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DISCUSSION PAPER SERIES

IZA DP No. 12022

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ABSTRACT

Gender-Targeted Job Ads in the Recruitment Process: Evidence from China*

We document how explicit employer requests for applicants of a particular gender enter the recruitment process on a Chinese job board. We find that 95 percent of callbacks to gendered jobs are of the requested gender; worker self-selection ("compliance" with employers' requests) and employer callback decisions from applicant pools ("enforcement") both contribute to this association, with compliance playing the larger role. Explicit gender requests account for over half of the gender segregation and gender wage gap observed on the board. Ad-level regressions with job title and firm fixed effects suggest that employers' explicit gender requests have causal effects on the gender mix of applications received, especially when the employer's likely gender preference is hard to infer from other contents of the ad. Application-level regressions with job title and worker fixed effects show that both men and women experience a callback penalty when applying to a gender-mismatched job; this penalty is significantly greater for women (44 percent) than men (26 percent).

JEL Classification: J16, J63, J71

Keywords: gender, discrimination, China, internet search, recruiting, screening

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Statements in a job ad that either men or women are preferred are widely used in emerging-economy labor markets.[1] This practice, which we call gender profiling, has been studied by Kuhn and Shen (KS, 2013) in China, and by Delgado Helleseter, Kuhn and Shen (DKS, forthcoming) in China and Mexico. Based on these studies, a number of empirical regularities have been established. For example, in all the data sets that have been studied so far, gender profiling is overall quite symmetric in the sense that a roughly equal number of job ads request men and women. Profiling is also job-specific in the sense that a substantial share of the variation in requested gender occurs across jobs within the same firm. In addition, gender profiling (in favor of both men and women) is much more common in jobs requiring low skill levels, whether measured by education or experience requirements or the offered wage. Finally, there is a strong interaction between employers' stated age and gender preferences, with the mix of requests strongly favoring women at young ages and men at higher ages. Some, but not all of this 'age twist' is connected to employers' frequent requests for young, physically attractive women in helping or customer-contact positions, and for older men in managerial positions.

While the above research has provided useful new facts about gender profiling, the scope of its contribution is constrained by the type of data used: these studies are based on samples of job *ads* only. Thus, while we now know what employers *ask for* (in terms of age and gender) in a large population of jobs, we do not yet know how workers respond to such requests in their application behavior, nor how serious employers are when they make such requests. At one extreme, advertised gender requests could be hard requirements in the sense that gender-mismatched applications are always rejected, or are successful only when no workers of the requested gender apply. If so, one might also expect workers' application decisions to strongly conform with firms' stated requests. At the other extreme, advertised gender requests could just be soft suggestions that a particular gender is preferred, or even that a particular gender might prefer working in that job (for example due to the presence of same-sex co-workers or a flexible work schedule). In this 'soft' case, gender-mismatched applicants could fare quite well, or indeed just as well as gender-matched applicants when they apply.

To measure how gendered job ads interact with workers' application decisions and employers' callback behavior, this paper studies applicant and callback pools to job ads on a Chinese job board (XMRC.com) over a six-month period in 2010. A key advantage of this data is

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[1] Appendix 1 provides examples of explicitly gendered job ads from the ten most populous countries served by Indeed.com ("the world's #1 job site"), representing 57 percent of the world's population. With the exception of the United States, gendered ads were easy to find on all the remaining platforms. A similar search on Computrabajo.com (which serves 20 Spanish-speaking countries) quickly detected explicit gender requests on all the larger platforms --including Colombia, Mexico, Colombia, Argentina, Peru and Venezuela-- with the exception of Spain and Chile.

that --in addition to knowing the characteristics of all the ads (including the requested gender, if any)-- we know the gender and qualifications of every person who applied to each ad, and of persons who were called back to a subset of the ads. This allows us to address three descriptive questions, and two causal questions, none of which to our knowledge have been addressed before.

On the descriptive side, our first goal is to measure the total amount of gender *matching* that occurs. Gender matching is a simple summary indicator of the relationship between gender requests in job ads and actual recruitment outcomes: In jobs that request a particular gender, what share of successful (i.e. called-back) applicants is of the requested gender? Having measured the amount of gender matching, we can then partition it into portions attributable to applicants' *compliance* with employers' gender requests (i.e. to applicant self-selection), and to employers' *enforcement* of their own requests when choosing workers from the applicant pool (i.e. to active selection by employers). In other words, if employers do indeed end up hiring the gender they requested, is that mostly because only workers of the requested gender apply, or because employers actively reject a large number of gender-mismatched applicants?

Our second descriptive task is to measure the total amount of gender *segregation* in successful applicant pools across occupations, firms and jobs, and to quantify the relationship between segregation and explicit gender designations in job ads. Are explicit gender labels so rare, or so weakly correlated with hiring decisions that they can play only a minor role in gender segregation among successful applicants? Or can the labels account for most of the *de facto* segregation that occurs? If so, does their role reflect mostly workers' compliance or firm's enforcement actions? Conceptually, these questions are isomorphic to quantifying the role of 'red lining' practices –the historic designation of U.S. urban neighborhoods by race -- in residential racial segregation (Aaronson et al., 2017). Abstracting from gendered job labels, we can pose an additional question about workplace gender segregation that to our knowledge has not been answered: does the observed level of gender segregation across *all* jobs –not just the gender-targeted ones-- result mostly from workers' self-sorting in deciding where to apply, or from employers' active selection among applicants? Existing studies of occupational segregation have not been able to address this question due to the absence of data on workers' application behavior.

Our third descriptive task is to measure the share of the gender *wage gap* that is associated with explicit gender requests. Specifically, suppose we knew nothing about jobs except their wage and the gender labels attached to them. What share of the market-wide gender wage gap could we account for with just this information?

On the causal side, our goals are to estimate the effects, in this labor market, of small, exogenous changes in the behavior of a single firm or worker on outcomes affecting that firm or worker.[2] For firms, we seek an answer to the following thought experiment: Holding constant the other contents of a single job ad (and of all other ads in the market), what would happen to the gender mix of applications the ad received if we exogenously switched its gender label from neutral (i.e. neither gender is specifically requested) to male or female? Answering this question reveals the extent to which the presence of one particular word in a job ad directs applicants' job search. To address this question, we regress the gender mix of applications to a job ad on indicators for explicit requests for men or women, with controls for an extensive list of ad and job characteristics, including the qualifications requested, the wage posted, firm fixed effects, and job title fixed effects. Importantly, Marinescu and Wolthoff (2017) show that job titles are more detailed and more predictive of wages and application decisions than are six-digit SOC codes. These detailed controls for job characteristics are critical because, for example, women may disproportionately apply to female-labeled jobs for a variety of reasons, including occupational preparation and working conditions, that are signaled by features of the job ad other than the requested gender.

On the worker side, imagine a worker who has submitted an application to a non-gendered job ad. Now, imagine that he or she re-directed that application to an ad that was identical in all respects (including the job title, firm, wage and requested qualifications) except that the ad requested a person of the opposite gender. How would the worker's callback probability change? Answering this question reveals how 'hard' employers' gender requests are in this market, i.e. the extent to which attaching a gender label to a job reflects a *ceteris paribus* intent by employers to enforce a particular gender preference when workers apply. To address this question, we regress an indicator of whether an application received a callback on indicators for the six possible matches between worker types (men and women) and job types (male, female, and no gender request). Included are detailed controls for firm and job characteristics, for the match between the job's requirements and the worker's qualifications, and most importantly both job title and worker fixed effects.

Controlling for worker fixed effects in this context is critical because, for example, workers who choose to apply to gender-mismatched jobs (e.g. women who apply to jobs that explicitly request men) may be highly selected. On the one hand, if most women who apply to male jobs do so because they are applying indiscriminately, those women are likely to be negatively selected (i.e. less productive than women who avoid gender-mismatched jobs).[3] In

[2] In making these comparisons, we are implicitly assuming that changing the gender label on a single job, or redirecting a single application made by one worker has no effect on aggregate behavior and expectations.
[3] To simplify the discussion, throughout the paper we refer to jobs that request men as "male jobs" or "men's jobs" and jobs that request women as "female jobs" or "women's jobs". "Gender-mismatched" applications refer to

that case, women's raw callback penalty from applying to a male job will overestimate the effect of applying to such a job on a woman of fixed ability. On the other hand, women who apply to male jobs may do so primarily because they feel they are *better* qualified on some dimension –such as education or experience—that compensates for being of the 'wrong' gender. In that case, naïve estimates will underestimate the penalty faced by equally-qualified women when they apply to men's jobs.

Our main results are as follows. First, we find that total gender *matching* is high: on a job board where 42 percent of the ads request a specific gender, 95 percent of callbacks to gendered jobs are of the requested gender. Worker compliance is also high, with 92.4 percent of *applications* to gendered job ads having the requested gender. Both of these figures are quite similar for male and female jobs, and are higher than matching and compliance rates defined analogously for employers' age, education and experience requests.[4] Firms' enforcement decisions reinforce these application patterns, but are far from lexicographic: Among applicants to explicitly female jobs, men are 80 percent as likely to get a callback as women; female applicants to male jobs are 45 percent as likely to be called back as men. Second, in an accounting sense, a large majority --74 percent-- of the gender matching between actual callback pools and firms' gender requests can be attributed to applicants' 'compliance', or self-selection into gender-targeted jobs.[5]

Third, turning from gender matching to gender *segregation*, we use noise-adjusted segregation measures (Carrington and Troske 1997) to calculate that 59 (59) [53] percent of the gender segregation across *all* jobs (firms) and [occupations] on this job board is associated with the explicit gender labels attached by employers to jobs. Like our results for gender matching, self-selection decisions by workers account for almost all of this label-linked segregation. Abstracting from gendered job labels, we find that workers' self-selection decisions can account for the vast majority –97 percent-- of overall gender segregation across the jobs, firms and occupations in our sample. The intuition is that application pools are so gender-segregated that –holding these pools fixed—even a completely gender-neutral callback policy would have little effect on overall segregation. Fourth, explicit gender labels on jobs can account for 61 percent of the gender *wage gap* among successful (called-back) applicants on this job board.

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mismatch between employers' requests and the applicant's gender. Later, when we use a machine-learning approach to predict the likelihood that a particular job title would request men, we refer to jobs whose titles are associated with frequent requests for men (women) as "implicitly male (female)" jobs.

[4] See Section 2 for our exact definitions of matching on these dimensions. For example, in the case of age we use the share of callbacks that fall into the age range that is explicitly requested in the job ad.

[5] We emphasize the 'accounting' nature of this exercise because high self-sorting could be caused by high enforcement, as we argue later in the paper.

Fifth, regression analysis strongly suggests that explicit gender requests in job ads have causal effects on workers' application decisions. With interacted fixed effects for firms and job titles, we estimate that the presence of a male job label reduces the female share of applicants to a job by 15 percentage points, while a female label raises the female share by 25 percentage points. Both of these effects, as well as the difference between them, are highly statistically significant. We conclude that explicit gender labels in job ads do appear to convey relevant information to prospective applicants that cannot be inferred from the other contents of the ad, and that this information directs workers' applications.

To understand why female job labels have a larger estimated effect on applicant gender mix than male labels do, we use a Bayesian machine learning approach (McCallum and Nigam 1998) to identify job ads whose gender preferences can be clearly predicted from other words in the job title, and those that cannot. Consistent with the hypothesis that prospective applicants try to infer their hiring prospects from all the information contained in the ad, we find that explicit gender labels have the largest effects on applicant gender mix in jobs whose title does not suggest a clear gender preference. Essentially, among those jobs, women tend to apply only when the job explicitly requests women, while men *abstain* from applying only when the job explicitly requests women. Thus, adding a female label has a more powerful effect on applicant gender mix. This pattern –that men are more likely than women to apply when jobs aren't clearly 'for' their gender-- echoes existing findings that female job searchers are more ambiguity-averse, and more responsive to affirmative action statements than men (Gee 2018, Ibanez and Reinter 2018).

Finally, regression analysis suggests that explicit gender labels in jobs also have ceteris-paribus effects on workers' callback chances, in the sense that labels predict how the same worker's callback chances would change when applying to identical jobs making different gender requests. Specifically, controlling for both worker and job title fixed effects, a man's callback probability is estimated to fall by 2.3 percentage points (or 26 percent) if he applies to an explicitly female job compared to a nongendered job. Women's callback probability is estimated to fall by a greater amount –3.8 percentage points or 44 percent-- if she applies to an explicitly male job compared to a nongendered job. Interestingly, both these effects are smaller in magnitude than the regression-unadjusted differentials, suggesting that, if anything, workers who apply to gender-mismatched jobs are negatively selected.[6]

Our paper contributes to a number of literatures, the first of which uses the contents of job ads to study labor markets. Such ad-content studies include Hershbein and Kahn (2015) and Modestino, Shoag and Balance (2015) both of whom ask whether employers request

[6] Point estimates indicate that this negative selection is greater for men applying to female jobs than vice versa, but this difference is not statistically significant.

higher qualifications for the same jobs when local labor market conditions make workers "easier to get". Brencic and Norris (2009, 2010, 2012), and Brencic (2010, 2012) use the same type of data to study aspects of employers' recruiting strategies, including whether to post a wage and whether to adjust ad contents during the course of recruitment. Relative to this literature, a key advance of our paper is the use of internal job board data to see whether and how such changes in ad content actually matter: do they direct workers' search, and do they inform potential applicants of how employers will respond when workers who do not meet the advertised criteria apply?

Second, our paper relates to a large literature that studies racial, gender, and other differentials in callback rates using resume audit methods (Bertrand and Mullainathan 2004, Kroft et al. 2013, Neumark et al. 2015). While our estimates of callback differentials are not experimentally based, a key advantage of our job-board-based approach is that it lets us study callbacks to the entire population of jobs on offer, which vary dramatically in their gender preferences. For example, even though a roughly equal number of jobs on XMRC request women and men, 85 percent of ads for front desk personnel explicitly request women, and 88 percent of ads for security personnel explicitly request men (DKS, forthcoming). This extreme heterogeneity poses a challenge for audit studies, which typically elicit an average race or gender preference in a relatively narrow set of jobs, often selected to be race- or gender-neutral.[7] In contrast, a key parameter in our approach *is* this heterogeneity, as captured by our *mismatch penalty* parameter: how does, say, a woman's callback probability change when she redirects her application from a nongendered to a female job? Notably, our estimates of the mismatch penalty control for unobserved worker quality by using worker fixed effects, since we can observe the same worker applying to different types of jobs.

Our job-board-based approach also broadens the study of race- and gender differentials in recruiting beyond callback differentials, to workers' application decisions and their interaction with callback differentials. When we do this, as noted we find that the vast majority of gender segregation in labor markets is not connected –at least directly—with the main parameter estimated in resume audit studies: how resumes are treated when they are submitted to employers. Instead, job segregation is closely connected to workers' choices on where to apply. Uniquely, job boards provide the opportunity to study application and callback decisions simultaneously across the entire spectrum of jobs on offer, and highlight the role of

[7] In addition to cost, a key reason for this narrow focus is the difficulty of constructing plausible resumes for a large variety of jobs, many of which are highly specialized. Thus, for example, both Bertrand and Mullainathan (2004) and Kroft et al. (2013) restrict their attention to four occupations: sales, administrative support, clerical, and customer service. Carlsson and Rooth's (2007) study is noteworthy for studying the heterogeneity in discrimination across 13 occupations.

job ad content, placement and targeting as potentially under-researched determinants of how workers are allocated to jobs.[8]

A third related literature is a substantial body of theory on directed search in labor markets (e.g. Albrecht et al., 2006). With a few recent exceptions, this literature has not examined data on how workers actually direct their applications. These exceptions include Marinescu and Wolthoff (2015); Belot, Kircher and Muller (2017); and Banfi and Villena-Roldan (forthcoming), all of whom study the effects of the posted wage on the number and quality of applications a firm receives. Marinescu and Rathelot (2015) study the geographic scope of workers' search, and Kudlyak, Lkhagvasuren and Sysuyev (2014) study how workers re-direct their search over the course of a search spell. Finally, Flory, Leibbrandt and List (2015) and Mas and Pallais (2017) study how workers' application decisions respond to competitive work environments and non-wage job attributes respectively. Given our strong estimated effects of attaching gender label to a job ad on application behavior, our results suggest that both search theorists and empirical researchers could profit from considering the effects of job ad characteristics *other than the posted wage* on workers' application decisions.

Finally, there is a large literature on gender differentials in labor markets, but very little of it has focused on the explicit gender profiling of jobs in emerging economy labor markets like the one we study here. Understanding this practice would seem to be an essential component of understanding gender differentials in labor markets in much of the world.

1. Data

As noted, our data consist of internal records of XMRC.com, an Internet job board serving the city of Xiamen. XMRC is a private firm, commissioned by the local government to serve private-sector employers seeking relatively skilled workers.[9] Its job board has a typical U.S. structure, with posted ads and resumes, on-line job applications and a facility for employers to contact workers via the site. XMRC went online in early 2000; it is nationally

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[8] An emerging concern in this regard derives from the increasing capacity to micro-target all types of online ads. For example, Verizon recently placed a job ad that was set to run "on the Facebook feeds of users 25 to 36 years old who lived in the nation's capital, or had recently visited there, and had demonstrated an interest in finance" (Angwin, Scheiber and Tobindec, 2017). In contrast to the Chinese case that we study –where all applicants can view all ads—in the Facebook case non-targeted workers were not even aware of the ad's existence.

[9] The other major local job site, XMZYJS, is operated directly by the local government. It serves private sector firms seeking production and low-level service workers. Unlike XMRC, XMZYJS does not host resumes or provide a service for workers and firms to contact each other through the site.

recognized as dominant in Xiamen, possibly due to its close links with the local government and social security bureau.[10]

To study the effect of gender profiling on application and callback patterns, we began with the universe of ads that received their first application between May 1 and October 30, 2010. We then matched those ads to all the resumes that applied to them, creating a complete set of applications. Finally, for the subset of ads that used XMRC's internal messaging system to contact applicants, we have indicators for which applicants were contacted after the application was submitted. This indicator serves as our measure of callbacks. Our primary dataset for the paper is this subset of ads for which callback information is available, which comprises 3,637/42,744 = 8.5 percent of all ads. Summary statistics for this sample are very similar to the universe of ads, shown in Appendix Table A1. In addition, Section 4 replicates our analysis of application decisions –which does not require information on callbacks—in both the larger and smaller samples, with very similar results.

Aside from being the only integrated dataset of ads, resumes, applications and callbacks we are aware of –especially in an environment that permits gendered job ads--, an important advantage of our 2010 XMRC sample is its simple and unambiguous indicator of employers' gender requests.[11] On many job boards (both in China and elsewhere), employers' gender requests must be inferred by parsing the text of the ad. In this process, the researcher needs first to identify all the different ways a firm *could* indicate a gender preference, as well as the many ways that gendered words serve a different purpose, like conveying information about the job (e.g. selling or making women's clothing), and 'inclusion' statements like "open to both men and women".[12] Sometimes judgment calls are necessary, for example in deciding whether the adjective 'beautiful' can describe both men and women. On XMRC, in contrast, employers are required to complete a 'desired gender' field (indicating male, female, or no preference) when creating a profile for each job. This datum is then made visible to workers (and can be entered by workers into a search query). Thus, our measure of whether the employer makes a gender preference statement is clear, standardized, and salient to all jobseekers on the site.

A second key advantage of our setting is the relatively simple nature of the search technology on the site: In 2010 (and still today), XMRC's site largely emulated printed job ads, where workers peruse ads using simple search filters to decide where to apply. More recently (and coming soon to XMRC), many job boards use machine learning to display suggested job

[10] XMRCs offices are in the same building as complementary local government offices (e.g. for social security and payroll taxation), offering employers the advantage of 'one-stop shopping' for employment-related services.
[11] Unfortunately, the callback indicator in our 2010 XMRC extract is not available for more recent years, because the firms using the site have transitioned away from using XMRC's internal messaging system as their means of contacting workers. As we discuss below, there may be other reasons to focus on data from before 2012 as well.
[12] This was the procedure used to identify gendered job ads on Zhaopin.com in Kuhn and Shen (2013).

matches to individual workers based on the worker's location, qualifications, employment history and recent searches. In these cases, the jobs a worker applies to are jointly determined by the jobs that are suggested to her by the board's algorithms *and* her choices from that set.[13] This joint determination does not apply to our data.

