

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 the role of class biases in **social networks** and in **referrals**

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Connections are central to the labor market

- Hiring via connections benefit firms and workers alike
 - 40-50% of all jobs found through social connections (Granovetter, 1995; Topa, 2019)
 - Higher hiring probability, lower turnover, and wage premiums for referred workers (Brown et al., 2016; Dustmann et al., 2016; Friebe et al., 2023)
- Network connections are not formed at random
 - Networks exhibit homophily in social class, as people connect more often with similar others (McPherson et al., 2001)
 - Initial differences in average network employment status or education level can propagate inequality in labor market outcomes (Calvó-Armengol and Jackson, 2004; Calvó-Armengol et al., 2009)
 - Unequal access to valuable connections disadvantage Low-SES individuals (Chetty et al., 2022; Lin et al., 1981; Mouw, 2003)

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Referrals amplify network effects

- Differential treatment within existing networks, e.g., referral of strong ties such as family and/or close friends (Beaman and Magruder, 2012; Hederos et al., 2025; Kramarz and Skans, 2014)
- As well as biases against groups, e.g., race and gender (Beaman et al., 2018; DiTomaso, 2013; Smith, 2005)
- Both could play against Low-SES who have different networks to begin with

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Contribution

- Unique setup where we observe both an entire network and referral behaviors within that network, isolating the processes driving Low-SES inequality

Research Questions

- *Could the class differences in labor market be driven by biases in referrals or by network structure?*
- *Do network structures differ by social class?*
- *Are there social class biases in referrals beyond the network structure?*

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Setting

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



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Design I: Referrals and Network

- Ask students to refer someone they have taken at least one course with
- Observe the entire co-enrollment network at UNAB
- Avoid biases in recall for network construction (+)
- A proxy/subset of actual friendship network (−)


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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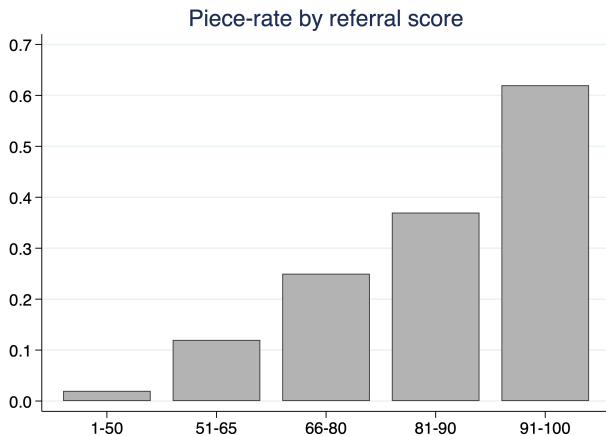
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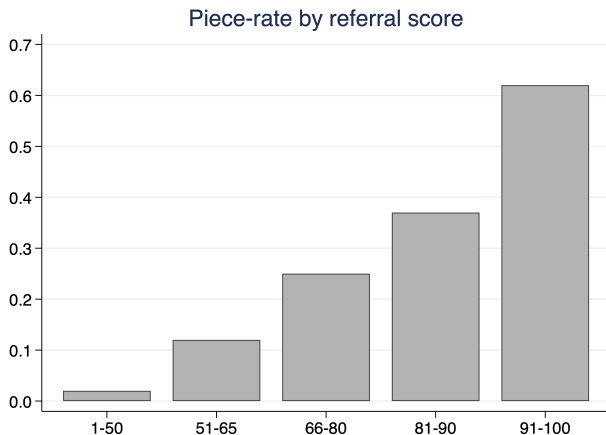
Design II: Incentives

- Pay according to the student's math and verbal scores in the national entry exam
- Incentivize better referrals by increasing monetary reward as referral score goes higher
- Objective and widely accepted performance measure (+)
- Not a real job opportunity (—)



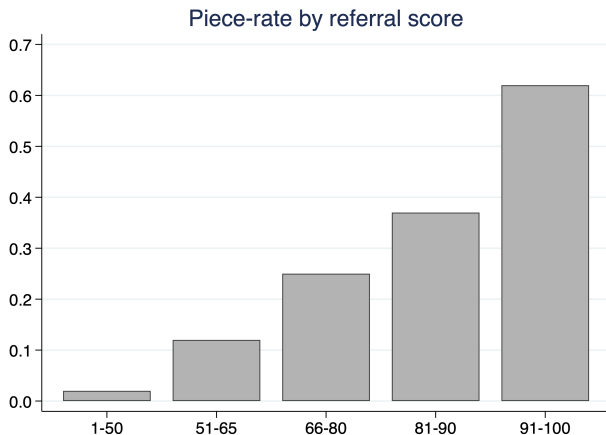
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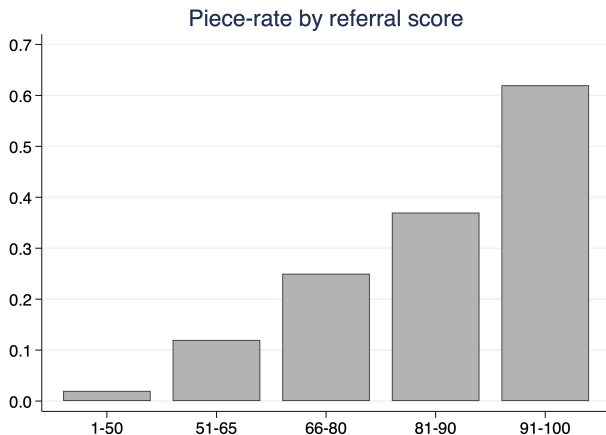
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Design III: Treatment

