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Do labour market conditions affect the extent of gender discrimination?

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Abstract: The market environment in which discriminatory firms operate may be a relevant determinant of their extent of discrimination. In this paper we aim at analysing the effect of local labour market conditions on a firm's decision to discriminate. We use a direct measure of discrimination using online job advertisements which use ascriptive characteristics (such as gender, age, marital status or even physique) to describe their ideal candidates, to which we will refer as explicit discrimination. In theory, the effect of the unemployment rate on discrimination is ambiguous. Using data from over 300,000 online job ads, we find suggestive, though not definitive, evidence that firms explicitly discriminate more when the unemployment rate is higher: a percentage point increase in the unemployment rate is correlated with a 0.7 percentage point increase in the probability that an ad is targeted. We also found that in slack labour markets, firms tend to target their ads to men more often than in tight labour markets. However, as the unemployment rate increases firms discriminate less on the basis of beauty.

Keywords: discrimination, gender, labour market tightness, job ads, Mexico
JEL classification: J10, J16, J70, O54

Tables and Figures: at the end of the paper.

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1 Introduction

Since the seminal work of Becker (1957), economists have been studying discrimination in the labor market, and other markets.[1] Despite the fact that recent literature in economics has made an increasing effort to measure the extent of discrimination in the labor market, less attention has been paid to the way discrimination responds to the environment in which employers operate. We would expect two variables affecting this environment to have a direct effect on discrimination. The first one was modeled by Becker (1957): taste-based employer discrimination would not survive in a competitive product market. There is a large literature that empirically tests that relationship.[2] The other variable would be the conditions in the local labor markets. According to Biddle and Hamermesh (2013) the effect of labor market tightness on discrimination is ambiguous due to the existence of two opposing effects. Knowing what the overall effect is has important implications regarding inequality during the business cycle. Our aim is thus to contribute to the discussion of whether we should observe more or less discrimination in tighter labor markets.

In our reading of the literature there are only two recent papers addressing our research question.[3] Biddle and Hamermesh (2013) analyze whether wage gaps in the United States vary with the business cycle. They look into wage gaps defined by the difference between the wages of non-Hispanic white men and either of the following three groups: white women, African American men, and Hispanic men. They find that the wage disadvantage of women and Hispanics is counter-cyclical (i.e. the wage gap grows during economic downturns or as unemployment rates increase) and that the wage disadvantage of African Americans is pro-cyclical. These effects include both the pure discrimination effect and a composition effect of those employed over the business cycle. Biddle and Hamermesh provide indirect evidence that the pro-cyclical behavior of the African American wage gap is mostly explained by a composition effect, and that, in contrast, the counter-cyclical behavior of the gender wage gap seems to be a pure discrimination effect.

In order to explain their findings, Biddle and Hamermesh develop an equilibrium search model with discrimination. In the model, the shocks are modeled as changes in the productivity of two types of workers, one of which is preferred. A negative shock to productivity has two opposing effects on the wage gap. First, the authors explain that a fall in the opportunity cost of waiting for the preferred candidate induces more employers to open discriminating positions in the margin. This *opportunity cost effect* will decrease the bargaining power of the minority. In our context, if this effect dominates, a higher unemployment rate leads to more discrimination in the job positions advertised. Second, since output is lower, the value of keeping vacancies open decreases for every type of employer; firms will thus destroy both discriminating and non-discriminating vacancies (this is what the authors call the infra-marginal positions). However, the market ends up destroying more discriminating positions than non-discriminating positions (*the*

[1] See the literature reviews in Altonji and Blank (1999), Bertrand (2011), Cain (1986), Fryer (2011), Pager (2007) and Pager and Shepherd (2008).

[2] See, for instance, Ashenfelter and Hannan (1986), Berson (2012), Black and Strahan (2001), Black and Brainerd (2004), Hellerstein et al. (2002), Heyman et al. (2013), Hirsch et al. (2014), and Weber and Zulehner (2014).

[3] Biddle and Hamermesh (2013) refer to some literature from the 1970s that tried to measure the response of wage differentials to the business cycle: Ashenfelter (1970), Freeman (1973), and O'Neill (1985). Kuhn and Shen's (2013) analysis could be included in this literature, but their analysis is in a different context. In their case, a tighter labor market is related to the scarcity of skilled workers relative to unskilled workers, thus the interpretation of tightness is not entirely the same.

relative destruction effect). This latter effect leads to a higher relative bargaining power of the minority candidates. In our context, there would be a change in the compositions of positions. If this effect dominates, then there will be less discrimination in the job positions advertised at higher unemployment rates. Thus the effect of an economic downturn (unemployment rates) on discrimination is ambiguous.

Baert et al. (2015) provide more direct evidence of the effect of labor market tightness on discrimination. They conducted a correspondence test in the Belgian labor market in which they sent fictitious Curriculum Vitaes (CVs) responding to online job ads. The origin of the worker was implied by her name as being either of Flemish origin or Turkish descent. In order to test for the effect of tightness, they selected occupations in tight and slack market conditions. They find that bottleneck occupations (i.e. those in a tight market) are as likely to call back a Turkish or a Flemish applicant. In contrast, non-bottleneck occupations discriminate against Turkish applicants. They performed various robustness checks to their research design. Given the illegality of discrimination in most countries, economists have resorted to this kind of correspondence studies to uncover discrimination. The problem with these correspondence studies is that their scope is very limited: their experiment was limited to Ghent and Antwerp, where they sent 752 CVs responding to 376 vacancies.

There are, however, some contexts in which discrimination is not entirely banned. For instance, job advertisements in some countries are permitted (or at least are not forbidden) to exclude entire segments of the population on the basis of gender, age, physical appearance, marital status and other ascriptive characteristics which are not directly related to labor productivity. We will refer to this phenomenon as explicit or overt discrimination in job ads. In this paper we exploit this explicit discrimination in order to study how discrimination is affected by labor market tightness. We address two important caveats of the recent literature on the topic. First, our study is not limited to a few cities, as in Baert et al. (2015) since it uses national data; and second, our measure of discrimination is very direct as opposed to wage gaps whose changes, as we explained, include composition and discrimination effects (Biddle and Hamermesh 2013).

The use of data from job advertisements to analyze discrimination is not entirely new. In this literature, overt or explicit discrimination refers to the behavior of employers who use ascriptive criteria in their descriptions of the ideal candidate for a job position in a job advertisement. For instance, job ads may be directed only to men, or only to women, or use other characteristics like age, height, or beauty to target their ads to a more specific set of candidates. Darity and Mason (1998) give an account of how in the pre-Civil Rights Act era job advertisements overtly discriminated against African Americans. The Civil Rights Act in 1964 prohibited such explicit exclusion, and thus, after its passing, job ads took less blatant forms of discriminating and eventually disappeared over time. Mostly for this reason, the literature on discrimination in advanced economies uses indirect ways to uncover discrimination such as wage gaps, occupational segregation, and correspondence and audit tests. This is not to say that countries which still allow for such overt discrimination in job ads do not exhibit differentials in other employment variables. Lawler and Bae (1998) are one early example of the use of job ads to study discrimination in the labor market. They want to test whether multinational firms are more or less gender discriminating in Thailand depending on the culture of the firm's country of origin.

More recently, Kuhn and Shen (2013) studied gender discrimination using explicit discrimination in job ads in China. They found that gender-targeted job ads are quite common, but among these ads roughly half request women. There are differences between job ads requesting women and men: ads requesting women tend to also make a statement about physical appearance, and ask for young applicants, whereas, ads requesting men ask for older applicants. Kuhn and Shen also find that high-skilled jobs target gender less often than low-skilled jobs, a feature they call negative skill targeting. Another interesting fact in their data is that a substantial part of the variation in gender-targeting occurs within firms rather than between firms, which means that a single firm may exhibit different gender preferences across its posted ads.

Those facts are hard to reconcile with common explanations about gender discrimination such as occupational segregation or glass ceilings. In order to better explain those facts, and in particular the negative relationship between skill and gender-targeting, Kuhn and Shen (2013) built a search model in which firms have a tradeoff between their gender preferences for a job position and the skill level of the job. They argue that as the skill level rises, the market becomes tighter, and thus the probability of filling a vacancy is more modest. The firms thus stop using gender as an ex-ante screening variable in the hiring process in order to find the most suitable candidate for that high-skilled position. They test their model empirically and find that jobs that require higher education levels, more experience or post higher wages have a lower propensity to gender-target the ad.

