Does Customer or Coworker Discrimination Prompt Employer advertisements for Attractive Employees ?[*]

Yuanting Wu

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Abstract

I provide a new method to decompose discrimination by Chinese employers into customer and coworker discrimination. Using data from an online job board, I relate employer advertisements for beautiful and tall applicants to occupational job requirements as measured by the American O*NET data. I find that employers hiring in occupations with more contact with both customers and coworkers are more likely to require beauty and height in the job ads. In terms of coefficients, customer discrimination and coworker discrimination have the same effect on the job ads physical appearance profiling but in terms of contributions to R-squared, coworker discrimination plays a more important role.

1 Introduction

Unconstrained by laws governing labor market discrimination, Chinese employers are free to post ads specifying applicants should be beautiful, tall, short, young, old, male or female. Chinese data may therefore be used to study the sources of employer discrimination in a way not possible elsewhere, while still possibly shedding light on global phenomena. Employment discrimination occurs when employees or job applicants are treated differently on the basis of the group (female, black, old, ugly, immigrants, etc.) with otherwise same characteristics and in similar circumstances. Economists often classify discrimination into one of two major types: statistical discrimination and taste discrimination. Statistical discrimination occurs when in the presence of imperfect information, firms make group-based inference based on statistical information.[1] For example, American employers may infer that a black applicant is more likely than a white applicant to have a criminal record based on disproportionate criminal records among blacks. [2] Statistical discrimination can help firms take advantage of the group characteristic information to reduce search costs and find better matched employees faster and more easily, however, it would also cause some problems like discouraging the disfavored group from participating in the market, therefore lowering the market efficiency. [3]

Taste discrimination occurs when members of one group have a taste or prejudice against interactions with another group.[4] Taste discrimination can be further divided into employer taste

[1] Arrow, K. (1973); Phelps, E. S. (1972)
[2] Agan and Starr (2017)
[3] Kenneth Arrow (1972) and George Borjas and Matthew Goldberg (1978) their models both assume that those firms taking fully use of the productivity information indicated by group are more efficient than those firms ignoring the information.
[4] Becker (1957)

discrimination, customer taste discrimination and coworker taste discrimination. Employer taste discrimination in a perfectly competitive market with not frictions may be inefficient because employers do not employ disfavored workers to the point where their wage equals their marginal product, meaning that prejudice reduces profits.[5] However, customer or coworker discrimination can be profitable for employers. If many customers or employees are members of the favored group and dislike interacting with employees from the disfavored group, restricting hiring to the favored can increase productivity and sales.[6] Customer and coworker discrimination can thus exist even in the competitive equilibrium, which renders ineffective solutions, for example, enhancing competition or reducing frictions in markets, that are effective for fixing employer taste discrimination.[7] Therefore, different types of discrimination have very different economic consequences. Figuring out the source of discrimination is not only important for fairness but also necessary for market efficiency.

Disentangling types of discrimination has proved difficult empirically. In this paper, I focus on employer demand for workers who are beautiful or tall, and estimate the degree to which customer or coworker discrimination is responsible for this demand. I use data created by Kuhn and Shen (2012) from a Chinese online job board, which contains rich information about both the explicit demographic requirements, such as, age, gender, etc. and relevant skills asked in job ads, such as, education, experience, and the firm information such as size, ownership, etc. I merge these with four new indices representing customer and coworker contact based on

[5] Becker (1971) shows that when the supply of workers in the favored group is less than the demand from prejudiced firms, the wage received by the disfavored group in a prejudiced firm can't fully compensate the productivity, therefore, it is inefficient for both the firms and the labor market.
[6] Goldberg (1982)
[7] Becker (1971); Nardinelli and Simon (1990); Black and Strahan (2002)

occupation tasks description data from the American O*NET website. I assume that if the employer appearance requirements are motivated by customer or coworker discrimination, firms are more likely to worry about the attractiveness of workers for jobs that have more contacts with customers or coworkers. Thus, they are more likely to post beauty or height requirements in these job ads.[8] If employer prejudice is the only reason for appearance attractiveness requirements, employers would favor attractive workers for all jobs, no matter whether face-to-face contact tasks are required. Thus, the posting of beauty requirements in job ads won't vary a lot across jobs with different degree of contact with customers or coworkers.

Furthermore, if part of the beauty or height requirements is caused by statistical discrimination, which means that firms like attractive workers because firms take beauty or height as an indicator of high productivity, we can assume that the more information about the productivity of applicants revealed to firms, the less emphasis they would put on their "beauty" or "height" indicator and thus, thus less likely to post beauty requirements in job ads. In other words, those job ads with more education and experience requirements (say, more productivity information revealed job ads) are less likely to have beauty or height requirements. Besides, I also test the effect of both discriminations on age and gender requirements to check whether these contact indices effects can be generalized into other requirements in job ads.

The main result of this paper is that employers are more likely to require beauty and height for jobs with more contact with both customers and coworkers in general. Specifically, a standard deviation increase in customer contact indices has approximately the same effect as an

[8] Holzer and Ihlanfeildt (1998) find that the customer racial composition has a large effect on the race of hired employees, Specifically for those jobs with direct contact with customers.

equivalent increase in coworker contact indices on ads physical attractiveness profiling and both indices contribute similar to the beauty requirement variance, but coworker contact contributes more to the height requirement variance. This result suggests that the employer advertisements of employers towards attractive employees are therefore almost equally motivated by both customer discrimination and coworker discrimination and coworker discrimination explains more to the height requirement variance.

I contribute to the literature in two understudied areas: testing types of discrimination and exploring the determinants of employer advertisements. Firstly, most studies in the literatures focus on distinguishing statistical discrimination from taste discrimination. Some (List, 2004; Knowles, Persico and Todd, 2005; Zussman, 2013) find discrimination is explained by statistical discrimination, some (Sanga, 2009; Kerwin and Guryan, 2013) find that it is explained by taste discrimination model, and some (Agan and Starr, 2017) find it is a combination of both. However, so far economists have done little work on breaking down the sources of taste discrimination. My paper does this, disentangling coworker discrimination and customer discrimination. Kuhn and Shen (2009), the most closely related paper to mine, find that cross-sectional patterns in job ads suggest some role for customer discrimination. They test for customer discrimination by establishing a dummy variable equal to one if they subjectively consider the respondent's occupation to involve high customer contact. The contact indices created in my paper are more objective and accurate and can provide more information. Furthermore, my indices make it possible for me to test for coworker discrimination in addition to customer discrimination and compare the importance of these two discrimination types. Stinebrickner, Stinebrickner and Sullivan (2018), another study that is close to mine, tease out

the employer taste discrimination from others in beauty wage premium by using job tasks information from the Berea Panel Study, and they find that the wide variation of beauty premia across jobs which can't be explained by employer taste discrimination might be explained by customer or coworker discrimination, but since the survey lacks information about the detailed sources of interaction in jobs, they admit that their paper is unable to further disentangle customer discrimination from coworker discrimination.

