Class differences in social networks: Evidence from a referral experiment

1-hour presentation

Manu Munoz [1] Ernesto Reuben [1,2] Reha Tuncer [3]

[1]Luxembourg Institute of Socioeconomic Research

[2]NYU Abu Dhabi

[3]University of Luxembourg

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Motivation and Research Question

- Understand persistent class differences in labor the market, like the underrepresentation of Low-SES researchers in top academic institutions [Stansbury and Rodriguez, 2024]
- Focus on class biases in referrals
    - Most jobs are found through referrals [Topa, 2011]
    - Refferals depend on social networks, which exhibit homophily [McPherson et al., 2001]
- Are there social class biases in referrals?
- If so, what are the potential drivers of these biases?

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- Universidad Autónoma de Bucaramanga (UNAB)
- Approx. 6000 students across all social classes
- Administrative data including gender, age, program, GPA, classes attended, year of entry, and the entry exam scores

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Design

- Ask students to refer someone they have taken at least one class with
- Pay according to the student's math and verbal scores in the national entry exam
- Incentivize better refferals by increasing reward as referral score goes higher

Your recommendation

We are interested in your recommendation of the person you consider best to solve similar problems to those in the **Math test**.

* Only someone with whom you have taken at least one class...

* We will not contact your recommendation...

Please write the name of your recommendation:

John
John Lennon (Music - 2018)
John Stuart Mill (Law - 2020)

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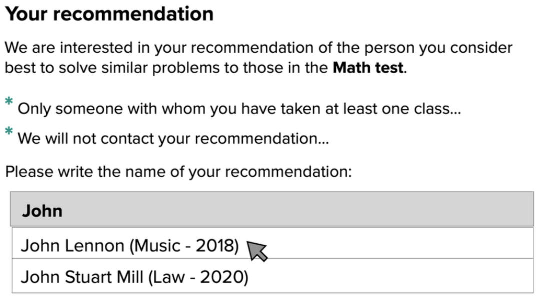

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Procedures

- Recruited participants by emailing 4500 students ($>$1st year)
- 30 minute online experiment in Qualtrics
- Average payment of 80 USD (lottery for 1 out of 10 participants)
- 840 complete responses
- Final sample 734 participants who referred someone they took a class with

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Selection into the experiment

- Higher performing students overrepresented See
- Low-SES overrepresented
- High-SES underrepresented

	Admin Data	Sample	p
Reading score	62.651	65.183	< 0.001
Math score	63.973	67.477	< 0.001
GPA	3.958	4.012	< 0.001
Low-SES	0.343	0.410	< 0.001
Med-SES	0.505	0.499	0.763
High-SES	0.153	0.091	< 0.001
Observations	4,417	734	

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Balance between treatments

- Successful randomization

	Baseline	Bonus	p
Reading score	64.712	65.693	0.134
Math score	67.366	67.597	0.780
GPA	4.003	4.021	0.445
Connections	173.40	176.88	0.574
Classes taken	3.939	3.719	0.443
Low-SES	0.419	0.401	0.615
Med-SES	0.492	0.506	0.714
High-SES	0.089	0.094	0.824
Observations	382	352	734

Network size and tie strength

- Classes taken with peers increase over time
- Connections peak around 7 semesters and decline as students change majors or graduate

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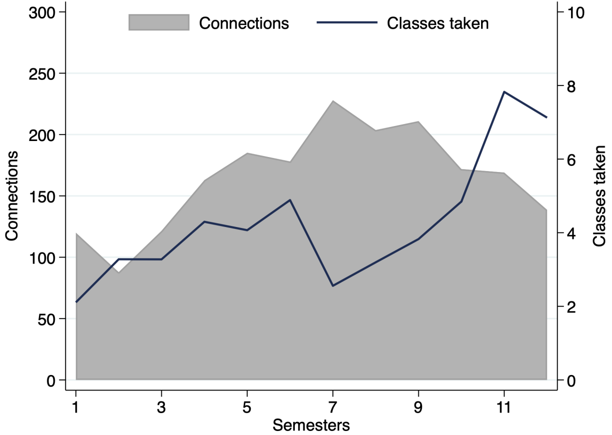
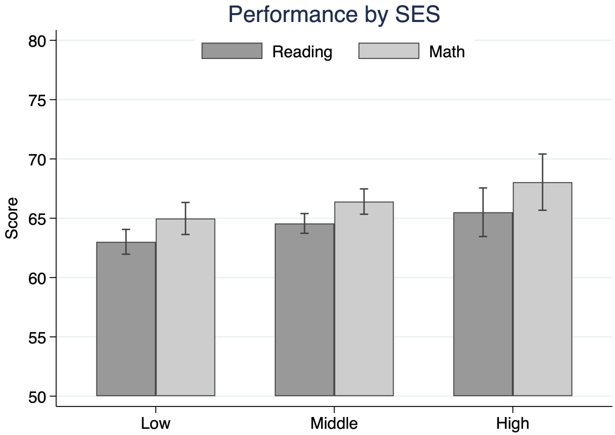