Delgado et al. (2016) extend Kuhn and Shen's (2013) analysis to include more job posting websites in China and a website in Mexico. In this paper, they emphasize a phenomenon they name "age-twist" in gender targeting: the preference of men over women increases as the required age increases. Delgado et al. (2016) advance that a combination of preference for gender, beauty, leadership skills and marital status may be driving the "age-twist". In this analysis, they are able to introduce marital status and leadership skills due to their use of Mexican data. Mexican employers also state such requirements in their gender ads when they have a strong preference for such candidates. However, neither Kuhn and Shen (2013) nor Delgado et al. (2016) include the effect of local labor market conditions on their analysis. As we explained, their notion of tightness comes from the relative scarcity of high-skilled workers relative to low-skilled workers; and, thus, is not the "macro" notion of tightness (as in Biddle and Hamermesh 2013) nor the "bottle-neck" notion of tightness (as in Baert et al. 2015).

In sum, according to Biddle and Hamermesh (2013) the effect of the business cycle on discrimination is ambiguous, and is thus an empirical question. In order to provide evidence towards the sign of this effect, we use explicit or overt discrimination in job advertisements posted in occmundial.com.mx in Mexico. This is a direct measure of discrimination in the labor market as opposed to wage gaps, a measure that confounds many causal variables, as in Biddle and Hamermesh (2013). We collected data on over a million job ads between August, 2014 and June, 2015. We have job ads for each of the 31 states in Mexico and Mexico City and, thus, it is not limited to a few cities as Baert et al. (2015). The data for local labor market conditions come from the National Labor Survey and cover the same period of the job ads data. Labor market tightness is measured with the unemployment rate, the job-searchers rate and a vacancy rate built up from the job ads data. Using this data we regressed the probability of gender targeting on our measures of tightness and various fixed effects to control for confounders of the effect of tightness.

We find evidence that firms explicitly discriminate more when the unemployment rate is higher: a percentage point increase in the unemployment rate is correlated with a 0.7 percentage point increase in the probability that an ad is targeted. We find that in slack labor markets, firms tend to target their ads to men more often than in tight labor markets. In this case the fall in the opportunity cost of waiting to fill the vacancy (opportunity cost effect) dominates the effect that the job destruction of discriminating positions has on the bargaining power of the dispreferred candidates (job destruction effect). We also tested whether other types of discrimination respond to unemployment rates. Our findings indicate that beauty and physique targeting decrease as the unemployment rate goes up. In this case, the job destruction effect dominates the opportunity cost effect.

The rest of the paper is organized as follows. Section 2 describes the research design starting with our data, descriptive statistics and then the empirical specification. Section 3 presents our main results and robustness checks. Finally, Section 4 discusses the implications of our results for public policy and concludes.

2 Empirical strategy

2.1 Data and descriptive statistics

Our data come from two main sources. First, we built a dataset from the universe of job ads posted by OCC Mundial August, 2014 and June, 2015. OCC Mundial is one of the largest online job boards in Mexico. In order to download the data, we used a web crawler programmed in Python which visited and downloaded the job postings in occmundial.com.mx twice per day.[4] After the job ads download stage, we used Natural Language Processing (NLP) and regular expressions in order to build the database itself. Each job ad has three main fields of data: 1) general information on the job ad: a title, firm and date posted;[5] 2) specific fields of the job ad such as wage, type of contract, category and subcategory of the job position, and the locality; and 3) the body of the job post which includes a description of the desirable candidates. We collected information (when available) on the date posted; job ad title; firm; firm's geographic location;[6] experience and education requirements; minimum and maximum wage offer; restrictions on gender, age, physical appearance,[7] and marital status; and other desirable characteristics of the job candidate.[8]

Table 1 reports the mean and standard deviation of the universe of job advertisements posted in OCC Mundial during the period of analysis. We have information on 1,010,884 job ads located in all 32 states in Mexico.[9] Of this universe, 12 percent of ads were gender-targeted and roughly an equal amount target women or men, which is also a stylized fact found in Kuhn and Shen (2013) and Delgado et al. (2016). Less than half of the ads specified the educational qualifications, about 27 percent required a candidate with a university degree, 13 percent of ads required applicants with at least high school qualifications, and the rest of the ads required lower qualifications or technicians. Another common skill requirement is years of experience. Around 24 percent of ads required the candidates to have a certain experience level, the most common

[4] Each job post survives until the firm decides to delete it, which may be due to having filled the vacancy or to having destroyed the vacancy.

[5] Even when this is a field that the employer is supposed to fill, about 10 percent of the ads do not have the firm's name.

[6] We have a lot of missing information on the firm's zip code (88 percent of the observations) and even the firm's city (74 percent of the ads). The data from ENOE can be used at the city level, but given the missing information we decided to aggregate the data at the state level.

[7] Physical appearance includes skin color, beauty (translated from *buena presentación* in Spanish, whose literal translation is "good presentation"), and physical constitution.

[8] These characteristics include (among others): bonuses and fringe benefits; English command; ability to work under pressure or in teams; being responsible, kind or obliging; having a driver's license; and whether the job ad required some command of certain software (though we did not collect the type of software).

[9] The sample size in descriptive statistics and regression results differs due to missing data. Please refer to Appendix A for a discussion on the differences between the complete sample and the estimating sample.

being 1 to 3 years of experience and the mean being 3.2 years of experience. Another useful measure of the skill level that Kuhn and Shen (2013) used in their paper is the expected wage to be earned in the job position. In contrast to that paper, more than half of the ads had information on the expected wage, the mean maximum monthly wage was $14,813 pesos and the minimum monthly wage was $11,581 pesos.[10] Although the Mexican Supreme Court recently ruled against age restrictions in job ads, we found that 36.5 percent of the job ads had age requirements. The mean minimum required age was 24.5 years and the mean maximum required age was 42 years. Also arguably unrelated to productivity, almost 1 percent of the ads required the applicants to be either married or single: 0.6 percent of ads solicited married applicants, and 0.4 percent, single applicants.

There were many other requirements listed in the ad; some related to productivity and others to the willingness of the applicant to work under certain conditions. In Mexico, 10 percent of ads solicited applicants with "good presentation", which we interpret as a request for beauty. Also 10 percent of ads requested a photograph in the curriculum vitae. We also found that 8.8 percent of the ads required candidates willing to travel, 13 percent requested having the ability to work under pressure, 1.1 percent requested kind and 11.4 percent obliging applicants, 16.7 percent requested a certain command of English, and 8.1 percent required the ability to work in teams. Even though we do not report it in the table, we also found three ads requesting a specific color of skin, and around 800 ads requiring a desirable constitution (mostly athletic or thin candidates, but also some ads requesting applicants with a plumper make-up). Table 1 also reports on the types of contracts explicitly offered in the ads. More than 20 percent of ads specified the type of contract: part-time jobs (1.7 percent), full-time jobs (21 percent), and whether the position was permanent (2.8 percent, which may have social security) or by fees (0.2 percent, which do not have social security). OCC Mundial allows for the classification of job ads into categories and subcategories of economic activity. Almost 50 percent of the ads were classified as services.[11]

The data on local labor market conditions come from the National Labor Survey in Mexico (ENOE for its Spanish acronym). This is the survey used to build national employment statistics in Mexico. The ENOE is a rotating panel that interviews households during five consecutive quarters, and then resamples the household. Each quarter ENOE surveys around 120,260 dwellings nationally. The survey is representative at the national, state, city, and urban/rural level. Using the data from the third quarter of 2014 to the second quarter of 2015, we estimated the unemployment rates in urban areas at the state level.[12] Given that the unemployment rate is not a good measure of the level of economic activity in the presence of a large informal sector, we also estimated informality rates, rates of sub-occupation, partial occupation and critical work conditions, which may also give an indication of local labor market tightness. In this paper, informality is defined by those without social security from their jobs; the sub-occupied population is defined by those in a work stoppage or whose labor supply in hours is restricted by

[10] The average exchange rate vis-à-vis the US dollar during the period was 14.54. Hence, the maximum wage amounts to US$1,018 and the minimum wage to US$796 per month on average. These are rather large figures as compared to the average monthly wage in Mexico.

