

Women in economics: the role of gendered references at entry in the profession

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14 December, 2022

The views and opinions expressed in this presentation are those of the authors and do not necessarily reflect those of the Bank of Italy or Bocconi University.

Under-representation of women in academia

- “likely hampers the discipline, constraining the range of issues addressed and limiting the ability to understand familiar issues from new and innovative perspectives” ([Bayer and Rouse, 2016](#))

However:

- It is a widespread phenomenon
- Especially in some fields 
- Especially at higher positions, “*leaky pipeline*” 
- Progress has stalled in recent years 

- Focus on transition from graduate program to work - Economics Job Market
- Build novel dataset on large sample of job market candidates and letter writers
- Analyze gender differences in how candidates are described in reference letters written by senior academics (does language convey implicit gender stereotypes?)
- Study influence on (early) career outcomes

1. Economics on roots of leaky pipeline in the profession:

- **Differences in observables:** graduate program organization (Boustan et al., 2020); peers (Bostwick and Weinberg, 2020); student-advisor matching (Hilmer and Hilmer, 2007); field of specialization (Fortin et al., 2021; Oaxaca and Sierminska, 2021)
- **Implicit discrimination and gender stereotypes:** among students (Paredes et al., 2020), among faculty (Jansson and Tyrefors, 2020), in reference letters (Eberhardt et al., 2022), in publication process (Sarsons, 2017; Sarsons et al., 2021; Hengel, 2017) and citation patterns (Koffi, 2021a,b), and seminars behavior (Dupas et al., 2021)

2. Psychology and linguistics on implicit gender bias in reference process:

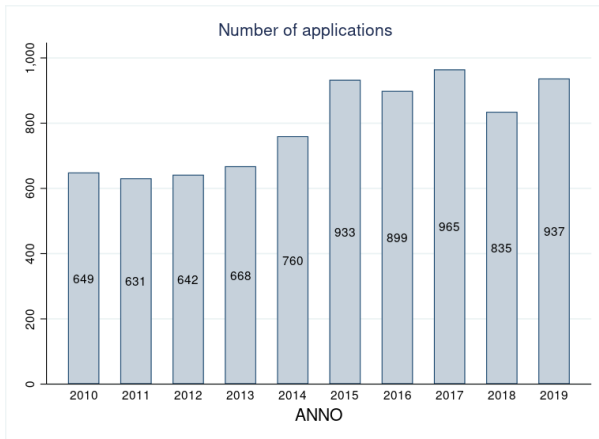
- **Linguistics:** letters for female applicants (to various jobs) are significantly different in style: shorter, incomplete, doubt-raising (Trix and Psenka, 2003); weaker in tone (Dutt et al., 2016)
- **Applied psychology:** letters for female candidates put more emphasis on inter-personal skills and personality characteristics and less emphasis on ability (Schmader et al., 2007; Madera et al., 2009; Chapman et al., 2020)

- 1 Shed light on the stepping stone of the economics profession
- 2 Bridge the two streams of literature:
 - apply modern text analysis tools to a large corpus of documents to obtain measures of implicit gender stereotypes in a *non-experimental setting*
 - incorporate them in a regression framework to analyze relationship with career outcomes
- 3 Highlight potential "institutional discrimination" - i.e., the rules of the game unintentionally harm one group - in hiring/promotions based on references

Data and descriptives

- Build a novel dataset containing all job market applications to two top institutions, based in Italy, hiring in the international job market (one is a University, for which we have data for two departments): 10 (5) years of data, $N_C \approx 8,000$
- Classify candidates and referees by gender using names libraries
- Retrieve info on pre-job market career from application forms and CVs
- Retrieve info on job market paper
- Collect all reference letters, $N_L \approx 25,000$
- Gather info on (current) career outcomes by scraping LinkedIn, Google Scholar and Repec, track about 94% of candidates
- Gather info on first placement through Scopus, LinkedIn, and manual search on candidates' webpages
- Match academic institutions (of origin and destination) with QS ranking of Universities and Repec ranking of Departments

Figure: Distribution of applications by year of application.



Source: Number of applications in the sample, by year. Years 2015-2019 include the two institutions, whereas years 2010-2014 only one.

Figure: Gender composition of applicants and letter-writers by year of application.