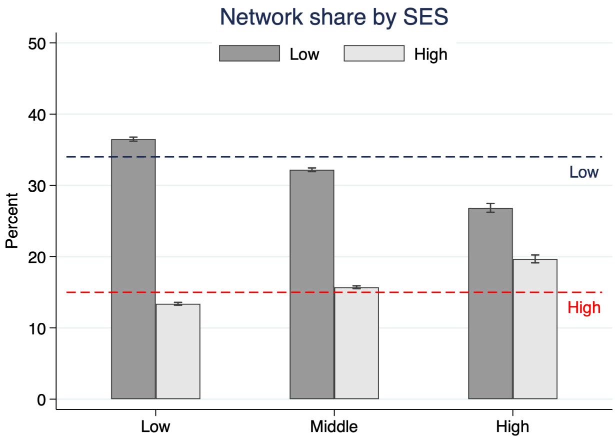
Entry exam performance across SES

- Very close distribution of entry exam scores in the sample because of selection



Network-level SES shares

- 35 % of UNAB is **Low-SES**, and 15 % **High-SES**
- Network shares are very different from the UNAB population
- Why?



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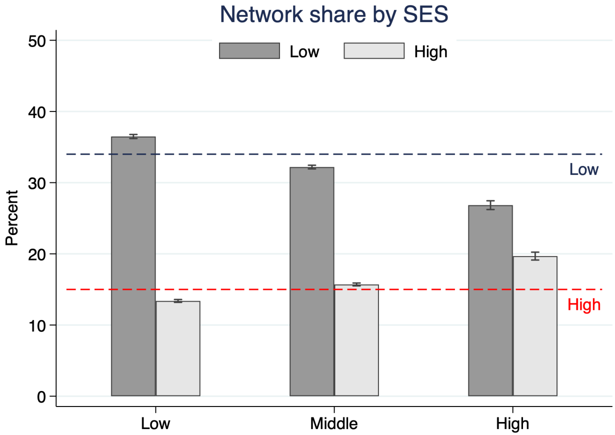

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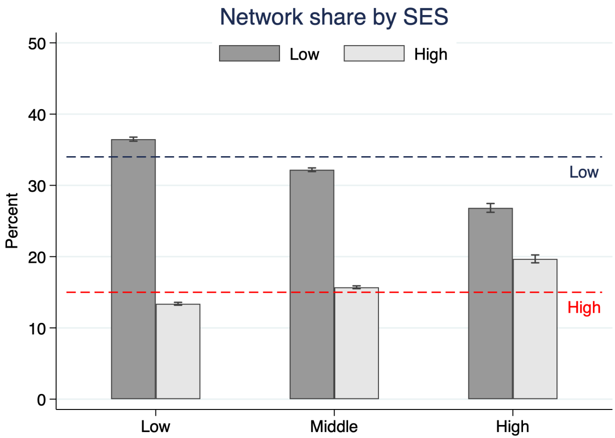
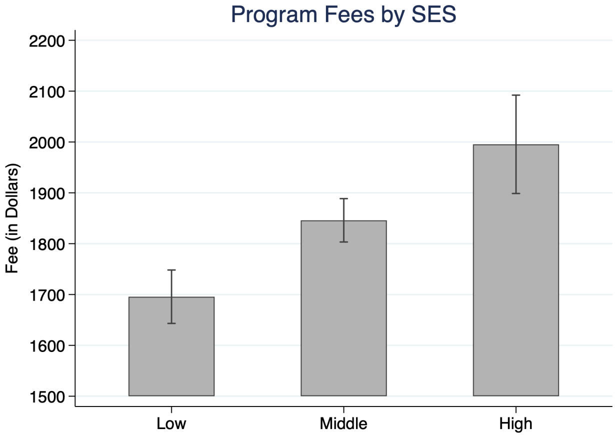


Selection into programs

- Low-SES study in more affordable programs
- Large difference as net average monthly salary around \$350