Secondly, my work can help to better understand employer advertisements and establish some new facts about the explicit beauty requirements in job ads.[9] Kuhn and Shen (2012) and Helleseter, Kuhn and Shen (2016) also study the employer explicit preferences in advertisements. They find that employers' valuations are highly specific to detailed jobs and occupations and they focus on job skill level to explore employer advertisements, while my study focuses on the degree of contact in jobs to explore the employer advertisements.

A caveat is that: the impact of discrimination found in the job posting stage is also quite different from the wage offering stage. It reflects the conscious choices of the employers, so it would be comparatively larger than the discrimination detected in other stages, which is a combination of both unconscious and conscious choices of the employers.[10]

[9] Hamermesh and Biddle (1994) find a large beauty premia exists by studying employer advertisements from two household surveys: The 1977 Quality of Employment Survey (QES) and the 1971 Quality of American Life survey (QAL).
[10] Kuhn and Shen (2012)

2 Data

I use the Chinese online job advertisement data collected by Kuhn and Shen (2012). Kuhn and Shen (2012) crawled and scraped all the unique job ads from zhaopin.com, the third largest Chinese online job board, during four observation periods: May 19th, 2008 – June 22th, 2008; Jan 19th, 2009 – Feb 22th, 2009; May 18th, 2009 – June 21th, 2009; Jan 18th, 2010 – Feb 21th, 2010 and built the ads dataset of 1,322,671 observations.[11] This dataset includes some variables reflecting the physical requirements in job ads, for example, "Any beauty requirement": is there any beauty requirement in the ad; "Any height requirement": is there any height requirement in the ad. Since I need occupation to get occupation information, I exclude the ads observations with variable "occupation" as "student" or "others" and study the remaining 1,300,118 observations.

Table 1 shows means of requirements in job ads. Column 1 shows means of requirements for whole sample. Among 1,300,118 ads studied in this paper, 105,078 (8.2%) of them have a beauty requirement and 2.9% have a height requirement. Columns 2 and 3 show more details of how different kinds of requirements in job ads vary by beauty requirement. Firstly, ads with a beauty requirement are 18.6 percentage points more likely to also have a height requirement. Secondly, ads with a beauty requirement are 19.9 percentage points more likely to also have any age requirement, and the preferred age is around 3.8 years younger than in ads without a beauty requirement. Thirdly, Ads with a beauty requirement are 20.9 percentage points more likely to also require workers to be female, however, there is not much difference for the requirement to be male. Fourthly, ads with a beauty requirement are more likely to also ask for relatively less

[11] The original dataset and more information about the procedures of collecting data can be found on Professor Kuhn's personal website: https://sites.google.com/view/peter-kuhn/

education, such as no school restrictions, junior middle school or below, high school and post-secondary, while ads with a beauty requirement are less likely to also ask for a higher education degree, such as undergraduate, master and Ph.D. Ads with a beauty requirement require around 1.16 more years of working experience than ads with no beauty requirement. Finally, ads with a beauty requirement are less like to be part-time jobs.

Columns 4 and 5 in Table 1 show details of different kinds of requirements on job ads vary by height requirement. Most results for height are similar to those for beauty. The only differences lie in the gender and part-time jobs requirements. Firstly, ads with a height requirement are more like to ask workers to be male, 8.4 percentage points more than ads without a height requirement, while there is no such difference as for beauty requirement. Besides, ads with a height requirement are more likely to be part-time jobs.

To measure the degree of contact for each occupation in job ads, I merge it with the data from the American O*NET database.[12] The procedure for merging these two datasets is described in Appendix. This database is the main source of the occupational information in U.S. It includes hundreds of standardized, occupation-specific descriptors and it is continuously being updated. The occupation data in American O*NET mainly focus on U.S. labor market. However, since there isn't such data for the Chinese labor market and most occupations have similar characteristics and tasks around the world, the American O*NET data is a relatively good choice.

[12] More information about the O*NET database can be found at https://www.onetonline.org/help/onet/

For each occupation code, I find four descriptors under "work context" content from O*NET very suitable for this study in terms of their definition: 1) "Communicating with Persons Outside the Organization", which is defined as "Communicating with people outside the organization, representing the organization to customers, the public, government, and other external sources. This information can be exchanged in person, in writing, or by telephone or e-mail." 2) "Performing for or Working Directly with the Public", which is defined as "Performing for people or dealing directly with the public. This includes serving customers in restaurants and stores, and receiving clients or guests." 3) "Communicating with Supervisors, Peers or Subordinates", which is defined as "Providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person." 4) "Face-to-Face Discussions", which is defined as "How often do you have to have face-to-face discussions with individuals or teams in this job." Since the level and importance dimensions reflect two different aspects of the same descriptor, combining them together can give a complete measure of the contact. I use the Cobb-Douglas function to combine them:[13]

$$Degree\ of\ customer\ contact_j = Level_j^{1/3} Importance_j^{2/3}$$

which is also commonly used in the literature (Firpo, Sergio, Nicole Fortin, and Thomas Lemieux, 2011; Goos, 2011; Lee and Shin, 2017). The two indices based on "Communicating with Persons Outside the Organization" and "Performing for or Working Directly with the Public" are treated as a potential motivation for customer discrimination, and the two indices based on "Communicating with Supervisors, Peers or Subordinates" and "Face-to-Face Discussions" are

[13] I have tried different functions to combine these two dimensions: sum, product and Cobb-Douglas. The results have not much different, so I finally decide to use the Cobb-Douglas function. The parameters of Cobb Douglas function come from Firpo, Sergio, Nicole Fortin, and Thomas Lemieux (2011)

treated as a potential motivation for coworker discrimination. To facilitate interpretation, I standardize the indices.

The means of the standardized job contact indices by beauty and height requirement are presented in Table 2. Column 1 and 2 in Table 2 show that all the contact indices have a higher score for the ads with a beauty requirement than those ads without a beauty requirement, and the gap is larger for indices contributing to the customer discrimination than the coworker discrimination. For example, the difference between ads with a beauty requirement and ads without a beauty requirement for communication with customer and working with the public (0.8 and 0.5 for each) is larger than the difference for communication with coworker and face-to-face discussion (0.3 and 0.3 for each). Column 3 and 4 in Table 2 show that all the contact indices also have a higher score for ads with a height requirement than those ads without and the gap is larger for indices motivating customer discrimination.

The means of the component parts are shown in Appendix Table A2. In addition, I also checked the correlations among all the contact indices and the result is presented in Appendix Table A3. It shows that most correlations among the four contact indices are less than 0.4, except for the correlation between two customer discrimination indices is 0.6.