- Female candidates and academics are a minority
- No improvement over last decade

Candidate descriptives: pre-job market

	N	Male	Female	Difference
Pre-JM:				
American/Canadian PhD	7077	0.532	0.484	0.048***
EU PhD	7077	0.433	0.476	-0.044***
Italian PhD	7077	0.066	0.100	-0.033***
Applied micro	7077	0.245	0.345	-0.100***
Macro/International/Finance	7077	0.444	0.395	0.048***
Theory/Quantitative	7077	0.242	0.197	0.044***
Top-20 QS	7063	0.171	0.151	0.020**
Top-20 Repec Econ	7063	0.267	0.214	0.052***
Phd ranking Repec Econ	7063	108.031	112.837	-4.806
# Publications pre-JM	7077	0.717	0.531	0.186***
		5041	2036	

Notes: * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

- Female candidates more likely to have EU Phds, come from lower ranked institutions, and have fewer pre-JM publications
- Significant gender differences in fields of research
- A representative sample of the (European) job market ▶ EJM sample

Candidate descriptives: job market

	N	Male	Female	Difference
References:				
# Letter writers	7077	3.249	3.211	0.038*
# Uploaded letters	7077	2.705	2.625	0.079**
# Female letter writers	7077	0.391	0.582	-0.190***
Main advisor female	7077	0.110	0.166	-0.055***
Average letter length	6028	1029.744	992.534	37.210***
JM paper:				
Published JM paper	7077	0.20	0.19	0.013
Published JM paper in Top 8	7707	0.03	0.02	0.007*
Published JM paper in Top 20	7707	0.03	0.03	0.006
Ranking of JM paper (Scimago 2021)	1156	151.94	153.46	-1.520
# Coauthors in JM paper	1387	0.89	0.77	0.127
Time to JM paper publication	1381	2.01	2.40	-0.390
		5041	2036	

- Gender differences in application package
- Small gender difference in (revealed) quality of JM paper

Candidate descriptives: career

	N	Male	Female	Difference
First placement:				
Academic Placement Linkedin	5803	0.81	0.81	-0.002
Placement Top 20 Repec Econ	5606	0.11	0.11	-0.001
Assistant professor or higher	4402	0.58	0.57	0.01
Post-doc	4402	0.22	0.25	-0.025*
Current placement and publications:				
Academic placement Linkedin	6641	0.754	0.747	0.007
Placement Top 20 Repec Econ	6641	0.08	0.08	-0.006
Associate professor	6641	0.168	0.118	0.050***
Assistant professor	6641	0.464	0.500	-0.036***
Post-doc	6641	0.120	0.133	-0.014
# Publications	7077	2.374	1.535	0.838***
Top 8 publication	7077	0.085	0.055	0.030***
# Citations (Repec)	7077	41.068	26.184	14.884***
		5041	2036	

- Small gender differences in first placement
- Worse outcomes as for position and publication records (in 2021)


Letter writer descriptives

	N	Male	Female	Difference
Gender of referee	8464	7,015	1,449	
Never uploaded	8464	0.132	0.161	-0.029***
# Letters written	8464	2.659	1.989	0.670***
Av. letter length (words)	7238	931.200	941.480	-10.281
At least 1 female advisee	7238	0.452	0.517	-0.065***
Academic affiliation	8464	0.777	0.743	0.034***
Full professor	8464	0.240	0.186	0.055***
First publication year	6683	1993.995	1997.974	-3.979***
# Articles Repec	8464	19.899	11.333	8.567***
# Publications GS	8464	70.797	46.529	24.268***
# Top 5 publications	7860	2.236	1.113	1.124***
At least 1 Top 5 publication	7860	0.424	0.342	0.082***
# Citations	8464	1006.266	533.296	472.970***

Notes: * denotes significance at 10%, ** significance at 5% and *** significance at 1%.

- Female referees write fewer but longer letters, more often for female students; less experienced and with lower academic achievement

Text Analysis of reference letters

- Exclude letters in Italian (≈ 100) and drop duplicates (4,000)
 - Anonymize texts
 - Pre-processing: trim headers/footers, split contractions, remove double spaces, punctuation, numbers and stopwords
 - *Tokenize* text, i.e. transform into a list of words
 - *Lemmatize* text, i.e. substitute words with their dictionary base form
- 
- 18,925 documents (D), 109,744 unique lemmas (V)
 - Each document is a vector of frequencies of words in V

Corpus description

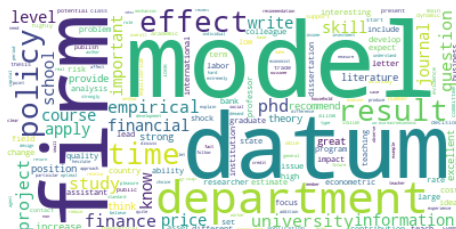
- Consider corpus just as a *bag of (lemmatized) words*
- Can show content of documents as set of *most frequent* words
- Or give more weight to words that most characterize each document:

$$tfidf_v = (1 + \log(tf_v)) \times (1 + \log \frac{N}{df_v})$$

Figure: Raw frequencies



Figure: Weighted frequencies (*tfidf*)



Supervised analysis: word embeddings

- What do sponsors say about candidates?
- Resort to a supervised approach
- Use the semantic categories identified in [Schmader et al. \(2007\)](#); [Madera et al. \(2009\)](#); [Chapman et al. \(2020\)](#):
- NB: all are positive words; yet - some will eventually appear to carry a higher value to career success

Standout

excellent,
outstanding,
unique,
exceptional,
best, wonderful,
extraordinary...