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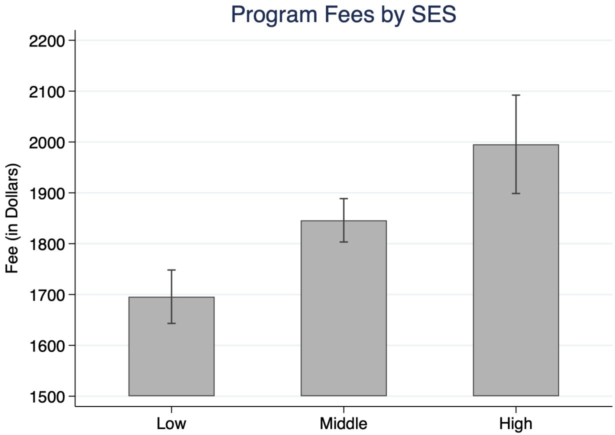
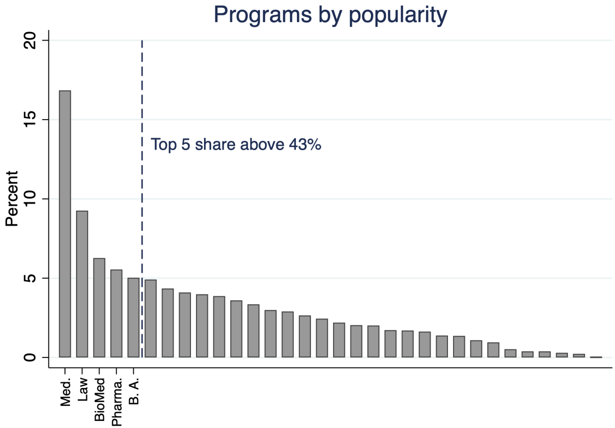


Selection into programs ctd.

- Largest programs are Medicine, Law, Biomedical Engineering, Pharmacology, and B. A.
- These comprise over 43% of all students
- But represent 60% of High-SES



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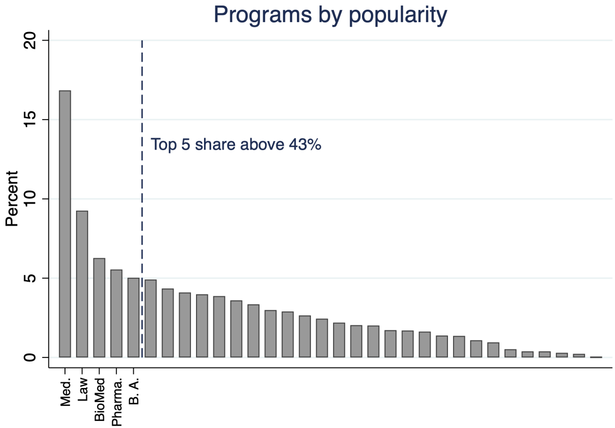

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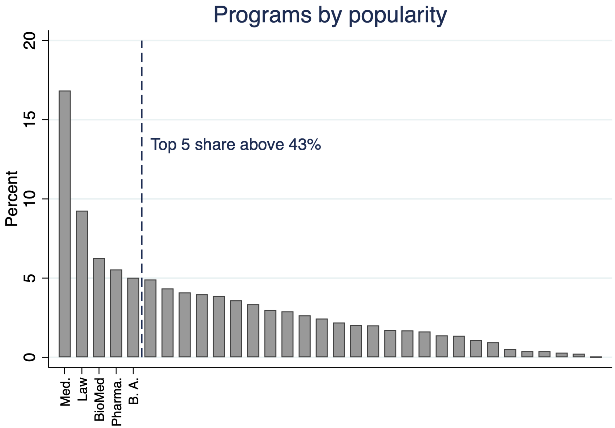
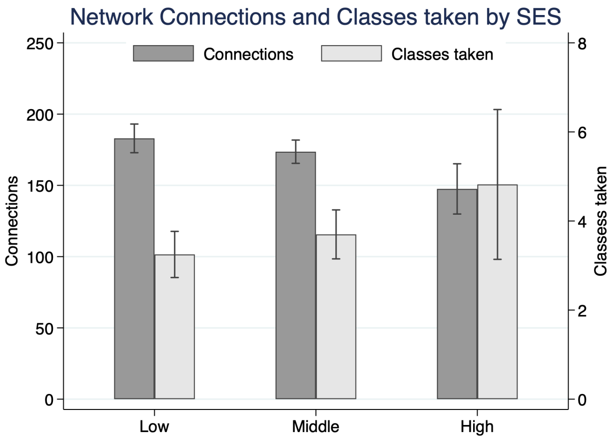


