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Do Employers Discriminate by Gender? A Field Experiment in Female-Dominated Occupations

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Abstract

We test for gender discrimination by sending fake CVs to apply for entry-level jobs. Female candidates are more likely to receive a callback, with the difference being largest in occupations that are more female-dominated.

JEL Codes: J71, C93

Keywords: discrimination, field experiments, employment, gender

1. Introduction

Much work on gender pay differentials focuses on observed wage data. Yet equilibrium outcomes may reflect both productive traits and labor market discrimination. An alternative approach – implemented relatively rarely when considering gender discrimination – is to conduct audit experiments, sending matched CVs to employers in response to job advertisements. If only the names are changed, such an approach provides an unbiased estimate of the degree of labor market discrimination at the hiring stage.

In the case of gender, such an approach has been carried out in several previous studies (e.g. Levinson 1975; Riach and Rich 1987; Neumark 1996; Riach and Rich 2006). The audit discrimination technique has also been used to measure discrimination on the basis of ethnicity/race, age, obesity, having a criminal record, facial attractiveness, and sexual orientation. Our contribution here is to analyze gender differences in callbacks for a large recent sample that allows us to compare across job types.

In a London-based field experiment, Riach and Rich (2006) found statistically significant discrimination *against* men in 'mixed' occupations (trainee accountants, 31 percent female; and computer analyst/programmers, 21 percent female) and in 'female' occupations (secretarial, 97 percent female). They attributed this to gender stereotyping on the part of those making the decisions about whom to call back. To further explore this unexpected finding, we chose for our field experiment four female-dominated occupations, ranging from 65 percent to 85 percent female. Where possible, we also obtained information about the gender of the person making the callback decision and whether or not it was through a recruitment agency.

2. Empirical Analysis

Our conjecture is that in female-dominated occupations, we will find a pro-female bias that increases with the proportion of women in the occupation. This is because we expect that the more skewed is an occupation's gender ratio, the greater the extent of gender stereotyping. To test this, we applied for several thousand jobs over six months from April to October 2007. This was a relatively tight period for the Australian labor market, with the unemployment rate in our three sample cities being 3.7 percent in Brisbane, 4.6 percent in Melbourne, and 4.8 percent in Sydney. These locations were chosen because they are the three largest cities in Australia. In selecting appropriate occupations, we focused on female-dominated jobs that did not require post-school qualifications, and which had a relatively straightforward application process.

We selected four kinds of jobs: waitstaff, data-entry, customer service, and sales. Waitstaff jobs included positions at bistros, cafés, bars, restaurants, and hotels. Data-entry positions included jobs at an airline, a radio station, a bank, and a charity. Customer service jobs included staffing the front desk at a bowling alley, answering customer support calls at a private health insurance company, and staffing the front desk at a parking garage. Sales positions included jobs at a tiling store, a supermarket, an electrical goods store, and a pizzeria.

For these occupations, Table 1 displays average wages (in Australian dollars) and the proportion of workers who are women. These four jobs are more feminized than the non-managerial workforce as a whole. Across the four jobs, workers are paid about three-quarters of average wages.

Table 1: Characteristics of the Jobs		
	Hourly Wage	**Share Female**
Waitstaff	$18.90	80%
Data entry	$19.10	85%
Customer service	$21.60	68%
Sales	$18.50	69%
All full-time non-managerial	*$26.00*	*46%*

Source: Australian Bureau of Statistics (2007), based on survey data from 2006. In that year, the average exchange rate is A$1=US$0.75.

For each job-category we created four fake CV templates, obtained from a broad Internet search for similar CVs and tailored to the particular job. Applicants' names appeared in large type at the top of the CV, and were randomized across CV types. All applications were submitted via a major job-finding website.

Another purpose of the study was to test for racial and ethnic discrimination (for results by race and a more detailed discussion of the methodology, see Booth, Leigh, and Varganova 2009). Accordingly, our sample comprises Anglo-Saxon names, and three groups of non-Anglo names – Indigenous, Italian, and Middle-Eastern.[1] All results presented here are robust to estimating regression models including a race dummy. If we discard the non-Anglo names the point estimates are similar, but statistical significance diminishes.

Table 2 shows our main results. Averaging across all jobs, we observe substantial discrimination against male candidates. The typical female applicant received a callback 32 percent of the time, while the typical male candidate received a callback 25 percent of the

[1] While our racial/ethnic study also included Chinese, we omit them here since we are concerned that Australian employers might be unable to distinguish male and female Chinese names. However, including them in the sample has virtually no impact on the results reported here.

time. Consequently, an average male candidate would have had to submit 28 percent more applications in order to receive the same number of callbacks.[2]

We also observed substantial heterogeneity across job types. For waitstaff and data-entry positions, gender differences in callback rates were very large, while for customer service and sales positions they were much smaller. For example, a male wishing to work as a waiter would have to submit 31 percent more applications to receive the same number of callbacks, while a male seeking work as a data-entry employee would have to submit 74 percent more applications. By contrast, the ratio of female callbacks to male callbacks is just 1.10 for customer service, and 1.04 for sales. A formal test easily rejects the hypothesis that gender discrimination is consistent across job types.

