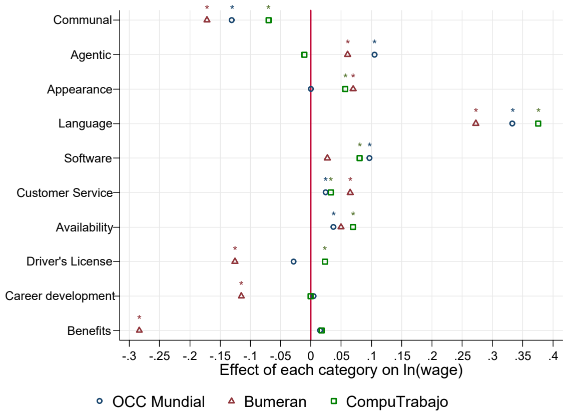
This regression is at the ad level. S*alary* is the real monthly salary specified, *skill* is a matrix of dummies of categories presented in Table 1 (*communal, agentic, appearance, language, software, customer service, availability, license, career development*, and *benefits*). This variable is equal to 1 if a word included in the category is included in the job ad, and 0 otherwise. The coefficients of interest are δ_j *and* β_j. δ_j is the effect of the category on the offered salary. β_j is the asymmetric effect of a category on salary of gender-targeted ads. $X_{i,base}$ is a matrix of demographic controls, which includes marital status, age, level of education, experience, and location. Finally, $d.X_{ad}$ is a matrix of dummy variables that denotes the presence of demographic characteristics in the ad, equal to 1 if the demographic characteristic is present, and 0 otherwise.

The Agentic and Language categories behave similarly. Both have a positive effect: words in the Agentic category increase the salary by 6-11 percent and those in the Language category increase it by 27- 37 percent. However, both categories are penalized if the ad is gender-targeted. The presence of Language category words in gender-targeted ads reduces the salary by 4-11 percent. The Language category is more frequent in ads directed at women, so they are penalized more than men.

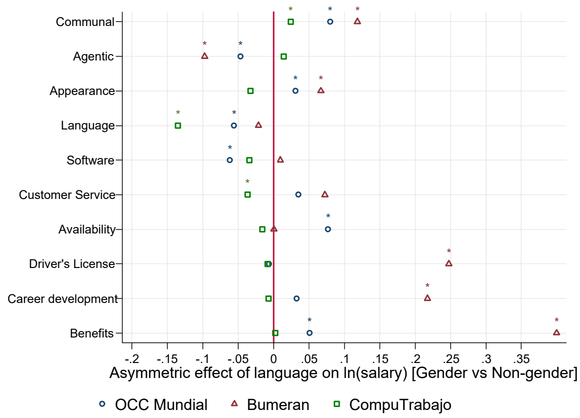
The presence of words in the Appearance category has a positive effect of 5-7 percent on the salary, except in OCC Mundial. However, for gender-targeted ads, words in this category have a positive and significant effect in OCC Mundial. This category, which is more common in ads directed at women, thus always has a positive effect for gender-targeted ads. The Customer Service category, which is also more frequent in ads directed at women, also has a positive effect on the salary. The Software and Availability categories both have a positive effect on the salary of 4-11 percent, regardless of whether the ad is gender-targeted or not. Availability words are more frequent in ads directed at men. Finally, words in the Benefits category have no effect on salary, unless the ad is gender-targeted. The presence of these words increases the salary by 6-35 percent in gender-targeted ads.

Figure 4: Effect of categories on salary (targeted vs. non-targeted)

Panel A: Effect of each category on salary



Panel B: Asymmetric effect of categories



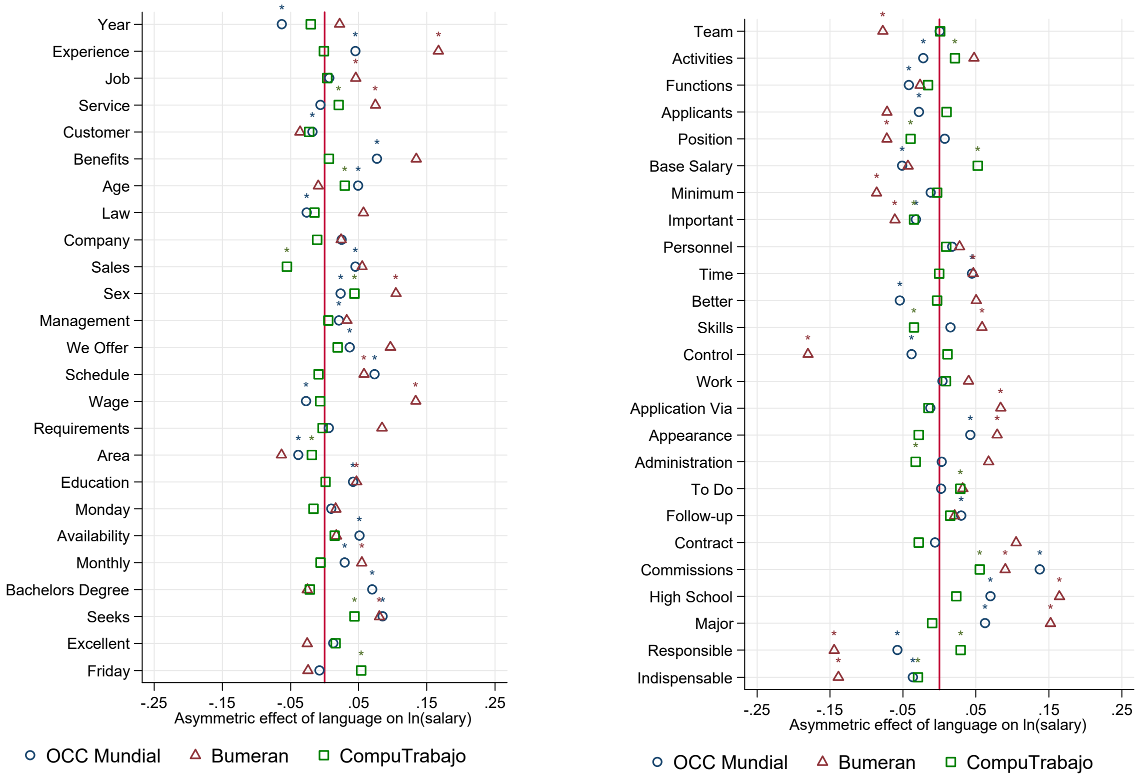
Note: Regression includes all advertisements from the three websites in the period analyzed. The dependent variable is the ln of real salary (July 2018=100). Each category is a dummy variable mean that represents the appearance of at least one component word in the advertisement. In Panel A, each point represents the coefficient of the ln(salary) in this dummy. In Panel B, each point represents the coefficient of the ln(salary) in the interaction of a dummy variable for gender-targeted with the dummy for presence of the category. The regression controls for the presence of the category and specifying a gender, state, age (minimum and maximum), experience, educational level. Asterisk (*) signifies that the regression is statistically significant at 5 percent; robust standard errors are clustered by location. Communal includes the words *commitment*, *punctual*, *honest*, *attentive*, *teamwork*, *helpful*, and *courteous*; Agentic includes the words *control*, *initiative*, *motivation*, *pressure*, *proactive*, *responsible*, *stress*, and *enthusiasm*. Appearance includes the words *photograph* and *appearance*. Language includes the word. Software includes the words *Excel*, *Word*, and *Windows*. Customer Service includes the words sales, customer, and follow-up, Availability includes the words *time* and *travel*. Career includes the words *growth*, *development*, and *training*. Benefits includes the words *bonus*, *benefits*, *Insurance*, *commissions*, and *base salary*.

We carry out the same analysis with dummy variables for the most frequently used words described in the previous section. The dummy variable is equal to 1 if the word appears in the advertisement, and 0 otherwise. We then interact this dummy variable with one that indicates whether the ad is gender-targeted. This coefficient is shown in Figure 5, which illustrates the differences in salary between gender-targeted and non-targeted ads for the most frequently used words.

The presence of the word *sex* has a robust positive effect on salary of 1-11 percent in gender-targeted advertisements. Advertisements for jobs with the same characteristics offer a higher salary when gender is specified, which could mean an implicit penalty if applicants do not meet the gender requirement. When there is explicit discrimination, as in gender-targeted ads, some agentic characteristics, such as those represented by the words *control* and *responsible*, have a salary penalty of 4-17 percent. Other characteristics are rewarded, such as those represented by the words *appearance* (4-7 percent) and *commissions* (4-14 percent). This result is similar to that found in availability category.

In sum, some characteristics, such as communal ones, have a negative effect on the salaries specified. Others, such as appearance, have a positive effect that is reinforced when the job advertisement is gender-targeted. Explicitly discriminatory advertisements specify characteristics at variance with those of the labor market in general. Specification of a gender can compensate for some salary penalties, such as those associated with communal characteristics, and penalize others, such as agentic characteristics and language.

Figure 5: Asymmetric effect of language on salary for 50 most frequently used words, in descending order of frequency



Note: Figure includes all advertisements from the three websites in the period analyzed. The dependent variable is the ln of real salary (July 2018=100). Each category is a dummy variable that indicates whether the word appeared in the job advertisement. Each point represents the coefficient of the ln(salary) in the interaction of a dummy variable for gender-targeted with a dummy for presence of the word. The regression controls for location, age (minimum and maximum), experience, and educational level. Asterisk (*) signifies that the regression is statistically significant at 5 percent; robust standard errors are clustered by location.

The second method is a LASSO regression. This method helps to select the most important characteristics that explain the variation in salary for each gender. A penalization parameter (lambda) for each characteristic expresses its importance. As we are interested in skills or characteristics, the regression does not penalize demographic characteristics (such as age, marital status, educational level, or location). The penalization parameter is selected by cross-validation of ten folds.[12] The post-LASSO

[12] $(\hat{\alpha},\widehat{\beta},\hat{\gamma}) = argmin(Ln\ salary_{ad} - \sum_j \lambda_j\ JobCharac_{ad} - \sum_k \gamma_k (X_{ad} - d.X_{ad}))^2$ subject to $\sum_j |\lambda_j| \leq t$. $Ln\ salary$ is the log of monthly salary specified. $JobCharac$ is a matrix of dummies of words describing the job and applicants' characteristics, as in Table 1 (communal character, agentic character, appearance, language, software,

regression estimates are an OLS regression with the non-zero coefficients from the LASSO regression.

