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An Analysis of Online Job Portal Data

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Abstract

Using online job portal data and probabilistic regression estimations, the paper investigates the explicit gender bias and salary gap in the Indian job market, reflected in more than 800,000 job recruitment advertisements. Exploring formal and informal sector occupations, the study finds high existence of employers' gender bias in hiring. Explicit gender preferences are highly job specific, and it is common to mention the preferred gender in job ads, which, in general, favor men over women. Although ads for professional occupations exhibit less explicit gender bias, they are not gender neutral. In all types of professional jobs, irrespective of the share of ads with preference for men or women, on average, ads targeting men specify/offer much higher salary. Employers in elementary sectors as well as blue-collar jobs express more segregated gender preference. The findings support the existing research that argues women are more preferred in low-quality, low-status, typically low-paid informal jobs. Targeting women for low-quality jobs explains half of the mean offered salary gap specified in ads; the rest is direct gender bias. The paper also suggests that, with the rise of new technology and sectors, gender bias in hiring in those new types of jobs is expected to decline.

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Reflections of Employers' Gender Preferences in Job Ads in India: An Analysis of Online Job Portal Data[1]

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I. Introduction

A striking feature of the Indian labor force and job market is the low participation rate of women. With only 27 percent in the labor force, India is among the lowest in the world. The global average is 52 percent and in South Asia it is 29 percent. Increased female education and decline in fertility failed to put any dent in this low level of participation, indicating the presence of deep-rooted gender imbalance in preferences, stereotypes and practices in the overall job market. Analyzing a sample of 830,929 job advertisements over the period between 2011 and July 2017, this study identifies employers' preferences that explain demand-side factors contributing to low female labor force participation. Data were obtained from an Indian online job portal, "Babajob (merged into QuikrJobs in June 2017)", that covers both formal and informal sector jobs. Job advertisements that allow mentioning the preferred gender of the incumbent employee provide us with a unique window to shed light on employers' gender preference and demand for a specific gender, irrespective of applicants' qualifications, in frequently advertised occupations.

The key contribution of this paper is that this study uses a unique data source to investigate the gender gaps in demand for workers and the salary specified in ads in both formal and informal sector occupations. To the best of our knowledge, this is the first study of employers' explicit gendered demand for labor analyzing profiles of online job ads in India. This study analyzes job recruitment advertisements listed in an online job portal only. Though the online job portal provides us with access to an enormous amount of data, it needs to be mentioned that the ads we analyzed may not represent the overall Indian labor market. But it provides a broad and reliable picture of urban Indian employers' gender preference at hiring. The explicit gender analysis has been possible as it is not illegal in India to hire workers based on their gender and employers often exercise their right to impose explicit gender-specific restrictions on job advertisements. Gender preference at hiring can be reflected at various stages of the hiring process: requesting a certain gender through job ads, offering gender-discriminatory wages, and systematically hiring one gender over the other irrespective of their qualifications. In this paper, we focus on the first two sources of gender bias and investigate mainly to answer two sets of questions: First, does systematic gender bias by occupation exist among employers in the Indian labor market? If so, which gender is preferred in which occupation categories? Second, do gender-targeted jobs offer higher salary? What does the gender gap in specified salary look like?

Our findings show gender targeting and discrimination are quite common in the Indian job market. For example, one-third of the job ads listed in the portal identifies either men or women as preferred candidate. Like Kuhn and Shen, 2013 and Anand 2013, we also found a negative skill-targeting relationship - occupations requiring high level of skills are less likely to prefer a certain gender. As one would expect, there exists high occupational gender segregation in the demand side. Like many other labor markets, in India too women are more preferred in teaching, clerical, and low-level jobs. Lower salary is offered if the ad targets women for all occupational categories except for clerical positions. For teaching, business process outsourcing (BPO), and service jobs, even though demand for women is higher, yet lower salary is specified in those ads targeting women compared to those targeting men.

II. Related Empirical Literature on Gender Discrimination in Job Advertisements

Demand for a particular gender for certain jobs indicates the existence of gender preference in the Indian labor market and the employers' inherent lopsided perception regarding men and women's capability, skills and productivity to perform the same job. Statistical discrimination theory[3] based on stereotypes might explain some of these lopsided perceptions and the rest can be due to taste or preference.[4] According to statistical discrimination theory, an employer can be unprejudiced but still prefer to hire members of certain demographic group due to lack of information about the workers from the other group's ability. Similarly, the gender gap in wage for performing the same task reflects a gap in productivity in some cases, but in many cases in perception. However, demand for a particular gender for jobs elicits the deep-rooted perception and culture about who should do what and who, a man or a woman, should perform the task irrespective of their qualifications and contributes to occupation segregation.

Empirical research on explicit/overt gender preference in job hiring is rare due to the issue of legality and lack of data on employers' gender preference of the incumbent employee. In most developed countries hiring based on gender let alone mentioning preferred gender in a job advertisement is illegal. In the United States, explicit/overt gender discrimination was legal until 1964 before the enactment/introduction of the Civil Rights Act (1964). Examples of discriminatory advertisements from leading U.S. newspapers in 1960 were documented by (Darity & Mason, 1998). Goldin studied historical gender gaps and both explicit and implicit discrimination in the U.S. labor market using individual and firm level data collected by the Women's Bureau of the Department of Labor. Data on firm policies in the 1920s and 1930s reveal explicit discrimination against women, particularly married women. Jobs restricted for 'women only' were often the dead-end jobs that did not lead to advanced positions; on the other hand, 'men only' jobs were the advanced positions. Goldin explains that asymmetric information concerning women's productivity and patriarchy are the reasons behind this job segregation created by employers, who in almost all the cases were men (Goldin, 2006) (Goldin, 1990).

Intriguing empirical evidence of explicit gender bias in job hiring in the Chinese job market has been recently analyzed and documented by Kuhn & Shen, 2013, and Kuhn & Shen, 2011. To our knowledge, these two are the only articles that undertook statistical analysis on explicit gender preferences in job hiring using a large sample of online job advertisements. Analyzing data acquired from advertisements on a Chinese Internet job board, they found a negative relation between gender preference and jobs' requirement of higher levels of skill. Employers' relative preferences for either male or female employees are occupation- and job-specific and more strongly related to the employers' preferred age, height, and beauty of the potential employee than to their job skill levels in China. Gao, 2008 also analyzed Chinese job ads from ChinaHR.com based on Beijing. Analyzing 1,000 ads, he found that women are preferred in clerical and sales

[3] The theory, based on stereotypes, was pioneered by Phelps, 1972 and Arrow, 1973. According to this theory, inequality may exist and persist between demographic groups as economic agents' perception may be based on the average behavior of the discriminated group.
[4] Taste-based model of discrimination was introduced by Becker, 1957.

jobs and a higher share of men are requested in professional and managerial jobs. Lawler & Bae, 1998 studied job announcement data for white-collar and professional jobs from newspapers between 1985 and 1996 in Thailand and analyzed explicit gender discrimination. However, the focus of their paper is on the impact of multinational corporations on overt gender discrimination in the hiring process.

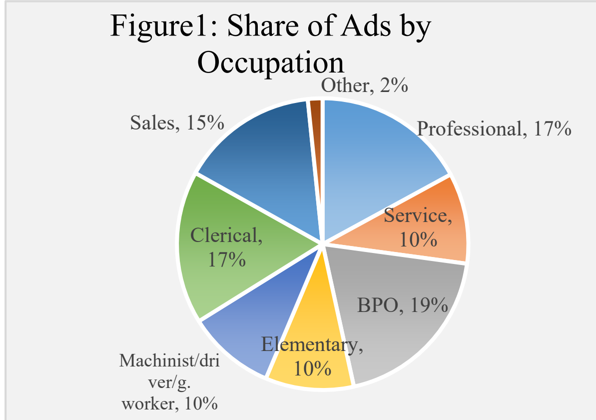
Anand, 2013 investigated gender stereotyping in job recruitment advertising in India using content analysis of 828 job advertisements collected from a widely-read English newspaper. The study found evidence of gender stereotyping in job ads across sectors in India; gender bias is less pronounced in professional jobs such as engineering, medical and other professional categories. On the other hand, a higher level of gender-targeting is found in jobs for secretary, receptionist, call center tele-callers, managerial jobs, teaching, clerical positions inter alia. In the sales sector, men are preferred for field positions and women are preferred for jobs involving tele-marketing.

