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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- 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; Friebel 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 biaseses against groups, e.g., race and gender (Beaman et al., 2018; DiTomaso, 2013; Smith, 2005)
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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

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- 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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Setting II: Inequality and social class in Colombia

- Third highest income inequality in the world according to World Bank
- Government assigned social class numbers classify each neighborhood
- Taxes from high-SES neighborhoods subsidize utilities for low-SES

Subsidio				Contribución
*Estrato 1	*Estrato 2	*Estrato 3	Estrato 4	*Estrato 5 y 6 Comercial / Industrial
$233,58	$291,98	$496,37	$583,97	$700,76
$211,26	$264,07	$448,93	$528,15	$633,78

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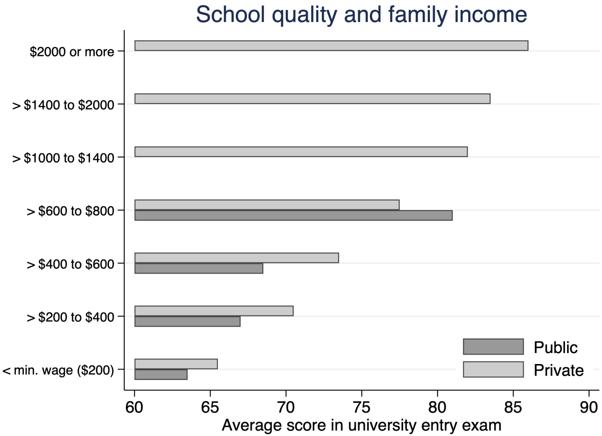
Setting III: Higher education in Colombia

- Families spend considerable amounts to provide kids with private higher education
- Non-elite private universities like UNAB cater to all social classes
- Figure from Fergusson and Flórez (2021)



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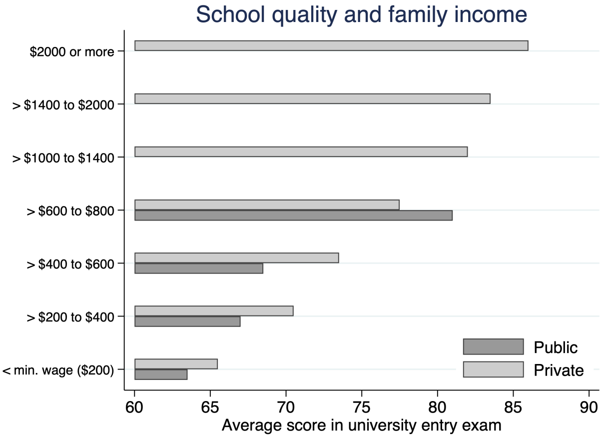

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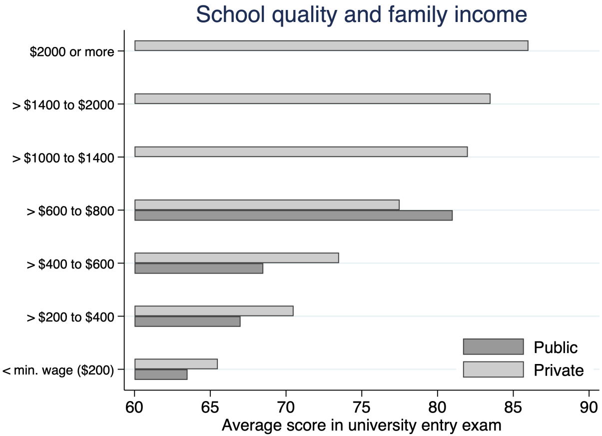

Design I: Referrals and Network

- 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

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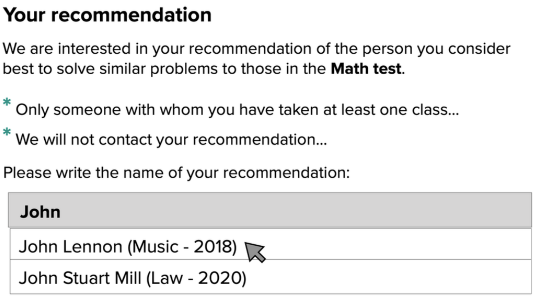

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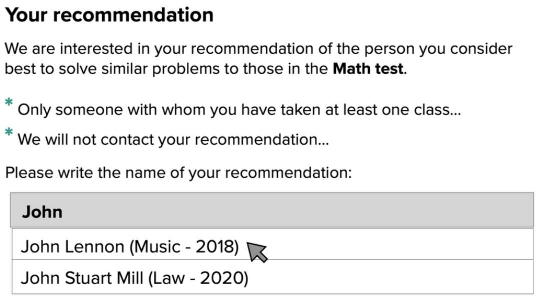