3 Methodology

I use linear probability regressions to test the type of discrimination. The main regression equation is:

$$Y_{ijf} = \beta_0 + \beta_1 Communication\ with\ customer_j + \beta_2 Working\ with\ the\ public_j + \beta_3\ Communication\ with\ coworker_j + \beta_4 Face\_to\_face\ discussion_j + \beta_5 x_{ijf} + \gamma_f + \varepsilon_{ijf}$$

where Y is either a beauty or a height requirement dummy, "i" indexes the advertisement, "j" indexes the occupation of the position in the advertisements and "f" indexes the firm posting the advertisements. "x" are control variables, includes: the age dummy, the gender dummy, the education dummy, the experience years, the part-time jobs dummy, period dummies and number of ads. "γ" stands for firm fixed effects. "ε" is the error term. Since the first two variables "Communication with customer" and "Working with the public" are treated as a potential motivation for customer discrimination, the coefficients β_1, β_2 together can be viewed as the effects of customer discrimination on the probability of having a beauty requirement in job ads. The latter two variables "Communication with coworker" and "Face-to-face discussion" are treated as a potential motivation for coworker discrimination, so coefficients β_3, β_4 together can be viewed as the effects of coworker discrimination on the probability of having a beauty requirement in job ads.

I will assess the importance of customer and coworker discrimination in two ways, considering first the coefficients associated with the four indices and second the contribution of the indices to

the R-squared. The comparison of coefficients of both customer indices and both coworker indices reflect which one has a larger effect on the probability of having a beauty requirement in job ads and the comparison of their ANOVA results reflect which one contributes more to the variation of the probability of having a beauty requirement in job ads.

Considering all the requirements in job ads are highly correlated with each other and could be caused by a same factor, I also do seemingly unrelated regression (SUR) in order to test formally whether the contact indices have the same effects on the beauty, height, age, and gender requirements. The SUR regressions take the same form as the main equation, but the estimation allows the error terms to be correlated.

4 Results

4.1 Main regression

To check the relationship of the beauty requirement in job ads and occupations' contact indices and then further uncover whether employer advertisements for attractive employees is prompted by customer or coworker discrimination, Table 3 presents regression results for the determinants of the beauty requirement. Six specifications with increasingly detailed controls are presented across columns from left to right. All the regressions include all four job contact indices, which are the main variables of interest in this paper. The first specification (column 1) controls for only these variables of interest. In columns 2 through 6, I gradually add first the age requirement dummy; next the education requirement dummy and experience years requirement; then the part-time jobs requirement dummy, period dummies, number of ads, and firm fixed effects; then the gender requirement dummy and finally the interaction terms.

Column 1 in Table 3a shows that an increase by one standard deviation in the index "communication with customer" would increase the probability of having a beauty requirement by 3.4 percentage points (on average, 8% of ads have a beauty requirement, so this represents a 43% increase on the mean), and the coefficient is statistically significant at 5% level; an increase in the index "working with the public" by one standard deviation would increase the probability of having a beauty requirement in ads by 3.3 percentage points (a 41% increase on the mean), and the coefficient is statistically significant at 5% level; the coefficient on the index "communication with coworker" is not statistically significant and one standard deviation increase in it would increase the probability of having a beauty requirement in ads by 2.1

percentage points (a 26% increase on the mean); an increase in the index "face-to-face discussion" by one standard deviation would increase the probability of having a beauty requirement in ads by 3.1 percentage points (a 39% increase on the mean), and the coefficient is statistically significant at 1% level. The coefficients are rather similar across the four indices, with the coefficient on the index "communication with worker" being slightly smaller.

Successive controls in columns 2-5 render the coefficients of all the indices become smaller, which shows that some of the beauty requirement can be explained by other requirements in ads. The index "Communication with customer" and the index "Face-to-face discussion" drop relatively larger (from 3.1 to 2.7 percentage points; from 2.4 to 2.0 percentage points) after controlling for the gender requirement dummy. This change indicates that these two indices have positive correlation with the gender requirement and some of their effects on the beauty requirement come from the gender requirement change raised by the indices.

Table 3b shows the coefficients for specification interaction terms with each of the contact indices controlled in Column 6 in Table 3a to get a richer picture of the role of customer and coworker discrimination. Most of the coefficients of interaction terms of contact indices and any age requirement are positive, which means that the effects of contact indices on the probability of having a beauty requirement are overall larger for ads with any age requirement than ads without. Since the average preferred age is rather young (31.3 years old), ads with any age requirement can be further explained as ads targeting younger workers.[14] In other words, employers of ads targeting younger workers are in general more sensitive to the degree of contact required by jobs.

[14] From Table 1

Specifically, among all the indices, only the coefficient of the index "communication with customer" is statistically significant and its magnitude is relatively larger: one standard deviation increase in it would increase the probability of having a beauty requirement by 1.8 percentage points (a 23% on the mean) more in ads with any age requirement than ads without.

Table 3b also shows the coefficients of the interaction terms of the contact indices and the gender requirement dummy. The sign of all the coefficients of the male interaction terms is negative shows that ads targeting male employees are less likely affected by contact indices than ads without any gender requirement in terms of the probability of asking for a beauty requirement. Specifically, among all the indices, the coefficient of the interaction term of the index "face-to-face discussion" is statistically significant at 5% level and its magnitude is relatively larger: its effect of one standard deviation increase on the probability of having a beauty requirement is 1.4 percentage points (a 18% on the mean) smaller in ads targeting male workers than ads without any gender requirement. The sign of the female interaction terms is not consistent across the indices. The coefficient of the interaction term of the index "communication with customer" is statistically significant at 1% level and its magnitude is a lot larger than others: its effect of one standard deviation increase on the probability of having a beauty requirement is 9.2 percentage points (a 115% on the mean) larger in ads targeting female workers than ads without any gender requirement.

Together, the interaction terms of the contact indices and the gender requirement dummy suggest that employers preferring male employees are less likely to worry about employees' beauty for jobs with more the face-to-face discussion and employers preferring female employees are more

likely to worry about employees' beauty for jobs with more communication with customers than employers without any gender preference.

In Table 4, I calculate the contributions of the two types of discrimination in whether firms have a beauty requirement by summing the coefficients. Column 1 shows that a one standard deviation increase in the two customer discrimination related indices would increase the probability of having a beauty requirement in job ads by 6.7 percentage points (84%) while a one standard deviation increase in the two coworker discrimination related indices would increase the probability of having a beauty requirement in job ads by 5.1 percentage points (64%). Both sums are statistically significant at 1% level. In the columns 2 to 4, the results become gradually smaller after adding more controls. The larger coefficient of the customer discrimination suggests that customer discrimination plays a more important role than coworker discrimination in whether employers determine to have a beauty requirement in job ads, but the p-values of the equality test in Table 4 show that the two effects are not statistically significantly different. Employer advertisements for good-looking workers are therefore prompted substantially similarly by customer and coworker discrimination.