- **Baseline:** Pay by referral score (Merit)
- **Bonus:** Pay by referral score and a fixed sum for the referred network member (Social concern)



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Procedures

- Recruited participants by emailing 4500 students (>1 st 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 course with

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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
Courses 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

Results I: Network

Network size and courses taken together

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



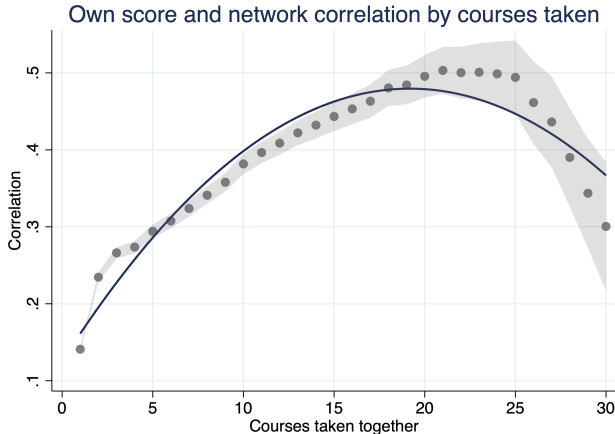
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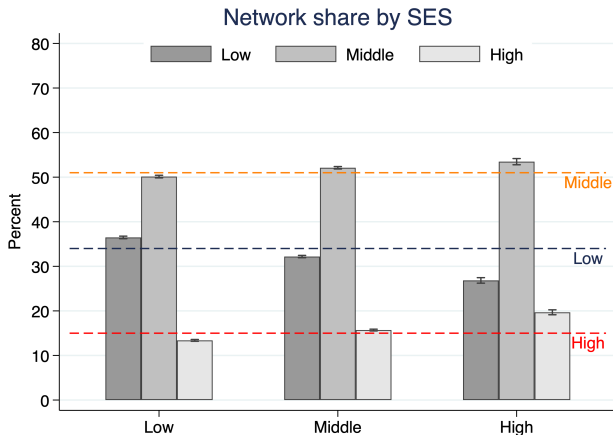
Courses taken together and performance

- Network homophily in terms of performance



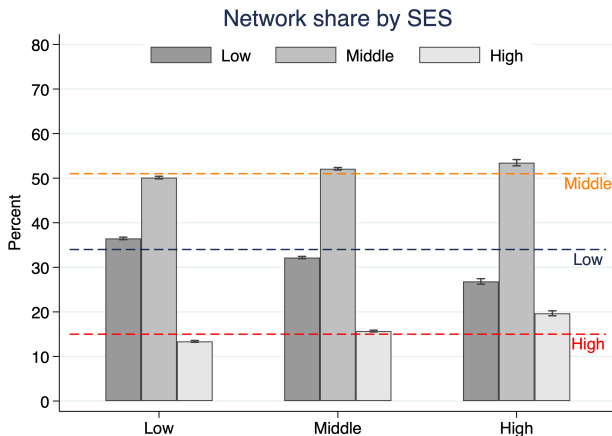
Network-level SES shares

- 51 % of UNAB is **Middle-SES**, 35 % **Low-SES**, and 15 % **High-SES**
- Network shares are very different from the UNAB population
- Why?



