Class differences in social networks: Evidence from a referral experiment

1-hour presentation

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Motivation

- Understand persistent class differences in labor the market, like the underrepresentation of Low-SES researchers in elite academic institutions [Stansbury and Rodriguez, 2024]
- Focus on class biases in referrals

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Referrals and Social Networks

- Most jobs are found through referrals [Topa, 2011]
- Refferals depend on social networks, which exhibit homophily [McPherson et al., 2001]
- Referrers tend to refer their strong ties, limiting diversity and reinforcing existing inequalities [Kramarz et al., 2014; Gee et al., 2017]
- *Are there social class biases in referrals?*
- *If so, what are the potential drivers of these biases?*

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- Approx. 6000 students across all social classes
- Administrative data including SES, age, program, GPA, classes attended, year of entry, and the entry exam scores

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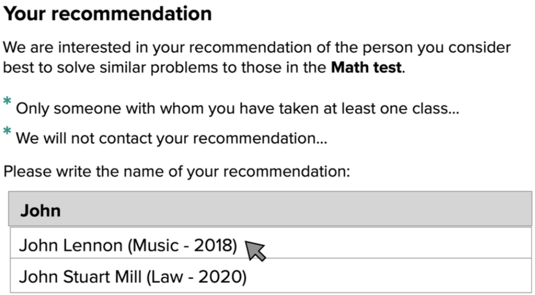
Design

- 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
- Treatments: Baseline vs. Bonus


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...

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Please write the name of your recommendation:

John

John Lennon (Music - 2018)

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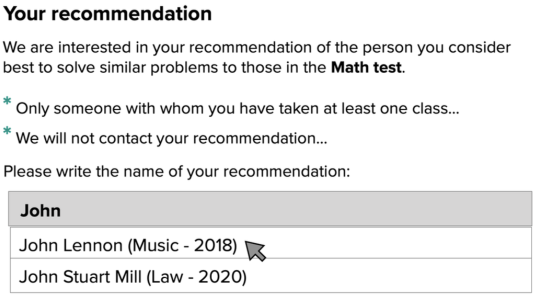

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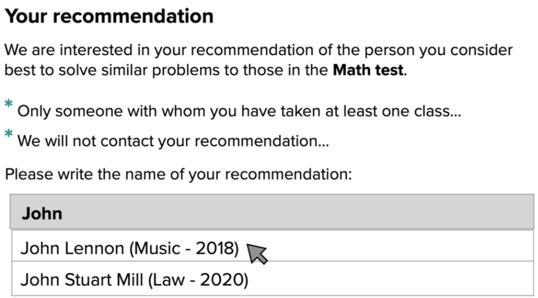
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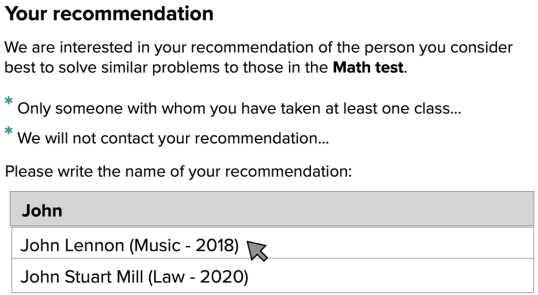

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Procedures

- Recruited participants by emailing 4500 students ($>$1st year)
- 30 minute online experiment in Qualtrics
- Average payment of 8 USD
- 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
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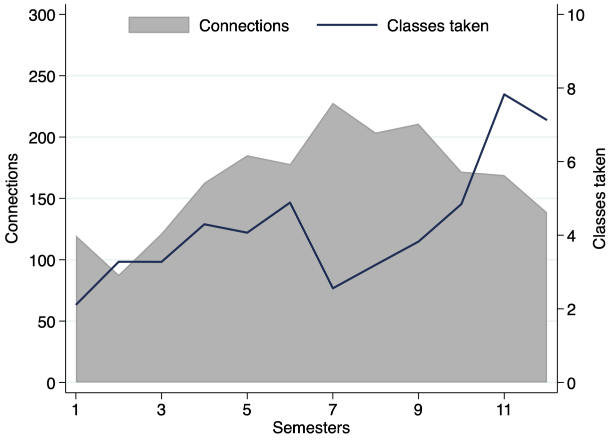
Balance between treatments