Column 6 to column 8 in Table 4 show the contributions of the two types of discrimination action in different subgroups of ad types: those with an age requirement, those preferring women and those preferring men in order to get a richer picture of the role of customer and coworker discrimination. Column 6 shows that one standard deviation increase in customer discrimination related indices would increase the probability of having a beauty requirement by 6.1 percentage points (76%) among ads with any age requirement and the coefficient is statistically significant

at 1% level, while the coefficient of coworker discrimination is smaller: 4.0 percentage points (50%) and statistically significant at 5% level. Column 7 shows that one standard deviation increase in customer discrimination related indices would increase the probability of having a beauty requirement by 11.8 percentage points (148%) among ads preferring female and the coefficient is statistically significant at 1% level, while the coefficient of coworker discrimination is much smaller and not statistically significant. And the p-value of the equality test in Column 7 shows that the customer discrimination related indices' effects are statistically significantly different from the coworker discrimination. This result means that it is customer interaction really driving the beauty requirements for jobs where employers want to hire female workers, therefore, customer discrimination plays a more important role. Column 8 shows similar results for ads preferring male to ads preferring female, but with a much smaller magnitude, however, the two effects are not significantly different from each other.

In addition to the beauty requirement, the height requirement also reflects employer preferences towards attractive workers. Table 5 shows the regression results for the determinants of the height requirement. The six specifications of Table 5 are the same as Table 3 except that the dependent variable in Table 5 is an indicator for a height requirement.

Column 1 in Table 5a shows similar results to those of the beauty requirement in Table 3, but with a much smaller magnitude and less statistical significance. All the coefficients are positive and rather similar across the four indices, with the coefficient on the index "communication with customer" being slightly smaller. From column 2 to column 5 in Table 5a, successively controlling more various requirements in ads renders the coefficients of all the indices become

slightly smaller, which shows that some of the height requirement can be explained by other requirements in ads but not much. Column 6 in Table 5a and Table 5b show the results of age and gender interaction terms with each of the contact indices. These interaction terms suggest that employers of ads targeting younger workers are in general more sensitive to the degree of contact required by jobs, employers preferring male employees are less likely to worry about employees' beauty for jobs with more communication with customers but more for jobs with more working with the public and communication with coworkers and employers preferring female employees are more likely to worry about employees' beauty for jobs with more communication with customers than employers without any gender preference.

In Table 6, I calculate the contributions of the two types of discrimination action by summing the coefficients of the height requirement (the same as Table 4). Table 6 shows similar results to those of the beauty requirement in Table 4, but with a smaller magnitude and less statistical significance. The larger coefficient of the customer discrimination suggests that customer discrimination plays a more important role than coworker discrimination in employers' determining whether or not having a height requirement in job ads, but the two effects are not statistically significantly different in any column. Employer advertisements for tall workers is therefore prompted approximately equally by customer and coworker discrimination.

Column 6 to column 8 in Table 6 show the contributions of the two types of discrimination action in different subgroups for the height requirement. Column 6 shows that the coefficients are rather similar, thus the two effects are approximately equal among ads targeting younger workers. Column 7 shows a consistent result with beauty requirement that one standard deviation

increase in customer discrimination related indices would increase the probability of having a height requirement by 8.3 percentage points (277%) among ads preferring female and the coefficient is statistically significant at 5% level, while the coefficient of coworker discrimination is negative and not statistically significant. The p-value in Column 7 shows that two effects are statistically significantly different, which again suggests that it is customer interaction that mainly motivate employers to advertise for taller female worker, thus suggests customer discrimination plays a more important role for jobs targeting female workers. Column 8 shows that one standard deviation increase in coworker discrimination related indices would increase the probability of having a height requirement by 3.2 percentage points (107%) among ads preferring male and the coefficient is statistically significant, while the coefficient of customer discrimination is smaller and not statistically significant, however, the two effects are not statistically different from each other.

4.2 ANOVA

To check which type of the discrimination explains more variation of the beauty and height requirements among occupations, Table 7 presents the ANOVA results. Two specifications each for both the beauty and height requirements are presented across columns from left to right, the first column of which includes the ANOVA results of all four job contact indices and the second one adds other covariates, including the age, gender, education, experience, part-time jobs, periods dummies and number of ads.

Column 1 in Table 7 shows that customer discrimination related indices can explain 0.8% (0.4% for "Communication with customer" and 0.4% for "Working with the public") of the variation in the beauty requirement among job ads, while the number for coworker discrimination related indices is 1.3% (0.2% for "Communication with coworker" and 1.1% for "Face-to-face discussion"). Therefore, coworker discrimination can explain more variation in the beauty requirement. Customer discrimination has a larger size of effects from the previous analysis in Table 4. However, there are actually more variation of coworker discrimination across occupations, which turns out to make coworker discrimination account more for the variation in the beauty requirement among job ads. By adding the covariates in column 2, the results become smaller. Coworker discrimination can explain slightly more for the beauty requirement variation than customer discrimination but the difference isn't significant. Therefore, they are about same for beauty, no matter the method.

Column 3 in Table 7 shows that customer discrimination related indices can explain 0.3% of the variation in the height requirement among job ads, but the number for coworker discrimination

related indices is larger (0.8%). Therefore, there are more variation of coworker discrimination across occupations and coworker discrimination explains more variation in the height requirement. By adding the covariates in column 4, the results become smaller and coworker discrimination keeps explaining more variation than customer discrimination. Therefore, coworker discrimination is more important for height.

4.3 Sur regression

Table 8 shows that the correlation of the residuals of equation “any beauty requirement” and equation “any height requirement”, of equation “any gender requirement” and “any age requirement” and of equation “any gender requirement” and “any age requirement” are relatively high, which is 0.27, 0.22 and 0.26 respectively. This result means that the error terms of these four equations are related with each other.

The coefficients and their standard errors for each regression are similar to the main regression results and are presented in Appendix Table 2. Table 9 shows various joint tests across different contact indices.

Panel A in Table 9 shows the joint tests for equation “any beauty requirement” and “any height requirement”. Column 1 shows the joint tests including all four contact indices. Its p value is zero suggests that the hypothesis that the overall effect of four contact indices on the beauty requirement is the same as the height requirement is rejected. Column 2 and column 3 further checks whether this difference comes from customer discrimination related indices or coworker discrimination related indices. Column 2 shows that the p value of customer discrimination related indices is zero, which suggests that the hypothesis that the customer discrimination has the same effect on the beauty requirement and the height requirement is rejected. However, the p value of coworker discrimination related indices in column 3 is relatively larger (0.01). Therefore, customer discrimination contributes more for the different effects of indices on the beauty requirement and the height requirement. From column 4 to column 7, I further check the p value of each index and show that the index “communication with customer” and the index

"face-to-face discussion" contributes more.