[11] OCC Mundial's classification is not good. Many of the subsectors listed within "Services" are in fact sales positions and other sectors could be classified as services, such as law and education. Many of the professional services listed could be hired within a given sector such as human resources personnel in the construction sector. Thus the extent of the service sector is not as straightforward as implied by OCC Mundial's classification of the job ads. Appendix Table A3 presents the distribution of job ads across OCC Mundial's sector classification. In comparison, workers in the service sector in national labor surveys represent just over 50 percent of the workforce (see Appendix Table A4).

[12] Urban areas are defined as those with more than 15,000 inhabitants.

the general economic activity; partial occupation is the sum of the unemployed and those working less than 15 hours per week; and those in critical work conditions work less than 35 hours per week, or more than 35 hours per week earning the minimum wage or less. Unemployment and partial occupation rates are estimated with respect to the labor force, and informality, sub-occupation and critical work conditions rates are estimated with respect to the employed population. Table 2 presents the summary statistics of these measures. Unemployment rates are typically low in Mexico, ranging around 5 percent during this period. The rates of partial occupation, sub-occupation and critical work conditions are much higher amounting to 10.6, 7.7 and 9.7 percent, respectively. Informality rates are very high among Mexican workers representing 54.7 percent of the working population in urban areas.

Table 3 compares the characteristics of the job ads to a representative sample of employees from the National Labor Survey. The first column presents the means for the ads dataset; the second column, the means for the urban sample of ENOE; the third column, the means for the employed in urban areas; and the fourth column, the means for the job searchers who are those unemployed and those who are looking for work on the job. The job ads data has younger people than ENOE, but its age is representative of the job-searchers in ENOE. OCC Mundial advertises jobs whose wages are almost six times higher on average than those of the employed population in ENOE. We estimated the proportion of ads for females, married applicants and by education level only for the ads listing each of those requirements. As we reported in Table 1, almost half of the gender-targeted ads solicit women, whereas 52.8 percent of the employed and 37.6 percent of the job searchers in urban areas are women. In addition, 62.3 percent of the ads targeting marital status solicit married applicants, while only 45 percent of the job searchers are married. Finally, our sample of ads with education requirements solicits candidates with higher skills than the average worker or job searcher at ENOE.

2.2 Is there gender discrimination in this labor market? Some stylized facts

Table 4 presents a descriptive analysis of the relation between discrimination in job ads and skills. As explained in Kuhn and Shen (2013), we expect that at higher skill levels, the proportion of ads with gender-targeting decreases given that skills are a scarce resource in this labor market. First, we use education as our measure of human capital and we find the same negative skill targeting as in Kuhn and Shen (2013) and Delgado et al. (2016): as the education requirements increases from lower-secondary to college, the amount of gender-targeted ads decreases. The least targeted ads in our data are those with no education requirements. Next, we looked into the relationship between explicit gender discrimination and years of experience required for the job. We find that there is also a decreasing relationship between the years of experience required and the percentage of gender-targeted ads: 66.67 percent of ads requiring no experience were targeted (to women), while 6.2 percent of ads requiring more than five years of experience solicit a specific gender.

Our last measure of human capital is the expected wage to be earned in the job. Here, we measured the wages at midpoint between the minimum expected wage and the maximum expected wage. First, we observe that if the ad posts an expected wage, there is less gender-targeting (6.5 percent of ads are gender-targeted) than if the ad does not post an expected wage (15.1 percent of ads are gender-targeted). Then we analyzed the relationship between the wage level and gender discrimination among the ads that did post a wage. We found a U-shaped relationship between the wage level and the percentage ads that are not gender-targeted. The ads offering between $6,000 and $9,999 Mexican pesos (ads with wages between the 25th percentile and the median) are the ones that gender-target the most, about 18 percent of the ads are gender-targeted. Ads offering more than $26,000 pesos (90th percentile) are the ones that target the least; approximately 6.8 percent of the ads are gender-targeted.

There is another interesting relationship between human capital and gender-targeting: the proportion of ads targeted to women decreases as the ads require more years of experience or offer a higher wage, though the relationship is non-monotonic (see Panel A and B in Figure 1). The relationship between women-targeting and education is not as clear. We find that ads requiring the least education qualifications target more men (73 percent of gender-targeted ads), ads requiring high school target more women (53 percent), and ads requiring college are more or less balanced between men and women (49 percent are women-targeted). Recall that when we look at all gender-targeted ads, half of the ads targeted men and half of the ads targeted women. Our findings here suggest that low-skilled jobs target women much more often than high-skilled jobs: a skill-twist in gender-targeting.

In sum, our data confirm the presence of a negative correlation between skills and the proportion of gender-targeted ads. We found this relationship when using education and experience as skill measures. When using wages as a measure of skill, we found an inverted U-shape relationship between offered wages and gender-targeting, but overall, low-pay jobs gender-target more than high-pay jobs. In addition we found that gender-targeted ads which require more experience or offer higher wages tend to target more men than women.

The ads list other sets of requirements which may or may not be directly related to productivity. Table 5 presents the proportion of ads targeted to women, men or both sexes by each of these additional requirements. We first look into age restrictions: ads with age restrictions gender-target more than ads without age restrictions (75 percent vs. 96 percent untargeted ads), independently of whether the restriction is a minimum age, a maximum age, or both. We also find that as the age restriction increases, the proportion of gender-targeted ads decreases in accordance with our finding on years of experience. If we focus on ads that are gender-targeted, we confirm Delgado et al.'s (2016) finding on an age-twist: even though there is an overall balance in ads targeted towards women and men, when ads requiring young applicants are primarily targeted towards women, and ads requiring older applicants are primarily targeted towards men (see Figure 2). Given the facts in Figure 1, we claim that more than an age-twist, we are in the presence of a skill-twist in female-targeted ads.

Table 5 also presents the proportion of targeted and untargeted ads by beauty requirements. Here we see that the proportion of targeted ads asking for beauty is above average, and that they predominantly target women (75 percent of gender-targeted ads). This finding is in accordance with the findings in Kuhn and Shen (2013) and Delgado et al. (2016). We also look into other traits listed in the ads. We find that those traits related to work conditions (such as willingness to travel, and the ability to work under pressure or with teams) have a greater propensity to target men, than those traits related to desired behavior (such as being kind or obliging, presumably towards customers) which are more prone to target women. Some ads also require English command. These ads exhibit below average gender-targeting and tend to be more directed towards women. Finally, Table 5 presents the proportions by type of contract. Here we do not find any significant differences with respect to the overall averages: these ads target gender around the average and are balanced across the sexes.

According to Kuhn and Shen's (2013) model, we would expect broader searches whenever the firms expect the labor market to be tighter. This translates into a broader search for high-skilled job positions as compared to low-skilled job positions because in an economy like China's skills are scarce. The same could be argued about Mexico, and our findings in Table 4 point in that direction. However, the scarcity of skills is not the only factor that determines labor market tightness. In an equilibrium search model, labor market tightness depends on the number of vacancies vis-à-vis the number of job searches in the market: the higher the number of vacancies or the lower the number of searchers *ceteris paribus*, the tighter the market.[13] Thus we would expect firms to search broadly when the vacancies rate is high or when the unemployment rate is low.

Figure 3 presents suggestive evidence in favor of that idea, where we use proxy measures of labor market tightness. The number of searchers is proxied by the job-search rate, the unemployment rate and the partial occupation rate. The number of vacancies is roughly proxied by the number of vacancies posted in OCC Mundial over the labor force. The figures present a scatterplot with the rates in the X-axis and the proportion of untargeted ads, a measure of a broader search, in the Y-axis. The line is just a linear fit between the proportion of untargeted ads and the corresponding rate. Panel A uses the job-search rate and we find the expected negative relationship between tightness and broadness of search: the greater the job-search rate, the less tight is the market, and thus firms are more prone to target their ads. Panel B uses the unemployment rate, and Panel C uses the partial occupation rate. Those measures also have a negative relationship with the proportion of untargeted ads. Finally, Panel D uses the vacancies rate. Recall that labor market tightness is positively related to the number of vacancies, thus the higher the vacancies rate, the tighter the market. Our hypothesis is that as the market gets tighter, the firms start searching broadly (the proportion of untargeted ads increases). This is precisely the positive correlation that we find in Panel D of Figure 3.[14] We interpret these findings as suggestive evidence that discrimination decreases when the firms face a tighter labor market. We will turn next to some econometric results to strengthen these findings.