- 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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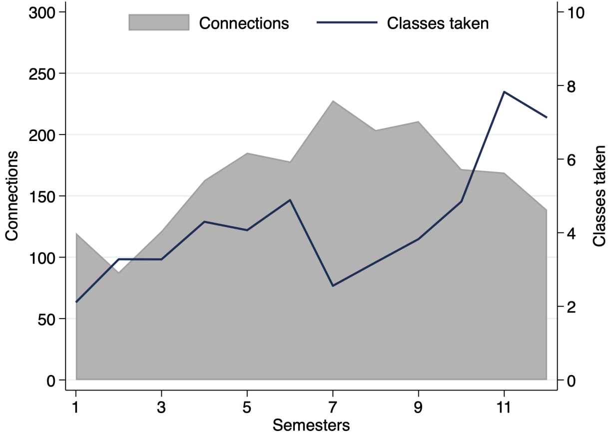
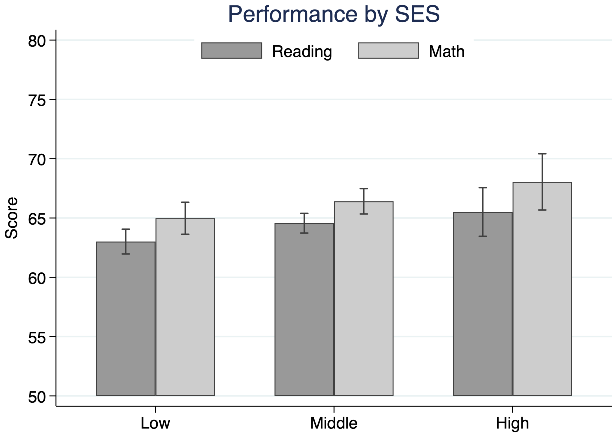


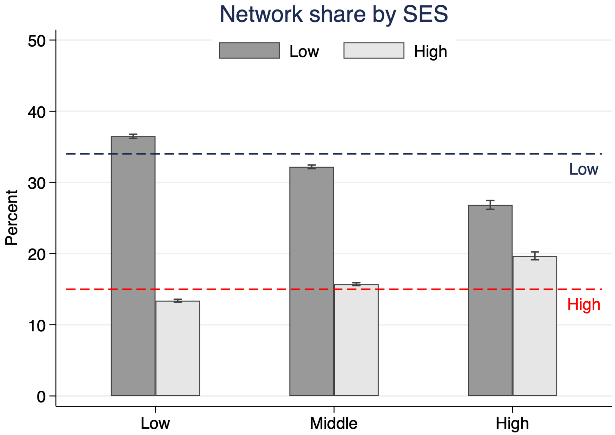
Entry exam performance across SES

- 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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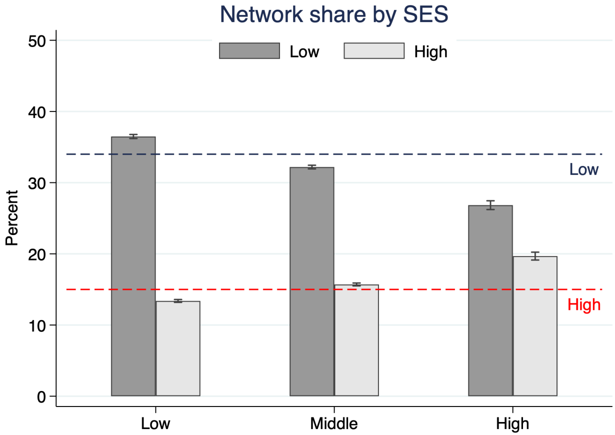

