EEA ESEM 2022

Words Matter: Gender, Jobs and Applicant Behavior

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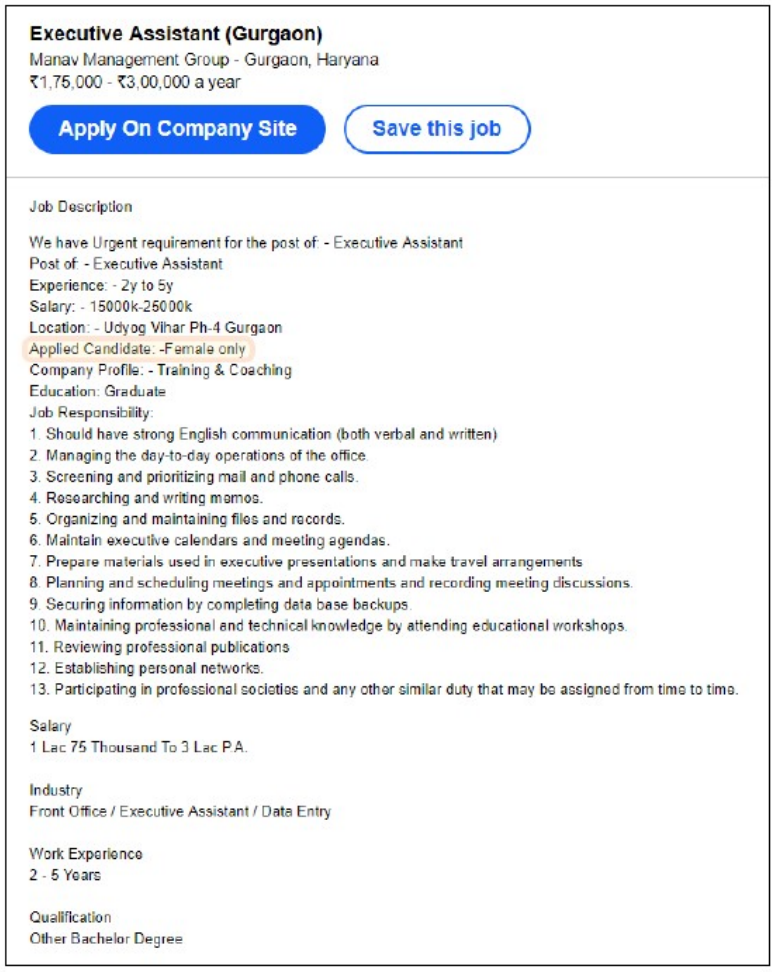
Motivation

- why do we observe gender disparities in labor market outcomes such as wages?
- women may apply to low-wage jobs due to
  1. actual/perceived discrimination
  2. stereotypes about roles suitable for women
  3. gender differences in WTP for job attributes such as flexibility
- we use data on job ads as well as applications made to these ads to study gender disparities arising at the job application stage
  1. how are words in job ads associated with posted/advertised wages?
  2. how do words in job ads direct where men and women apply for jobs?

Female



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

Apply On Company Site | Save this job

Job Description

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

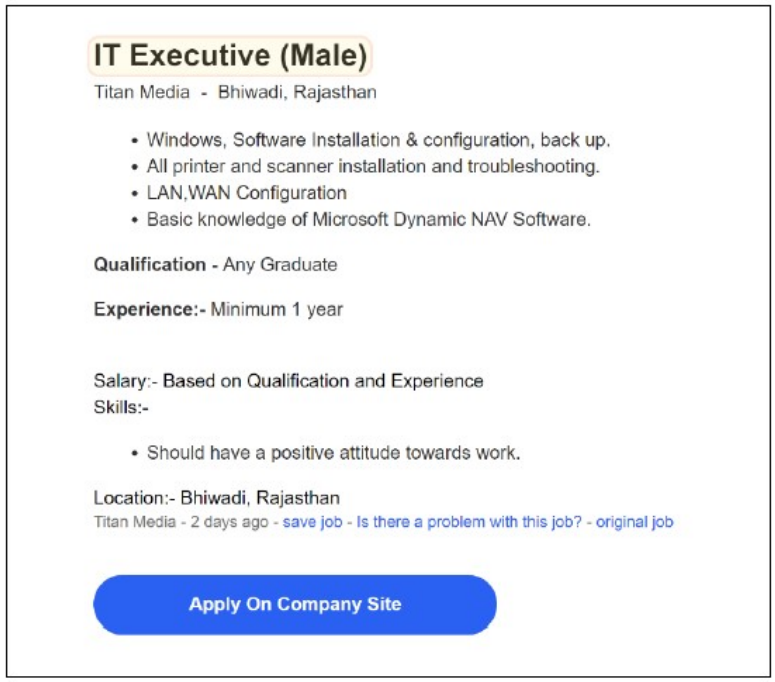
Salary
1 Lac 75 Thousand To 3 Lac P.A.

Industry
Front Office / Executive Assistant / Data Entry

Work Experience
2 - 5 Years

Qualification
Other Bachelor Degree

Male



IT Executive (Male)
Titan Media - Bhiwadi, Rajasthan

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

Qualification - Any Graduate

Experience:- Minimum 1 year

Salary:- Based on Qualification and Experience
Skills:-

- Should have a positive attitude towards work.

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

Apply On Company Site

Source: Kuhn et al, 2020

Contribution to the literature

- employer's gender preferences in job ads: Kuhn and Shen (2013), Ningrum et al. (2020), Helleseter et al. (2020), Chowdhury et al. (2018), Kuhn et al (2020), Card et al. (2021)
- sources of gender wage gaps: Olivetti and Petrongolo (2016), Blau and Kahn (2017), Goldin and Katz (2011), Goldin (2014), Fluchtmann et al. (2022)
- job attributes, workplace flexibility, and gender wage gaps: Mas and Pallais (2017), Wiswall and Zafar (2017), He et al. (2019), Bustelo et al. (2020), Fluchtmann et al. (2022)
- Directed search models: Dal Bo et al. (2013), Belot et al. (2017), Banfi and Villena-Roldan (2019), Marinescu and Wolthoff (2020)

Data: constructed variables and descriptive statistics

- use job ads posted between July 2018 and February 2020 on a leading Indian job portal which is used primarily by young, urban job seekers with a university education
- employers post an advertised wage for 87% of job ads on this portal which is much higher than is typical in the literature (15–25%)
- use data on 6.45 million applications made by 1.06 million job seekers to $\approx 160,000$ job ads
- search text contained in the title and description of a job ad for words indicating an **explicit female preference** such as *female* or *woman* (F jobs)
- use a similar approach for jobs with an **explicit male preference** (M jobs)