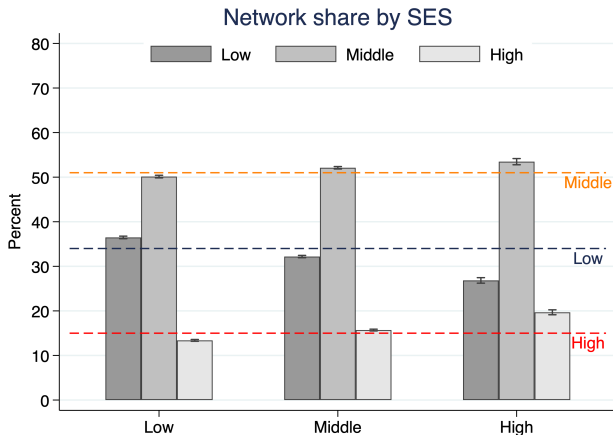
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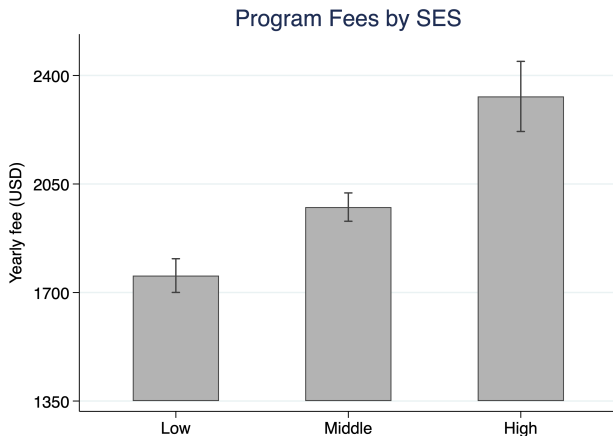
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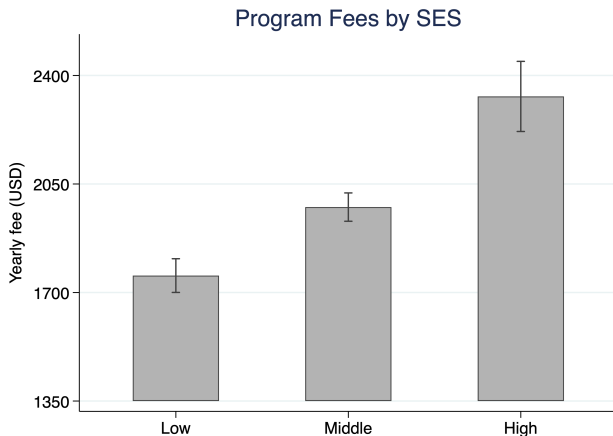
Selection into programs

- UNAB prices each program differently
- Low-SES study in more affordable programs
- Large difference as net average monthly salary around \$350



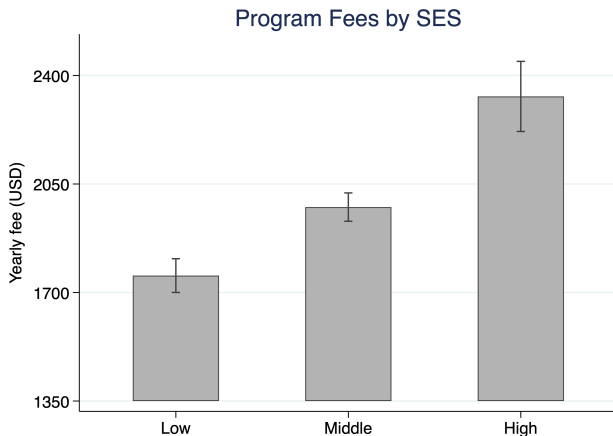
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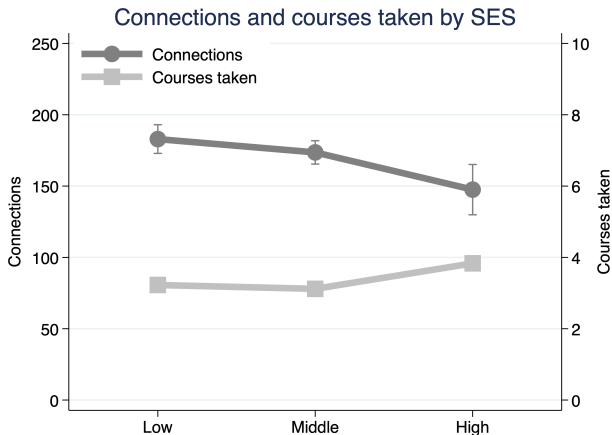
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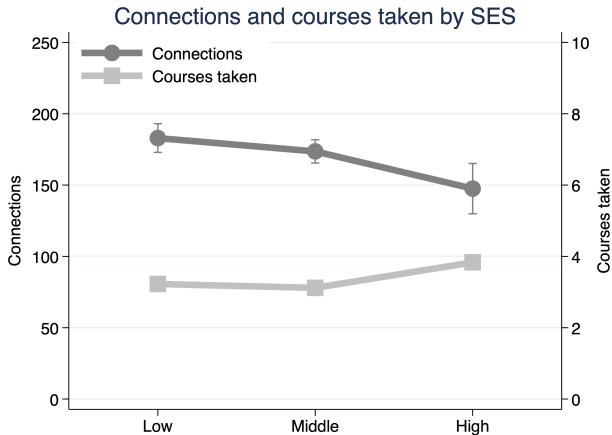
Network dynamics by SES

- Connections decrease with SES
- Courses taken with peers increases with SES
- High-SES take more courses with their own [See](#)



