Appendix A: Details for Literature Review

Appendix A1: Summary of Predictions on Gender-Related Bias

Variable of Interest	Predicted Direction of Bias	Related Works
Competency	In favor of Males	Fiske et al. (2002), Kuhn and Skuterud (2004)
Warmth/Trustworthiness	In favor of Females	Fiske et al. (2002), Pope and Sydnor (2009), Ravina (2012)
Cooperativeness	In favor of Females	Eckel et al. (2008), Steffens et al. (2009)
Physical Attractiveness	In favor of Females	Eagly et al. (1991), Hancock and Toma (2009), Ravina (2012)
Moderating Variable	**Predicted Impact on Bias**	**Related Works**
Employer Experience	Greater experience → Less bias	Pavlou and Gefen (2004), Stewart (2003)
Worker Country of Origin	Workers from developed countries → Less bias	Hofstede (1983)
Occupation Type	Gender-typed job → Directionality of bias dependent on occupation type	Perry et al. (1994), Zebrowitz et al. (1991)
Employer Gender	Female employers → More bias	Darley and Smith (1995), Myers-Levy and Sternthal (1991)

Appendix B: Details for Empirical Methodology

Appendix B1: Matching Procedure Details and Assessment of Matching Validity

As a baseline, we employ one-to-one matching under common support, with a caliper size of 0.01 to locate similar male and female workers within the same job category (e.g., administrative support, web development, sales and marketing) and the same job posting, respectively. To assess the robustness of the main results with respect to different matched samples, we further utilize a stricter caliper size of 0.001 in our matching algorithm. Table B1 shows the balance check results for the matching. For all matched covariates, the standardized bias in the matched sample is within the recommended cut-off threshold of 0.05 across all matching schemes (Caliendo and Kopeinig 2008). We also note that the biases between the treated and the control groups are greatly reduced after matching, with a 60 to 100 percentage reduction in bias across most covariates after matching. This set of balance statistics suggests the matching technique has helped to produce statistically similar sets of female and male applicants. Figure B1 shows that the propensity score distribution of male workers becomes more similar to that of female workers after matching. Additionally, in the graph depicting the unmatched sample, we see that the distribution of male workers spans the entire propensity score range of female workers, which means that female workers in the original sample do not hold traits that make them highly dissimilar to male workers.

Table B1: Balance Check of Covariates after Matching

	Job Category Match, Caliper Size = 0.01				Job Category Match, Caliper Size = 0.001			
Variable	**Mean of Female**	**Mean of Male**	**Standardized Bias**	**Percentage Improvement**	**Mean of Female**	**Mean of Male**	**Standardized Bias**	**Percentage Improvement**
Job-specific attributes:								
Log(Hourly Wage)	1.2612	1.2161	0.046	78.5	1.2416	1.2086	0.034	84.2
Received Employer Invitation	0.07326	0.07326	0.000	100	0.06915	0.06915	0.000	100
Sent Cover Letter	0.13135	0.13860	0.022	57.5	0.13060	0.13964	0.027	47.0
Previously Hired	0.00945	0.00945	0.000	100	0.00755	0.00789	0.000	100
Worker-Declared attributes:								
Education	2.7387	2.7488	0.009	73.2	2.7433	2.7462	0.002	93.0
Number of Certifications	0.54504	0.56097	0.013	90.4	0.54028	0.56011	0.016	88.0
Past Employment	1.7836	1.7717	0.006	96.8	1.7799	1.7585	0.011	94.2
English Proficiency	4.8822	4.8790	0.007	54.1	4.8871	4.8779	0.020	-35.4
Number of Portfolio Items	6.5729	6.3147	0.019	91.0	6.5103	6.3055	0.015	92.9
Country								
Bangladesh	0.35264	0.35927	0.014	93.5	0.24056	0.25220	0.027	93.7
India	0.24107	0.25167	0.025	90.3	0.24022	0.25139	0.026	89.7
Philippines	0.25338	0.25543	0.005	99.2	0.07633	0.06595	0.035	87.6
Pakistan	0.07264	0.06432	0.029	89.3	0.25913	0.26239	0.008	98.9
United States	0.05015	0.04363	0.031	85.7	0.04867	0.04141	0.034	84.1
China	0.00668	0.00460	0.019	84.1	0.00673	0.00464	0.019	84.0
Ukraine	0.00655	0.00541	0.012	86.6	0.00653	0.00547	0.011	87.4
Sri Lanka	0.00708	0.00641	0.008	86.8	0.00720	0.00649	0.008	86.2
Russia	0.00292	0.00230	0.009	90.0	0.00294	0.00233	0.008	90.1
United Kingdom	0.00688	0.00694	0.001	97.4	0.00631	0.00656	0.003	89.8
Platform-Verified attributes:								
Number of Tests	5.1071	5.1469	0.010	93.2	5.06420	5.14350	0.020	86.5
Feedback Rating	3.3477	3.2957	0.024	65.2	3.33450	3.28870	0.022	69.4
No. of Online Jobs	13.3220	13.1270	0.007	89.1	13.0340	12.9750	0.002	96.7
Agency Contractor	0.25334	0.25334	0.000	100	0.24739	0.24739	0.000	100

Table B1: Balance Check of Covariates after Matching (continued)