Network dynamics and program selection

- Connections decrease with SES
- Classes taken with peers increases with SES



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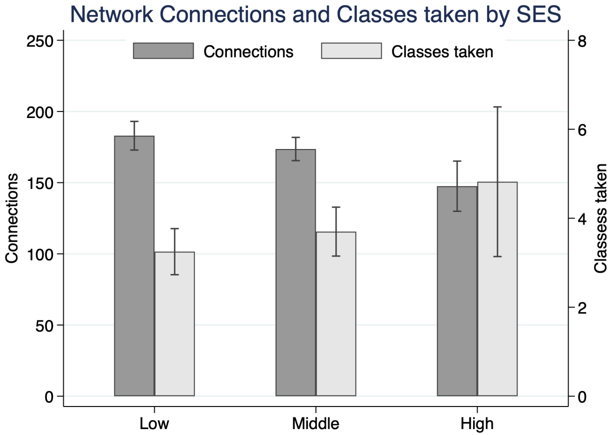
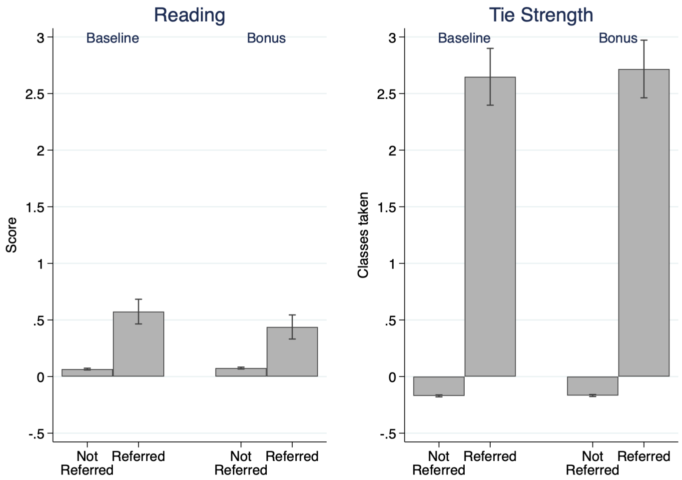


Referrals for Reading

- Referrals have higher reading scores and much higher tie strength
- No treatment effect on the referred (t-tests, $p > 0.08$)



Referrals for Math

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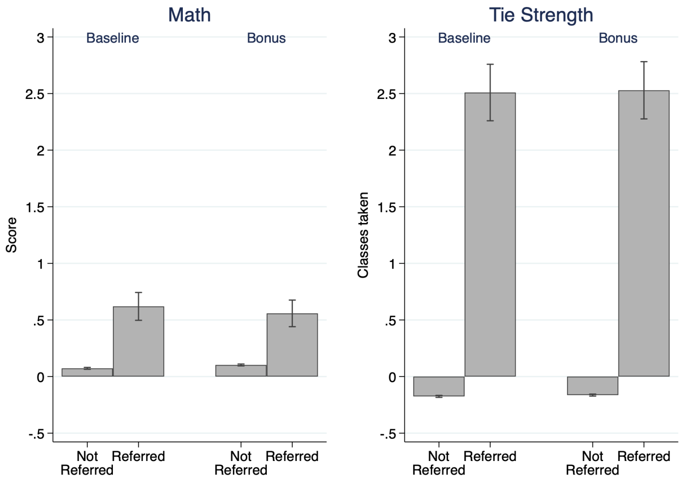
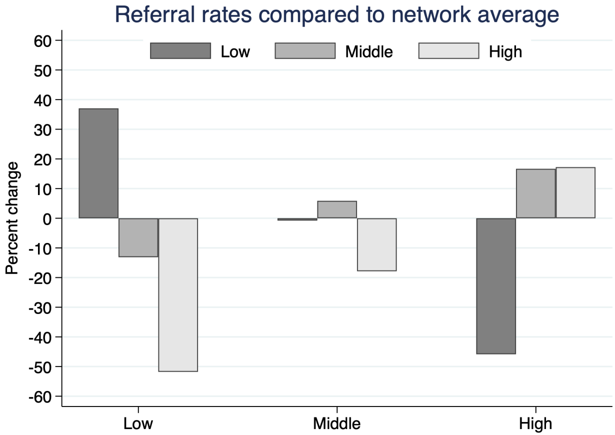


Referral SES composition

- Stark differences in referral rates considering network compositions were imbalanced to begin with
- Do differences persist after fixing scores and classes taken?



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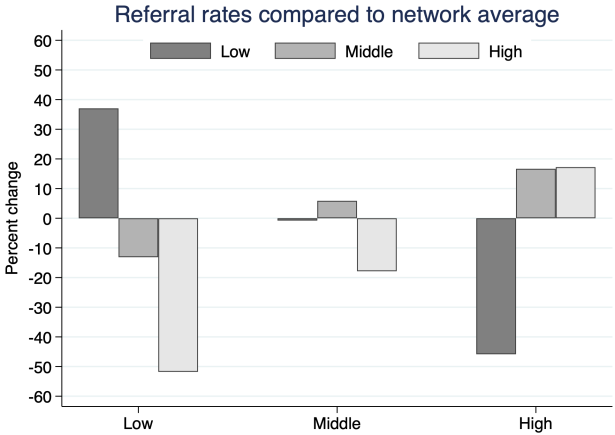

Is there a SES bias in referrals?