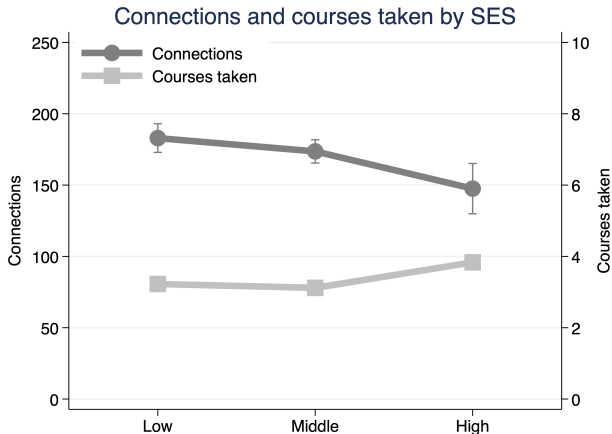
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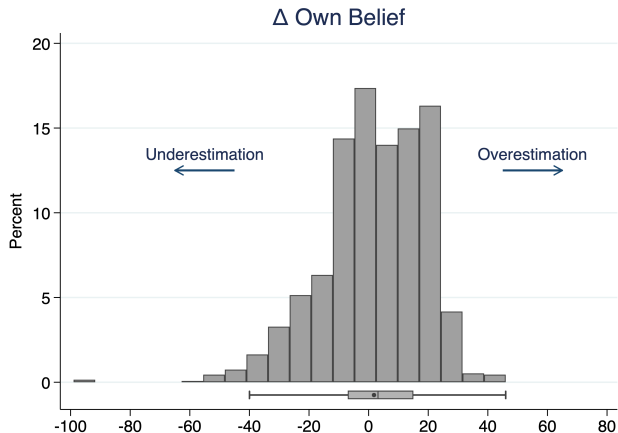
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Results II: Referrals

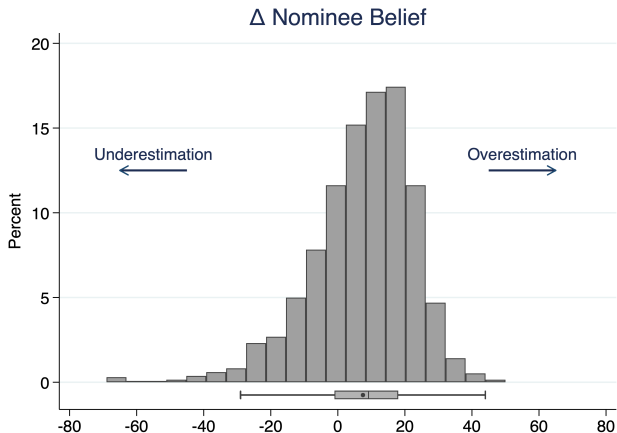
Referrers know their own scores

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



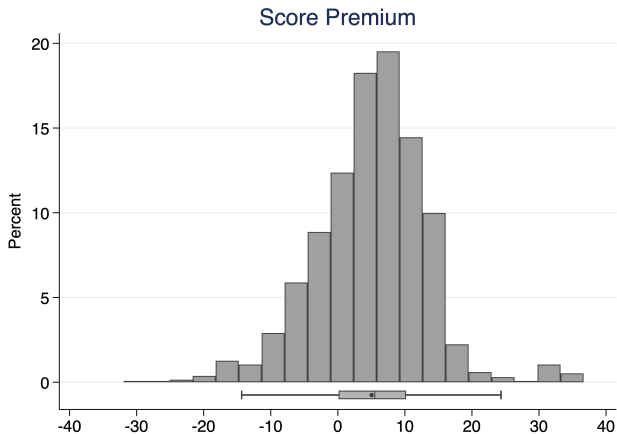
Referrers know their nominees' scores

- Defined as referrer i 's beliefs about nominee j minus j 's score across Math and Reading
- No difference between SES groups [See](#)



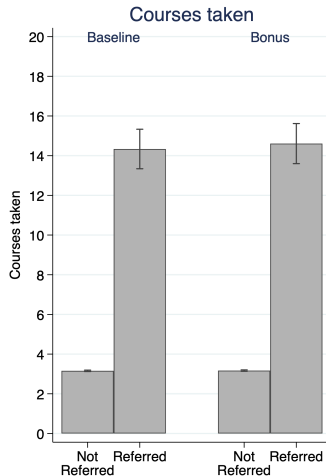
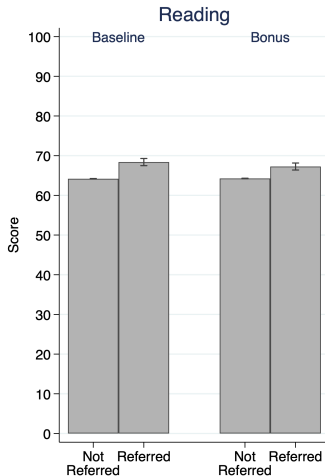
Referrals are better than network average