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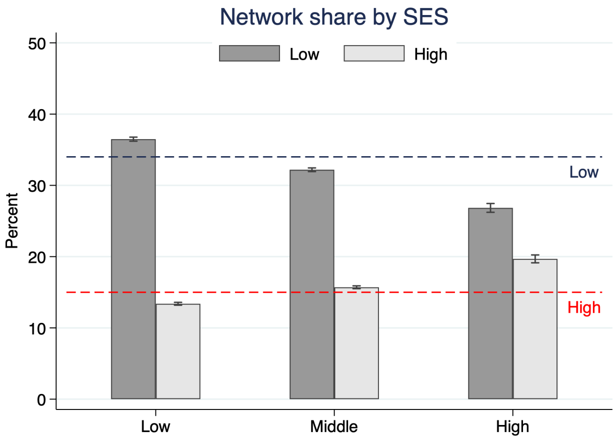
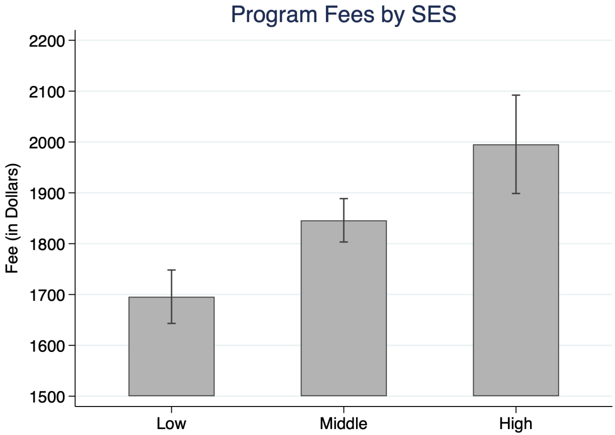


Selection into programs

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



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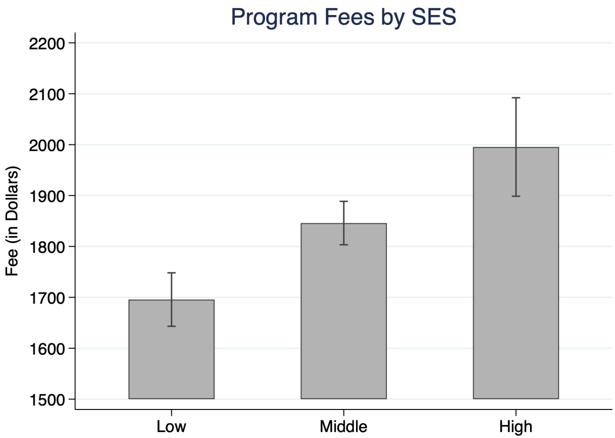
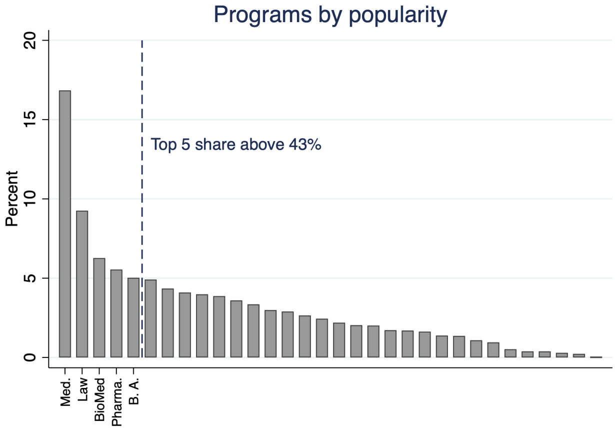


Selection into programs ctd.

- 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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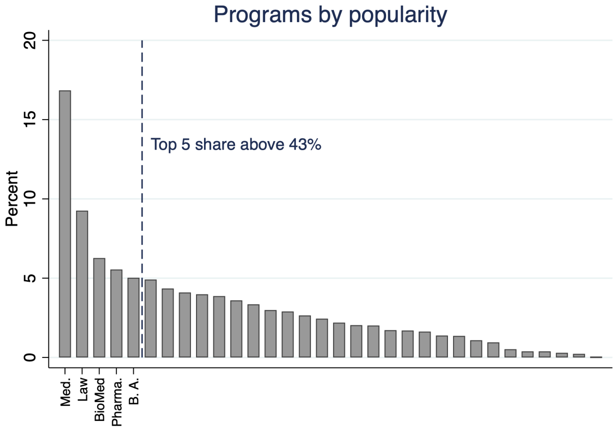