III. Data and Sample

Our data were acquired from India's leading job-matching website – Babajob.com, established in 2007, recently bought by and merged with QuikrJobs.com. In 10 years, between 2007 and 2017 more than 1.25 million jobs were posted on the site and over half a million employers and over 5 million jobseekers were registered. The ads posted in the portal include almost equal share of both white- and blue-collar jobs. A variety of access options have been made available for job seekers to utilize the service and ensure better access to the disadvantaged population (Nomura, et al., 2017).

The final sample we used for the analysis includes 830,929 unique job advertisements posted between May 2011 and April 2017 in the top 20 cities. Our final sample constitutes 65 percent of all ads that span from May 2007 to May 2017. From the complete list of Babajob ads, we disregarded the 3 percent that were posted without any offered salary and another 0.6 percent of ads with salary outliers either under Rs. 800 or over Rs. 68,000. We deflated salaries using the monthly state-level urban consumer price index (CPI). Since CPIs were not available for years before 2011, we further restricted our sample to ads posted either in 2011 or later. Once an ad is posted it can stay in the portal for 90 days before it expires. We removed the duplicate ads if those were posted within 90 days of the first listing. There were 50,819 duplicate ads which got removed in the process. Each job ad comes with a location that mentions state, city and pincode. We ranked the cities based on the number of ads posted under each city. The final sample of 830,929 ads are only from the top 20 cities. The cities included in the sample are Ahmedabad, Bangalore, Chandigarh, Chennai, Coimbatore, Delhi, Gurgaon, Hyderabad, Indore, Jaipur, Kolkata, Luchknow, Ludhiana, Mumbai, Nagpur, Noida, Patna, Pune, Ranchi, and Thane. Half of the jobs advertised in our sample were based in three major cities – Bangalore, Delhi, and Mumbai.

In the website, Babajob used its own categorization of jobs, which has 27 categories. Based on that original categorization, we created occupation codes using the aggregated ISCO-1 classification, with separating 'teaching' and 'Business Process Outsourcing (BPO)' jobs out. The broader occupation categories of job ads are professional, service-oriented, elementary, machine-related, clerical, sales-related, and other.[5] About one-fifth of the ads were for BPO jobs. Including BPO jobs, the service sector has the largest number of job postings, 245,031, about 30 percent of all ads. Clerical and professional are the other two occupational categories with another one-third of ads. One-tenth of the ads are for elementary jobs.

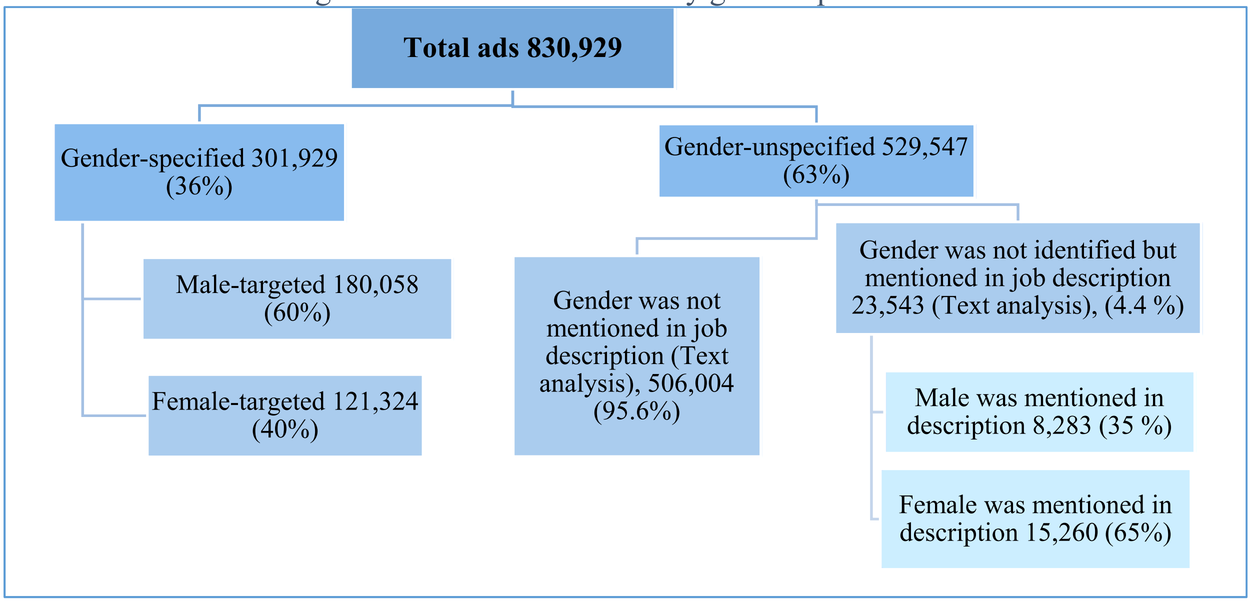


Gender profiling of online job advertisements

There is high existence of gender-targeted ads and explicit gender bias is highly job-specific. In the portal, there is an option for the employer to identify the gender of a preferred candidate, which has been utilized by many employers. Gender was specified in about one-third of the job advertisements in our sample. Not surprisingly, the share of ads with gender specification favors men over women, 60 percent of all gender-targeted ads mentioned men as preferred candidates in contrast with Kuhn and Shen's 2013 experience with China's job portal data where the share of ads favoring men or women is roughly equal. We conducted text analysis of the job description of the gender-unspecified ads to identify the presence of any implicit gender-preference in the description despite the ad not being explicitly gender-biased. Out of all 529,547 gender-unspecified ads, we found female-bias in 15,260 ads, which accounts for about 3 percent of all unspecified ads. Male-bias was present in 8,283 ads accounting for about 1.6 percent of those ads. We use explicit gender information for all our analysis and text-based implicit bias for robustness check of our main findings. Table 1 shows the share of ads by gender specification and ad characteristics.

[5] Professional jobs include jobs in management, engineering, IT professionals, and finance; service-oriented jobs include beautician, cook, nanny, nursemaid, and steward; elementary jobs include maid, cook-maid, delivery collector, gardener, watchmen, laborer; machine-related jobs include machinist, driver, and garment worker; clerical jobs include office clerk, office helper, and receptionist; sales jobs include jobs related to sales, and retail clerk.

Figure 2: Distribution of Ads by gender specification



Source: Babajob job portal data

Our descriptive statistics show a higher share of job ads posted by households and small or medium enterprises (SME) explicitly specify gender in the ads. Other than households where women are hired mostly as maids, all other hiring agencies such as SME, human resource (HR) enterprise, and staffing companies that listed gender-targeted ads prefer men over women. BPO job ads are the most gender-neutral with only 14 percent specifying gender. Ads for elementary occupations, machinist, driver and garment workers are the ones with higher share of gender targeting.

Table 1: Share of Job Ads by Gender Specification and Ad Characteristics

Characteristics	Gender unspecified Ad	Gender specified (men/women) Ad	Ad specifies men	Ad specifies women
	1	2	2(a)	2(b)
Required experience				
None or not specified	69	31	18	13
Less than 1 year,	71	29	17	11
1 to 2 years	55	45	26	19
2 to 3 years	47	53	32	20
3 to 4 years	47	53	34	18
4 to 5 years	44	56	40	16
5 years or more	43	57	42	15
Firm Ownership Type				
HR enterprise	67	33	21	12
SME	59	41	25	16
Staffing company	74	26	17	9
Household	46	54	20	34
Unknown	68	32	20	11
Work Shift				
Full-time	57	43	27	16
Part-time	55	45	20	25

Night-shift	81	19	14	5
Day-shift	52	48	27	21
Live-in	37	63	16	46
Not mentioned	78	22	12	10
Occupation sector				
Professional	73	27	15	12
Service	52	48	19	29
BPO	86	14	4	10
Elementary	43	57	33	24
Machine-related	48	52	51	1
Clerical jobs	59	41	17	24
Sales-related	60	40	34	6
Other	76	24	15	9
Offered mean monthly salary (Rs.)	8,811	7,391	7,926	6,598
Number of ads	529,547	301,929	180,058	121,324

IV. Employers' Potential Employee Search Preference

IV.A. Model Specification

Our descriptive statistics (Table 1) show high variation of gender-specified job ads by job category. The high variation in salary listed in the ads for men- and women- specified and gender-unspecified jobs is also robust and a striking feature of our data. We use two different model specifications to unravel the correlations between explicit gender bias with various factors in a more structured way.

