Are Students *Really* Biased against Female Professors? - Experimental Evidence from India

Puneet Arora
Management Development Institute
Gurgaon

Moumita Roy
Ahmedabad University

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Motivation

- Worldwide under-representation of women in faculty positions:
  - share of tenure-track women faculty in PhD-granting economics departments in the US was 21.7% (Chevalier, 2020).
  - proportion of female economics professors in the UK has increased by only two percentage points since 2012 (from 13% to 15%)(Bateman et al., 2021).

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- Potential explanation: Gender bias against female instructors in student evaluations of teaching (SET) scores in developed countries (Boring, 2017; Mengel et al., 2019).
- Lower SET scores may lead to reduced time for research, hindering career progression and tenure for female instructors.

Gap in literature

- Previous studies use observational/quasi-experimental data - controlling for teaching quality is challenging.
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  - one of the *lowest* female labor force participation in the world - 23%. (World Bank, 2022).
  - Large evidence of gender inequality in Indian labor market (Budhwar et al., 2005; Zimmermann, 2012; Batra and Reio Jr, 2016)

Gap in literature

- **Why India?**
  - one of the *lowest* female labor force participation in the world - 23%. (World Bank, 2022).
  - Large evidence of gender inequality in Indian labor market (Budhwar et al., 2005; Zimmermann, 2012; Batra and Reio Jr, 2016)
  - Women account for just about 37.8% of university-level faculty in India (AISHE, 2022-23).
  - *Leaky pipeline* exists in India: 76 females per 100 male Assistant Professors, 60 females per 100 male Associate Professors, and 40 females per 100 male Professor (AISHE, 2022-23).

Statistical discrimination theory

- Teaching dimensions that students value in instructors tend to correspond to gender stereotypes (MacNell et al., 2015; Boring, 2017):
  - Male instructors $---->$ leadership skills, animation skills.
  - Female instructors $--->$ preparation of classes, quality of instruction materials.

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- Female instructors are **rewarded for more time-consuming skills**.
- To get better SET scores, women have to **demonstrate competence in both male and female stereotypical characteristics**, but..
- ..they can also be penalized for being authoritative.

Role model theory

- Based on identity economics (Akerlof and Kranton, 2000)
- Students identify more closely with instructors of their own gender.

Statistical discrimination theory + role model theory

−− >>>> Male students give higher ratings to male instructors; female students will be in a double bind.

−− >>>> Gender bias in SETs.

Mitigation

- Information interventions are used to reduce statistical discrimination in the evaluations of employees and job candidates.(Neumark, 2018)
- Providing information on students' gender bias reduces bias against female instructors (Peterson et al., 2019; Boring and Philippe, 2021; Genetin et al., 2022).
- Information which decreases the salience of gender as a characteristic and increases the salience of other characteristics can reduce gender bias (Heilman, 1984).

Information intervention

−− >>>> Information interventions reduces gender bias against female instructors

Preview of Findings

- **Does gender bias exist in student evaluations of teaching (SET) scores in India?**
- **If it exists, does information provision act as a bias-mitigating strategy?**
- **What are the underlying mechanisms?**

Preview of Findings

- **Does gender bias exist in student evaluations of teaching (SET) scores in India?**
- Encouragingly, we do not find evidence of gender bias in SET scores.
- **If it exists, does information provision act as a bias-mitigating strategy?**
- Interestingly, information provision generated a bias in favor of female instructors.
- **What are the underlying mechanisms?**
- Female students drive the bias in favor of female instructors.

Literature Review

- Gender bias in SET scores against female instructors:
  - Europe (France, Iceland, Spain) (Boring, 2017; Ayllón, 2022; Sigurdardottir et al., 2022)
  - Australia (Fan et al., 2019)
  - United States (Mengel et al., 2019)
  - online settings (MacNell et al., 2015; Chávez and Mitchell, 2020; Arbuckle and Williams, 2003)

- Bias driven by male students (Boring and Ottoboni, 2016; Mengel et al., 2019; Ayllón, 2022) [Exception:Boring and Ottoboni (2016)]

- Few papers show bias in favor of female instructors or no bias (Rowden and Carlson, 1996; Bachen et al., 1999; Chisadza et al., 2019; Andersson et al., 2023)

Experimental Design

Goal: We use a randomized natural field experiment to study the causal effect of gender identity (and information provision) on SET scores in India by controlling for teaching quality and style in a hybrid lecture.