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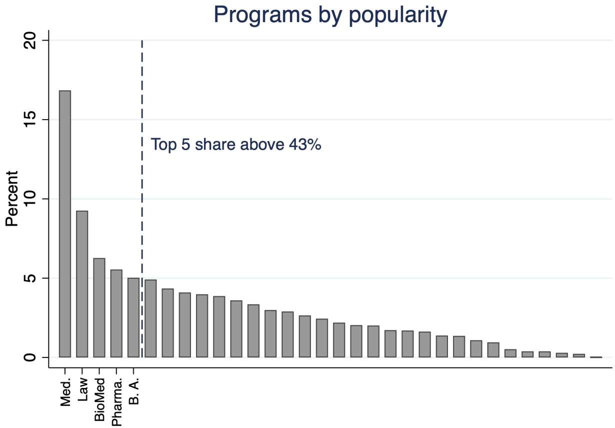
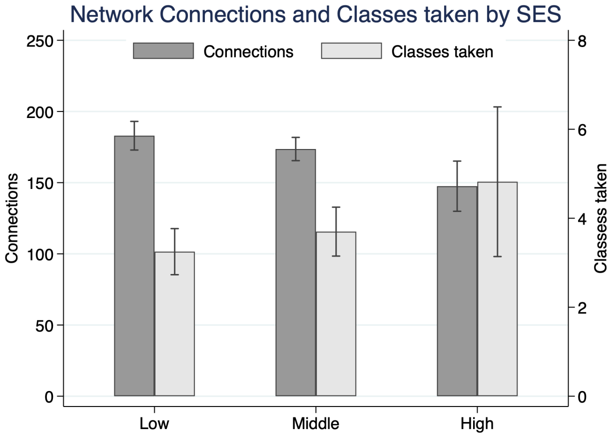


Network dynamics and program selection

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



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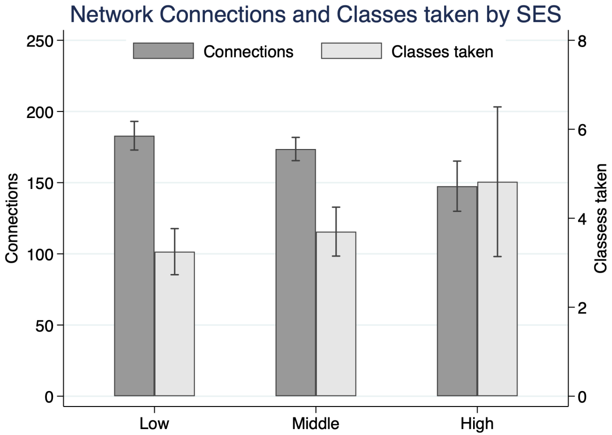
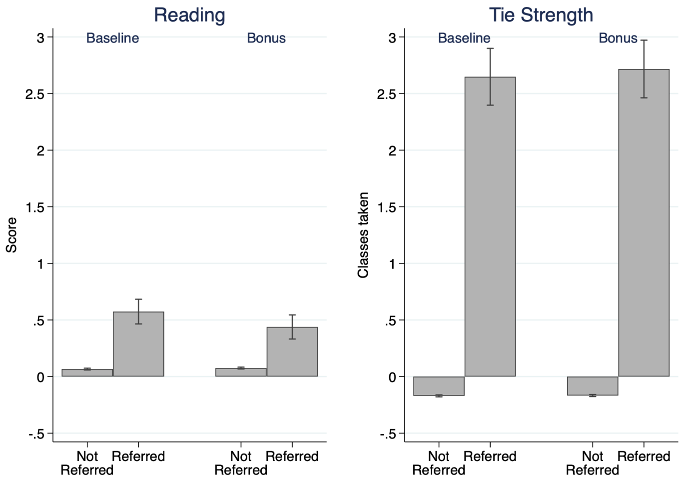


Referrals for Reading

- 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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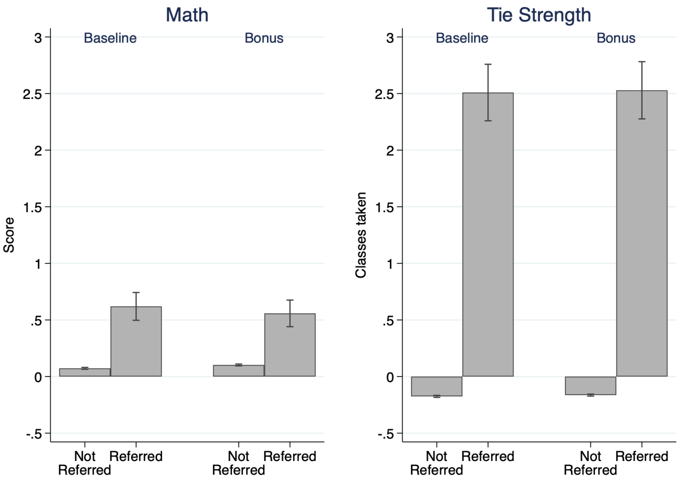
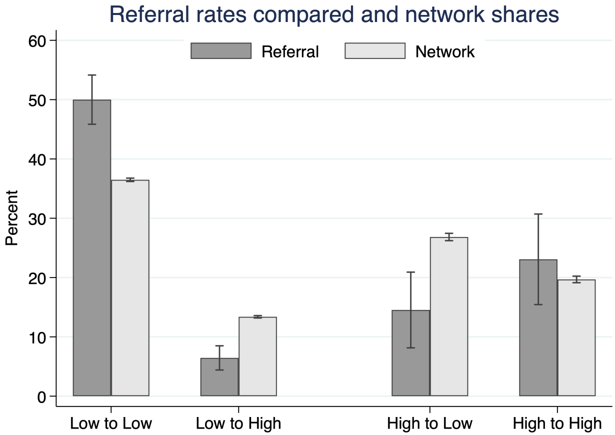