To the extent that data-entry positions can be regarded as analogous to secretarial jobs, our finding is consistent with the pro-female bias in US secretary applications submitted in the 1970s (Levinson 1975) and UK secretary applications submitted in the 2000s (Riach and Rich 2006). However, our results differ from the finding of Riach and Rich (1987) who used data from Melbourne in 1983-86. They found that for 'computer operator' positions, women and men were equally likely to receive a callback.[3]

[2] Gender discrimination does not seem to differ much between the cities in our study. Male/female callback rates were 30%/36% in Brisbane, 19%/25% in Melbourne, and 27%/36% in Sydney.

[3] Across all seven occupations in their study, Riach and Rich (1987) found that male candidates received 5 percentage points more callbacks than female candidates (though their occupations are not directly comparable with ours).

Table 2: Callback rates by perceived gender of name and job type	Callback rate	Ratio (female rate/ male rate)	Difference (female rate − male rate)	P-value on difference
Panel A: All Jobs				
Female (N=1725)	32%	-	-	-
Male (N=1640)	25%	1.28	0.07	0.0000
Panel B: Waitstaff				
Female (N=430)	40%	-	-	-
Male (N=433)	30%	1.31	0.10	0.0034
Panel C: Data Entry				
Female (N=428)	33%	-	-	-
Male (N=423)	19%	1.74	0.14	0.0000
Panel D: Customer Service				
Female (N=392)	29%	-	-	-
Male (N=440)	26%	1.10	0.03	0.3816
Panel E: Sales				
Female (N=390)	26%	-	-	-
Male (N=429)	25%	1.04	0.01	0.7436
Does gender discrimination differ across job types?		$Chi^2(3)=11.44$ P-value<0.01		

Note: To test whether gender discrimination differs significantly by job, we run the probit regression

$$\text{Interview}(0,1) = \alpha + \beta \mathbf{I}^{\mathbf{JobType}} + \gamma \mathrm{I}^{\mathrm{Female}} + \lambda(\mathbf{I}^{\mathbf{JobType}} \times \mathrm{I}^{\mathrm{Female}}) + \varepsilon$$

The dependent variable is a dummy for receiving an interview, while $\mathbf{I}^{\mathbf{JobType}}$ and $\mathrm{I}^{\mathrm{Female}}$ are, respectively, indicators for each of three job types (omitting waitstaff), and being a female applicant. The Chi^2 test above is a test for the joint significance of the three $\boldsymbol{\lambda}$ coefficients. The test is significant regardless of which of the four job type indicators are omitted.

3. Discussion

Can our data provide more demand-side information as to why there is a pro-female bias in callbacks? One conjecture is that firms where the contact person on the job advertisement is female might be differentially prone to recruit women.[4] To test this, we run a probit regression for obtaining an interview, and include an interaction between female applicant and female contact person where the gender of the latter was known (51 percent of our job applications). Although positive, the estimated coefficient on this interaction was not

[4] The only study we know to have explicitly addressed this is Bagues and Esteve-Volart (2010), using public-examinations data for positions in the Spanish Judiciary. They found that female candidates were significantly less likely to be hired whenever randomly assigned to a committee with a relatively greater share of female evaluators.

statistically significant. Another conjecture is that recruitment agencies might have a differential propensity to discriminate (e.g. they might discriminate less if they are better-trained in equal opportunity legislation; or discriminate more if they reflect their clients' biases plus their own). To examine this, we included an interaction between female applicant and an indicator for whether recruitment was done by a professional recruitment company. (We have this information for our full sample of job applications.) This too was positive but statistically insignificant. Thus, neither the gender of the contact person nor the use of a professional recruitment agency explains the average pro-female bias in callbacks for our sample of female-dominated occupations.

In summary, we find a pro-female bias in callbacks only in occupations in which the percentage of females is 80 percent or more. For less female-dominated occupations, we find no significant bias towards either sex, in contrast to Riach and Rich (2006). What might cause this pro-female bias in occupations that are heavily female? One explanation is gender-stereotyping. If certain jobs are perceived as more appropriate for women, male applicants may be (implicitly or explicitly) evaluated less favorably because they do not fit society's prescriptions about what is appropriate for men. More research remains to be done in teasing out the workings of these demand-side mechanisms.