V.A.a. Model for gender preference in hiring

We are interested to find out whether the probability of a job ad being gender-specified is correlated with occupation, experience required, and offered salary in the ad, controlling for other factors that can influence the correlation. Therefore, a probability model would better serve our purpose. The probabilistic nature of gender-targeted ads can be described through a logistic regression model. We used the following logistic regression to determine which factors were statistically related to the probability of a job advertisement being gender-specified:

$$\text{Logit}(\Pr(Y_i = 1)) = \beta_0 + \beta_1 J_i + \beta_2 X_i^a + \beta_3 X_i^E + \beta_4 T_i + \beta_5 S_i + \delta_i + \varepsilon_i \qquad (1)$$

where $I = 1, 2, \ldots n$

The dependent variable, Y_i, is an indicator of whether the advertisement i is gender-specified or not, which takes value 1 if an ad is gender-specified and 0 otherwise. The explanatory variables included in the regression model are (1) a set of occupation categories, J_i, of the advertisement. We included dummy variables for each of the occupational categories – professional, teaching, BPO, service, clerical, elementary, machine-related including drivers and garment workers, and sales. Jobs in categories other than the ones mentioned is the base category; (2) a vector of characteristics, X_i^a, of the employer and the job, including four dummy variables to capture different types of employers such as HR enterprise, household, small- and medium-sized enterprise (SME) with staffing company being the base category, number of vacancies under each ad, and two dummy variables to capture special work shift of the advertised job such as part-time and jobs that require night shift; (3) a vector of experience characteristics, X_i^E, which includes years of experience mentioned in the ad; (4) A vector of time dummies, T_i, which includes 6 dummy variables for each year from 2012 to 2017 indicating the year the ad was posted online with 2011 being the base year; (5) A measure of perceived productivity/remuneration, S_i, of the potential incumbent employee, which is the natural log of offered monthly salary adjusted for state-level inflation over time. Natural log of salary has been used to normalize the skewed distribution of offered salary. We also included city fixed effects, δ_i, to account for any conditions at the city level that we did not observe but could influence employers' preference regarding potential employees' gender within cities in similar fashion, such as labor market conditions, law, governance and security issues, social restrictions and stereotypes, and city policies regarding women's status.

We use the same model (eq 1) to explore and answer the gender-preference questions that we have identified to explore in this study. We use a sub-sample of gender-specified ads for professional jobs to explore employers' gender preference within the sub-categories of professional jobs.

However, to explore whether men or women are more preferred for certain jobs, we use the following multinomial logistic regression specification, as the dependent variable is categorical. In that case, we estimate the dependent variable, Zi, simultaneously utilizing the following two specifications, where i=1,2…n…

$$\text{Logit}\,(\Pr(Zi = 1)) = \beta 0+\beta 1Ji + \beta 2Xia + \beta 3XiE + \beta 4Ti + \beta 5Si + \delta i + \varepsilon i \quad (2)$$

$$\text{Logit}\,(\Pr(Zi = 2)) = \beta 0+\beta 1Ji + \beta 2Xia + \beta 3XiE + \beta 4Ti + \beta 5Si + \delta i + \varepsilon i \quad (3)$$

The dependent variable takes the value 1 if an ad specifies male as preferred candidate, takes the value 2 if female is preferred, zero if gender is not specified at all. The explanatory variables are the same as in equation 1.

V.A.b. Model for differential wage offer by gender

To analyze gender-targeted and male-female salary gaps in a systematic way, we use the following linear regression model (ordinary least squares OLS specification) for continuous outcomes,

$$Y_i = \beta_0+\beta_1 G_i + \beta_2 X_i^o + \beta_3 G_i.Xi^o + \beta_4 X_i^v + \varepsilon_i \quad (4)$$

where Y_i is the outcome of interest, natural log of salary, listed in ad i. G_i is the gender dummy, for gender-targeting model G_i represents whether the ad is gender-targeted or not, and for male-female salary analysis within gender-targeted pool of ad G_i takes the value 1 if the ad is female targeted. X_i^o represents 8 dummy variables for each occupational category with 'other job category' being the base. $G_i.Xi^o$ is the interaction between gender and occupation dummies. The explanatory variable X_i^v includes other job and employer specific characteristics such as work shift, type of employer, 6 dummy variables to capture the time the ad was listed, and years of experience required for the job.

IV.B. Regression result: Existence of gender preference

The goals of our regression analyses in section *V.A.a.* are (1) to determine whether gender-bias in hiring varies by occupations after controlling for attributes influencing hiring preferences, (2) to see if the hypothesis of negative skills relationship in general, that is professional and high-skilled jobs projecting less gender-preference, holds after controlling for other ad characteristics.

Coefficients, standard errors associated with coefficients, and odds ratios of logistic estimation are presented in Table 2. In all three regressions, the dependent variable Y_i equals 1 if the ad specifies either male or female as preferred and 0 otherwise. We use city-level fixed effect (20 cities) to control for any unobserved city-level heterogeneity. Model A shows the estimates only controlling for occupational category. We add additional employer and ad characteristics as well as independent variables of our interest as we move across columns. The subsequently added variables in Model B are type of employer, number of vacancies under each ad, whether the job is part-time, whether the job requires work at night shift, natural log of offered salary, preferred experience measured in years, and year dummy variables to capture period effect. The column for Model C presents the estimates for the full model with city fixed effect.