Data: constructed variables and descriptive statistics

- some ads include words related to both genders but most have no gender related words (N jobs)
- 7.7% job ads have explicit gender preference (4.2% *F* jobs; 3.5% *M* jobs)
- use words in the title of a job ad to carry out occupation categorisation: topic model, distinctive trigrams/bigrams/unigrams
- job ads: 51% jobs require at least college education and 67% require less than one year of experience; average offered wage is Rupees 213,000 Table
- applicants: average job seeker is 24 years old, 86% have a university degree, and 35% are women Table
- posted wages are 21% higher compared to a nationally representative and comparable sample of urban Indian workers Table

Implicit *femaleness* and *maleness*

- define implicit "*femaleness*" (F_p) and "*maleness*" (M_p) of a job ad as:

$$F_p \equiv \text{Prob(explicit female request} \mid \text{job text)}$$

$$M_p \equiv \text{Prob(explicit male request} \mid \text{job text)}$$

- use a multinomial logistic regression classifier to infer F_p and M_p from the job ad text:
  - high F_p: **beautician**, **personal secretary**, and **school teacher**
  - high M_p: **cargo loader**, **delivery executive**, and **network engineer**
  - F_p and M_p can vary within the same occupation/job title as well
- heat map visualization of words in distinctive job ads: Figure

Gender preferences, wages, and applicant behavior

1. jobs with higher skill requirements are less likely to have an explicit gender preference (negative skill-targeting) Table
2. jobs with an explicit female preference have lower advertised wages, after controlling for education and experience requirements as well as (occupation $\times$ state) FEs
3. explicit gender preferences in a job ad are associated with reduced total applications and a higher share of female applicants to an ad Table
4. within *N* jobs, higher implicit *femaleness* is associated with a reduction in the advertised wage Table
5. higher implicit *femaleness* is also associated with a higher share of female applicants, for all kinds of jobs Figure

Wage decompositions

- quantify impact of gender requests on the gender wage gap in applications by using semi-parametric decomposition from DiNardo et al. (1996): Table
- baseline gender wage gap in applications is the difference in the average log wage across job ads that men and women send their applications to, given that female applicants have the same observable characteristics as men
- baseline gender wage gap in applications in our sample is 3.5% of which:
  - 45% is explained by men and women making applications across different occupations and locations
  - an additional 7% is explained by gender requests in job ads, while 17% is explained by implicit gender associations together with gender requests

Deconstructing implicit *femaleness* and *maleness*

- what kind of words contribute to implicit gender associations?
- use the Local Interpretable Model-agnostic Explanations (LIME) algorithm (Ribeiro et al. 2016) which gives the relevance of individual words in a job ad towards implicit *femaleness* (F_p) and *maleness* (M_p)
- use 3,113 words which occur ≥ 10 times in F and M jobs; these words form 92% of all word occurrences by volume in N jobs as well
- classify these words into four categories: **hard skills**, **soft skills**, **personality/appearance** and **job flexibility**
- obtain **net relevance scores** for each word by taking the difference between the word's relevance score for the female vs the male class
- a +ve (-ve) net score reflects higher relative contribution towards female (male) requests

Gendered Words: Hard & Soft Skills

(I)	(II)	(III)	(IV)
Hard skills		**Soft skills**	
Female	Male	Female	Male
autocad	hardware	telugu	arabic
facial	wpm	fluent	supervise
pedicure	rcm	malayalam	pitch
manicure	regulation	talk	negotiate
ppt	qc	counsel	verbally
tally	manual	speak	marathi
computer	mysql	gujarati	persuade
cake	scan	edit	punctuation
auto	machine	verbal	write
coral	sql	bengali	french
hashtag	audit	hindi	liaise
zoho	troubleshoot	crm	motivate
word	receivable	accommodate	read
ms	rf	oral	communicate
ledger	trouble	convince	advise
expense	visual	english	ar
manuscript	demat	etiquette	grammar
makeup	instagram	coordinate	rapport
keyword	outward	story	relationship
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Gendered Words: Personality/Appearance & Flexibility

(I)	(II)	(III)	(IV)
Personality/Appearance		**Job Flexibility**	
Female	Male	Female	Male
personality	honest	home	petrol
punctual	energetic	skype	night
presentable	pressure		relocate
patiently	cm		shift
smile	empathy		fuel
confidence	calm		weekend
mature	impression		outstation
keen	passionate		weekday
getter	honesty		travel
height	prompt		rotational
pleasant	ethical		
polite	complexion		
flair	problem		
adaptability	methodical		
proactive	enthusiastic		
rejection	chest		
entrepreneurial	listener		
positive	scar		
careful	resourceful		
tone	creatively		

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careful	resourceful		
tone	creatively		

Dependent variable: ln(wage)

Sample:	*F* Jobs		*N* Jobs		*M* Jobs	
	(I)	(II)	(III)	(IV)	(V)	(VI)
$NS^{+}_{hard-skills}$	–0.044***	–0.025***	–0.031***	–0.014***	–0.022***	–0.021***
	(0.006)	(0.005)	(0.003)	(0.002)	(0.008)	(0.008)
$NS^{+}_{soft-skills}$	–0.009	–0.009*	–0.000	–0.001	–0.003	–0.004
	(0.006)	(0.004)	(0.002)	(0.002)	(0.006)	(0.006)
$NS^{+}_{personality}$	0.011*	0.005	0.018***	0.005***	0.019***	–0.001
	(0.005)	(0.005)	(0.003)	(0.002)	(0.006)	(0.005)
$NS^{+}_{flexibility}$	0.009	0.003	0.006***	0.003	–0.000	0.002
	(0.008)	(0.008)	(0.002)	(0.002)	(0.006)	(0.005)
$NS^{-}_{hard-skills}$	–0.025*	–0.014	0.008**	0.006***	–0.019***	0.005
	(0.012)	(0.012)	(0.004)	(0.002)	(0.006)	(0.007)
$NS^{-}_{soft-skills}$	–0.006	–0.003	0.017***	0.011***	0.011	0.010
	(0.007)	(0.005)	(0.002)	(0.002)	(0.008)	(0.010)
$NS^{-}_{personality}$	–0.001	0.003	0.008***	0.005***	–0.003	–0.002
	(0.007)	(0.006)	(0.002)	(0.002)	(0.006)	(0.005)
$NS^{-}_{flexibility}$	0.044***	0.027***	0.027***	0.018***	0.013*	0.010*
	(0.013)	(0.007)	(0.003)	(0.002)	(0.007)	(0.005)
Fixed Effects	month	month, occ × state	month	month, occ × state	month	month, occ × state
N	5727	5727	124654	124654	4795	4795