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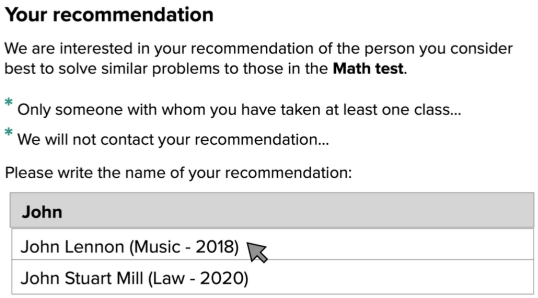
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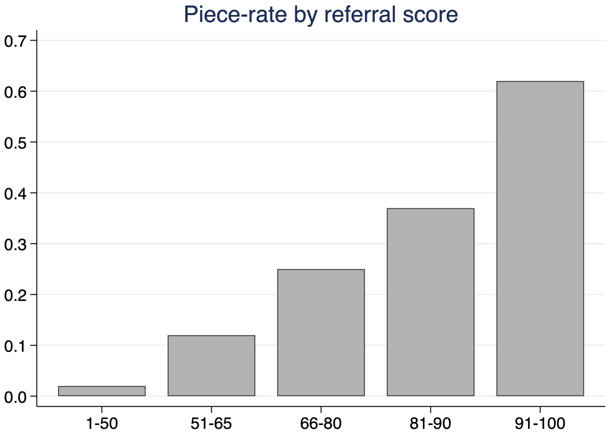
Design II: Incentives

- Pay according to the student's math and verbal scores in the national entry exam Beliefs
- 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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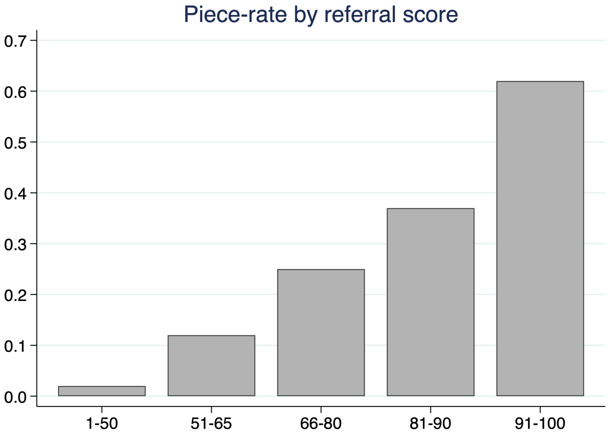

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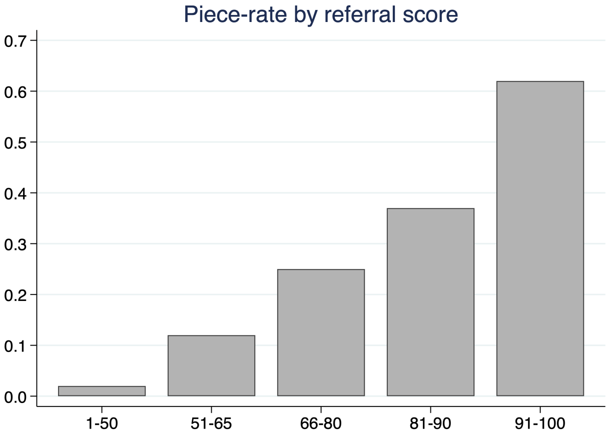

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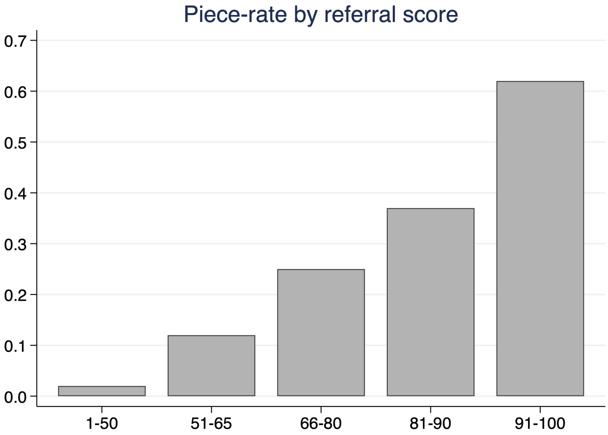

Design III: Treatment

- **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 ($>$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 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

Networks: A driver of class segregation?