Referral SES composition

- 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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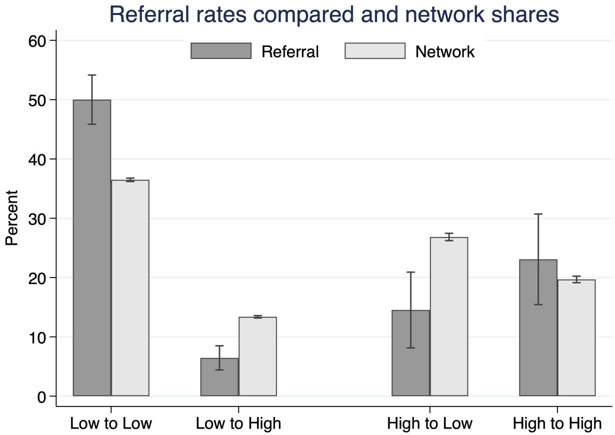

Is there a SES bias in referrals?

FE Logit:

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

- 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
- $\text{Classes taken}_{ij}$: Standardized number of classes taken together for i and j
- α_i: Individual fixed effect for referrer i

Is there a SES bias in referrals?

- Aggregate bias against High-SES
- Score and classes taken are strong predictors of referrals
- Small interaction between score and classes taken
- 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)
Classes taken		0.916***	0.894***
		(0.026)	(0.026)
Score × Classes taken			0.059***
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Observations	256997	256997	256997
Ind.	734	734	734
Chi-test	17.44	1602.42	1640.06

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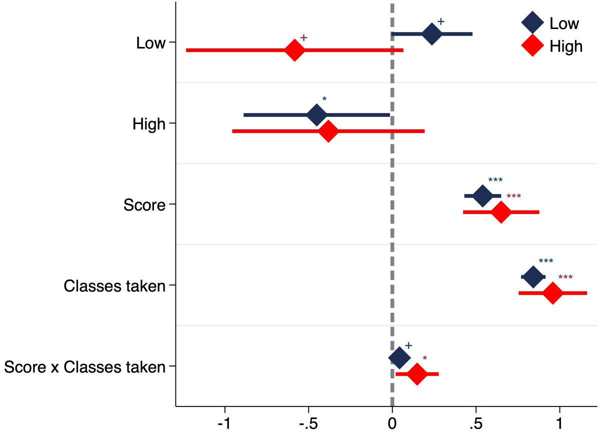
- Do these biases impact referral performance?



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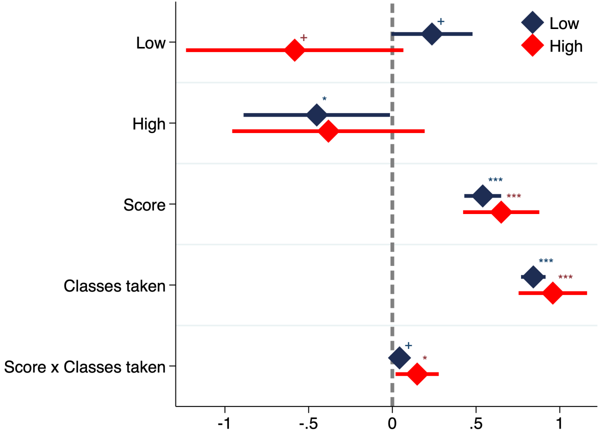