Grindstone

hardworking,
conscientious,
meticulous,
thorough, effort,
diligent, careful,
dedicated...

Communal

agreeable, quite,
considerate,
helpful, friendly,
interpersonal,
warm, pleasant,
humble...

Agentic

assertive,
confident,
independent,
ambitious,
successful,
tenacious...

Supervised analysis: word embeddings

- Each target word is transformed in a low dimensional object (vector) which represents its "meaning":
 - it is constructed by looking at co-occurrence patterns in a *local* context
"You shall know a word by the company it keeps" (Firth, 1957)
 - its position and relative proximity to other words/vectors capture their semantic similarity
- Similarity is defined through **cosine distance**: word vectors with smaller angles are more similar

Cosine similarity = -1 \rightarrow opposite vectors/antonyms;
 0 \rightarrow orthogonal vectors/unrelated;
 1 \rightarrow overlapping vectors/synonyms

▶ Example

Computing word embeddings

- Use `word2vec` tool
- Choose *embedding dimension*=100 and *window size*=6
- Algorithm will give a vector of dimension 100 for each target word (42)
- Start from a random embedding and iterate minimizing a *loss function*, which combines prob. of observing each term within the context of a target word and prob. of not observing it
- Intuitively, *fridge magnets*
- Stop after 100 iterations
- Compute *average vectors* of embeddings of words in the same category

Computing cosine similarities

- 1 For each target semantic category (standout, grindstone, communal, agentic) compute WE of each word and then the *average vector*
- 2 We replace each reference to candidate with an anonymous token (*candidate_male_ID*, *candidate_female_ID*) and compute WE for each
- 3 Compute (cosine) distance between (1) and (2) using full corpus
→ How candidate i is described in all her/his reference letters, irrespective of who wrote them
- 4 Repeat with *candidate_refID*
→ How letter writer j describes his/her students, irrespective of their identity and gender
- 5 Repeat with *candidate_male_refID*, *candidate_female_refID*
→ How letter writer j describes his/her female and male students, irrespective of their identity

Results: candidates

Table: Cosine similarity between reference to candidate and target average vectors, by candidate's gender

	(1)	(2)	(3)	(4)	(5)
	Cosine Similarity			Difference	Cond. Diff.
	Obs	Male	Female	(2)-(3)	(2)-(3)
Standout	6004	0.245	0.240	0.005***	0.005***
Grindstone	6004	0.216	0.224	-0.008***	-0.005***
Communal	6004	0.217	0.219	-0.002	0.002
Agentic	6004	0.236	0.242	-0.005***	-0.001

Notes: The conditional differences in column 5 are computed net of year of application, department to which application was sent, field of research, candidates' PhD institution fixed effect, and an indicator for the candidate's JM paper being published in a Top 8 journal. * $p < 0.1$, ** $p < .05$, *** $p < 0.01$

- Female candidates are described more in terms of grindstone, and less in terms of standout words [▶ Figure](#)

Results: Letter writers

Table: Cosine similarity between reference to candidate and target average vectors, by letter writer's gender

	(1)	(2)	(3)	(4)	(5)
	Cosine Similarity			Difference	Cond. Diff.
	Obs	Male	Female	(2)-(3)	(2)-(3)
Standout	7097	0.237	0.237	0.001	0.000
Grindstone	7097	0.195	0.210	-0.016***	-0.014***
Communal	7097	0.189	0.195	-0.006***	-0.005***
Agentic	7097	0.213	0.225	-0.012***	-0.011***

Notes: The conditional differences in column 5 accounts for indicators for those with an academic affiliation, with full professorship, and with at least one female advisee, and for the letter writer institution of affiliation fixed effects. * $p < 0.1$, ** $p < .05$, *** $p < 0.01$

- Female letter writers tend to emphasize candidate personal traits more compared to male letter writers, with the exception of standout

Results by gender of letter writer and of candidate

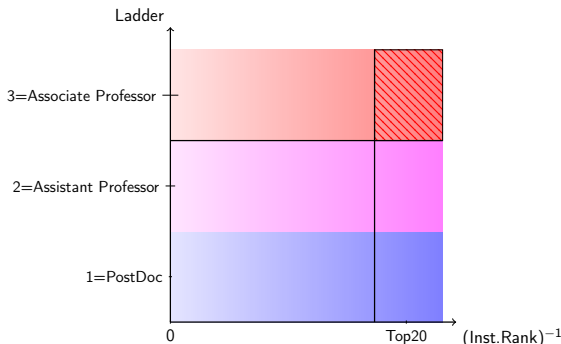
Table: Cosine similarity between reference to candidate and target average vectors, by candidate and letter writer gender