Panel B in Table 9 shows the joint tests for equation "any beauty requirement" and "any age requirement". Column 1 shows the joint tests including all four contact indices. Its p value is 0.25. This large p value suggests that the hypothesis that the overall effect of four contact indices on the beauty requirement is the same as the gender requirement can't be rejected.

Panel C in Table 9 shows the joint tests for equation "any beauty requirement" and "any gender requirement". Column 1 shows the joint tests including all four contact indices. Its p value is zero suggests that the hypothesis that the overall effect of four contact indices on the beauty requirement is the same as the gender requirement is rejected. Column 2 and column 3 further checks whether this difference comes from customer discrimination related indices or coworker discrimination related indices. Column 2 shows that the p value of customer discrimination related indices is zero, which suggests that the hypothesis that the customer discrimination has the same effect on the beauty requirement and the gender requirement is rejected. And the p value of coworker discrimination related indices in column 3 is much larger (0.7). Therefore, customer discrimination contributes more for the different effects of indices on the beauty requirement and the gender requirement. From column 4 to column 7, I further check the p value of each index and show that the index "communication with customer" contributes more to the difference.

5 Conclusion

I provide a new and effective method to test the type of discrimination by Chinese employers. Using limited data, I create the contact indices, categorize them into customer discrimination and coworker discrimination and compare their effects. I find that both customer discrimination related indices and coworker discrimination related indices have significantly positive effects on the probability of having beauty and height requirements. A one standard deviation increase in customer discrimination related indices increases the chance of having a beauty requirement in job ads by 6.7 percentage points (84%) and the chance of having a height requirement by 2.2 percentage points (76%). A one standard deviation increase in the two coworker discrimination related indices increases the probability of having a beauty requirement by 5.1 percentage points (64%) and the probability of having a height requirement by 2.4 percentage points (83%). The variance analysis further finds that customer discrimination and coworker discrimination have similar explanation power for the variance of having a beauty requirement but coworker discrimination can explain more for the variance of having a height requirement. These results suggest that both customer discrimination and coworker discrimination play an important role in prompting employer advertisements of attractive employees.

In addition, by analyzing different subgroups, I find that it is customer interaction really driving both the beauty and height requirements for jobs targeting female workers. Therefore, customer discrimination plays a more important role for employers who want to hire female workers.

However, from the SUR regression, I find that the results found for beauty and height requirements can't be further generalized to other job requirements, such as, age requirement,

gender requirement.

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Appendix

According to Kuhn and Shen (2012), the occupation categories are those supplied by Zhaopin.com (firms choose from a list on the website) and they restricted the sample to ads for a single occupation. The occupation categories in Kuhn and Shen are relatively brief while the occupation categories in O*NET are in more details. So, I first find each occupation in Kuhn and Shen (2012) its correspondent Job Family in O*NET and then I give its specific occupation code within the Job Family by searching it in Zhaopin.com for more details. For example, for the occupation "translation" in job ads data, I first locate that it is under the job family "Arts, Design, Entertainment, Sports, and Media". Searching more about this occupation in the Zhaopin.com helps me to get to know that most jobs tagged with "translation" are actually hiring translator, which allows me to assign it the closest occupation code "27-3091.00: Interpreters and Translators". The merged table for all occupations in job ads data are presented in Appendix Table A1.

Table 1

Means of Requirements in Ads

	All	Without beauty requirement	With beauty requirement	Without height requirement	With height requirement
	(1)	(2)	(3)	(4)	(5)
Any beauty requirement	0.081	0	1	0.067	0.552
	(0.273)	/	/	(0.249)	(0.497)
Any height requirement	0.029	0.014	0.200	0	1
	(0.169)	(0.119)	(0.400)	/	/
Any age requirement	0.240	0.224	0.423	0.231	0.557
	(0.427)	(0.417)	(0.494)	(0.421)	(0.497)
Ad specifies a minimum age	0.167	0.155	0.300	0.160	0.400
	(0.373)	(0.362)	(0.458)	(0.366)	(0.490)
Ad specifies a maximum age	0.200	0.184	0.375	0.190	0.512
	(0.400)	(0.388)	(0.484)	(0.393)	(0.500)
Male preferred	0.055	0.057	0.040	0.053	0.137
	(0.228)	(0.231)	(0.196)	(0.224)	(0.344)
Female preferred	0.053	0.036	0.245	0.042	0.413
	(0.224)	(0.187)	(0.430)	(0.201)	(0.492)
No school restrictions	0.197	0.194	0.232	0.194	0.303
	(0.398)	(0.396)	(0.422)	(0.396)	(0.459)
Junior middle school or below	0.008	0.007	0.022	0.006	0.057
	(0.089)	(0.082)	(0.147)	(0.078)	(0.233)
High school	0.095	0.089	0.164	0.090	0.268
	(0.293)	(0.284)	(0.370)	(0.286)	(0.443)
Post-secondary	0.367	0.363	0.413	0.369	0.273
	(0.482)	(0.481)	(0.492)	(0.483)	(0.445)
Undergraduate	0.321	0.335	0.164	0.328	0.096
	(0.467)	(0.472)	(0.370)	(0.469)	(0.294)
Master	0.012	0.012	0.006	0.012	0.004
	(0.108)	(0.111)	(0.074)	(0.109)	(0.060)
Ph.D. and above	0.001	0.001	0.000	0.001	0.000
	(0.029)	(0.030)	(0.014)	(0.030)	(0.007)
Experience years required	2.726	2.819	1.662	2.764	1.446
	(2.813)	(2.858)	(1.956)	(2.827)	(1.936)
Job is part-time	0.015	0.015	0.012	0.014	0.025
	(0.120)	(0.120)	(0.111)	(0.118)	(0.158)
Number of ads	1,300,118	1,195,040	105,078	1,262,090	38,028
Preferred age*	31.317	31.861	28.034	31.679	26.393
	(7.592)	(7.537)	(7.082)	(7.552)	(6.318)
Number of ads	317,777	272,619	45,158	296,016	21,761

Notes: Data refer to ads downloaded from Professor Kuhn's website. Unweighted means, standard deviations in parentheses." Any age requirement" is a dummy variable: it equals 1 if the job ads require any age requirement, 0 if else. "Male preferred" ("Female preferred") is a dummy variable valuing 1 if the job ads require male (female) workers and 0 if else. All education variables are dummy variables, for example, the dummy variable "High school" equals 1 if the education requirement in ads is "high school or above". Ads without specifying education requirements entry the category "No school restrictions" and its dummy variable "No school restrictions" equals 1. Variable "experience years required" describe the experience year required in job ads and its value of ads with no experience requirement is 0.