Table 2 shows the results. Communal characteristics have a negative effect both on men and on women; this result is robust for all three databases and both genders. Salary is 5.2-9.4 percent less in advertisements that use words referring to communal characteristics. In the previous analysis of asymmetric effects, we found that communal characteristics have a negative effect on salary, which is offset in gender-targeted ads. In this analysis, we confirm that these characteristics carry a penalty for the salary specified, even in gender-targeted ads. Agentic characteristics have an ambiguous effect by gender and website. The previous analysis shows that the presence of these characteristics increases the salary, except in gender-targeted ads; this characteristic has no consistent effect on salary in gender-targeted ads.

The use of words in the Appearance and Software categories have a robust positive coefficient for both genders. The specified salary increases 1.2-16.8 percent when appearance or photographs are mentioned, consistent with the previous analysis. Language is associated with salary in all three websites. Salary is 26.7-39.2 percent higher when English is mentioned. This estimate is among the largest effects of skill on salary and is also consistent with the previous analysis.

Customer service has a positive coefficient for men; the salary specified is 1.4-12.6 percent greater where follow-up, sales, or customers are mentioned in advertisements

customer services, availability, license, career development, benefits, and occupational classification). λ_j is the penalization term for each word. Finally, X_{ad} are sociodemographic characteristics that are not penalized, such as minimum age, maximum age, and location. $d.X_{ad}$ is a matrix of dummy variables that indicate the presence of sociodemographic characteristics in the ad. Dummies are equal to 1 if the characteristic is present in the ad, and 0 otherwise.

targeted to men. As seen in the previous analysis, these advertisements are less likely to mention words referring to customer service. Availability has a positive coefficient for all three websites and for both genders: the use of words in this category are associated with salaries that are 5.6-13.8 percent higher. In advertisements directed at women, the mention of driver's licenses is associated with an 8.5-10.9 percent increase in salary, but has no effect in advertisements directed at men.

In sum, characteristics such as knowledge of English and computer software are valued with a wage premium for both genders. Characteristics such as appearance and availability seem to be valued by employers only in female workers. Characteristics relating to customer service are important in advertisements directed at men. Communal characteristics are penalized in the job market.

Table 2: LASSO Post-Estimation Results

	OCC Mundial		Bumeran		CompuTrabajo	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
Communal	-0.054	-0.055	-0.094	-0.062	-0.053	-0.052
	[.004]	[.004]	[.01]	[.008]	[.005]	[.006]
Agentic	0.070	0.030	-0.041		0.015	
	[.004]	[.004]	[.011]		[.005]	
Appearance	0.012	0.044	0.168	0.094	0.009	0.050
	[.006]	[.004]	[.013]	[.008]	[.008]	[.007]
Language	0.322	0.267	0.392	0.328	0.278	0.280
	[.008]	[.006]	[.02]	[.014]	[.02]	[.013]
Software	0.048	0.026	0.096	0.045	0.026	0.085
	[.006]	[.005]	[.015]	[.01]	[.009]	[.009]
Customer Service	0.057	0.028	0.126	0.034	0.014	
	[.004]	[.004]	[.01]	[.009]	[.005]	
Availability	0.094	0.138	0.071	0.111	0.060	0.056
	[.006]	[.007]	[.015]	[.019]	[.009]	[.011]
Driver's License	-0.074	0.100	0.028	0.085		0.109
	[.006]	[.017]	[.017]	[.043]		[.032]
Career Development	0.025	0.028	0.114	0.114		-0.019
	[.004]	[.004]	[.011]	[.009]		[.006]

Benefits	0.057	0.073	0.032	0.125		0.027
	[.005]	[.005]	[.019]	[.014]		[.01]
N	58464	55748	15265	15899	19349	14775
Adj. R^2	0.429	0.305	.313	0.306	0.384	0.328

Note: Dependent variable is ln(salary). Coefficients presented are the result of OLS post-estimation of a LASSO regression. All regressions are controlled without penalty for the following characteristics specified in the advertisement: education, minimum and maximum age, marital status, and job location. Robust standard errors in bold. Communal includes the words *commitment*, *punctual*, *honest*, *attentive*, *teamwork*, *helpful*, and *courteous*; Agentic includes *control*, *initiative*, *motivation*, *pressure*, *proactive*, *responsible*, *stress*, and *enthusiasm*; Appearance includes *photograph* and *appearance*; Language includes *English*; Software includes *Excel*, *Word*, and *Windows*; Customer Service includes *sales*, *customer*, and *follow-up;* Availability includes *time* and *travel*; Career includes *growth*, *development*, and *training*; Benefits includes *bonus*, *benefits*, *insurance*, *commissions*, and *base salary*.

Finally, an analysis of adjusted R-squared is performed to determine which characteristics explain most of the variance in the wage specified. The LASSO regression examines which factors have the greatest positive effect on gender-targeted job advertisements and which are the most significant for each gender. The objective of the adjusted R-squared analysis is to rank characteristics in order of importance in explaining the salary specified in the ads.

A LASSO regression is performed as above. The penalization parameter is varied to obtain the top five characteristics responsible for the variation in salary: Figure 6 shows the order of importance. The x-axis of the graphs is the ranking, which is the number of variables selected by the regression after increasing the penalization parameter. The y-axis represents the goodness-of-fit in terms of adjusted R-squared. We included a horizontal dotted line in the figure that shows the adjusted R-squared for demographic characteristics only. Using this dotted line, we can see that the initial goodness-of-fit is higher for men than for women, because demographic controls better capture the variation in salary for men. However, when other characteristics are included, the increase in adjusted R-squared is greater for women. This means that these specific characteristics explain slightly more of the variation in salary for women than for men.

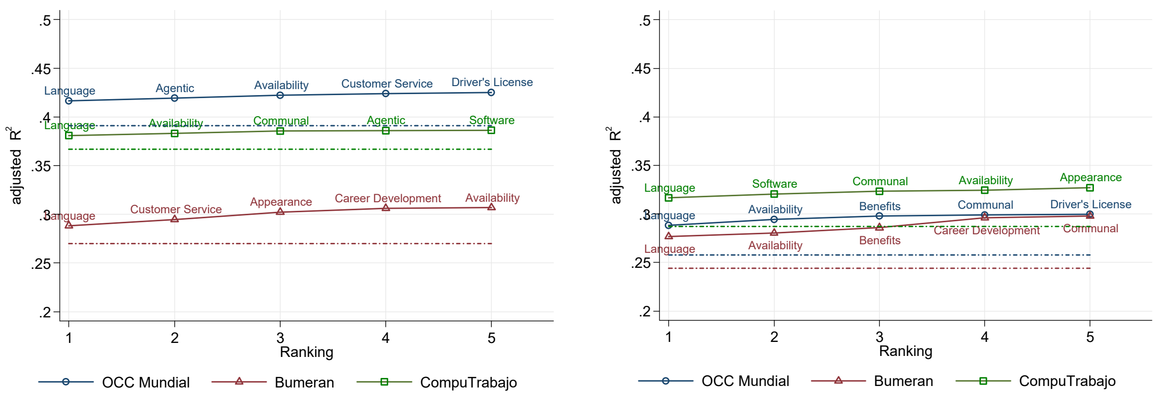
The inclusion in the regression of the five characteristics shown explains almost all the variation found in the optimal LASSO regression shown in Table 2. For example, the adjusted R-squared for men in OCC Mundial with five categories is .425, compared to 0.429 in the model with all characteristics (see Table 2).

The most important category for both genders on all three websites is Language. Speaking English is the key characteristic that explains most of the variation in salary. As this characteristic is more prevalent in advertisements directed at women, the benefit to them is greater. Another frequently used category for women is Appearance, which ranks among the top five on all three websites. This result is consistent with the LASSO analysis, which also found that Appearance was an important characteristic explaining the salary specified in ads directed at women; for men, Appearance is important only on one of the websites. Availability is another important characteristic on all three websites explaining salary variation in ads directed at women; for men, it is important only on two.

In sum, controlling for sociodemographic variables, one of the most important characteristics that explains the variation in salary is language, specifically English. Some of the characteristics most frequently mentioned for both genders are associated with higher salaries. Appearance, especially for women, explains more of the variation in salary than other characteristics.

Figure 6. Goodness-of-fit analysis

Panel A: Male **Panel B: Female**



Note: Dependent variable is ln(salary). All regressions are controlled for sociodemographic characteristics, which include location, marital status, type of job, educational level, experience, and minimum and maximum age. Ranking explains the importance of the word in terms of its adjusted R-squared. Ranking 1 explains the most; ranking 5 the least. The dotted line shows the R-squared for demographic characteristics only.

3.3 Out-of-Sample Predictions

Approximately 10 percent of ads are gender-targeted. However, it is possible that other ads are targeting women using words expressing gender stereotypes. The goal of this analysis is to determine whether ads that do not explicitly target men or women can be classified as doing so. We use a random forest (RF) model[13] to find which are the most important words and characteristics in job advertisements for predicting whether they are targeted at women or men. We use the prediction model to define a threshold to determine which ads are targeted.

We divide the sample into ads that are explicitly targeted at men, ads that are explicitly targeted at women, and ads that are not explicitly gender-targeted. We use a randomly chosen three-fourths of the gender-targeted samples as training samples for the models, and then make predictions using the remaining fourth. Then we use the

[13] An additional analysis with a LASSO model is also included in the Supplementary Materials.

model to predict the implicitly targeted gender of the third group.[14] To predict the implicit gender target of the ad, we use dummy variables for selected words from Table 1 and the 50 most frequent words presented in Section I. We choose a Random Forest model because it can detect nonlinearities and interactions between variables (Chen et al., 2019). The final model is the one with the lowest prediction error for the test sample.

We use RF regression instead of RF classification to obtain a prediction parameter between 0 and 1. This allows us to obtain a mean probability of implicit gender targeting for each ad and manually select the desired threshold for classification. We obtain the gender-targeted ad prediction for the non-explicitly gender-targeted sample by defining thresholds to ensure that we do not take into account ads that are targeted to both genders: a prediction parameter of 0-0.33 is considered implicitly targeted to men; 0.34-0.66 as a missing value (gender targeting not identifiable), and 0.67-1 as implicitly targeted to women.

Table 3 shows the RF confusion matrix for the explicitly discriminating test sample. This table is useful for analyzing false positives and false negatives and has two axes. One axis is the predicted value, obtained with the RF algorithm, and the other axis is the actual value, based on explicit gender targeting in an advertisement. False assignments (predicting targeting of men when the ad actually targets women, or vice versa) are less than 9 percent of the total observations for the three websites. The proposed algorithm is better at predicting ads implicitly targeted at women, with fewer false predictions than for ads targeted at men.