Design:

- Large private university in Western India.
- 504 students from 7 sections of a mandatory Principle of Microeconomics class.
- Students choose sections based on class timings and not section professors.
- Intervention:
  - primer audio-visual lecture on the foundational concepts.
  - Recorded lecture with identical slides and scripts.
  - Lecture was modulated into Male and Female voices

Treatments

- 2 x 2 design.
- **Gender No-Information treatments (M-NoInfo & F-NoInfo):** randomly varying perceived gender.
- Instructors were given (hypothetical) non-reserved categories Hindu identities with names that might indicate that the professor is from Northern or Western India.
- Mengel et al. (2019) find that seniority can be a possible mechanism of conveying authority and competence.
- Hypothetical profiles were of senior instructors (Assistant Professors) with 3 years of teaching experience.
- An icon was included to control for differences in body language or facial expressions.

Treatments

- **Gender Information treatments (M-Info & F-Info):** randomly varying perceived gender + students received information about the instructor's accomplishments.
- We provide information about instructor's accomplishments as a signal of competence.
- Objective: reduce information gaps of instructor groups.

Gender-Information treatments

A little bit about Dr.Sunita Sharma

- Teaching Experience:
  - Microeconomics (ECO 100)-2020, 2021
- Educational qualifications:
  - PhD in Economics, Pennsylvania State University, USA, 2019.
  - MA in Economics, Delhi School of Economics, 2014.
- Research Interest:

  Applied Microeconomics, Behavioral Economics, Experimental Economics.
- Professional Services: Economist at the International Monetary Fund (2019)

Gender-Information treatments

A little bit about Dr.Amit Agarwal

- Teaching Experience:
  - Microeconomics (ECO 100) - 2020, 2021
- Educational qualifications:
  - PhD in Economics, Pennsylvania State University, USA, 2019.
  - MA in Economics, Delhi School of Economics, 2014.
- Research Interest:

  Applied Microeconomics, Behavioral Economics, Experimental Economics.
- Professional Services: Economist at the International Monetary Fund (IMF), 2019.

Experimental Design

- Short quiz after lecture -> student performance.
- SET -> ratings on individual teaching characteristics **-quality of instructional materials, teaching effectiveness, preparation and organization of class, clarity of evaluation criteria**, and **overall quality of lecture and instructor**.
- Survey.
- Our experimental design ensured 100 % response rate in SETs.

Experiment Timeline

Timeline

- Step 1: Random assignment at individual level (1 week before experiment)
- Step 2: Email sent about room assignment (2 days before experiment)
- Step 3: Recorded lecture (Experiment day)
- Step 4: Quiz (Experiment day)
- Step 5: SET, Demographics, and Survey (Experiment day)

See SET Questions

Data

Table: Treatment Assignment (2 X 2)

Treatment	**No Information**	**Information**
Female Instructor	132 students	125 students
Male Instructor	124 students	123 students

Summary Statistics

Table: Demographics

	All	Female No Info	Male No Info	Female With Info	Male With Info	p-value
Female	0.50	0.48	0.50	0.52	0.50	0.95
	(0.501)	(0.502)	(0.502)	(0.502)	(0.502)	
Age	17.78	17.89	17.79	17.72	17.72	0.14
	(0.643)	(0.677)	(0.662)	(0.506)	(0.700)	
University State	0.72	0.72	0.73	0.69	0.72	0.92
	(0.451)	(0.452)	(0.445)	(0.464)	(0.449)	
Year of undergraduate	1.12	1.15	1.13	1.08	1.15	0.64
	(0.487)	(0.472)	(0.545)	(0.351)	(0.557)	
Non-STEM	0.98	0.97	1.00	0.99	0.96	0.07
	(0.144)	(0.177)	(0)	(0.0925)	(0.207)	
Received Scholarship	0.08	0.07	0.05	0.11	0.07	0.36
	(0.266)	(0.260)	(0.220)	(0.316)	(0.259)	
Score in Grade 10	0.83	0.84	0.84	0.82	0.83	0.13
	(0.0683)	(0.0692)	(0.0613)	(0.0686)	(0.0731)	
Score in Grade 12	0.85	0.85	0.85	0.84	0.85	0.65
	(0.0660)	(0.0637)	(0.0672)	(0.0595)	(0.0737)	
Done Math in Grade 12	0.36	0.37	0.36	0.33	0.37	0.93
	(0.480)	(0.485)	(0.482)	(0.473)	(0.484)	
Obs.	472	124	119	117	112	