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



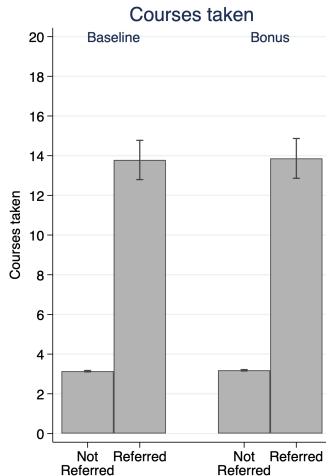
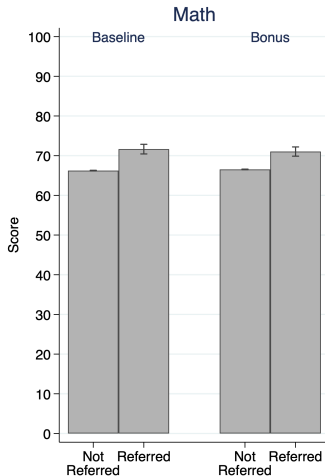
Referrals for Reading

- Referrals have higher reading scores (.5 SD) and much higher tie strength (2.5 SD)
- No treatment effect on the referred (t -tests, $p > 0.08$)



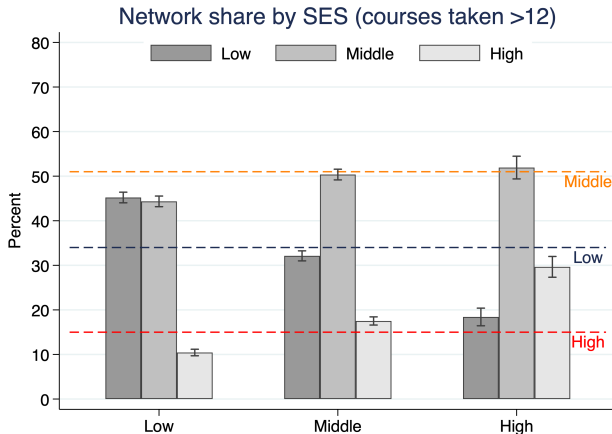
Referrals for Math

- Referrals have higher math scores (.5 SD) and much higher tie strength (2.5 SD)
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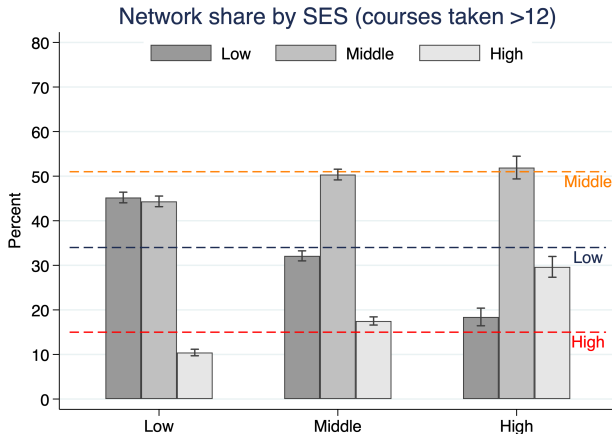
Ex post referral choice sets

- By restricting the network to courses taken above 12, we observe even larger differences in SES shares
- Own SES shares are even higher than network averages except for Middle-SES



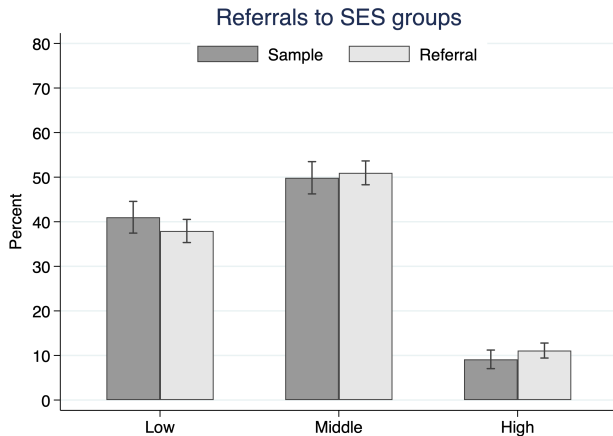
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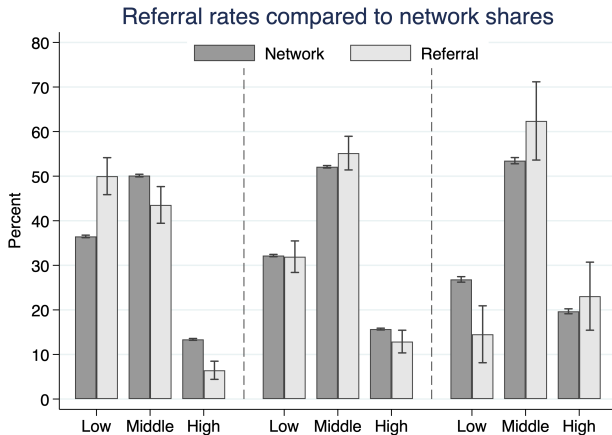
Referrals are balanced

- No differences at the sample-level (all $p > 0.1$)



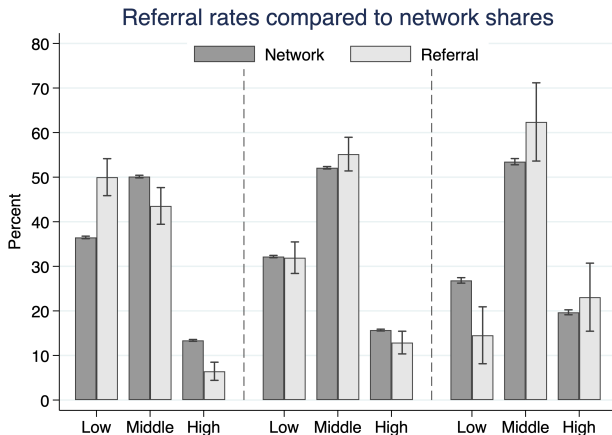
Referral SES composition

- 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?