**"preferred age" is the mean of max and min age when either is specified in Ads. The default min age is 16 when max age is only specified and the default max age is 62.5 when min age is only specified.*

Table 2

Means of the Standardized Job Contact Indices

	Without beauty requirement	With beauty requirement	Without height requirement	With height requirement
	(1)	(2)	(3)	(4)
Communication with customer	-0.065	0.745	-0.018	0.596
	(0.995)	(0.717)	(0.998)	(0.883)
Working with the public	-0.04	0.457	-0.013	0.445
	(1.009)	(0.748)	(1.003)	(0.758)
Communication with coworker	-0.027	0.308	-0.006	0.188
	(0.979)	(1.172)	(0.997)	(1.092)
Face-to-face discussion	-0.029	0.324	-0.013	0.445
	(0.990)	(1.056)	(0.998)	(0.950)
N	1,195,040	105,078	1,262,090	38,028

Notes: Means of standardized indices. Standard deviations in parentheses. Communication with customer: Communicating with people outside organization measured by $Importance^{2/3} * Level^{1/3}$*; Working with the public: Performing for or working directly with the public measured by* $Importance^{2/3} * Level^{1/3}$*; Communication with coworker: Communicating with supervisors, peers, or subordinates measured by* $Importance^{2/3} * Level^{1/3}$*; Face-to-face discussion: The frequency of Face-to-Face Discussions.*

Table 3a

Effects of Job's Degree of Contact Demands on the Probability an Ad Is Beauty-targeted

	(1)	(2)	(3)	(4)	(5)	(6)
Communication with customer/100	3.38**	3.33**	3.42***	3.05***	2.73***	2.00***
	(1.32)	(1.29)	(1.14)	(0.92)	(0.79)	(0.74)
Working with the public/100	3.34**	2.97**	2.34*	1.97*	1.64*	1.76*
	(1.43)	(1.39)	(1.23)	(1.05)	(0.93)	(0.88)
Communication with coworker/100	2.09	2.01	1.78	1.76*	1.52*	1.47*
	(1.28)	(1.24)	(1.14)	(0.94)	(0.80)	(0.78)
Face-to-face discussion/100	3.06***	2.78***	2.62***	2.35***	2.00***	1.67**
	(0.87)	(0.82)	(0.75)	(0.73)	(0.66)	(0.66)
Ad specifies a minimum age		0.06***	0.05***	0.05***	0.04***	0.03***
		(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Ad specifies a maximum age		0.09***	0.08***	0.07***	0.06***	0.05***
		(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Preferred age*Any age requirement/100		-0.20***	-0.16***	-0.15***	-0.11***	-0.11***
		(0.06)	(0.06)	(0.04)	(0.03)	(0.03)
Male preferred					-0.02***	-0.02***
					(0.01)	(0.01)
Female preferred					0.20***	0.15***
					(0.03)	(0.03)
Education & Experience	NO	NO	YES	YES	YES	YES
Other covariates	NO	NO	NO	YES	YES	YES
Firm fixed effects	NO	NO	NO	YES	YES	YES
Interaction terms	NO	NO	NO	NO	NO	YES
R-squared	0.06	0.07	0.08	0.34	0.36	0.36

Notes: OLS estimates. Dependent variable in all columns equals 1 if the ad explicitly requests beauty, and 0 otherwise. I have standardized the job contact indices and their coefficients are multiplied by 100. There are 1,300,118 observations.

**** p<0.01, ** p<0.05, * p<0.1.*

Table 3b
Effects of Job's Degree of Contact Demands on the Probability an Ad Is Beauty-targeted --- Interaction Terms

Any age requirement*Communication with customer/100	1.81***
	(0.46)
Any age requirement*Working with the public/100	0.54
	(0.53)
Any age requirement*Communication with coworker/100	-0.01
	(0.37)
Any age requirement*Face-to-face discussion/100	0.90*
	(0.45)
Male preferred*Communication with customer/100	-0.68
	(0.98)
Female preferred*Communication with customer/100	9.22***
	(2.00)
Male preferred*Working with the public/100	-1.57
	(1.08)
Female preferred*Working with the public/100	-1.19
	(2.28)
Male preferred*Communication with coworker/100	-0.61
	(0.95)
Female preferred*Communication with coworker/100	-1.53
	(2.26)
Male preferred*Face-to-face discussion/100	-1.44**
	(0.64)
Female preferred*Face-to-face discussion/100	0.40
	(2.24)

*Notes: OLS estimates. Dependent variable in all columns equals 1 if the ad explicitly requests beauty, and 0 otherwise. I have standardized the job contact indices and their coefficients are multiplied by 100. Other covariates are the same as the column 6 in the Table 3a. There are 1,300,118 observations. *** p<0.01, ** p<0.05, * p<0.1.*

Table 4

Relative Importance of Customer and Coworker Discrimination Coefficients for Targeting Beauty in Ads

	All ads					Ads with any age requirement	Ads preferring female	Ads preferring male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer discrimination	6.72***	6.29***	5.75***	5.01***	4.36***	6.11***	11.80***	1.51**
	(0.93)	(0.85)	(0.77)	(0.74)	(0.65)	(0.73)	(1.96)	(0.65)
Coworker discrimination	5.11***	4.75***	4.37***	4.08***	3.49***	4.03**	2.01	1.09
	(1.64)	(1.58)	(1.39)	(1.40)	(1.22)	(1.16)	(2.28)	(0.83)
P-Value of equality test	0.330	0.329	0.333	0.474	0.465	0.089	0.001	0.678

Notes: Each column refers to the sum of corresponding column's coefficients in Table 3 and columns 6-8 refer to the coefficients for each subgroup based on column 6 in Table 3. Standard errors are in parentheses. There are 1,300,118 observations.