	(1)	(2)	(3)	(4)
	Cosine Similarity:		Difference, (1)-(2):	
	Male cand.	Female cand.	all	lett. writer FE
A. Male letter writers				
Standout	0.231	0.227	0.004**	0.003
Grindstone	0.193	0.200	-0.007***	-0.013***
Communal	0.188	0.185	0.003*	-0.005***
Agentic	0.210	0.213	-0.002	-0.010***
Observations			7,613	3,394
B. Female letter writers				
Standout	0.225	0.226	-0.001	-0.004
Grindstone	0.210	0.215	-0.005	-0.0002
Communal	0.196	0.192	0.004	0.0006
Agentic	0.223	0.223	-0.000	-0.005
Observations			1,459	556

- Gendered language only in letters written by male advisors; female advisors are instead gender-neutral
- True also controlling for letter writer FE \Rightarrow quality likely very similar among students supervised by the same advisor

Relationship with career outcomes

- How to define career success?



- Relationship of career outcomes with job market package observables, conditional on cohort:

$$y_i = \alpha + \beta_1 \text{Female}_i + \beta_2 \text{Candidate_}X_i + \beta_3 \text{LetterWriter_}X_i + \\ + \beta_4 \text{Letters_}X_i + \beta_5 \text{WE}_i + \tau_t + \varepsilon_i$$

Table: Probability of holding an Assistant Professorship (or higher) in a Top 20 Institution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.00953 (0.00794)	0.0111 (0.00870)	0.0146* (0.00869)	0.0120 (0.00879)	0.0107 (0.00864)	0.0129 (0.00865)	0.0158* (0.00868)
# Publications Pre-JM			0.00350 (0.00239)				0.00234 (0.00233)
Main lett. writer female				-0.00645 (0.0104)			-0.00624 (0.0101)
# Top 5 public. (main lett. writer)				0.00123 (0.000822)			0.00108 (0.000780)
Full professor (main lett. writer)				0.0142 (0.00886)			0.0144* (0.00876)
# Letter writers					0.0327*** (0.00675)		0.0300*** (0.00677)
Average letter length (std)					0.0261*** (0.00473)		0.0236*** (0.00476)
Standout cos. sim.						0.243*** (0.0615)	0.182*** (0.0606)
Grindstone cos. sim.						-0.151** (0.0677)	-0.0291 (0.0680)
Mean dependent variable men							
Raw	✓	✓					
Candidate chars			✓				✓
Letter writer chars				✓			✓
Letter chars					✓		✓
WEs						✓	✓
R ²	0.114	0.115	0.137	0.117	0.130	0.119	0.155
N	4282	3790	3790	3790	3790	3790	3790

Notes: Robust Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.00921*** (0.00309)	-0.00906*** (0.00343)	-0.00642* (0.00343)	-0.00753** (0.00341)	-0.00781** (0.00343)	-0.00829** (0.00342)	-0.00536 (0.00342)
# Publications Pre-JM			0.00212** (0.000985)				0.00195** (0.000980)
Main lett. writer female				0.00193 (0.00484)			0.00113 (0.00481)
# Top 5 public. (main lett. writer)				0.00150*** (0.000378)			0.000940** (0.000424)
Full professor (main lett. writer)				0.00768* (0.00395)			0.00785* (0.00404)
# Letter writers					0.00992*** (0.00282)		0.00721** (0.00283)
Average letter length (std)					0.0118*** (0.00217)		0.00876*** (0.00227)
Standout cos. sim.						0.0574* (0.0295)	0.0317 (0.0302)
Grindstone cos. sim.						-0.0519* (0.0286)	0.00525 (0.0318)
Mean dependent variable men	0.017	0.017					
% Raw Gap Explained			29.1	16.9	13.8	8.5	40.8
Raw	✓	✓					
Candidate chars			✓				✓
Letter writer chars				✓			✓
Letter chars					✓		✓
WEs						✓	✓
R ²	0.0106	0.0113	0.0335	0.0221	0.0208	0.0123	0.0429
N	6511	5699	5699	5699	5699	5699	5699

Notes: Robust Standard errors in parentheses. * $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Dimension 1: Associate professor

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.0440*** (0.00830)	-0.0409*** (0.00911)	-0.0362*** (0.00914)	-0.0404*** (0.00916)	-0.0401*** (0.00910)	-0.0389*** (0.00913)	-0.0340*** (0.00921)
# Publications Pre-JM			0.0235*** (0.00314)				0.0232*** (0.00313)
Main lett. writer female				-0.00100 (0.0126)			-0.00110 (0.0126)
# Top 5 public. (main lett. writer)				0.000419 (0.000575)			0.000776 (0.000626)
Full professor (main lett. writer)				-0.00216 (0.00917)			-0.00233 (0.00917)
# Letter writers					0.0132* (0.00714)		0.0109 (0.00717)
Average letter length (std)					0.00747* (0.00417)		0.0120*** (0.00438)
Standout cos. sim.						0.286*** (0.0673)	0.215*** (0.0684)
Grindstone cos. sim.						-0.0369 (0.0723)	0.0213 (0.0762)
Mean dependent variable for men	0.159	0.159					
Raw	✓	✓					
Candidate chars			✓				✓
Letter writer chars				✓			✓
Letter chars					✓		✓
WEs						✓	✓
R ²	0.120	0.141	0.168	0.141	0.142	0.143	0.172
N	6913	5699	5699	5699	5699	5699	5699