Third, the environment in Xiamen in 2010 was remarkably free of legal impediments to posting a gendered job ad, and free of stigma attached to employers posting such ads. While China's constitution has formally given women equal rights since 1982, these principles had few practical consequences for labor markets until July 2012, when the first lawsuit claiming gender discrimination in employment was filed. The first regulations that appear to have constrained firms' ability to post gendered job ads appeared in May 2016, when China's Ministry of Industry and Information Technology clearly specified fines for both job boards and employers posting such ads.[14] Since then, some Chinese job boards (especially those serving highly skilled workers) have responded by eliminating –or at least making it hard to find-- overtly discriminatory job ads on their sites. Others, including XMRC, continue to host gendered ads despite the new regulations. Even boards that have eliminated gendered ads, however, continue to allow indirect signals of their employers' desired gender (such as "gentleman" (绅士), "beautiful face" (面容姣好), and "little brother" (小哥哥)). Perhaps more importantly, these sites also allow recruiters to filter applications and resumes by gender, making it easy to restrict their attention to a preferred gender.[15]

In sum, while gendered recruitment by employers is still present in China's new legal environment, it is more varied in form and harder to detect because of the new incentives to hide it. XMRC in 2010 thus provides a much cleaner picture of how employers would choose to advertise jobs when unconstrained, and of how employers treat applications that do not match a measure of gender preferences that employers have few incentives to misrepresent. Arguably, our XMRC data may also provide insights for how gendered job ads work in countries where they remain largely unregulated.

In all, our primary dataset comprises 229,616 applications made by 79,697 workers (resumes) to 3,637 ads, placed by 1,614 firms, resulting in 19,245 callbacks. Thus there was an average of 63 applications per ad and 5.3 callbacks per ad. One in twelve applications received a callback, while one in four resumes received a callback. Descriptive statistics are provided in Tables 1 and 2 for ads and applications respectively. Table 1 shows that 867/3,637 = 24 percent of ads requested female applicants, 18 percent requested male applicants and the remaining 58

[13] We do not observe which ads were viewed by workers; thus our estimated effects should be viewed as incorporating workers' decisions regarding which types of jobs to search for.
[14] See Appendix 2 for additional details on China's labor laws as they apply to gender profiling in job ads.
[15] See Appendix 3 for a survey of gender targeting on Chinese job boards today.

percent did not specify a preferred gender.[16] The average years of requested education were 12.2, and were more than a year higher in jobs requesting women than men. Forty-eight percent of ads specified a preferred worker age; the mean requested age was 28. Consistent with the age twist identified in DKS, the requested age was considerably lower for jobs specifically requesting women. On average, one year of experience was requested. 58 percent of ads posted a wage; the mean posted wage was 2,446 RMB per month overall but only 2,001 RMB in jobs requesting women.

Table 2 shows that 124,275/229,616 = 54 percent of applications came from women. The typical application had 14.35 years of education, with women holding about half a year more education than men. Average applicant age was 24.0 years. Other applicant characteristics observed in our data (and used in the regression analysis) include experience, new graduate status, marital status, current wage (when provided), myopia, height, the number of experience and job spells listed, and whether an English version of the resume is available.

To provide some context for the sample of jobs and workers on XMRC, Table A2 compares the characteristics of job ads on XMRC with those of private-sector employees in Xiamen and in urban China, respectively.[17] The employment data are taken from the 2005 Chinese Census 1% microdata sample. Clearly, the ads on XMRC seek workers who are considerably younger, better educated, better paid, and more female than the employed population of Xiamen, or of a typical large Chinese city. This is as we might expect, for three reasons. The first is XMRC's explicit niche in the local labor market: to serve relatively skilled workers. Second, due to a massive recent expansion of China's education system, younger cohorts are much better educated than their parents. Thus, any job board seeking skilled workers will naturally be disproportionately seeking young workers.[18] Third, as on any job board, the ads and resumes on XMRC represent a population of vacancies and jobseekers, not of employed workers. Thus we would expect new labor market entrants (who are all looking for work) and young workers (who turn over more frequently than other workers) to be substantially overrepresented relative to the currently employed population.

Finally, the bottom panel of Table A2 attempts to compare the broad occupation distributions of XMRC ads to China's and Xiamen's urban labor force. This is challenging because of the occupational classification system used by XMRC, which uses 37 categories that

[16] This compares to 19, 18 and 63 percent in the universe of job ads. See Table A1.

[17] 'Urban China' in Table A2 and throughout this paper refers to China's largest cities –specifically the four municipalities directly under the jurisdiction of the central government (Beijing, Shanghai, Tianjin and Chongqing) plus the 15 subprovincial cities.

[18] Rapid educational upgrading since the 2005 Census also implies that Table A2 is likely to overstate the education gap between the XMRC ads and Xiamen's 2010 labor force.

were created by the website; mapping these into Census categories is a fairly subjective exercise. With these cautions in mind, Table A2 indicates that jobs in production, construction and manufacturing are under-represented on XMRC, while professional and technical jobs are highly over-represented. Again, this is consistent with XMRC's focus on skilled workers, a population we know is less subject to gender profiling than less-skilled workers.

2. Descriptive Analysis—Gender Matching

Descriptively, our first goal is to measure the extent to which the final pool of successful applicants to a job ad (i.e. the *callback pool*) reflects the employer's stated gender preferences. This concept of gender matching, *G*, applies only to explicitly gendered ads. We also wish to measure the relative contributions of workers' *compliance* with firms' requests and employers' *enforcement* of their own stated requirements to the total amount of gender matching that occurs. The analysis begins with some basic descriptive statistics on applications and callbacks in Table 3.

Starting with total gender matching, row 1 of Table 3 shows the share of callbacks that are female (δ) for the three job types in our data: jobs requesting women (*F* jobs), jobs requesting men (*M* jobs) and jobs that do not state a gender preference (*N* jobs). These statistics indicate a high congruence of the callback pool with firm's stated requests. Specifically, 94.0 percent of callbacks to *F* jobs are female and 100 - 3.7 = 96.3 percent of callbacks to *M* jobs are male. Combining *F* and *M* jobs, 94.8 percent of callbacks to gendered job ads are of the requested gender. Row 2 shows the share of *applications* to the three job types that are female (α). It suggests that applicants' compliance with employers' gender requests plays a substantial role in accounting for this high level of gender matching, since applicant pools are almost as highly sorted by gender as callback pools. Specifically, 92.6 percent of applications to *F* jobs are female and 100 - 7.9 = 92.1 percent of applications to *M* jobs are male. Combining *F* and *M* jobs, 92.4 percent of applications to gendered job ads are of the requested gender.

The remaining rows of Table 3 show that employers' enforcement of their own stated requests also helps to account for the overall amount of gender matching that occurs. Specifically, in jobs explicitly requesting female applicants, men who do apply are only 1/1.246 = 80.3 percent as likely to be called back as women. In jobs requesting men, female applicants are only 44.5 percent as likely to be called back as a man. Thus, at least in the raw data, employers' enforcement of their own gender requests is stronger against women applying to male jobs than men applying to women's jobs.

To get a better sense of the overall amount of gender matching and its components, it is useful to define the following index of gender matching:

$$G = \frac{g - g_0}{1 - g_0} \qquad (1)$$

where g is the share of gendered ads that are of the requested gender and g_0 is the share of gendered ads that *would be* of the requested gender if there was no gender matching (i.e. if we re-allocated the total population of called-back workers across all jobs --whether *F*, *N* and *M*-- so that the total number of callbacks to each job remained the same, but the gender mix of callbacks was equalized across all jobs). Thus G=1 if all callbacks to gendered jobs match the employers' request, and G=0 if the female share of callbacks (δ) equals its population average in all jobs. In our data, g =.948 and g_0 = .501, so our overall index, G = .897. In other words, on a scale where zero indicates no gender matching and 10 indicates perfect matching, the total amount of matching equals 9.

With this index in hand, we can now assess the relative contributions of compliance and enforcement to gender matching, G, using the identity:

$$\delta^J = \frac{\theta^J \alpha^J}{\theta^J \alpha^J + (1 - \alpha^J)} \qquad (2)$$

where J = *F, N,* or *M* and θ is women's relative risk of being chosen from the applicant pool, i.e. the ratio of callback rates (f/m). Equation (2) allows us to compute two counterfactual levels of g and G.[19] *Counterfactual 1* (no compliance) keeps enforcement, θ, at its actual level in each of the three job types, but sets α (the share of women in the *applicant* pool) at its population mean level in all jobs (i.e. at .541, from Table 3). *Counterfactual 2* (no enforcement) keeps compliance, α, at its actual level in each job type, but sets θ (women's relative risk of being picked from the applicant pool) at its population average .866 in all jobs. The results are reported in Table 4.

According to row 2 of Table 4, eliminating worker compliance while maintaining actual levels of enforcement would reduce the share of callbacks that are of the requested gender, g, from .948 to .617. The corresponding decline in the gender matching index, G, is from .897 to .232. Thus, workers' compliance with employers' gender requests accounts for (0.897-0.232)/0.897 = 74 percent of the gender matching in our data. According to row 3, eliminating employers' enforcement while maintaining actual levels of worker compliance would have a much smaller impact, reducing g from .948 to .921 and G from .897 to .842. Thus, active

[19] Like other indices used in this paper, the G index depends on the relative sizes of the three job types (J), as well as on the overall share of workers who are called back to each job type. Throughout the paper, we design our counterfactual thought experiments to hold both of these quantities constant, varying only the gender *mix* of workers who apply to different job types (or firms, occupations, etc.) and the gender *mix* of callbacks.

enforcement by employers of their own gender requests accounts for only (.897-.842)/.897 = 6 percent of the gender matching in our data. Because the decomposition in equation (2) is exact but nonlinear, the remaining 20 percent of gender matching is due to the interaction between compliance and enforcement.[20] We conclude that *compliance, i.e. applicants' self-sorting according to employers' gender requests in job ads, accounts for the vast majority of gender matching in gendered ads.* The intuition is straightforward: Because applicant pools are so highly gender-segregated, even completely equal treatment of male and female applicants in all job types would have only a small impact on the gender mix of callbacks to each job if application patterns are held fixed.

To put our estimates of gender-matching, compliance and enforcement in context, Table A3 presents comparable measures of those three quantities for employers' gender, age, education and experience requests, as well as for the match between the posted wage and the applicant's current wage (when reported). Thus, for example, row 2 shows the share of *called-back workers* whose age is within the ad's requested age range (e.g. 24-28), the share of *applications* whose age is in the requested range, and the share of age-mismatched applications that are rejected.[21] Interestingly, compliance, enforcement and total matching are all greater for gender than for these other four characteristics. While these differences are particularly dramatic on the worker self-selection side, substantial enforcement differences are also present: The shares of age-, education-, experience-. or wage-mismatched applicants that are called back all exceed 25.2 percent, compared to 5.2 percent of gender-mismatched applicants. Together, these statistics suggest an especially important role for gender, relative to these other characteristics, in what employers and employees consider to be a good match.

3. Descriptive Analysis—Gender Segregation and the Gender Wage Gap

In this second part of our descriptive analysis, we broaden our focus beyond the gendered jobs to all the jobs in our sample. Motivated by evidence of high levels of gender segregation across occupations (Blau et al. 2013), across firms (Card et al. 2016) and across jobs within firms (Bielby and Baron 1984), we wish to assess the contribution of the explicit job labels (F, N and M) to gender segregation across all these partitions of the labor market. As noted, measuring the contribution of explicit gender designations for jobs to gender segregation is mathematically analogous to the measuring the association of *red-lining* with urban residential segregation (Aaronson et al., 2017), a practice which in some cases gave

[20] By 'exact' we mean that eliminating both compliance and enforcement would reduce G to zero.
[21] Mismatch in education, experience and wages is measured by the indicators used in Table 9's callback regressions, which are based on broad categories. For example, education is measured using five categories (primary, middle, technical school, post-secondary and university) and a match occurs when the job's request and the employee's actual education fall into the same category. Additional details are provided in Table A3.

official government sanction to explicit racial categorization of neighborhoods.[22] In our case, neighborhoods that would be categorized as black, mixed, or white are directly analogous to employers' explicit designation of jobs as *F*, *N* or *M*. In the urban context, these labels presumably allocated home seekers to neighborhoods both by directing where home seekers search for housing (compliance) and via landlords' and home sellers' refusals to transact with 'race-mismatched' persons who offer to purchase or rent a home (enforcement).

In addition to measuring the total contribution of job profiling to gender segregation, this Section also decomposes that contribution into its compliance and enforcement components. Finally, we measure the connection between gendered job ads and the gender wage gap: To what extent do explicitly gendered jobs account for the gap in wages available to successful job applicants on this job board?

3.1 Measuring Segregation

To measure segregation, we use Duncan and Duncan's (1955) segregation index, applied to the set of successful applicants (i.e. callbacks) in a unit, *i*, which can be a job ad, a firm, or an occupation. The index, *S*, can be calculated from the female shares, δ_i, in those units as:

$$S = \frac{\sum_i \gamma_i |\delta_i - \Delta|}{2\Delta(1-\Delta)} \qquad (3)$$

where δ_i is the female share in unit *i*, Δ is the female share in the population, and γ_i is unit *i*'s share of the callback population. Thus, *S* is the population-weighted mean absolute deviation of the female share from its global mean, divided by its maximum attainable value, 2Δ(1-Δ).[23] Like our gender matching index *G*, Duncan and Duncan's *S* index varies between 0 and 1. It is widely used in studies of residential segregation (Cutler et al. 1999, Logan et al. 2004). Duncan and Duncan's *S* also has a well-known, natural interpretation: In our context, it gives the share of men (or women) who would have to be reassigned to a different unit (job, firm, occupation, etc.) in order for men and women to be distributed identically across units.[24]

To use Duncan and Duncan's index in our context, however, we need to address an issue that doesn't usually arise in the residential segregation context: the effect of small unit sizes.

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[22] For an example of officially sanctioned residential redlining, see Section 980 (3) of the Federal Housing Association's 1938 Underwriting Manual, which recommends "Prohibition of the occupancy of properties except by the race for which they are intended" in restrictive housing covenants. (Federal Housing Association, 1938).

[23] Equivalently, *S* can be calculated via the better known formula, $S = \frac{1}{2}\sum_j \left[\frac{\phi_i}{\Phi} - \frac{\mu_i}{\mathrm{M}}\right]$, where ϕ_i is the share of callbacks in unit *i* that go to women, $\mu_i = 1 - \phi_i$ is the share of callbacks in unit *i* that go to men, and Φ and $\mathrm{M} = 1 - \Phi$ are their population equivalents.

[24] This property is independent of which group is being re-allocated and of the relative size of the two groups (Zoloth 1976). Notably, however, the counterfactual reallocation of residents underlying this interpretation does not preserve the total populations of the units.

This effect is most important when we wish to measure and decompose segregation across individual job ads, since the average size of the callback pool to an ad in our data is 5.3 workers. Thus, purely random variation in where workers send their resumes and in which resumes are picked from the application pool could generate a considerable amount of *de facto* segregation.[25] To adjust our segregation index for the effects of random matching, we extend the one-stage sample-shuffling approach developed by Carrington and Troske (1997) to reflect the fact that the allocation of workers to jobs is actually the outcome of two random processes: the allocation of applicants to jobs, and the selection of successful applicants from applicant pools. In addition to incorporating that fact, our two-stage approach allows us to conduct counterfactual exercises that quantify the roles of compliance and enforcement in the segregation process.

More specifically, Carrington and Troske estimated the amount of racial segregation across Chicago workplaces we would expect if we took as given total employment at each workplace, and then imagined that the actual population at each workplace was a random draw from a binomial distribution whose mean black share was the population average. Simulating the Duncan-and-Duncan segregation index over multiple replications, then taking the mean of the resulting indices gave them an estimate of the amount of segregation we'd see if workers were allocated to jobs in a race-blind way. Here, we take as given the total number of applications and callbacks at every job ad. We then simulate the amount of segregation we would expect if the gender mix of applications to each ad, *and* of callbacks to each ad was the result of a random draw from binomial distributions with parameters derived from the population mean levels of α and θ. The idea is to hold fixed the total number of applications men and women make, the number of applications arriving at each job, and the total number of 'interview slots' (callbacks) available for each job. With these 'structural' features of the labor market fixed, we then assume that workers direct their applications randomly and that firms select candidates randomly. How much gender segregation would we expect to see?

In more detail, recall that the overall mean of α, $\bar{\alpha}$ =.541 and consider an ad that received 80 applications and issued 5 callbacks. We first simulate the number of female and male applications to that ad (a^f and a^m) as a random draw of 80 applications from a pool with population parameter.541, i.e. $a^f \sim B(n,p) = B(80, .541)$, $a^m = 80 - a^f$, and B indicates the binomial distribution. Next, taking this randomly-generated application pool as given (say, 51 women and 29 men), we simulate the number of male and female callbacks (c^f and c^m) as a random draw of 5 callbacks from a pool with population parameter given by:

[25] To see the point, note that if each firm calls back only one worker, segregation will always be complete: every firm's callback pool will be entirely male or entirely female.

$$p^c = \frac{\bar{\theta} a^f}{\bar{\theta} a^f + a^m} \qquad (4)$$

where $\bar{\theta}$ = .866 is the overall mean of women's relative callback risk. Thus, $c^f \sim B(n, p)$ = B(5, p^c); c^m = 5 - c^f. Doing this for every job, then calculating the realized segregation index, *S*, completes a single iteration.

Figure A1 plots the distribution of realized *S* values from 1000 iterations in this baseline scenario where there is no systematic variation across jobs in either application or callback behavior. It shows a surprisingly concentrated distribution with a mean of .317 and all values falling between .30 and .34. Thus, while random matching can generate a high level of measured segregation, the amount of segregation it generates is tightly constrained by the distribution of applicant pool sizes and callback pool sizes and the overall share of men and women in the population.

Finally, to remove the effects of this randomness, we follow Carrington-Troske by defining a *noise-adjusted* segregation measure, $\tilde{S}$, as:

$$\tilde{S} = \frac{S - S_0}{1 - S_0} \qquad (5)$$

where *S* is the unadjusted segregation index from equation (3) and $S_0 = .317$ is the mean level of segregation expected from noise in matching. Since *S* = .732, the noise-adjusted index of gender segregation across jobs in our data is given by $\tilde{S} = \frac{.732 - .317}{1 - .317} = .607$. Interestingly, this level essentially coincides with Cutler et al.'s (1999) threshold of 0.6 for defining a U.S city as having a residential ghetto.

3.2 Counterfactual Segregation Indices

Having developed a noise-adjusted measure of gender segregation across jobs, we next ask how much of this segregation is associated with gender profiling, and how much of that 'label-linked' segregation, in turn, is associated with compliance versus enforcement. To that end, we use different assumptions on α and θ to generate five counterfactual $\tilde{S}$ indices. Of these, *counterfactual A* measures the total contribution of the three job *types* (the equivalent of 'redlining' in the residential segregation context) to gender segregation across jobs. Here, instead of a common α and θ for all ads, we simulate *S* allowing both α and θ to take three levels, one for each job type. *Counterfactuals B and C* parse counterfactual A into portions related to active selection by employers versus self-selection by workers, by letting only one of α and θ vary across job types. Finally, *counterfactuals D and E* ignore the job labels (*F*, *N*, and *M*) and divide the total amount of gender segregation across jobs into a worker self-selection component and an active employer selection component. In the former case, we simulate *S* using the actual numbers of applications received by each ad, while imposing the same relative risk, θ, for all jobs. Counterfactual *E* is the mirror image of this case.

The mean levels (across 1000 iterations) of noise-adjusted segregation from all the above simulations are displayed in Table 5.[26] According to counterfactual A, if the parameters α and θ differ *only* across the three job categories (*F*, *N* and *M*), mean noise-adjusted segregation, $\tilde{S}$, would equal .359, which is 59.2 percent of all the gender segregation across jobs. Thus, about 60 percent of the total gender-segregation in the populations of successful job applicants across individual job ads on this job board is associated with the explicit gender labels employers attach to ads. To express this result more concretely, it may help to re-state the thought experiment underlying it, which imagines that there are only three types of jobs on XMRC (*F, N* and *M*) in this economy. The three job types differ in their tendency to attract female applicants (α) and in employers' propensity to select women from applicant pools; within each job type all jobs are identical. How much gender segregation would there be, compared to what we actually see? The answer is 60 percent. The remaining 40 percent (much of it within the *N* jobs) is not associated with employers' explicit requests, and is presumably similar to the type of segregation that prevails in countries that do not practice explicit gender profiling in jobs.

Turning to the contributions of compliance and enforcement to the 'label-linked' segregation identified above, B and C show that essentially all of the label-linked job segregation is due to self-sorting: allowing only α to differ across the three categories leads to a level of noise-adjusted segregation that is 57.8 percent of the actual level, while allowing only θ to differ generates only 6.6 percent of actual noise-adjusted segregation. Thus, in the analogy to residential segregation, home seekers' (job seekers') compliance with the designations of three neighborhood (job) types accounts for 57.8 percent of the census-block level (job-level) segregation in the city (labor market). These results mirror the dominant role of self-selection in accounting for gender-matching (*G*) which we have already identified.