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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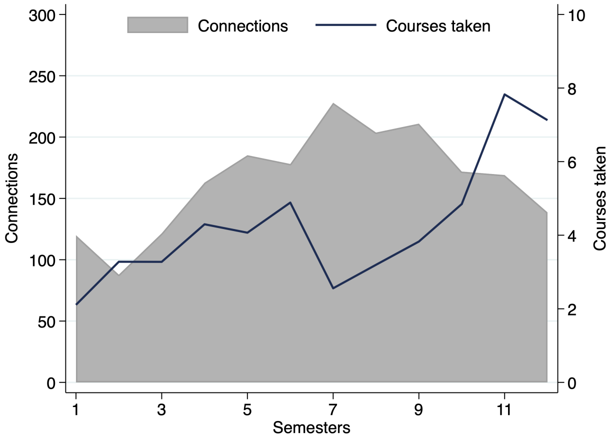
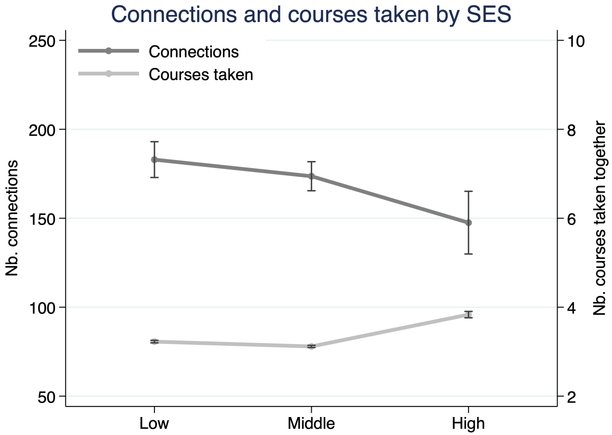


Network characteristics by SES

- Connections decrease with SES
- Courses taken with peers increases with SES
- High-SES take more courses with their own See



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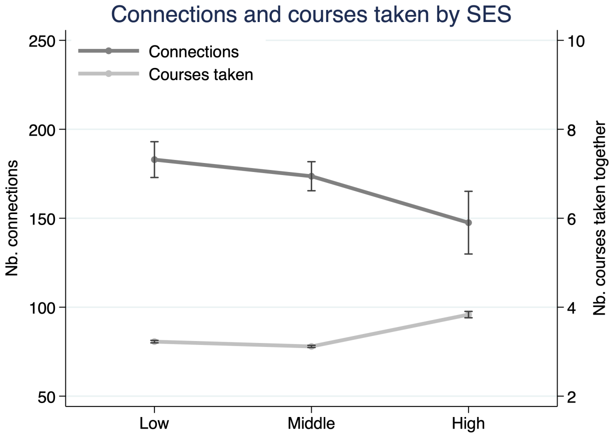

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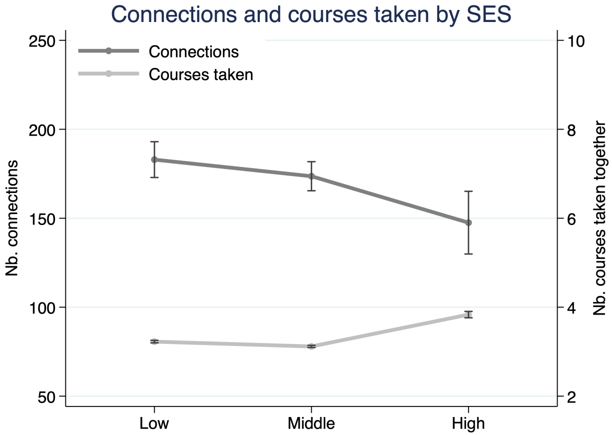
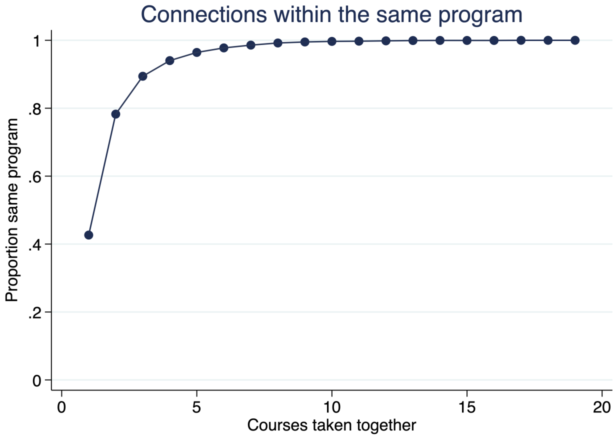


Courses taken together and programs

- Taking more than 5 courses together implies studying in the same program
- Networks within the same program are much smaller