Table2: Binary logistic estimation of Gender-Targeting in job ads

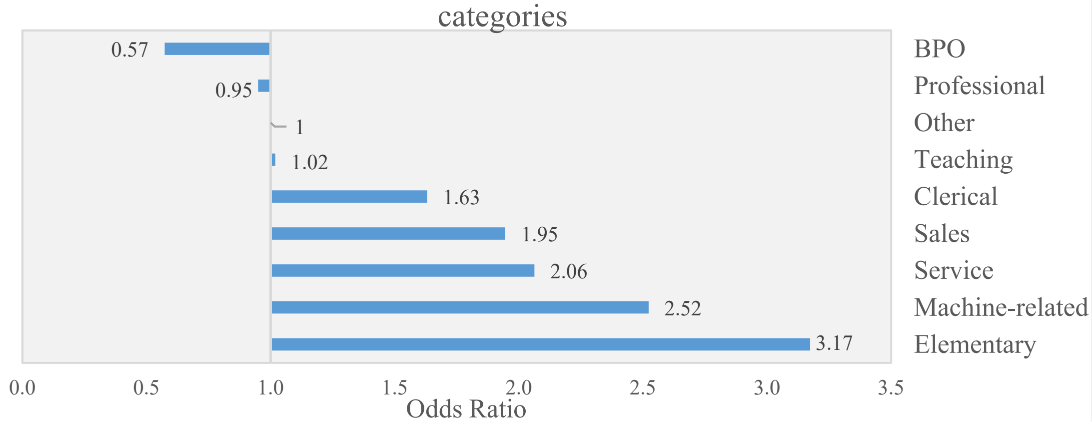
	Model A			Model B (With employer, job & time variables)			Model C (With additional city fixed effect)		
	Coef.	(S.E.)	OR	Coef.	(S.E.)	OR	Coef.	(S.E.)	OR
Occupation category (base=other)[6]									
Professional	0.077***	(0.021)	1.08	-0.05**	(0.02)	0.95	-0.05**	(0.02)	0.95
Teaching	0.36***	(0.024)	1.43	0.02	(0.02)	1.02	0.02	(0.02)	1.02
BPO	-0.69***	(0.021)	0.50	-0.57***	(0.02)	0.57	-0.56***	(0.02)	0.57
Service	1.07***	(0.021)	2.91	0.72***	(0.02)	2.06	0.72***	(0.02)	2.06
Clerical	0.65***	(0.021)	1.92	0.49***	(0.02)	1.63	0.49***	(0.02)	1.63
Elementary	1.43***	(0.021)	4.17	1.15***	(0.02)	3.17	1.15***	(0.02)	3.17
Machine-related	1.25***	(0.021)	3.48	0.92***	(0.02)	2.52	0.93***	(0.02)	2.52
Sales	0.76***	(0.021)	2.13	0.67***	(0.02)	1.95	0.66***	(0.02)	1.95
Type of employer (base= Staffing company)									
HR enterprise				0.23***	(0.01)	1.26	0.23***	(0.01)	1.26
Household				0.29***	(0.01)	1.34	0.30***	(0.01)	1.35
Unknown				-0.04***	(0.01)	0.96	-0.04***	(0.01)	0.97
SME				0.29***	(0.01)	1.34	0.29***	(0.01)	1.34
Job characteristics									
No. of vacancies				-0.01***	(0.00)	0.99	-0.01***	(0.00)	0.99
Shift: Part-time				0.31***	(0.01)	1.36	0.31***	(0.01)	1.37
Shift: Night				-0.02	(0.03)	0.98	-0.03	(0.03)	0.97
Log (Real offered salary)				-0.36***	(0.01)	0.70	-0.36***	(0.01)	0.70
Experience (years)				0.21***	(0.00)	1.23	0.21***	(0.00)	1.23
Period Dummy									
Year 2012				-0.05***	(0.01)	0.95	-0.05***	(0.01)	0.95
Year 2013				0.03**	(0.01)	1.03	0.03**	(0.01)	1.03
Year 2014				-0.06***	(0.01)	0.94	-0.06***	(0.01)	0.94
Year2015				-0.27***	(0.01)	0.76	-0.26***	(0.01)	0.77
Year2016				0.08***	(0.01)	1.08	0.08***	(0.01)	1.09
Year 2017				-0.49***	(0.02)	0.61	-0.49***	(0.02)	0.61
City fixed effect							YES		
Constant	-1.147***	-0.02	0.32	2.06***	(0.06)	7.86	2.03***	(0.06)	7.58
Pseudo R2		0.075			0.110			0.111	
Observation		830,929			830,929			830,929	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

[6] ISCO1 classification has been used to categorize ads by occupation except for teaching and BPO which have been kept separate because of their sheer volume and importance as occupations.

The odds ratios associated with gender-targeting in different occupations obtained through logistic regression presented in Table 2 (Model C) and graphed in Figure 3 shows that gender-targeting varies significantly by occupation categories. The odds ratios provide us with a comparative picture holding all else equal and we use 'other occupations' as our base category. Thus, an odds ratio taking the value 1 indicates no specific bias towards any gender compared to 'other occupations'. An odds ratio greater than 1 indicates positive gender bias compared to 'other occupations' and less than 1 indicates negative gender-targeting. Our results show that elementary job ads, in general, are the most gender-biased. It is interesting and encouraging to see ads for teaching jobs lose statistical significance of being gender-biased compared to jobs in 'other' categories once job and employer characteristics are held constant. As expected BPO, the emerging job category and professional jobs requiring specific skills in general have lower odds to be gender targeted. Another informative finding is that gender-targeted ads are significantly more likely to offer less salary for a similar job that is not targeted towards any specific gender.

Figure 3: Odds Ratio of an ad being gender-targeted by job categories



Note: The bars on the right reflects higher odds of being gender-specified and the bars on left reflects lower odds.

Consistent with Kuhn and Shen's, 2013 finding,[7] we also observe a negative skill-targeting relationship with gender preference: ads for professional jobs requiring high level of skills and educational qualifications are significantly less likely to be associated with gender targeting. Gender preference is higher among blue collar jobs, particularly among traditionally male or female occupations.

IV.C. Regression Result: Whom do employers want to hire? Men or women? And for which occupations?

We use both logistic binary (eq 1) and multinomial regression (eq 2,3) results presented in Table 3 to analyze demand-side gender-bias by occupation. However, we focus on logistic estimation while discussing results and multinomial estimation are presented here to show the robustness of the results. The logistic estimation in Model B provides the coefficients and odds of a gender-targeted ad identifying female as preferred candidate for each occupational category controlling for relevant factors.

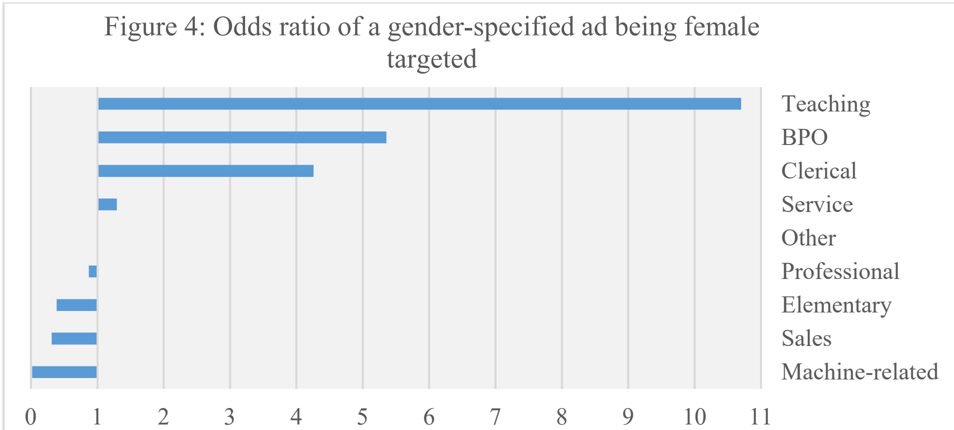
[7] Anand, 2013 also found a negative skill-gender targeting relationship in Indian job ads.

Table 3: Multinomial and logistic estimation of an ad being male- or female-specified compared to being gender-unspecified and female-specified compared to being male-specified

	Model A -Men (base=gender-unspecified)		Model A- Women (base= gender-unspecified)		Model B - Women (base= men)	
	Coef.	RRR	Coef.	RRR	Coef.	OR
Occupation category (base=other)						
Professional	0	1.00	-0.18***	0.84	-0.14***	0.87
Teaching	-1.55***	0.21	0.76***	2.13	2.37***	10.70
BPO	-1.49***	0.22	0.21***	1.24	1.68***	5.36
Service	0.54***	1.71	0.75***	2.12	0.26***	1.30
Clerical	-0.32***	0.73	1.12***	3.06	1.45***	4.26
Elementary	1.45***	4.25	0.60***	1.83	-0.944***	0.39
Machine-related	1.57***	4.80	-2.15***	0.12	-3.89***	0.02
Sales	0.97***	2.63	-0.24***	0.79	-1.16***	0.31
Type of employer (base = staffing company)						
HR enterprise	0.20***	1.22	0.30***	1.35	0.06**	1.06
Household	-0.43***	0.65	1.25***	3.47	1.95***	7.00
Unknown	-0.11***	0.90	0.09***	1.10	0.18***	1.20
SME	0.26***	1.30	0.37***	1.44	-0.01	0.99
Job characteristics						
No. of vacancies	-0.01***	0.99	-0.03***	0.97	-0.02***	0.98
Shift: Part-time	0.16***	1.17	0.43***	1.54	0.32***	1.38
Shift: Nights	0.61***	1.85	-0.84***	0.43	-1.62***	0.20
log (Real offered salary)	-0.07***	0.94	-0.71***	0.49	-0.78***	0.46
Experience	0.19***	1.21	0.23***	1.26	0.02***	1.02
Period Dummy						
Year 2012	-0.25***	0.78	0.33***	1.39	0.43***	1.54
Year 2013	-0.32***	0.73	0.63***	1.88	0.83***	2.30
Year 2014	-0.47***	0.63	0.63***	1.87	1.02***	2.77
Year2015	-0.67***	0.51	0.41***	1.50	0.87***	2.38
Year2016	-0.33***	0.72	0.77***	2.15	0.80***	2.23
Year 2017	-0.81***	0.45	0.04*	1.05	0.91***	2.49
City Fixed Effect		YES			YES	
Constant	-0.70***	0.50	3.52***	2.78	5.67***	289.78
Observations		830,929			301,382	
Pseudo R2		0.166			0.311	