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Appendix Tables

Table A1: Gendered First Names Used in the Study

	Female	Male
Anglo	Jennifer, Lisa, Kimberly, Sarah, Amy	Martin, Andrew, Phillip, Adam, Brian
Non-Anglo (used in main analysis)	Fatima, Lala, Nadine, Anan, Hiyam, Betty, Winnie, Daisy, Dorothy, Peggy, Maria, Anna, Rosa, Angela, Giovanna	Ahmed, Hassan, Bilal, Mahmoud, Rafik, Bobby, Jimmy, Tommy, Wally, Ronnie, Giuseppe, Giovanni, Antonio, Mario, Luigi
Non-Anglo (dropped from main analysis)	Ping, Ming, Xiu, Ya, Nuying	Tai, Hong, Yin, Peng, Hu

Note: Chinese names are not used in the main analysis. See Table A2 for results including these names.

Table A2: Callback rates by perceived gender of name - robustness checks

	Callback rate	Ratio (female rate/ male rate)	Difference (female rate − male rate)	P-value on difference
Main Sample				
Female (N=1725)	32%	-	-	-
Male (N=1640)	25%	1.28	0.07	0.0000
Anglo Names Only				
Female (N=434)	38%	-	-	-
Male (N=403)	33%	1.13	0.04	0.1932
Main Sample Plus Chinese Names				
Female (N=2128)	30%	-	-	-
Male (N=2082)	25%	1.21	0.05	0.0001

Note: 'Main sample' is the specification shown in Table 2, Panel A. Male-female difference in Anglo-only sample is 4 percent rather than 5 percent due to rounding.

Table A3: Callback rates by perceived gender of name and city

	Callback rate	Ratio (female rate/ male rate)	Difference (female rate − male rate)	P-value on difference
Brisbane				
Female (N=545)	36%	-	-	-
Male (N=571)	30%	1.22	0.06	0.0235
Melbourne				
Female (N=581)	25%	-	-	-
Male (N=539)	19%	1.33	0.06	0.0107
Sydney				
Female (N=514)	36%	-	-	-
Male (N=615)	27%	1.35	0.09	0.0007

Note: Sample is the same as in Table 2.

Table A4: Interactions with gender of contact person, responding person, and human resources firm

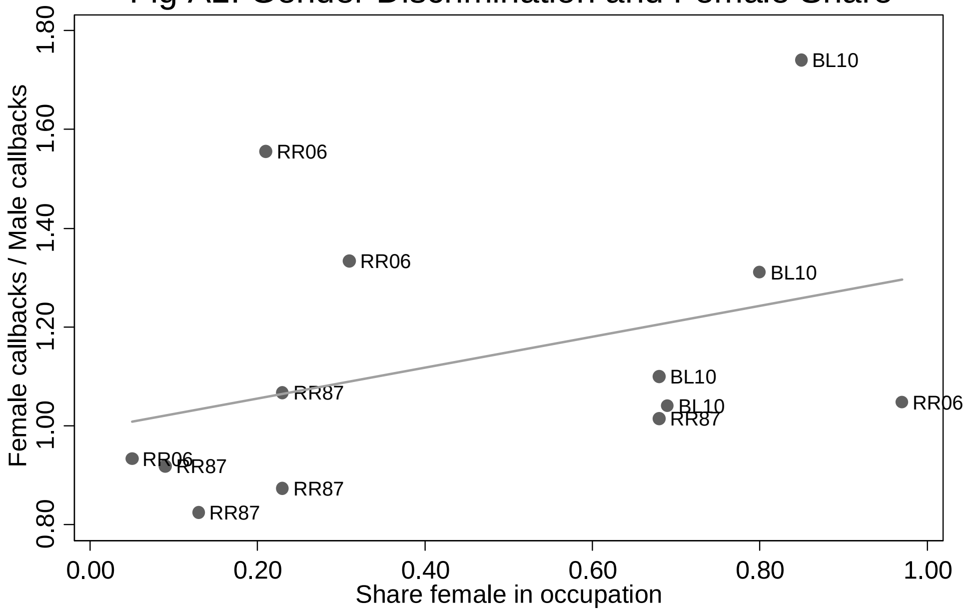
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Sample:	**Full sample**	**Contact gender known**	**Contact gender interaction**	**Responder gender known**	**Responder gender interaction**	**Contact/ responder gender known**	**Contact/ responder gender interaction**	**HR firm interaction**
Female candidate	0.074***	0.085***	0.062*	0.115***	0.111***	0.091***	0.066*	0.070***
	[0.016]	[0.023]	[0.036]	[0.024]	[0.042]	[0.019]	[0.034]	[0.017]
Female contact person at firm (mean=61%)			0.023					
			[0.034]					
Female responding person at firm (mean=69%)					0.002			
					[0.036]			
Female contact person or female responding person at firm (mean=67%)							0.071**	
							[0.029]	
Female candidate × Female firm			0.038		0.005		0.036	
			[0.047]		[0.051]		[0.042]	
Recruitment via human resources firm (mean=16%)								0.021
								[0.032]
Female candidate × Recruitment via human resources firm								0.023
								[0.044]
Observations	3365	1700	1700	1862	1862	2542	2542	3365
Pseudo R^2	0.03	0.04	0.05	0.05	0.05	0.04	0.04	0.03