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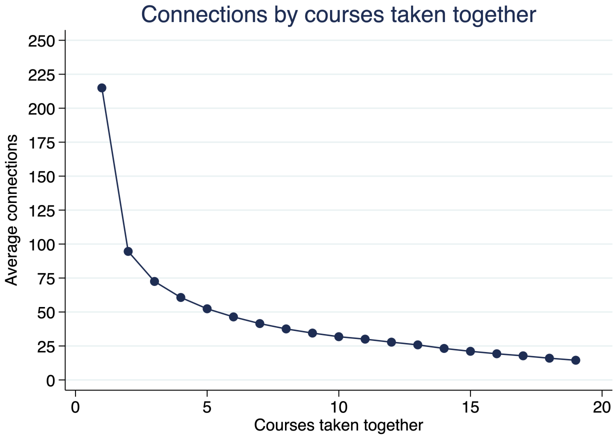
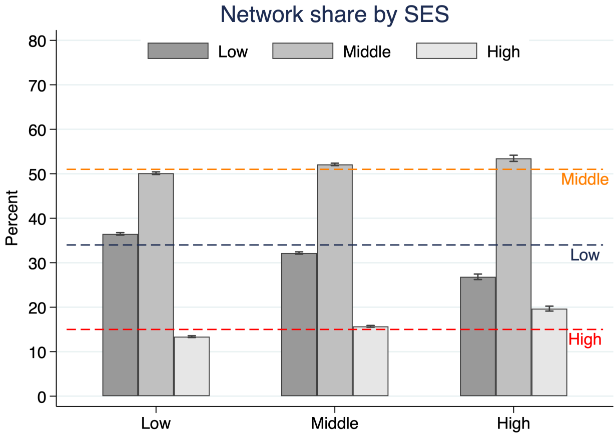


Network-level SES shares

- 51 % of UNAB is **Middle-SES**, 34 % **Low-SES**, and 15 % **High-SES**
- Network shares are very different from the UNAB population
- Why?



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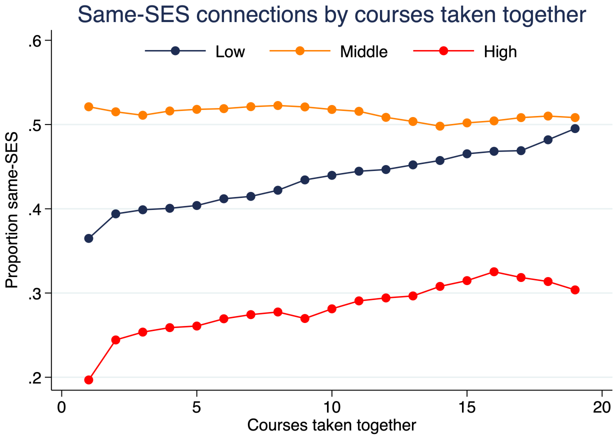
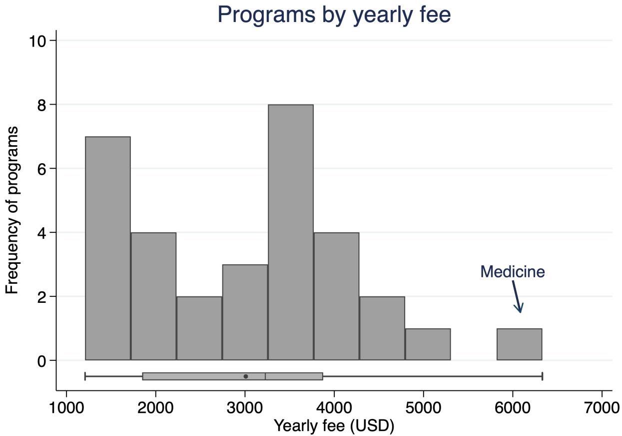


Selection into programs

- UNAB prices each program differently based on its cost
- Medicine is the largest and the most expensive program at UNAB
- A much larger share of High-SES study in medicine
- Minimum legal monthly wage at $200 and average monthly net wage at $350