Finally, counterfactuals D and E abstract completely from the gender labels attached to job ads and simply ask what share of noise-adjusted sex segregation in the successful applicant pools across individual job ads is associated with men's and women's differential application patterns, versus their differential success rates conditional on applying. Together these two counterfactuals show that *self-sorting* (both directed and undirected) *accounts for 97 percent of all the systematic gender segregation* across jobs in our data.[27]

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[26] The distributions of *S* values across these counterfactual simulations are also highly concentrated, similar to the baseline, 'noise-only' simulation.

[27] Enforcement alone –without any self-selection—can account for as much as 18 percent. The enforcement and compliance shares now add up to more than 100 percent because (in contrast to Table 4) these counterfactuals

The preceding methods for computing actual and counterfactual noise-adjusted segregation indices across jobs can also be applied to segregation across other labor market units, including occupations, firms, and occupation*firm cells. The results of these calculations are summarized in Table 6. Notice first that --as one might expect-- the impact of noise-adjustment on the estimated level of segregation diminishes as the unit size increases (from jobs through occupations). In fact it is minimal in the case of occupations, where the unit size is the largest, but it plays non-negligible roles in the remaining cases. At $\tilde{S}$= .561, Table 6 shows that gender segregation is almost as high across firm*occupation cells as across individual job ads, and that explicit gender profiling accounts for 59 percent of that segregation. Segregation across firms and occupations is lower, though it is interesting to note that $\tilde{S}$ is slightly higher across the 36 occupation categories on the XMRC website than across the much larger number of firms in our sample. This is consistent with a long literature documenting the importance of occupational sex segregation and with DKS's finding that a large share of the variance in employers' gender requests occurs *within* firms. Column 4 of Table 6 shows that explicit gender profiling accounts for 59 percent of the gender segregation across firms and for 53 percent of the gender segregation across occupations.

A final perspective on the contribution of explicit gender labels to gender segregation examines the amount of gender segregation that is present within the 58 percent of our job ads that are not explicitly gendered: If explicit labels are epiphenomena that do not affect the allocation of workers to firms, we might expect to see just as much segregation within the nongendered ads as in the entire sample. Perhaps employers' gender preferences and workers' job preferences are just as highly gendered even when –as in the United States-- no public gender labels are attached to the jobs. We perform these calculations in Appendix Table A4, and find much less gender segregation within sample of nongendered ads than in our sample overall. Compared to .607 overall, noise-adjusted gender segregation within the sample of nongendered jobs is only .417. Occupational segregation by gender is .446 overall, but only .300 in non-gendered jobs. These figures suggest, but do not prove, that gendered job ads have real effects on the allocation of labor in China.

Summarizing our descriptive analysis of gender segregation in callback pools, we find that jobs on XMRC are highly gender-segregated, with a noise-adjusted Duncan and Duncan segregation index of .607. In other words, 60.7 percent of either men or women would have to change jobs to equate the gender ratio across all jobs. Explicit gender profiling in turn accounts for 59 percent of that job-level segregation. Gender profiling also accounts for 59 percent of

add enforcement and compliance, in turn, into a baseline scenario where neither is present, rather than subtracting them from a scenario where both are present. Analogous to adding regressors to an equation sequentially, the share explained by the first factor considered is larger in the absence than in the presence of a control for the second.

the gender segregation across firms, and for 53 percent of the gender segregation across occupations. Finally, the vast majority of the association of gender profiling with all the outcomes studied in this Section is through workers' compliance with firms' advertised requests when deciding where to send their resumes, rather than through active denials of callbacks to gender-mismatched applicants.

3.3 Actual and Counterfactual Gender Wage Gaps

With some minor modifications, the methods developed in Sections 3.1 and 3.2 can be adapted to measure the association between gendered job ads and the gender wage gap. To that end, we begin by estimating the gender wage gap among successful job applicants on XMRC, then decompose that gap into portions associated with gendered job ads, and (within that portion) to compliance versus enforcement processes. While a measure of the gender gap in *advertised* wages is readily available from our sample of job ads, most existing estimates of gender wage gaps refer to the gap in wages earned by employed workers. To approximate this measure more closely, we use a worker-based approach. Essentially, we treat callbacks as job offers and measure a jobseeker's wage as the highest posted wage he or she was offered, regardless of the type of job (*F*, *N* or *M*) it was from.[28] Calculating mean wages this way yields a gender wage gap, ω, of 0.146 log points.[29]

How much of this gender wage gap is associated with explicitly gendered job ads? To answer this question, we create the same 1000 simulated, counterfactual assignments of applications to callbacks we used in Section 3.2: recall that these simulations assumed that all assignments were random except for the fact that there were three types of jobs (*F*, *N* or *M*), each with its own gender mix of applicants, α, and its own relative propensity to pick women from the applicant pool, θ. However, instead of calculating a segregation index for each assignment, we calculate an economy-wide gender wage gap, ω by assigning each callback the mean wage for that *job type*, $\overline{w}^F, \overline{w}^N$, or $\overline{w}^M$. Finally, the gender wage gap that is associated with the three job types is just the mean gap across these 1000 iterations. Re-doing these simulations while allowing *only* α or θ to differ across the three job types shows the relative contribution of compliance and enforcement to that gap.

The results of these calculations are reported in Table 7. Overall, the log wage gap implied by the three explicit job types equals .089. In other words, the fact that the three explicit job types –each of which has its own α and θ-- pay different mean wages can account for 60.8 percent of the overall gender gap in wages. As in our analysis of gender matching and

[28] Thus, for workers who did not receive any callbacks, or whose callbacks did not post any wages, we do not observe a wage.

[29] Interestingly, this turns out to be very similar to the gender gap *advertised* wages on XMRC, of 0.172 log points. Both gaps are, however, considerably smaller than the.280 log point gender wage gap reported in Table A2 for the city of Xiamen as a whole. Recall that our XMRC sample is much younger than Xiamen's employed workforce; gender wage gaps tend to be much smaller early in workers' careers.

gender segregation, decomposing this 'explained' portion of the gender wage gap into compliance and enforcement effects attributes the vast majority to compliance, for the simple reason that the types of callbacks workers get are determined almost exclusively by where they choose to apply.

4. Regression Analysis—Compliance

Our analysis so far paints the first statistical portrait of how gendered job ads enter into the recruitment process. As a descriptive exercise, however, it does not identify a causal effect of job profiling on either workers' application behavior or employers' selection behavior. In this Section, we focus on application behavior --compliance-- and define a causal effect of gender profiling on workers' application decisions as the outcome of the following thought experiment: Imagine that the observed patterns of job profiling and application decisions in our data constitute a labor market equilibrium in the sense that employers' advertising and selection decisions are optimal given workers' application behavior, and vice versa. In this equilibrium, row 2 of Table 3 indicates that *F*, *N* and *M* job ads attract applicant pools that are 92.6, 44.7 and 7.9 percent female respectively. Now suppose we exogenously switch the explicit gender label attached to just one of the many *N* jobs to *F* or to *M*, keeping everything else –including the labels on all the other jobs-- unchanged.[30] What will happen to the share of applicants to that job that are female? If this share does not change, then the large differences in the gender mix of the three job types in Table 3 are not causal, in the sense that the gender labels do not actually direct workers' application decisions. Instead, the labels may simply be standing in for other features of the job (such as the occupation) that tend to attract applicants of different genders.

Accordingly, our econometric attempts to isolate a causal effect of gender labels on application behavior will focus on controlling as tightly as possible for other characteristics of jobs (or job ads) that might also explain why different ads attract different mixes of men and women. We take two complementary approaches. In the first, in addition to a detailed list of skill requirements and other desiderata in in the job ad, we control for firm fixed effects and job title fixed effects. Job titles are the main heading in every job ad. They provide a brief description of the job and can run up to 18 words in XMRC. For example, here is a random sample of ten (translated) job titles on the XMRC website: front desk administration assistant, project engineer, quality control, shift leader, customer service maintenance specialist,

[30] Because it fixes the application and callback rates in all other jobs, note that this thought experiment implicitly holds fixed the *beliefs* of prospective applicants about their callback chances in the three job types (*F*, *N* and *M*). In essence, if attaching a male job label on an XMRC job signals to female applicants that their chances of getting a callback are X percent lower than they would have been otherwise, our regression estimates incorporate the effects of those applicant beliefs on women's application strategies.

administration, ME product engineer, experienced two-dimension designer, customer service engineer, and front desk clerk. Job titles provide considerably more relevant information about the type of work than even the most granular standardized occupational classification systems. For example, Marinescu and Wolthoff (2015) found that job titles on Careerbuilder.com were much more predictive of advertised wages than 6-digit SOC codes, and were essential controls for identifying the effect of advertised wages on the number and quality of applications an ad received. Thus, in this approach we will be comparing two observationally identical ads for a very narrowly defined type of work, holding constant the identity of the firm advertising the job.

In our second approach, we replace the job title fixed effects in the above analysis by indicators of the predicted, or *implicit* 'maleness' or 'femaleness' of the job derived from a machine learning analysis of the words in the titles. Essentially, we use the words in the title to predict whether a person reading it can infer whether the job is likely to request men, or to request women. While these two predicted probabilities (*Mp* and *Fp*, respectively) absorb less variation in job characteristics than the full set of title fixed effects, they provide a simple structure that helps us see precisely where –i.e. in which types of jobs—inserting a gender label into a job ad has the largest impact on application behavior. Notably, in both approaches, we use the entire sample of job ads available to us, not just the subset for which callback behavior is observed. To check for robustness, we replicated both analyses for the 'callbacks' subsample with very similar results.

4.1 Approach 1: Job Title Fixed Effects

As noted, here we run regressions in our entire sample of 42,744 ads, where the dependent variable is the share of applications that are female (α). The regressors of interest are the labels attached to the ad (*F*, *N* or *M*). In more detail, we estimate:

$$\alpha_j = a + bF_j + cM_j + dX_j + e_j \quad (6)$$

where *j* indexes jobs (ads), *F* (*M*) is a dummy for whether the job requests women (men) and *N* is the omitted job type. In column 1, we include no controls (X_j). Column 2 adds controls for the following job characteristics: requested education, experience, and age; the advertised wage; a dummy for whether a new graduate is requested; the number of positions advertised; plus dummies for missing education, age, wage and number of positions. Columns 3-5 in turn add occupation, job title and firm fixed effects, and column 6 interacts these job title and firm fixed effects. Thus, column 6 compares applicant pools across ads posted by the same firm for the same detailed job title, but with different gender requests. The extent to which the *b* and *c* coefficients attenuate as we add these controls captures the extent to which explicit gender labels are correlated with other features of job ads (such as a typically male occupation or job title) that allow applicants to infer the ad's desired gender even in the absence of an explicit gender request.

Table 8 shows that, as expected, the unadjusted effects of both the *M* and *F* job labels attenuate substantially --from -35 to -15 percentage points for *M* labels and 50 to 25 percentage points for *F* jobs-- as we add detailed controls for job characteristics, including interacted firm and job title fixed effects. Thus, a substantial share of the correlation between jobs' gender labels and the gender mix of applicants reflects the fact that men and women apply to different types of jobs, regardless of whether those jobs are explicitly targeted at their gender. Still, the estimated effects of the gender labels remain economically large and highly statistically significant, even when comparing the same job title in the same firm with different gender labels attached. [31] This suggests that an explicit gender request in a job ad may have substantial causal effects on the gender mix of applications it will receive. In other words, employers' gender requests appear to direct workers' applications.[32]

4.2 Approach 2-- Implicit Maleness and Femaleness

To better understand the source of the apparent compliance effect identified in Table 8, we now try to identify the types of jobs in which making an explicit gender request has the largest effects on application mix. If prospective applicants are using gender labels and other features of the job ad to predict whether a person of their gender would have a good chance of receiving a callback, we would expect explicit requests to have the largest impact on applications *in jobs where it is difficult for workers to infer the employer's gender preferences from the other contents of the ad.* To formalize this notion, we now replace the job title fixed effects in Table 8 by predicted probabilities that the job requests men (women), calculated from the words that appear in the title. Treating each ad's job title as a document, we calculate the implicit maleness and femaleness of each job using the Bernoulli naïve Bayes classifier (McCallum and Nigam 1998) for document classification; classifiers of this type are widely used in predicting whether a document is of a given type, for example a spam email.

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[31] As column 6 indicates, our estimates with title*firm fixed effects are identified by 1,448 job ads for which a firm*job title cell made different gender requests at different times. Importantly, these estimates are not driven by a single large firm, job title or title*firm cell: these 1,448 ads represent 416 distinct job titles posted by 505 different firms, and comprise 686 title*firm cells. Histograms of estimates that leave out one job title at a time in Figure A2 are highly concentrated: all estimates of the request-male effect are between -.155 and -.136 and statistically significant (p<.01). All estimates of the request-female effect are between .238 and .265 and highly statistically significant (p<.01).

[32] Table 8 is replicated for the subsample of jobs for which we have callback information in Table A5, with similar results: Here, the most saturated specification we can estimate replicates column 5, where firm and job title fixed effects are entered separately. In that specification, the estimated effects of male and female labels are -.103 and -.240 respectively; both are highly statistically significant.

Briefly –exact details are available in Appendix 6-- for each word, *w*, that appears in our entire set of job titles, we first estimate the probability of observing that word in the title of a job that requests men, Prob (observe word *w* | job requests men) using empirical frequencies. Next, treating job titles as 'baskets of words' which appear independently, we can compute the probabilities of observing a given job title, *k*, given the job requests men, Prob (observe title *k* | job requests men) from its constituent words. Finally, using Bayes formula plus an assumption about workers' prior beliefs, we can compute the predicted maleness of each job title based on the words it contains.[33] Using the same procedure to predict each title's femaleness yields the two continuous variables,

$$M_p \equiv Prob(job\ explicitly\ requests\ men |\ job\ title\ k) \qquad (7)$$

$$F_p \equiv Prob(job\ explicitly\ requests\ women |\ job\ title\ k) \qquad (8)$$

which we use in our empirical analysis to represent the information contained in the job title about whether the job is likely to request men or women. Overall, *Mp* and *Fp* are quite predictive of employers' actual requests, with correlations of .411 and .402 with actual requests for men and women respectively. As we might expect, they identify what we might think of as stereotypically male and female jobs: the five 'most female' job titles (starting with the highest) are "front office desk staff", "administration office staff", "office staff", "cashier" and "administration assistant". The five 'most male' are "driver", "technician", "warehouse managing staff", "warehouse manager, and "production manager".[34] These indices of implicit maleness or femaleness allow us to estimate the effect on application behavior of adding an explicit gender request to jobs that 'look the same' in terms of an employer's likely gender preference, and to see in which types of jobs the effect of explicit requests on application behavior is the greatest.

More specifically, we now regress the female share of applicants to a job, α_j, on employers' explicit gender requests (*F* and *M*), plus all the control variables used in column 5 of Table 8 (other than the job title fixed effects) plus quartics in the implicit maleness or femaleness of the job that workers could infer from the job's title (*Fp* and *Mp*). In addition, each of these quartics is interacted with the three explicit job types, *F*, *N* and *M*. These interactions allow, for example, the effect of an explicit request for women to be either stronger or weaker in jobs that are stereotypically male (based on the words that appear in the job title) than in jobs whose titles do not convey an obvious gender preference.

[33] We adopt the naïve prior that the unconditional chances a job requests men equals 50 percent. This simplifies the computations and reflects the idea that individual jobseekers may not have access to good summary statistics on the share of jobs of different types available to them.

[34] Additional examples of job titles at different levels of *Fp* and *Mp* are provided in Appendix Table A6.

Predicted male and female applicant shares from these regressions are shown in Figure 1. Part (a) of the Figure shows the predicted female applicant share as a function of the predicted femaleness of the job based on the words in the job title, separately for the three types of jobs (*F*, *N*, and *M*). Predicted maleness is held fixed at its mean. Part (b) is the parallel figure for male applicant shares as a function of perceived maleness, holding predicted femaleness at its mean. Finally, part (c) shows the effects of encountering a request for a particular gender (relative to a non-gendered job) on the share of that gender in the applicant pool, with 95 percent confidence bands. These are the distances between the top two curves in parts (a) and (b).

Figure 1 shows, first of all, that explicit requests for male and female applicants have stronger effects on the gender mix of applications when the words in the job title do not send strong signals about whether the employer is likely to prefer men or women (i.e. when *Mp* and *Fp* are low). For example, when *Fp* is near zero, the predicted effect on the female applicant share of inserting an explicit request for women into an *N* job is about 53 percentage points. This effect diminishes to about 26 percentage points when *Fp* equals 0.7. A similar pattern is present for men, though it is less pronounced.

Second, there is a subtle but interesting gender difference regarding *when* explicit requests matter. In 'not-obviously-female' (low *Fp*) jobs, women comprise a relatively large share of applicants *only when* the job explicitly requests women. In 'not-obviously-male' (low *Mp*) jobs, men comprise a relatively large share of applicants both when men are explicitly requested, *and* when the job does not have a gender label. Together these patterns help us understand the much larger impact of *F* labels than *M* labels on the applicant mix in Table 8. Essentially, the main gender difference in application behavior occurs in jobs that –based on their title—are neither stereotypically male nor female. If we think of applying for jobs as entering a competition to get hired, these patterns are evocative of well-known gender differences in entry into competition (Niederle and Vesterlund 2007), and of less-well known gender gaps in the propensity to apply for jobs in the presence of ambiguity (Gee, forthcoming).[35]

We conclude our discussion of compliance effects with a reminder that our substantial estimated effects are consistent with at least two underlying mechanisms. One is that job labels communicate information about a worker's chances of getting a callback; in this view, women avoid male jobs because they know they have a much lower chance of getting those jobs if they apply. The second mechanism is that –much like labels on men's and women's

[35] To probe robustness to functional form, Figure A3 forces predicted applicant shares to be between zero and one by changing the dependent variable from α (the female share) to log ($\alpha/(1-\alpha)$), and replacing the quartics in *Fp* and *Mp* by linear terms (still interacted with *F*, *N* and *M*). In both cases, our main conclusions --including the larger effects of *F* labels than *M* labels on applicant mix-- continue to hold.

clothing—job labels communicate information about whether the worker is likely to want the job, without conveying any reluctance by the firm to transact with the worker. In this mechanism, women avoid male jobs because women dislike certain job attributes –perhaps competitive pay policies, long and inflexible hours, or even the absence of female co-workers—associated with those jobs. Assessing the relative importance of these two mechanisms requires an analysis of how gender-mismatched applications are treated when they are made, which is our goal in the next Section.

5. Regression Analysis—Enforcement

As noted, our goal in this Section is to estimate the effect of exogenously re-directing a single worker's *application* from a non-gendered (*N*) job to an identical gender-mismatched job, i.e. to a job that explicitly requests the opposite gender from the worker's. If little or nothing happens to the worker's chances of receiving a callback, then employers' advertised gender preferences are 'soft' preferences, in the sense that job labels may convey information about workplace characteristics that men and women may evaluate differently, but gender-mismatched applicants are evaluated on the same basis as the other applications that arrive. If instead there is a large gender *mismatch penalty*, gendered job labels are hard requirements imposed by employers.

To set the stage for our analysis, we begin by considering the naïve estimates of men's and women's mismatch penalties that emerge directly from our descriptive analysis. According to Table 3, women's apparent callback penalty from applying to an *N* versus an *M* job is 8.7 - 4.3 = 4.4 percentage points, or a 51 percent reduction in the chances of getting a callback. Similarly, men's penalty equals 9.0 – 5.8 = 3.2 percentage points, or a 36 percent reduction. Together, these numbers suggest that –while hardly absolute—employers' enforcement of their advertised gender requests is moderately 'hard'. Our main goal in this Section is to empirically distinguish two distinct scenarios that could account for these numbers. The difference between the scenarios hinges on the types of people who choose to apply to gender-mismatched jobs.

Consider scenario 1, in which selection into gender mismatch is positive. Here, applications that are made to gender-mismatched jobs are, on average, better qualified, and better matched (on dimensions other than gender) than other applications. This makes sense, for example, if the women who choose to apply to jobs requesting men are better qualified on dimensions like education, experience, and unobserved ability that the applicants hope will compensate for being of the 'wrong' gender. Related, when applying to explicitly male jobs, women may restrict their attention to the jobs fit their qualifications most closely. In this scenario, Table 3's raw mismatch penalties will underestimate the adverse effects of gender mismatch on the callback rate (because the people who cross-apply are better-qualified and better matched than those who do not). Adding controls for worker qualifications and job-worker match should increase the magnitude of the estimated penalty towards its true, larger value.

Now consider scenario 2, where selection is negative. Here, applications that are made to gender-mismatched jobs are, on average, less qualified, and worse matched (on dimensions other than gender) than other applications. This makes sense, for example, if the women who apply to jobs requesting men are primarily people who apply to jobs indiscriminately, for example because they have low application costs, are highly motivated to find a job, or are simply careless. In all of these cases, applicants who ignore explicit gender requirements might also ignore education, experience and other important requirements, so their applications are more poorly matched on average. In this case, Table 3's 4.4 percentage point mismatch penalty for women will overestimate the callback penalty associated with applying to an *M* job for a woman of fixed ability. Adding controls for worker qualifications and job-worker match should attenuate the magnitude of the estimated penalty towards its lower, true value. Indeed, if negative selection is strong enough, the true mismatch penalty could be zero. Here –since our best estimates of worker compliance are large—the most natural interpretation of our data would be one where advertised gender labels communicate job attributes that men and women care differently about, as in the example of men's and women's clothing.