Conditional FE Logit:

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

- 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
- Courses_{ij} : Standardized number of courses 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 courses taken are strong predictors of referrals
- Small interaction between score and courses taken

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

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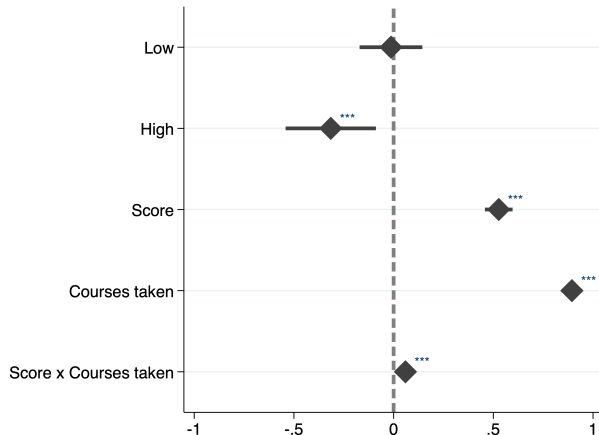
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Low-SES referrers are biased

- Marginal bias for favoring own SES
- Strong bias against High-SES nominees

	(1)	(2)	(3)
Low	0.453*** (0.109)	0.242** (0.123)	0.237* (0.124)
High	-0.584*** (0.211)	-0.445** (0.222)	-0.451** (0.223)
Nominee score		0.607*** (0.052)	0.540*** (0.056)
Courses taken		0.859*** (0.036)	0.842*** (0.037)
Score x Courses taken			0.043* (0.022)
Observations	110142	110142	110142
Ind.	301	301	301
Chi-test	33.47	789.87	804.58

Middle-SES referrers are not biased

- Marginal bias against High-SES nominees

	(1)	(2)	(3)
Low	-0.019 (0.098)	-0.159 (0.114)	-0.155 (0.114)
High	-0.255* (0.145)	-0.274* (0.157)	-0.281* (0.157)
Nominee score		0.587*** (0.047)	0.503*** (0.049)
Courses taken		0.948*** (0.038)	0.930*** (0.039)
Score x Courses taken			0.057*** (0.021)
Observations	127088	127088	127088
Ind.	366	366	366
Chi-test	3.18	756.06	766.33

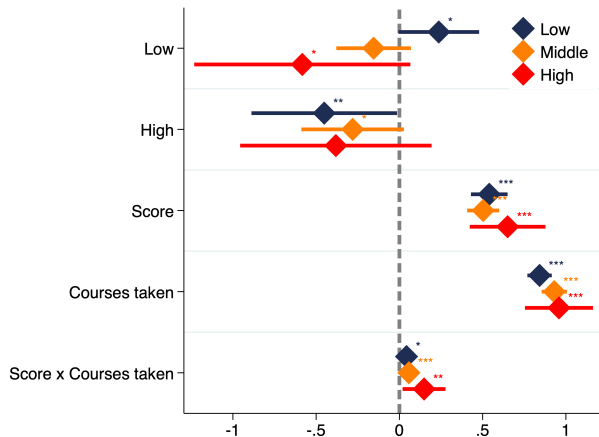
High-SES referrers are not biased

- Marginal bias against Low-SES nominees
- No positive bias for own SES

	(1)	(2)	(3)
Low	-0.710** (0.333)	-0.600* (0.327)	-0.583* (0.331)
High	0.001 (0.261)	-0.345 (0.287)	-0.382 (0.293)
Nominee score		0.883*** (0.111)	0.650*** (0.116)
Courses taken		1.043*** (0.118)	0.959*** (0.104)
Score x Courses taken			0.148** (0.066)
Observations	19767	19767	19767
Ind.	67	67	67
Chi-test	4.94	120.54	144.77

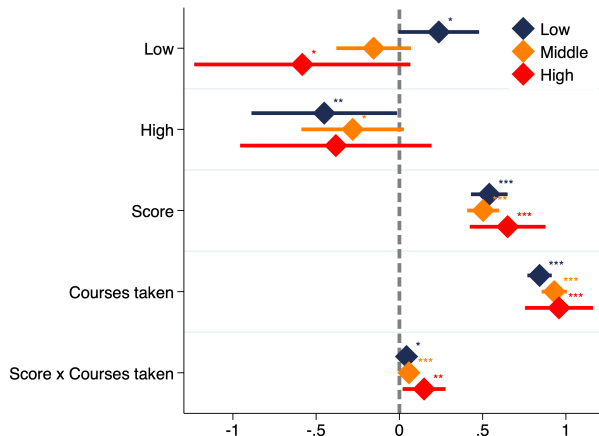
No bias against Low-SES in referrals

- Low-SES referrers are biased against High-SES and favor their own
- Middle-SES referrers are not biased and do not favor their own
- High-SES referrers are not biased against and do not favor their own