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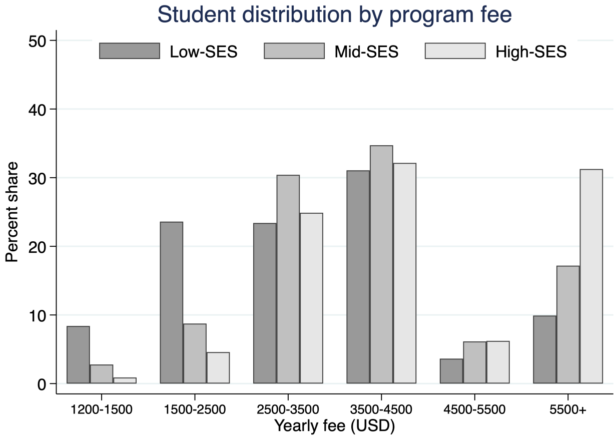
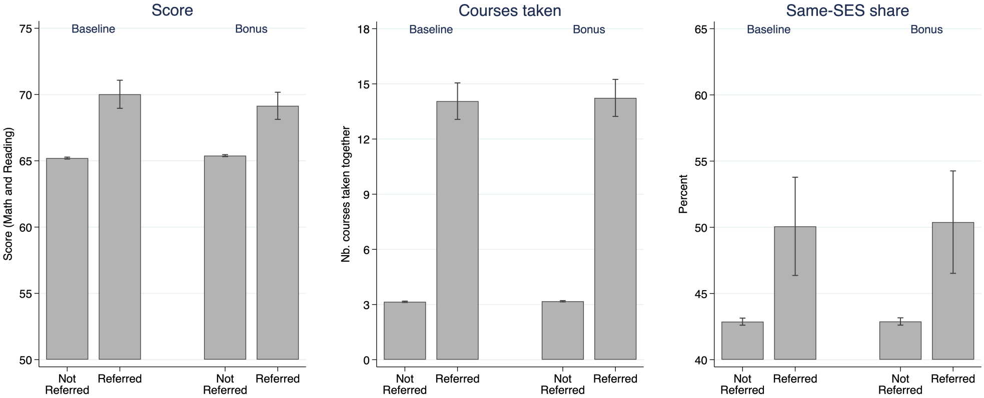


Root of the problem: Referrals versus Networks

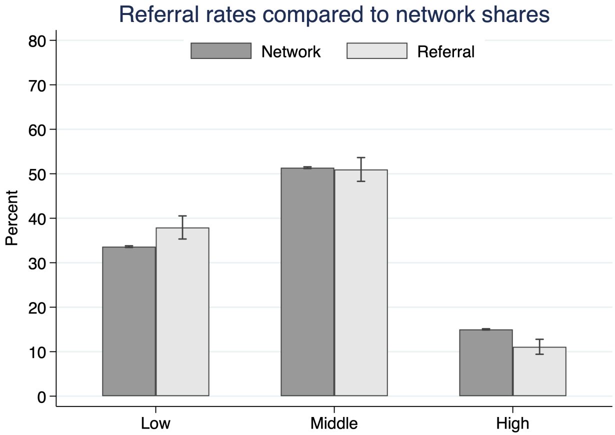
Who gets the referral?



- Higher scores, more courses together, and more often same-SES Distributions
- Marginal treatment effect on the referred scores (t-test, $p = 0.08$)

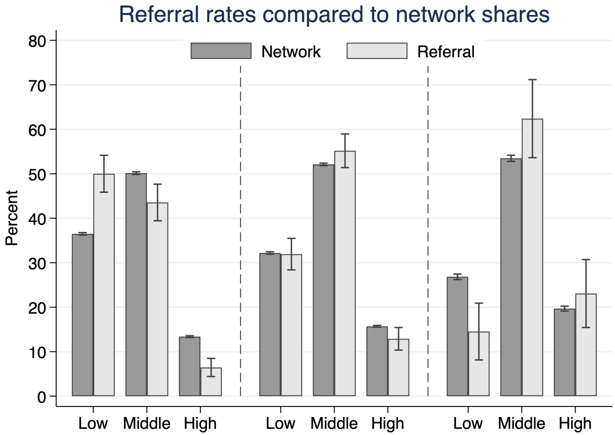
No overall bias against low-SES in referrals

- More referrals for Low-SES and less for High-SES



Referral SES composition

- Stark differences in referral rates by SES
- Is program selection driving differences in referrals?



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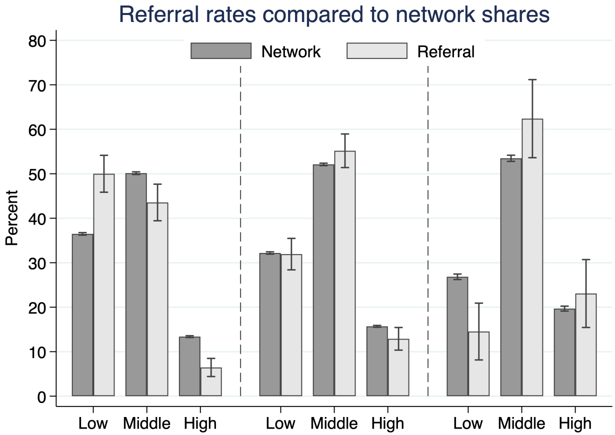
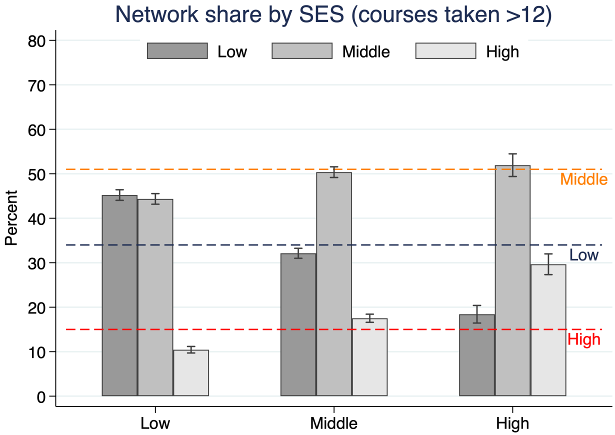


Referrer networks may drive differences

- 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
- Do differences persist after controlling for classes taken?