[14] This algorithm was implemented in Python with sklearn, and random state 12345 with 200 trees, to create the ensemble. This model is an ensemble learning method composed of decision trees. An ensemble method combines predictions for each outcome of each tree. The outcome of random forest regression models is the mean prediction (regression) of the individual trees.

Table 3: Random Forest Confusion Matrix

			Predicted Value			
			Male	**Female**	**Missing**	**Total**
Actual Value	**OCC Mundial**	**Male**	69.25	8.19	22.56	14,515
		Female	6.66	69.46	23.88	14,048
	Bumeran	**Male**	94.95	1.17	3.88	5,643
		Female	0.88	95.07	4.05	6,045
	CompuTrabajo	**Male**	78.82	4.79	16.39	10,217
		Female	6.30	72.10	21.60	8,355

Note: Data include all ads that explicitly discriminate, including test and training samples.

Table 4 analyzes the gender of ads not in the sample, that is, of non-gender-targeted ads. More than half of the advertisements on all three websites can be identified as targeting women: 55 percent on OCC Mundial, 77.5 percent on Bumeran, and 55.6 percent on CompuTrabajo.

Table 4: Out-of-Sample Prediction (Non-Gender-Targeted Ads)

	Out-of-Sample Prediction			
	Male	**Female**	**Missing**	**Total**
OCC Mundial	24.95	30.52	44.53	1,446,467
Bumeran	11.10	38.28	50.62	508,842
CompuTrabajo	23.37	29.26	47.37	448,159

Note: Data include all ads that do not explicitly discriminate.

To identify the characteristics intended to target a specific gender, we analyze the out-of-sample descriptive statistics predicted by the random forest model. Table 5 shows the ratios of percentage of occurrence of each characteristic of women relative to men (complete descriptive statistics can be found in the Supplementary Material); it has the same structure as Table 1. The ratios between models are similar.

In Table 5 the ratio of the characteristics targeting women is 1.25-3.45 times greater than that targeting men. The proportion of job advertisements specifying salary is also similar for women and men. Interestingly, the magnitudes of the ratios shown are generally in agreement with the previous analyses. When marital status is specified, there is a preference for married men and single women, but the number of ads with this specification is small. There is a difference in the level of education specified for women and men: ads targeted at women ask for students, high school graduates, college graduates, or those with unfinished education, but those targeted at men ask for junior high school graduates, those with technical certificates, or engineers. There are specific characteristics for each gender: women are asked to be attentive, helpful, and to have a good appearance; men are asked to be honest, to have the ability for teamwork, and to be available to travel. The type of compensation is also different: women are more frequently offered commissions.

Table 5: Out-of-Sample Ratio Analysis

		OCC	Bum	CT
Demographic Characteristics	Number of observations	1.22	3.45	1.25
	Includes salary	1.00	0.92	0.91
	Mean real salary	0.83	0.74	0.92
	Includes age	1.10	0.79	0.96
	Minimum age	0.90	0.91	0.95
	Maximum age	0.89	0.96	0.92
	Includes location	1.00	1.01	0.95
	Experience	1.10	1.01	0.95
	Married	0.04	0.17	0.02
	Single	2.52	7.44	3.79
	Student	4.47	1.80	2.64
	Junior high school	0.14	0.15	0.14
	High school	1.94	2.04	1.99
	Some school	3.19	2.43	2.84
	Technician	0.23	0.12	0.17

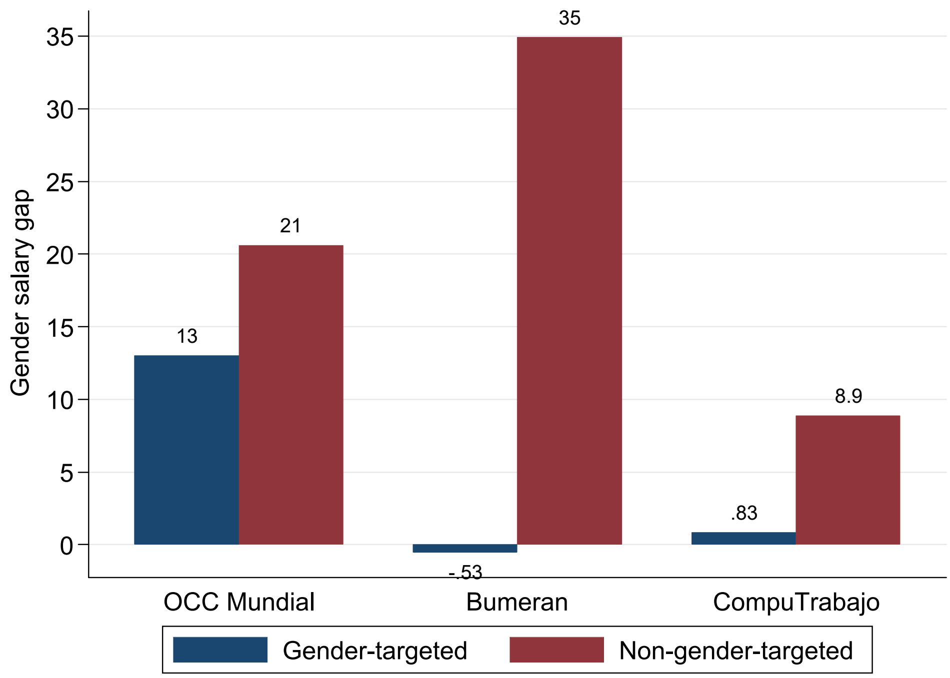
	Bachelor's degree	3.21	2.32	1.98
	Engineering degree	0.10	0.07	0.04
Communal	Commitment	0.42	1.30	1.19
	Punctual	0.93	1.25	0.98
	Honest	0.91	0.58	0.54
	Attentive	4.51	2.63	4.37
	Teamwork	0.56	1.03	0.76
	Helpful	2.08	1.80	1.37
	Courteous	3.19	1.20	2.98
Agentic	Control	0.71	0.55	0.64
	Initiative	1.33	1.25	1.20
	Motivation	1.17	1.92	1.77
	Pressure	1.12	1.01	0.86
	Proactive	1.06	0.88	0.83
	Responsible	1.55	1.69	1.13
	Enthusiasm	1.77	3.20	1.60
Appearance	Requests photograph	2.13	1.26	2.24
	Requests good appearance	6.92	7.01	11.69
Language	English	1.20	1.27	1.15
	Common computer software	1.77	1.18	1.12
Customer service	Sales	1.98	2.54	2.14
	Customer	1.99	2.61	3.39
	Follow-up	2.33	1.70	2.69
Availability	Availability	1.42	0.54	1.01
	Travel	0.18	0.23	0.26
	Driver's license	0.05	0.01	0.04
Career	Growth	2.23	1.42	1.16
	Development	2.73	3.26	2.65
	Training	2.29	2.18	1.60
Benefits	Bonus	1.69	1.91	1.71
	Benefits	0.94	0.90	0.96
	Insurance	1.27	0.32	1.64
	Commissions	7.64	4.54	4.31

Base salary	2.21	1.24	1.36

Note: Summary statistics calculated using data from OCC Mundial, Bumeran, and CompuTrabajo. Each word is represented by a dummy variable equal to 1 if the word appears in the job description, or 0 otherwise. See Table S1 for the Spanish words used.

Surprisingly, even though the frequencies of some characteristics are similar to those in the analysis of explicit discrimination, the gender salary gap is greater in job ads that implicitly discriminate. The ratio of the mean salary of women to men is 0.74-0.92; in gender-targeted ads the ratio is .88-1.01. Figure 7 shows the gender salary gap for gender-targeted and non-gender-targeted job advertisements. The gender salary gap is greater if we also take into account the predicted gender targeting in ads where discrimination is not explicit.

Figure 7: Gender Salary Gap in Gender-Targeted and Non-Gender-Targeted Job Advertisements



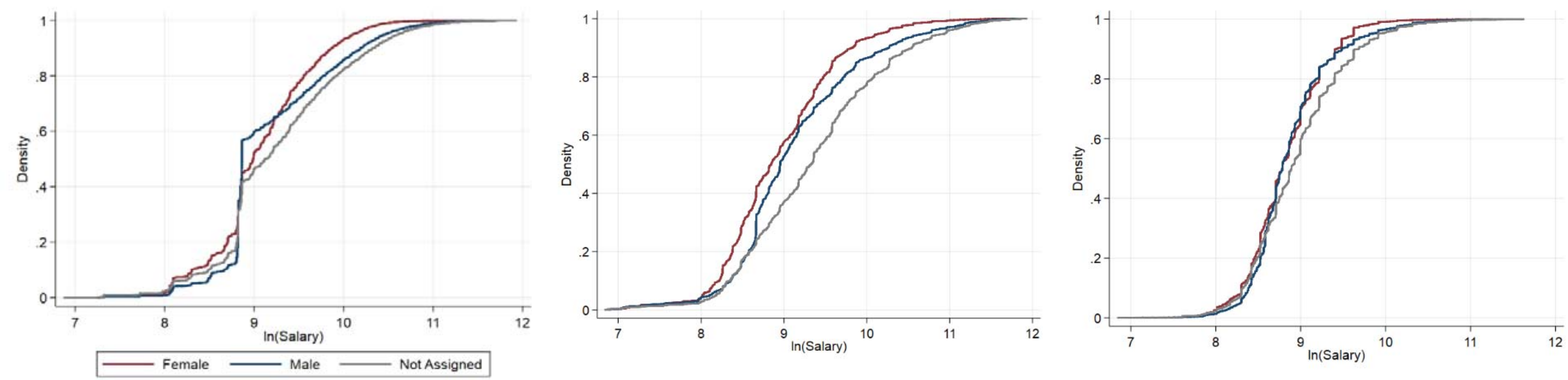
Notes: Gender salary gap is the difference between the mean salary in ads explicitly or implicitly targeted at women and the salary in ads explicitly or implicitly targeted at men. "Implicitly targeted" refers to prediction of targeted gender using the random forest algorithm.

Using our prediction of implicit gender targeting, we can calculate the gender salary distribution in non-targeted ads. Figure 8 includes the cumulative distribution function of the (ln) salary for the three samples of non-gendered-targeted ads. It shows that ads directed at women are more likely to specify a lower salary everywhere except in the middle of the distribution.