	Job Posting Match, Caliper Size = 0.01				Job Posting Match, Caliper Size = 0.001			
Variable	**Mean of Female**	**Mean of Male**	**Standardized Bias**	**Percentage Improvement**	**Mean of Female**	**Mean of Male**	**Standardized Bias**	**Percentage Improvement**
Job-specific attributes:								
Log(Hourly Wage)	1.05960	1.01720	0.043	79.8	0.84996	0.83069	0.020	90.8
Received Employer Invitation	0.03097	0.02910	0.007	94.6	0.02133	0.02089	0.002	98.7
Sent Cover Letter	0.12737	0.13914	0.035	31.0	0.12880	0.14181	0.039	23.7
Previously Hired	0.00011	0.00011	0.000	100	0.00004	0.00004	0.000	100
Worker-Declared attributes:								
Education	2.73320	2.75850	0.021	39.0	2.73070	2.74870	0.015	56.5
Number of Certifications	0.57026	0.60626	0.029	78.2	0.60457	0.63565	0.025	81.2
Past Employment	1.58890	1.61870	0.016	91.9	1.52010	1.53720	0.009	95.4
English Proficiency	4.89200	4.88980	0.005	67.2	4.90290	4.89680	0.014	9.3
Number of Portfolio Items	5.94520	6.03200	0.006	97.0	5.20660	5.3470	0.010	95.1
Country								
India	0.24889	0.24541	0.008	96.8	0.20905	0.21398	0.012	95.5
Bangladesh	0.43632	0.45197	0.034	84.7	0.51718	0.52555	0.018	91.8
Philippines	0.19235	0.19620	0.009	98.6	0.17096	0.17305	0.005	99.2
Pakistan	0.08005	0.07159	0.029	89.1	0.07346	0.06346	0.034	87.1
United States	0.01854	0.01450	0.019	91.1	0.00994	0.00809	0.009	96.0
Ukraine	0.00494	0.00429	0.007	92.3	0.00330	0.00272	0.006	93.2
China	0.00602	0.00506	0.009	92.6	0.00410	0.00357	0.005	95.9
Russia	0.00229	0.00192	0.005	94.0	0.00157	0.00136	0.003	96.6
United Kingdom	0.00233	0.00251	0.002	92.6	0.00117	0.00134	0.002	93.1
Sri Lanka	0.00828	0.00657	0.019	66.6	0.00927	0.00686	0.027	53.0
Platform-Verified attributes:								
Number of Tests	5.00050	5.14470	0.036	75.4	4.83740	4.98250	0.036	75.3
Feedback Rating	3.25900	3.29230	0.016	77.7	3.11750	3.18850	0.033	52.5
Number of Online Jobs	10.9230	11.0740	0.005	91.6	9.28380	9.58570	0.011	83.1
Agency Contractor	0.23129	0.22275	0.020	75.6	0.19489	0.18828	0.016	81.2

Notes: The figures reported for standardized bias are in absolute levels. Percentage improvement refers to the reduction in standardized bias in the matched sample compared to the unmatched sample. Country is coded as dummy variables.