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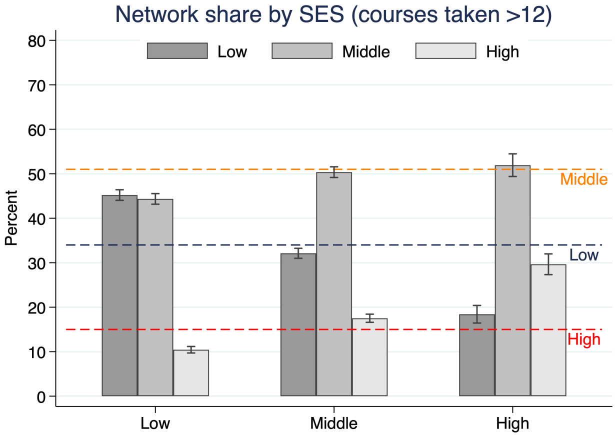

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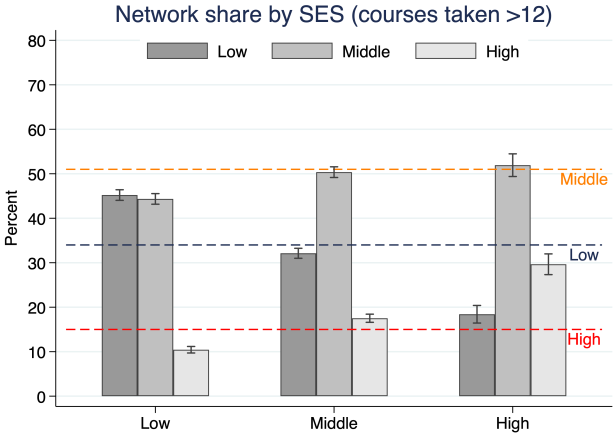


Is there a SES bias in referrals beyond networks?

Conditional FE Logit:

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

- Refer_{ij}: Binary outcome indicating whether individual i refers individual j
- SES_j: Referral j is Low, Middle, or High SES
- $\mathrm{Courses}_{ij}$: Standardized number of courses taken together for i and j
- Score_j: Standardized Math or Reading score of referral j
- α_i: Individual fixed effect for referrer i
- Pool for each SES group

Low-SES referrers are biased

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

	(1)	(2)	(3)
Low	0.453***	0.242**	0.237*
	(0.109)	(0.123)	(0.124)
High	-0.584***	-0.445**	-0.451**
	(0.211)	(0.222)	(0.223)
Courses taken		0.859***	0.842***
		(0.036)	(0.037)
Nominee score		0.607***	0.540***
		(0.052)	(0.056)
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	-0.159	-0.155
	(0.098)	(0.114)	(0.114)
High	-0.255*	-0.274*	-0.281*
	(0.145)	(0.157)	(0.157)
Nominee score		0.587***	0.503***
		(0.047)	(0.049)
Courses taken		0.948***	0.930***
		(0.038)	(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