Dimension 2: Top 20 placement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.00570 (0.00747)	0.0106 (0.00831)	0.0179** (0.00817)	0.0158* (0.00824)	0.0151* (0.00820)	0.0144* (0.00832)	0.0220*** (0.00812)
# Publications Pre-JM			0.00117 (0.00181)				0.000452 (0.00182)
Main lett. writer female				0.0164 (0.0110)			0.0126 (0.0107)
# Top 5 public. (main lett. writer)				0.00595*** (0.000648)			0.00332*** (0.000648)
Full professor (main lett. writer)				0.0147* (0.00777)			0.0161** (0.00768)
# Letter writers					0.0421*** (0.00608)		0.0314*** (0.00596)
Average letter length (std)					0.0427*** (0.00403)		0.0274*** (0.00417)
Standout cos. sim.						0.302*** (0.0581)	0.196*** (0.0571)
Grindstone cos. sim.						-0.250*** (0.0575)	-0.0826 (0.0602)
Mean dependent variable men	0.078	0.078					
Raw	✓	✓					
Candidate chars			✓				✓
Letter writer chars				✓			✓
Letter chars					✓		✓
WEs						✓	✓
R ²	0.00167	0.00216	0.0622	0.0393	0.0342	0.00824	0.0926
N	6511	5699	5699	5699	5699	5699	5699

- Do effects on placement reflect onto research output?
- Focus on candidates' top publication record in economics and finance:

$$y = 1(\# \text{ Top8 publications} > 0)$$

- Robustness checks:
 1. Overall publication count: $\log(1 + \# \text{ publications from Repec})$
 2. Citations: $\log(1 + \# \text{ citations to articles from Repec})$

Research productivity: 1 (Top 8 publications)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.0272*** (0.00647)	-0.0276*** (0.00730)	-0.0208*** (0.00720)	-0.0240*** (0.00730)	-0.0243*** (0.00725)	-0.0256*** (0.00734)	-0.0174** (0.00719)
# Publications Pre-JM			0.0285*** (0.00324)				0.0282*** (0.00324)
Main lett. writer female				0.00812 (0.0103)			0.00254 (0.0100)
# Top 5 public. (main lett. writer)				0.00392*** (0.000583)			0.00275*** (0.000617)
Full professor (main lett. writer)				0.00551 (0.00752)			0.00704 (0.00735)
# Letter writers					0.0213*** (0.00609)		0.0147*** (0.00579)
Average letter length (std)					0.0313*** (0.00369)		0.0280*** (0.00385)
Standout cos. sim.						0.190*** (0.0551)	0.127** (0.0541)
Grindstone cos. sim.						-0.106* (0.0578)	0.0558 (0.0590)
Mean dependent variable men	0.077	0.075					
Raw	✓	✓					
Candidate chars			✓				✓
Letter writer chars				✓			✓
Letter chars					✓		✓
WEs						✓	✓
R ²	0.0283	0.0350	0.101	0.0510	0.0498	0.0371	0.119
N	6913	5699	5699	5699	5699	5699	5699

Notes: Robust Standard errors in parentheses. * $p < 0.1$, ** $p < .05$, *** $p < 0.01$

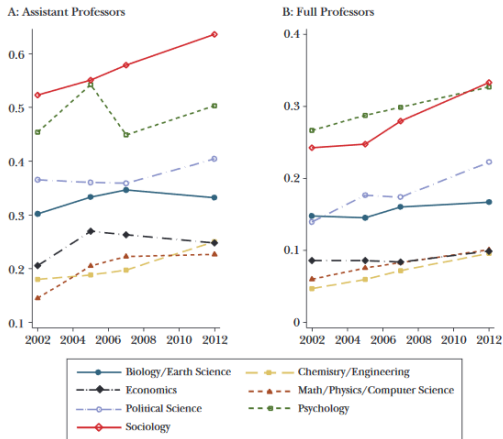
- Referral process on the academic job market in economics is not gender neutral
- Female candidates receive different support relative to males, quantitatively (fewer letters) and qualitatively (more emphasis on grindstone rather than standout personality traits)
- Use of gendered language mainly driven by male letter writers
- The way candidates are described relates to early career outcomes
- Use of references for hiring and promotions to be carefully managed, especially in highly male-dominated work environments

Thank you!