2.3 Empirical specification

The empirical specification follows both Kuhn and Shen (2013) in the definition of the dependent variables, and Biddle and Hamermesh (2013) in the addition of local labor market conditions to the regression in order to test our working hypothesis. Kuhn and Shen's theoretical model can be tested using an ordered probit where the dependent variable is the probability that the job advertisement is targeted to women, to both sexes or to men. However, the ordered probit cannot be estimated because of its intractability in the presence of a large number of firm fixed effects. The authors argue that the coefficients of the ordered probit can be identified up to a factor of proportionality by means of two OLS regressions. First, we estimate the following regression:

$$(P^M + P^F)_{ist} = \alpha + \beta T_{st} + \gamma \log(wage)_{isqt} + \delta_{FE} + \varepsilon,$$

[13] In the equilibrium search literature, labor market tightness is defined by the ratio $\frac{v}{u}$, where v is the number of vacancies posted by firms, and u is the number of unemployed workers looking for jobs (Rogerson, Shimer and Wright 2005).

[14] Figure A1 in the Appendix presents similar scatterplots but using the informality rate, the sub-occupation rate and the critical work conditions rate. The informality rate and the critical work conditions exhibit a positive correlation with the proportion of untargeted job ads. This finding runs counter to our working hypothesis; however, it may be the case that these are not good measures for the number of job searchers. Not all of the informal sector can be seen as a fallback option to unemployment. There is increasing evidence favoring the notion that the Mexican labor market is integrated, or at least not completely segmented (Bosch and Campos-Vázquez 2014; Juárez 2008; Maloney 1999). Thus, the informality rate may provide other kinds of information about the labor market, other than how tight the market is. On its part, the sub-occupation rate also exhibits a negative relationship with the proportion of untargeted ads. This is why we only interpret this graphical evidence as suggestive.

where P^M is the probability that the ad *i* is targeted to men; P^F, the probability that the ad is targeted to women; *s* denotes the state, and *t* time; T_{st} is a measure of labor market tightness; *wage* is the ad's wage offer; and δ_{FE} denotes various fixed effects at the state, time, firm, or occupation level. Since the sum of those two probabilities is equal to the probability that an ad is gender-targeted, then the dependent variable is just a dichotomous variable equal to one if the ad is gender targeted and zero otherwise. And hence, this equation estimates the determinants of gender targeting. The logarithm of wages is used as a control variable given that in the previous section we found that gender targeting is correlated to human capital measures. We do not include education and experience in the regression analysis as in Kuhn and Shen (2013) because there is a large proportion of ads that have these data missing. In fact, we have more ads with a wage offer than either education or experience requirements.[15]

The second regression is given by:

$$P^M - P^F = \alpha + \beta T_{st} + \gamma \log(wage)_{isqt} + \delta_{FE} + \varepsilon,$$

where $P^M - P^F$ takes values -1, 0 or 1. This equation identifies the vector of coefficients that explain whether a firm targets to women (-1), to both sexes (0), or to men (1); that is, the regression explains the direction of the gender targeting. The next section presents the results of these estimating equations.

3 Results

Table 6 presents the estimations for the probability of gender-targeting. Each column in the table controls for different subsets of fixed effects. The standard errors in our estimates are clustered at the state and quarter level. The first column controls for state fixed effects. Here we find that a percentage point increase in the unemployment rate leads to a 0.733 percentage point increase in the probability of an ad being gender targeted. This estimate is robust to the inclusion of firm fixed effects, the interaction of firm and occupational categories, and the interaction of firm and occupational subcategories, ranging between 0.73 and 0.67. However, the estimate is not robust to the inclusion of quarter fixed effects. Recall that we only have a year of unemployment rate data, and thus with the inclusion of quarter fixed effects we are close to saturating the model.[16] According to these results, the opportunity cost effect on discrimination dominates the job destruction effect, thus firms indulge more on discrimination when the unemployment rate is higher.

An interesting result in Table 6 is that gender targeting responds to wages in a non-linear fashion. This result runs counter to the evidence found in Delgado et al. (2016) for another job board in Mexico and China, and to Kuhn and Shen (2013) for China, where they find that as wages increase, gender targeting decreases. In our descriptive analysis we found that there was a U-shaped relationship between gender targeting and wages, a result that we corroborate in our regression results.

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[15] This may be due to the fact that OCC Mundial has the minimum and maximum wage offer as fields to be filled in their system, but there are no such fields for education and experience.

[16] When using both state and quarter fixed effects we would be identifying the parameter of interest using within state quarterly deviations of the unemployment rate from a quarterly average. So it is possible that we are eliminating much of the variation in unemployment rates, especially for a period with no serious shocks to the economy.

Table 7 presents the estimates of the determinants of gender targeting but now using various measures of labor market tightness. As we mentioned before, the unemployment rate may not be the ideal measure of labor market tightness in a developing country given the existence of a large underground economy. As expected, given our finding in Figure 3, our findings are robust to the use of the job-search rate and the partial employment rate as measures of tightness. The job-search rate is dominated by the unemployment rate, so this result was entirely expected. The coefficients on the informality rate, although insignificant in most cases, at least have the sign predicted by the theory. In contrast, the coefficients on the sub-occupation rate, the critical work conditions rate and the vacancies rate change signs across estimations. These latter measures of tightness and the informality rate may be capturing different aspects regarding the functioning of labor markets that are unrelated to tightness. We are worried that the quality of jobs is varying over the business cycle, and that this quality is somehow related to discrimination. Finally, our results are not very robust to the vacancies rate measure of tightness; the sign is as expected only once we include quarter fixed effects. Recall that the vacancies rate was estimated using the vacancies data from OCC Mundial. We estimated the correlation between the vacancies rates and the unemployment rate and found that it is positive. Since our measure of the unemployment rate covers all the local labor market, and the measure of the vacancies rate covers only a share of the online vacancies, it is possible that there is a change in the composition (or advertisement means) of vacancies at different levels of the unemployment rate. We cannot test this hypothesis with our data.[17]

Table 8 considers the direction of the gender target. Recall that if the ad is targeted to females, the dependent variable $P^M - P^F$ takes on a value of -1; if it is targeted to men, a value of 1; and if there is no target, a value of zero. In this case, the unemployment rate has a positive coefficient and it is very robust across specifications. A positive coefficient on the unemployment rate means that as the market gets slacker, firms tend to target their ads more towards men.

Finally, Table 9 presents estimates of the effect of the unemployment rate on other measures of discrimination. In this table, our measures of discrimination are: any targeting, age targeting, physique targeting and beauty targeting. "Any targeting" measures whether the job ad was targeted toward a specific gender, an age group or a type of physique. For its part, "physique targeting" measures whether the ad was targeted towards a skin color, a particular physical constitution or to beautiful candidates. We find that the effect of labor market tightness on "any targeting" is negative and statistically significant. After disaggregating this effect into the different types of discrimination, we found that the negative effect is driven by beauty targeting: an increase in the unemployment rate leads to less beauty targeting. We find the unemployment rate is mostly negatively related to age targeting, but the coefficients are not statistically significant. In the case of beauty, the job destruction effect dominates the opportunity cost effect, and thus firms indulge less on discrimination on the basis of beauty. We can also imagine that the rate at which beautiful people arrive at vacancies drops much more than the rate at which non-beautiful people arrive.[18] Hence firms are more willing to open vacancies that admit all types of people.

[17] It is important to notice that the models with quarter fixed effects in the regressions that use the informality rate and the vacancies rate as a tightness measure produce statistically significant results that are "correctly" signed in the light of the unemployment rate suggestive evidence.

[18] This may happen if the search value for beautiful people drops more relative to the search value of non-beautiful people.

