Class differences in social networks: Evidence from a referral experiment

1-hour presentation

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- 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)
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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)
- 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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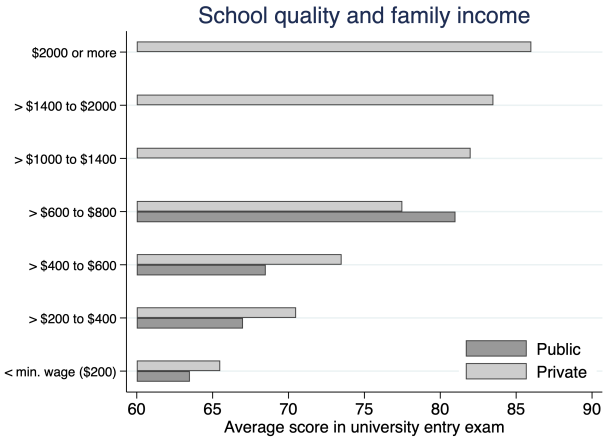
Setting II: Inequality and social class in Colombia

- Families spend considerable amounts to provide kids with private higher education
- Non-elite private universities like UNAB cater to all social classes



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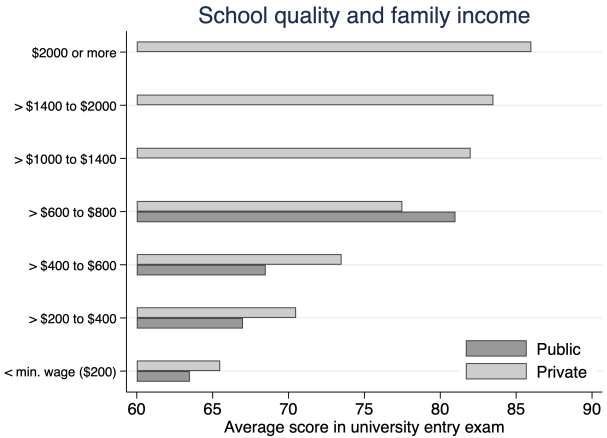

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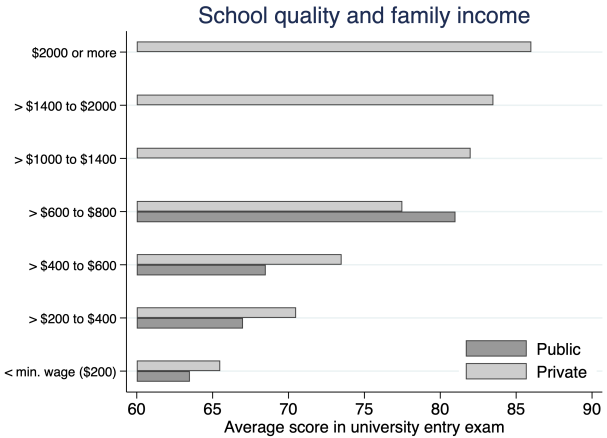

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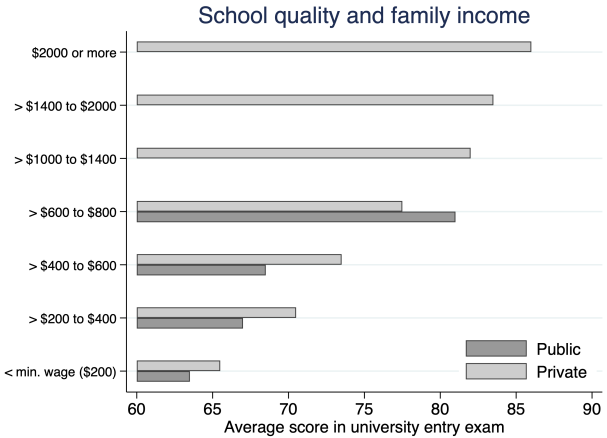