Explicitly gender-targeted ads specify characteristics associated with gender stereotypes. We examine words describing these characteristics to predict the implicit targeting of men of women in job ads that do not explicitly discriminate. This implicit targeting implies that employers are thinking about characteristics associated with gender stereotypes in describing the positions advertised. We find that implicit discrimination occurs in almost half of the job advertisements that do not explicitly discriminate, that this discrimination targets women over men, and that the salary gap in these advertisements is greater than that in explicitly discriminatory job ads.

Figure 8: Cumulative Density Functions of Salary by Predicted Gender Target, Using Random Forest Algorithm

OCC | Bumeran | CompuTrabajo



Note: Sample includes advertisements predicted to be gender-targeted.

4. Discussion

Our results show that explicit discrimination accounts for little of the salary penalty for women in job advertisements on three employment search websites in Mexico. The gender salary gap is at most 12 percent in explicitly gender-targeted ads. However, in our analysis of implicit discrimination, the gap increases to almost 30 percent. We analyze the frequency of words used to specify sociodemographic characteristics and qualifications in job advertisements. Using a random forest algorithm, we predict gender-targeting in ads that do not explicitly discriminate. The descriptive statistics obtained allow us to analyze the characteristics that differentiate ads targeted to different genders. Characteristics associated with gender stereotypes are found in numerous advertisements. For example, ads targeted at women more commonly specify a high school diploma or college degree, while those directed at men are more likely to specify an engineering degree, technical certificate, or completion of junior high school. Ads targeting women also describe qualifications using terms like *attentive*, *helpful*, and *good appearance*, while those targeting men refer to *honesty*, *teamwork*, *travel*, and *time*. Where discrimination is explicit the salary gap is not large. However, where discrimination is implicit, women are penalized.

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Supplementary Materials

Table S1: Glossary of Characteristics in Table 1

English	Spanish	English	Spanish	English	Spanish
Some school	Trunca	Proactive	Proactivo	Availability	Disponibilidad
Commitment	Compromiso	Responsible	Responsable	Travel	Viajar
Punctual	Puntual	Pressure	Estrés	Driving license	Licencia de conducir
Honest	Honesto	Enthusiasm	Ganas	Growth	Crecimiento
Attentive	Atento	Photograph	Fotografía	Development	Desarrollo
Teamwork	Trabajo en equipo	Appearance	Presentación	Training	Capacitación
Helpful	Servicial	English	Inglés	Bonus	Bono
Courteous	Amable	Software	Software	Benefits	Beneficio
Control	Control	Sales	Ventas	Insurance	Seguro
Initiative	Iniciativa	Customer	Cliente	Commissions	Comisiones
Motivation	Motivación	Follow-up	Seguimiento	Base Salary	Base
Pressure	Presión				

Table S2. Descriptive Statistics of Occupations

	OCC Mundial			Bumeran (Bum)			CompuTrabajo (CT)			*p*-value Ho: male=female		
Category	Neutral	Male	Female	Neutral	Male	Female	Neutral	Male	Female	OCC	Bum	CT
% of sample assigned	0.78	0.79	0.86	0.77	0.82	0.85	0.84	0.83	0.86			
Other specialists and technicians, not previously classified	0.22	0.15	0.27	0.24	0.18	0.28	0.19	0.12	0.23	0.00	0.00	0.00
Sales Clerks	0.17	0.07	0.18	0.22	0.07	0.20	0.21	0.06	0.21	0.00	0.00	0.00
Other service managers and department heads, not classified	0.13	0.19	0.11	0.09	0.08	0.07	0.09	0.09	0.08	0.00	0.00	0.00
Secretaries, data entry personnel, cashiers, file clerks, and drivers	0.08	0.11	0.12	0.05	0.11	0.13	0.08	0.14	0.12	0.00	0.00	0.00
Researchers and specialized personnel in physical and biological sciences, engineering, computing, and telecommunications	0.05	0.03	0.01	0.04	0.01	0.00	0.03	0.02	0.01	0.00	0.00	0.00
Street vendors	0.05	0.03	0.04	0.05	0.06	0.06	0.08	0.05	0.08	0.00	0.18	0.00
Management professionals, specialists in social sciences, arts, and humanities	0.04	0.05	0.04	0.03	0.02	0.03	0.04	0.03	0.03	0.00	0.00	0.28
Other secretaries, data entry personnel, cashiers	0.04	0.03	0.13	0.03	0.02	0.10	0.04	0.03	0.13	0.00	0.00	0.00
Customer information personnel	0.04	0.01	0.04	0.12	0.01	0.05	0.05	0.01	0.04	0.00	0.00	0.00
Technicians in physical and biological sciences, engineering, computing, and telecommunications	0.03	0.09	0.00	0.02	0.08	0.00	0.03	0.08	0.01	0.00	0.00	0.00
Mining, construction, and industrial laborers	0.03	0.04	0.00	0.01	0.07	0.01	0.03	0.09	0.01	0.00	0.00	0.00
Protective services personnel	0.02	0.04	0.00	0.01	0.06	0.00	0.01	0.05	0.00	0.00	0.00	0.00
Drivers and heavy equipment operators	0.01	0.06	0.00	0.01	0.07	0.00	0.02	0.09	0.00	0.00	0.00	0.00
Food service workers	0.01	0.01	0.00	0.01	0.01	0.00	0.02	0.02	0.00	0.00	0.00	0.00

Domestic workers, cleaners, and laundry workers	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.02	0.79	0.01	0.41

Note: Occupations classified according to SINCO (2011)

Table S3: Glossary of Words in Figure 1

English	Spanish	English	Spanish	English	Spanish
Year	Año	Monday	Lunes	Applicants	Interesados
Experience	Experiencia	Area	Zona	Work	Laboral
Job	Trabajo	Seeks	Solicita	Bachelor's degree	Licenciatura
Benefits	Prestaciones	Activities	Actividades	Important	Importante
Management	Manejo	Service	Atención	Appearance	Presentación
Law	Ley	Excellent	Excelente	Time	Tiempo
Sex	Sexo	Friday	Viernes	Monthly	Mensual
Company	Empresa	Personnel	Personal	To Do	Realizar
Age	Edad	Service	Servicio	High School	Bachillerato
Requirements	Requisitos	Skills	Conocimientos	Contract	Contrato
We offer	Ofrecemos	Control	Control	Major	Carrera
Salary	Sueldo	Functions	Funciones	Area	Área
Hours	Horario	Administration	Administración	Responsible	Responsable
Education	Escolaridad	Position	Puesto	Indispensable	Indispensable
Customer	Cliente	Base Salary	Base		
Availability	Disponibilidad	Medium	Medio		
Sales	Ventas	Minimum	Mínima		
Team	Equipo	Follow-up	Seguimiento		

Table S4: Glossary of Bigrams in Figure 2

English	Spanish	English	Spanish	English	Spanish
Years Age	Años Edad	Better Law	Ley Superiores	Direct Hiring	Contratación Directa
Law Benefits	Ley Prestaciones	Requirements Sex	Requisitos Sexo	Under Pressure	Bajo Presión
We Offer Salary	Ofrecemos Sueldo	Better Benefits	Prestaciones Superiores	Excellent Environment	Ambiente Excelente
Years Experience	Años Experiencia	Years Education	Años Escolaridad	Leading Company	Empresa Líder
Monday Friday	Lunes Viernes	Grocery Vouchers	Despensa Vales	Similar Position	Puesto Similar
Year Sex	Años Sexo	Minimum Education	Educación Mínima	Work Hours	Horario Trabajo
Hours Monday	Horario Lunes	Contract Time	Contrato Tiempo	Direct Company	Directa Empresa
Customer Service	Atención Cliente	Full Time	Completo Tiempo	Years Minimum	Anos Mínima
Teamwork	Equipo Trabajo	Excellent Appearance	Excelente Presentación	AM PM	AM PM
Work Area	Trabajo Zona	Life Insurance	Seguro Vida	Contract Type	Contrato Tipo
Base Salary	Base Sueldo	Savings Fund	Ahorro Fondo	Bachelor's Degree	Escolaridad Licenciatura
Important Company	Empresa Importante	Work Environment	Ambiente Trabajo	Team Part	Equipo Parte
Availability Travel	Disponibilidad Viajar	Communication Skills	Facilidad Palabra	Technical Studies	Carrera Técnica
Minimum Experience	Experiencia Mínima	Employment Stability	Estabilidad Laboral	High School Diploma	Escolaridad Preparatoria
Schedule Availability	Disponibilidad Horario	Any Marital Status	Civil Indistinto	Work Location	Lugar Trabajo
Age Requirements	Edad Requisitos	Apply Here	Medio Postularse	Junior High School Education	Escolaridad Secundaria
Attitude Service	Actitud Servicio	Under Work	Bajo Trabajo		

Table S5: Example of announces using selected words

English	Spanish	Use of the word	Example of announce
Law	Ley	Law [ley] is usually used to compare the offered benefits with labor law regulations as a benchmark	¡Cambiar vidas para lograr sueños! Buscamos personas interesadas y comprometidas en apoyar con su talento a lograr los sueños de muchas mujeres mexicanas emprendedoras y contribuir así a cambiar la vida de miles de familias. Asesor de crédito para sucursal Gómez Palacio. Requisitos: secundaria terminada, gusto por las ventas, cambaceo y cobranza facilidad de palabra, disponibilidad de horario, excelente actitud de servicio. Ofrecemos: sueldo base más bonos por resultados prestaciones de ley **[Law]** y superiores, uniformes, herramientas de trabajo, capacitación, constante, crecimiento dentro de la empresa. "Únete a nuestra gran familia contigo", envía tu información al correo mencionado.
Seeks	Solictia	Seeks [solicita] is used to-invite applications	Importante empresa líder en marketing digital solicita **[seeks]** experto en redes sociales recién egresados Lic. ciencias de la comunicación, diseño gráfico, diseño digital o carrera afín actividades y habilidades: domine redes sociales, (Facebook, Twitter, Pinterest, YouTube, LinkedIn e Instagram, creación de contenido y desarrolle contenido social. Responsable organizado trabaje bajo presión lugar a laborar Narvarte poniente. Ofrecemos: sueldo más bono de productividad mensual, prestaciones de ley, membresía corporativa. Lunes a viernes de 7:00am a 15:45pm.
Base salary	Base	The original word is base [base], but this word usually refers to base salary.	Solicitamos personal femenino. Edad de 22 a 30 años, con excelente presentación experiencia en el área de crédito y cobranza, facturación, manejo en software de adminpaq, Excel y Word. Que vivan cercas del municipio de Zapopan. Ofrecemos: contratación directa por la empresa, sueldo base **[base salary]** y prestaciones de ley, servicio de comedor, pagos puntuales y horario corrido de lunes a viernes de 9 a 18:00 horas.