4 Discussion and conclusions

The environment in which discriminatory employers operate is an important determinant of the extent of their discriminatory behavior. The literature has mostly focused on testing Becker's prediction that discriminatory firms disappear in the face of competition. In this paper our aim was to find out if there is a relationship between discrimination and labor market tightness, another variable describing such an environment. In theory, we would expect that market tightness induces firms to discriminate less because the option value of keeping a vacancy unfilled decreases. Biddle and Hamermesh (2013) and Baert et al. (2015) are the most recent papers empirically addressing this prediction.

In this paper, we use data from job advertisements, some of which explicitly exclude potential candidates on the grounds of their gender, age, or physical appearance. We collected data from over a million job ads from an online job board (occmundial.com.mx). The data has a description of the ideal candidate as well as some of the conditions of the job position, such as a wage offer, the type of contract and whether the worker will receive any other type of fringe benefits. The use of this data allows us to have a direct measure of discrimination, as opposed to the use of wage gaps (Biddle and Hamermesh 2013) which may be contaminated with composition effects. Furthermore, our data covers the whole country and, thus, is not limited to a few regions as in Baert et al.'s (2015) correspondence study.

Our results suggest that there is a negative relationship between labor market tightness and the extent of discrimination. In particular, we found that a one percentage point increase in the unemployment rate induces an increase of 0.7 percentage points in the probability of a job ad being gender targeted. This estimate is robust to the inclusion of firm fixed effects, the interaction of firm and occupational categories, and the interaction of firm and occupational subcategories. However, the estimate is not robust to the inclusion of quarter fixed effects. We also find that when the unemployment rate increases, firms start targeting their ads more to men than to women.

An obvious limitation of our work is due to the fact that, even though overt discrimination is a direct way to measure the phenomenon, this type of discrimination is only present in a job ad, that is, the very beginning of the hiring process. As such, we cannot make any claims of the response of discrimination to unemployment in hiring, wages, promotions and so on. However, if we can probably make a point that if employment opportunities are limited from the outset, and more limited to women than men when unemployment is high, then the odds of getting hired are not in women's favor.

A restriction on the use of these types of ads may be of no consequence in a country like Mexico. In November 2014 the Supreme Court in Mexico ruled that job ads could not discriminate on the basis of age. Our data were collected from August 2014 to September 2015, and age restrictions in job ads were still pervasive (37 percent of ads have age restrictions) after November 2014. This can only mean that the ability to enforce these rulings is lacking in Mexico. Moreover, this kind of restriction may have no effect if the information on age can be obtained with relative ease (for instance, just by looking at the candidate's resume). However, in an institutional framework with a strong rule of law, prohibiting discriminatory ads may lessen the extent of discrimination (for instance, the United States post-Civil Rights Act in 1964).

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Tables and Figures

Table 1: Job ads descriptive statistics

	Complete sample	
Variable	Mean	S.D.
Gender-targeting:		
Female	0.056	0.229
Male	0.056	0.231
No-targeting	0.888	0.315
Education requirements:		
Junior high school	0.025	0.156
High school	0.130	0.337
Technician	0.053	0.224
University degree	0.268	0.443
No education posted	0.591	0.492
Experience requirements:		
Experience in years	3.237	1.764
None or not posted	0.762	0.426
1 to 3 years	0.172	0.378
4 to 5 years	0.052	0.221
More than 5 years	0.014	0.117
Wage offered:		
Wage posted	0.543	0.498
Maximum wage*	14812.76	21897.64
Mimimun wage*	11581.25	15478.65
Age requirements:		
Has age requirement	0.365	0.481
Has minimum age req.	0.363	0.481
Has maximum age req.	0.364	0.481
Minimum age	24.009	3.660
Maximum age	42.692	17.335
Marital status requirements:		
Single	0.004	0.059
Married	0.006	0.076
No marital status req.	0.991	0.096
Other job requirements:		
Beauty	0.104	0.306
Photograph in CV	0.104	0.306
Willingness to travel	0.088	0.283
Work under pressure	0.130	0.336
Kind	0.011	0.105
Obliging	0.114	0.317
English	0.167	0.373
Team work	0.081	0.272

Table 1: Job ads descriptive statistics (continued)

Variables	Complete sample Mean	S.D.
Type of contract:		
Part-time	0.017	0.129
Full-time	0.210	0.408
Undefined contract	0.778	0.416
Permanent position	0.028	0.166
Position by fees	0.002	0.050
Number of ads	972,013	

Notes: *Wages are measured in Mexican pesos per month. The average exchange rate during the period was about 15.5 pesos per US dollar.

Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015.

Table 2: Measures of labor market tightness

Rate of	Mean	S.D.
Job-search	0.0935	0.0285
Unemployment	0.0494	0.0103
Partial occupation	0.1063	0.0199
Informality	0.5477	0.0971
Sub-occupation	0.0770	0.0374
Critical working conditions	0.0971	0.0441
Observations	128	

Source: Estimations by authors using data from ENOE.

Table 3: Comparison of samples: OCC Mundial ads vs. ENOE

Variable	OCC Mundial	ENOE		
	Job ads	All	Employed	Job searchers[e]
Age[a]	33.3588	39.8823	39.1676	33.4372
Wage[a]	13673.17	2353.56	4076.24	1657.05
Female[b]	0.4970	0.5289	0.4090	0.3765
Married[c]	0.6229	0.5604	0.6101	0.4505
Junior high school[d]	0.0613	0.3097	0.3029	0.3346
High school[d]	0.3188	0.2469	0.2540	0.2743
College or more[d]	0.6567	0.1583	0.2063	0.2079

Notes: [a]Variables defined at midpoint of reported minimum and maximum in OCC Mundial, and levels reported in ENOE.
[b]Mean taken over the ads with gender restrictions.
[c]Mean taken over the ads with marital status restrictions.
[d]Mean taken over the ads with education requirements.
[e]Job searchers include those unemployed (by definition) and those employed looking for jobs.

Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015; and data from ENOE for the 3rd and 4th quarters of 2014, and the 1st and 2nd quarters of 2015.

Table 4: Share of gender-targeted ads by skill requirements

	Women-targeted	Men-targeted	No targeting
Job skill indicators			
Education requirements			
Junior high school	0.0692	0.1888	0.7420
High school	0.0984	0.0856	0.8160
College	0.0705	0.0733	0.8562
No education specified	0.0389	0.0347	0.9264
Experience requirements			
0 years	0.6667	0.0000	0.3333
1 to 3 years	0.0619	0.0764	0.8618
4 to 5 years	0.0275	0.0661	0.9064
More than 5 years	0.0142	0.0473	0.9385
Not posted	0.0569	0.0513	0.8918
Wages posted?			
Posted wage	0.0331	0.0323	0.9345
Did not post wage	0.0745	0.0765	0.8490
Mean by wage*			
Less than $4,000	0.0677	0.0481	0.8842
$4,000 – $5,999	0.0823	0.0784	0.8393
$6,000 – $9,999	0.0971	0.0835	0.8193
$10,000 - $14,999	0.0740	0.0755	0.8505
$15,000 – $25,999	0.0396	0.0681	0.8923
$26,000 or more	0.0189	0.0490	0.9322

Notes: *Estimated at mid-point between maximum and minimum.

Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015.

Table 5: Share of gender-targeted ads by other ad requirements

	Women-targeted	Men-targeted	No targeting
Other job ad requirements:			
Age requirements			
No age restrictions	0.0190	0.0181	0.9628
Minimum age restriction	0.1195	0.1229	0.7576
Maximum age restriction	0.1195	0.1230	0.7575
Has both restrictions	0.1196	0.1230	0.7574
Mean by age*			
Less than 25	0.2035	0.0872	0.7092
25–28	0.1936	0.1114	0.6950
29–31	0.1316	0.1264	0.7420
32–34	0.0807	0.1443	0.7750
35–39	0.0681	0.1437	0.7882
40 or more	0.0470	0.0943	0.8587
Beauty	0.1585	0.0517	0.7898
Willingness to travel	0.0452	0.0935	0.8613
Ability to work under pressure	0.0672	0.0781	0.8547
Ability to work in teams	0.0591	0.0615	0.8794
Being kind	0.1747	0.0624	0.7629
Being obliging/helpful	0.0821	0.0602	0.8577
English command	0.0397	0.0310	0.9293
Type of contract			
Full-time contract	0.0724	0.0784	0.8492
Undefined contract	0.0509	0.0508	0.8983
Permanent position	0.0554	0.0562	0.8884

Notes: *Estimated at mid-point between maximum and minimum.

Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015.

Table 6: Probability that an ad is gender targeted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment rate	0.733**	-0.080	0.670**	0.722***	0.717**	-0.121	-0.200	-0.192
	[0.312]	[0.362]	[0.296]	[0.275]	[0.329]	[0.357]	[0.345]	[0.512]
Log(wage)[a]	-0.237***	-0.239***	-0.230***	-0.229***	-0.209***	-0.232***	-0.230***	-0.210***
	[0.040]	[0.040]	[0.039]	[0.041]	[0.058]	[0.039]	[0.041]	[0.058]
Square of Log(wage)	0.017***	0.017***	0.016***	0.016***	0.014***	0.017***	0.016***	0.014***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.001]	[0.001]	[0.003]
Other controls:								
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE		Y				Y	Y	Y
Firm FE			Y			Y		
Firm * Occupation category FE				Y			Y	
Firm * Occupation subcategory FE					Y			Y
Observations	362,094	362,094	362,094	362,094	362,094	362,094	362,094	362,094

Notes: [a] Wage offer is estimated at mid-point between the minimum and the maximum wage offer. The estimated model is a linear probability model. The unemployment rate is measured as a proportion. Standard errors clustered at the state and quarter level are presented in parentheses. ***, **, and * denote significance at the 1%, 5% and 10%, respectively.

Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015, and ENOE data from III:2014 to II:2015.

Table 7. Gender targeting and labor market tightness using other measures of tightness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Job-search rate	0.820***	-0.143	0.738***	0.605**	0.600	-0.166	-0.150	-0.007
	[0.248]	[0.263]	[0.244]	[0.263]	[0.370]	[0.262]	[0.270]	[0.422]
Partial employment rate	1.086***	0.084	1.013***	1.015***	1.076***	0.072	-0.019	0.082
	[0.248]	[0.340]	[0.245]	[0.211]	[0.318]	[0.332]	[0.318]	[0.428]
Informality rate	0.243	0.416*	0.281	0.207	0.079	0.441*	0.479**	0.375
	[0.379]	[0.228]	[0.365]	[0.323]	[0.366]	[0.228]	[0.236]	[0.328]
Sub-occupation rate	0.220	-0.275	0.185	-0.014	-0.002	-0.266	-0.197	-0.106
	[0.314]	[0.219]	[0.302]	[0.258]	[0.322]	[0.205]	[0.205]	[0.255]
Critical work conditions rate	0.057	-0.358	0.002	-0.122	-0.071	-0.397	-0.423	-0.352
	[0.408]	[0.325]	[0.384]	[0.344]	[0.327]	[0.323]	[0.328]	[0.341]
Vacancy rate	4.754***	-7.724***	4.358***	2.530*	1.635	-7.450***	-6.692***	-6.641**
	[0.950]	[1.467]	[1.007]	[1.320]	[2.694]	[1.514]	[1.695]	[2.774]
Other controls:								
Log(wage)[a] and its square	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE		Y				Y	Y	Y
Firm FE			Y			Y		
Firm * Occupation category FE				Y			Y	
Firm * Occupation subcategory FE					Y			Y
Observations	338,681	338,681	338,681	338,681	338,681	338,681	338,681	338,681

Notes: The estimated model is a linear probability model. Each of the rates is measured as a proportion. Each coefficient presented in the table comes from a different regression where the explanatory variable of interest is each of the alternative labor market tightness measures. Standard errors clustered at the state and quarter level are presented in parentheses. ***, **, and * denote significance at the 1%, 5% and 10%, respectively.

Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015, and ENOE data from III:2014 to II:2015.

Table 8: Direction of gender preferences and labor market tightness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment rate	0.443***	0.528***	0.432***	0.500***	0.263*	0.472**	0.673***	0.326
	[0.104]	[0.175]	[0.102]	[0.105]	[0.134]	[0.184]	[0.218]	[0.288]
Log(wage)	-0.015	-0.014	-0.013	-0.011	0.020	-0.012	-0.010	0.020
	[0.036]	[0.035]	[0.036]	[0.038]	[0.034]	[0.036]	[0.038]	[0.034]
Square of log(wage)	0.002	0.002	0.002	0.002	-0.001	0.002	0.002	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Other controls:								
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE		Y				Y	Y	Y
Firm FE			Y			Y		
Firm * Occupational categories FE				Y			Y	
Firm * Occupation subcategories FE					Y			Y
Observations	338,681	338,681	338,681	338,681	338,681	338,681	338,681	338,681

Notes: [a] Wage offer is estimated at mid-point between the minimum and the maximum wage offer. The estimated model is a linear probability model. The unemployment rate is measured as a proportion. Standard errors clustered at the state and quarter level are presented in parentheses. ***, **, and * denote significance at the 1%, 5% and 10%, respectively.

Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015, and ENOE data from III:2014 to II:2015.

Table 9: Other targeting and labor market tightness using unemployment rate

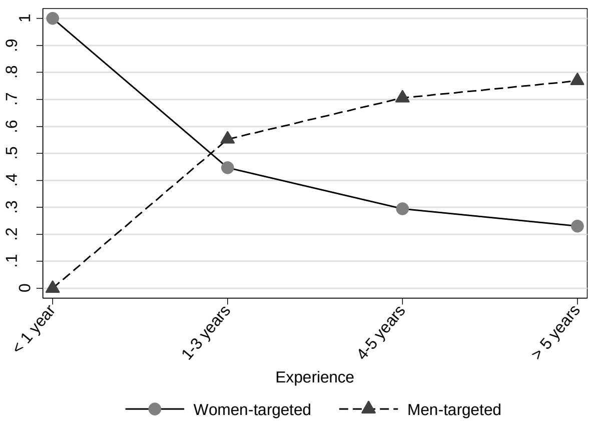
Dependent variable	Coefficients on the unemployment rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any targeting=1	-0.786***	-0.578	-0.650***	-0.760***	-0.506	-0.593	-0.437	-0.185
	[0.265]	[0.593]	[0.222]	[0.204]	[0.366]	[0.585]	[0.527]	[0.586]
Age targeting=1	-0.284	-0.141	-0.159	-0.293	-0.151	-0.182	-0.005	0.107
	[0.400]	[0.470]	[0.345]	[0.268]	[0.460]	[0.454]	[0.404]	[0.480]
Physique targeting=1	-0.517***	-0.683*	-0.494***	-0.546***	-0.112	-0.696*	-0.643*	-0.328
	[0.183]	[0.388]	[0.184]	[0.192]	[0.243]	[0.383]	[0.353]	[0.546]
Beauty targeting=1	-0.364***	-0.697***	-0.354**	-0.410***	-0.131	-0.710***	-0.643***	-0.592*
	[0.130]	[0.241]	[0.139]	[0.135]	[0.167]	[0.243]	[0.233]	[0.317]
Other controls:								
Log(wage)[a] and its square	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter-year FE		Y				Y	Y	Y
Firm FE			Y			Y		
Firm * Occupation category FE				Y			Y	
Firm * Occupation subcategory FE					Y			Y
Observations	338,681	338,681	338,681	338,681	338,681	338,681	338,681	338,681

Notes: [a] Wage offer is estimated at mid-point between the minimum and the maximum wage offer. The estimated model is a linear probability model. Each coefficient presented in the table comes from a different regression where the explanatory variable of interest is the unemployment rate, which is measured as a proportion, and the dependent variable is a measure of discrimination in the labor market. “Any targeting” is a dummy variable of whether the ad was targeted to a gender, an age group, or physical characteristics. “Physique targeting” is a dummy variable of the ad and was targeted to a physical constitution, a skin color or beauty. Standard errors clustered at the state and quarter level are presented in parentheses. ***, **, and * denote significance at the 1%, 5% and 10%, respectively.