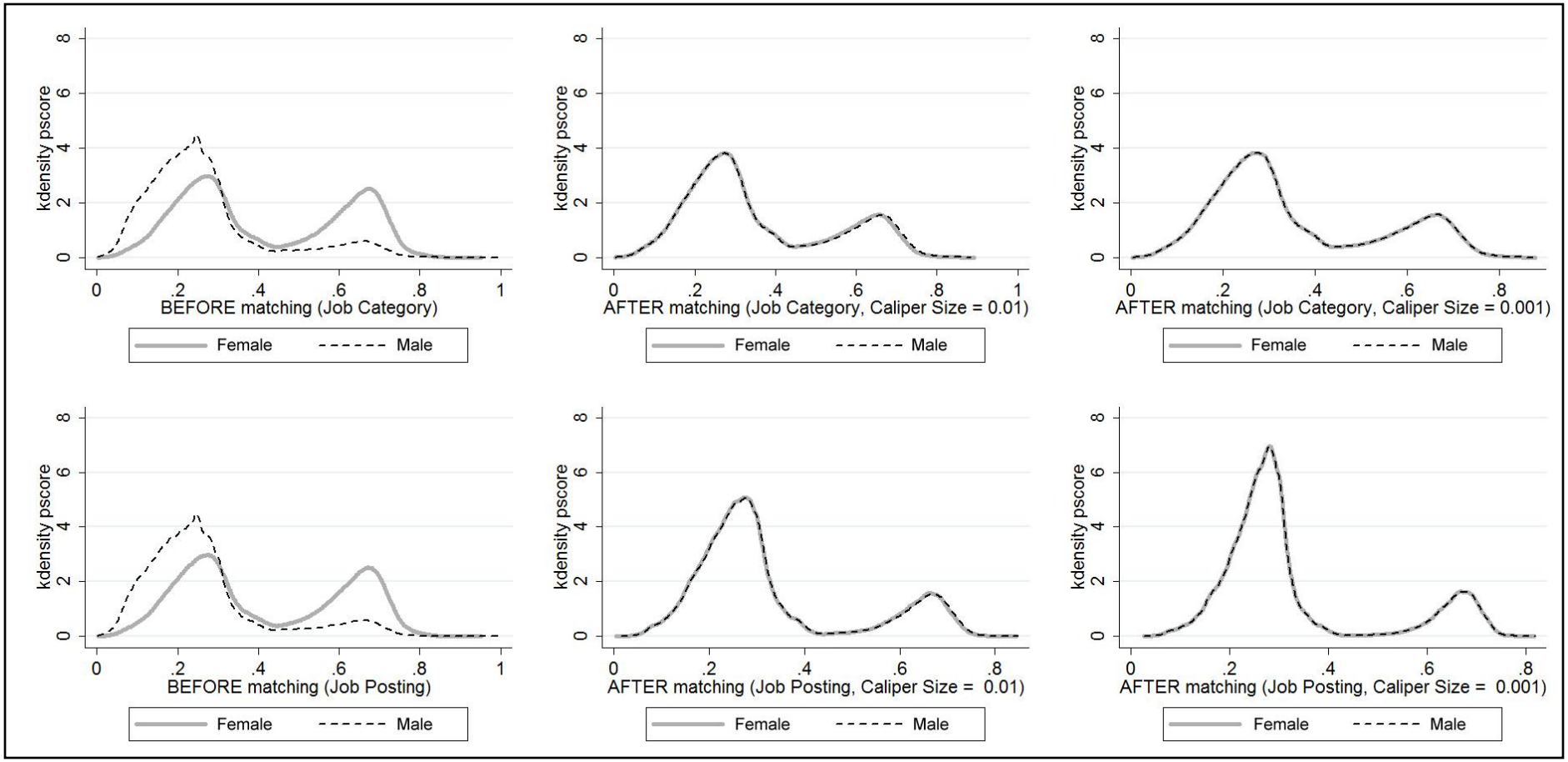

Figure B1: P-Score Distribution of Female and Male Workers Before and After Matching

Appendix B2: Categorization of Job Postings

In the process of categorizing the list of online jobs into each type, we look towards salient gender attributes that are identified in the literature. In addition to the competency-by-warmth distinction that men and women have (McClelland 1975), males tend to perform better on tasks such as mental rotation, mechanical reasoning, math, and science knowledge, while females excel in verbal fluency, speech articulation, reading, and writing (Halpern 1997). Based on these distinctions across genders, jobs with major responsibilities in servicing others and having elements of frequent interpersonal communications are likely regarded as feminine occupations, and jobs that primarily involve technical problem solving, logic induction, and spatial design are likely associated as masculine occupations. Amidst the jobs available in our study context, administrative support and customer service distinctly fit the criteria of feminine occupations, while software development and web development are strongly aligned with the expectations of masculine occupations. Jobs such as design and multimedia, and sales and marketing do not exhibit salient attributes associated with either gender, and are likely to be gender-neutral jobs. We further rely on two external sources of information to affirm the job classifications. First, we tabulate the proportion of male to female applicants for these job categories and determine if they fall above or below the average male–female ratio of workers on the platform. Second, we rely on the occupation gender composition information provided by the Bureau of Labor Statistics (BLS; see http://www.bls.gov) to identify gender-dominated jobs. The categorization results based on these two alternative sources agree with our categorization.

Table B2: Demographics of AMT Raters

Demographic Attributes	Frequency	Percentage
Education Degree		
No schooling completed	2	0.012195
High school graduate	50	0.304878
Associate degree	27	0.164634
Bachelors degree	64	0.390244
Masters degree	11	0.067073
Professional degree	5	0.030488
Doctorate degree	3	0.018293
Unknown	2	0.012195
Annual Household Income		
Less than $10,000	7	0.042683
$10,000 to $29,999	41	0.25
$30,000 to $59,999	65	0.396341
$60,000 to $99,999	34	0.207317
$100,000 to $149,999	13	0.079268
$150,000 or more	3	0.018293
Unknown	1	0.006098

Appendix C: Data Descriptive Details

Table C1: Comparison of Worker Attributes 30 Days Before and After Photo Posting

Worker Characteristic	T-value	P-value
Hourly Wage Rate	1.326	0.185
Number of Employment Records	0.115	0.909
Number of Certificates	0.807	0.420
Number of Standardized Tests Passed	1.531	0.126
Proportion of Applications in Admin Support	0.578	0.564
Proportion of Applications in Sales & Marketing	1.153	0.249
Proportion of Applications in Web Development	0.805	0.421

Table C2: Statistics of Applicants' Country of Origin

Country	Frequency	Percentage of Total	Cumulative Percentage
Bangladesh	963,323	30.39%	30.39%
India	770,587	24.31%	54.70%
Philippines	554,340	17.49%	72.19%
Pakistan	319,716	10.09%	82.28%
United States	118,371	3.73%	86.01%
China	43,256	1.36%	87.37%
Ukraine	35,421	1.12%	88.49%
Sri Lanka	26,452	0.83%	89.32%
Russia	21,395	0.67%	89.99%
United Kingdom	17,352	0.55%	90.54%

Notes: The top ten countries are listed in this table. The remaining countries make up 9.46 percent of the sample, with each country making up less than 0.55% of the total sample.