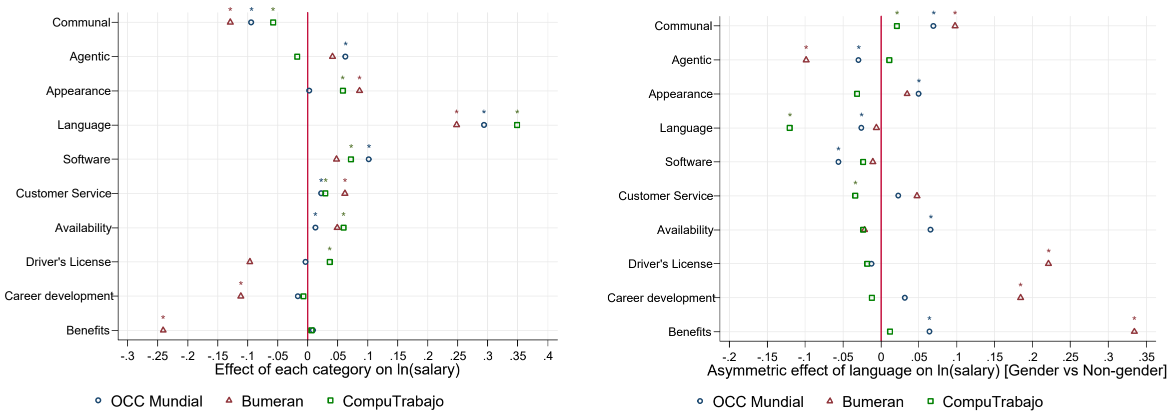
Major	Carrera	Major [carrera] usually refers to college or university major.	Practicante de diseño. Requisitos: estudiante activo de 5to, a 8vo semestre de la carrera **[major]** de, diseño gráfico o afín. Horario de 8:30 am a 5:00 pm. Sexo: femenino. Actividades: diseño gráfico para medios impresos y digitales, conocimiento en prensa, edición de fotografía, buena ortografía y redacción, conocimiento en: Adobe Suite cs6, Indesign, Ilustrador, Photoshop office. Ofrecemos: convenio con caintra. Sueldo: $5,000.00. Comedor sin costo.
Applicants	interesados	Applicants [interesados] is used to describe the people who apply for a job.	"Empresa de la industria automotriz solicita líder de producción que cumpla con las siguientes características: Requisitos: ingeniero industrial, manufactura, calidad o afín experiencia mínima de 8 años en área de producción, manejo de personal y enfoque a seguridad y calidad. Habilidad de liderazgo con don de mando y buena comunicación. Sexo masculino. Edad indistinta (buena condición física para caminar por toda el área) inglés a nivel conversacional disponibilidad para rolar turnos de preferencia experiencia en industria automotriz conocimientos: conocimiento de flujo de materiales control de producción kpis, manejo de presupuesto, indicadores de producción, mejora continua, enfoque a procesos y sistemas. serán el encargado de área en su turno, sin tener a cargo el personal. son líderes del área que se aseguraran, que durante el turno se cubra todo lo necesario para no parar producción interesados **[applicants]** que cumplan al 100% con el perfil, mandar curricular actualizado con fotografía a la dirección que aparece en la publicación. *solo se tomarán en cuenta postulaciones vía correo electrónico".
Service	Atención	Service [atención] is usually used to describe customer service activities.	Sexo femenino de 25 a 35 años, con preparatoria, experiencia en atención a clientes **[customer service],** manejo de conmutador, apoyo a labores administrativas, por el momento solo para cubrir incapacidad por maternidad 3 meses, y con la posibilidad de quedarse de planta".

Follow-up	Seguimiento	Advertisements mentioning follow-up [seguimiento] typically refer to interaction with other people in order to achieve specific tasks.	Requisitos. Escolaridad: preparatoria o carrera trunca vivan en el área de: Atizapán de Zaragoza, Tlalnepantla, Vallejo, Tultitlan, y Cuautitlán. Edad: 28 y a 40 años; sexo: masculino; edo. civil: indistinto; buena presentación; habilidades de negociación; conocimientos en almacén e inventarios; experiencia: 1 año en el puesto similar; manejo de office e internet alto sentido de responsabilidad en la elaboración, colocación y seguimiento **[follow-up]** de las órdenes de compra. Horario de trabajo: tiempo completo. Lunes a jueves de 8:00 a 18:00 horas y viernes 8:00 a 18:30 horas. Disponibilidad de ampliar el horario para trabajar y licencia de manejo vigente ofrecemos salario: 8,000.00 mensuales prestaciones de ley (IMSS, Infonavit, aguinaldo, vacaciones) premio de asistencia y puntualidad semanal de 200”
skill	conocimiento	Skill [conocimiento] typically refers to a list of specific computer or other skills.	Empresa mexicana con 35 años de experiencia dedicada a la fabricación de productos de limpieza industrial e institucional solicita: ejecutivos de venta edad: 24 años a 35 años. Estado civil: indistinto. Sexo: femenina escolaridad: bachiller concluido. Experiencia: 6 meses a 1 ano en venta directa, presentación ejecutiva, requisito: contar con vehículo; buscamos personal altamente acostumbrado a trabajar por retos, capaz de establecer y concretar una venta solo personas acostumbradas a trabajar por comisiones *proactiva *empática *capacidad de manejo de objeciones *conocimiento **[skill]** en técnicas de venta. *conocimiento en prospección y cierre de ventas. Ofrecemos-garantía de ingreso por 3 meses -excelente esquema de comisiones -uniformes-capacitación-buen ambiente laboral-crecimiento profesional-ayuda para gasolina”
Appereance	Presentación		“empresa líder en su ramo solicita asistente administrativo. Excelente presentación **[appearance],** sexo femenino. Carrera técnica trunca, buen carácter, edad: 25 a 34 años, viva zona norte, facilidad de palabra, tolerancia a la frustración, buen manejo de Excel, ofrecemos: prestaciones de ley agradable ambiente de trabajo 7,000 pesos mensuales
Apply here	Medio-Postularse	Apply here refers to the preferred form of contact.	Forma parte de nuestro equipo de trabajo chofer ejecutivo para fines de semana requisito: experiencia de 5 años o más como chofer ejecutivo *trato cordial y profesional * conocer rutas de la ciudad y alrededores *hombre *edad 40 a 50 años *disponibilidad de horario y requiera un trabajo de fin de semana horario de trabajo : viernes 5:00 pm al domingo 6:00 pm sueldo $8000 mensuales + viáticos si estas

			interesado postúlate por este medio **[Apply-here]** y enviar tu CV al correo antes mencionado indicando tus pretensiones económicas
Direct-Company	Directo-Empresa	Direct-Company refers to direct hiring, that is without an intermediary or outsourcing arrangement	Auxiliar de almacén edad: 20 a 27 años escolaridad: preparatoria terminada género: masculina experiencia: mínimo 6 meses en almacén o puesto similar office intermedio recibo de mercancía inventarios funciones y responsabilidades: recepción de proveedores, contra recibo de facturas, expedición de guías para envíos locales y foráneos, control de inventarios, mercancía, transferencias, devoluciones, control de merma. Acomodo del producto, verificación de producto. escaneo de recepción de producto y sensorio de producto ofrecemos: excelente sueldo base prestaciones de ley y superiores (IMSS, vacaciones, prima vacacional, aguinaldo, descuento de empleado excelente ambiente de trabajo contratación directa con la empresa **[Direct-Company]**
Under-work	Trabajo bajo	Under-work is used to specify the conditions of work and activities.	¡Únete a nuestro exitoso equipo de trabajo! Generalista de capital humano. Requisitos: licenciatura terminada. Mayores de 25 años. Mínimo 2 años de experiencia como generalista de RH. Experiencia: reclutamiento y selección masiva (preferentemente fuerzas de ventas). Administración de plantilla mínimo 150 personas. Relaciones laborales. Manejo y análisis de indicadores de RH. Trabajo en campo (reclutamiento y visitas a sucursales). Atención y servicio al cliente. Competencias: Habilidades de negociación. Integración de equipos de trabajo. Disponibilidad de horario y para desplazarse dentro de Qro. Acostumbrado a trabajar bajo **[Under-Work]** objetivos. Interesados enviar su CV especificando la ciudad de la vacante

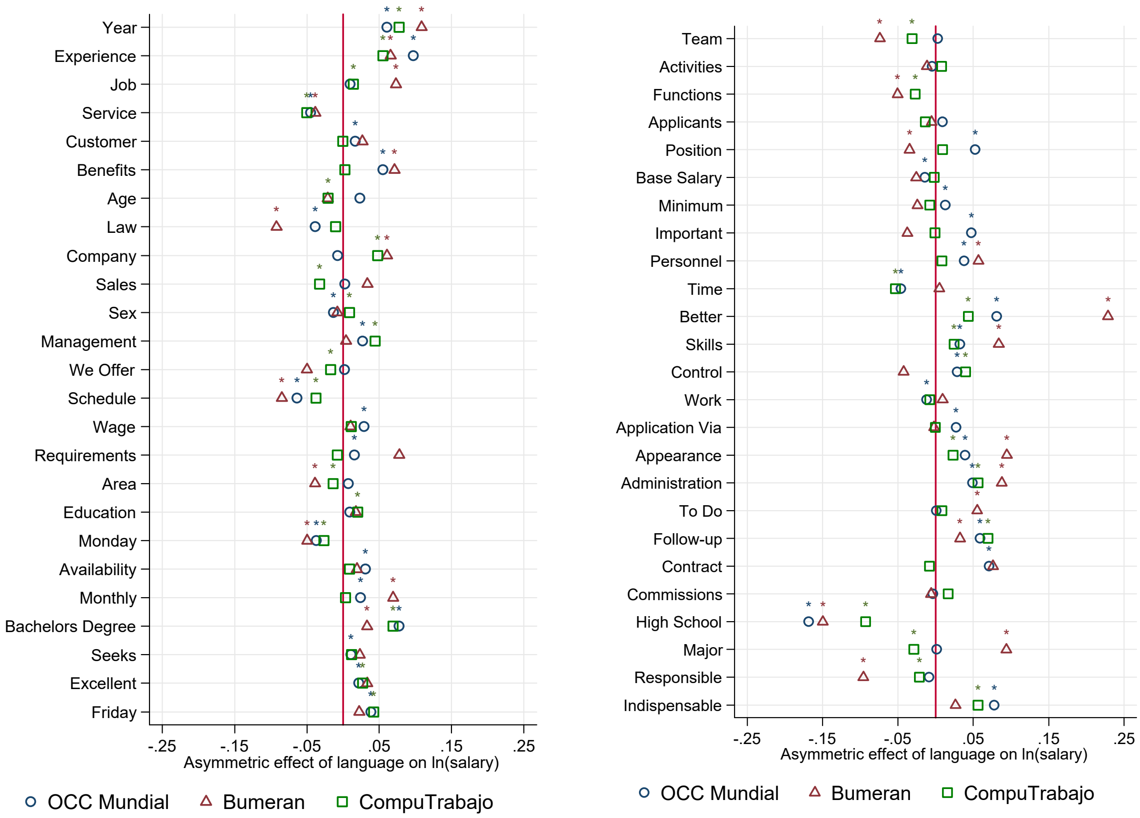
Figure S1: Effect of categories on salary, controlling for occupation (women vs. men) [Figure 4]