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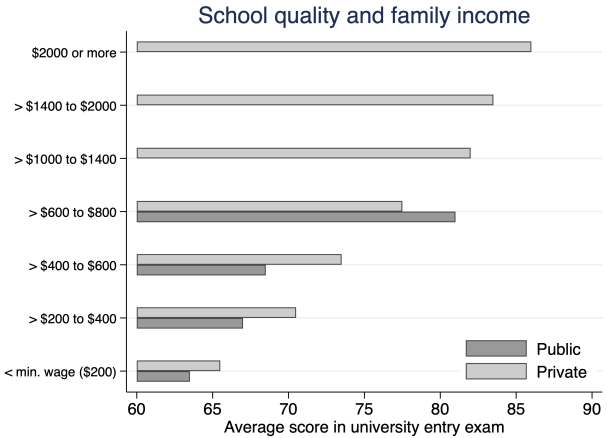
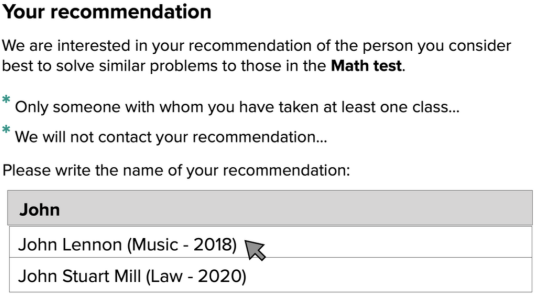


Design I: Referrals and Network

- 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 (−)



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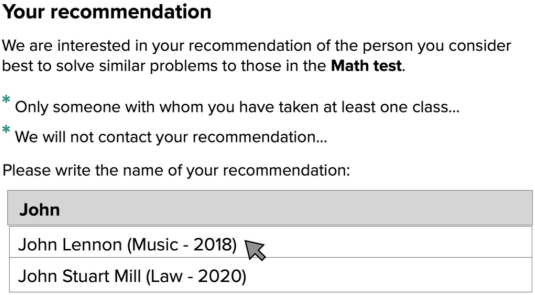

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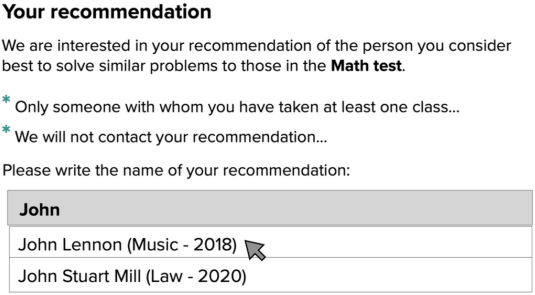

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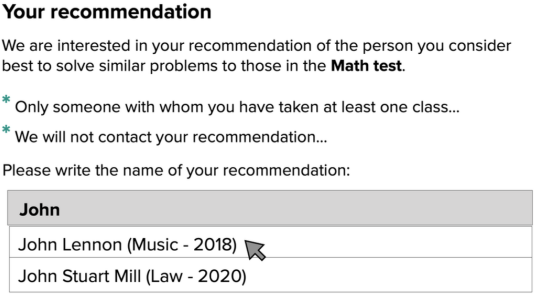

Design II: Incentives

- Pay according to the student's math and verbal scores in the national entry exam
- Incentivize better refferals by increasing monetary reward as referral score goes higher
- Objective and widely accepted performance measure (+)
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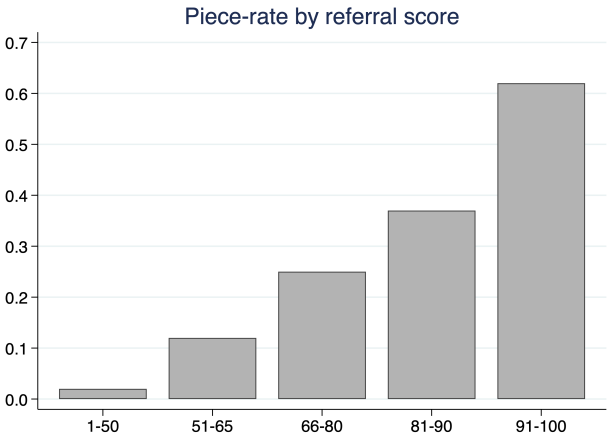