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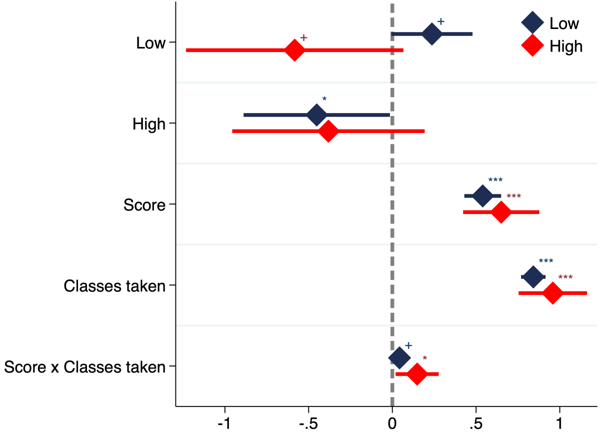


Who makes better referrals?

OLS:

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

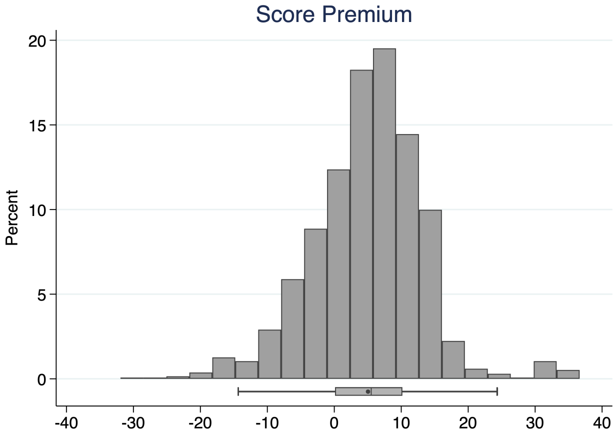
- Premium_i: Nominee j's test z-score minus mean score of i's network
- SES_i: Referrer i's socioeconomic status (Low, Middle, High)
- ΔOBlf_i, ΔNBlf_i: i's beliefs on own and nominee test scores minus actual scores (standardized)
- Score_i: Referrer i's own test z-score

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

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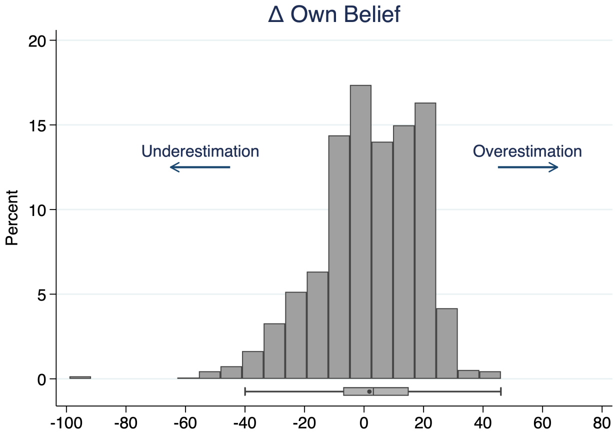
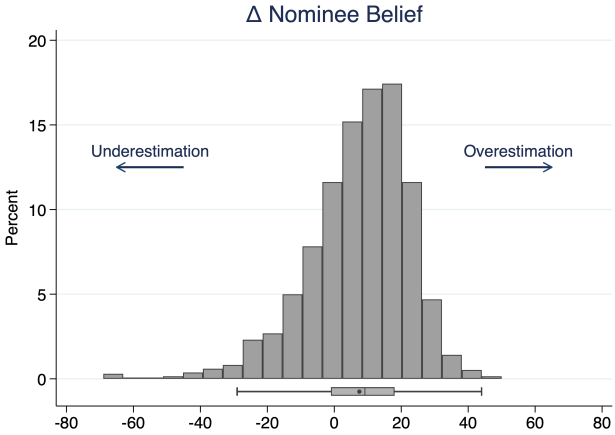


Beliefs about nominees reveal a positive bias

- 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



Who makes better referrals?