Dependent variable: Fraction female applicants

Sample:	*F* Jobs		*N* Jobs		*M* Jobs	
	(I)	(II)	(III)	(IV)	(V)	(VI)
$NS^{+}_{hard-skills}$	0.004	0.002	0.011***	0.004***	0.000	–0.001
	(0.005)	(0.003)	(0.002)	(0.001)	(0.004)	(0.003)
$NS^{+}_{soft-skills}$	–0.002	–0.003	0.006***	0.002**	0.006	0.002
	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)
$NS^{+}_{personality}$	0.001	0.001	0.001	0.001	0.008	0.002
	(0.004)	(0.002)	(0.002)	(0.001)	(0.004)	(0.003)
$NS^{+}_{flexibility}$	–0.002	–0.000	0.001	0.001	0.004	0.001
	(0.004)	(0.004)	(0.001)	(0.001)	(0.003)	(0.001)
$NS^{-}_{hard-skills}$	–0.036***	–0.013**	0.005***	–0.001	0.011***	0.003
	(0.009)	(0.005)	(0.002)	(0.001)	(0.002)	(0.001)
$NS^{-}_{soft-skills}$	–0.006	0.001	0.002	0.001	–0.001	0.001
	(0.006)	(0.003)	(0.001)	(0.001)	(0.005)	(0.004)
$NS^{-}_{personality}$	0.003	0.000	0.001	–0.001	0.002	–0.005**
	(0.005)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
$NS^{-}_{flexibility}$	–0.022***	–0.014***	–0.007***	–0.006***	0.004	–0.007**
	(0.004)	(0.004)	(0.002)	(0.001)	(0.003)	(0.003)
Fixed Effects	month	month, occ × state	month	month, occ × state	month	month, occ × state
N	5839	5839	144117	144117	4944	4945

Robustness checks

- alternative specification to control for applicant characteristics Tables
- alternative occupation classification, (firm $\times$ state) fixed effects, (firm $\times$ occupation $\times$ state) fixed effects Tables
- alternative specification with quartics in net scores Tables, Figures

Words associated with a higher share of female applicants

- find words in job ads that attract a higher share of female applicants:
  - regress the female applicant share on job characteristics and (occupation $\times$ state) FEs for N jobs to obtain residuals
  - use these residuals as the dependent variable to estimate a ridge regression model and obtain a coefficient for each word
  - interpret coefficients as marginal effect on female applicant share
- correlation between words predictive of employer's gender preference (gendered words) and those that attract a higher share of female applications:
  - 0.23 for hard skills; 0.50 for flexibility; 0.03 for soft skills; -0.12 for personality traits

(I)	(II)	(III)	(IV)
Hard skills/Skills		**Soft skills**	
Female	Male	Female	Male
makeup (0.106)	python (-0.115)	write (0.057)	collaborate (-0.048)
legal (0.076)	desktop (-0.061)	bengali (0.055)	ar (-0.040)
facial (0.066)	robotic (-0.055)	guide (0.053)	telugu (-0.039)
architectural (0.062)	quantitative (-0.047)	counsel (0.052)	negotiate (-0.032)
rf (0.061)	install (-0.043)	coordinate (0.043)	speak (-0.030)
manuscript (0.057)	machine (-0.039)	rapport (0.037)	fluency (-0.026)
compute (0.051)	server (-0.038)	relationship (0.036)	supervise (-0.023)
court (0.048)	plc (-0.036)	english (0.035)	speech (-0.023)
cnc (0.045)	guest (-0.036)	story (0.030)	verbal (-0.021)
content (0.044)	statement (-0.034)	coordination (0.029)	read (-0.020)
proofread (0.044)	configuration (-0.033)	french (0.028)	edit (-0.017)
draft (0.040)	repair (-0.032)	crm (0.025)	marathi (-0.016)
database (0.038)	adobe (-0.032)	ordinate (0.025)	articulate (-0.015)
software (0.038)	es (-0.031)	fluent (0.025)	persuade (-0.015)
risk (0.036)	network (-0.031)	communicate (0.022)	neutral (-0.013)
cake (0.034)	knowledgeable (-0.030)	feedback (0.021)	engage (-0.013)
demonstration (0.033)	erp (-0.030)	verbally (0.020)	pitch (-0.012)
animation (0.032)	ui (-0.030)	influence (0.018)	clientele (-0.011)
automation (0.031)	collate (-0.028)	liaise (0.016)	malayalam (-0.011)
regulation (0.031)	seo (-0.027)	color (0.016)	etiquette (-0.010)

(I)	(II)	(III)	(IV)
Personality/Appearance		**Job Flexibility**	
Female	Male	Female	Male
personality (0.053)	punctual (-0.034)	skype (0.026)	night (-0.103)
appearance (0.046)	smile (-0.032)	weekday (0.020)	travel (-0.049)
ethic (0.042)	adapt (-0.028)	outstation (0.015)	petrol (-0.041)
mile (0.042)	tone (-0.026)		fuel (-0.019)
resourceful (0.040)	dedicate (-0.024)		rotational (-0.016)
initiative (0.039)	keen (-0.024)		relocate (-0.013)
motivation (0.039)	pleasant (-0.021)		shift (-0.012)
determination (0.031)	neat (-0.021)		
proactively (0.031)	chest (-0.019)		
zeal (0.027)	entrepreneurial (-0.019)		
responsive (0.027)	adaptability (-0.019)		
proactive (0.026)	confident (-0.018)		
creative (0.026)	vigilant (-0.017)		
passionate (0.022)	enthusiasm (-0.017)		
rejection (0.021)	hardworke (-0.017)		
thinker (0.021)	height (-0.017)		
attitude (0.020)	initiate (-0.017)		
persuasive (0.019)	learner (-0.016)		
professionalism (0.018)	empathy (-0.015)		
creatively (0.016)	dedication (-0.013)		

Conclusion

- young, skilled women in the urban Indian labor market apply to lower wage jobs than comparable men
- employers' gender requests can explain as much as 7% of the gender wage gap in applications, while gender associations in job ad text together with gender requests can explain 17% of this gap
- gendered words related to hard skills and job flexibility play an important role
- gender wage gap in applications could explain as much as 73 percent of the residual gender gap in realized starting wages (Fluchtmann et al., 2022)
- gender differences at an early career stage for the job-seekers we look at are also likely to have important cumulative consequences for future labor market returns (Oyer, 2006; Kahn, 2010; Oreopoulos et al., 2012; Rothstein, 2020)