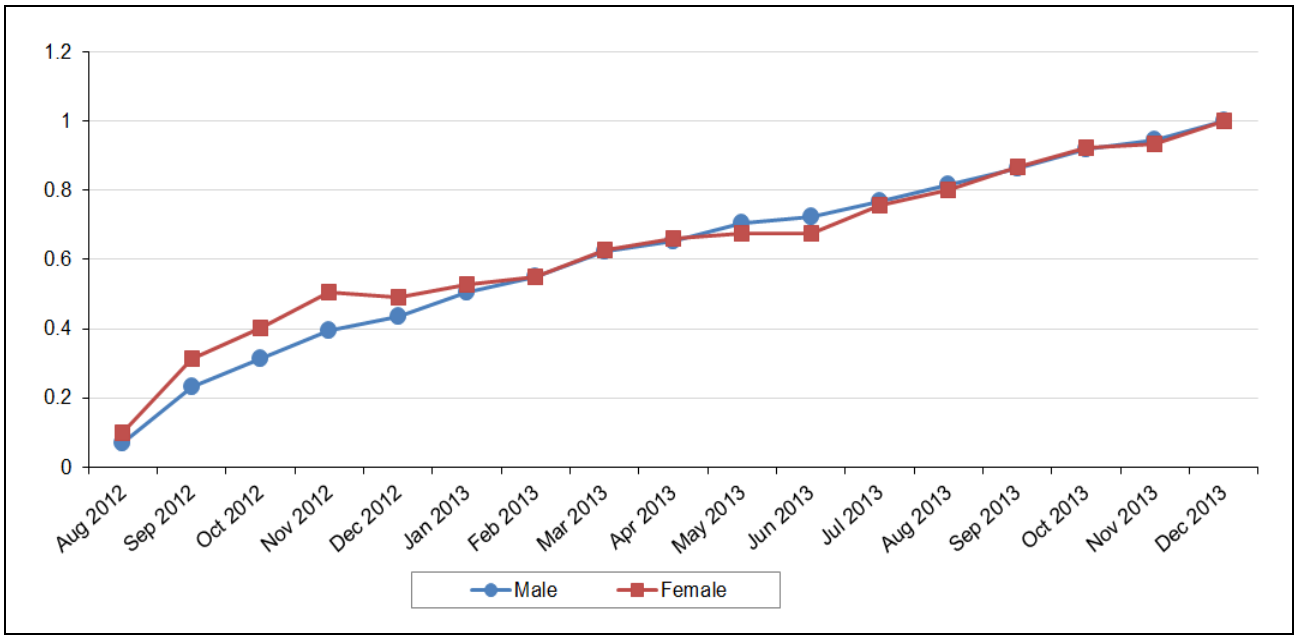

Figure C1: Share of workers who posted photos in each month, split by gender

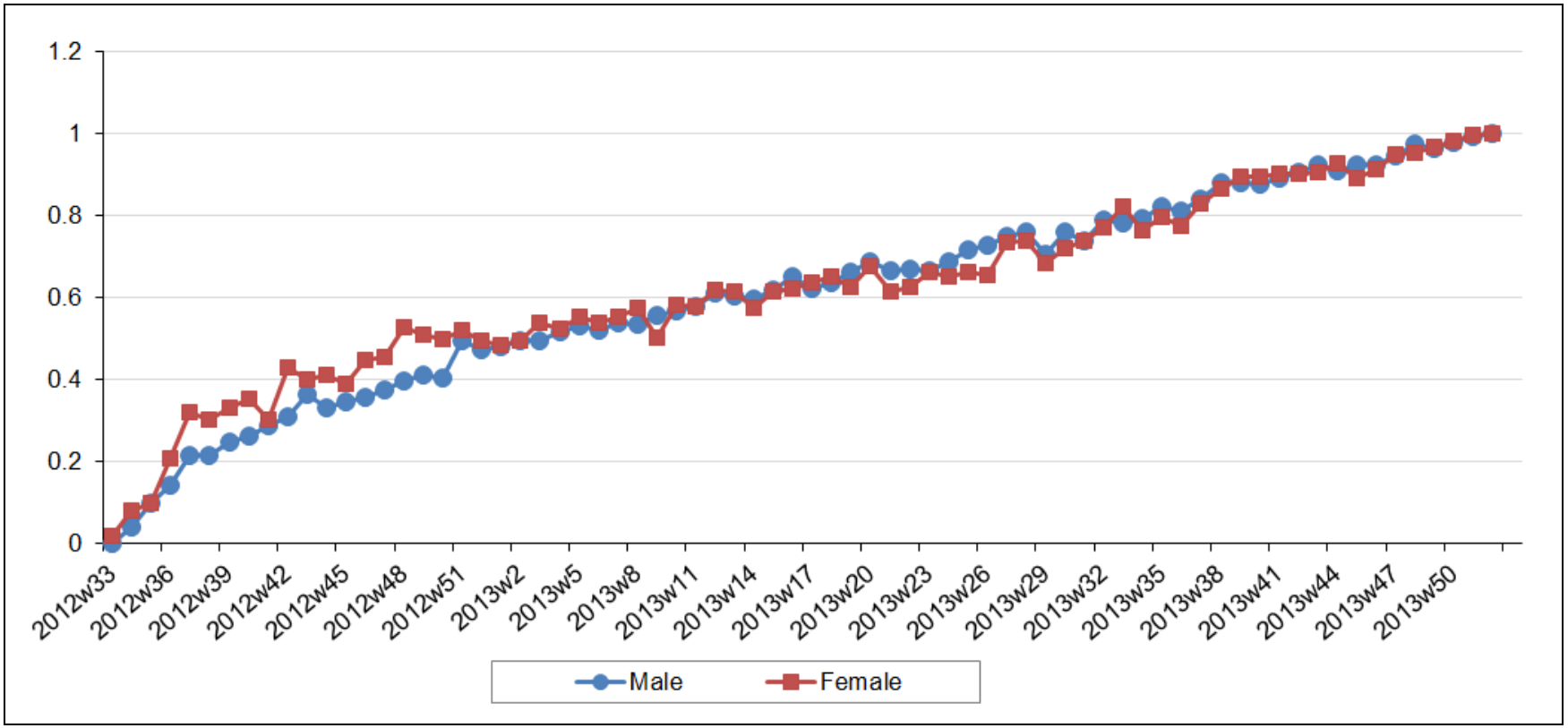

Figure C2: Share of workers who posted photos in each week, split by gender

Note: The x-axis starts with Week 33 in 2012 and ends with Week 51 in 2013. The scale starts from Week 1 for periods in 2013.