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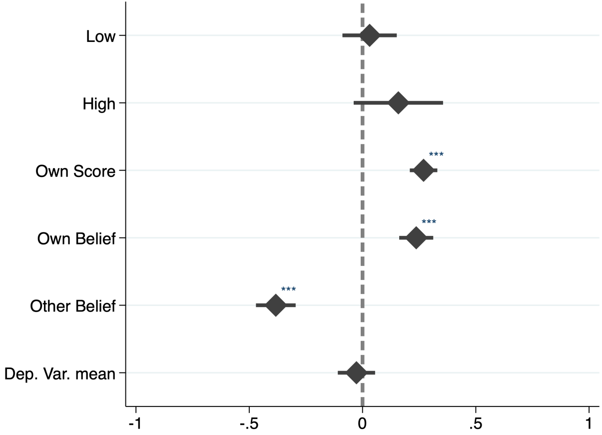
- Referrer's knowledge of own scores increases premium See
- Referrer's knowledge of nominee's score increases premium See
- No effect of SES on referral premium



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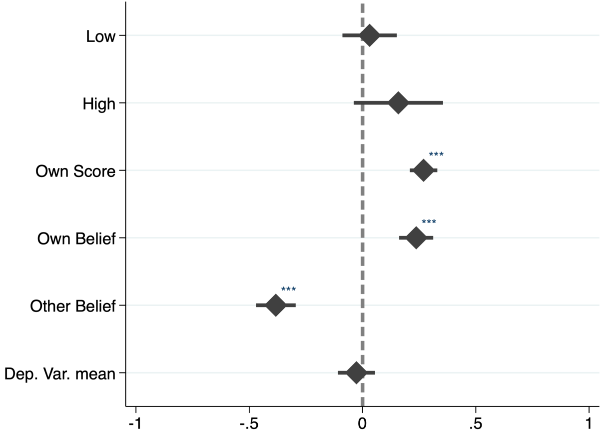

Who makes better referrals?

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- Referrer's knowledge of own scores increases premium See
- Referrer's knowledge of nominee's score increases premium See
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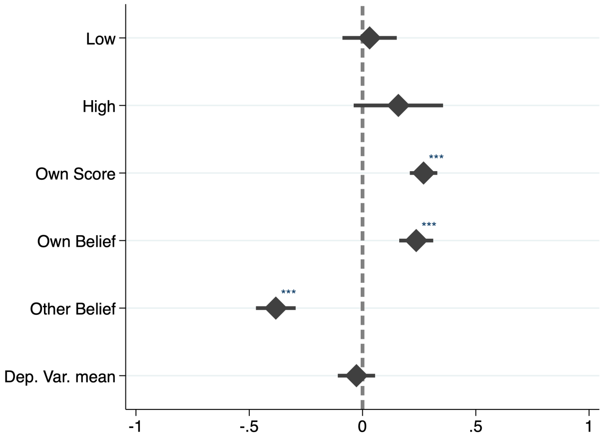

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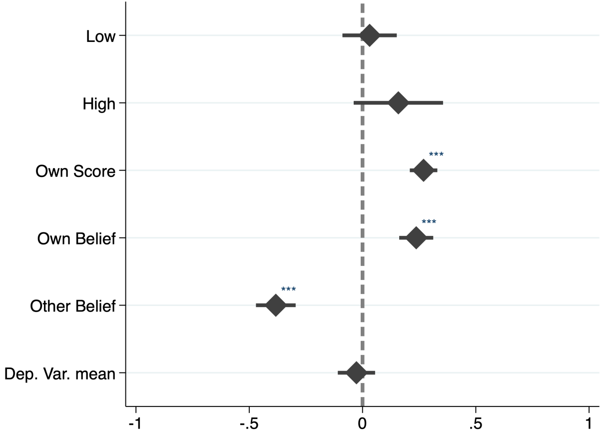

No heterogeneity in beliefs and performance

- **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

Summary

- Networks are separated by SES
- Low and High-SES exhibit bias against one another and worsen the network effect in referrals
- All referrers uniformly nominate better as their own scores get higher, have more accurate beliefs about own and nominee scores

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Next steps & Conclusion

- Robustness check on the bias findings with the conditional logit model
- Start writing!
- Individuals across SES refer equally well . . .
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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 (1)	Other-SES (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