**** p<0.01, ** p<0.05, * p<0.1.*

Table 5a

Effects of Job's Degree of Contact Demands on the Probability an Ad Is Height-targeted

	(1)	(2)	(3)	(4)	(5)	(6)
Communication with customer/100	0.45	0.42	0.63	0.74*	0.57	0.52*
	(0.92)	(0.85)	(0.65)	(0.43)	(0.35)	(0.26)
Working with the public/100	1.78*	1.50	0.98	0.53	0.32	-0.14
	(1.01)	(0.90)	(0.69)	(0.50)	(0.42)	(0.28)
Communication with coworker/100	0.74	0.67	0.46	0.47	0.29	0.06
	(0.93)	(0.88)	(0.73)	(0.41)	(0.33)	(0.26)
Face-to-face discussion/100	1.63**	1.42**	1.21**	0.83***	0.56**	0.29
	(0.66)	(0.61)	(0.52)	(0.29)	(0.25)	(0.22)
Ad specifies a minimum age		0.05**	0.05***	0.04***	0.04***	0.03***
		(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Ad specifies a maximum age		0.06**	0.06***	0.05***	0.04***	0.03***
		(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Preferred age*Any age requirement/100		-0.17**	-0.15**	-0.15***	-0.14***	-0.13***
		(0.07)	(0.06)	(0.04)	(0.04)	(0.03)
Male preferred					0.04***	0.04***
					(0.01)	(0.01)
Female preferred					0.15***	0.11***
					(0.03)	(0.03)
Education & Experience	NO	NO	YES	YES	YES	YES
Other covariates	NO	NO	NO	YES	YES	YES
Firm fixed effects	NO	NO	NO	YES	YES	YES
Interaction terms*	NO	NO	NO	NO	NO	YES
R-squared	0.02	0.04	0.06	0.35	0.38	0.38

Notes: OLS estimates. Dependent variable in all columns equals 1 if the ad explicitly requests height, and 0 otherwise. I have standardized the job contact indices and their coefficients are multiplied by 100. There are 1,300,118 observations.

**** p<0.01, ** p<0.05, * p<0.1.*

Table 5b
Effects of Job's Degree of Contact Demands on the Probability an Ad Is Height-targeted --- Interaction Terms

Any age requirement*Communication with customer/100	0.16
	(0.36)
Any age requirement*Working with the public/100	1.07**
	(0.39)
Any age requirement*Communication with coworker/100	0.59
	(0.36)
Any age requirement*Face-to-face discussion/100	0.80***
	(0.20)
Male preferred*Communication with customer/100	-3.57**
	(1.45)
Female preferred*Communication with customer/100	7.37**
	(2.87)
Male preferred*Working with the public/100	4.32**
	(1.91)
Female preferred*Working with the public/100	0.54
	(3.38)
Male preferred*Communication with coworker/100	3.76**
	(1.46)
Female preferred*Communication with coworker/100	-5.42
	(3.54)
Male preferred*Face-to-face discussion/100	-0.88
	(1.01)
Female preferred*Face-to-face discussion/100	2.91
	(2.51)

Notes: OLS estimates. Dependent variable in all columns equals 1 if the ad explicitly requests height, and 0 otherwise. I have standardized the job contact indices and their coefficients are multiplied by 100. Other covariates are the same as the column 6 in the Table 5a. There are 1,300,118 observations.
**** p<0.01, ** p<0.05, * p<0.1.*

Table 6

Relative Importance of Customer and Coworker Discrimination Coefficients for Targeting Height in Ads

	All ads					Ads with any age requirement	Ads preferring female	Ads preferring male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer discrimination	2.23***	1.92***	1.61***	1.27***	0.89***	1.61***	8.29**	1.13
	(0.81)	(0.70)	(0.57)	(0.26)	(0.20)	(0.33)	(2.28)	(1.22)
Coworker discrimination	2.35**	2.08**	1.66**	1.3**	0.83*	1.73**	-2.17	3.23*
	(0.96)	(0.91)	(0.75)	(0.58)	(0.48)	(0.65)	(3.17)	(1.82)
P-Value of equality test	0.919	0.886	0.960	0.944	0.908	0.823	0.011	0.255

Notes: Each column refers to the sum of corresponding column's coefficients in Table 5 and columns 6-8 refer to the coefficients for each subgroup based on column 6 in Table 5. Standard errors are in parentheses. There are 1,300,118 observations.

**** p<0.01, ** p<0.05, * p<0.1.*

Table 7

The Percent of the Sum of Squares(SS) Explained by Job's Degree of Contact Covariate (ANOVA)

	Any beauty requirement		Any height requirement	
	(1)	(2)	(3)	(4)
Communication with customer	0.44%	0.36%	0.02%	0.02%
	(6,048)	(5,313)	(268)	(310)
Working with the public	0.38%	0.11%	0.28%	0.03%
	(5,221)	(1,646)	(3,717)	(504)
Sum of customer discrimination	*0.82%*	*0.47%*	*0.30%*	*0.05%*
Communication with coworker	0.23%	0.12%	0.07%	0.01%
	(3,146)	(1,774)	(983)	(127)
Face-to-face discussion	1.10%	0.56%	0.81%	0.22%
	(15,248)	(8,305)	(10,794)	(3,284)
Sum of coworker discrimination	*1.33%*	*0.68%*	*0.88%*	*0.23%*
Other covariates	NO	YES	NO	YES
R-squared	0.06	0.12	0.02	0.11

Notes: ANOVA results. The job contact indices are defined in Table 2. "Other covariates" refer to additional controls: gender, age, education, experience, part time, periods, and numbers of ads. F values are in parentheses. There are 1,300,118 observations.

Table 8

Correlation Matrix of Residuals

	Any beauty requirement (1)	Any height requirement (2)	Any age requirement (3)	Any gender requirement (4)
Panel A: no covariates				
Any beauty requirement	1.00			
Any height requirement	0.27	1.00		
Any age requirement	0.09	0.10	1.00	
Any gender requirement	0.14	0.22	0.26	1.00
Panel B: with covariates				
Any beauty requirement	1.00			
Any height requirement	0.28	1.00		
Any age requirement	0.10	0.11	1.00	
Any gender requirement	0.15	0.23	0.27	1.00

Notes: Breusch-Pagan test of independence: chi2(6) = 3.26e+05, P = 0.0000. There are 1,300,118 observations.

Table 9

Tests of Equality of Coefficients

Coefficient comparisons of beauty requirement and	P-Value (1)	Covariate coefficients tested: Communication with customer (2)	Working with the public (3)	Communication with coworker (4)	Face-to-face discussion (5)
Height requirement	0.0000	Y	Y	Y	Y
	0.0000	Y	Y	-	-
	0.0105	-	-	Y	Y
	0.0017	Y	-	-	-
	0.0863	-	Y	-	-
	0.1015	-	-	Y	-
	0.0049	-	-	-	Y
Age requirement	0.2518	Y	Y	Y	Y
	0.8288	Y	Y	-	-
	0.6312	-	-	Y	Y
	0.5511	Y	-	-	-
	0.7051	-	Y	-	-
	0.3506	-	-	Y	-
	0.5655	-	-	-	Y
Gender requirement	0.0000	Y	Y	Y	Y
	0.0000	Y	Y	-	-
	0.7237	-	-	Y	Y
	0.0201	Y	-	-	-
	0.8900	-	Y	-	-
	0.8458	-	-	Y	-
	0.4366	-	-	-	Y

Notes: Based on SUR. Tests of whether contact indices have the same effects on the beauty, height, age and gender requirement. There are 1,300,118 observations.