Note: Estimates are marginal effects from a probit model. Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All estimates include race, city, and job type fixed effects. Female contact person means that the name of the person listed on the job advertisement sounded female. Female responding person means that the name of the person who called back to the candidates sounded female (this requires that at least one applicant received an acceptance or rejection from that firm). Female contact person or female responding person denotes that either the contact person or the responding person had a name that sounded female. Female firm is shorthand for the contact person, the responding person, or either (depending upon the specification). Human resources firms are all instances in which the job's contact details were for an employment agency. Column 1 replicates the 7 percentage point difference reported in Table 2, Panel A. Columns 2, 4, and 6 repeat the analysis, but restricting the sample to firms for which the gender of the contact person, responding person, or either is known (such a robustness check is unnecessary for the human resources firm interaction, since we have this information for all firms).

Table A5: Share Female and Gender Callback Differentials Across Three Studies			
Study and occupational category	**Share female in occupation**	**Ratio (female rate/ male rate)**	**Difference (female rate − male rate)**
Riach & Rich 1987			
Computer analyst - programmer	0.23	0.87	-0.07
Computer operator	N.R.	0.95	-0.02
Computer programmer	0.23	1.07	0.03
Gardener	0.13	0.82	-0.07
Industrial relations officer	N.R.	1.06	0.02
Management accountant	0.09	0.92	-0.04
Payroll clerk	0.68	1.01	0.01
Riach & Rich 2006			
Chartered accountant	0.31	1.33	0.03
Computer analyst - programmer	0.21	1.56	0.08
Engineer	0.05	0.93	-0.01
Secretary	0.97	1.05	0.00
Booth & Leigh 2010 (this study)			
Waitstaff	0.80	1.31	0.10
Data entry	0.85	1.74	0.14
Customer service	0.68	1.1	0.03
Sales	0.69	1.04	0.01

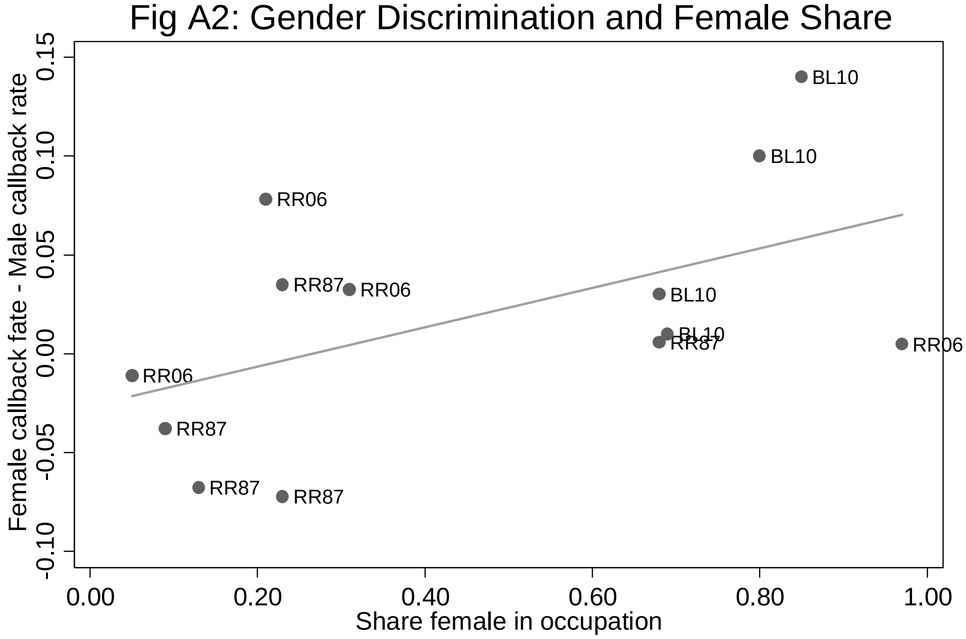
N.R.=Not Reported

Fig A1: Gender Discrimination and Female Share



Fitted line is Ratio = 0.99 + 0.31*Female Share (t=1.33)

Fig A2: Gender Discrimination and Female Share



Fitted line is Difference = -0.03 + 0.10*Female Share (t=2.06)