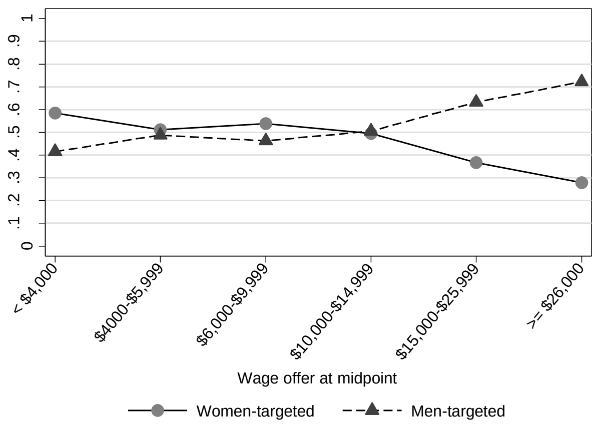
Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015, and ENOE data from III:2014 to II:2015.

Figure 1: The skill-twist in gender-targeted ads

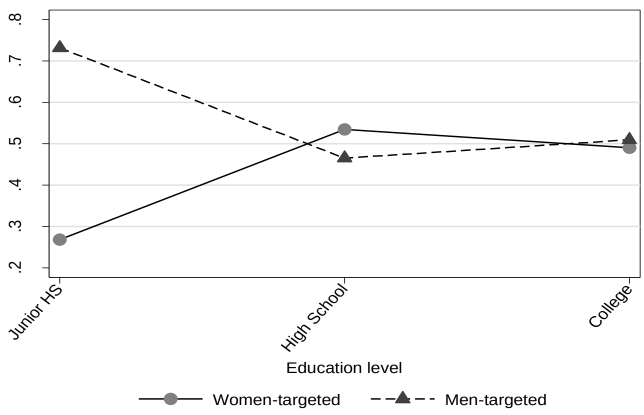
Panel A. Experience



Panel B. Wage offers

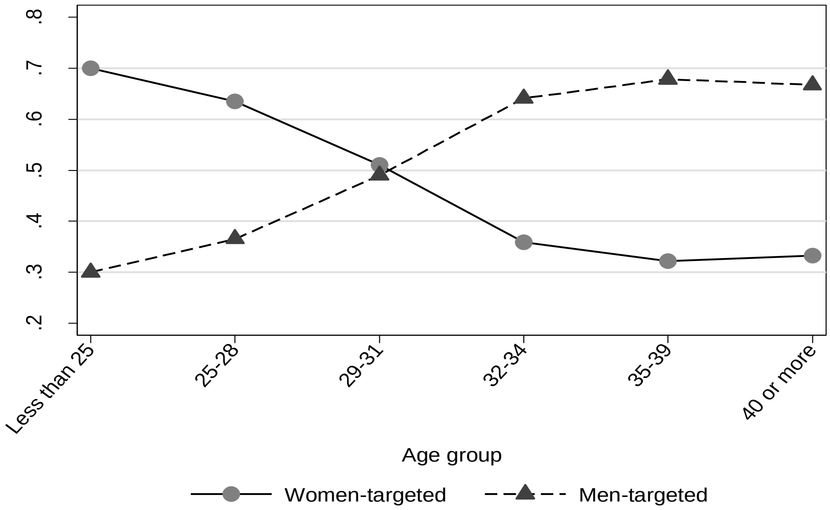


Panel C. Education



Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015.

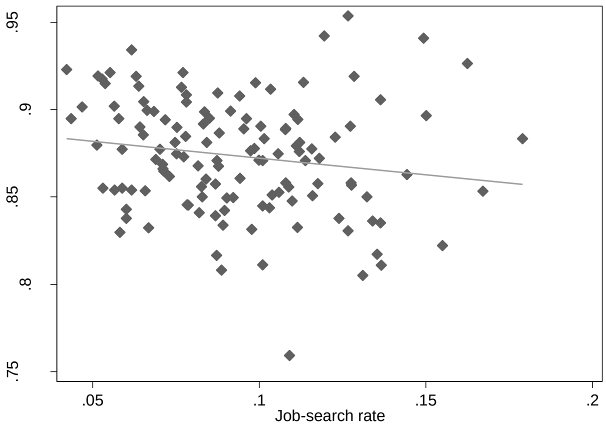
Figure 2: Age-twist in gender-targeted ads



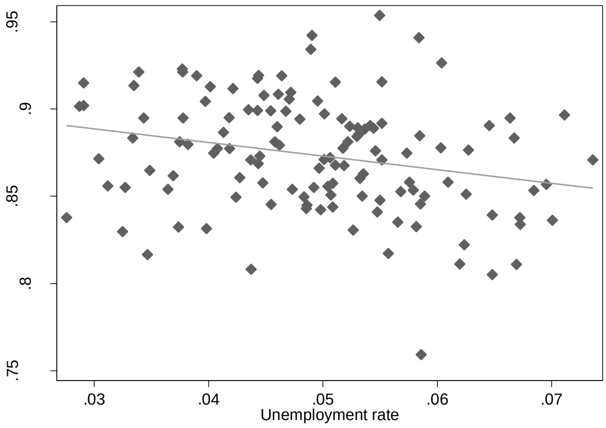
Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015.

Figure 3: Labor market tightness and proportion of untargeted ads

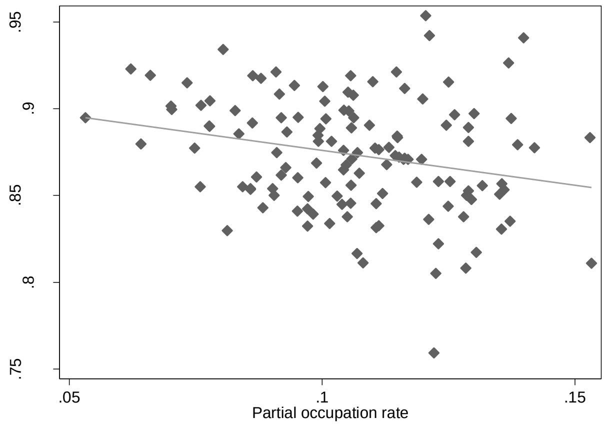
Panel A. Job-search rate



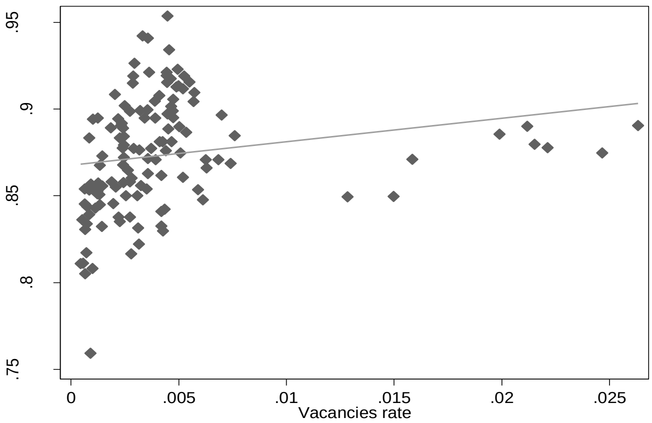
Panel B. Unemployment rate



Panel C. Partial occupation rate



Panel D. Vacancies rate



Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015, and ENOE data from III:2014 to II:2015.

Appendix A

A.1 Missing data

We collected data from 1,010,884 job advertisements. However, we lost a sizable portion of the sample in our estimations due to missing values. Table A1 presents the variables in our regression equations with missing values. The main source of data loss is that firms do not report the wage offered to the job seekers. This variable alone reduces our sample by more than half. Some firms do not disclose their name, and hence we cannot produce a firm identifier. Here we lose another 65,000 observations. Finally, some firms do not report the sector and subsector of the job position. Here we lose about 61,000 additional observations.

It would be worrisome if the missing data is not random. In order to gauge how selective our sample is, Table A2 presents the descriptive statistics for the estimating sample (without missing values) and the sample dropped due to missing information (columns 3 and 4). Columns (5) and (6) present the difference and the standard error of the difference in means. According to this test there are statistically significant differences in almost all variables in our sample between the estimating sample and the dropped sample. In general, the ads in the estimating sample seem to provide more information on all variables. The estimating sample discriminates more on the basis of gender, age and beauty than the sample with missing information.

Given that our research design uses within firm-sector-subsector variation in order to identify the effect of the unemployment rate, this sample selection would be an issue if ads at the firm-sector-subsector level with all data being reported respond differently than ads at this same level that do not report all the data. *A priori* there is no reason to believe that that is the case.