Panel A. Effect of category on salary **Panel B. Asymmetric effect of categories**



Note: Data include all gender-targeted ads. The dependent variable is the log of real salary (July 2018=100). Each category is a dummy variable representing at least one component word appearing in the job advertisement. In Panel A, each point represents the coefficient of the ln(salary) of a dummy variable for the presence of the category. In Panel B, each point represents the coefficient of the ln(salary) for the interaction of a dummy for ad targeted at women with a dummy for the presence of the category. The regression controls for the presence of the category and specifying a gender, location, age (minimum and maximum), experience, educational level, and occupation. Asterisk (*) signifies that the regression is statistically significant at 5 percent; robust standard errors are clustered by location. Communal character includes use of the words *commitment*, *punctual*, *honest*, *attentive*, *teamwork*, *helpful*, and *courteous*; Agentic character includes *control*, *initiative*, *motivation*, *pressure*, *proactive*, *responsible*, *stress*, and *enthusiasm*. Appearance includes *photograph* and *appearance*. Language includes *English*. Software includes *Excel*, *Word*, and *Windows*. Customer Service includes *sales*, *customer*, and *monitoring*, Availability includes *time* and *travel*. Career includes *growth*, *development*, and *training*. Benefits includes *bonus*, *benefits*, *insurance*, *commissions*, and *base salary*.

Figure S2: Effect of words on salary for 50 most frequently used words, controlling for occupation, in descending order of frequency [Figure 5]



Note: Data include all advertisements. The dependent variable is the log of real salary (July 2018=100). Each category is a dummy variable representing that the word appeared in the job advertisement. Each point represents the coefficient of the ln(salary) in the interaction of a dummy variable for ad targeted for gender with a dummy for the presence of the word. The regression controls for occupation, location, age (minimum and maximum), experience, and educational level. Asterisk (*) signifies that the regression is statistically significant at 5 percent; robust standard errors are clustered by location.

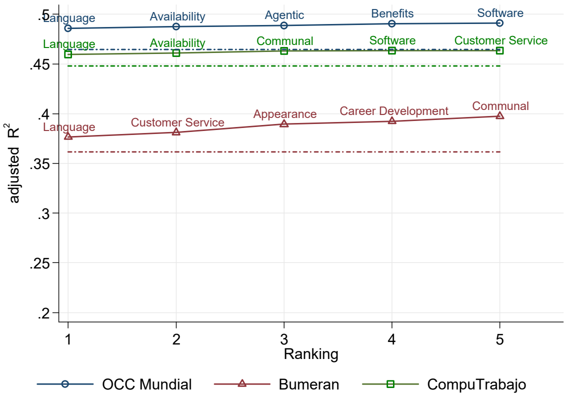
Table S6: Lasso Post-Estimation Results, Controlling for Occupation [Table 2]

	OCC Mundial		Bumeran		CompuTrabajo	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
Communal	-0.042	-0.027	-0.086	-0.034	-0.045	-0.034
	[.004]	[.004]	[.01]	[.008]	[.005]	[.006]
Agentic	0.048	0.020	-0.074			-0.026
	[.004]	[.004]	[.01]			[.006]
Appearance	0.019	0.052	0.184	0.091		0.050
	[.005]	[.004]	[.013]	[.008]		[.007]
Language	0.301	0.267	0.371	0.317	0.256	0.268
	[.008]	[.006]	[.019]	[.014]	[.019]	[.013]
Software	0.044	0.034	0.076	0.039	0.026	0.085
	[.006]	[.005]	[.014]	[.009]	[.008]	[.009]
Customer Service	0.028	0.014	0.118	0.014	0.010	-0.009
	[.004]	[.004]	[.011]	[.01]	[.005]	[.007]
Availability	0.072	0.106	0.042	0.096	0.046	0.049
	[.005]	[.007]	[.014]	[.019]	[.008]	[.011]
Driver's License	-0.046	0.094	0.030	0.046	0.003	0.107
	[.006]	[.016]	[.017]	[.041]	[.008]	[.031]
Career Development	0.016		0.109	0.088	-0.003	-0.034
	[.004]		[.011]	[.009]	[.005]	[.006]
Benefits	0.064	0.078		0.109	0.012	0.026
	[.005]	[.005]		[.014]	[.007]	[.009]
N	58464	55748	15265	15899	19349	14775
Adj. R^2	0.493	0.369	0.401	0.356	0.463	0.384

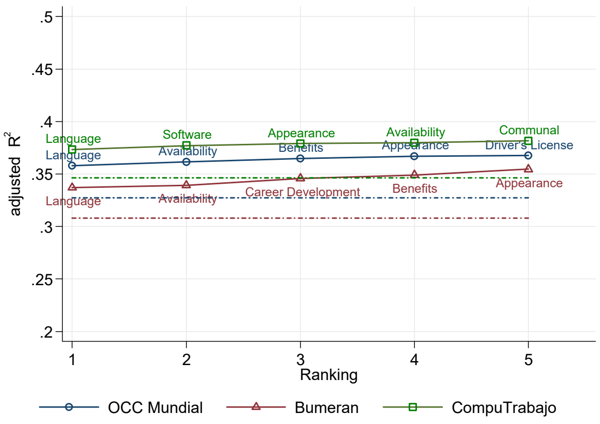
Note: Data include gender-targeted ads. Dependent variable is ln(salary). Coefficients presented are the result of OLS post-estimation of a LASSO regression. Regressions are controlled without penalization for level of education, occupation, minimum age, maximum age, marital status, and job location. Robust standard errors in bold. Communal category includes use of the words *commitment*, *punctual*, *honest*, *attentive*, *teamwork*, *helpful*, and *courteous*; Agentic category includes *control*, *initiative*, *motivation*, *pressure*, *proactive*, *responsible*, *stress*, and *enthusiasm*. Appearance includes *photograph* and *appearance*. Language includes *English*. Software includes *Excel*, *Word*, and *Windows*. Customer service includes *sales*, *customer*, and *monitoring*, Availability includes *time* and *travel*. Career includes *growth*, *development*, and *training*. Benefits includes *bonus*, *benefits*, *insurance*, *commissions*, and *base salary*.

Figure S3: Goodness-of-fit analysis, controlled for occupation [Figure 6]

Panel A: Male



Panel B: Female



Note: Data include gender-targeted ads. Dependent variable is ln(Salary). The regressions are controlled for sociodemographic characteristics, which include location, marital status, occupation, level of education, experience, and minimum and maximum age. Ranking describes the importance of the word in terms of its adjusted *R*-squared (a ranking of 1 explains the most; a ranking of 5 explains the least). Dotted line shows the regressions controlling only for sociodemographic characteristics.

Table S7: Descriptive Statistics for Out-of-Sample Random Forest Analysis

		OCC Mundial			**Bumeran (Bum)**			**CompuTrabajo (CT)**			***p*-value Ho: male=female**		
Category		Neutral	Male	Female	Neutral	Male	Female	Neutral	Male	Female	**OCC**	**Bum**	**CT**
	Number of observations	644,040	360,937	441,490	257,559	56,495	194,788	212,272	104,752	131,135			
	Number of observations Initial date to final date	**February 2018 to January 2020**			**February 2018 to January 2020**			**February 2018 to May 19, 2018 and December 2018-January 2020**					
Sociodemographic Characteristics	Specifies man	0	1	0	0	1	0	0	1	0			
	Specifies woman	0	0	1	0	0	1	0	0	1			
	Gender-neutral	1	0	0	1	0	0	1	0	0			
	Includes Salary	0.99	1	1	0.60	0.59	0.54	0.37	0.39	0.35	0.00	0.00	0.00
	Mean real salary (MXN/mo.)	14,351	12,608	10,456	17,121	13,302.38	9,860	9,283	8,245	7,574	0.00	0.00	0.00
	Includes age	0.19	0.19	0.21	0.32	0.45	0.35	0.80	0.84	0.81	0.00	0.00	0.00
	Minimum age	24.90	25.94	23.28	22.68	23.76	21.69	23.01	23.10	21.95	0.00	0.00	0.00
	Maximum age	39.99	42.44	37.94	42.79	43.57	41.90	42.96	44.10	40.56	0.00	0.00	0.00
	Includes location	0.98	0.99	0.99	0.92	0.93	0.94	0.86	0.90	0.85	0.00	0.00	0.00
	Experience	0.71	0.68	0.75	0.77	0.79	0.80	0.75	0.83	0.79	0.00	0.00	0.00
	Married	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
	Single	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Student	0.04	0.01	0.03	0.05	0.02	0.03	0.04	0.01	0.02	0.00	0.00	0.00