To distinguish these two scenarios empirically, we run linear probability regressions in a sample of applications, where the dependent variable is an indicator for whether the worker received a callback. In doing so, we try to control as tightly as possible for other aspects of match and worker quality that might affect callback rates. Of particular note, we control for unobserved worker ability by using worker fixed effects—i.e. we will compare the callback rates of the same worker who sends her resume to two observationally-identical jobs that differ only in their explicit gender label. We control for the detailed type of work using job title fixed effects. To account for the fact that people who apply to jobs requesting the 'other' gender might be better- or worse matched to the job on dimensions other than gender, we also include detailed controls for matching on a variety of characteristics.

In more detail, we estimate the following linear probability model:

$$Callback_i = \alpha + \beta_1 FtoF_i + \beta_2 FtoM_i + \beta_3 MtoF_i + \beta_4 MtoM_i + \delta Mworker_i + \varphi X_i + \varepsilon_i \quad (9)$$

where *i* indexes *applications*. Of the six possible application types, women applying to nongendered jobs (*FtoN*) is the omitted type. In this specification, β_1 and β_2 give the effect on women of applying to *M* and *F* jobs (relative to nongendered jobs), while β_3 and β_4 give the effect on men of applying to *M* and *F* jobs (again, relative to nongendered jobs). The parameter δ gives the callback gap between men and women applying to nongendered jobs. Our main focus will be on the *gender mismatch penalties* associated with applying to a job that is targeted at the 'other' gender, β_2 and β_3.

Column 1 of Table 9 estimates equation 9 without controls, replicating the unadjusted gaps in Table 3. Column 2 adds controls for the job's requested level of education, experience and age; the advertised wage; and an indicator for whether a new graduate is requested. Also included are indicators of the match between the applicant's characteristics and those requirements, including indicators for whether the applicant's education, age and experience are below or above the requested level, the match between the advertised wage and the applicant's current or previous wage, and the match between requested and actual new-graduate status. Column 3 adds controls for the following worker (CV) characteristics: whether he/she attended a technical school; the applicant's *zhicheng* rank; whether an English CV is available; the number of schools attended, experience spells and certifications reported.[36] Indicators for applicant height, myopia and marital status are also included, all interacted with the applicant's gender.[37]

Column 4 adds fixed effects of the occupation of the advertised job, using XMRC's occupational categories. Column 5 adds job title fixed effects plus two indicators of the amount of competition for the job: the number of positions advertised and the number of persons who applied to the ad.[38] Column 6 adds a full set of worker fixed effects; in this case, the effects of fixed applicant characteristics ("detailed cv controls" and the main gender effect) are not identified. Interactions between applicant gender and job type, which are our main coefficients of interest, however, remain identified. In effect, column 6 compares the outcomes of *the same worker* who has applied to observationally identical jobs that differ only according to the gender label (*F*, *N* or *M*) attached to the job, while allowing for this effect to differ according to the applicant's gender.

Before discussing our main coefficients of interest, it is worth noting that whenever they are statistically significant, observable indicators of the match between worker qualifications and job requirements are of the expected signs in Table 9: workers who have less education or experience than requested, or are older than requested are less likely to be called back. Finally,

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[36] *Zhicheng* is a nationally-recognized worker certification system that assigns an official rank (from one through six) to workers in almost every occupation. Ranks are based on education, experience and in some cases nationwide or province-wide exams.

[37] These 'detailed CV controls' introduced in column 3 are not requested in job ads very often, so it is not practical to construct variables summarizing their match with the job's requirements.

[38] These 'queue length' or 'submarket tightness' controls account for the possibility that overall competition for callbacks might be systematically stiffer in some job types than others. For example, callback rates in jobs that request women might be lower for *all* applicants if women 'crowd into' those jobs more than men crowd into jobs that request men (Sorensen 1990).

the job competition controls (not shown) are always highly statistically significant, verifying that the ratio of applicants to open positions in any ad has strong effects on the chances of being called back. Also of some interest, workers with *more* education than the job requests also experience a statistically significant callback penalty in all specifications but one (Shen and Kuhn 2013).

Turning to the mismatch penalties, both men's and women's penalties attenuate somewhat as we add covariates in Table 9. This consistent pattern supports scenario 2 – in which gender mismatched applicants are negatively selected and Table 3's raw mismatch penalty overstates the true penalty—over scenario 1 in which gender-mismatched applicants are positively selected. That said, the mismatch penalty remains both economically and statistically significant in the presence of worker fixed effects (column 6). For a woman, applying to a job requesting men reduces her callback chances by 3.8 percentage points, only a little less than the unadjusted effect (4.4 percentage points). For men, the attenuation is more pronounced –from 3.2 to 2.3 percentage points—suggesting a greater amount of negative self-selection into gender-mismatched applications among men.

In sum, our preferred estimates in Table 9 (column 6) imply that both men and women face substantial callback penalties when they apply to jobs that request the 'other' gender. These large and significant callback penalties point away from the extreme 'clothing labels' version of scenario 2 –where women's reluctance to apply to explicitly male jobs is due purely to the applicants' own tastes—as the best representation of our data. In addition, there is some gender asymmetry in our estimated callback penalties, with women's penalty for applying to explicitly male jobs (3.8 percentage points, or 44 percent) exceeding men's when applying to female jobs (2.3 percentage points, or 26 percent). This gender difference is highly statistically significant.

Two potential concerns with the above estimates are the possibility of gender misclassification and the effects of luck in the application process. Concerning gender misclassification, if some workers' genders are miscoded in their XMRC profiles we would expect to see the misclassified workers to apply to an unusually large number of apparently gender-mismatched jobs. To see if this could be driving our results, in Appendix 5 we exclude from the estimations the very small number of workers who direct more than half of their applications to opposite-gender jobs, with very little change in the results.[39]

[39] Miscoding of the *requested* gender is not a concern since our data are the exact record of requested gender that workers observe on the job board when deciding where to apply. See Appendix 5 for additional discussion of how gender is coded on the job board and on how we construct our "gender misclassification-robust" subsample of applications.

Concerning luck, our results could overstate employers' openness to gender-mismatched applicants if a significant number of wrong-gendered applicants are being called back only because no candidates of the preferred gender applied to the job (Lang, Manove and Dickens 2005; Lazear, Shaw and Stanton 2018). While our job competition controls capture some of these effects, a more direct test is to look directly at applicant pools containing zero applicants of the requested gender. As it happens, none of the 666 male jobs in our dataset received zero male applicants. We did find five female jobs that received no female applicants, and these jobs did call back some men. However, these jobs constitute less than 0.6 percent of the 867 female jobs in our sample.

We conclude this Section with two important caveats regarding the interpretation of our enforcement estimates. The first is that the substantial and robust mismatch penalties in callback rates we estimate here do not in themselves constitute evidence for any particular form of discrimination, such as taste-based or statistical discrimination. Indeed, mismatch penalties are consistent with a number of underlying processes, including gender differences in productivity (both real and imagined), and the tastes of employers, recruiters, co-workers and customers, with the important proviso that any such productivity or taste differences must be highly *job-specific* to explain the patterns in our data. To distinguish among these possible sources of mismatch penalties, research needs to examine the precise types of jobs in which they occur. For example, to assess the role of job-specific productivity differences one could look at tasks where there is established evidence of gender differentials in performance (Baker and Cornelson 2016, Cook et al, 2017). Customer tastes could be isolated by looking at jobs involving customer contact, and at whether gender requests are accompanied by requests for a photograph or for applicant beauty. More detailed parsing of the words in job titles can also provide useful clues. Indeed, DKS (forthcoming) parse job titles in their study of employers' *decisions to post* gendered job ads, finding some support for a customer-tastes explanation of a significant share of these posts. Specifically, they find a large group of ads requesting young, attractive women in customer-contact jobs.

A second caveat concerns treatment effect heterogeneity. Specifically, while we have a number of controls for the quality of the match between the worker and the job, it is important to remember that our estimates still represent *treatment-on-the-treated* effects on the sample of applications people choose to make to gender-mismatched jobs. If –as we might expect-- workers disproportionately apply to the gender-mismatched jobs where they know their personal gender mismatch penalty (i.e. their treatment effect) is small, our estimates in Table 9 would underestimate the callback penalty associated with a randomly-selected gender-mismatched job. Of course, if selection on treatment effects is negative (such that the workers who apply to gender-mismatched jobs are the most harmed by doing so), the mismatch penalty for a randomly-selected job would be smaller than the one we estimate here.

6. Summary and Discussion

We believe that this is the first paper to study the (proximate) *consequences* for workers and firms of a common practice in the world's labor markets: job advertisements that request workers of a specific gender. Using internal application and callback information from a Chinese Internet job board, we find a high degree of correspondence between the gender employers request in a job ad and actual outcomes of the recruiting process: nearly 95 percent of successful applications (callbacks) to explicitly gendered jobs are of the requested gender. We then partition this high level of gender-matching into two components—the propensity of workers to apply where they are requested (compliance) or employers' active rejection of gender-mismatched applicants (enforcement). Of these, compliance, or worker self-selection, plays the dominant role. Gendered job ads also account for a substantial share of the gender segregation observed in our data across jobs, firms and occupations, mostly through worker self-selection as well. Intuitively, since so few workers apply to gender-mismatched jobs, total gender segregation would change very little in a counterfactual world where employers ignored gender in all their callback decisions, but application patterns were held constant. In addition, gendered job ads, which comprise 40 percent of the ads in our data, can account for 60 percent of the gender wage gap in the data.

In addition to painting this statistical portrait of how gendered job ads enter the recruitment process, we have attempted to answer two causal questions: In this labor market, what would be the effect on an employer's application pool of adding an explicit request for male or female applicants to a job ad, with no other changes to the ad? And what would be the consequences for a worker's chances of getting a callback, of redirecting his (her) application from a nongendered job ad to an identical ad that requested the opposite gender? Using firm and job title fixed effects in the former case, and worker and job title fixed effects in the latter, we find that these consequences appear to be substantial: explicit gender requests are not just superfluous information that can be inferred from other contents of the job ad. Instead, gendered job ads appear to direct workers' application decisions *and* to predict how employers will treat applicants of the 'wrong' gender.

While we believe that our analysis has increased our understanding of the role of gendered job ads in the recruitment process, an important caution is that our results are not directly informative about what would happen if a country successfully banned such ads, as the United States and Austria did in 1974 and 2004 respectively.[40] One reason is the fact that employers might respond to a ban by crafting other, legal signals that direct the same workers

[40] In 1973, gendered job ads were prohibited by the U.S. Supreme Court. (*Pittsburgh Press Co. v. Pittsburgh Commission on Human Relations et al*). In 2004, the Austrian government instituted a 360 Euro per-ad fine on gendered job ads as part of the Austrian Equal Treatment Act. See Walsh et al. (1975, chapter 5) for a fascinating study of gendered job ads in the United States prior to the 1973 prohibition.

to the previously-labeled jobs, resulting in little or no change to application and callback patterns.[41] A second reason relates to the endogeneity of workers' application decisions (the α's in our decompositions) and of employers' callback decisions (the θs) to a gendered-ad ban. To see this, imagine first --as seems likely-- that a ban increased the number of workers applying to (formerly) gender-mismatched jobs, because all jobs now appear equally 'open' to both men and women. If women's relative callback rates (θ) remained unchanged in all jobs after such a ban, the ban's primary first-order effect would be to increase labor market frictions (because it now will be harder for workers to avoid jobs where their gender is dispreferred). On the other hand, if employers' openness to (formerly) gender-mismatched applicants (the θs) also changes when a ban is introduced, a ban's effects on labor market frictions --and on other outcomes like gender segregation and gender wage gaps-- could conceivably go in either direction. Further research, perhaps drawing on the natural experiments associated with historical bans, would be needed to identify these more complex effects.

[41] For example, as discussed in Appendix 3, recent attempts to discourage gendered job ads in China have led some employers to use code words to avoid detection. In addition, job boards have made it easy to filter resumes by gender, both within the applicant pool and when a recruiter is searching through resumes posted on the site.

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Tables and Figures

Table 1: Descriptive Statistics: Ad Sample

	Ad Requests Women (*F* jobs)	**Gender not specified (*N* jobs)**	**Ad Requests Men (*M* jobs)**	**All Ads**
Education specified?	0.961	0.899	0.925	0.919
Education Requested (years), if specified	12.70	12.31	11.25	12.21
Tech School Requested?	0.301	0.165	0.206	0.207
Desired Age Range specified?	0.638	0.390	0.566	0.481
Desired Age, if Requested (midpoint of interval)5r	25.91	28.81	29.47	28.03
Experience Requested (years)	0.785	0.997	1.215	0.987
New Graduate Requested?	0.069	0.023	0.030	0.035
Wage Advertised?	0.638	0.557	0.556	0.576
Wage, if advertised (yuan/month, midpoint of interval)	2,001	2,658	2,439	2,446
Number of positions specified?	0.964	0.923	0.971	0.941
Number of positions, if specified	1.915	2.249	2.033	2.130
Number of applicants	79.49	62.56	46.55	63.66
Sample Size	867	2,104	666	3,637

Table 2: Descriptive Statistics: Application Sample

	Applications from Women	Applications from Men	All Applications
Education (years)	14.56	14.11	14.35
Completed Tech School?	0.155	0.164	0.159
Age (years)	23.24	24.86	23.99
Experience (years)	2.674	3.886	3.230
New Graduate?	0.210	0.155	0.185
Current wage listed?	0.688	0.702	0.694
Current wage, if listed (yuan/month)	2,090	2,462	2,263
Married (if marital status listed)	0.140	0.215	0.174
Occupational Qualification (*Zhicheng*)[1]	1.086	1.403	1.231
Myopic	0.328	0.268	0.301
Height (cm)	160.6	171.5	165.6
English CV available?	0.145	0.104	0.126
Number of Schools listed	0.312	0.279	0.297
Number of Experience Spells	2.678	2.606	2.645
Number of Certifications	1.462	0.886	1.198
Sample Size	124,275	105,341	229,616

Notes:

1. *Zhicheng* is a nationally-recognized worker certification system that assigns an official rank (from one through six) to workers in almost every occupation. Ranks are based on education, experience and in some cases nationwide or province-wide exams.

Table 3: Application and Callback Patterns by Job Type

	Ad Requests Women (*F* jobs)	Gender not specified (*N* jobs)	Ad Requests Men (*M* jobs)	All Ads
1. Share of callbacks that are female (δ)	0.940	0.437	0.037	0.505
2. Share of applications that are female (α)	0.926	0.447	0.079	0.541
3. women's callback rate (f)	0.072	0.087	0.043	0.078
4. men's callback rate (m)	0.058	0.090	0.096	0.090
5. ratio of callback rates ($\theta = f/m$)	1.246	0.958	0.445	0.866
N (ads)	867	2,104	666	3,637
N (callbacks)	4,859	11,569	2,817	19,245
N (applications)	68,638	130,266	30,712	229,616

Table 4: Actual and Counterfactual Gender-Matching Rates

	Share of callbacks that are of the requested gender (g) (1)	Gender-matching index (G)[3] (2)
Baseline: Actual values	0.948	0.897
Counterfactual 1-- no compliance: Equal female share in applications, α, across all jobs[1]	0.617	0.232
Counterfactual 2:-- no enforcement: Equal female callback advantage (θ) in all jobs[2]	0.921	0.842

Notes:

1. Applies the population female applicant share (α) (.541) to all three job types.
2. Applies the population female risk ratio (θ) (.866) to all three job types.
3. $G = \frac{g-g_0}{1-g_0}$ and g_0 = .501.

Table 5: Actual and Simulated Noise-Adjusted Segregation Indices across Jobs (Ads)

	Noise-Adjusted Segregation Index ($\tilde{S}$)	Share of noise-adjusted segregation explained ($\tilde{S}$ simulated/$\tilde{S}$ actual)
ACTUAL	**0.607**	**1.000**
SIMULATIONS:		
Effects of job categories (*F*, *N* and *M*) on segregation:		
A. Total effect of job categories: both α and θ vary across job categories	0.359	0.592
B. Effect of self-sorting across the three job categories: α varies across job categories, θ is the same in all ads	0.351	0.579
C. Effect of enforcement in the three job categories: θ varies across job categories, α is the same in all ads	0.040	0.066
Effects of applicant self-sorting and employer choice on segregation:		
D. Effect of self-sorting across all jobs: each job has its own α, all jobs have the same θ	0.588	0.969
E. Effect of employer choice within all jobs: each job has its own θ, all jobs have the same α	0.107	0.176

Table 6: Actual and Counterfactual Segregation across Job Titles, Occupations and Firms

Gender Segregation across:	Raw segregation index (S) (1)	Noise-adjusted segregation ($\tilde{S}$) (2)	Noise-adjusted segregation associated with job profiling (Counterfactual A) (3)	Share of noise-adjusted segregation associated with job profiling (3/2) (4)
Jobs (from Table 5)	0.732	0.607	0.359	0.592
Firm*Occupation cells	0.662	0.549	0.322	0.587
Firms	0.506	0.395	0.234	0.592
Occupations	0.405	0.385	0.204	0.531

Table 7: Actual and Simulated Gender Wage Gaps

	Gender Wage Gap (ω actual)	Share of gender wage gap explained (ω simulated/ ω actual)
ACTUAL	0.146	1.000
SIMULATED WAGE GAPS:		
A. Total effect of job categories: both α and θ vary across job categories	0.089	0.608
B. Effect of self-sorting across the three job categories: α varies across job categories, θ is the same in all ads	0.089	0.608
C. Effect of enforcement in the three job categories: θ varies across job categories, α is the same in all ads	0.011	0.076

Table 8: Effects of Employers' Gender Requests on the share of female applications received (α)

	(1)	(2)	(3)	(4)	(5)	(6)
Ad requests men (*M*)	-0.3547***	-0.3226***	-0.2459***	-0.1222***	-0.1203***	-0.1462***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.025)
Ad requests women (*F*)	0.4954***	0.4519***	0.3736***	0.2263***	0.2339***	0.2462***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.028)
Primary School		0.0247**	0.0095	-0.0019	-0.0057	-0.0292
		(0.011)	(0.009)	(0.005)	(0.006)	(0.026)
Middle School		-0.0627***	-0.0507***	0.0036	-0.0055	-0.0343
		(0.011)	(0.011)	(0.006)	(0.007)	(0.033)
Tech School		0.0673***	0.0477***	0.0004	-0.0014	-0.0415*
		(0.008)	(0.007)	(0.005)	(0.005)	(0.024)
Post-secondary		0.1159***	0.0639***	-0.0016	-0.0061	-0.0408
		(0.008)	(0.007)	(0.004)	(0.005)	(0.027)
University		0.1203***	0.0499***	-0.0137**	-0.0125*	-0.0189
		(0.010)	(0.008)	(0.006)	(0.007)	(0.045)
Number of positions advertised		-1.7400***	-0.9615***	-0.1220	-0.1338	-0.5756
		(0.164)	(0.121)	(0.124)	(0.130)	(0.571)
Occupation Fixed Effects			Yes	Yes	Yes	Yes
Job Title Fixed Effects				Yes	Yes	
Firm Fixed Effects					Yes	
Title*Firm Fixed Effects						Yes
N (ads)	42,744	42,744	42,744	42,744	42,744	42,744
"Effective" *N*	42,744	42,744	42,744	25,438	23,819	1,448
R^2	0.554	0.590	0.721	0.925	0.950	0.974

Standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1

Notes: in addition to the covariates shown, columns 2-5 also control for the following job ad characteristics: requested experience level (quadratic), requested age level (quadratic in midpoint of range), advertised wage (quadratic in midpoint of bin; 8 bins), dummy for whether new graduate requested, number of positions advertised, plus dummies for missing education, age, wage and number of positions. All regressions are weighted by the total number of applications received. 'Effective' *N* excludes job titles, firm IDs, and title*firm cells that only appear in one ad in columns 4, 5 and 6 respectively.