FE Logit:

$$\Pr(\text{Refer}_{ij} = 1) = \Lambda\left(\beta_1 \text{SES}_j + \beta_2 \text{Score}_j + \beta_3 \text{Tie}_{ij} + \beta_4 \text{Score}_j \times \text{Tie}_{ij} + \alpha_i\right)$$

- Refer_{ij}: Binary outcome indicating whether individual i refers individual j
- SES_j: Referral j is Low, Middle, or High SES
- Score_j: Standardized Math or Reading score of referral j
- Tie_{ij}: Standardized number of classes taken together for i and j
- α_i: Individual fixed effect for referrer i

Bias against High-SES in aggregate

- Bias against High-SES
- Score and tie strength are strong predictors of referrals
- Small interaction between score and tie strength
- How about by referrer SES?

	(1)	(2)	(3)
Low	0.152**	-0.013	-0.013
	(0.070)	(0.080)	(0.080)
High	-0.300***	-0.306***	-0.315***
	(0.108)	(0.115)	(0.116)
Nominee score		0.618***	0.527***
		(0.034)	(0.035)
Tie		0.916***	0.894***
		(0.026)	(0.026)
Score x Tie			0.059***
			(0.015)
Observations	256997	256997	256997
Ind.	734	734	734
Chi-test	17.44	1602.42	1640.06

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SES extremes reveal the origin of biases

- Low-SES referrers are biased against High-SES and vice-versa
- Mid-SES show smallest bias to either extreme
- Does the bias impact referral performance?

	Low-SES (1)	Middle-SES (2)	High-SES (3)
Low	0.237*	-0.155	-0.583*
	(0.124)	(0.114)	(0.331)
High	-0.451**	-0.281*	-0.382
	(0.223)	(0.157)	(0.293)
Nominee score	0.540***	0.503***	0.650***
	(0.056)	(0.049)	(0.116)
Tie	0.842***	0.930***	0.959***
	(0.037)	(0.039)	(0.104)
Score x Tie	0.043*	0.057***	0.148**
	(0.022)	(0.021)	(0.066)
Observations	110142	127088	19767
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Chi-test	804.58	766.33	144.77

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Who makes better referrals?

OLS:

$$\text{Premium}_{ij} = \beta_0 + \beta_1 \text{SES}_i + \beta_2 \text{Score}_i + \beta_3 \Delta\text{OBlf}_i + \beta_4 \Delta\text{NBlf}_i + \text{X}_i'\gamma + \epsilon_i$$

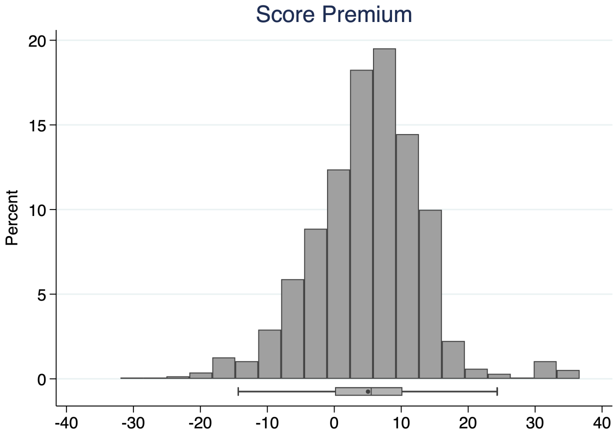
- Premium_i: Nominee j's test z-score minus mean score of i's network
- SES_i: Referrer i's socioeconomic status (Low, Middle, High)
- ΔOBlf_i, ΔNBlf_i: i's beliefs on own and nominee test scores minus actual scores (standardized)
- Score_i: Referrer i's own test z-score

Controls:

- Referrer i's treatment (Baseline vs. Bonus)
- Test area indicator (Math vs. Reading)
- Number of classes taken together for i and nominee j

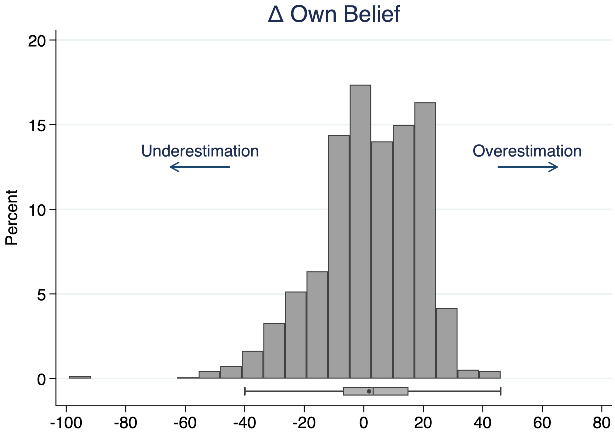
Referals are better than network average