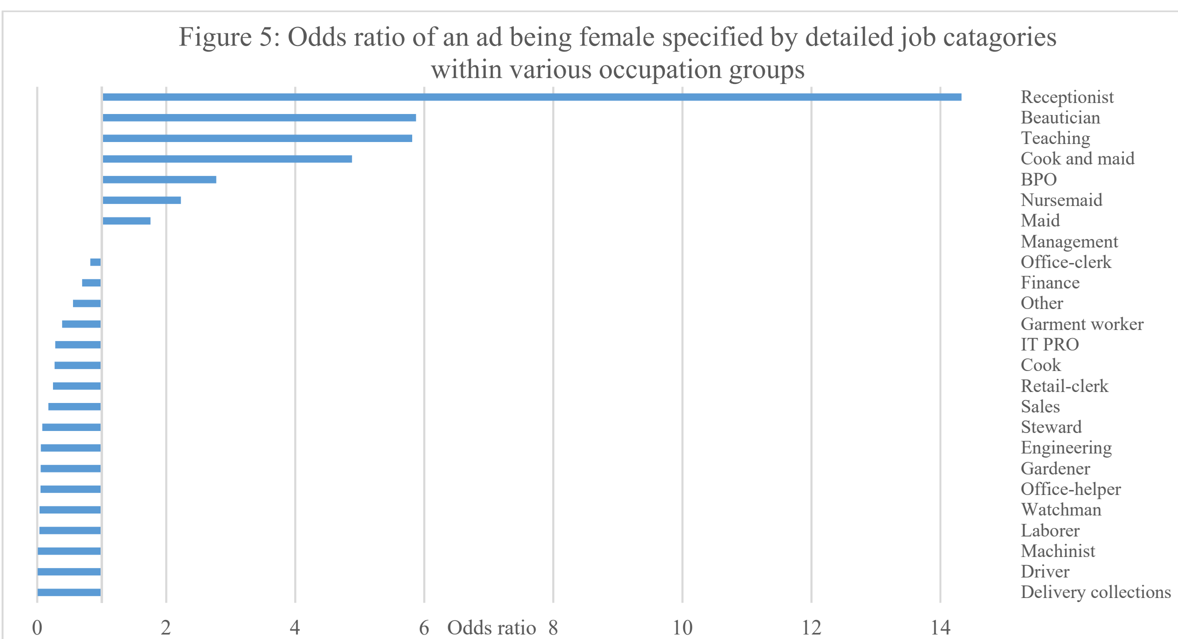
*** p<0.01, ** p<0.05, * p<0.1

There exists high variation of gender-bias, favoring men for certain occupations and women for others, which ultimately contributes to occupational gender segregation in the labor market. Based on our results, women are favored for clerical jobs; a gender-specified ad for a clerical job is more than 4 times as likely to target women than men compared to the base category. On the other hand, men are preferred in sales, and elementary occupations. We have already seen that professional, teaching and BPO jobs are less likely to be gender-targeted, however, among the gender-specified ads in those categories, teaching and BPO jobs have high female bias and professional jobs in general are slightly biased towards men (Figure 4). The statistical significance of the period dummy indicates that demand for female workers is increasing over time.



Note: The bars on the right reflects higher odds of being female-targeted and the bars on left reflects lower odds.

To understand if there exist any common trends or understanding that drives employers' preference to hire men or women and to identify which jobs are male jobs and which are viewed as female jobs, we ran a regression with job categories within various occupation groups (presented in appendix, Table A1). Instead of occupation groups themselves as independent variable, the odds ratio of an ad being female-targeted for each job category is presented in figure 5. Our analysis suggests jobs for positions in sales, retail clerk, office helper, high-intensive outdoor labor work such as laborer, gardener, watchman, delivery collection, and machine-related tasks such as garment worker, machinist, and driver are considered as male jobs. Among indoor low-end jobs, cook and steward are male jobs. On the other hand, women are disproportionately more preferred in household elementary jobs and caregiving jobs, as well as beautician and receptionist positions. Among professional jobs, teaching and management are relatively female jobs, and engineering and IT profession are considered male jobs.



Note: The bars on the right reflects female preferred and the bars on left reflects male-preferred jobs

IV.D. Regression result: Analysis of salary specified in ads - Do male-specified job ads offer higher salary than female-specified ones?

Job ads usually come with offered salary; hence, employers in many cases explicitly stipulating for male or female employee provides us with the opportunity to directly observe how employers value and perceive men and women's productivity. Of all 830,929 ads that come with specified salary, average salary specified per month is 11,841 rupees. Average monthly salary specified by ads with and without gender specification are 10,581 rupees and 12,558 rupees, respectively. It has already been shown that ads for lower-end jobs have higher odds of being gender-targeted. And that could be the reason for this mean salary gap. However, results from our OLS regression analysis with occupation category fixed effect (see Table A2 in appendix) show salary specified in gender-targeted ads on average is less by 6 percent after controlling for within-occupation category variation, job and employer characteristics such as years of experience required, work shift, type of employer, and the year the ad was listed.

Now within the pool of gender-specified ads, salaries specified in female-targeted ads are on average lower by 10 percentage points controlling for all occupation categories and other covariates (see Table 4). We use teaching as the base category for two reasons: firstly, though teaching falls under professional category, salary for teachers is not only the lowest among all professional categories but also comparable to that of all other occupations; and secondly, teaching is one of the least gender targeted occupations. We use the result of OLS estimation of extended model with interaction terms (Model 5B) to predict the log of salaries, the pairwise predictive margins between male and female salary and the contrast between the margins. The predictive margins take care of both sources of discrimination – 1. being a female in general in the job market and 2. being a female within each occupation group. Figure 6 shows the gender gap in ad-specified salary for each occupation group based on predictive margins.

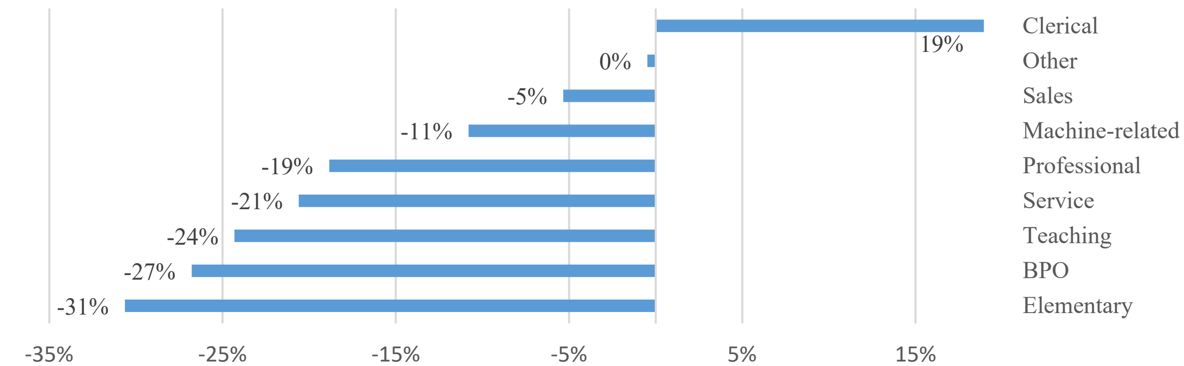
Table 4: OLS estimation of (log of) specified salary within gender-targeted pool of ads