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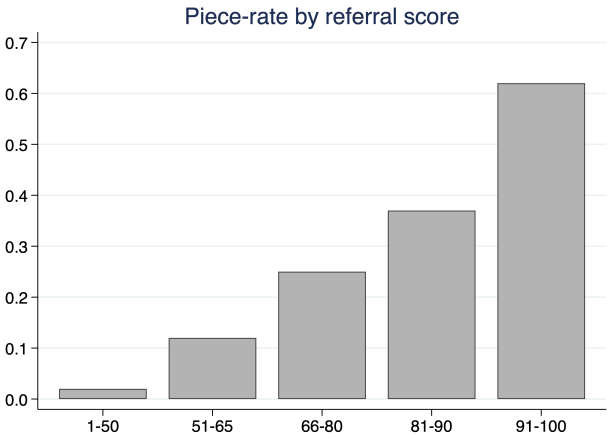

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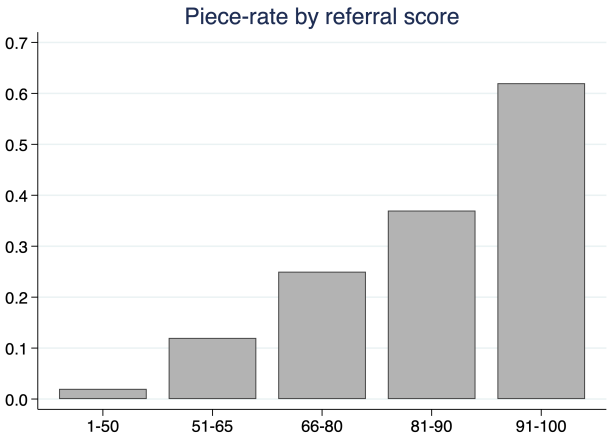

Design III: Treatment

- **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

Network descriptives

Network size and courses taken together

- Connections peak around 7 semesters and decline as students change majors or graduate
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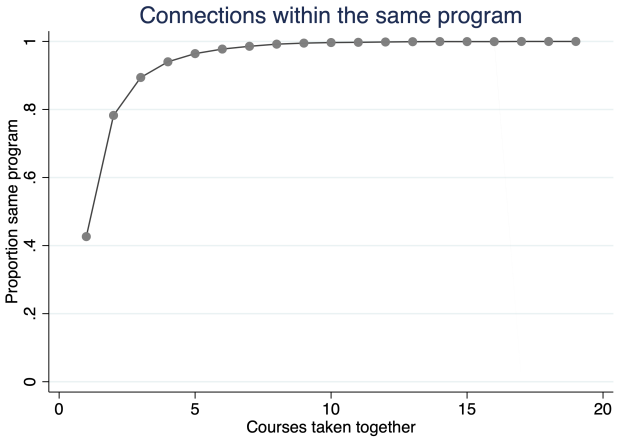
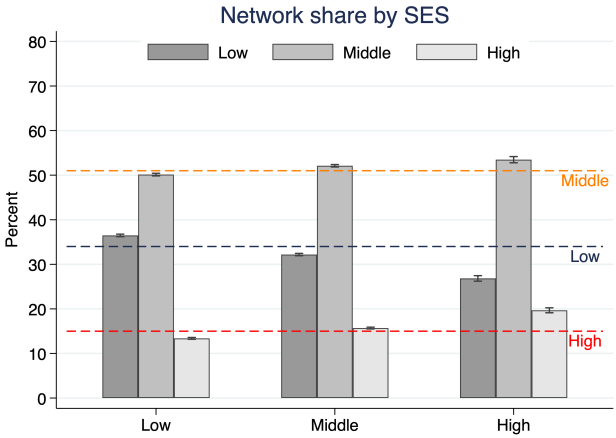
Courses taken together