Table 9: Effects of Job Labels (*F*, *N* and *M*) on Callback Rates

	(1)	(2)	(3)	(4)	(5)	(6)
Female Worker * Female Job	-0.0149***	-0.0106***	-0.0103***	-0.0103***	-0.0147***	-0.0163***
	(0.009)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Female Worker * Male Job	-0.0440***	-0.0432***	-0.0431***	-0.0425***	-0.0333***	-0.0377***
	(0.013)	(0.004)	(0.004)	(0.004)	(0.006)	(0.008)
Male Worker * Female Job	-0.0328***	-0.0273***	-0.0274***	-0.0214***	-0.0229***	-0.0230***
	(0.010)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Male Worker * Male Job	0.0054***	0.0015	0.0016	0.0037*	-0.0064	-0.0164***
	(0.009)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
Male Worker	0.0038**	0.0004	-0.0030	-0.0065***	-0.0172***	
	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	
Education less than requested		-0.0054**	-0.0049*	-0.0076***	-0.0087***	-0.0115***
		(0.002)	(0.003)	(0.003)	(0.002)	(0.004)
Education more than requested		-0.0042***	-0.0070***	-0.0044**	0.0012	0.0061**
		(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Age less than requested		-0.0004	-0.0017	-0.0019	-0.0034*	-0.0019
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age more than requested		-0.0330***	-0.0309***	-0.0283***	-0.0203***	-0.0213***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Experience less than requested		-0.0063***	-0.0067***	-0.0081***	-0.0095***	-0.0071***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Experience more than requested		0.0005	0.0021	0.0014	-0.0011	0.0012
		(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Wage below advertised		-0.0009	-0.0007	-0.0017	0.0000	-0.0013
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Wage above advertised		0.0009	0.0007	0.0002	-0.0060***	-0.0046
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Detailed CV controls			Yes	Yes	Yes	
Occupation Fixed Effects				Yes	Yes	Yes
Competition Controls					Yes	Yes
Job Title Fixed Effects					Yes	Yes
Worker Fixed Effects						Yes
N (ads)	229,616	229,616	229,616	229,616	229,616	229,616
'Effective' *N*	229,616	229,616	229,616	229,616	229,590	192,681
R^2	0.001	0.005	0.005	0.016	0.198	0.387

Standard errors in parentheses, clustered by worker. *** p<0.01, ** p<0.05, * p<0.1

Notes to Table 9:

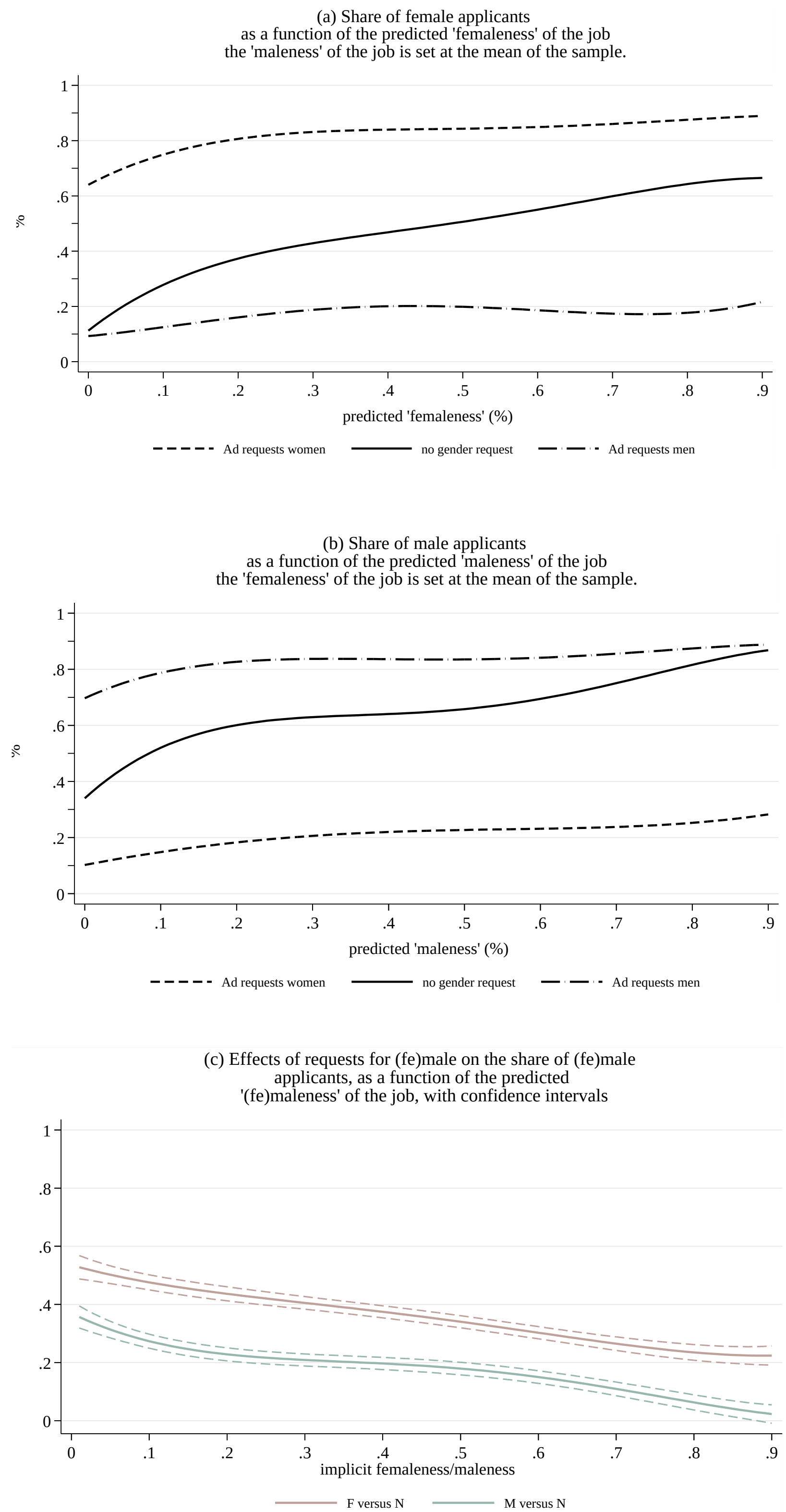
In addition to the covariates shown, columns 2-6 include the following controls for *ad characteristics*: requested education (5 categories), experience (quadratic), age (quadratic), the advertised wage (quadratic in midpoint of bin; 8 bins) and a dummy for whether a new graduate is requested. Columns 2-6 also include a dummy for whether the applicant's new graduate status matches the requested status, plus indicators for missing age and wage information for either the ad or the worker.

"Detailed CV controls" (used in columns 3-6) are an indicator for attending technical school; the applicant's *zhicheng* rank (6 categories); an English CV indicator; the number of schools attended, job experience spells and certifications reported; and the following characteristics interacted with gender: height, myopia, and marital status (interacted with applicant gender)

Occupation fixed effects control for the 36 categories used on the XMRC website.

'Effective' *N* excludes job titles-and worker IDs that only appear in one ad in columns 5 and 6 respectively.

Figure 1: Effects of Gender Requests (*F* and *M*) and Predicted Gender (*Fp* and *Mp*) on the Female Share of Applicants



Notes to Figure 1:

Figures represent predicted values of the female share of applicants (α) from a specification identical to column 5 in Table 8, where the job title fixed effects are replaced by quartics in *Fp* and *Mp*, each interacted with explicit job type (*F*, *N* and *M*). Predictions in part (a), which shows the effect of implicit femaleness (*Fp*), hold *Mp* at its mean. Predictions in part (b), which depicts the implicit maleness (*Mp*), hold *Fp* at its tenth mean. All other characteristics are set at their means. The regression is weighted by the number of applications to each ad, and standard errors are clustered at the occupation(firm) level.

Part (c) shows the predicted effects of attaching an explicit male (female) label to a job ad (relative to an *N* label) at different levels of implicit maleness (femaleness), with 95 percent confidence bands. Notably, both effects are larger in jobs whose title does not convey a clear preference for the applicant's gender. In addition, the effects of explicit requests for women on application behavior are significantly larger (both economically and statistically) than the effects of explicit requests for men.

Predictions for values of *Fp* or *Mp* greater than 0.9 are imprecise and not shown; only 2,462 ads have values in this range, comprising .0377 and .0330 of the sample respectively.

Appendix—for online publication

Appendix 1: Examples of Gendered Job Ads from Indeed.com

Accurate measures of the share of ads on a job site that are gender-targeted cannot be generated by conducting searches on the site's public portals, for a number of reasons. First, the ads on the site at a point in time represent a stock sample with potentially many stale ads. Second, unless the job board has chosen to collect and to publicize an unambiguous indicator of the employer's gender preference (as XMRC does), gender preferences can be expressed in many different ways, some of which are evasive, others of which are costly to detect.[42] Third, jobseekers' search results are often prioritized in ways that are opaque to the user. And finally, without a well-defined sample that has been drawn from the board's internal database, researchers are forced to rely on denominators provided by the job board, which are not clearly defined and prone to exaggeration.[43]

With these cautions in mind, we can arguably get some indicators of at least the presence and typical form of explicit gender requests by conducting keyword searches for jobs through the worker portal on a site. In this document we present examples of the results of such searches on Indeed.com, which currently operates job search platforms in 63 countries. The ads reproduced in the following pages were collected from Indeed.com's international portal: https://www.indeed.com/worldwide on November 12, 2018. In all cases, we searched for the terms "male" and "female" in the sites' native languages (this was English in India and Pakistan), then –where necessary--- used Google to translate the results. Since "male" and "female" can be used in several ways that do not request a specific gender for the job (including saying that both men and women are welcome), we manually searched through the ads till we found ads that expressed a preference for one gender. We never had to go beyond the first 50 search results to find such ads. Noting that Indeed, as a U.S.-owned company, may be more sensitive to stigma associated with posting gendered ads, and that its international sites tend to serve educated and disproportionately English-speaking workers, it seems likely that gendered ads would be even easier to find on locally-owned and operated sites.

In all cases the searches were done without creating an account on Indeed, and without specifying a type of work or location—the only search term was "male" or "female". No other filtering or ordering of results was done. The countries searched are the ten countries represented by Indeed with the largest populations. Since Indeed serves ten of the eleven largest countries, our results are for the world's 11 most populous countries with exception of Bangladesh, representing 57.4% of the world's population. The ads are numbered by country population rank.

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[42] The use of gendered job titles (such as abogada and abogado in Spanish) is particularly burdensome to measure each title expresses gender in a different way.

[43] Another emerging difficulty is the possibility that job boards are designing their worker-facing search algorithms to make certain forms of explicit gender requests hard to find via a keyword search, even though these requests are still present in ads (that are found via other keywords). We report some suggestive evidence of this in Section 3.2.

1. China—female

admin officer

米高蒲志(Michael Page) 169 reviews - 上海市 静安区

查看详情或申请 保存职位

- competitive salary and benefits
- promosing and good culture in working environment

关于我们的客户

our client has strong background invested by Canada top fund and local state-on wed company.

职责描述

- support total 10 staff in 2 projects,
- support finance director for daily cash-er job,
- in charge vendor management,
- in charge office purchasing, office relocation and renovation.

理想的求职者

- female, married with kid or single.
- at least 3-5 years in office management role of small size office.
- outgoing, passionate personality.
- good English.

薪酬待遇

promising and good culture in working environment

competitive salary and benefits

联系:
Martina Zhu
职位编号: 3972202
+86 6122 2645

our client has strong background invested by Canada top fund and local state-on wed company.

职责描述

-support total 10 staff in 2 projects, -support finance director for daily cash-er job, -in charge vendor management, -in charge office purchasing, office relocation and renovation.

理想的求职者

-female, married with kid or single. -at least 3-5 years in office management role of small size office. -outgoing, passionate personality. -good English.

薪酬待遇

1. China- male

找工作 发布招聘职位（免费）

indeed

关键词
职务、公司或技能

工作地点
省市县区镇名

业务员

深圳市汇力货运代理有限公司 - 中山市

查看详情及申请该职位

所属行业：交通/运输/物流

分享到：
职位类别：销售 > 销售代表

工作性质
全职
招聘人数
1
月薪（人民币）
面议

外语要求

工作经验要求
1-2年
学历要求
本科

性别要求
不限

职位描述：

- Analytical,out-going,self-motivated,aggressive and able to develop new business
- Frequent to travel our clients in most of industrial areas of Zhongshan,Jiangmen,Zhuhai and Shunde is required.
- PC knowledge of Power Point,Word,Excel,Chinese Work Processing and fast typing skill in English.

任职条件说明：

- Local resident of Zhongshan.
- Diploma or University Degree holder.
- Over 1 year working experience as Sales/Marketing job is preferable.
- Good command in both written and spoken English(i.e.CET 4 or above),Mandarin and Cantonese
- The positions to be recruited only male

爱聘才招聘网 - 7天前 - 保存招聘职位 - 原网站职位

2. India—female

Executive Assistant (Gurgaon)
Manav Management Group - Gurgaon, Haryana
₹1,75,000 - ₹3,00,000 a year

Apply On Company Site   Save this job

Job Description

We have Urgent requirement for the post of: - Executive Assistant
Post of: - Executive Assistant
Experience: - 2y to 5y
Salary: - 15000k-25000k
Location: - Udyog Vihar Ph-4 Gurgaon
Applied Candidate: -Female only
Company Profile: - Training & Coaching
Education: Graduate
Job Responsibility:
1. Should have strong English communication (both verbal and written)
2. Managing the day-to-day operations of the office.
3. Screening and prioritizing mail and phone calls.
4. Researching and writing memos.
5. Organizing and maintaining files and records.
6. Maintain executive calendars and meeting agendas.
7. Prepare materials used in executive presentations and make travel arrangements
8. Planning and scheduling meetings and appointments and recording meeting discussions.
9. Securing information by completing data base backups.
10. Maintaining professional and technical knowledge by attending educational workshops.
11. Reviewing professional publications
12. Establishing personal networks.
13. Participating in professional societies and any other similar duty that may be assigned from time to time.

Salary
1 Lac 75 Thousand To 3 Lac P.A.

Industry
Front Office / Executive Assistant / Data Entry

Work Experience
2 - 5 Years

Qualification
Other Bachelor Degree

2. India—male

what
job title, keywords, or company

where
city, state, or pin code

IT Executive (Male)

Titan Media - Bhiwadi, Rajasthan

- Windows, Software Installation & configuration, back up.
- All printer and scanner installation and troubleshooting.
- LAN,WAN Configuration
- Basic knowledge of Microsoft Dynamic NAV Software.

Qualification - Any Graduate

Experience:- Minimum 1 year

Salary:- Based on Qualification and Experience
Skills:-

- Should have a positive attitude towards work.

Location:- Bhiwadi, Rajasthan
Titan Media - 2 days ago - save job - Is there a problem with this job? - original job

Apply On Company Site

3. USA:

We searched for “male” and “female” as keywords without registering as workers and without specifying a location or type of worker.

All of the **first 50 hits for “men”** were used to convey:

-a “genuine” job requirement (e.g. housekeeper for a men’s locker room, male clothing model, male urine sample collection specialist)

-a feature of the work environment (e.g. hairstylist for male clientele, clerk in male inmate facility), or

-a military draft requirement (e.g. “Census enumerator--all male applicants must be registered with Selective Service system”.

with one possible exception: “male on-camera sports host”.

All of the **first 50 hits for “women”** were used to convey:

-a “genuine” job requirement (e.g. customer service swimwear, TSA pat-down officer)

-a feature of the work environment (e.g. “female run and managed company”, support staff for female clients in drug recovery)

-a diversity statement (e.g. "EOE/Minorities/Females/Veterans/Disabled", in 39/50 ads)

-different physical qualifications for men and women (e.g. “Correctional officer … 4 pushups female, 8 pushups male)

with one possible exception: “front desk agent--we are looking to add another female to our front desk position… professional appearance"

4. Indonesia-- female

Receptionist

Ahloo ID - Indonesia

Apply On Company Site

Save this job

Responsibilities

- Greet and welcome the guests and directing them to the correct person or department.
- Answer all incoming calls and redirect them or keep messages.
- Sorting and distributing incoming documents.
- Prepare the outgoing mails.
- Managing a booking system (for meetings and interviews).
- Keeping the reception area tidy and clean.

Requirements

- Female.
- Maximum age 28 years old.
- At least 1 year(s) of working experience in the related field is requires for this position.
- Minimum education Diploma from any major.
- Have good communication skills, friendly, and attractive.
- Able to operate Microsoft Word, Excel, & internet.
- Proficient in English (oral and written).

In several countries, requests for a specific gender are frequently accompanied by a desired age range as well. See Delgado Helleseter, Kuhn and Shen (forthcoming) for detailed evidence on age*gender interactions in job ads from China and Mexico.

4. Indonesia—male

Chemist

Geoservices ★★★★☆ 51 reviews - Karawang

Apply On Company Site

Save this job

- Male, 25 – 35 years old
- Candidate must possess at least Bachelor's Degree, Chemistry.
- At least 2 years of working experience in the related field is required for this position
- Able to operating instruments tools ICP/ AAS/ XRF/ LECO
- Have a good quality control skill
- Proficiency in English both oral & written
- Candidate must be willing to placement in Cikarang and other site area.

5. Brazil—female

Auxiliar Administrativo Feminino em Lavras

Traço RH - Lavras, MG
R$ 1.000 por mês

Visualizar ou candidatar-se à vaga

Salvar esta vaga

- PRÉ – REQUISITO
- ✓ Possuir 01 ano de experiência na área administrativa;
- ✓ Conhecimento em informática e boa digitação.
- PRINCIPAIS ATIVIDADES:
- ✓ Atuar com atendimento ao cliente, confecção de contratos, rescisões, atendimento telefônico, resolver pendência sobre imóveis e demais atividades.
- ✅ HORÁRIO:
- Segunda a Sexta: 08:30 – 18:00 hs.
- Sábados eventuais.
- Remuneração: R$ 1.000,00

5. Brazil—male

Auxiliar Administrativo Masculino

Traço RH - Lavras, MG

R$ 1.300 por mês

Visualizar ou candidatar-se à vaga

Salvar esta vaga

×

- **Os candidatos podem residir em:**
- **ITUTINGA,**
- **NAZARENO;**
- **LAVRAS (se residir em Lavras, possui disponibilidade de ficar em alojamento durante a semana).**
- Sexo: MASCULINO
- PRÉ – REQUISITOS:
- Possuir 01 ano de experiência na área administrativa;
- É um diferencial para empresa ter atuado antes no segmento de reflorestamento ou produção de carvão;
- **Habilitação AB, com prática em ambas;**
- Informática básica.
- PRINCIPAIS ATIVIDADES:
- ✓ Irá dar suporte nos serviços administrativos nas fazendas em Lavras, São João Del Rei, São Sebastião da Vitória e Itutinga.
- Conferência de documentos, controle, agendamento de exames, enviar documentos a contabilidade, organizar frentes de trabalho, alojamentos e demais atividades.
- HORÁRIOS:
- Segunda a Quinta-feira: 07:00 – 17:00
- Sexta: 07:00 – 16:00
- Remuneração: R$ 1.300,00 e Almoço no Local de Trabalho.
- Veículo da empresa disponível para trabalho.

A large number of Indeed's Brazilian ads say the job is open to both men and women, but single-sex ads like these also exist.

This is an interesting example of the same company is advertising similar jobs for men and women, but offering a 30 percent higher wage in the male ad.

6. Pakistan—female

Female Receptionist

F S Engineering - Lahore

Rs 15,000 - Rs 20,000 a month

Apply Now

Save this job

Good looking personality

Computer knowledge

Minimum education intermediate

Filing

Spoken skills

Job Type: Full-time

Salary: Rs15,000.00 to Rs20,000.00 /month

Experience:

- receptionist: 1 year (Preferred)

Requests for women in customer-contact jobs like this one frequently include explicit requests for beauty (Delgado Helleseter, Kuhn and Shen forthcoming).

6. Pakistan—male

Cashier- Male

Hampton Bay L.L.C - Lahore

Apply On Company Site

Save this job

Looking for Cashier- Male, Graduate having 2 yrs of working experience. This is a Lahore based position. Candidates with similar experience can share their resume with title Cashier- Male

7. Nigeria—female

Female Marketer

- Lagos

Apply On Company Site

Save this job

Fifth Quadrant Performance Limited

Marketing & Communications

Fifth Quadrant Performance Limited

Marketing & Communications

Lagos|Full Time|Real Estate|
NGN Confidential
1mo

Job Summary

Fifth Quadrant Performance Limited is in need of a Female Marketer.

- Minimum Qualification: HND
- Experience Level: Entry level
- Experience Length: 1 year

Job Description

Fifth Quadrant Performance Limited - Our client, a fast-rising Real Estate Company that is into the development of luxurious apartments in choice areas on the Lagos Island, requires the services of a qualified candidate to fill the position of a Marketer

Job Description

- We are in need of Female Marketers to help engage it's High Network Clients with the products of the company.
- The qualified candidates will be located at the companies strategically located offices that enables her to meet and interact with the target market.

Requirements

- She must be fluent in English (additional languages will be an added advantage)
- She must be presentable and carry herself well
- She must have sales experience
- She must be strong willed and be able to follow up on clients
- She must have finished NYSC
- She must have at least B.Sc or HND.