	Junior High School	0.07	0.27	0.04	0.12	0.22	0.03	0.10	0.31	0.04	0.00	0.00	0.00
	High school	0.19	0.15	0.30	0.24	0.23	0.48	0.31	0.23	0.45	0.00	0.00	0.00
	Some school	0.07	0.04	0.12	0.09	0.06	0.14	0.10	0.05	0.15	0.00	0.00	0.00
	Tech. cert.	0.02	0.03	0.01	0.02	0.04	0.01	0.02	0.04	0.01	0.00	0.00	0.00
	Bachelor's degree	0.38	0.15	0.49	0.38	0.20	0.47	0.40	0.21	0.42	0.00	0.00	0.00
	Engineering degree	0.18	0.34	0.03	0.18	0.34	0.02	0.09	0.25	0.01	0.00	0.00	0.00
Communal	Commitmen t	0.10	0.15	0.06	0.04	0.02	0.03	0.03	0.01	0.02	0.00	0.00	0.00
	Punctual	0.07	0.07	0.06	0.08	0.07	0.09	0.08	0.07	0.07	0.00	0.00	0.21
	Honest	0.02	0.02	0.02	0.03	0.03	0.02	0.03	0.03	0.02	0.00	0.00	0.00
	Attentive	0.18	0.10	0.43	0.25	0.17	0.45	0.27	0.12	0.53	0.00	0.00	0.00
	Teamwork	0.22	0.31	0.17	0.13	0.09	0.09	0.10	0.09	0.07	0.00	0.05	0.00
	Helpful	0.07	0.04	0.08	0.09	0.04	0.08	0.09	0.06	0.08	0.00	0.00	0.00
	Courteous	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00
Agentic	Control	0.18	0.18	0.12	0.14	0.16	0.09	0.15	0.16	0.10	0.00	0.00	0.00
	Initiative	0.03	0.02	0.02	0.03	0.02	0.02	0.03	0.02	0.02	0.00	0.00	0.00
	Motivation	0.01	0.00	0.01	0.02	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00
	Pressure	0.09	0.06	0.07	0.10	0.07	0.07	0.10	0.08	0.07	0.00	0.48	0.00
	Proactive	0.08	0.06	0.06	0.09	0.07	0.06	0.09	0.07	0.06	0.00	0.00	0.00
	Responsible	0.08	0.05	0.07	0.09	0.05	0.09	0.08	0.07	0.08	0.00	0.00	0.00
	Enthusiasm	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00
Appearanc e	Requests photograph	0.04	0.02	0.05	0.03	0.02	0.03	0.04	0.02	0.05	0.00	0.00	0.00
	Requests good appearance	0.06	0.03	0.22	0.07	0.03	0.20	0.06	0.02	0.28	0.00	0.00	0.00
Language	English	0.20	0.13	0.16	0.24	0.12	0.15	0.12	0.09	0.10	0.00	0.00	0.00

	Common computer software	0.12	0.06	0.10	0.12	0.06	0.07	0.12	0.09	0.10	0.00	0.00	0.00
Customer service	Sales	0.32	0.21	0.42	0.40	0.22	0.55	0.42	0.27	0.58	0.00	0.00	0.00
	Customer	0.42	0.28	0.56	0.44	0.24	0.63	0.40	0.19	0.66	0.00	0.00	0.00
	Follow-up	0.17	0.09	0.21	0.19	0.10	0.16	0.15	0.07	0.20	0.00	0.00	0.00
Availability	Availability	0.03	0.02	0.02	0.04	0.05	0.02	0.04	0.04	0.04	0.00	0.00	0.72
	Travel	0.07	0.13	0.02	0.04	0.07	0.02	0.06	0.08	0.02	0.00	0.00	0.00
	Driver's license	0.02	0.05	0.00	0.01	0.06	0.00	0.02	0.06	0.00	0.00	0.00	0.00
Career	Growth	0.17	0.09	0.21	0.28	0.23	0.33	0.26	0.23	0.27	0.00	0.00	0.00
	Development	0.04	0.01	0.03	0.04	0.01	0.04	0.02	0.01	0.03	0.00	0.00	0.00
	Training	0.19	0.10	0.24	0.25	0.15	0.32	0.27	0.19	0.31	0.00	0.00	0.00
Benefits	Bonus	0.19	0.14	0.24	0.25	0.21	0.40	0.26	0.18	0.31	0.00	0.00	0.00
	Benefits	0.65	0.73	0.69	0.51	0.67	0.61	0.60	0.71	0.68	0.00	0.00	0.00
	Insurance	0.05	0.03	0.04	0.03	0.07	0.02	0.05	0.03	0.05	0.00	0.00	0.00
	Commissions	0.11	0.03	0.25	0.17	0.09	0.41	0.22	0.10	0.43	0.00	0.00	0.00
	Base salary	0.26	0.15	0.33	0.35	0.33	0.42	0.35	0.32	0.44	0.00	0.00	0.00

Note: Summary statistics calculated using data from OCC Mundial, Bumeran, and CompuTrabajo. Each word is represented by a dummy variable equal to 1 if the word appears in the job description, or 0 otherwise. See Table S1 for the Spanish words used.

Table S8: Random Forest Confusion Matrix, Controlled for Occupation [Table 3]

			Predicted Value			
			Male	**Female**	**Missing**	**Total**
Actual Value	**OCC Mundial**	**Male**	71.96	8.23	19.81	14,515
		Female	5.22	73.21	21.56	14,048
	Bumeran	**Male**	95.29	1.17	3.54	5,643
		Female	0.83	95.80	3.37	6,045
	CompuTrabajo	**Male**	80.86	5.10	14.05	10,217
		Female	5.47	77.35	17.18	8,355

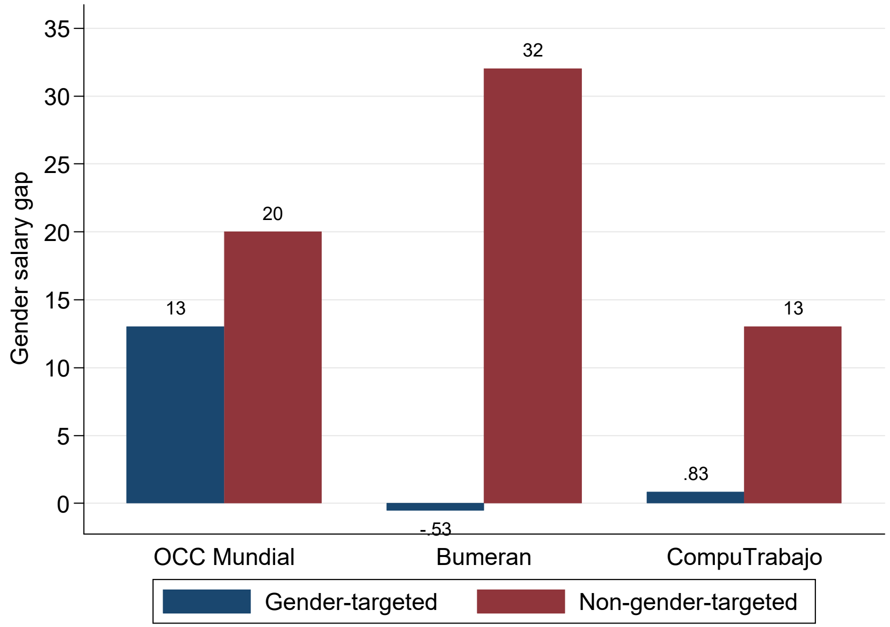
Note: Data include all advertisements that explicitly discriminate, including test and training samples.

Table S9: Random Forest Out-of-Sample Prediction for Non-Gender-Targeted Ads, Controlled for Occupation [Table 4]

	Out-of-Sample Prediction			
	Male	**Female**	**Missing**	**Total**
OCC Mundial	22.38	29.25	48.36	1,446,467
Bumeran	13.45	41.18	45.37	508,842
CompuTrabajo	20.27	33.27	46.45	448,159

Note: Data include all advertisements that do not explicitly discriminate.

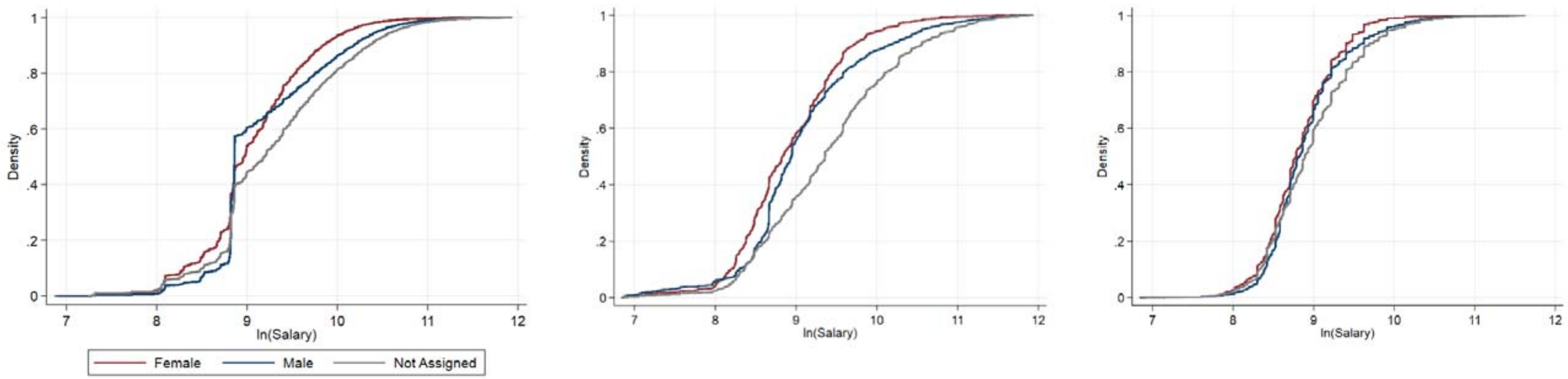
Figure S4: Gender Salary Gap in Gender-Targeted and Non-Gender-Targeted Ads, Controlled for Occupation [Figure 7]



Notes: Gender gap is calculated as the difference between the mean salary in ads targeted at women and ads targeted at men. "Gender-targeted" ads refers to those explicitly targeted to men or women. "Non-gender-targeted" refers to our prediction of implicit gender target using the random forest algorithm.

Figure S5: Cumulative Density Functions of Salary by Predicted Gender, Controlled for Occupation [Figure 8]

OCC Mundial	Bumeran	CompuTrabajo



Note: Data include ads with predicted gender targeting, based on the random forest algorithm.

Table S10: LASSO Confusion Matrix, Not Controlled for Occupation [Table 3]

			Predicted Value			
			Male	Female	Missing	Total
Actual Value	OCC Mundial	Male	48.45	9.54	42.00	14,515
		Female	7.39	48.07	44.54	14,048
	Bumeran	Male	46.45	9.82	43.74	5,643
		Female	7.56	52.14	40.30	6,045
	CompuTrabajo	Male	54.13	6.95	38.93	10,217
		Female	10.26	40.68	49.06	30,915

Note: Data include all ads that explicitly discriminate, including test and training samples.

Table S11: LASSO Confusion Matrix, Controlled for Occupation [Table 3]

			Predicted Value			
			Male	Female	Missing	Total
Actual Value	OCC Mundial	Male	53.50	9.92	36.58	14,515
		Female	5.50	54.98	39.52	14,048
	Bumeran	Male	49.28	10.54	40.17	5,643
		Female	4.22	58.35	37.44	6,045
	CompuTrabajo	Male	60.14	8.11	31.74	10,217
		Female	6.9	52.0	41.1	30,915

Note: Data include all ads that do not explicitly discriminate.