- Taking more than 5 courses together implies studying in the same program



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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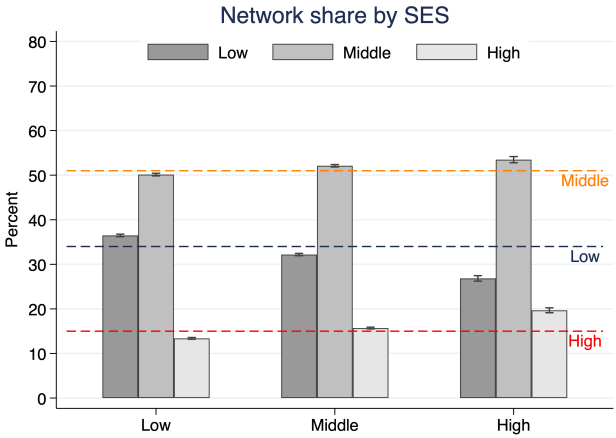

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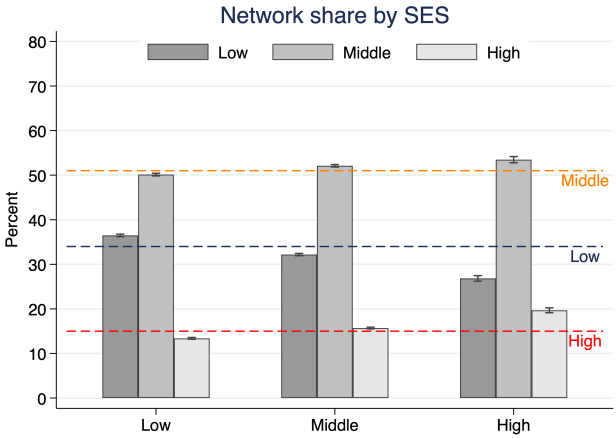
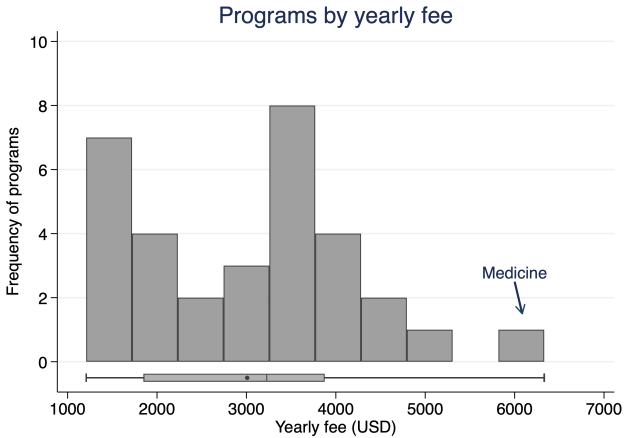


Selection into programs

- 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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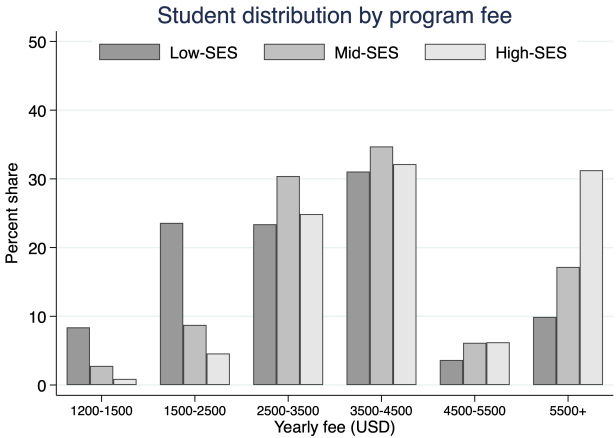
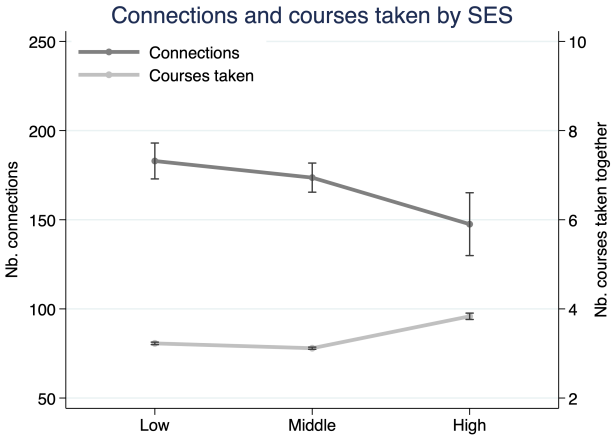