7. Nigeria-- male

Male Front Line/ Customer Service Officer

- Lagos

Apply On Company Site

Save this job

Doculand Business Solutions Limited

Administrative

Doculand Business Solutions Limited

Administrative

Lagos|Full Time|Retail & FMCG|
NGN Confidential
1mo

Job Summary

Doculand Business Solutions Limited is recruiting to fill the role of a Male Front Line/ Customer Service Officer.

- Minimum Qualification: HND
- Experience Level: Entry level
- Experience Length: 1 year

Job Description

Doculand Business Solutions Limited is Nigeria's foremost professional print and copies business center. We originated in Lebanon and we have branches in Jordan and Lagos. We are sought after for our excellent work, creativity and great customer service. We have a team of professionals who ensure we attain levels in customer expectations and fulfillment.

Job Descriptions

- Welcome customer
- Take all details needed for the order
- Give prizes to the customer
- Upselling for both services and stationary section
- Report to Supervisor
- Client inquiry & feedback

8 Bangladesh—does not have an Indeed site

9. Russia—female

Packer

KC Aquarium - Saratov

25 000 rubles per month

Apply for job

Save job

At the meat-processing production in the women's team requires a specialist in cutting meat.
We consider no work experience.

Those who are looking for a job packer / to, packer / to, cook, molder / to, we suggest you consider the vacancy Resident / K

Conditions:

- free training at the enterprise;
- special clothes;
- production in the Vso region;
- decent wages

Duties:

- separation of meat from films and veins.

Requirements:

- work experience is not required;
- desire and ability to work and earn money

Call from 8:00 to 17:00.
After the specified time you can write a message indicating your contact number, we will contact you

9. Russia—male

Porter to the warehouse of ceramic products

Lighthouse ★★★☆☆ 5 reviews - Moscow

54 000 rub. per month - rotational method

Apply for job

Save job

Russian company for the production of ceramic tiles. Recruiting men

Responsibilities: packing by boxes, pallet assembly and treatment

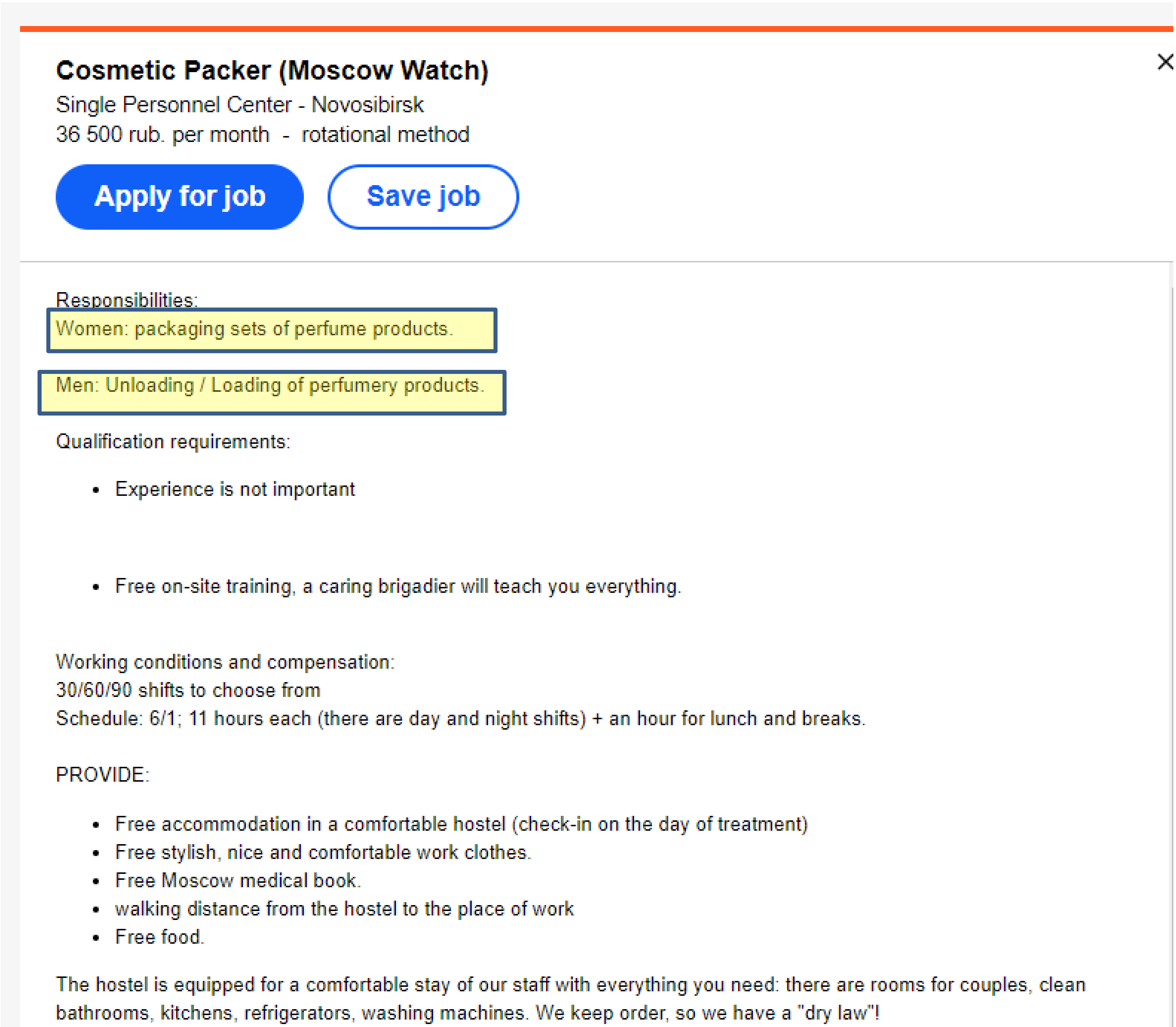
Requirements; willingness to hard physical labor.

Conditions: the hostel is available 20 minutes from the object. watch from 45 days the entire salary is paid at the end of the watch, weekly 1500r for minor expenses.

Registration under the Contract.

With the 2nd watch rate increase!

9. Russia—gendered duties



Cosmetic Packer (Moscow Watch)
Single Personnel Center - Novosibirsk
36 500 rub. per month - rotational method

Apply for job
Save job

Responsibilities:
Women: packaging sets of perfume products.

Men: Unloading / Loading of perfumery products.

Qualification requirements:

- Experience is not important

- Free on-site training, a caring brigadier will teach you everything.

Working conditions and compensation:
30/60/90 shifts to choose from
Schedule: 6/1; 11 hours each (there are day and night shifts) + an hour for lunch and breaks.

PROVIDE:

- Free accommodation in a comfortable hostel (check-in on the day of treatment)
- Free stylish, nice and comfortable work clothes.
- Free Moscow medical book.
- walking distance from the hostel to the place of work
- Free food.

The hostel is equipped for a comfortable stay of our staff with everything you need: there are rooms for couples, clean bathrooms, kitchens, refrigerators, washing machines. We keep order, so we have a "dry law"!

Ads of this type—where a company requests both men and women, but for different duties within the firm—were much more common on Indeed's Russia site than ads requesting a single gender only.

10. Mexico—female preferred

Buscar empleos   Evaluaciones de empresa   Buscar candidatos   Empresas / Publicar empleos

indeed

qué
título, palabras clave o empresa

dónde
ciudad o estado

Buscar emp

Contador(a)

Two Spoons - Álvaro Obregón, D. F.

Ver empleo

$15,000 - $17,000 al mes

Nomenclatura del puesto: Contador(a)

Sexo: Indistinto (preferentemente femenino).

Edad: Entre 28 y 35 años.

Escolaridad: Licenciatura en contabilidad, mínimo pasante.

Estado civil: Indistinto.

Experiencia laboral: Mínimo 3 años en puesto similar.

Conocimientos: Dominio de Excel, manejo de sistemas ASPEL (COI y SAE); deseables Word y Power Point.

Conocimientos deseables: Dentro del área fiscal, implementando estrategias de planeación y control, manejo de contabilidad general, impuestos, conciliaciones, etc.

10. Mexico—female required

Auxiliar de Recursos Humanos

RAMATY - Ciudad de México, D. F.

$8,000 al mes

Ver o postular al empleo

Guardar este empleo

DESCRIPCIÓN DE LA EMPRESA

Ramaty es una empresa que ha crecido por la disciplina, el trabajo de un equipo comprometido y, en especial, por la pasión al diseño y la apertura a nuevas tendencias. Comenzó como un pequeño proyecto de diseño textil enfocado a la moda de caballeros, con un perfil clásico; con los años se ha consolidado como una de las marcas más reconocidas en el país y preferidas por jóvenes y adultos que encuentran cortes clásicos pero con ese sello distintivo: diseños únicos con una gran variedad, textiles de calidad e innovación en detalles de diseño.

DESCRIPCIÓN DEL PUESTO

APOYO EN ELABORACIÓN DE NÓMINA (NOI)
CONTROL DE TIEMPO EXTRA Y PERMISOS
MANEJO DE RELOJ CHECADOR
MANEJO DE SUA
INTEGRACIÓN DE EXPEDIENTES
ARCHIVO
DIVERSAS ACTIVIDADES ADMINISTRATIVAS
RECLUTAMIENTO DE PERSONAL

PERFIL

EDAD: 18 A 30 AÑOS
SEXO: FEMENINO
ESCOLARIDAD: TRUNCA O TITULADO EN ADMINISTRACIÓN

CONSEJOS

INDISPENSABLE MANEJO NOI

10. Mexico—male preferred

Auxiliar de Recursos Humanos Y Seguridad

Border Express de México S.A. de C.V - Ciudad Juárez, Chih.
Indefinido

Ver o postular al empleo   Guardar este empleo

Descripción y detalle de las actividades

Habilidad para manejar gente
Buen pensamiento analitico
Habilidad para la resolución de problemas
Habilidad de retención
Habilidad de negociación
Facilidad de palabra
Excelente manejo de la comunicación
Habilidad para determinar las necesidades del cliente
Alto sentido de urgencia

Aptitudes:

Alto sentido de pertenencia y lealtad
Tolerante
Proactivo
Auto dirigido
Actitud de servicio
Responsable

Experiencia y requisitos

Excelente presentación
Edad: Mayor de 25 años
Estado Civil: indistinto
Sexo: Indistinto (Masculino preferentemente)
Idioma: inglés 50%

Experiencia:
En el Ramo del transporte.
En trámites de Recursos humanos y seguridad patrimonial, auditorias, etc.

Educación: LAE, enfermería o trunco.

10. Mexico—Male Required

Asesor Financiero

TIP Consulting - Puebla, Pue.

Ver o postular al empleo

Guardar este empleo

- **REQUISITOS :**
- Sexo: Masculino
- Edad: 25 a 60 años
- Educación mínima: Bachillerato General
- Experiencia: Minimo 3 - 5 años en puesto similar
- Empresa con 18 años de experiencia en brindar alternativas de crédito Te invitamos a participar en nuestra vacante de : - Asesor Financiero / ventas de intangibles- Requisitos: * Sexo: indistinto * Edad: de 25 a 60 años * Escolaridad: bachillerato o carrera trunca * Experiencia mínimo de 1 año en ventas * Disponibilidad de horario * Facilidad de palabra * Acostumbrado a trabajar bajo presión * Comisionista Conocimientos: Ventas, Rutas de trabajo, conocimiento de Puebla y alrededores, conocimiento de negociación Experiencia: un año en ventas de productos intangibles (financieros, seguros, prestamos, etc) Percepción: Por comisiones ascendentes conforme a ventas. Ofrecemos: Atractivas comisiones

11. Japan

The Japanese Equal Employment Opportunity Law prohibits employers from saying that they prefer to hire men (women). However, job ads on Indeed's Japan site frequently say that men (women) are playing "active roles", or 'thriving' in these jobs or in the firm. The intent appears to be to signal that the jobs in question are suited to a particular gender.

11. Japan—female (google translation)

(Female in active) General Affairs / General Affairs Let's take a job upgraded in Marunouchi I admire Major company work

Kokuyo & Partners Co., Ltd. - Tokyo

Monthly salary 245,000 yen - Contract employee

Apply

Save this job

[Affairs, human resources, labor, general administrative and general affairs]

office work in the "Marunouchi" leading companies working longing of leave your work up a notch in the affairs and general affairs yearning of Marunouchi

ways of working of the ideal in a stable foundation company do not you get +:? ...: + +: ...: + +: ...: + +: ...: + +: ...: +

monthly salary 245,000 yen

annual leave 120 days or more and overtime almost without

Marunouchi work and a 2-minute walk from the nearest station and the access preeminent

+: ...: + +: ...: + +: ...: + +: ...: + +: ...: +

this time by Mitsubishi Heavy Industries, Ltd. is a business partner

we are looking for affairs and general affairs staff.

Work location, the beautiful office to open in Marunouchi in November 2018

, such as containing the fashionable cafes and brand shops in the building,

with a fully equipped, offers active in the new office

longing in "Marunouchi" a stable foundation

as our member of the Kokuyo group,

or does not achieve a fulfilling work life?

[job Description]: your job of back office of a leading company that represents Japan:

- Marunouchi's place of work I just worked at an office
- Revenue is stable at the start of 245,000 yen / month
- Overtime work average about 10 hours and almost None As a member of the KOKUYO group, at a business partner Mitsubishi Heavy Industries,

A better translation of the job title is probably: "(Women thriving) General Affairs. Asked to perform a step-up task in the enviable Marunouchi area. Working for major corporations." This is a job ad for a contract firm. The successful applicant would work in a brand new office of this contract firm in a brand new building in Marunouchi area, and work for one of its clients, Mitsubishi Heavy Industry.

11. Japan—female (original Japanese version)

求人検索　検索オプション

(女性活躍中)総務・庶務 憧れの丸の内でワンランク上のお仕事をお任せ 大手企業勤務

コクヨ&パートナーズ株式会社 - 東京都
月給 24.5万円 - 契約社員

応募する　この求人を保存する

【総務、人事、労務、一般事務・庶務】

総務・庶務 憧れの丸の内でワンランク上のお仕事をお任せ 大手企業勤務 憧れの「丸の内」でのオフィスワーク
安定基盤のある会社で理想の働き方を手に入れませんか? +: ｡.｡: + +: ｡.｡: + +: ｡.｡: + +: ｡.｡: + +: ｡.｡: +
月給24万5000円~
年休120日以上&残業ほぼなし
丸の内勤務&最寄駅から徒歩2分とアクセス抜群
+: ｡.｡: + +: ｡.｡: + +: ｡.｡: + +: ｡.｡: + +: ｡.｡: +

今回はお取引先である三菱重工業株式会社にて
総務・庶務スタッフを募集しています。

勤務地は、2018年11月に丸の内にオープンするキレイなオフィス
ビル内にはおしゃれなカフェやブランドショップが入っているなど、
充実した設備を持つ、新オフィスでご活躍いただけます

憧れの「丸の内」で安定基盤のある
コクヨグループの当社の一員として、
充実したワークライフを実現しませんか?

【仕事内容】：日本を代表する大手企業でのバックオフィスのお仕事：

- 勤務地は丸の内 OPENしたばかりオフィスで働ける
- 月給24万5000円スタートで収入も安定
- 残業月平均10時間程度とほぼなし コクヨグループの一員として、取引先である三菱重工業株式会社にて、

社内の「オフィスサービスセンター」での問い合わせ業務全般をお任せします。

≪具体的には≫
サービスセンターでのお問い合わせ対応

11. Japan—male (google translation)

General manager · Accounting men active during career upgrading possible stable companies / _ regular employees _ general affairs · personnel affairs · legal · intellectual property · public relations · IR // 0016882673-1

Nara Hino Motors Limited - Nara Prefecture

Monthly salary ¥ 182,000 yen - Full-time employee

Apply

Save this job

Full-time employee [Inexperienced welcome]
General manager · Accounting men active During career improvement at stable companies possible!

- Posting period: 2018/11/07 - 2018/12/04

Stable foundation of the manufacturer wholly owned subsidiary
want to work and laid the waist in Nara! To your
break even break even, Hino of Niton
familiar in such a CM, Hino Motors.
As a leader in heavy-duty vehicles such as trucks and buses,
domestic large and medium-sized truck share
boasts the No. 1 record for 44 consecutive years.

As a wholly owned subsidiary of Hino Motors,
we are doing sales and after-follow in Nara Prefecture.
In such company, Konotabi who support the company
to recruit the staff of the General Affairs Department!

Many staff that could be active longer,
teamwork is outstanding.
I do not have to worry about holding something I do not understand alone.

A better translation of the job title is probably: "General Affairs or Accounting. Men thriving. Possible to advance your career in a stable company."

11. Japan—male (original Japanese version)

求人検索 検索オプション

総務・経理男性活躍中安定企業でキャリアアップ可能/_正社員_総務・人事・法務・知財・広報・IR//0016882673-1

奈良日野自動車株式会社 - 奈良県
月給 18.2万円 - 正社員

応募する この求人を保存する

正社員[未経験歓迎]
総務・経理 男性活躍中 安定企業でキャリアアップ可能!

- 掲載期間:2018/11/07 ~ 2018/12/04

メーカー100%子会社の安定基盤
奈良で腰をすえて働きたいあなたへ!
トントントントン、日野のニトン
そんなCMでおなじみの、日野自動車。
トラックやバスなど大型車両のリーディングカンパニーとして、
国内大・中型トラックシェアは
44年連続No.1の実績を誇っています。

日野自動車の100%子会社として、
奈良県内での販売やアフターフォローをしている私たち。
そんな当社で、このたび社内を支えてくださる
総務部のスタッフを募集します!

長く活躍してくれているスタッフが多く、
チームワークは抜群。
わからないことを一人で抱え込む心配はありません。

研修なども充実しており、
ゆくゆくは会社の中枢となって
経営にも携わるチャンスがあるので、
これからスキルアップしたい人にもピッタリですよ。

This Appendix was prepared with the assistance of Steve Li and Jia You, undergraduate students at UCSB.

I thank Takao Kato, Professor of Economics, Colgate University for helping me understand the Japanese ads.

Appendix 2: Legislation Affecting Gender-Targeted Job Ads in China

A2.1 Early laws and regulations concerning gender discrimination

China's constitution and labor law have prohibited gender discrimination since at least 1982. For example, Article 48 of the Constitution of the People's Republic of China (1982) grants women "equal rights with men in all spheres of life, political, economic, cultural, social, and family life", and affirms the principle of equal pay for equal work for men and women. With the exception of "types of work that are not suitable for females", the *Labor Law of the PRC* (1994; Article 13) prohibits using sex as a pretext for excluding females from employment or for raising recruitment standards; similar provisions are found in the *Law of the PRC on the Protection of Rights and Interests of Women* (2005; Article 22), and the *Law of the PRC on Promotion of Employment* (2007, Articles 26 and 27.) The latter law also prohibits employment contracts that restrict female workers from getting married or bearing a child.

While a ban on ads (of any kind) that "carry any nationality, religious or sex discriminating information" has been in place since 1994 (*Advertisement law of the PRC*, Articles 7 and 39), the earliest regulations we are aware of that specifically prohibit gender discrimination by labor market intermediaries date from 2007. At that time, the Ministry of Labor and Social Security's *Regulations on Employment Service and Employment Management* prohibited intermediaries from "releasing any information indicating employment discrimination" (Articles 58 and 74).

Enforcement of China's anti-discrimination laws before 2010 however, is widely perceived to have been weak (Human Rights Watch 2018), and our previous studies of online job boards (Kuhn and Shen 2013; Delgado Helleseter, Kuhn and Shen forthcoming) suggest that these laws did not seriously constrain employers' use of explicitly gendered job ads during that period.

A2.2 Court Cases

According to FlorCruz (2014), the first lawsuit claiming gender discrimination in China's labor market was filed in July 2012. After graduating from a Beijing university, Ju Cao was told that she was not qualified for an administrative assistant job because "this was a position for men, we would not consider you although you are qualified". As part of an out-of-court settlement, the firm made a public apology to Ms. Cao. In 2014, another new graduate, Guo Mou was rejected from a copywriting job at Hangzhou's prestigious New East Cuisine Education school, for the reason that "men are more qualified for this position". The school was ordered to pay Ms. Guo 2,000 yuan for "spiritual injury" (CCTV.com, 2015). In China's first lawsuit on gender discrimination against a state-owned enterprise (SOE), Hu Ma was rejected for a delivery job with China Post. In response to her lawsuit, submitted on January 26,. 2015, China Post argued that delivery required workers to hold heavy objects, which met the legal exception of not being "suitable for females". The Court of Beijing rejected China Post's argument and ordered them to compensate Ms. Hu (Zhang, 2016).

Since the latter two lawsuits, the plaintiffs (Guo and Hu), have become activists against gender discrimination in employment. As part of their efforts, they have collected gender-targeted job ads on sites including Zhaopin.com, 51job.com, 58.com, Chinahr.com, and reported them to Ministry of Labor and Social Security.