Thank you

Comments welcome!
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	Prefer female	No pref.	Prefer male	Total
Education requirements:				
Other (education not specified)	0.006	0.004	0.004	0.004
None (illiterate)	0.018	0.014	0.042	0.015
Secondary education	0.113	0.099	0.322	0.108
Senior secondary education	0.318	0.263	0.259	0.265
Diploma	0.075	0.090	0.077	0.089
Undergraduate degree, STEM	0.034	0.089	0.054	0.086
Undergraduate degree, non-STEM	0.425	0.424	0.237	0.417
Postgraduate degree, STEM	0.003	0.007	0.000	0.006
Postgraduate degree, non-STEM	0.006	0.007	0.002	0.006
Experience requirements:				
$0 - 1$ years	0.688	0.663	0.687	0.665
$1 - 2$ years	0.215	0.177	0.202	0.179
> 2 years	0.096	0.160	0.111	0.155
Other job requirements:				
Age requirement present	0.073	0.083	0.187	0.086
Minimum age requirement present	0.059	0.075	0.173	0.078
Maximum age requirement present	0.066	0.078	0.168	0.080
Beauty requirement present	0.118	0.057	0.060	0.059
Advertised wage:				
Wage not specified	0.021	0.134	0.033	0.126
Annual wage, if wage specified in job ad	177100	216807	183293	213648
N (jobs with advertised wage)	6413	126152	5407	137972
Applications:				
Share of female applicants	0.521	0.319	0.129	0.321
Number of applications	17.416	42.274	31.296	40.854
N (all jobs)	6551	145748	5589	157888

Back

	Female	Male	Total
Education:			
Other (education not specified)	0.002	0.002	0.002
None (illiterate)	0.000	0.000	0.000
Secondary education	0.004	0.016	0.012
Senior secondary education	0.030	0.068	0.054
Diploma	0.030	0.087	0.066
Undergraduate degree, STEM	0.535	0.545	0.541
Undergraduate degree, non-STEM	0.155	0.135	0.142
Postgraduate degree, STEM	0.122	0.067	0.087
Postgraduate degree, non-STEM	0.122	0.080	0.095
Experience:			
$0 - 1$ years	0.799	0.736	0.758
$1 - 2$ years	0.069	0.079	0.075
> 2 years	0.132	0.185	0.166
Age:			
Age at registration	23.460	23.863	23.720
Applied wage:			
Mean annual wage	257177	256810	256939
Number of applications:			
Number of applications	6.148	6.048	6.083
N (Applicants)	374804	685927	1060731

Back

	Female	Male	Total
Panel A: Age 16-60			
Education:			
None (illiterate)	0.159	0.075	0.094
Less than Secondary education	0.254	0.335	0.317
Secondary education	0.074	0.147	0.131
Senior secondary	0.075	0.117	0.108
Diploma	0.020	0.026	0.025
Graduate degree	0.263	0.216	0.226
Postgraduate degree	0.155	0.083	0.098
Age:			
Age	35.417	36.030	35.897
Salary:			
Annual Wage	167983	207824	199217
Observations	2954	10853	13807
LFPR	0.226	0.821	0.529
Panel B: Age 18-32			
Education:			
None (illiterate)	0.089	0.052	0.060
Less than Secondary education	0.170	0.321	0.288
Secondary education	0.075	0.140	0.125
Senior secondary	0.079	0.129	0.118
Diploma	0.028	0.035	0.033
Graduate degree	0.361	0.244	0.270
Postgraduate degree	0.196	0.079	0.105
Age:			
Age	26.417	26.436	26.432
Salary:			
Annual Wage	167490	178405	176001
Observations	1166	4382	5548
LFPR	0.242	0.774	0.518

Back

i. **SOFTWARE TRAINEE**: lady faculty for following subjects - basic of computer having complete knowledge of ms office. friendly with internet. advance english with grammar. personality development classes having good comunication skills. basic & accounting with taly & gst

ii. **BUSINESS DEVELOPMENT MANAGER**: language:- bengali (fluently speak), english (read, write & fluently speak), hindi (fluently speak) grooming must (looking like air hostess) job role:- manager, hr, student, counselling, employee handling, eod report sharing (total office management) bond applicable for this employee qualification (preferable) :- minimum graduate, mba in marketing, master in psychology. only female candidates applicable. (good looking with smart candidates) computer

(a) Female preference

i. **SOFTWARE TRAINEE**: qualification: b.e/ b.tech/b.sc/bca mca msc freshers – 2018 & 2019 passed out requirement: candidates from it/ computer science background are preferred. Excellent verbal and written communication skills should have basic knowledge on it technologies quick learners should be able to work in rotational shifts only male candidates are preferred

ii. **BUSINESS DEVELOPMENT MANAGER**: we are looking for energetic candidates for the post of bdm who has experience in b2b sales and has good communication skills, only boys with two-wheelers. Salary will be 4-6 lakhs p.a. jd – you have to set up and deliver sales presentations, demo on a daily basis, to identify potential clients and implementing innovative business