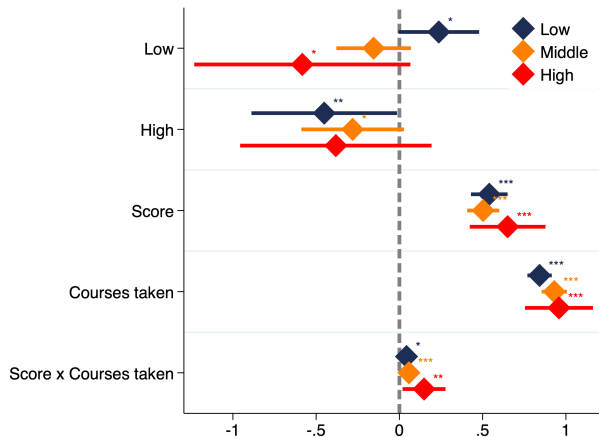
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Summary

- Networks are separated by SES
- Referrers refer equally well across SES, and pick close ties with higher scores
- Little to no bias in referrals in contrast to stark differences in network structures

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Implications

- Individuals across SES refer equally well with proper incentives and without bias
- Differences in network structures lie at the heart of the problem for solving inequality

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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* (0.086)	-0.007 (0.101)	-0.007 (0.102)
High-SES	-0.293** (0.128)	-0.271* (0.139)	-0.275** (0.139)
Nominee score		0.566*** (0.044)	0.513*** (0.048)
Tie		0.949*** (0.031)	0.939*** (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

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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* (0.086)	-0.013 (0.099)	-0.015 (0.100)
High-SES	-0.309** (0.131)	-0.343** (0.142)	-0.361** (0.144)
Nominee score		0.662*** (0.040)	0.546*** (0.042)
Tie		0.885*** (0.029)	0.851*** (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** (0.083)	0.041 (0.100)	0.042 (0.100)
Nominee Score		0.561*** (0.044)	0.509*** (0.048)
Tie		0.951*** (0.031)	0.941*** (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*** (0.083)	0.049 (0.097)	0.050 (0.098)
Nominee Score		0.653*** (0.040)	0.538*** (0.041)
Tie		0.887*** (0.029)	0.854*** (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* (0.155)	-0.202 (0.149)	-0.275 (0.369)
High-SES	-0.307 (0.268)	-0.254 (0.186)	-0.511 (0.377)
Nominee score	0.548*** (0.076)	0.483*** (0.067)	0.553*** (0.179)
Tie	0.873*** (0.046)	0.991*** (0.046)	0.986*** (0.128)
Score x Tie	0.019 (0.027)	0.021 (0.027)	0.145** (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** (0.153)	-0.160 (0.137)
Nominee score	0.545*** (0.076)	0.486*** (0.062)
Tie	0.876*** (0.046)	0.996*** (0.044)
Score x Tie	0.019 (0.027)	0.036 (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 (1)	Middle-SES (2)	High-SES (3)
Low-SES	0.208 (0.150)	-0.101 (0.145)	-0.986** (0.469)
High-SES	-0.619** (0.283)	-0.313 (0.195)	-0.269 (0.381)
Nominee score	0.540*** (0.064)	0.526*** (0.060)	0.730*** (0.128)
Tie	0.814*** (0.041)	0.870*** (0.043)	0.929*** (0.128)
Score x Tie	0.067** (0.028)	0.096*** (0.029)	0.160 (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

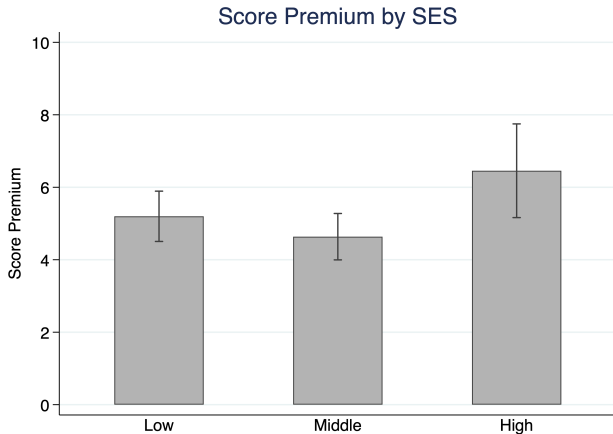
[Return](#)