A2.3 Responses of the Job Boards

In addition to the above court cases, a recent regulatory development seems to have prodded China's largest job boards to actively discourage and remove gendered job ads from their sites. In May 2016, China's Ministry of Industry and Information Technology issued a regulation aimed directly at gendered job ads on online job platforms. A key component of this regulation clarified the division of fines between the job board (30%) and the firm placing the ad (70%). This appears to have been at least partially effective: by October 2018, explicit requests for men or women ads were effectively absent from the two of largest privately operated job boards: 51 job and Zhaopin (see Appendix 3).

Some insight into how this change occurred is available from our conversations with officials at Liepin.com, a 'high-end' job board catering to executive-level positions. After receiving notice of the May 2016 regulation, Liepin sent a letter to all HR personnel using their website, stating that the HR personnel would not be allowed to post new job ads stating an explicit preference for one gender. Hiring managers were also asked to revise existing ads by removing any gender labels or other statements of gender preference.

At the same time, Liepin developed and improved its own filtering system to detect gendered job ads. Focusing first on newly-posted ads, Liepin tagged ads including statements like "male first", or "only for women" "male engineer" etc. and asked HR personnel to change these ads. Starting in July 2016, Liepin actively revised previously-posted ads by removing the gender requests without changing anything else. All such ads were replaced by the end of August, 2016. Since then, in part due to increased scrutiny from applicants who are willing to report violations to the government, Liepin has improved its screening for words that may convey a preferred gender, using human screeners to examine jobs that are considered suspect by Liepin's algorithms. Notably, throughout this process, Liepin continued to allow HR personnel to filter job applications by gender, so that the firm could choose to see only applications from one gender regardless of who applied. Thus, at least on Liepin, internal filters seem to have replaced public gender requests.

References

CCTV.com (2015). "The Communist Party announced the top ten cases of labor violations: the first case of employment gender discrimination ranked first" *CCTV News,* February 02, 2015 (accessed November 18, 2018).

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Zhang, Yuanyuan (2016)."Ma Hu v. Beijing Post Employment Sex Discrimination Case Second Trial" *China Women's News*, January 29, 2016 (accessed November 18, 2018).

Appendix 3: Gendered Job Ads in China Today

A3.1. Methods

As noted in Appendix 1, accurate measures of the share of ads on a job site that are gender-targeted cannot be generated by conducting searches on the site's public portals. As we did in Appendix 1 for the international context, however, this Appendix attempts to document the presence and typical form of gender requests on various Chinese job sites by searching for jobs using gender-related keywords. Specifically, entering the sites via their jobseeker portals, we searched for words that *might* convey a gender preference by the employer. Then, we inspected the first page of results (usually 50 ads) to count the number of those hits in which the keyword was used to request a specific gender (as opposed to describing the product/service, or inviting both genders to apply). In performing these searches, we did not create a worker profile on the site or specify any worker characteristics, nor did we enter any search terms for the location and type of work sought. All searches were performed in October 2018. The only search terms we entered were the following (one at a time):

(1) Direct gender indicators: "man (男)" and "woman (女)" (This includes "men" and "women" in Chinese).

(2) Transformed gender indicators: "nan" (the pronunciation for man, or 南 meaning south, which has the same pronunciation with man in Chinese), and "nv" (the pronunciation for woman; nv is the Chinese phonetic of women). These indicators have been used by employers to evade some recent enforcement activities (Human Rights Watch, 2018).

(3) Gendered adjectives: handsome (帅), gentleman (绅士), and "tall and strong" (高大健壮) for men; beautiful (美丽), lady (淑女), and "beautiful face" (面容姣好) for women.

(4) New "web words": little brother (小哥哥), little sister (小姐姐). These new words refer in a polite way to someone who is young and good-looking. They are more widely used by young people, and in job ads aimed at younger workers, such as social media jobs.

In the rest of this Appendix, we provide a verbal overview of these search results. Tabular results with additional details and commentary are available from the authors.

A3.2. 51job.com and Zhaopin.com

51job and Zhaopin are China's two largest job boards. Both are privately run and cater to private-sector firms and workers. Our searches of these sites revealed no uses of the 'direct' indicators "man (男)" and "woman (女)" to request a specific gender, and only a few uses of the transformed indicators "nan", or "nv" . One likely reason is enforcement: these boards now face a risk of being fined if they post gendered jobs; in response, the boards seem to have improved the screening of sensitive words so they no longer appear in workers' search results. In addition, these boards now discourage recruiters from making gender requests in job ads.[44] A second possible reason is that these boards cater to highly skilled workers; this may leave the boards more vulnerable to disapproval on social media if they post gendered ads. A third contributing factor may be the fact that employers' demand for gender profiling was relatively low in highly skilled jobs to begin with, even when this practice was widely tolerated (Kuhn and Shen 2013; Delgado, Kuhn and Shen, forthcoming), thus reducing the cost of compliance with the new restrictions.

This being noted, our analysis also shows that these job boards still accept subtler gender signals in ads, such as the gendered adjectives and the new "web words" we examined. For example, even though searches for "woman" yielded no results, searches for compound words like "lady" = "gentle+woman" (two characters) yielded several pages of results (though most of these refer to the names, products or brand of the firms). In addition, the adjectives "handsome", "gentleman", and "tall and strong" were frequently used to request men in jobs that included fitness instructors, sales, and warehouse work. "Beautiful", "lady", and "beautiful face" were used to request women in jobs that included customer service, front desk and modeling. Finally, the new web words "little brother" and "little sister" were also used to convey a clear gender preference. For example "little brother" was frequently used to request (young) men for (electric bicycle) delivery jobs, and "little sister" for camgirl jobs.[45] Also of interest, both Zhaopin and 51job allow recruiters to select a filter *that will only show the recruiter the applications from a particular gender*.[46] Overall, prohibition of gendered job ads has pushed formerly overt discrimination into more hidden forms on these platforms.

A3.3 Chinahr.com

We conducted a comparable search of Chinahr.com, a national job board that caters more to blue collar workers than Zhaopin and 51job. Here, the terms "man" and "woman' each yielded more than one page of search results.[47] Inspecting the first page of these revealed that 17 (or 43%) of the uses of "man" were explicit gender requests, as were 15 (or 38%) of the uses of "woman". Interestingly, here the transformed gender terms "nan" and "nv" were almost never used to request an applicant gender, perhaps because direct requests were still feasible.

---

[44] Zhaopin's portal states "Please do not include words that have the meaning of gender discrimination". Chinahr says "To make sure the job ad can pass checking, please do not enter repeat or meaningless information, and do not enter discriminating information, such as 'women first', or 'only for men'".

[45] The delivery jobs in question involve driving electric bicycles with packages or meals; pay is commission-based and the jobs are short term and relatively dangerous. Because most of the employees are young men, they are typically called "delivery little brother".

[46] The same is true for Liepin.com, a recruiting site focusing on higher managerial positions.

[47] On Chinahr, a page of search results comprises 40 job ads.

Perhaps for the same reason, gendered adjectives and new web words –while present—weren't used much to request candidates of a specific gender either. We speculate that Chinahr is more tolerant of gender profiling by employers than 51job and Zhaopin because of its focus on blue collar jobs, where, as noted, employers' demand for gender profiling appears to be much higher (Delgado, Kuhn and Shen, forthcoming; Kuhn and Shen 2013), and where both stigma and enforcement may be weaker.

A3.4 Local Internet Job Boards

Parallel to the private-sector boards discussed above, China has a system of government-run or government-sponsored job boards that operate at the city or province level. These boards' names end in RC, GGZP or HR; XMRC is one of them. In general, these boards tend to serve lower skill levels than the national boards described previously. Like the national job boards, however, all of these boards serve private-sector employers and workers; recruiting for government jobs takes place via other channels. In a comprehensive web search we were able to find 33 such boards of non-negligible size.[48]

When we examined the recruiter portals of these 33 sites, we found that 11 of them (including XMRC) ask employers to specify the gender of the worker they were seeking when the employer fills out a template for a job ad. Four of the sites (also including XMRC) allowed workers to filter job ads based on these employer requests. Keyword searches for "male" and "female" produced hits on all but two of these sites, and examination of the first 50 hits on each site revealed that these terms were frequently used to express a preference for male or female applicants. Code words like "nan" and "nv" turned up almost no results, perhaps because direct gender requests are still possible on these sites.

In sum, compared with private job boards, government-sponsored local job sites have more explicitly gendered job ads. We can think of three possible reasons for this. First, these sites tend to be relatively small, so they may so far have escaped the attention of regulators. Second, these sites –especially the pure job-posting services—serve less-skilled jobs and workers, where employers' demand for gender filters is considerably greater. Finally, in China, workers may be much less inclined to report government-sponsored sites for regulatory violations, compared to privately operated sites.

A3.5 Other Internet Job Boards

58.com is China's largest online job board serving temporary and part time jobs. In contrast to the job sites discussed previously, employers on 58.com include a large number of individuals, not just firms. Most of the jobs posted have low skill requirements and are informal in nature (in the sense that they do not participate in the social insurance system). A search of

[48] We found 57 boards in total, but 24 of these claimed to host 1000 or fewer job ads.

58.com, parallel to those of 51job, Zhaopin and Chinahr, indicated that both the words “man” and “woman” and their transformations are frequently used to request workers of a particular gender.[49] This may be due, in part, to workers’ unwillingness to report individuals (as opposed to firms) for discrimination, and the small stakes involved in doing so. And again, demand for gendered ads may be higher due to the less-skilled nature of these jobs.

Finally, **Yingjiesheng.com** is a website that aggregates information about job openings for new university graduates from a number of sources, including the job boards described above. In addition to referring applicants to those job postings, Yingjiesheng provides information about the recruitment plans of firms attending campus job fairs, and about the recruitment plans posted by firms on their own websites. These plans frequently include explicit gender preferences, which can often vary within firms. For example, a firm’s official, posted recruitment plan might say, “We are hiring 5 men for position A, 10 men for position B, and 5 women for position C”.

This Appendix was prepared with the assistance of Naijia Wu, an undergraduate student at UCSB.

[49] Notably, this is despite the fact that 58’s employer portal asks job posters, “Please do not include special symbols or any gender discriminating information”.

Appendix 4: Additional Tables and Figures

Table A1: Descriptive Statistics: Full Ad Sample

	Ad Requests Women (*F* jobs)	Gender not specified (*N* jobs)	Ad Requests Men (*M* jobs)	All Ads
Education specified?	0.946	0.886	0.931	0.906
Education Requested (years), if specified	12.83	12.74	11.71	12.57
Tech School Requested?	0.282	0.138	0.182	0.175
Desired Age Range specified?	0.576	0.321	0.530	0.408
Desired Age, if Requested (midpoint of interval)	26.37	29.54	30.32	28.85
Experience Requested (years)	0.837	1.158	1.348	1.129
New Graduate Requested?	0.036	0.017	0.019	0.021
Wage Advertised?	0.509	0.385	0.445	0.420
Wage, if advertised (yuan/month, midpoint of interval)	2,013	2,730	2,515	2,520
Number of positions specified?	0.960	0.933	0.963	0.944
Number of positions, if specified	1.602	1.821	1.698	1.756
Number of applicants	58.99	42.45	36.96	44.96
Sample Size	8,324	26,769	7,651	42,744

Table A2: Comparing XMRC Ads to the Employed, Private-Sector Population in Xiamen and Urban China

	(1)	(2)	(3)
Worker Characteristics	XMRC job ads	Xiamen employed population	Urban China employed population
Female (percent of gendered ads)	56.56	46.75	44.23
Education (years)	12.21	10.56	10.59
Age (years)	28.03	30.77	32.64
Monthly wage (RMB)	2,446	2,185	2,147
Broad occupation (percent):			
Management	1.68	4.3	4.59
Sales and Procurement	18.64	18.31	21.25
Service Occupations	15.40	21.68	22.28
Professional/Technical	27.30	7.99	8.21
Production, Construction, Manufacturing	29.39	47.71	43.68
Other	7.59	.	.
Number of observations	3,637	1,163	99,768

Employment data are from the 2005 Census, 1% sample, persons currently living in urban regions, who are currently employed in the private sector (i.e. excluding SOEs, government and collectives). "Urban China" comprises the four municipalities directly under the jurisdiction of the central government (Beijing, Shanghai, Tianjin and Chongqing) plus the 15 sub-provincial cities: Changchun, Chengdu, Dalian, Guangzhou, Hangzhou, Harbin, Jinan, Nanjing, Ningbo, Qingdao, Shenyang, Shenzhen, Wuhan, Xiamen, and Xi'an. Chinese wages have been adjusted for per capita GDP growth between 2005 and 2010 using IMF GDP statistics.

Table A3: Matching, Compliance and Enforcement Rates for Age, Education and Experience Requests

	Matching (Share of callbacks that match the employer's request)	**Compliance** (Share of applications that match the employer's request)	**Enforcement** (Share of mismatched applications that are rejected)
	(1)	**(2)**	**(3)**
Gender	0.948	0.925	0.947
Age[1]	0.748	0.734	0.925
Education[2]	0.436	0.444	0.917
Experience[3]	0.602	0.597	0.917
Wage[4]	0.495	0.501	0.916

Notes:

1. Age matching means the applicant is within the age range requested in the job ad.

2. Education matching means the candidate's education falls into the education category that is requested in the ad. The five education categories are: primary or less (6 years), junior middle school (9 years), high school (12 years), college or technical school (15 years) and university (16 years).

3. Experience matching means the candidate's experience equals the amount requested in the ad, or exceeds the request by no more than three years.

4. Wage matching means the applicant's current wage is in the same wage category as the job's advertised wage. The wage categories (in RMB/month) are "around 1000", 1000-1999, 2000-2999, 3000-3999, 4000-4999, 5000-5999, 6000-7999, and 8000-9999. Since 99 percent of offered and current wages are below 6000, this means that the candidate's wage is, on average, within about 1000 RMB/month of the offered wage, or within about one standard deviation.

Table A4: Actual and Counterfactual Segregation across Job Titles, Occupations and Firms—Nongendered Job Ads Only

Gender Segregation across:	Actual, noise-adjusted segregation ($\tilde{S}$) (1)	Segregation associated with self-sorting (Counterfactual *D*) (2)	Segregation associated with employer choice (Counterfactual *E*) (3)
Jobs:			
Segregation Index ($\tilde{S}$)	0.417	0.392	0.099
Share of Actual	1.000	0.941	0.239
Firm*Occupation cells:			
Segregation Index ($\tilde{S}$)	0.386	0.359	0.083
Share of Actual	1.000	0.929	0.214
Firms:			
Segregation Index ($\tilde{S}$)	0.298	0.289	0.071
Share of Actual	1.000	0.97	0.239
Occupations:			
Segregation Index ($\tilde{S}$)	0.300	0.324	0.041
Share of Actual	1.000	1.077	0.137

Table A5: Effects of Employers' Gender Requests on the share of female applications received (α)—callback sample only

	(1)	(2)	(3)	(4)	(5)
Ad requests men (*M*)	-0.3680***	-0.3270***	-0.2350***	-0.1368***	-0.1034***
	(0.020)	(0.019)	(0.017)	(0.019)	(0.032)
Ad requests women (*F*)	0.4790***	0.4243***	0.3603***	0.2037***	0.2401***
	(0.014)	(0.016)	(0.016)	(0.012)	(0.024)
Primary School		0.0292	-0.0113	0.0063	0.0502
		(0.034)	(0.029)	(0.019)	(0.032)
Middle School		-0.0683*	-0.0518**	-0.0087	0.0346
		(0.036)	(0.023)	(0.021)	(0.027)
Tech School		0.0587**	0.0287	-0.0125	-0.0322
		(0.026)	(0.021)	(0.016)	(0.027)
Post-secondary		0.1275***	0.0600***	0.0033	0.0215
		(0.024)	(0.020)	(0.016)	(0.029)
University		0.1062***	0.0361	-0.0113	-0.0757
		(0.038)	(0.027)	(0.025)	(0.064)
Number of positions advertised		-1.2386***	-0.8558***	0.3736	0.5534
		(0.330)	(0.268)	(0.288)	(0.512)
Occupation Fixed Effects			Yes	Yes	Yes
Job Title Fixed Effects				Yes	Yes
Firm Fixed Effects					Yes
Title*Firm Fixed Effects					
N (ads)	3,637	3,637	3,637	3,637	3,637
'Effective' *N*	3,637	3,637	3,637	1,627	840
R^2	0.571	0.620	0.738	0.936	0.980

Standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1

Note to Table A5:

In addition to the covariates shown, columns 2-5 also control for the following job ad characteristics: requested experience level (quadratic), requested age level (quadratic in midpoint of range), advertised wage (quadratic in midpoint of bin; 8 bins), dummy for whether new graduate requested, number of positions advertised, plus dummies for missing education, age, wage and number of positions. All regressions are weighted by the total number of applications received. 'Effective' *N* excludes job titles and firm IDs that only appear in one ad in columns 4 and 5 respectively. The column 6 specification in Table 8 cannot be estimated in the callback sample due to insufficient degrees of freedom.

Table A6: Selected job titles, by predicted 'maleness' and 'femaleness'

maleness (*Mp*)	femaleness (*Fp*)	job title	English meaning	femaleness (*Fp*)	job title	English meaning
[0,0.1)	[0,0.1)	外贸业务员	international trade person	[0.5,0.6)	采购文员	purchasing clerk
[0.1,0.2)		行政司机	administrative driver		统计	statistic clerk
[0.2,0.3)		仓库管理员	warehouse manager		总监助理	general manager assistant
[0.3,0.4)		电脑技术员	computer technician		董事长秘书	assistant to the chairman
[0.4,0.5)		技术员	technician		签约法务	signing legal
[0.5,0.6)		施工员	construction worker		生产班组长	production team leader
[0.6,0.7)		司机	driver		测量员	surveyor
[0.7,0.8)		保安	security person		CNC 编程员	CNC programmer
[0.8,0.9)		货车司机	truck driver		组装线线长（班长）	Assembly line leader (shift leader)
[0.9,1)		大货车司机	big truck driver		高管司机（总管理处）	driver for high management (general management division)
femaleness	**maleness**	**job title**	**English meaning**	**maleness**	**job title**	**English meaning**
[0,0.1)	[0,0.1)	外贸业务员	international trade person	[0.5,0.6)	施工员	contruction worker
[0.1,0.2)		人事专员	personnel specialist		外勤	field staff
[0.2,0.3)		业务助理	business assistant		总务课长	manager for the general affairs division
[0.3,0.4)		会计	accountant		物料员	material keeper
[0.4,0.5)		行政助理	administrative assistant		总账会计	general ledger accountant
[0.5,0.6)		采购文员	purchasing clerk		生产班组长	production group leader
[0.6,0.7)		出纳	cashier		教务专员（急聘）	teaching affair specialist (urgent recruitment)
[0.7,0.8)		文员	clerk		出纳员	cashier
[0.8,0.9)		前台接待	front desk receptionist		账务员	accounting clerk
[0.9,1)		前台文员	front desk clerk		研究生教学秘书	graduate studies teaching secretary

Figure A1: Simulated segregation indices with random allocation of applications to jobs, and random selection of callbacks from all applicant pools