(b) Male preference

Back

Dependent variable:	any gender preference			male preference		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Education:						
Senior secondary	–0.0642***	–0.0273***	–0.0249***	–0.0709***	–0.0361***	–0.0376***
	(0.0104)	(0.0077)	(0.0078)	(0.0118)	(0.0080)	(0.0082)
Diploma	–0.0796***	–0.0299***	–0.0277***	–0.0569***	–0.0378***	–0.0405***
	(0.0129)	(0.0076)	(0.0077)	(0.0151)	(0.0079)	(0.0080)
Undergraduate, STEM	–0.1014***	–0.0371***	–0.0261***	–0.0486***	–0.0338***	–0.0323***
	(0.0129)	(0.0074)	(0.0075)	(0.0153)	(0.0079)	(0.0080)
Undergraduate, non-STEM	–0.0810***	–0.0325***	–0.0255***	–0.0745***	–0.0397***	–0.0415***
	(0.0127)	(0.0073)	(0.0075)	(0.0148)	(0.0080)	(0.0083)
Postgraduate, STEM	–0.1148***	–0.0549***	–0.0454***	–0.0836***	–0.0338***	–0.0299*
	(0.0146)	(0.0093)	(0.0128)	(0.0168)	(0.0100)	(0.0142)
Postgraduate, non-STEM	–0.0901***	–0.0403***	–0.0045	–0.0884***	–0.0366***	–0.0442**
	(0.0147)	(0.0107)	(0.0176)	(0.0169)	(0.0118)	(0.0194)
Experience:						
1 – 2 years	0.0191***	0.0129***	0.0214***	–0.0006	–0.0017	–0.0023
	(0.0039)	(0.0025)	(0.0029)	(0.0041)	(0.0023)	(0.0028)
$>$ 2 years	–0.0111***	–0.0035	0.0125***	0.0090***	0.0043	0.0026
	(0.0025)	(0.0022)	(0.0030)	(0.0025)	(0.0023)	(0.0032)
Other job requirements:						
Age requirement present	0.0233	0.0501***	0.0675***	0.0579***	0.0381***	0.0446***
	(0.0122)	(0.0091)	(0.0107)	(0.0155)	(0.0073)	(0.0085)
Beauty requirement present	0.0295***	0.0286***	0.0280**	–0.0584***	–0.0550***	–0.0576***
	(0.0108)	(0.0106)	(0.0112)	(0.0072)	(0.0081)	(0.0084)
Advertised wage:						
ln(wage)			–0.0363***			0.0063*
			(0.0035)			(0.0032)
Fixed Effects	month	month, occ × state	month, occ × state	month	month, occ × state	month, occ × state
N	157888	156221	136453	157888	156221	136453

Back

Dependent variable:	total applications			share of female applications		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Female preference (F_e)	–20.686***	–8.079***	–5.455***	0.206***	0.156***	0.155***
	(2.654)	(0.821)	(0.803)	(0.014)	(0.006)	(0.007)
Male preference (M_e)	–3.677	–0.996	–2.710	–0.133***	–0.099***	–0.095***
	(4.542)	(4.691)	(2.955)	(0.009)	(0.005)	(0.005)
ln(wage)			18.927***			–0.000
			(2.744)			(0.002)
Fixed Effects	month	month, occ × state	month, occ × state	month	month, occ × state	month, occ × state
N	157888	156221	136453	157888	156221	136453

- an explicit female preference is associated with 5.5 fewer applications (= 13% of mean)
- consistent with directed search models higher posted wages increase the number of applications to a job ad
- an explicit female preference is associated with 15.5 pp increase in the share of female applicants (= 48% of mean) while an explicit male preference is associated with a 9.5 pp decrease (= 30% of mean)

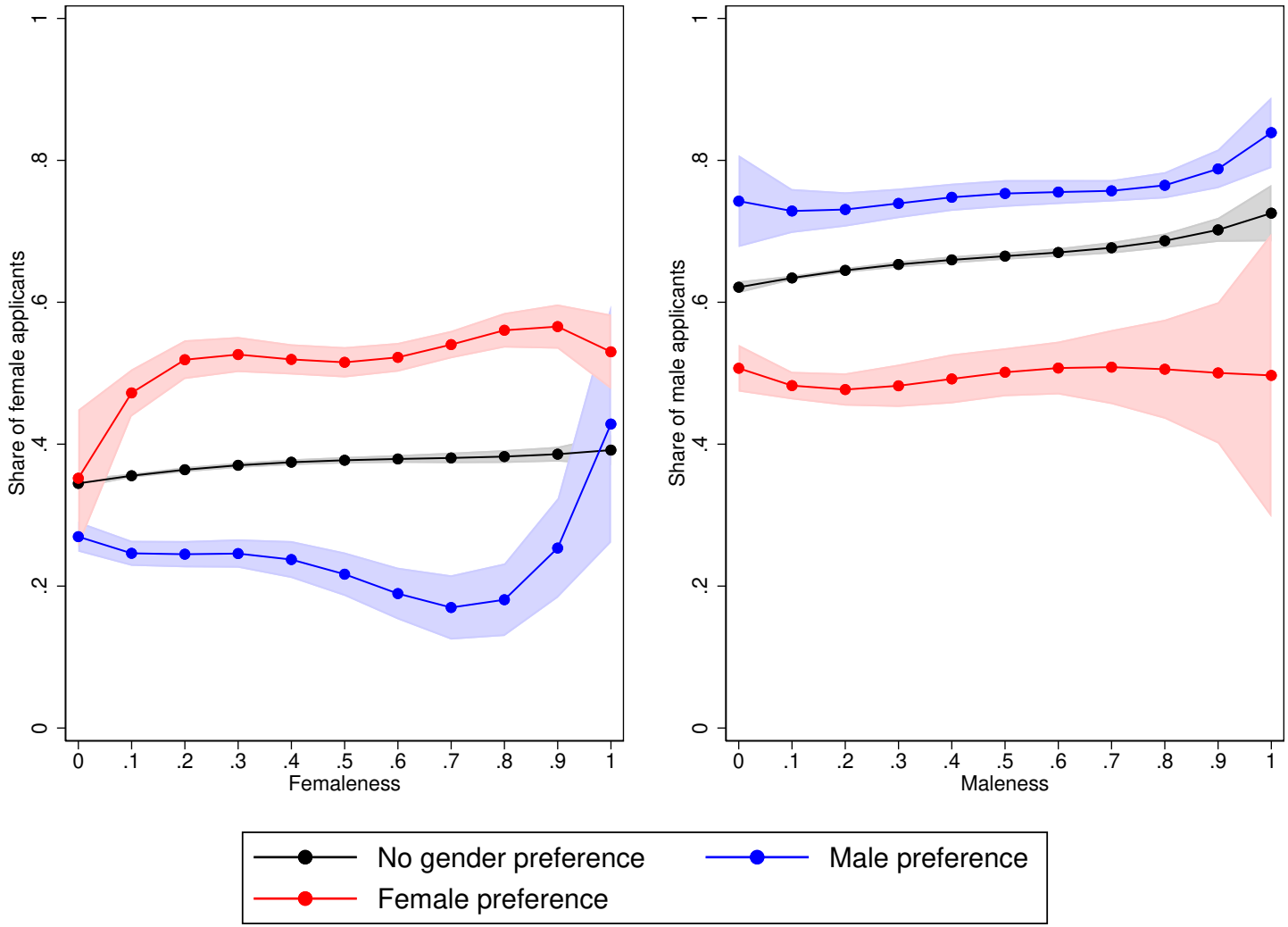
Back

Dependent variable: log(wage)