Table A1: Sources of missing data

	Number of observations	Additional observations lost	Cumulative observations lost
Total	1,010,884		
Variables in the estimations with missing data:			
Log(wage)	522,419	522,419	522,419
Firm identifier	118,275	65,430	587,849
Sector identifier	153,219	60,941	648,790
Subsector identifier	153,219	0	648,790
Estimating sample	362,094		

Notes: The table presents the variables with missing data and the number of observations lost per variable.

Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015.

Table A2: Job ads descriptive statistics

Sample:	Without missing values		With missing values			
	Mean	S.D.	Mean	S.D.	Difference	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Gender-targeting:						
Female	0.073	0.260	0.050	0.219	0.023***	[0.001]
Male	0.074	0.261	0.052	0.222	0.022***	[0.001]
No-targeting	0.853	0.354	0.898	0.303	-0.044***	[0.001]
Education requirements:						
Junior high school	0.038	0.191	0.020	0.141	0.018***	[0.000]
High school	0.180	0.384	0.113	0.316	0.068***	[0.001]
Technician	0.065	0.246	0.050	0.219	0.014***	[0.000]
University degree	0.316	0.465	0.261	0.439	0.056***	[0.001]
No education posted	0.490	0.500	0.619	0.486	-0.129***	[0.001]
Experience requirements:						
Experience in years	3.011	1.512	3.139	1.641	-0.128***	[0.007]
None or not posted	0.186	0.389	0.764	0.424	-0.004***	[0.001]
1 to 3 years	0.046	0.209	0.175	0.380	0.011***	[0.001]
4 to 5 years	0.008	0.090	0.050	0.219	-0.005***	[0.000]
More than 5 years	0.760	0.427	0.010	0.101	-0.002***	[0.000]
Wage offered:						
Wage posted	1.000	0.000	0.333	0.471	0.667***	[0.001]
Maximum wage*	14,518	18,353	12,835	24,095	1,683.279***	[60.127]
Minimum wage*	10,555	13,067	11,103	13,592	-548.605***	[43.971]
Age requirements:						
Has age requirement	0.490	0.500	0.330	0.470	0.160***	[0.001]
Has minimum age req.	0.489	0.500	0.329	0.470	0.160***	[0.001]
Has maximum age req.	0.489	0.500	0.330	0.470	0.160***	[0.001]
Minimum age	23.999	3.608	24.011	3.710	-0.012	[0.012]
Maximum age	42.741	16.901	42.833	17.771	-0.092*	[0.056]
Marital status requirements:						
Single	0.004	0.066	0.003	0.058	0.001***	[0.000]
Married	0.008	0.087	0.005	0.073	0.002***	[0.000]
No marital status req.	0.988	0.109	0.991	0.093	-0.003***	[0.000]
Other job requirements:						
Beauty	0.133	0.340	0.098	0.297	0.035***	[0.001]
Photograph in CV	0.134	0.341	0.098	0.298	0.036***	[0.001]
Willingness to travel	0.097	0.297	0.076	0.266	0.021***	[0.001]
Work under pressure	0.133	0.340	0.132	0.338	0.001*	[0.001]
Kind	0.013	0.115	0.010	0.101	0.003***	[0.000]
Obliging	0.113	0.317	0.122	0.327	-0.008***	[0.001]
English	0.141	0.348	0.168	0.374	-0.027***	[0.001]
Team work	0.081	0.273	0.082	0.275	-0.001**	[0.001]

Table A2: Job ads descriptive statistics (continued)

Sample:	Without missing values		With missing values			
	Mean	S.D.	Mean	S.D.	Difference	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Type of contract:						
Part-time	0.022	0.145	0.013	0.115	0.008***	[0.000]
Full-time	0.263	0.440	0.159	0.366	0.104***	[0.001]
Undefined contract	0.723	0.448	0.831	0.375	-0.108***	[0.001]
Permanent position	0.028	0.165	0.018	0.133	0.010***	[0.000]
Position by fees	0.003	0.055	0.002	0.045	0.001***	[0.000]
Number of observations	362,094		648,790		1,010,884	

Notes: *Wages are measured in Mexican pesos per month. The average exchange rate during the period was about 15.5 pesos per US dollar. ***, **, and * denote significance at the 1%, 5% and 10%, respectively.

Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015.

Table A3: Distribution of job ads across sectors

Sector	Frequency	Percent
Managerial	34,166	4.06
Biology	317	0.04
Communications	595	0.07
Construction	3,173	0.38
Construction and real estate	14,207	1.69
Accounting	23,752	2.82
Creativity, production and commercial design	1,811	0.22
Law	2,608	0.31
Education	2,551	0.3
Industry	72,600	8.63
Engineering	15,620	1.86
Logistics, transportation and distribution	13,142	1.56
Manufacturing	12,783	1.52
Marketing	6,309	0.75
Human resources	22,006	2.62
Health and beauty	17,885	2.13
Health sector	5,855	0.7
Insurance	2,283	0.27
Services	419,360	49.85
Information technologies	30,711	3.65
Tourism and restaurants	3,767	0.45
Sales	135,074	16.06
Veterinary and zoology	629	0.07
Total	841,204	

Notes: These sectors are the ones provided by OCC Mundial.

Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015.

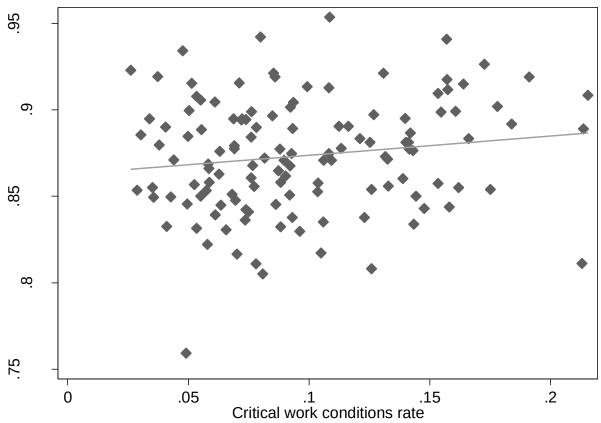
Table A4: Sector occupation of employed workers

Sector	Percent
Agriculture	7.9
Construction	15.98
Manufacturing	21.28
Commerce	51.63
Services	1.03
Other	1.63
No specification	0.55

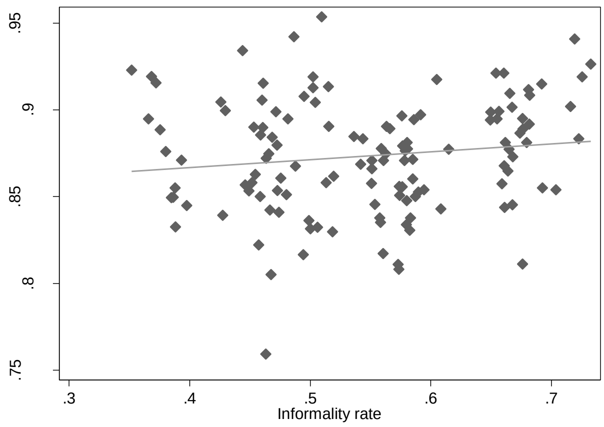
Source: Authors' calculations using ENOE data.

Figure A1: Labor market tightness and proportion of untargeted ads

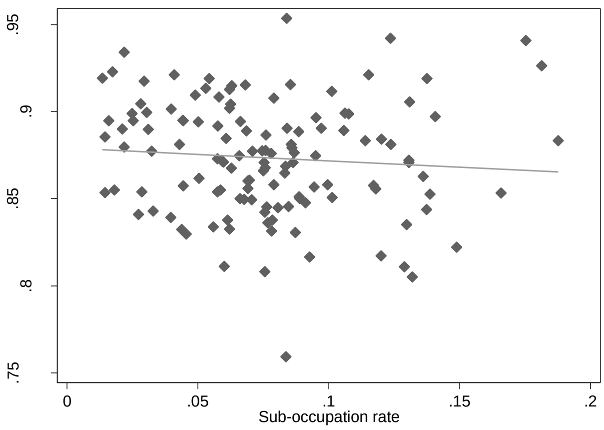
Panel A. Critical work conditions rate



Panel B. Informality rate



Panel C. Sub-occupation rate



Source: Estimations by authors using data downloaded from occmundial.com.mx from August, 2014 to July, 2015, and ENOE data from III:2014 to II:2015.