Table S12: Out-of-Sample LASSO Prediction (Non-Gender-Targeted Ads), Not Controlled for Occupation [Table 4]

	Out-of-Sample Prediction			
	Male	**Female**	**Missing**	**Total**
OCC Mundial	22.01	24.30	53.69	1,446,467
Bumeran	15.55	33.36	51.09	508,842
CompuTrabajo	20.84	23.45	55.71	448,159

Note: Data include all ads that do not explicitly discriminate.

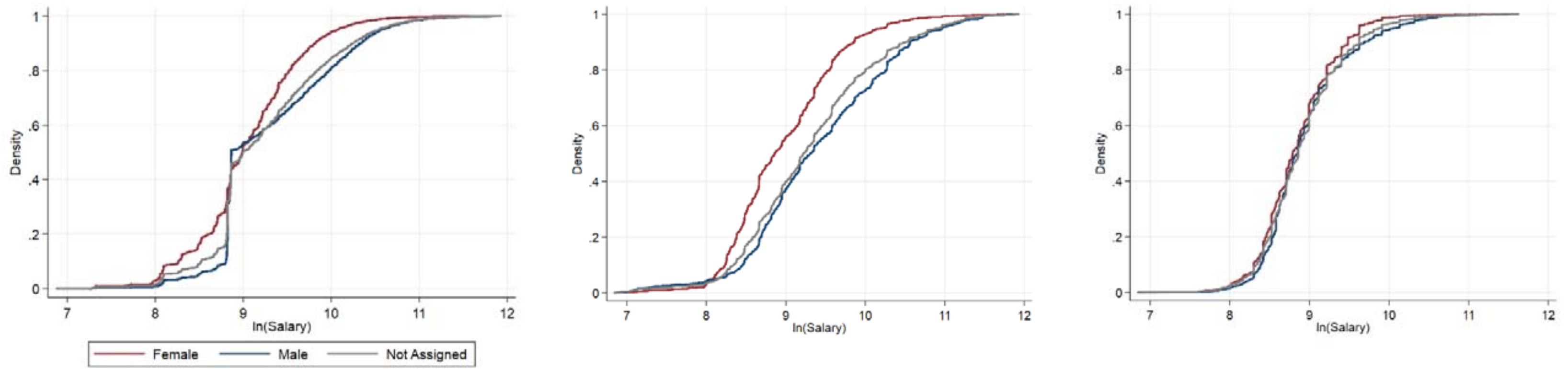
Table S13: Out-of-Sample LASSO Prediction (Non-Gender-Targeted Ads), Controlled for Occupation [Table 4]

	Out-of-Sample Prediction			
	Male	**Female**	**Missing**	**Total**
OCC Mundial	22.38	29.25	48.36	1,446,467
Bumeran	13.45	41.18	45.37	508,842
CompuTrabajo	20.27	33.27	46.45	448,159

Note: Data include all ads that do not explicitly discriminate.

Figure S6: Cumulative Density Functions of Salary by Predicted Gender, Controlled for Occupation [Figure 8]

OCC Mundial	Bumeran	CompuTrabajo



Note: Data include ads with predicted gender targeting, based on the random forest algorithm..

Figure S9: Total number of job advertisements, by date

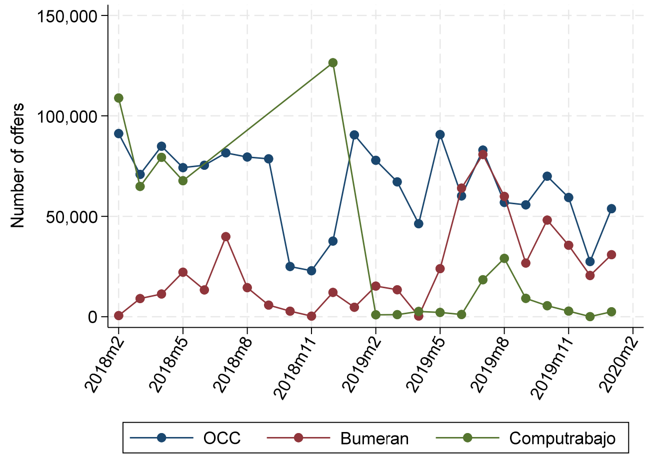


Figure S10: Percentage of advertisements including salary, by date

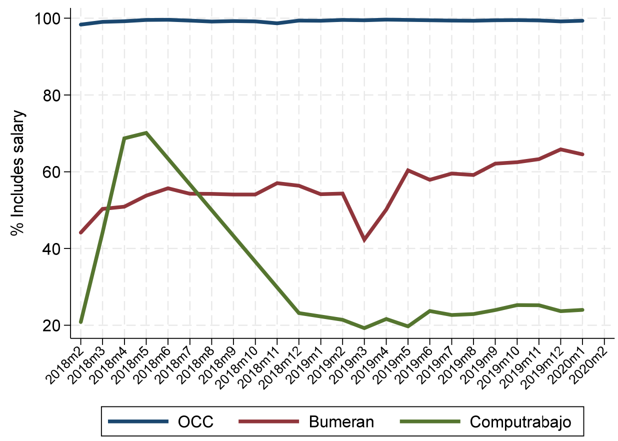


Figure S11: Percentage of advertisements specifying age, by date

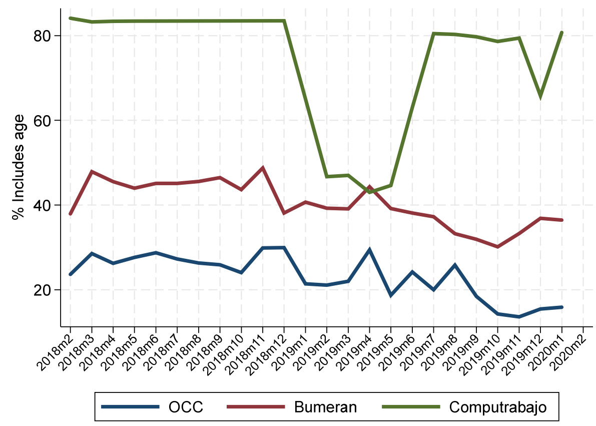
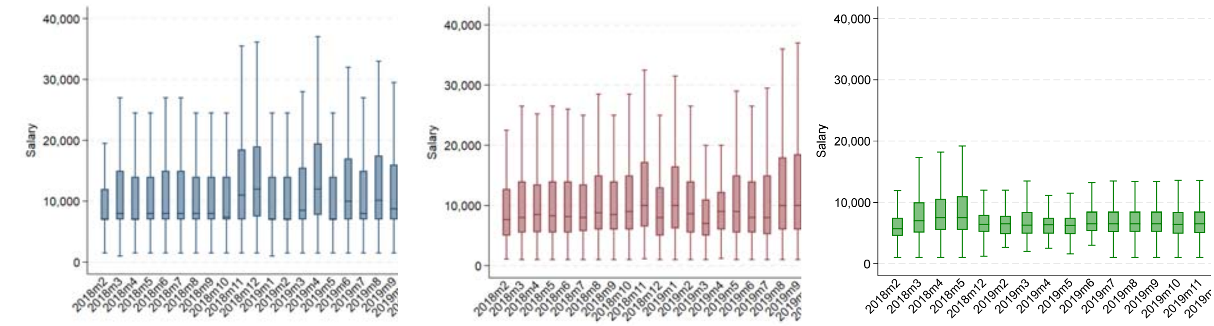


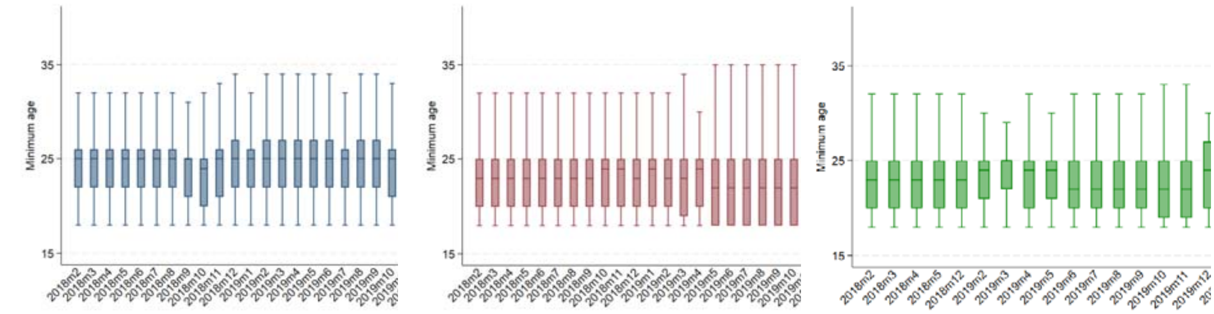
Figure S12: General descriptive statistics specified in ads, by date

OCC Mundial	Bumeran	CompuTrabajo

Panel A. Salary (MXN/mo.)



Panel B. Minimum age



Panel C. Maximum age

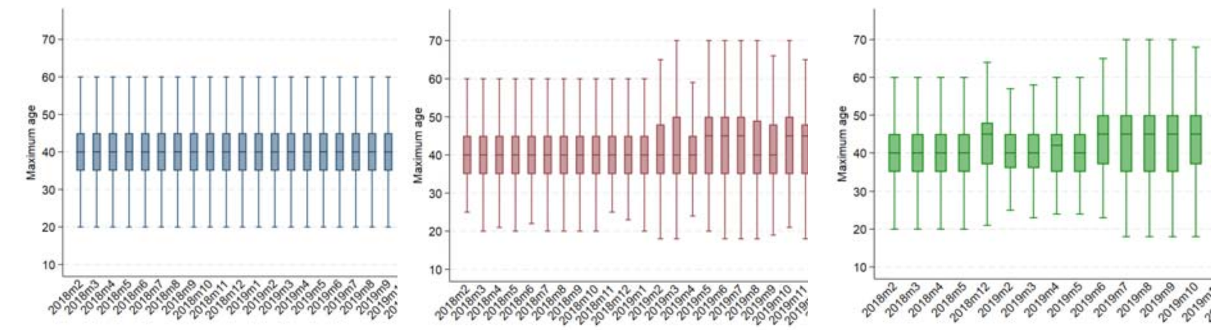


Figure S13: Descriptive statistics specified in ads, by date