Appendix D: Robustness Checks

In Column 1 of Table D1, we estimate a basic model based on the entire sample of workers to understand the effect of gender on the likelihood of getting hired. In Column 2, covariates are added to control for factors such as worker's wage rate, ability, and credentials. In Columns 3 and 4, we repeat the same analysis on job openings that consist of applicants from countries that represent the top 90 percent of the study sample. This is done with the aim of deriving results from a more homogenous sample of jobs in which workers are more comparable to one another, so as to abstract away potential outlier effects stemming from observations with uncommon characteristics.[1] Finally, in Column 5, we include country fixed effects to control for heterogeneity in hiring preferences towards workers' country of origin. The result in Column 1 shows a positive female coefficient statistically significant at the 1% level,[2] suggesting that female workers experience a higher likelihood of getting hired compared to their male counterparts. Upon the addition of covariates in Column 2, we find that the magnitude of the female coefficient dips a little but continues to be positive and significant. In Columns 3 and 4, the female coefficient is highly comparable to the respective coefficients in Columns 1 and 2, indicating that the female effect on hiring outcomes is robust with the removal of outlier observations. In Column 5, we see that the magnitude of the female coefficient drops by half when the country fixed effects are added, but retains its statistical significance.

[1] Workers removed in this step represent rare instances of the sample. Each of these workers' country of origin constituted less than 0.55 percent of the study sample.

[2] Following the guideline in Lin et al. (2013) which treats observations greater than 10,000 as a large sample size, we adopt a cutoff point of 1% when interpreting statistical significance for such instances in our study context.

Table D1: Worker's Gender and Hiring Probability (Without Matching)

	All Countries		Countries in Top 90% of Sample		
	(1)	(2)	(3)	(4)	(5)
Female	0.261***	0.204***	0.269***	0.214***	0.111***
	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
Job-Specific Controls:					
Log (Hourly Rate)		-0.192***		-0.233***	-0.329***
		(0.006)		(0.007)	(0.007)
Employer Invitation		1.640***		1.706***	1.647***
		(0.014)		(0.016)	(0.016)
Sent Cover Letter		0.214***		0.230***	0.240***
		(0.011)		(0.013)	(0.013)
Previously Hired		2.166***		2.226***	2.237***
		(0.031)		(0.036)	(0.036)
Worker-Declared Attributes:					
Education		-0.010***		-0.006*	0.005
		(0.003)		(0.003)	(0.003)
Number of Certificates		-0.025***		-0.026***	-0.012***
		(0.003)		(0.003)	(0.003)
Past Employment		0.028***		0.030***	0.017***
		(0.002)		(0.002)	(0.002)
English Proficiency		0.046***		0.075***	0.128***
		(0.008)		(0.010)	(0.011)
Number of Portfolio Items		-0.001***		-0.001***	0.000
		(0.000)		(0.000)	(0.000)
From Developing Country		-0.532***		-0.687***	-
		(0.012)		(0.017)	
Platform-Verified Attributes:					
Number of Tests		0.003***		0.005***	0.007***
		(0.001)		(0.001)	(0.001)
Feedback Rating		0.124***		0.133***	0.134***
		(0.002)		(0.003)	(0.003)
Number of Online Jobs		0.003***		0.004***	0.004***
		(0.000)		(0.000)	(0.000)
Agency Contractor		-0.441***		-0.415***	-0.402***
		(0.011)		(0.012)	(0.012)
Worker Country Fixed Effects					✓
Log Likelihood	-231988.4	-213881.6	-187485.1	-171799.5	-170469.9
Observations	1,907,940	1,907,940	1,558,390	1,558,390	1,558,390

***Notes*:** All models are conditional logistic regressions with job posting fixed effects. The outcome variable is whether a worker is hired. * Significant at 10% level, ** significant at 5% level, and *** significant at 1% level. We adopt a cut-off point of 1% level in our interpretation for specifications that have large sample sizes (> 10,000). Coefficient for From Developing Country in column 5 is not estimated as country fixed effects are applied in this specification.