Natural log of monthly salary	Model 5A: Basic		Model 5B: Extended with interactions	
	Coef.	Std. Err	Coef.	Std. Err
Experience	0.03	0.00***	0.03	0.00***
Work shift (base: Not mentioned)				
Full	-0.05	0.00***	-0.06	0.00***
Part-time	-0.22	0.00***	-0.22	0.00***
Day time	-0.04	0.00***	-0.05	0.00***
Night shift	0.03	0.01**	0.00	0.01
Employer Type (base: SME & staffing company)				
Unknown	0.00	0.00*	0.00	0.00
Household	-0.14	0.00***	-0.09	0.00***
HR enterprise	0.12	0.00***	0.11	0.00***
Period Dummy				
Year 2012	0.17	0.00***	0.16	0.00***
Year 2013	0.21	0.00***	0.20	0.00***
Year 2014	0.26	0.00***	0.25	0.00***
Year2015	0.24	0.00***	0.23	0.00***
Year2016	0.09	0.00***	0.09	0.00***
Year 2017	0.32	0.01***	0.30	0.01***
Occupation categories (base=Teaching)				
Professional	0.38	0.01***	0.28	0.01***

Service	-0.02	0.00***	-0.10	0.01***
BPO	0.17	0.01***	0.17	0.01***
Elementary	-0.13	0.00***	-0.19	0.01***
Machine-related	0.17	0.01**	0.03	0.01*
Clerical	0.00	0.00***	-0.29	0.01***
Sales	0.27	0.00***	0.14	0.01***
Other	0.28	0.01***	0.11	0.02***
Female	-0.10	0.00***	-0.24	0.01***
Interaction between occupation categories and female				
Professional*female			0.05	0.01***
Service*female			0.04	0.01***
BPO*female			-0.02	0.01*
Elementary*female			-0.06	0.01***
Machine-related*female			0.14	0.02***
Clerical*female			0.43	0.01***
Sales*female			0.19	0.01***
Other*female			0.24	0.02***
Constant	8.58	0.01***	8.715	0.01***
Number of observations	301,380		301,380	
Adjusted R-squared	0.2419		0.2705	

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

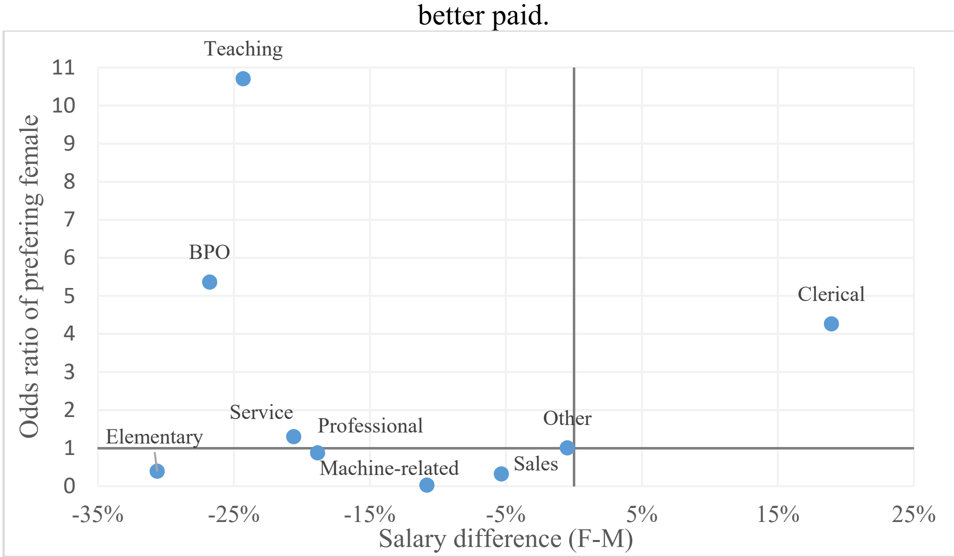
Figure 6: Predictive Margins - Ad-specified salary gap by gender



Note: Bars on the right-side (left-side) indicate higher (lower) salary for female-specified job compared to salary offered in male-specified jobs.

Other than clerical positions, there exists high discrimination against women in specified-salary in job ads in all other occupational categories. Ads for clerical positions not only show female-bias, an ad targeting women also specifies 19 percent higher salary than the ones targeting men. Among all occupations, ads for elementary occupations have the highest odds of being gender-targeted, they also have the highest gender gap in specified-salary. In general, a job ad in an elementary occupation offers 31 rupees less in a female-targeted ad for each 100 rupees offered in a male-targeted one. However, this is not unexpected as there exists high segregation by job category and men are targeted in relatively high-intensive outdoor jobs. Interestingly, though teaching and BPO jobs are the ones with the least gender-targeted ads and the ones that come with gender preference are more likely to target women – are associated with high salary gap favoring men. In gender-targeted ads, ads seeking women offer 27 percent and 24 percent lower salary for BPO and teaching jobs, respectively. Similarly, professional jobs (teaching, finance, IT professional, engineering, management) appear to project relatively less gender bias at the first stage of hiring, i.e., job advertisement, an ad for a professional job targeting women is associated with 19 percent lower salary than an ad targeting men after controlling for job and employer characteristics. Ads for machine-related occupations such as machinist, driver or garment worker and for sales jobs with high male-preference have relatively lower gender gap in specified salary. Jobs in the service sector (beautician, cook, nanny, nursemaid, steward) show relatively high gender preference by employers and specified salary is higher in male-targeted ads by 21 percent than female-targeted ones. Based on employers' gender targeting and specified salary in the job ads, we categorize all available occupations in four groups – i. Female-preferred and female better paid, ii. Male-preferred and female better paid, iii. Male preferred and male better paid, and iv. female preferred and male better paid. Figure 7 below shows the graphical presentation of the categorization of each occupation. The last quadrant with female preferred and male better paid (BPO, teaching, and service) seems puzzling for the presence of a seemingly inconsistent relationship between demand and salary offered as higher demand for female employees should result in higher specified-salary as well. Our data do not allow us to explore further and unravel the puzzle. However, we suspect the supply side plays a salient role in this case and the specified-salary gap reflects the hedonic price of hiring men vs. women.

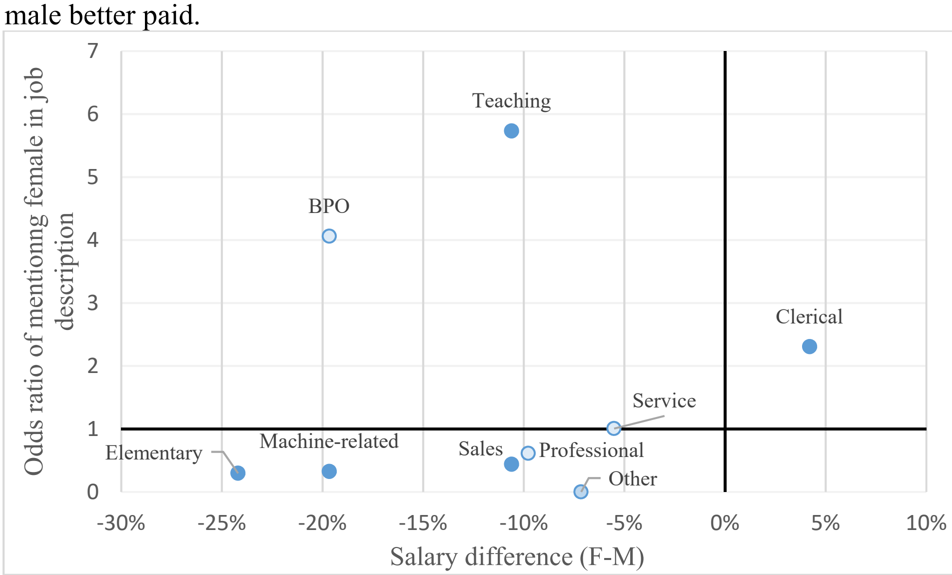
Figure 7: Occupations under four different categorization (clockwise): female-preferred & female better paid, male-preferred &female better paid, male-preferred & male better paid, female-preferred & male better paid.