- Defined as nominee j's score minus network average for each referrer i across Math and Reading
- No difference between SES groups See



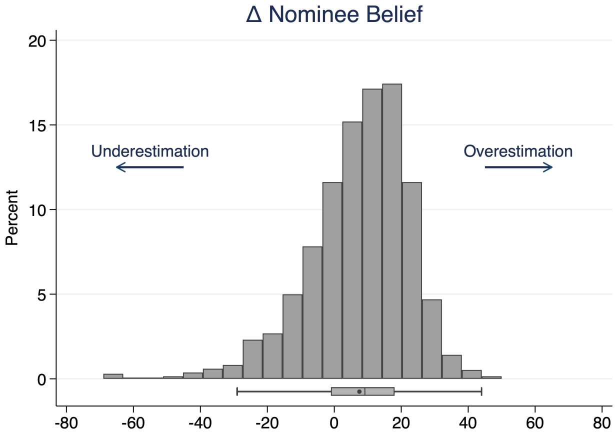
Beliefs about own scores are accurate

- Defined as referrer i's own beliefs minus their score across Math and Reading
- No difference between SES groups See



Beliefs about nominees reveal a positive bias

- Defined as referrer i's beliefs about nominee j minus j's score across Math and Reading
- No difference between SES groups See
- Did not collect beliefs about SES group performance in general



Referrer beliefs and scores matter

- Referrer *i*'s score predicts premium
- Accuracy on own scores increases premium See
- Accuracy on nominee beliefs increases premium See
- No effect of SES
- How about the interaction between SES, scores and beliefs?

	(1)	(2)	(3)
Low	0.068	0.031	0.026
	(0.066)	(0.061)	(0.061)
High	0.219**	0.158	0.155
	(0.099)	(0.100)	(0.100)
Own score		0.269***	0.264***
		(0.031)	(0.032)
Δ own belief		0.237***	0.241***
		(0.038)	(0.038)
Δ nominee belief		-0.383***	-0.378***
		(0.045)	(0.044)
Controls	No	No	Yes
Observations	1,342	1,342	1,342
Ind.	734	734	734

No heterogeneity in beliefs and performance

- **Marginally** stronger effect of own score for Low-SES (joint F-test $p < 0.1$)
- Effect of own belief driven by outliers

	(1)
Own score x Low	0.128*
	(0.065)
Own score x High	-0.043
	(0.101)
Δ own belief x Low	0.009
	(0.082)
Δ own belief x High	-0.248**
	(0.118)
Δ nominee belief x Low	0.002
	(0.094)
Δ nominee belief x High	0.039
	(0.159)
Observations	1,342
Individuals	734

Conclusion

- Networks are separated by SES
- Low and High-SES exhibit bias against one another and worsen the network effect in referrals
- All referrers pick those with whom they take a lot of courses and better performers from network
- All referrers uniformly nominate better as their own scores get higher, have more accurate beliefs about own and nominee scores
- Individuals across SES refer equally well ...
- ... but **prefer** nominating similar others in SES

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Reading

- Reading score and tie strength are strong predictors of referrals
- No interaction between reading score and tie strength
- No evidence for a Low-SES bias Alt. Specification

	(1)	(2)	(3)
Low-SES	0.143*	-0.007	-0.007
	(0.086)	(0.101)	(0.102)
High-SES	-0.293**	-0.271*	-0.275**
	(0.128)	(0.139)	(0.139)
Nominee score		0.566***	0.513***
		(0.044)	(0.048)
Tie		0.949***	0.939***
		(0.031)	(0.032)
Score x Tie			0.030
			(0.018)
Observations	128847	128847	128847
Ind.	673	673	673
Chi-test	10.81	1117.46	1145.58

Math

- Math score and tie strength are strong predictors of referrals
- Significant but small interaction between math score and tie strength
- No evidence for a Low-SES bias Alt. Specification

	(1)	(2)	(3)
Low-SES	0.161*	-0.013	-0.015
	(0.086)	(0.099)	(0.100)
High-SES	-0.309**	-0.343**	-0.361**
	(0.131)	(0.142)	(0.144)
Nominee score		0.662***	0.546***
		(0.040)	(0.042)
Tie		0.885***	0.851***
		(0.029)	(0.029)
Score x Tie			0.089***
			(0.019)
Observations	128150	128150	128150
Ind.	669	669	669
Chi-test	12.38	1122.75	1154.40