Sample:	F jobs		N jobs		M jobs	
	(I)	(II)	(III)	(IV)	(V)	(VI)
Implicit *femaleness* (F_p)	–0.185***	–0.202***	–0.379***	–0.264***	–0.320***	–0.192***
	(0.052)	(0.039)	(0.023)	(0.017)	(0.069)	(0.069)
Implicit *maleness* (M_p)	–0.107	–0.085	–0.123***	–0.136***	–0.116*	–0.151***
	(0.064)	(0.062)	(0.019)	(0.013)	(0.052)	(0.045)
Fixed Effects	month	month, occ × state	month	month, occ × state	month	month, occ × state
femaleness = maleness (p-value)	0.226	0.033	0.000	0.000	0.001	0.472
N	5727	5727	124654	124654	4795	4795

- for jobs without an explicit gender preference or *N* jobs:
  - a 1 SD increase in *implicit femaleness* is associated with a reduction in wages by 5.2 log points within an occupation and state
  - a similar increase in *implicit maleness* is associated with a significantly smaller decline in the advertised wage

Back


Share of female applicants
0
.2
.4
.6
.8
1
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
Femaleness
Share of male applicants
0
.2
.4
.6
.8
1
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
Maleness
No gender preference
Male preference
Female preference

Back

	(1)	(2)	(3)	(4)
	Baseline wage gap	Explained	Residual	Description
Panel A: All jobs				
Model 1	0.0349	0.0156	0.0193	Explained by differential applications by gender across
	(.0011)	(0.0014)		job location and occupation
Model 2	0.0349	0.0180	0.0169	Explained by differential applications by gender across
	(.0011)	(0.0014)		F_e and M_e as well as job location and occupation
Model 3	0.0349	0.0215	0.0134	Explained by differential applications by gender across
	(.0011)	(.0014)		F_e and M_e interacted with quartics in F_p and M_p as well as job location and occupation
Panel B: N jobs				
Model 1	0.0294	0.013	0.0165	Explained by differential applications by gender across
	(.0011)	(0.0014)		job location and occupation
Model 2	0.0294	0.0161	0.0133	Explained by differential applications by gender across
	(.0011)	(0.0014)		quartics in F_p and M_p as well as job location and occupation

Back

Robustness checks: controls for applicant characteristics

Dependent variable: 1 if female applicant

	(I)	(II)	(III)
Female preference (F_e)	0.204***	0.167***	0.166***
	(0.012)	(0.006)	(0.006)
Male preference (M_e)	–0.118***	–0.090***	–0.092***
	(0.007)	(0.006)	(0.005)
Fixed Effects	month	month, occ × state	month, occ × state
N	6401972	6401972	5332833

Dependent variable: 1 if female applicant

Sample:	*F* Jobs		*N* Jobs		*M* Jobs	
	(I)	(II)	(III)	(IV)	(V)	(VI)
$NS^{+}_{hard-skills}$	0.004	0.006**	0.010***	0.004***	0.001	0.006
	(0.004)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)
$NS^{+}_{soft-skills}$	0.001	–0.001	0.005***	0.002***	0.005	–0.001
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
$NS^{+}_{personality}$	0.001	–0.002	0.002	0.001	0.005	0.003
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
$NS^{+}_{flexibility}$	–0.001	0.000	0.001	0.000	–0.000	0.001
	(0.003)	(0.002)	(0.001)	(0.000)	(0.003)	(0.001)
$NS^{-}_{hard-skills}$	–0.048***	–0.019***	0.004*	–0.001	0.010***	0.002
	(0.009)	(0.006)	(0.002)	(0.001)	(0.002)	(0.003)
$NS^{-}_{soft-skills}$	–0.005	0.002	0.001	–0.001	–0.002	0.001
	(0.006)	(0.003)	(0.001)	(0.001)	(0.004)	(0.003)
$NS^{-}_{personality}$	0.000	–0.000	0.000	–0.001	0.004	–0.003
	(0.006)	(0.003)	(0.001)	(0.001)	(0.003)	(0.002)
$NS^{-}_{flexibility}$	–0.019***	–0.008***	–0.007***	–0.007***	0.002	–0.007**
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Fixed Effects	month	month, occ × state	month	month, occ × state	month	month, occ × state
N	112876	112876	6115802	6115802	173188	173188

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Robustness checks: alternative occupations, firm fixed effects

Dependent variable: log wage

	(I)	(II)	(III)
Implicit *femaleness* F_p	–0.225***	–0.283***	–0.127***
	(0.013)	(0.019)	(0.018)
Implicit *maleness* M_p	–0.105***	–0.076***	–0.095***
	(0.012)	(0.017)	(0.019)
Fixed Effects	month, alt occ × state	month, firm × state	month, firm × occ × state
Femaleness = Maleness, p-value	0.000	0.000	0.152
N	121931	74729	42059

Dependent variable:	total applications			share of female applications		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Female preference (F_e)	–6.291***	–8.499***	–4.105***	0.150***	0.195***	0.139***
	(0.690)	(0.926)	(0.920)	(0.006)	(0.010)	(0.010)
Male preference (M_e)	1.235	–7.468***	1.163	–0.087***	–0.120***	–0.091***
	(3.720)	(2.702)	(3.827)	(0.005)	(0.009)	(0.009)
Fixed Effects	month, alt occ × state	month, firm × state	month, firm × occ × state	month, alt occ × state	month, firm × state	month, firm × occ × state
N	152568	102203	62089	152568	102203	62089

Dependent variable:	log of advertised wage			share of female applications		
	(I)	(II)	(III)	(IV)	(V)	(VI)
$NS^{+}_{hard-skills}$	–0.011***	–0.010***	–0.006*	0.002***	0.009***	0.002
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
$NS^{+}_{soft-skills}$	–0.002	–0.005***	–0.001	0.001*	0.004***	0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
$NS^{+}_{personality}$	0.004***	–0.000	–0.003	0.001	0.003**	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
$NS^{+}_{flexibility}$	0.001	–0.002	0.002	0.000	–0.001	0.000
	(0.002)	(0.003)	(0.002)	(0.000)	(0.001)	(0.001)
$NS^{-}_{hard-skills}$	0.006***	0.012***	0.002	–0.000	–0.001	–0.001
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
$NS^{-}_{soft-skills}$	0.009***	0.004	–0.001	0.001	–0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
$NS^{-}_{personality}$	0.005***	–0.000	–0.008***	0.000	–0.002	–0.001
	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)
$NS^{-}_{flexibility}$	0.016***	0.009***	0.007***	–0.005***	–0.009***	–0.004***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Fixed Effects	month, alt occ × state	month, firm × state	month, firm × occ × state	month, alt occ × state	month, firm × state	month, firm × occ × state
N	122163	74913	42141	140763	93930	57427