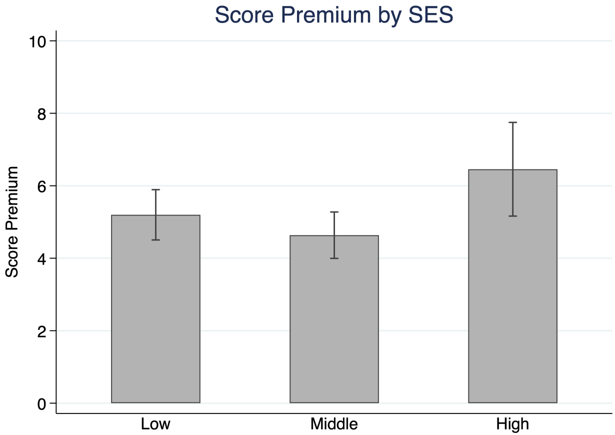
Return

	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

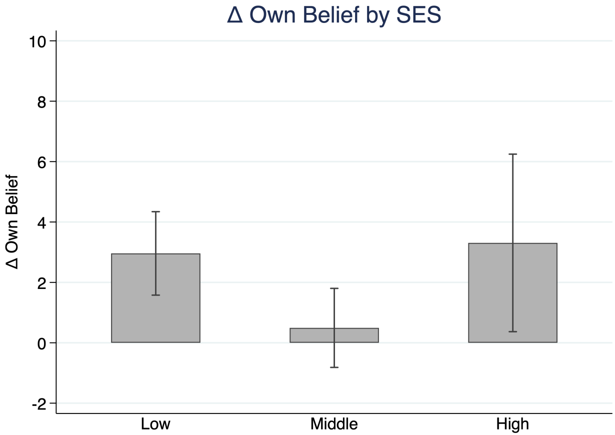
- Middle-SES refer slightly worst (joint F-test, $p < 0.1$)

Return



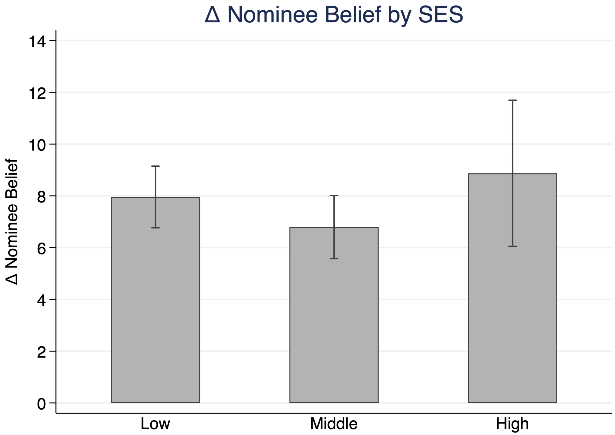
No differences for own score beliefs by SES

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



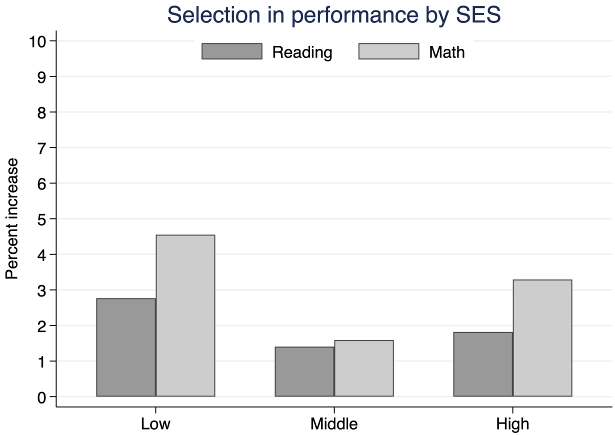
No differences for nominee score beliefs by SES

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



Strong selection by Low-SES

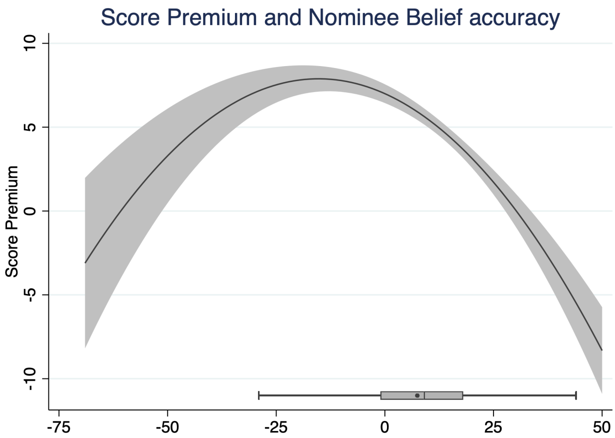
- Significant Low-SES selection (t-tests, $p < 0.01$)
- Other SES groups do select less (t-tests, $p > 0.05$) Return



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