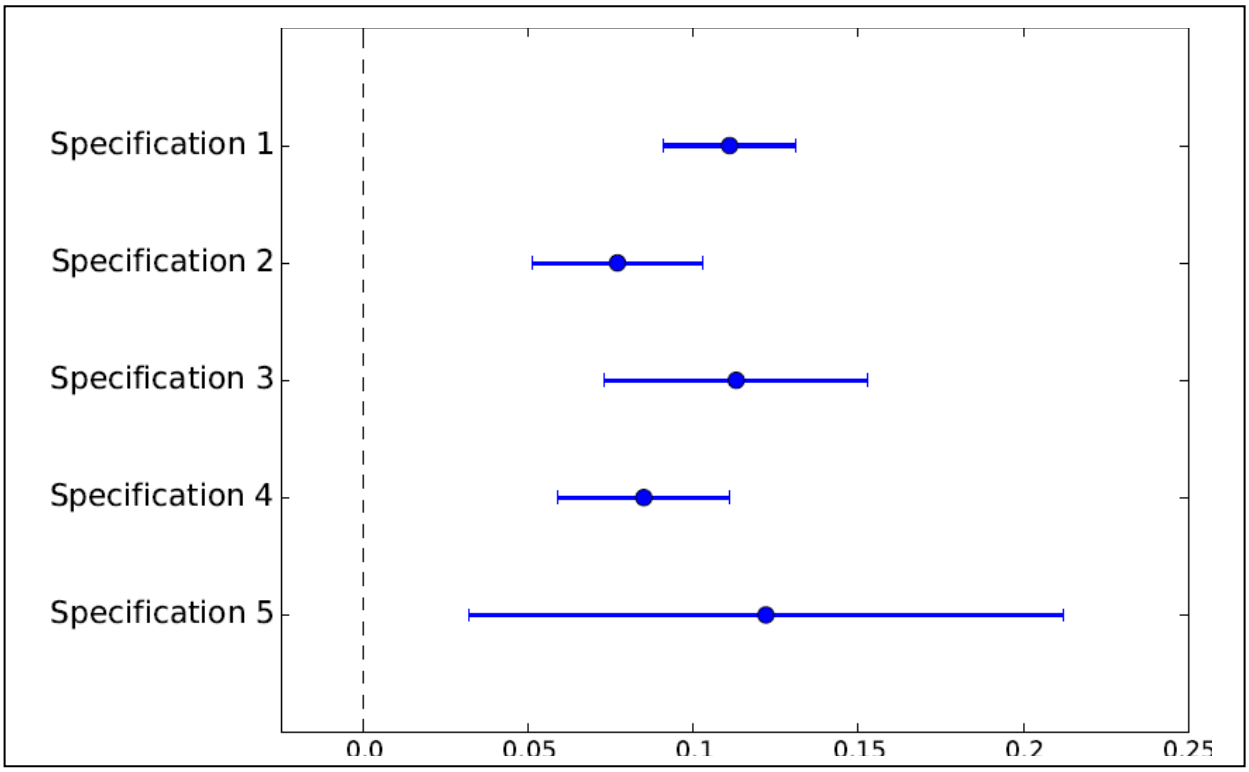

Figure D1: The 95% Confidence Intervals for the Female Coefficient in Table 2

Table D2: Robustness Checks

		Job Category Match		Job Posting Match	
	No Matching	**Caliper Size = 0.01**	**Caliper Size = 0.001**	**Caliper Size = 0.01**	**Caliper Size = 0.001**
(A) Alternative DV: Employer Invitation	0.097*** (0.010)	0.239*** (0.015)	0.243*** (0.015)	0.259*** (0.025)	0.210*** (0.058)
(B) Alternative DV: Interview Request	0.113*** (0.007)	0.173*** (0.009)	0.183*** (0.009)	0.234*** (0.013)	0.273*** (0.025)
(C) Observations without cover letter	0.092*** (0.011)	0.067*** (0.015)	0.074*** (0.015)	0.108*** (0.023)	0.120** (0.050)
(D) Alternative DV: Shortlisted Worker	0.192*** (0.008)	0.164*** (0.011)	0.169*** (0.011)	0.206*** (0.014)	0.224*** (0.028)
(E) Observations from Fixed-Fee Contracts	0.090*** (0.010)	0.087*** (0.014)	0.089*** (0.014)	0.147*** (0.023)	0.172*** (0.056)

Notes: All reported estimates are the coefficients for female variable in our conditional logit model. Control variables are the same as those used in the main models, except for (A): the hourly wage displayed on the worker's profile page is used in place of proposed hourly wage, since the worker has not applied for the job at the time of invitation. We adopt a cut-off point of 1% significance level in our interpretation for specifications that have large sample sizes (> 10,000). * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

Appendix E: Additional Analyses

Employer Experience

To understand whether increased employer experience weakens the influence of gender heuristics on hiring decisions, we evaluate the moderating effect of employer experience on female hiring bias. In particular, we rerun the conditional logit regressions on different subsamples of employers, split by their hiring experience on the platform. In this analysis, we measure employers' experience using the number of filled job postings (i.e., postings with hires made) on the platform. To differentiate between high and low experience levels, we split the sample of employers into upper and lower quartiles of the hiring experience. We report the results of this analysis below in Table E1.

Table E1: Moderating Effect of Employer Experience

Lower Quartile (Low Experience Employers)	**No Matching**	**Job Category Match**		**Job Posting Match**	
		Caliper Size = 0.01	Caliper Size = 0.001	Caliper Size = 0.01	Caliper Size = 0.001
Female	0.168***	0.118***	0.125***	0.170***	0.265***
	(0.016)	(0.022)	(0.022)	(0.035)	(0.079)
Controls Added	✓	✓	✓	✓	✓
Country Fixed Effects	✓	✓	✓	✓	✓
Log Likelihood	-60289.91	-21195.44	-20347.83	-6317.80	-1049.44
Observations	458,636	124,800	119,807	43,959	6,475
Upper Quartile (High Experience Employers)	**No Matching**	**Job Category Match**		**Job Posting Match**	
		Caliper Size = 0.01	Caliper Size = 0.001	Caliper Size = 0.01	Caliper Size = 0.001
Female	0.009	-0.018	-0.012	0.017	-0.148
	(0.022)	(0.028)	(0.028)	(0.043)	(0.095)
Controls Added	✓	✓	✓	✓	✓
Country Fixed Effects	✓	✓	✓	✓	✓
Log Likelihood	-37980.42	-14024.74	-13545.01	-4882.68	-914.10
Observations	398,651	112,787	109,697	47,234	8,468

***Notes*:** All models are conditional logistic regressions with job posting fixed effects. Control variables are the same as those used in the main models. To conserve space, covariate estimates are omitted. * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

Across various matching criteria, we see that the gender coefficients from the *low experience* employers are positively significant, while those for *high experience* employers are nonsignificant. These results indicate that hiring bias mainly exists for new employers who have little hiring experience on the labor platform, and the bias diminishes as employers make more hires on the platform. Furthermore, we note that the magnitude of the female coefficient for employers with low hiring experience is about 10 times as large as that for employers with high hiring experience. This set of result provides further indication that gender cues represent a cognitive proxy for trustworthiness, which becomes less pertinent as employers

develop trust for all workers on the platform through their past interactions with other workers.