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Dependent variable: log wage

Sample:	*F* Jobs		*N* Jobs		*M* Jobs	
	(I)	(II)	(III)	(IV)	(V)	(VI)
$NS_{hard-skills}$	−0.019	−0.013	−0.035***	−0.018***	−0.010	−0.020*
	(0.012)	(0.012)	(0.004)	(0.003)	(0.013)	(0.010)
$NS^2_{hard-skills}$	−0.022***	−0.014***	−0.008***	−0.002	−0.011***	−0.006***
	(0.005)	(0.005)	(0.002)	(0.001)	(0.002)	(0.002)
$NS^3_{hard-skills}$	−0.000	−0.000	0.001*	0.000	0.000	−0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
$NS^4_{hard-skills}$	0.000*	0.000*	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$NS_{soft-skills}$	−0.001	−0.002	−0.011***	−0.009***	−0.004	−0.012
	(0.008)	(0.007)	(0.003)	(0.002)	(0.012)	(0.011)
$NS^2_{soft-skills}$	−0.003	−0.002	0.003***	0.001	0.002	0.002
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
$NS^3_{soft-skills}$	0.000	0.000	−0.000	−0.000	−0.001	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
$NS^4_{soft-skills}$	0.000	−0.000	−0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$NS_{personality}$	0.002	0.002	0.007	−0.002	0.023*	0.009
	(0.011)	(0.009)	(0.004)	(0.002)	(0.011)	(0.010)
$NS^2_{personality}$	0.001	0.001	0.003***	0.001	0.001	−0.003
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
$NS^3_{personality}$	0.000	0.000	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$NS^4_{personality}$	−0.000	−0.000	−0.000***	−0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$NS_{flexibility}$	−0.065***	−0.050***	−0.049***	−0.028***	−0.021	−0.018
	(0.016)	(0.018)	(0.006)	(0.005)	(0.019)	(0.016)
$NS^2_{flexibility}$	0.005	−0.003	−0.000	0.000	−0.003	−0.003
	(0.007)	(0.008)	(0.003)	(0.003)	(0.006)	(0.005)
$NS^3_{flexibility}$	0.002	0.000	0.001	0.001	−0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
$NS^4_{flexibility}$	0.000	0.000	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed Effects	month	month, occ × state	month	month, occ × state	month	month, occ × state
N	5727	5727	124654	124654	4795	4795

Dependent variable: share of female applications

Sample:	*F* Jobs		*N* Jobs		*M* Jobs	
	(I)	(II)	(III)	(IV)	(V)	(VI)
$NS_{hard-skills}$	0.036***	0.014**	0.001	0.004***	–0.024***	–0.014**
	(0.008)	(0.006)	(0.002)	(0.001)	(0.007)	(0.006)
$NS^2_{hard-skills}$	–0.009**	–0.003	0.005***	0.001*	–0.001	–0.000
	(0.004)	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)
$NS^3_{hard-skills}$	–0.002*	–0.001	0.000***	–0.000	0.001	0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$NS^4_{hard-skills}$	0.000***	0.000**	–0.000***	–0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$NS_{soft-skills}$	0.008	–0.002	0.005**	0.002	0.014**	0.004
	(0.007)	(0.004)	(0.002)	(0.001)	(0.006)	(0.005)
$NS^2_{soft-skills}$	–0.005	–0.001	0.001	0.000	–0.002	–0.001
	(0.002)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)
$NS^3_{soft-skills}$	–0.000	–0.000	–0.000	–0.000	–0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
$NS^4_{soft-skills}$	0.000***	0.000	0.000	0.000	0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$NS_{personality}$	0.003	0.003	0.001	0.002**	0.006	0.008**
	(0.006)	(0.004)	(0.002)	(0.001)	(0.005)	(0.003)
$NS^2_{personality}$	0.001	0.000	0.000	–0.000	0.002	–0.001
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
$NS^3_{personality}$	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$NS^4_{personality}$	0.000	0.000	–0.000	0.000	–0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$NS_{flexibility}$	0.037***	0.019	0.007	0.007	–0.012	0.009
	(0.013)	(0.010)	(0.004)	(0.004)	(0.009)	(0.005)
$NS^2_{flexibility}$	–0.004	–0.000	0.000	–0.000	–0.004	–0.000
	(0.005)	(0.004)	(0.002)	(0.001)	(0.005)	(0.003)
$NS^3_{flexibility}$	–0.001	–0.000	0.000	–0.000	–0.001	–0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
$NS^4_{flexibility}$	–0.000	–0.000	0.000	–0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed Effects	month	month, occ × state	month	month, occ × state	month	month, occ × state
N	5839	5839	144117	144117	4945	4945

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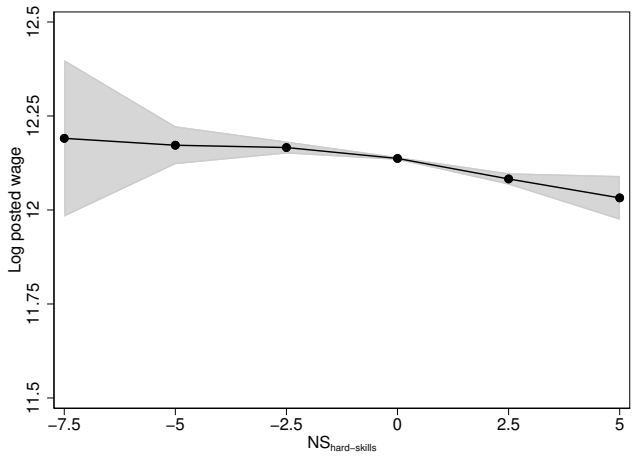
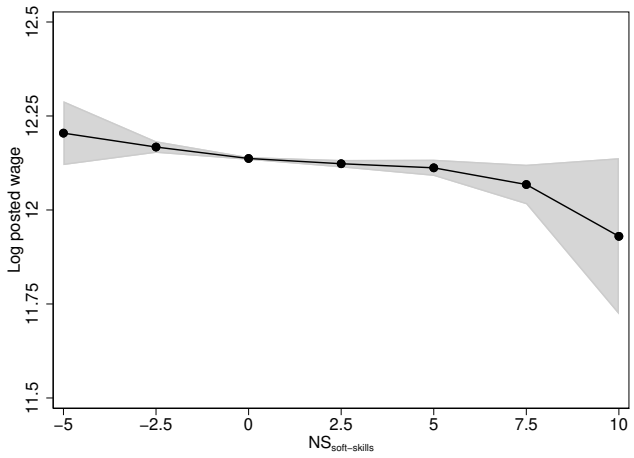
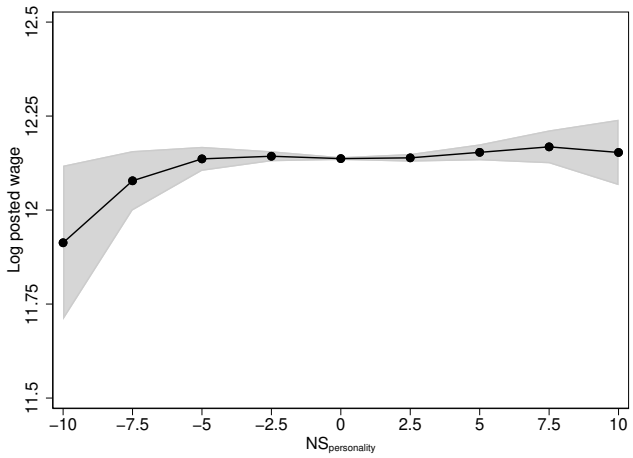
Net scores and predicted wages