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

No differences for Score Premium by SES

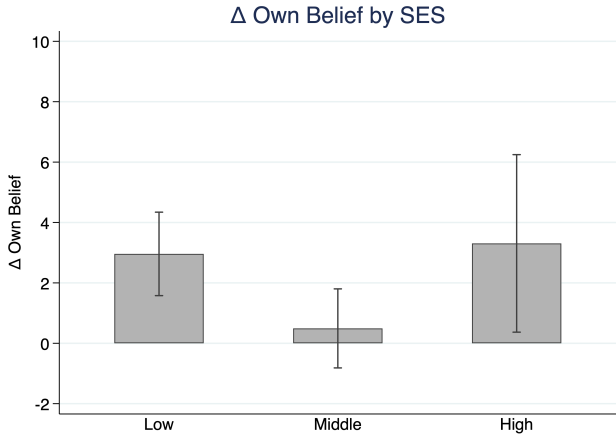
- Middle-SES refer slightly worst (joint F-test, $p < 0.1$)

[Return](#)



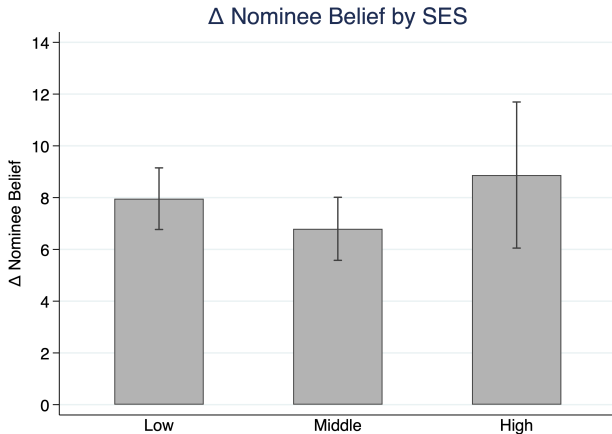
No differences for own score beliefs by SES

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



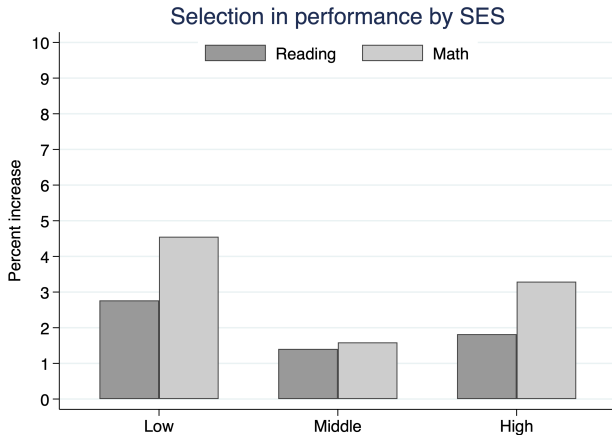
No differences for nominee score beliefs by SES

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



Strong selection by Low-SES

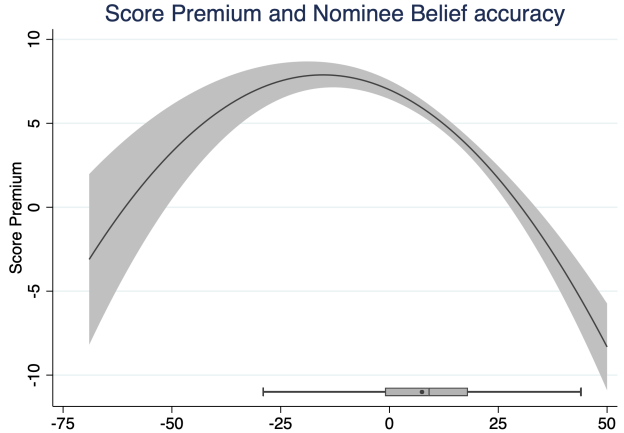
- Significant Low-SES selection (t -tests, $p < 0.01$)
- Other SES groups do select less (t -tests, $p > 0.05$) [Return](#)



Nominee Beliefs are rewarded for accuracy

- Negative coefficient is explained by quadratic shape

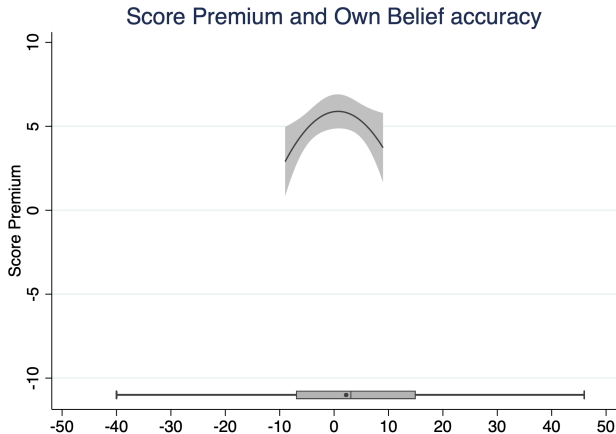
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Own score beliefs are rewarded for accuracy

- Positive coefficient is explained by quadratic shape and extreme outliers

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Courses taken by SES

- High-SES take almost twice more courses with their own

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