Worker's Country of Origin

Next, we examine the moderating relationship between worker's country of origin and the worker's gender. As revealed in our literature review, the worker's country of origin can serve as a critical source of information that mitigates the uncertainty in hiring, and acting as a substitute for trustworthiness provided by the gender cue. If this is indeed true, we would expect the female hiring bias to be weaker in cases where employers are able to select applicants from developed countries, and vice versa.

Table E2: Moderating Effect of Worker's Country of Origin

Developed Countries	**No Matching**	**Job Category Match**		**Job Posting Match**	
		Caliper Size = 0.01	Caliper Size = 0.001	Caliper Size = 0.01	Caliper Size = 0.001
Female	-0.011	-0.039	-0.004	0.049	-0.636
	(0.036)	(0.048)	(0.050)	(0.110)	(0.495)
Controls Added	✓	✓	✓	✓	✓
Country Fixed Effects	✓	✓	✓	✓	✓
Log Likelihood	-8928.00	-3821.77	-3497.15	-388.88	-23.24
Observations	31,154	12,623	11,409	1,276	88
Developing Countries	**No Matching**	**Job Category Match**		**Job Posting Match**	
		Caliper Size = 0.01	Caliper Size = 0.001	Caliper Size = 0.01	Caliper Size = 0.001
Female	0.125***	0.097***	0.098***	0.129***	0.146***
	(0.011)	(0.014)	(0.014)	(0.021)	(0.046)
Controls Added	✓	✓	✓	✓	✓
Country Fixed Effects	✓	✓	✓	✓	✓
Log Likelihood	-147222.20	-52079.44	-50459.65	-19189.41	-3633.41
Observations	1,387,565	381,830	371,142	167,873	28,455

***Notes*:** All models are conditional logistic regressions with job posting fixed effects. Control variables are the same as those used in the main models. To conserve space, covariate estimates are omitted. * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

We examine the moderating effect of worker's country of origin by running our main analyses using samples split by workers from developed and developing countries. Results of this analysis are presented in Table E2. We see the female hiring bias is present only in the sample of workers from developing countries across all specifications. In fact, the female coefficients for the observations from developed countries are close to zero,[3] signifying that a gender hiring bias is absent for these workers. The magnitude of the female coefficient for workers from developing countries is highly comparable to the

[3] This is true for all specifications except for the matched sample derived under job posting matching with a caliper size of 0.001. We note the coefficient size in this specification should be interpreted with caution as the sample size is greatly reduced under this stringent form of matching.

respective coefficients in main analyses in Table 2, suggesting that the female hiring bias uncovered in this study is likely to arise mainly from situations where employers are considering applicants from developing countries. This result supports the argument that employers are less dependent on gender heuristics when there are other trust-related indicators available for consideration.

Occupation Types

We attempt to investigate the interrelationship between gender-typed occupations and the online hiring bias by examining their interaction effects. To do so, we repeat our estimations separately for feminine jobs, gender-neutral jobs, and masculine jobs. In Table E3, we report the regression results under different matching schemes. Across various matching schemes, we see that the female variable holds positive and significant coefficients for feminine jobs, signifying that female workers have a higher probability of being hired in administrative support and customer support positions. In contrast, the female variable in masculine jobs is negative and does not show consistent statistical significance across matching schemes, which suggests that male candidates do not enjoy an employment advantage in masculine occupations. This result is surprising as it deviates from the expectation that males are generally favored in masculine jobs. We posit that this aberrant trend results from the unique characteristics associated with the male heuristic cue. Concerned with the uncertainty and opportunism within the online market, employers may perceive male traits of self-centeredness and aggressiveness as factors that can undermine the success of their outsourced projects. In other words, the male heuristic cue lacks qualities such as concern for others and the desire to maintain interpersonal harmony, which are essential trust-related traits needed in online contexts involving economic transactions.

Interestingly, we note that the female coefficient is positive for jobs posted under the gender-neutral occupations. While the coefficients are not significant across different matching schemes, the direction of the coefficient is consistent in showing a positive bias toward female workers for gender-neutral jobs. The positive magnitude observed in gender-neutral jobs may partly account for the overall positive female hiring bias seen in the main analyses. Similar to the arguments made earlier, characteristics associated with female stereotypes may be perceived as crucial evaluation criteria for hiring employees in online environments, leading to a preference for female candidates for gender-neutral jobs in which no specific gender has a clear advantage in terms of competency.