Appendix

Table A1
Correspondent O*NET Job Information of Jobs in Ads

	Job family name (1)	Occupation Code (2)
Sales	Sales and related	41-9011.00
IT	Computer and mathematical	15-1131.00
Marketing	Business and financial operations	13-1161.00
Accounting	Office and administrative support	43-3021.02
Administration	Management	11-1011.00
Construction	Construction and extraction	47-2073.00
Production	Production	17-3029.09
Human resource	Office and administrative support	43-4161.00
Finance	Business and financial operations	13-1031.02
Customer service	Sales and related	41-2031.00
Commerce trade	Business and financial operations	13-1199.06
Tourism	Personal care and service	39-7012.00
Communication logistics	Computer and mathematical	15-1122.00
High management	Management	11-9199.01
Electronics	Architecture and engineering	17-3012.01
Design	Arts, design, entertainment, sports, and media	27-1021.00
Education training	Education, training, and library	25-1081.00
Media	Arts, design, entertainment, sports, and media	27-3021.00
Retail	Sales and related	41-3011.00
Quality control	Life, physical, and social science	19-4099.01
Construction machinery	Construction and extraction	47-5041.00
Consultancy	Business and financial operations	13-1199.02
Technical workers	Installation, maintenance, and repair	49-3011.00
Biomedical	Architecture and engineering	17-2171.00
Healthcare	Healthcare support	31-9092.00
Other	Other	/
Law	Legal	23-1012.00
Temporary	Temporary	/
Communication tech	Computer and mathematical	15-1141.00
Translation	Arts, design, entertainment, sports, and media	27-3091.00
Students	Students	/
Energy	Architecture and engineering	17-3029.12
Chemical	Life, physical, and social science	19-4031.00
Labor domestic service	Building and grounds cleaning and maintenance	37-1012.00
Environment protection	Life, physical, and social science	19-4041.02
Research	Education, training, and library	25-1191.00
Agriculture, forest, fishery	Farming, fishing, and forestry	45-2093.00
Public servant	Community and social service	21-1021.00
Textile	Production	51-6062.00
Vehicle	Transportation and material moving	53-6041.00

*Notes: Job information downloaded from O*NET website.*

Table A2

Summary Statistics of The Component parts of The Job Contact Indices

	All			Without beauty requirement	With beauty requirement	Without height requirement	With height requirement
	Min	Max	Mean	Mean	Mean	Mean	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Communicating with persons outside the organization:							
Importance	22.000	90.000	65.518	64.473	77.397	65.245	74.574
	/	/	(16.485)	(16.500)	(10.614)	(16.479)	(13.935)
Level	19.000	84.000	55.768	54.807	66.693	55.484	65.198
	/	/	(15.107)	(14.887)	(13.181)	(15.048)	(14.017)
Performing for or working directly with the public:							
Importance	1.000	94.000	50.223	49.077	63.258	49.839	62.969
	/	/	(30.373)	(30.607)	(23.983)	(30.478)	(23.331)
Level	0.000	81.000	42.832	41.831	54.214	42.493	54.060
	/	/	(22.703)	(22.945)	(15.781)	(22.769)	(16.921)
Communicating with supervisors, peers or subordinates:							
Importance	62.000	95.000	76.477	76.235	79.222	76.456	77.147
	/	/	(8.454)	(8.169)	(10.831)	(8.365)	(11.004)
Level	41.000	79.000	61.805	61.561	64.581	61.702	65.209
	/	/	(10.542)	(10.465)	(10.998)	(10.562)	(9.196)
N	1,300,118	1,300,118	1,300,118	1,195,040	105,078	1,262,090	38,028

*Notes: Summary statistics of job descriptors downloaded from O*NET website. Standard deviations in parentheses.*

Table A3

Correlation Matrix of the Job Contact Indices

	Communication with customer (1)	Working with the public (2)	Communication with coworker (3)	Face-to-face discussion (4)
Communication with customer	1.00			
Working with the public	0.60	1.00		
Communication with coworker	0.29	-0.40	1.00	
Face-to-face discussion	0.00	-0.28	0.24	1.00

Notes: There are 1,300,118 observations.

Table A4

Effects of Job's Degree of Contact Demands on the Probability an Ad Is beauty (Height, Age, Gender)-targeted (SUR)

	Any beauty requirement (1)	Any height requirement (2)	Any age requirement (3)	Any gender requirement (4)
Communication with customer/100	3.38**	0.45	1.84	-0.95
	(1.32)	(0.92)	(2.42)	(2.07)
Working with the public/100	3.34**	1.78*	4.31*	3.58*
	(1.43)	(1.01)	(2.37)	(1.96)
Communication with coworker/100	2.09	0.74	0.23	1.80
	(1.28)	(0.93)	(1.92)	(1.94)
Face-to-face discussion/100	3.06***	1.63**	4.04***	3.80***
	(0.87)	(0.66)	(1.54)	(0.99)
R-squared	0.06	0.02	0.02	0.02

Notes: SUR regressions. Dependent variable in column 1 (2,3,4) equals 1 if the ad explicitly requests beauty (height, age, gender), and 0 otherwise. The job contact indices are defined in Table 2. Standard errors (in parentheses) are robust and clustered at the firm level. There are 1,300,118 observations.

**** p<0.01, ** p<0.05, * p<0.1.*

Table A5

Effects of Job's Degree of Contact Demands on the Probability an Ad Is Beauty (Height, Age, Gender)-targeted (SUR with Controls)

	Any beauty requirement (1)	Any height requirement (2)	Any age requirement (3)	Any gender requirement (4)
Communication with customer/100	3.54***	0.68	2.34	-0.46
	(1.15)	(0.68)	(1.87)	(1.48)
Working with the public/100	2.55**	1.15	3.00	2.31
	(1.25)	(0.73)	(1.92)	(1.46)
Communication with coworker/100	1.82	0.50	0.15	1.46
	(1.15)	(0.75)	(1.48)	(1.48)
Face-to-face discussion/100	2.81***	1.36**	3.18**	3.15***
	(0.78)	(0.54)	(1.27)	(0.87)
Other covariates	YES	YES	YES	YES
R-squared	0.07	0.04	0.04	0.04

Notes: SUR regressions. Dependent variable in column 1 (2,3,4) equals 1 if the ad explicitly requests beauty (height, age, gender), and 0 otherwise. The job contact indices are defined in Table 2. "Other covariates" refer to additional controls: education, experience, part time, periods, and numbers of ads. Standard errors (in parentheses) are robust and clustered at the firm level. There are 1,300,118 observations.

**** p<0.01, ** p<0.05, * p<0.1.*