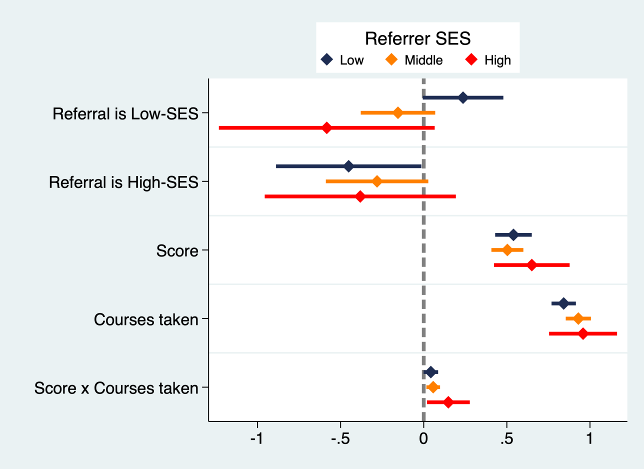
High-SES referrers are not biased

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

	(1)	(2)	(3)
Low	-0.710**	-0.600*	-0.583*
	(0.333)	(0.327)	(0.331)
High	0.001	-0.345	-0.382
	(0.261)	(0.287)	(0.293)
Nominee score		0.883***	0.650***
		(0.111)	(0.116)
Courses taken		1.043***	0.959***
		(0.118)	(0.104)
Score × 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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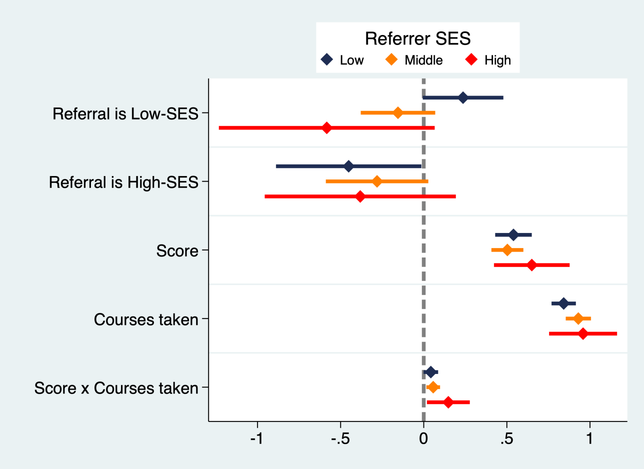

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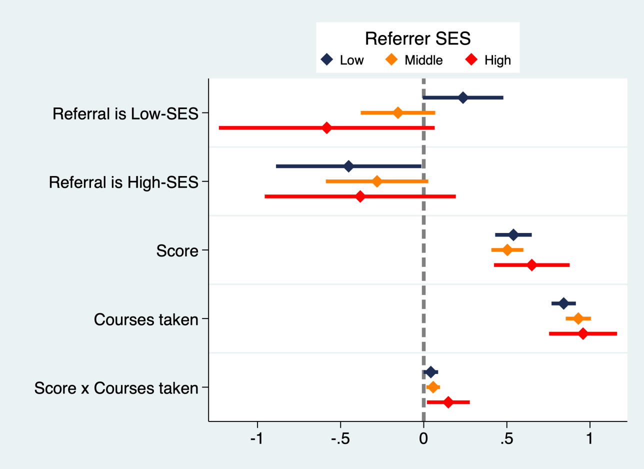

Summary

- 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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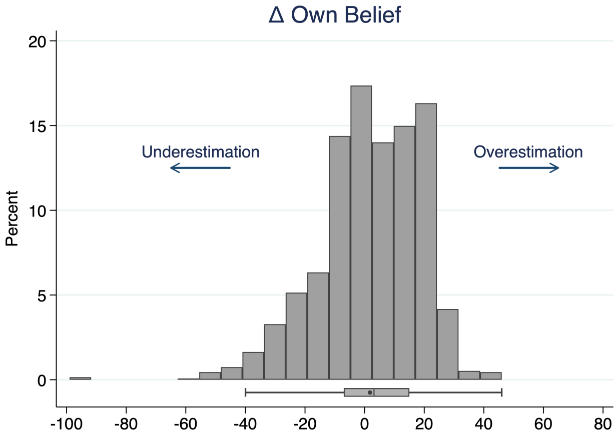
Beliefs about own and nominee exam ranking

- Defined as referrer *i*'s belief minus actual rank across Math and Reading
- Participants know their own ranking at UNAB
- Participants know their referral's ranking at UNAB
- No differences between SES groups for both See
- Return



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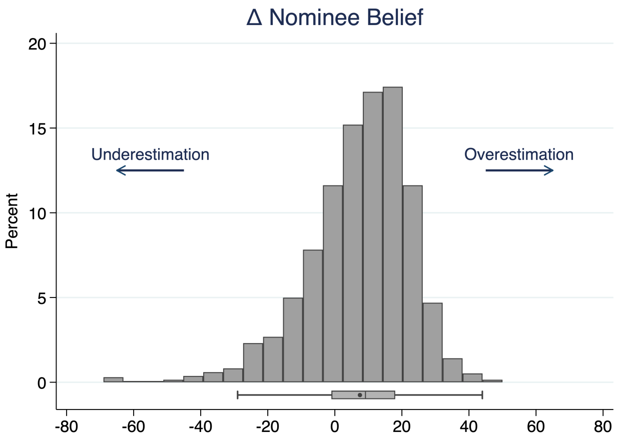
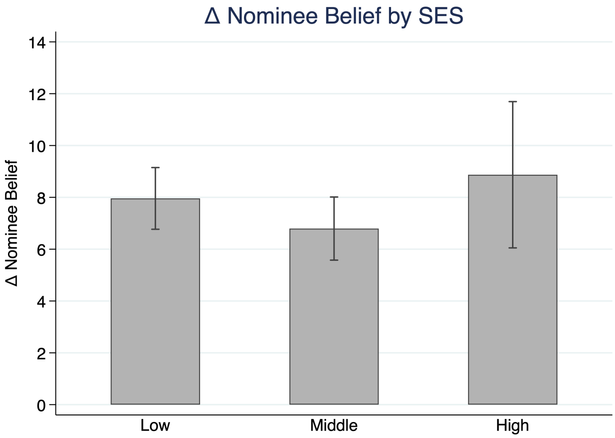