V. Robustness check

We conducted text analysis to identify the presence of implicit gender-targeting using gender-specific word(s) in the job description of the ads that did not explicitly specify preferred gender of the potential employee and listed as gender-unspecified. This implicit gender-targeting then has been used to check the robustness of our findings. As noted earlier, out of all 529,547 gender-unspecified ads, 15,260 and 8,283 ads (23,543 ads total) which account for 3 percent and 1.6 percent of unspecified ads respectively turned out to have implicit female and male bias. To check the validity of the results of our gender analysis, we ran regressions on the sub-sample of those 23,543 gender-unspecified ads to analyze employers' implicit gender-bias by occupation and then the same sub-sample of implicitly targeted ads within the pool of gender-unspecified ads have been used to check gender discrimination in salary. The regression results for gender-targeting are presented in Table A4 in the appendix followed by the associated odds ratios. The regression results for salary gap and the associated predictive margins are presented in Table A3 (last 2 columns) and Figure A1, respectively, in the appendix as well. We reproduced the graph of female-targeting and salary gap in Figure 8 using the subsample of cases with no explicit gender-preferences but presence of gender-specific words in the job description to see if employers' gender preferences are robust enough and their implicit preferences resonate with their explicit ones. The implicit (Figure 8) and explicit (Figure 7) preferences follow the same patterns.

Figure 8: Reproduction of Figure 7 using implicit gender preference in job description obtained through text analysis- Occupations under four different categorization (clockwise): female-preferred & female better paid, male-preferred &female better paid, male-preferred & male better paid, female-preferred & male better paid.



Note: The light blue dots indicate statistically insignificant salary gap. Sample size for this analysis is 23,543 ads-gender-unspecified but with male or female bias in the job description.

VII. Source of Offered Salary Discrimination

Employers' discrimination in hiring can come from two sources, first, by hiring women for low-level jobs, and second by offering lower salary to women irrespective of experience and qualifications. We conducted Blinder-Oaxaca decomposition[8] to understand the sources of ad-specified wage differences (Table 5). The decomposition result shows a male -female wage gap of 0.197. This gap is then divided into three parts. The first part shows the mean increase in female-targeted job offer (wage) if the ads had the same characteristics as male-targeted jobs. The increase

[8] For details on the Oaxaca-Blinder decomposition and its method, see Oaxaca, 1973; Blinder, 1973; Oaxaca and Ransom, 1994; Jann, B 2008.

of .0965 indicates that difference in endowments request accounts for half of the wage gap, meaning half of the gender wage gap would disappear if women are not targeted for low-quality, low-skill jobs. The second part ‘difference in coefficients’ quantifies the change in offered women’s wages when applying men-targeted ads’ coefficients to the women-targeted jobs’ characteristics. Thus, 59 percent of the wage differential comes from this unexplained source. The third part is the interaction term that measures the simultaneous effect of differences in endowment request and coefficients, which is -8 percent.

Table 5: Oaxaca-Blinder decomposition of Male-Female ad-specified (log) wage differential

	Coefficient	Std. Err	Percentage
Male-female offered log wage differential	0.197***	(0.00171)	
Difference in endowments request	0.0965***	(0.00304)	49%
Difference in coefficients	0.116***	(0.00205)	59%
Interaction	-0.0155***	(0.00325)	- 8%

VIII. Discussion and Conclusion

The findings of this study demonstrate strong and persistent existence of gender bias among Indian employers in hiring for various job positions across sectors. Like other studies on job recruitment ads, we also found lower presence of gender-targeting in occupations that require high skills. Based on the patterns of gender preference for particular jobs, we claim that the demand side of the job market represents and reinforces the existing societal gender norms and occupational segregation. This finding supports the existing research that argues women are more preferred in low-quality, low-status, typically low-paid informal jobs (Heintz, 2006) (Goldin, 1990) (Gregory, 2003).

In India, recent technological changes and advancement in communications and networking infrastructure have given rise to new types of jobs that are not traditionally associated with any particular gender. Based on the theory on female labor force participation, women’s level of participation is expected to increase with the rise of any new technological advancement as it shifts production and labor demand from physical- to mental-intensive tasks where men do not have a comparative advantage (Goldin, 1990). Jobs in Business Process Outsourcing (BPO) and the IT sector fall in such category of new types of jobs. India’s BPO industry has experienced rapid growth with 30 to 40 percent average annual growth rates from 2000 to 2008 (National Association of Software and Service Companies, NASSCOM, 2009). By bringing new types of jobs on the table, this growing sector is expected not to show any particular gender preference and as one would expect we do see that the ads for BPO jobs are the most gender neutral, half as likely to be gender-targeted compared to ‘other’ jobs. This suggests with the rise of new technologies and sectors, gender preference in hiring in those new types of jobs is expected to decline.

Gender stereotyping and bias further lead to salary discrimination. To answer the question about how Indian employers value potential men versus women employees, the answer is, in general men are valued more by employers. Thus, employers are willing to offer higher salary when they target men over women. Half of the mean salary gap *ceteris paribus* between male- and female-targeted ads arises as employers seek female incumbents for low-quality low-skill jobs. The rest of the gap is simple discrimination. Gender stereotyping and availability of jobs influence and shape job-seekers perception about availability and quality of jobs. Thus, this gender-bias on the demand side perpetuates and reproduces stereotypes among job-seekers, which further contributes to occupation segregation.

One might argue that required time commitment might be different for male and female targeted jobs. Job ads catering to women might be less demanding regarding time, commitment, and effort, and thus differential treatment could be justified. Also, employers are likely to factor in the added responsibility while hiring a woman due to the insecurity women face in public places and while commuting. However, this line of argument actually supports the above-mentioned claim as it suggests employers perceive potential women employees as less reliable and seek them for inferior jobs. Whether this perception is due to inherent gender discrimination of the employer or merely due to statistical discrimination or due to the restrictions and risks associated with women is beyond this study. But it is an important question to seek to answer if the country attempts to level the playing field to achieve gender equality and encourage higher female participation in the labor market to achieve sustainable economic development.

We have seen that professional occupations and new types of jobs have lower gender bias in terms of whom to hire. At the same time, demand for female employees is increasing over time. With increasing female education, especially at the tertiary level, and emergence of new types of jobs in the local and global market, one can expect the decline of the gender-gap in hiring in the Indian job market in the near future. However, the decline of the gender-based salary gap might take longer.

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Appendix

Table A1: Binary logistic estimation: Odds ratio of a gender-specified ad being female targeted with detailed job categories

	Odds ratio	S.E.
Job category (base=other)		
Management	1.80	0.08***
Engineering	0.10	0.01***
IT professional	0.50	0.03***
Finance	1.25	0.05***
Teaching	10.46	0.54***
Beautician	10.57	0.56***
BPO	4.95	0.20***
Cook	0.49	0.02***
Nanny	42.39	3.65***
Nurse-maid	4.01	0.22***
Steward	0.14	0.01***
Maid	3.15	0.14***
Cook & maid	8.75	0.78***
Delivery collector	0.01	0.00***
Gardener	0.10	0.02***
Watchman	0.07	0.01***
Laborer	0.06	0.01***
Machinist	0.02	0.00***
Driver	0.01	0.00***
Garment worker	0.69	0.04***
Office clerk	1.47	0.06***
Office helper	0.09	0.00***
Receptionist	25.69	1.18***
Retail clerk	0.44	0.02***
Sales	0.31	0.01***
Type of employer (base= Staffing company)		
Hiring agency	1.03	0.03
Household	2.99	0.09***
Unknown	0.99	0.02
SME	0.96	0.02*
Vacancies	0.99	0.00***
Shift: Part-time	1.57	0.05***
Shift: Nights	0.21	0.01***
log of real salary	0.45	0.01***
Experience (years)	0.96	0.00***
Period Dummy		
Year 2012	1.72	0.05***
Year 2013	2.41	0.06***
Year 2014	2.74	0.07***
Year2015	2.26	0.06***
Year2016	2.27	0.06***
Year 2017	2.18	0.08***
Constant	370.99	49.14***
Observations	301,380	
Pseudo R2	0.4815	