Table E3: Hiring Likelihood for Different Occupation Types

	No Matching			Job Category Match			Job Posting Match		
	Feminine	Neutral	Masculine	Feminine	Neutral	Masculine	Feminine	Neutral	Masculine
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	0.340***	0.056***	-0.024	0.406***	0.023	-0.105***	0.507***	0.036	-0.043
	(0.023)	(0.017)	(0.020)	(0.029)	(0.021)	(0.029)	(0.087)	(0.071)	(0.093)
Job-Specific Controls:									
Log (Hourly Rate)	-0.609***	-0.267***	-0.297***	-0.726***	-0.308***	-0.398***	-1.165***	-0.490***	-0.518***
	(0.016)	(0.013)	(0.013)	(0.025)	(0.018)	(0.029)	(0.095)	(0.084)	(0.164)
Employer Invitation	1.800***	1.848***	1.651***	2.190***	1.813***	1.687***	2.956***	3.137***	2.269***
	(0.041)	(0.029)	(0.026)	(0.069)	(0.041)	(0.059)	(0.304)	(0.215)	(0.287)
Sent Cover Letter	0.416***	0.262***	0.147***	0.453***	0.330***	0.135**	0.366**	0.165	0.346*
	(0.030)	(0.020)	(0.028)	(0.042)	(0.027)	(0.057)	(0.151)	(0.104)	(0.203)
Previously Hired	2.616***	2.191***	2.241***	2.784***	2.084***	1.758***	-	-	-
	(0.083)	(0.066)	(0.058)	(0.177)	(0.129)	(0.168)			
Worker-Declared Attributes:									
Education	0.036***	-0.013**	-0.013**	0.014	-0.022**	0.001	0.013	-0.053	0.038
	(0.009)	(0.006)	(0.006)	(0.013)	(0.009)	(0.012)	(0.047)	(0.036)	(0.048)
Number of Certificates	-0.015**	-0.019***	-0.015**	-0.007	-0.025***	0.000	-0.060	-0.137***	0.123
	(0.006)	(0.006)	(0.007)	(0.011)	(0.009)	(0.017)	(0.046)	(0.047)	(0.079)
Past Employment	0.017***	0.017***	0.010**	0.018***	0.031***	0.012	0.049*	0.102***	-0.079
	(0.004)	(0.003)	(0.004)	(0.006)	(0.005)	(0.010)	(0.025)	(0.031)	(0.058)
English Proficiency	0.203***	0.094***	0.103***	0.207***	0.101***	0.140***	0.364***	-0.022	-0.063
	(0.025)	(0.020)	(0.018)	(0.038)	(0.030)	(0.046)	(0.136)	(0.141)	(0.206)
Number of Portfolio Items	0.007***	0.000	0.000	0.007***	0.001	0.002	0.004	0.015***	-0.005
	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.011)	(0.005)	(0.007)
Platform-Verified Attributes:									
Number of Tests	0.015***	0.008***	0.000	0.020***	0.005*	0.003	0.012	0.003	-0.017
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.016)	(0.013)	(0.019)
Feedback Rating	0.170***	0.143***	0.107***	0.170***	0.143***	0.122***	0.216***	0.214***	0.169***
	(0.006)	(0.005)	(0.004)	(0.008)	(0.006)	(0.008)	(0.029)	(0.024)	(0.036)
Number of Online Jobs	0.004***	0.003***	0.004***	0.004***	0.004***	0.004***	0.009***	0.004**	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.002)	(0.002)
Agency Contractor	-0.440***	-0.160***	-0.466***	-0.335***	-0.183***	-0.552***	-0.658***	-0.170	-0.629***
	(0.039)	(0.022)	(0.017)	(0.054)	(0.030)	(0.034)	(0.241)	(0.115)	(0.149)
Country Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Log Likelihood	-34931.95	-51984.68	-47651.46	-14264.35	-25062.49	-10641.47	-5531.44	-7055.77	-3690.73
Observations	472,074	516,300	330,760	125,960	199,708	50,615	53,590	69,720	17,232

***Notes*:** All models are conditional logistic regressions with job posting fixed effects. Control variables are the same as those used in Table 2. Coefficient for Previously Hired in Columns 7-9 is not estimated as there is no variation for the variable in the matched sample within each job posting. We adopt a cut-off point of 1% level in our interpretation for specifications that have large sample sizes (> 10,000). * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

Employer Gender

Finally, we examine whether the employer's gender moderates online hiring bias. We study this moderating effect by examining whether the positive female hiring bias is stronger for female or male employers. In executing the analysis, we split the job postings into two groups consisting of male and female employers and rerun the regression models on each sample separately. Table E4 presents the results of this analysis. We find that the positive female hiring bias is present for both male and female employers. Of greater interest, we find that female employers exhibit a stronger female-oriented hiring bias compared to male employers. In particular, female employers are about two times more likely to hire female workers, relative to male employers. This result suggests that female applicants are generally favored by employers of both genders, but relatively more so by female hirers. Such a result is in agreement with the existing literature which suggests that the processing strategy of male hirers reduces their tendency to rely on peripheral gender cues in evaluating candidates.

Table E4: Moderating Effect of Employer Gender

Male Employer	**No Matching**	**Job Category Match**		**Job Posting Match**	
		Caliper Size = 0.01	Caliper Size = 0.001	Caliper Size = 0.01	Caliper Size = 0.001
Female	0.099***	0.063***	0.064***	0.108***	0.112**
	(0.013)	(0.016)	(0.017)	(0.026)	(0.056)
Controls Added	✓	✓	✓	✓	✓
Country Fixed Effects	✓	✓	✓	✓	✓
Log Likelihood	-109752.96	-39104.28	-37594.53	-13125.07	-2429.11
Observations	1,006,854	278,267	268,548	113,284	18,738
Female Employer	**No Matching**	**Job Category Match**		**Job Posting Match**	
		Caliper Size = 0.01	Caliper Size = 0.001	Caliper Size = 0.01	Caliper Size = 0.001
Female	0.222***	0.178***	0.194***	0.295***	0.335***
	(0.026)	(0.034)	(0.035)	(0.056)	(0.127)
Controls Added	✓	✓	✓	✓	✓
Country Fixed Effects	✓	✓	✓	✓	✓
Log Likelihood	-23077.94	-8946.54	-8649.72	-2586.17	-444.803
Observations	205,406	58,208	56,200	21,224	3,370

***Notes*:** All models are conditional logistic regressions with job posting fixed effects. Control variables are the same as those used in the main models. To conserve space, covariate estimates are omitted. * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

References

Caliendo, M., & Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys*, *22*(1), 31-72.