Program selection and network characteristics

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



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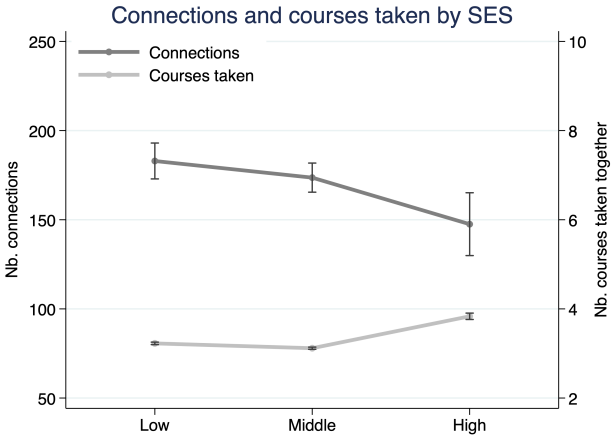

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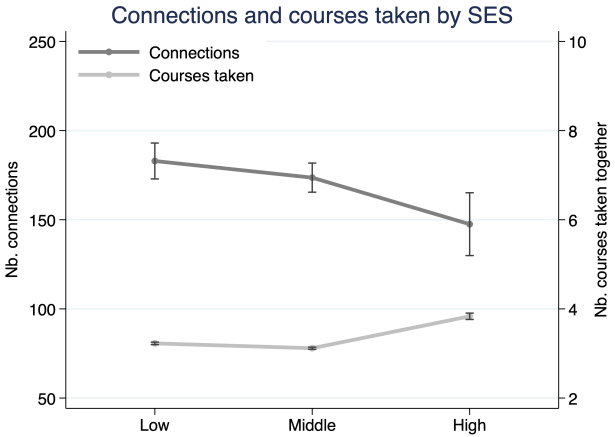
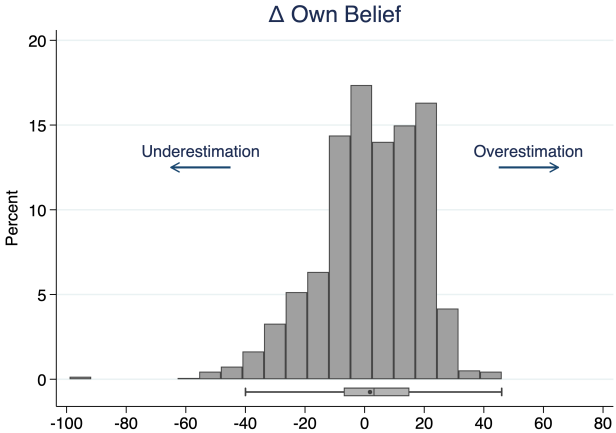


Results: Referrals versus Networks

Participants know their own exam ranking

- Defined as referrer *i*'s own ranking belief minus their actual rank across Math and Reading
- No difference between SES groups See



Participants know their nominees' exam ranking

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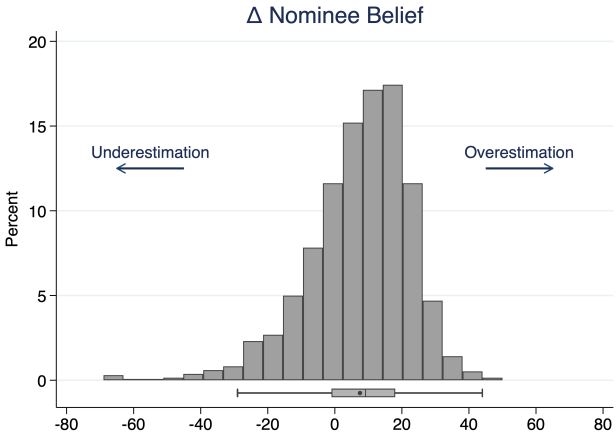