Empirical Model 1: Existence of Gender-bias

$$Y_{is} = \alpha_0 + \alpha_1 Z_{is} + \alpha_2 X_{is} + \mu^0{}_s + \epsilon^0{}_{is} \quad (1)$$

- Y_{is} are the SET scores given by student i in section s
- Z_{is} is the treatment dummy (=1 if Female Instructor, 0 otherwise)
- X_{is} is a vector of individual-level student characteristics
- $\mu^0{}_s$ is section fixed effect
- $\epsilon^0{}_{is}$ is the idiosyncratic error term

Our main coefficient of interest is α_1 which estimates gender-bias on SET scores. A positive value would imply bias in favor of female instructors.

Result: Existence of Gender Bias

Table 2: Treatment Effect on SET Scores

Panel A: All

	(1) Quality	(2) Prep	(3) Effective	(4) Clarity	(5) Lecture	(6) Overall	(7) Average
Female Prof	0.150*	0.222***	0.167***	0.128	0.197**	0.196**	0.176***
	(0.0807)	(0.0782)	(0.0628)	(0.0813)	(0.0826)	(0.0782)	(0.0609)
	[0.08]	[0.008]	[0.008]	[0.11]	[0.02]	[0.01]	[0.005]
Control Mean	3.65	3.50	3.70	3.68	3.55	3.61	3.65
Obs.	504	504	504	504	504	504	504

Panel B: Treatment with No Information

	Quality	Prep	Effective	Clarity	Lecture	Overall	Average
Female Prof	-0.00502	0.0755	0.0145	0.104	0.0139	0.140	0.0389
	(0.118)	(0.108)	(0.0914)	(0.122)	(0.117)	(0.114)	(0.0892)
	[0.97]	[0.46]	[0.87]	[0.40]	[0.90]	[0.23]	[0.67]
Control Mean	3.77	3.63	3.76	3.65	3.64	3.64	3.71
Obs.	256	256	256	256	256	256	256

Panel C: Treatments with Information

	Quality	Prep	Effective	Clarity	Lecture	Overall	Average
Female Prof	0.307***	0.351***	0.335***	0.166	0.369***	0.252**	0.318***
	(0.115)	(0.115)	(0.0878)	(0.108)	(0.121)	(0.113)	(0.0851)
	[0.007]	[0.003]	[0.000]	[0.15]	[0.003]	[0.02]	[0.002]
Control Mean	3.53	3.37	3.63	3.72	3.47	3.59	3.58
Obs.	248	248	248	248	248	248	248

Notes: Panel A presents the gender bias by students across all 4 treatments. Panel B considers only M-NoInfo and F-NoInfo samples, and Panel C considers only M-Info and F-Info samples. We categorize SET score variables into different qualities representing a professor and her/his teachings, shown in Table A2. Each teaching dimension is rated on 1 to 5 scale, with 1 representing "Strongly disagree" and 5 representing "Strongly agree". Each model is estimated using Ordinary Least Squares model, and controls for student age, gender, type of degree programme, state of birth, baseline test score (grade 12), whether math done in grade 12, whether received scholarship, mother's education, father's education and family income. Each model also includes section fixed effects and reports robust standard errors in parenthesis. $p^* < 0.10, p^{**} < 0.05, p^{***} < 0.01$. Randomization inference p-values with 1000 permutations are presented in square brackets. Control means represent average SET scores received by male professors in M-NoInfo and M-Info treatments in Panel A; only in M-NoInfo treatment in Panel B; and only in M-Info treatment in Panel C.