Extra material

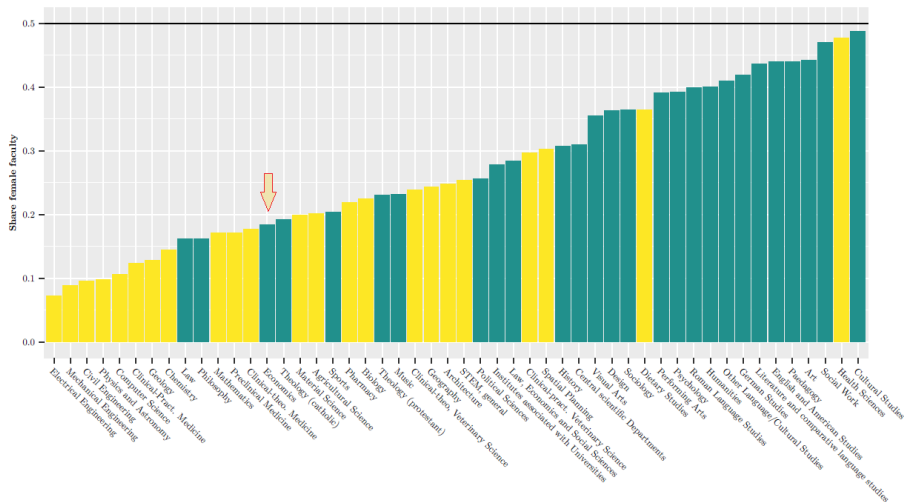
Evidence across fields [1]: US (Lundberg and Stearns, 2019)

Representation of Women in Top-50 Departments, 2002–2012
(share female)



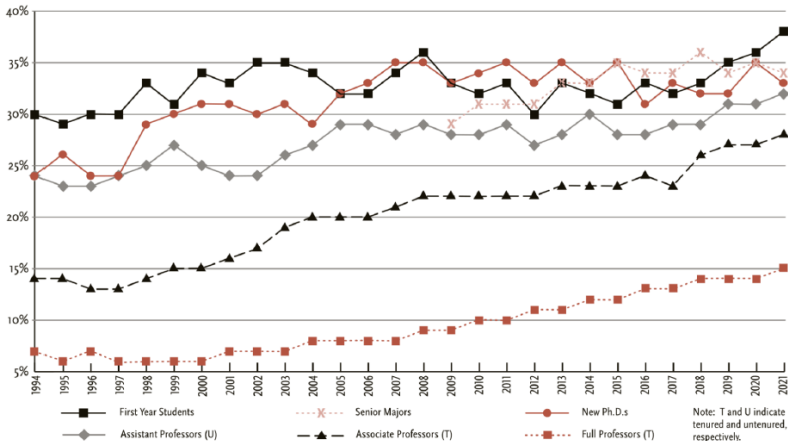
Evidence across fields [2]: Germany (Janys, 2022)

Share of female faculty by discipline



Evidence from US (Chevalier, 2022)

Figure 1. The Pipeline for Departments with Doctoral Programs: Percent of Doctoral Students and Faculty who are Women, 1994–2021



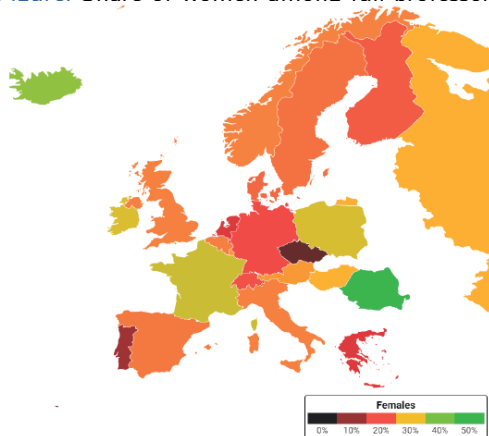
Introduction

Evidence from EU econ departments ([Auriol et al., 2020](#))

Table: Share of women in EU econ departments

Position	All	Top-100
Research associate	39.11	35.31
Entry level	38.78	36.44
Associate professor	33.48	32.37
Research Fellow	30.07	26.26
Full Professor	22.52	19.93
Total	31.51	28.19

Figure: Share of women among full professors

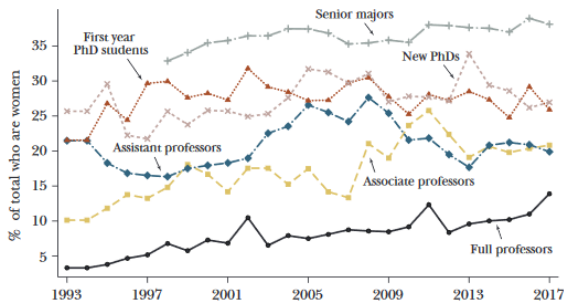


▶ back

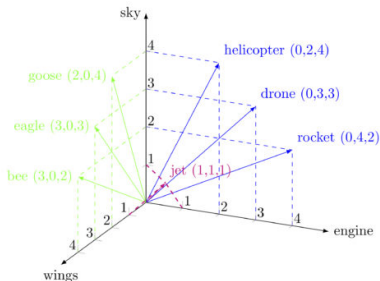
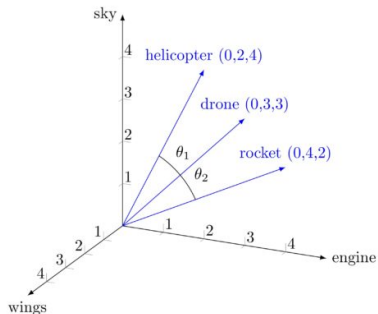
Evidence from top US econ departments ([Lundberg and Stearns, 2019](#))