Reading (Low-SES vs others)

- Alternative specification with binary Low-SES
- No evidence for a Low-SES bias
- Consistent with main model

Return

	(1)	(2)	(3)
Low-SES	0.199**	0.041	0.042
	(0.083)	(0.100)	(0.100)
Nominee Score		0.561***	0.509***
		(0.044)	(0.048)
Tie		0.951***	0.941***
		(0.031)	(0.032)
Score x Tie			0.029
			(0.018)
Observations	128,847	128,847	128,847
Ind.	673	673	673
Chi-test	5.73	1100.40	1127.92

Math (Low-SES vs others)

- Alternative specification with binary Low-SES
- No evidence for a Low-SES bias
- Consistent with main model

Return

	(1)	(2)	(3)
Low-SES	0.220***	0.049	0.050
	(0.083)	(0.097)	(0.098)
Nominee Score		0.653***	0.538***
		(0.040)	(0.041)
Tie		0.887***	0.854***
		(0.029)	(0.030)
Score x Tie			0.088***
			(0.019)
Observations	128,150	128,150	128,150
Ind.	669	669	669
Chi-test	7.02	1124.24	1156.08

Reading across SES

- Restrict sample by referrer SES
- Low-SES bias against other SES
- No evidence for a bias against Low-SES Alt. Specification

	Low-SES (1)	Middle-SES (2)	High-SES (3)
Low-SES	0.266*	-0.202	-0.275
	(0.155)	(0.149)	(0.369)
High-SES	-0.307	-0.254	-0.511
	(0.268)	(0.186)	(0.377)
Nominee score	0.548***	0.483***	0.553***
	(0.076)	(0.067)	(0.179)
Tie	0.873***	0.991***	0.986***
	(0.046)	(0.046)	(0.128)
Score x Tie	0.019	0.021	0.145**
	(0.027)	(0.027)	(0.072)
Observations	54611	64596	9640
Ind.	275	340	58
Chi-test	531.49	553.06	97.57

Reading across SES (Low-SES vs others)

- Alternative specification with binary Low-SES
- Low-SES bias against other SES
- No evidence for a bias against Low-SES
- Consistent with main model

Return

	Low-SES	Other-SES
	(1)	(2)
Low-SES	0.312**	-0.160
	(0.153)	(0.137)
Nominee score	0.545***	0.486***
	(0.076)	(0.062)
Tie	0.876***	0.996***
	(0.046)	(0.044)
Score x Tie	0.019	0.036
	(0.027)	(0.025)
Observations	54611	74236
Ind.	275	398
Chi-test	517.41	627.40

Math across SES

- Restrict sample by referrer SES
- Low-SES bias against High-SES
- High-SES bias against Low-SES Alt. Specification

	Low-SES	Middle-SES	High-SES
	(1)	(2)	(3)
Low-SES	0.208	-0.101	-0.986**
	(0.150)	(0.145)	(0.469)
High-SES	-0.619**	-0.313	-0.269
	(0.283)	(0.195)	(0.381)
Nominee score	0.540***	0.526***	0.730***
	(0.064)	(0.060)	(0.128)
Tie	0.814***	0.870***	0.929***
	(0.041)	(0.043)	(0.128)
Score x Tie	0.067**	0.096***	0.160
	(0.028)	(0.029)	(0.097)
Observations	55531	62492	10127
Ind.	283	327	59
Chi-test	525.71	561.64	110.76

Math across SES (Low-SES vs others)

- Alternative specification with binary Low-SES
- Low-SES bias against other SES
- No evidence for a bias against Low-SES
- Consistent with main model

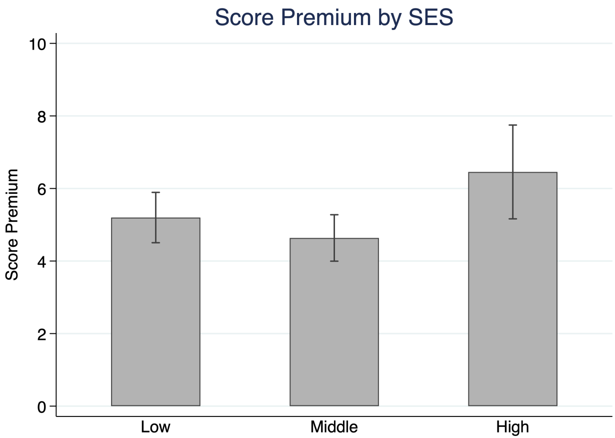
Return

	Low-SES (1)	Other-SES (2)
Low-SES	0.296**	-0.138
	(0.147)	(0.136)
Nominee score	0.533***	0.541***
	(0.063)	(0.055)
Tie	0.820***	0.882***
	(0.042)	(0.042)
Score x Tie	0.064**	0.106***
	(0.028)	(0.027)
Observations	55531	72619
Ind.	283	386
Chi-test	523.84	647.99