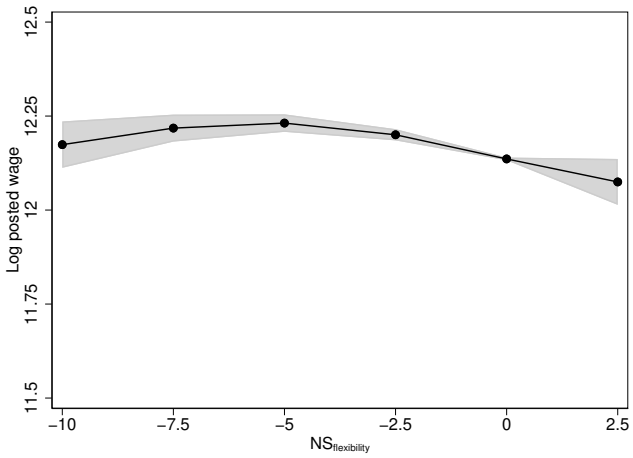
(a) Hard-skills



(b) Soft-skills

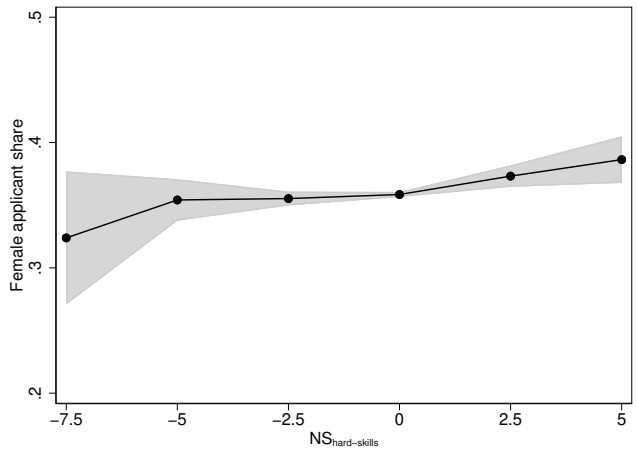


(c) Personality

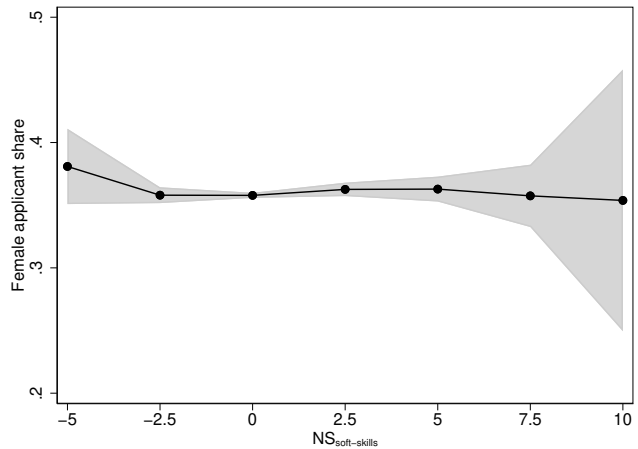


(d) Flexibility

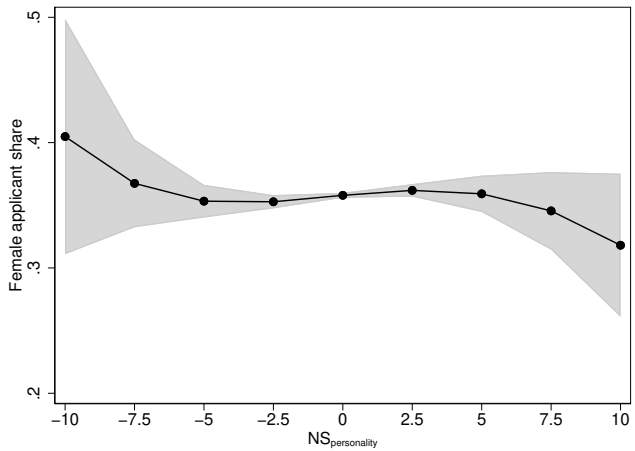
Net scores and the predicted share of female applicants



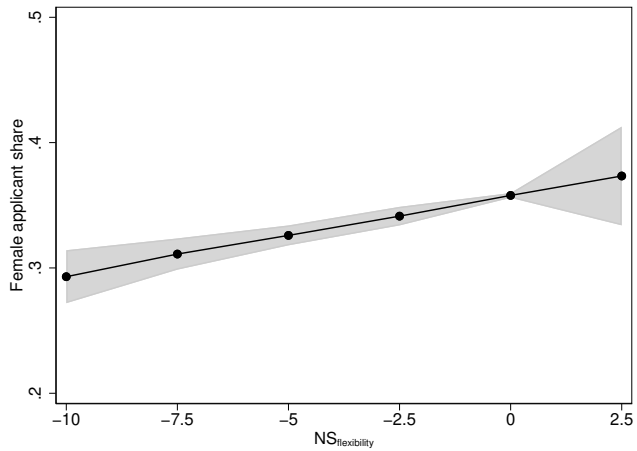
(a) Hard-skills



(b) Soft-skills



(c) Personality



(d) Flexibility

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