Ranking beliefs across SES

- Middle-SES are marginally more accurate (joint F-test, $p < 0.1$)
- No difference (joint F-test, $p = 0.41$) Return



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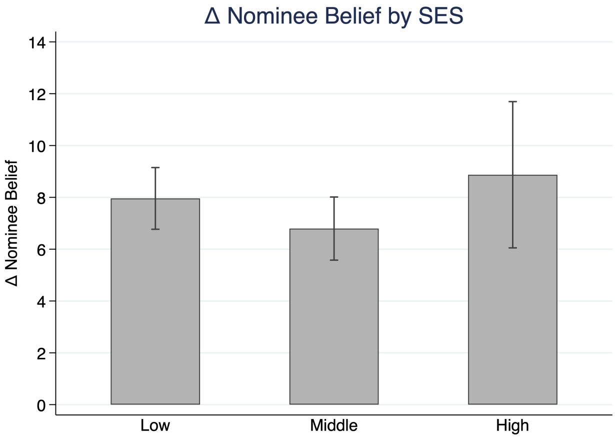


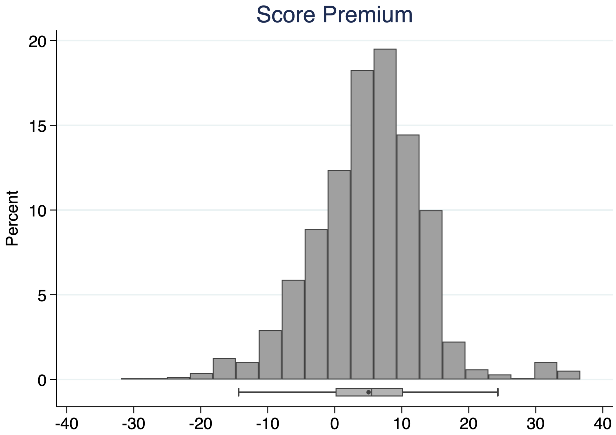
Courses taken by SES

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

Return

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 Return



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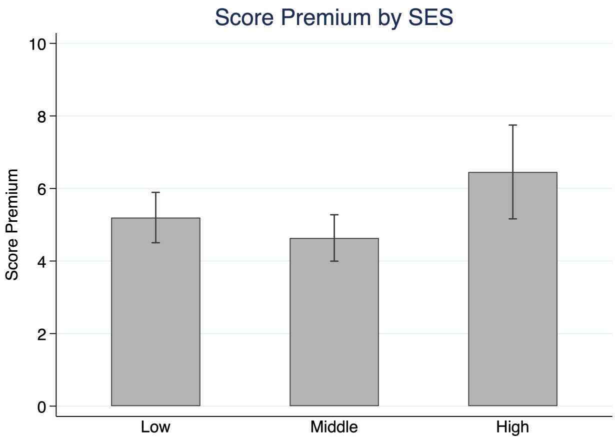
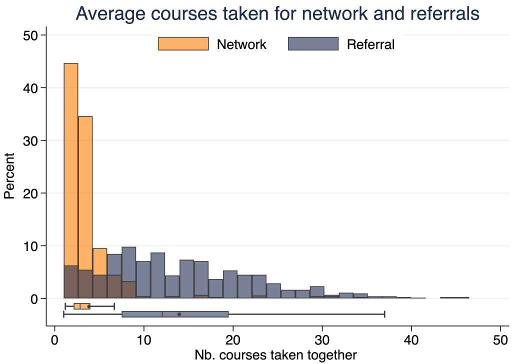
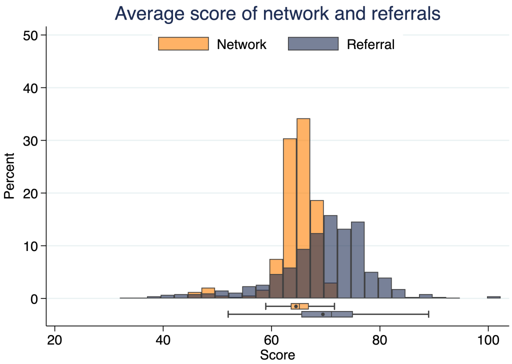


Distribution of outcome variables





- Visibly different for both variables Return