Empirical Model 2: Effect of Information

$$Y_{is} = \gamma_0 + \gamma_1 Z_{is} + \gamma_2 X_i + \gamma_3 Info_{is} + \gamma_4 Z_{is} * Info_{is} + \mu^2{}_s + \epsilon^2{}_{is} \quad (2)$$

- Y_{is} are the SET scores given by student i in section s
- Z_{is} is the treatment dummy (=1 if Female Instructor, 0 otherwise)
- $Info_{is}$ is the treatment dummy (=1 if Information about instructor shared, 0 otherwise)

Our main coefficient of interest is γ_4 which estimates the marginal effect of Information intervention on SET scores of Female instructors. A positive value would imply that information benefits female instructors more than male instructors.

Effect of Information

Aggregate Data:

Table: Treatment Effect

	(1) Quality	(2) Prep	(3) Effective	(4) Clarity	(5) Lecture	(6) Overall	(7) Average
Female Prof	-0.00131	0.0891	0.00810	0.0943	0.0317	0.143	0.0387
	(0.116)	(0.108)	(0.0908)	(0.121)	(0.115)	(0.111)	(0.0882)
Info	-0.248**	-0.274**	-0.149	0.0617	-0.178	-0.0665	-0.155*
	(0.121)	(0.118)	(0.0946)	(0.124)	(0.119)	(0.112)	(0.0906)
Female Prof# Info	0.305*	0.265*	0.323**	0.0709	0.335**	0.106	0.277**
	(0.163)	(0.158)	(0.126)	(0.163)	(0.165)	(0.158)	(0.123)
Control Mean	3.77	3.63	3.76	3.65	3.64	3.64	3.71
Obs.	504	504	504	504	504	504	504

Female instructors receive higher ratings after students receive information about the female instructor's accomplishments.

Empirical Model 3: Mechanism

$$Y_{is} = \beta_0 + \beta_1 Z_{is} + \beta_2 X_{is} + \beta_3 Female_{is} + \beta_4 Z_{is} * Female_{is} + \mu^1{}_s + \epsilon^1{}_{is} \quad (3)$$

- Y_{is} are the SET scores given by student i in section s
- Z_{is} is the treatment dummy (=1 if Female Instructor, 0 otherwise)
- $Female_{is}$ is the gender indicator of student (=1 if female, 0 if male)

Our main coefficient of interest is β_4 which estimates in-group bias. A positive value would imply that female students rate female instructors more favorably than male instructors.

Mechanism: Ingroup Bias

Aggregate Data:

	(1) Quality	(2) Prep	(3) Effective	(4) Clarity	(5) Lecture	(6) Overall	(7) Average
Female Prof	0.0355	0.126	-0.00840	-0.0173	0.0234	-0.00200	0.0180
	(0.118)	(0.117)	(0.0941)	(0.117)	(0.124)	(0.116)	(0.0920)
Female Student	-0.0738	0.0747	-0.0468	-0.0847	-0.0831	-0.0460	-0.0359
	(0.119)	(0.122)	(0.0973)	(0.129)	(0.119)	(0.112)	(0.0930)
Female Prof#	0.232	0.192	0.355***	0.294*	0.351**	0.400***	0.319***
Female Student	(0.159)	(0.157)	(0.127)	(0.166)	(0.162)	(0.154)	(0.122)
Control Mean	3.65	3.50	3.70	3.68	3.55	3.61	3.65
Obs.	504	504	504	504	504	504	504

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Obs.	504	504	504	504	504	504	504

Female students give significantly higher ratings to female instructors

Mechanism: Ingroup Bias

Gender No-Information Treatments:

	(1) Quality	(2) Prep	(3) Effective	(4) Clarity	(5) Lecture	(6) Overall	(7) Average
Female Prof	-0.142	-0.0146	-0.142	0.0370	-0.107	-0.00881	-0.0959
	(0.166)	(0.155)	(0.133)	(0.181)	(0.175)	(0.168)	(0.132)
Female Student	0.0458	0.152	0.0501	0.168	0.108	0.155	0.0871
	(0.170)	(0.176)	(0.133)	(0.193)	(0.149)	(0.152)	(0.128)
Female Prof#	0.278	0.182	0.317*	0.135	0.244	0.302	0.273
Female Student	(0.230)	(0.218)	(0.181)	(0.245)	(0.228)	(0.216)	(0.174)
Control Mean	3.77	3.63	3.76	3.65	3.64	3.64	3.71
Obs.	256	256	256	256	256	256	256

No significant difference in ratings by female and male students.