Referrals are better than network average

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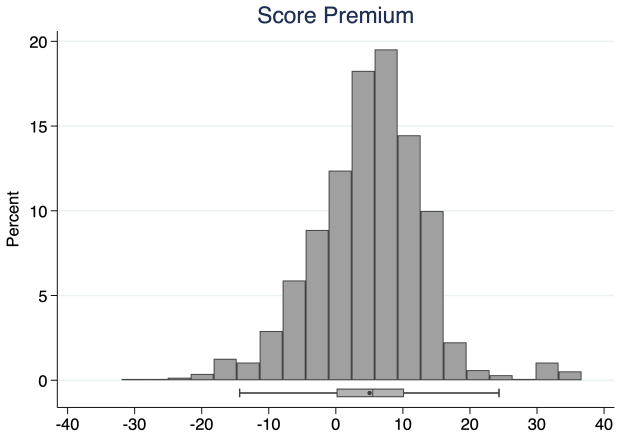
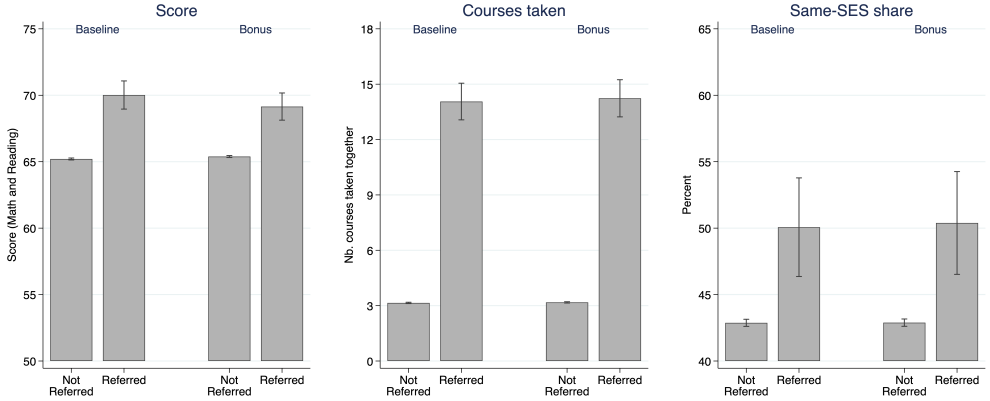


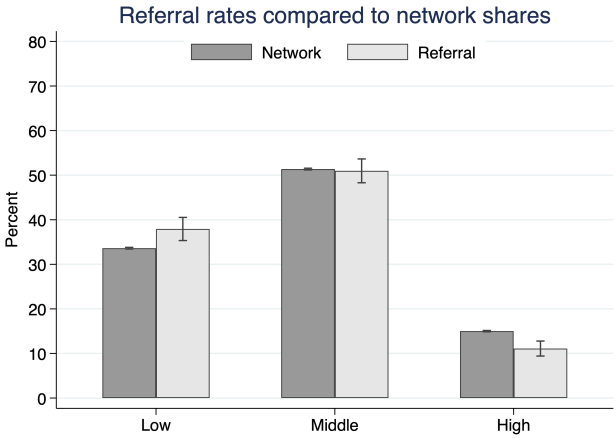
Who gets the referral?



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

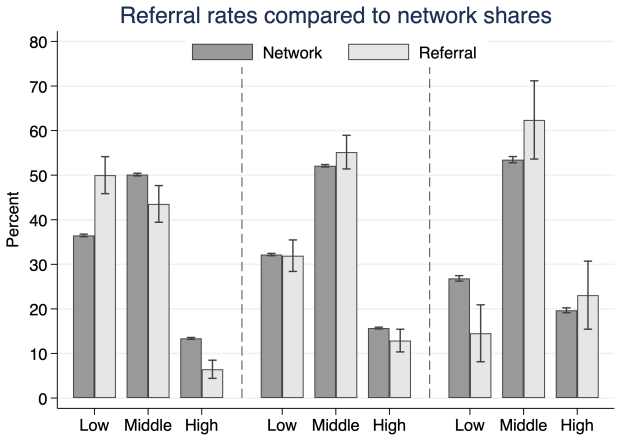
No overall bias against low-SES in referrals