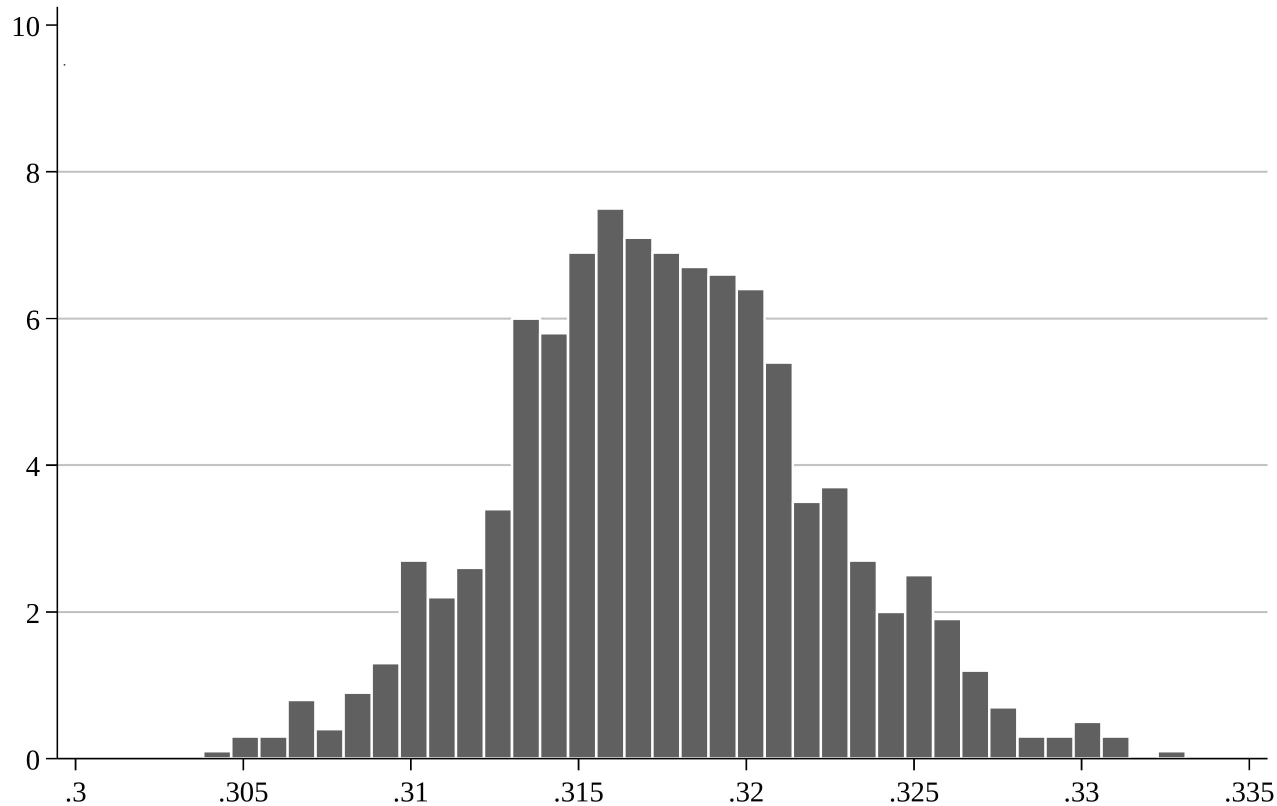
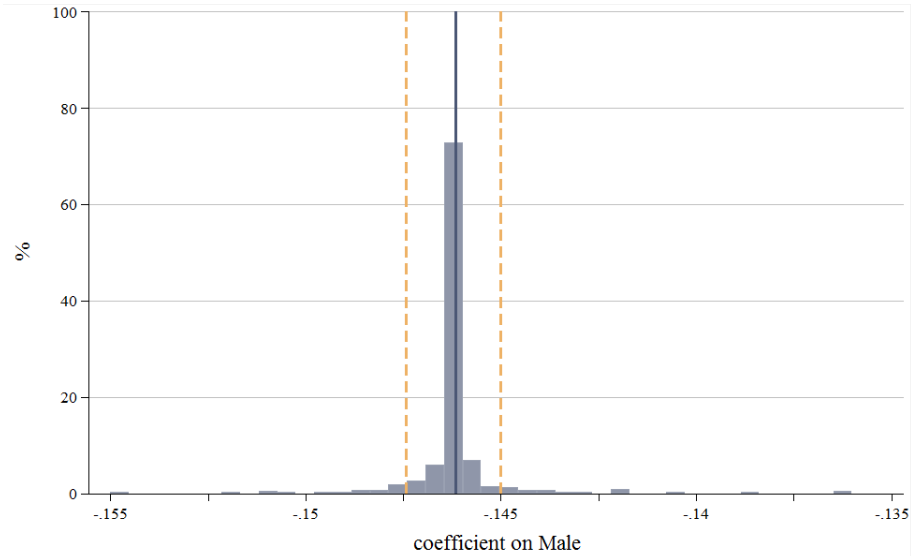
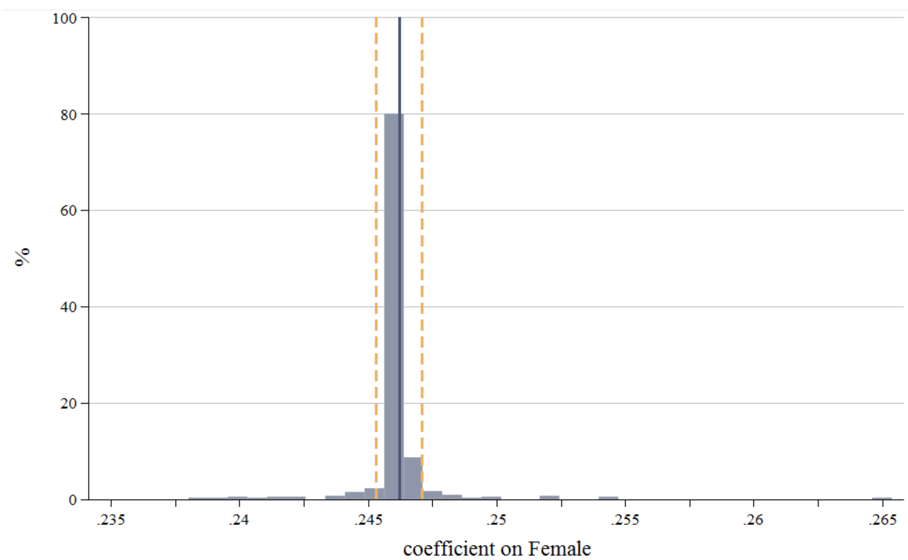


Figure A2: Distribution of leave-out-one-title estimates of gender request effects on female applicant shares

a) Effect of a request for men:

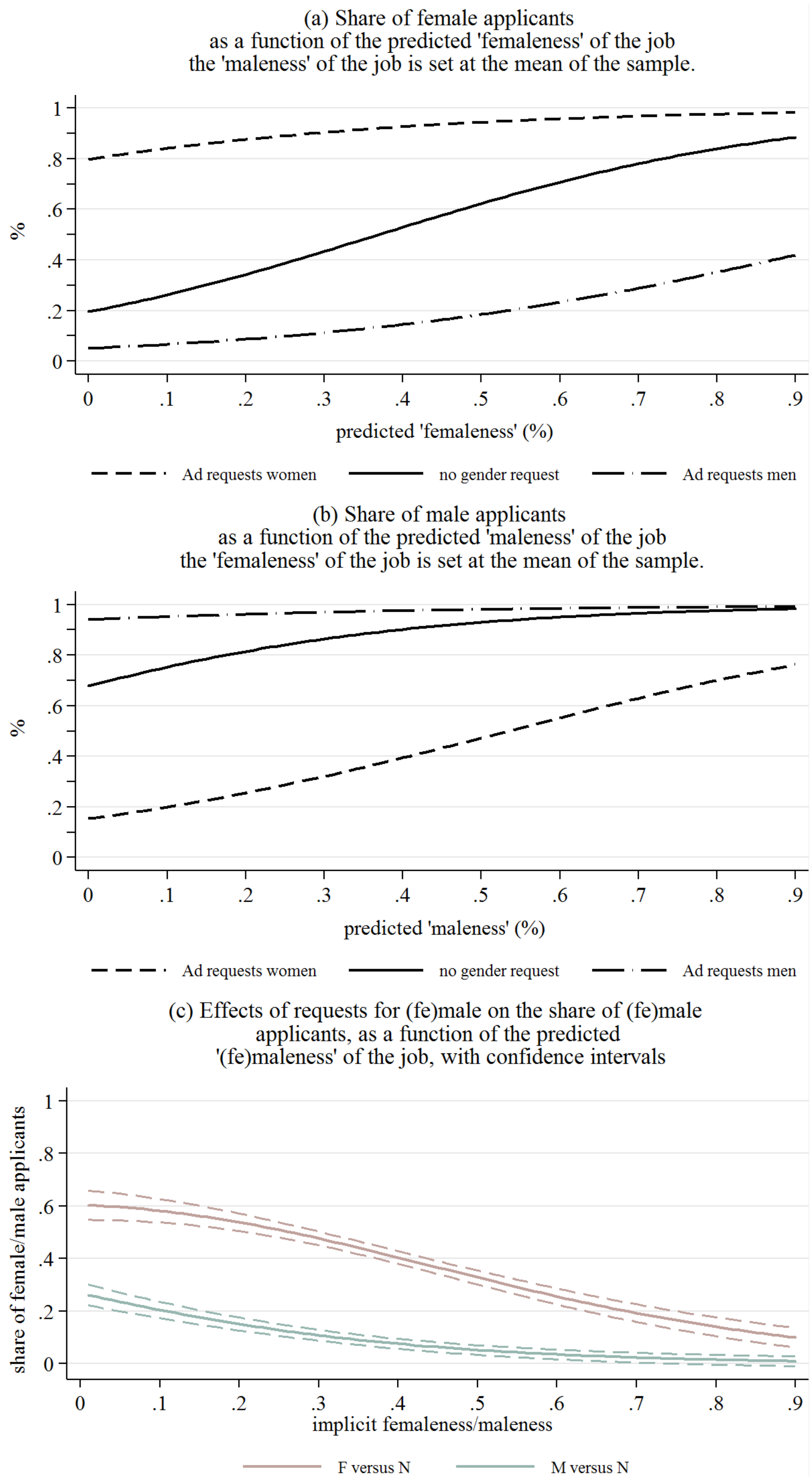


b) Effect of a request for women:



Note: Figures present estimates of the "Ad requests men" and "Ad requests women" coefficients in column 6 of Table 8. These coefficients are identified by 416 distinct job titles; the Figures report the distribution of estimates when one job title is dropped at a time. Vertical blue line represents the entire-sample estimate; vertical orange lines show the 5th and 95 percentiles of the estimates.

Figure A3: Effects of Gender Requests (*F* and *M*) and Predicted Gender (*Fp* and *Mp*) on the Female Share of Applicants (Full Ad Sample, log-odds specification)



Note to Figure A3:

Figures represent predicted values of the female share of applicants (α) from a specification identical to Figure 1, with the following changes. The dependent variable α, is now log ($\alpha/(1-\alpha)$), and the quartics in *Fp* and *Mp* (each interacted with *F*, *N* and *M*) are replaced by linear terms (again interacted with *F*, *N* and *M*). 'Corner' values of α are accommodated by setting $\alpha = 0.5/A$ when α=0 and setting $\alpha = (A-0.5)/A$ when α=1, where *A* is the total number of applications to the ad.

As in Figure 1, predictions in part (a) hold *Mp* at its mean, and predictions in part (b) hold *Fp* at its tenth mean. All other characteristics are set at their means. The regression is weighted by the number of applications to each ad, and standard errors are clustered at the firm level.

Appendix 5: Gender Misclassification

Miscoding of the *requested* gender is not a concern for our application analysis, since our data are the exact record of requested gender that workers observe on the job board when deciding where to apply. Miscoding of the requested gender could account for the relatively high success rates of gender-mismatched applicants if employers sometimes specify a gender requirement without intending to. If so, advertised gender requirements would be *de facto* rather soft. We view this as a possible interpretation of the relatively weak mismatch penalty in callbacks in our data.

Another possibility is that workers miscode their own gender when using the drop-down menu in the application process. The very high compliance rates we observe suggest that this is not a major concern. Nevertheless, we checked to see if miscoded applicant gender could account for the relatively weak enforcement in our data by re-running the main analysis on a restricted subsample for whom we are confident we have the right gender.[50]

To construct this sample, we first use the universe of applications, with no restrictions, to calculate the share of applications each CV in the sample sends to jobs which request the opposite gender. We then drop all the CVs in our sample for whom this share is 0.5 or higher. We also drop all CVs who submit fewer than 5 applications in the unrestricted data, because we may not have enough observations on them to reliably assess their application behavior. These restrictions only drop approximately 15,000 applications, leaving a sample size of 213,719.

We then re-run the application-level regressions from Table 8, and the results are very similar to those presented in the main analysis, which gives us confidence that the results are not being driven by misreported gender. They are reported in Table A3. Results for other cutoffs are not materially different.

[50] Note that miscoded applicant gender cannot explain weak enforcement if firms use resume-processing software to pre-screen resumes based on coded gender: such screens would eliminate both actual and false gender mismatches from consideration, generating a high level of *measured* enforcement. Miscoded applicant gender can only explain low compliance if employers can see that some apparently mismatched applicants are in fact of the requested gender (for example from the photo, name or other features of the resume.

Effects of Job Labels (*F*, *N* and *M*) on Callback Rates for Gender Misclassification Robust Sub-Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Female Worker * Female Job	-0.0140***	-0.0095***	-0.0092***	-0.0097***	-0.0142***	-0.0164***
	(0.009)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Female Worker * Male Job	-0.0429***	-0.0422***	-0.0422***	-0.0415***	-0.0341***	-0.0372***
	(0.013)	(0.004)	(0.004)	(0.005)	(0.006)	(0.008)
Male Worker * Female Job	-0.0341***	-0.0290***	-0.0291***	-0.0235***	-0.0240***	-0.0231***
	(0.010)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Male Worker * Male Job	0.0044**	0.0011	0.0012	0.0030	-0.0065	-0.0166***
	(0.009)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
Male Worker	0.0036**	0.0006	-0.0023	-0.0064***	-0.0165***	
	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	
Education less than requested		-0.0066***	-0.0063**	-0.0086***	-0.0093***	-0.0111***
		(0.002)	(0.003)	(0.003)	(0.002)	(0.004)
Education more than requested		-0.0034**	-0.0061***	-0.0039**	0.0007	0.0055**
		(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Age less than requested		-0.0007	-0.0019	-0.0022	-0.0042**	-0.0020
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age more than requested		-0.0320***	-0.0300***	-0.0277***	-0.0205***	-0.0214***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Experience less than requested		-0.0060***	-0.0063***	-0.0077***	-0.0094***	-0.0073***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Experience more than requested		0.0006	0.0018	0.0014	-0.0009	0.0014
		(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Wage below advertised		-0.0020	-0.0019	-0.0028	-0.0002	-0.0005
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Wage above advertised		0.0010	0.0008	0.0002	-0.0057**	-0.0046
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Detailed CV controls			Yes	Yes	Yes	
Occupation Fixed Effects				Yes	Yes	Yes
Competition Controls					Yes	Yes
Job Title Fixed Effects					Yes	Yes
Firm Fixed Effects						
Worker Fixed Effects						Yes
N (ads)	213,719	213,719	213,719	213,719	213,719	213,719
'Effective' *N*	213,719	213,719	213,719	213,719	213,676	189,485
R^2	0.001	0.004	0.005	0.015	0.194	0.382

Standard errors in parentheses, clustered by ad. *** p<0.01, ** p<0.05, * p<0.1

Appendix 6: Modeling Implicit 'Maleness' and 'Femaleness' of Job Titles: A Naïve Bayes Approach

This note describes how we construct a measure of the perceived, or 'implicit' maleness of each job title using a Naïve Bayes approach based on the words in all the job titles. The same method can be used to derive job titles' femaleness and follows the algorithm described in Mitchell (1997). More specifically, our approach, which is commonly used in textual analysis, is referred to as the multi-variate Bernoulli event model by McCallum and Nigam (1998).

A6.1 Description of the problem

Let J be the set of jobs in our data, K be the set of job titles that ever appear in the job set J, and W be the set of words that ever appear in the job title set K. Define $|A|$ to be the number of elements in set A. Similarly, $|J|$ is the number of jobs in our data, $|K|$ is the number of unique job titles and $|W|$ is the number of unique words in the job titles.

For any job $j \in J$, let $k(j) \in K$ be its title, and let $\omega(j) \in \{0,1\}$ indicate whether this job explicitly prefer men. In other words, $\omega(j) = 1$ if this job explicitly prefers men, and 0 otherwise. For any job title $k \in K$, let $W^k \subseteq W$ be the set of words that appear in this job title.

The implicit maleness of a job title k with word set W^k can then be expressed using Bayes rule as follows,

$$P(\omega = 1|W^k) = \frac{P(W^k|\omega = 1) \cdot P(\omega = 1)}{P(W^k)} \qquad (1)$$

A6.2 Solving the problem

Notice that $P(\omega = 1|W^k)$ can be rewritten as follows,

$$P(\omega = 1|W^k) = \frac{1}{1 + \frac{P(W^k|\omega = 0) \cdot P(\omega = 0)}{P(W^k|\omega = 1) \cdot P(\omega = 1)}}\,. \qquad (2)$$

A6.2.1 The prior probabilities

One option for modelling the prior probabilities $P(\omega = 1)$ and $P(\omega = 0)$ is to use the overall share of jobs that explicitly prefer men and that of jobs that do not explicitly prefer men in the sample. This approach is indeed widely used in commonly text classification. While this information is available to us, it may not be available to individual jobseekers, whose perceptions we are attempting to model.

Thus we adopt the naïve assumption that $P(\widehat{\omega = 1}) = P(\widehat{\omega = 0}) = 0.5$. Graham (2002) also argues for this assumption in the spam-filtering setting. Thus, equation 2 simplifies to

$$P(\omega \widehat{= 1} | W^k) = \frac{1}{1 + \frac{P(W^k|\omega = 0)}{P(W^k|\omega = 1)}}. \qquad (2b)$$

A6.2.2 The conditional probabilities: from words to job titles

It is more challenging to estimate $P\left(W^k|\omega\right)$. To simplify the estimation, the Naïve Bayes approach assumes that

1) the appearance of each word is independent and

2) the ordering of the words in a job title is irrelevant.

This implies that

$$P\left(W^k|\omega = 1\right) = \prod\nolimits_{w \in W^k} P(w|\omega = 1) \qquad (3a)$$

and

$$P\left(W^k|\omega = 0\right) = \prod\nolimits_{w \in W^k} P(w|\omega = 0). \qquad (3b)$$

A6.2.3 Estimation of each word's conditional probability

For the estimation of $P(w|\omega)$, if we have a large enough sample we can use

$$a \cdot P(\widehat{w|\omega}) = P(\omega|w) = \frac{\left|\{j: j \in J, w \in W^{k(j)}, \omega(j) = \omega\}\right|}{\left|\{j: j \in J,\ w \in W^{k(j)}\}\right|} \qquad (4)$$

where $= \frac{P(w)}{P(\omega)}$, which is assumed to be a constant and canclled out in the division in (2b).

In practice, however, even large samples frequently yield zeros in (4). Given equations 3a and 3b, we would then get zeros for the entire job title regardless of the other words in the title. To avoid this problem, we use a weighted average of $P(\widehat{w|\omega})$ and a constant number close to one as our estimate of $P(w|\omega)$. The formula is

$$P(\widehat{w|\omega}) = \frac{\left|\{j: j \in J,\ w \in W^{k(j)}\}\right|}{\left|\{j: j \in J,\ w \in W^{k(j)}\}\right| + C} \cdot P(\widehat{w|\omega}) + \frac{C}{\left|\{j: j \in J,\ w \in W^{k(j)}\}\right| + C} \cdot \frac{C-1}{C} \qquad (5)$$

Furthermore, notice it is particularly important to adjust the $P(\widehat{w|\omega})$'s when the total number of $\left|\{j: j \in J,\ w \in W^{k(j)}\}\right|$ is small. That is, we do not want to have a linear adjustment. Instead, we want to pull $P(\widehat{w|\omega})$ towards $\frac{C-1}{C}$ more strongly the less frequently a word appears in job titles.

In the literature, the recommended value of C is $|W|$. For maleness, $\frac{1}{|W|}\sum_{w\in W} P(\widehat{w|\omega}) \approx 0.212$, $\frac{1}{|W|} = \frac{1}{5954} = 0.00017$. If we were to use $|W|$ as C, $P(\widetilde{w|\omega})$ would be substantially higher than $P(\widehat{w|\omega})$ for most words. Therefore, to keep the distortion to a minimum, we choose C to be the average number of $\left|\{j: j \in J,\ w \in W^{k(j)}\}\right| \approx 15.04$. Combining (4) and (5), we can get $P(\widetilde{w|\omega})$ as presented in (6c).

To sum up, our estimator for the implicit maleness of a job title k is

$$P(\widehat{\omega = 1}|W^k) = \frac{1}{1 + e^{f(\omega=1|W^k)}} \qquad (6a)$$

where

$$f(\omega = 1|W^k) = \sum\nolimits_{w\in W^k} \{\ln[1 - P(w|\widetilde{\omega = 1})] - \ln P(w|\widetilde{\omega = 1})\} \qquad (6b)$$

$$P(w|\widetilde{\omega = 1}) = \frac{\left|\{j: j: j \in J, w \in W^{k(j)}, \omega(j) = 1\}\right| + C - 1}{\left|\{j: j \in J, w \in W^{k(j)}\}\right| + C}. \qquad (6c)$$

where $C = \frac{1}{|W|}\sum_{w\in W}\left|\{j: j \in J, w \in W^{k(j)}\}\right|$

A6.3 Final remarks

This note has described our machine-learning approach to estimating the likelihood that a job title will explicitly request men (or women) based on the words contained in the title. Notably, the purpose of our approach differs from the usual application of document classification algorithms, which in this case would be to produce the best possible forecast of the gender label an employer will attach to a job from all the data available to us. Instead we seek to model the perceptions of individual jobseekers who have less information than us, and who face time constraints and limited cognitive capacity. Thus we have adopted a relatively simple approach with a naïve prior, and abstained from elements that would be considered in an industrial textual analysis setting, such as a more detailed tokenization of words, dropping less frequent words, or using a term frequency–inverse document frequency (TF-IDF) approach to identify the more informative words in each job title.

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