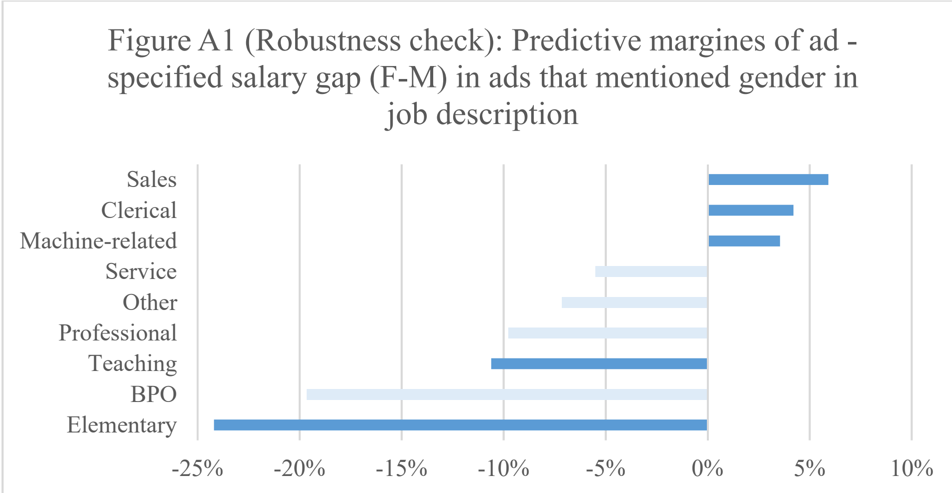
Table A2: OLS estimation of (log of) specified salary with job category fixed effect to identify if gender-specified ads offer lower/higher salary

	Coef.	Std. Err	t
Gender-specified ad	-0.064	0.001***	-61.97
Work experience	0.033	0.000***	101.27
Work shift (Not mentioned)			
Full-time	-0.049	0.001***	-46.04
Part-time	-0.188	0.003***	-63.69
Day-time	-0.055	0.002***	-29.67
Night-time	0.197	0.004***	46.73
Employer type (base= SME)			
Unknown	0.025	0.001***	19.97
HH	-0.096	0.002***	-49.27
HR enterprise	0.086	0.002***	44.42
Period Dummy			
Year 2012	0.154	0.002***	62.73
Year 2013	0.195	0.002***	82.41
Year 2014	0.281	0.002***	122.77
Year2015	0.257	0.002***	109.45
Year2016	0.138	0.002***	56.36
Year 2017	0.345	0.003***	112.55
Job category Fixed Effect		YES	
Constant	8.309	0.008***	1088.38
Number of observations = 830,929			
Adjusted R-squared = 0.267			

*** p<0.001, ** p<0.01, * p<0.5

Table A3: OLS estimations of (natural log of) specified salary to measure salary gap by gender, in general, and in each occupation

	Main Analysis				Robustness check			
	Basic Model		Extended Model		Basic Model		Extended Model	
	Coef.	S.E.	Coef.	S.E	Coef.	S.E	Coef.	S.E
Experience	0.03	0.00***	0.03	0.00***	0.04	0.00	0.04	0.00***
Work shift (base: Not mentioned)								
Full	-0.05	0.00***	-0.06	0.00***	-0.034	0.01***	-0.02	0.01***
Part-time	-0.22	0.00***	-0.22	0.00***	-0.14	0.02***	-0.15	0.02***
Day time	-0.04	0.00***	-0.05	0.00***	-0.00	0.01	0.00	0.01
Night shift	0.03	0.01**	0.00	0.01	0.18	0.04***	0.17	0.04***
Employer Type (base: SME)								
Unknown	0.00	0.00*	0.00	0.00	0.00	0.01	0.01	0.01
Household	-0.14	0.00***	-0.09	0.00***	-0.29	0.01***	-0.25	0.01
HR enterprise	0.12	0.00***	0.11	0.00***	0.09	0.01***	0.09	0.01
Period Dummy								
Year 2012	0.17	0.00***	0.16	0.00***	0.21	0.04***	0.20	0.04
Year 2013	0.21	0.00***	0.20	0.00***	0.20	0.04***	0.18	0.04
Year 2014	0.26	0.00***	0.25	0.00***	0.25	0.04***	0.24	0.04
Year2015	0.24	0.00***	0.23	0.00***	0.23	0.04***	0.21	0.04***
Year2016	0.09	0.00***	0.09	0.00***	0.11	0.04***	0.10	0.04***
Year 2017	0.32	0.01***	0.30	0.01***	0.29	0.04***	0.28	0.04***
Occupation categories (base=Teaching)								
Professional	0.38	0.01***	0.28	0.01***	0.24	0.02***	0.21	0.05***
Service	-0.02	0.00***	-0.10	0.01***	0.03	0.02***	-0.03	0.06
BPO	0.17	0.01***	0.17	0.01***	0.10	0.02	0.18	0.06***
Elementary	-0.13	0.00***	-0.19	0.01***	-0.12	0.02***	-0.09	0.05*
Machine-related	0.17	0.01**	0.03	0.01*	0.13	0.02	0.04	0.06
Clerical	0.00	0.00***	-0.29	0.01***	-0.01	0.02	-0.13	0.05**
Sales	0.27	0.00***	0.14	0.01***	0.22	0.02***	0.13	0.05**
Other	0.28	0.01***	0.11	0.02***	0.17	0.02***	0.14	0.06**
Female	-0.10	0.00***	-0.24	0.01***	-0.05	0.01***	-0.11	0.06*
Interaction between occupation categories and female								
Professional*female			0.05	0.01***			0.01	0.06
Service*female			0.04	0.01***			0.05	0.06
BPO*female			-0.02	0.01*			-0.09	0.06
Elementary*female			-0.06	0.01***			-0.14	0.06
Machine-related*female			0.14	0.02***			0.14	0.06**
Clerical*female			0.43	0.01***			0.15	0.06**
Sales*female			0.19	0.01***			0.16	0.06***
Other*female			0.24	0.02***			0.03	0.07
Constant	8.58***	0.01	8.715	0.01***	8.65	0.042***	8.71	0.07***
Number of observation	301,380		301,380		23,543		23,543	
Adjusted R-squared =	0.2419		0.2705		0.1429		0.1525	



Note: Light blue bar indicates statistically insignificant salary gap within occupation

Table A4: Robustness Check – Logistic estimation of Gender targeting through using gender-specific words in job description

	Coef.	Std. Err.	Odds Ratio
Professional	-0.49	0.09***	0.61
Teaching	1.75	0.16***	5.73
BPO	1.40	0.09***	4.06
Service	0.01	0.10	1.01
Clerical	0.84	0.09***	2.31
Elementary	-1.22	0.09***	0.30
Machine-related	-1.12	0.11***	0.33
Sales	-0.82	0.09***	0.44
Type of employer			
Hiring agency	0.39	0.06	1.48***
Household	1.51	0.08	4.54***
Unknown	0.11	0.05	1.12**
SME	0.26	0.05	1.29***
Job characteristics			
Vacancies	-0.01	0.00	0.99***
Shift: Part-time	0.17	0.11	1.19
Shift: Nights	-0.35	0.21	0.71
log (Real offered salary)	-0.34	0.04	0.71***
Experience	-0.08	0.01	0.92***
Period Dummy			
Year 2012	0.42	0.21	1.52*
Year 2013	0.55	0.20	1.73***
Year 2014	0.28	0.20	1.33
Year2015	0.25	0.20	1.28
Year2016	0.05	0.20	1.05
Year 2017	0.46	0.21	1.58*
City Fixed Effect			
Constant	3.12	0.38	22.62***
Observations		23,543	
Pseudo R2		0.1509	

Figure A2 (Robustness Check): Odds ratio of an explicitly gender-unspecified but implicitly-targeted ad being female-targeted