Figure: Share of women, by position in Top-20 US Econ Departments

**Representation of Women among First-Year PhD Students, New PhDs, and Faculty
by Rank: Top 20 Economics Departments, 1993–2017**



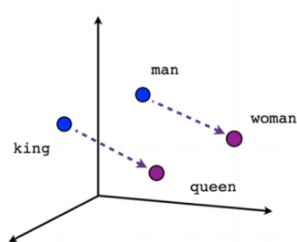
Example of word embedding



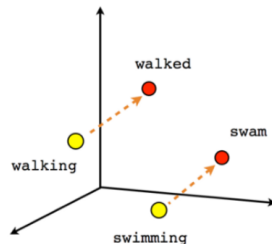
	bee	eagle	goose	helicopter	drone	rocket	jet
bee	1.00						
eagle	0.98	1.00					
goose	0.87	0.95	1.00				
helicopter	0.50	0.63	0.80	1.00			
drone	0.39	0.50	0.63	0.95	1.00		
rocket	0.25	0.32	0.40	0.80	0.95	1.00	
jet	0.80	0.82	0.77	0.77	0.82	0.77	1.00

Example of word embedding

- Position also allows to capture semantic relation between words



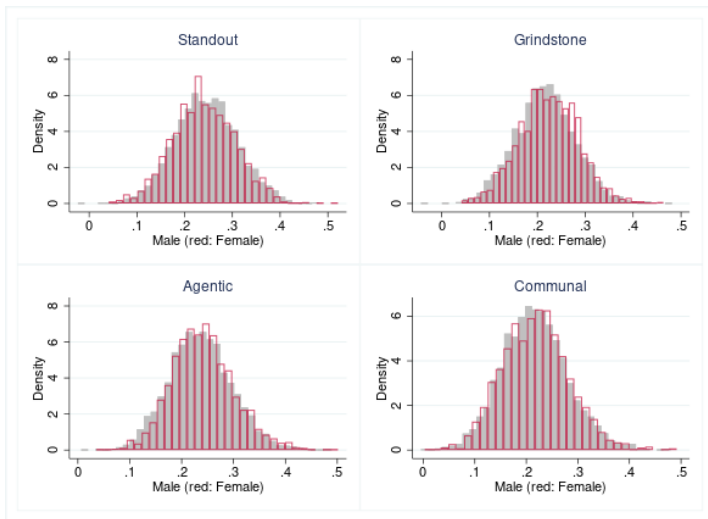
Male-Female



Verb tense

<https://github.com/Eligijus112/word-embedding-creation>

Figure: Cosine similarity to adjective categories, by candidate's gender



Descriptive statistics: EJM candidate directory 2020/2021

	N	Male	Female	Difference
American/Canadian PhD	787	0.438	0.416	0.022
EU PhD	787	0.436	0.490	-0.054
Italian PhD	787	0.033	0.049	-0.016
Applied micro	787	0.515	0.671	-0.156***
Macro/International/Finance	787	0.210	0.156	0.053*
Theory/Quantitative	787	0.193	0.136	0.057*
Phd Uni Top20 (QS)	787	0.149	0.132	0.017
Phd Uni Top20 Econ	787	0.256	0.198	0.058*
Observations	787			

▶ Back

- Use `word2vec` tool
- Choose *embedding dimension=100* and *window size=6*
- Algorithm gives a vector of dimension 100 for each target word (42)
- Uses a *skipgram model*, computes probability of observing each word in the window given the target word
- Start from a random embedding and iterate minimizing a *loss function*
- Intuitively, *fridge magnets*
- Stop after 100 iterations
- Compute *average vectors* of embeddings of words in the same category
- Compute the distance between the 4 average vectors and the tokens *candidate__maleID*, *candidate__femaleID*