No differences for Score Premium by SES

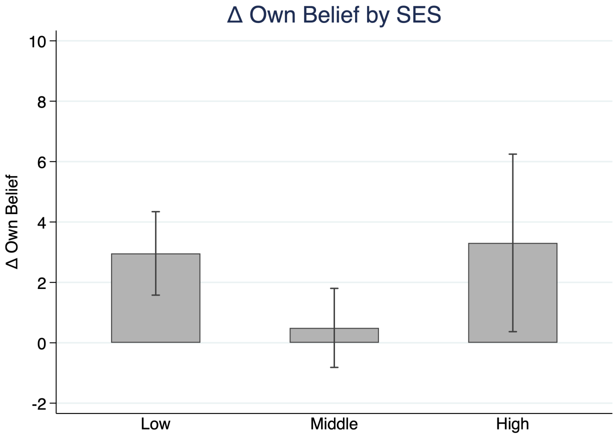
- Middle-SES refer slightly worst (joint F-test, $p < 0.1$)

  Return



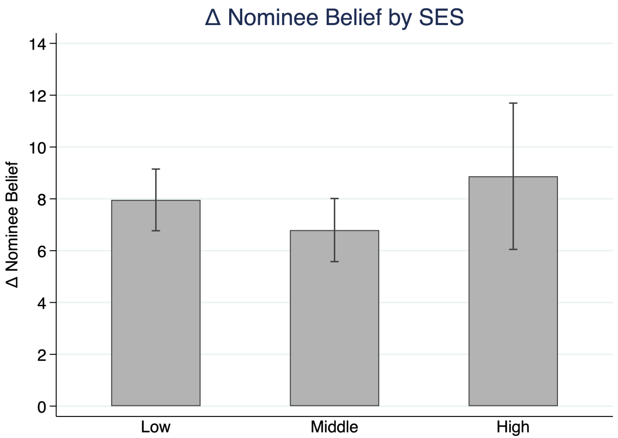
No differences for own score beliefs by SES

- Middle-SES are slightly more accurate (joint F-test, $p < 0.1$) Return



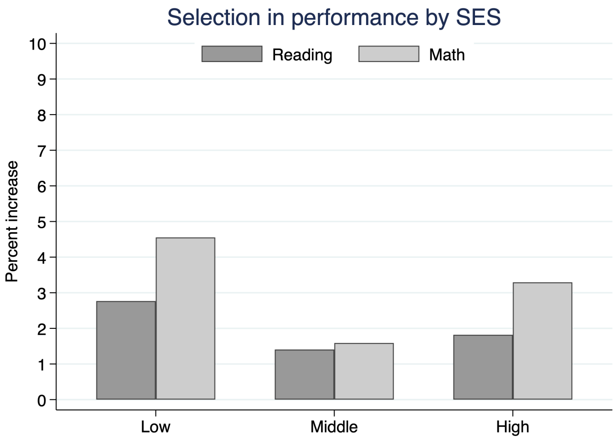
No differences for nominee score beliefs by SES

- No difference (joint F-test, $p = 0.41$) Return



Strong selection by Low-SES

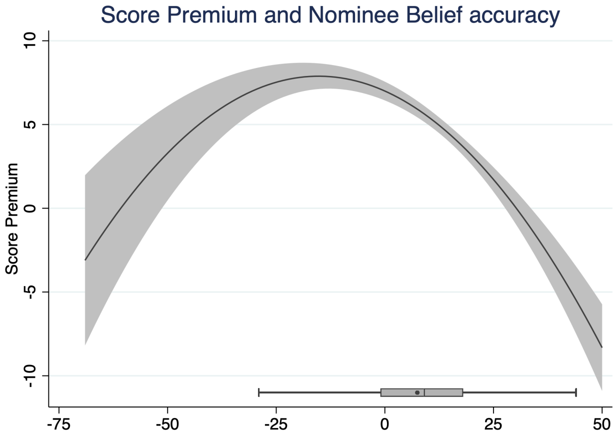
- Significant Low-SES selection (t-tests, $p < 0.01$)
- Other SES groups do select less (t-tests, $p > 0.05$) Return



Nominee Beliefs are rewarded for accuracy

- Negative coeffient is explained by quadratic shape

Return



Own score beliefs are rewarded for accuracy

- Positive coeffient is explained by quadratic shape and extreme outliers Return