Mechanism: Ingroup Bias

Gender Information Treatments:

	(1) Quality	(2) Prep	(3) Effective	(4) Clarity	(5) Lecture	(6) Overall	(7) Average
Female Prof	0.247	0.264	0.140	-0.0705	0.127	0.00585	0.140
	(0.175)	(0.173)	(0.130)	(0.147)	(0.181)	(0.166)	(0.126)
Female Student	-0.130	0.0230	-0.126	-0.337**	-0.300*	-0.223	-0.141
	(0.164)	(0.173)	(0.140)	(0.166)	(0.181)	(0.160)	(0.131)
Female Prof#	0.122	0.174	0.391**	0.476**	0.486**	0.495**	0.359**
Female Student	(0.221)	(0.228)	(0.170)	(0.218)	(0.225)	(0.218)	(0.164)
Control Mean	3.53	3.37	3.63	3.72	3.47	3.59	3.58
Obs.	248	248	248	248	248	248	248

Female students give higher ratings to female instructors.

Effect on Test Scores

Table: Treatment Effect on Test Scores

	(1) (All) Test scores	(2) (No Info) Test scores	(3) (Info) Test scores
Female Prof	0.000181	0.260	-0.272
	(0.127)	(0.180)	(0.179)
	[0.99]	[0.13]	[0.13]
Control Mean	4.29	4.19	4.38
Obs.	504	256	248

Student achievement is not correlated with SET scores

Summary

- No bias in SET scores in Gender No-Information treatments $---$ >>> ***suggests that gender bias against female instructors in SET scores is context-dependent.***

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- Bias in favor of female instructors in Gender Information treatments $---$ >>> ***suggests that information as a signal may be interpreted differently for each gender.***

Summary

- No bias in SET scores in Gender No-Information treatments
  $---$ >>> ***suggests that gender bias against female instructors in SET scores is context-dependent.***

- Bias in favor of female instructors in Gender Information treatments
  $---$ >>> ***suggests that information as a signal may be interpreted differently for each gender.***

- Higher rating of female instructors driven by female students
  $---$ >>> ***suggests in-group bias***..

Summary

- No bias in SET scores in Gender No-Information treatments $---$ >>> ***suggests that gender bias against female instructors in SET scores is context-dependent.***
- Bias in favor of female instructors in Gender Information treatments $---$ >>> ***suggests that information as a signal may be interpreted differently for each gender.***
- Higher rating of female instructors driven by female students $---$ >>> ***suggests in-group bias***..
- ..***but not role model effects*** because student learning is not significantly higher with female instructors.
- Policy Implication: SET scores do not necessarily measure actual teaching effectiveness.

Thank you!

moumita.roy@ahduni.edu.in

SET Questions

Quality of instructional materials:

- The lecture was well designed and got me interested in the subject.

Preparation and organization of class

- The instructor has used appropriate technology to support teaching and learning.
- The teaching methodology was innovative.

Clarity of Evaluation Criteria

- The instructor clearly explained the assessment criteria of the lecture.

SET Questions

Teaching effectiveness

- The instructor conducted himself/herself in a professional manner.
- The instructor was knowledgeable about the subject matter of the lecture.
- The instructor has shown enthusiasm in teaching.
- The instructor was able to explain concepts well.
- The instructor encouraged me to practice critical thinking.
- The instructor was able to communicate well.
- The instructor was able to contribute well to my intellectual development.

Overall an interesting lecture

- Overall, this was an interesting lecture, and I learned a lot from this lecture.

Overall evaluation of instructor

- Overall, I enjoyed learning from this instructor.

Timeline

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