Table: Specification checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Academic ladder							
Female	-0.244*** (0.0637)	-0.265*** (0.0690)	-0.186*** (0.0710)	-0.262*** (0.0696)	-0.256*** (0.0693)	-0.259*** (0.0691)	-0.180** (0.0719)
% Raw Gap Explained			29.8	1.1	3.4	2.3	32.1
B. Academic ranking							
Female	-6.838* (3.727)	-9.295** (3.966)	-10.57*** (3.853)	-11.55*** (3.922)	-11.84*** (3.830)	-11.82*** (3.950)	-13.40*** (3.764)
% Raw Gap Explained			13.7	24.3	27.4	27.2	44.2
C. Academic ranking conditional on ladder							
Female	-4.588 (3.764)	-7.603* (4.012)	-9.263** (3.903)	-9.523** (3.958)	-10.34*** (3.836)	-10.13** (3.993)	-12.23*** (3.775)
% Raw Gap Explained			21.8	25.3	36.0	33.2	60.9
D. Career success with PhD institution FE							
Female	-0.00767** (0.00331)	-0.00703* (0.00371)	-0.00562 (0.00376)	-0.00679* (0.00375)	-0.00664* (0.00372)	-0.00662* (0.00371)	-0.00495 (0.00377)
% Raw Gap Explained			20.1	3.4	5.5	5.8	29.6
E. Top 8 publications with PhD institution FE							
Female	-0.0210*** (0.00691)	-0.0222*** (0.00774)	-0.0197** (0.00778)	-0.0223*** (0.00776)	-0.0208*** (0.00769)	-0.0208*** (0.00776)	-0.0170** (0.00774)
% Raw Gap Explained			11.3	-5.0	6.3	6.3	23.4
Raw	✓	✓					
Candidate chars			✓				✓
Letter writer chars				✓			✓
Letter chars					✓		✓
WEs						✓	✓

Notes: In panel A, B and C the sample is restricted to candidates who currently hold a position in academia. In panel A the estimated model is an ordered logistic one, in panel B and C a Tobit model with upper censoring at 309, in panels D and E linear models with binary outcomes. Robust Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

- Gaps due more to differences in *returns* than in observable characteristics

Table: Oaxaca-Blinder decomposition

	(1)	(2)	(3)	(4)
	Career success		Top 8 publications	
	Coefficient	std. err.	Coefficient	std. err.
Prediction male	.0209552***	.0022361	.0889376***	.0044438
Prediction female	.0112853***	.0026452	.0595611***	.0059266
Difference	.0096699***	.0034636	.0293765***	.0074076
Decomposition:				
Endowments	.0017603	.0013526	.0104758***	.0035962
Coefficients	.0057514*	.0034346	.0190865***	.0073399
Interaction	.0021582	.0018523	-.0001857	.0038886

Table: Career success

	(1)	(2)	(3)	(4)
Female	-0.00781** (0.00343)	0.0196 (0.0195)	-0.00829** (0.00342)	0.0140 (0.0147)
# Letter writers	0.00992*** (0.00282)	0.0122*** (0.00352)		
# Letter writers × Female		-0.00815 (0.00607)		
Average letter length (std)	0.0118*** (0.00217)	0.0112*** (0.00246)		
Average letter length (std) × Female		0.00234 (0.00418)		
Standout cos. sim.			0.0574* (0.0295)	0.0879** (0.0382)
Standout cos. sim. × Female				-0.109** (0.0545)
Grindstone cos. sim.			-0.0519* (0.0286)	-0.0552 (0.0371)
Grindstone cos. sim. × Female				0.0184 (0.0507)
R ²	0.0208	0.0211	0.0123	0.0129
N	5699	5699	5699	5699

- Same returns to letter characteristics; standout words benefit only male candidates

Table: Ranking of first placement institution: probability of being affiliated to a Top 20 Institution 1 to 3 years after the job market

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.0199 (0.0134)	-0.0153 (0.0153)	-0.00277 (0.0149)	-0.00668 (0.0152)	-0.00923 (0.0152)	-0.0100 (0.0153)	0.00355 (0.0149)
# Publications Pre-JM			0.00189 (0.00274)				0.00124 (0.00276)
Main lett. writer female				0.0630*** (0.0229)			0.0547** (0.0216)
# Top 5 public. (main lett. writer)				0.00799*** (0.00125)			0.00414*** (0.00126)
Full professor (main lett. writer)				-0.0421*** (0.0140)			-0.0270** (0.0136)
# Letter writers					0.0600*** (0.0119)		0.0430*** (0.0110)
Average letter length (std)					0.0383*** (0.00714)		0.0138* (0.00733)
Standout cos. sim.						0.453*** (0.108)	0.336*** (0.105)
Grindstone cos. sim.						-0.379*** (0.114)	-0.196* (0.115)
Mean dependent variable men	0.11	0.11					
% Raw Gap Explained			81.9	56.3	39.7	34.6	-
Raw	✓	✓					
Candidate chars			✓				✓
Letter writer chars				✓			✓
Letter chars					✓		✓
WEs						✓	✓
R ²	0.00308	0.00304	0.120	0.0507	0.0306	0.0133	0.148
N	2557	2132	2132	2132	2132	2132	2132

Notes: Robust Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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