- 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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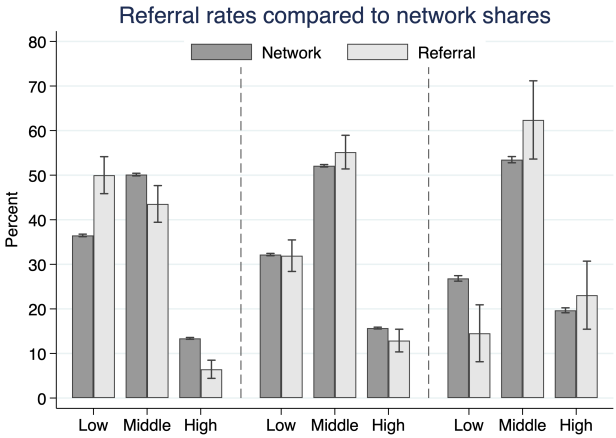
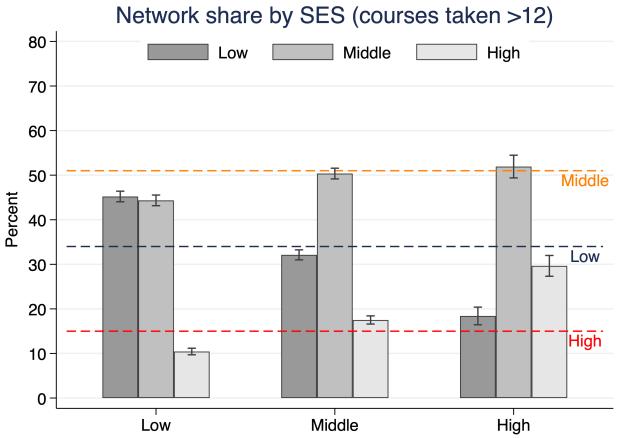


Referrer networks may drive differences

- 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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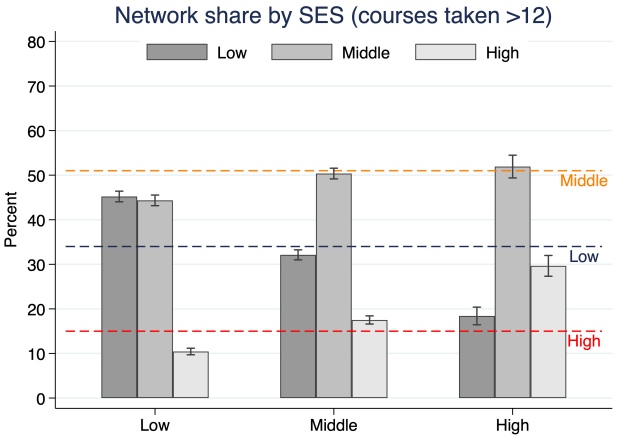

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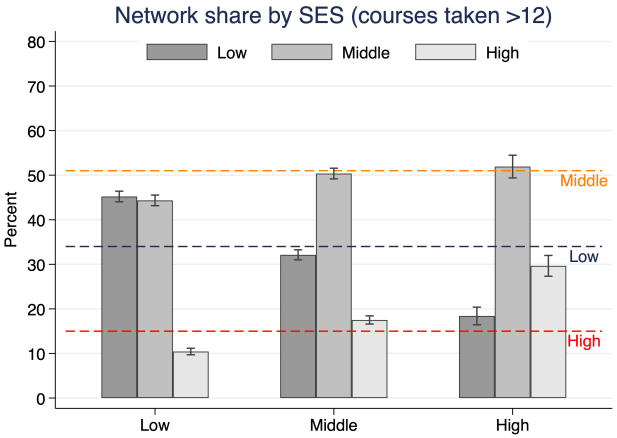


Is there a SES bias in referrals?

Conditional FE Logit:

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

- Refer_{ij}: Binary outcome indicating whether individual i refers individual j
- SES_j: Referral j is Low, Middle, or High SES
- 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

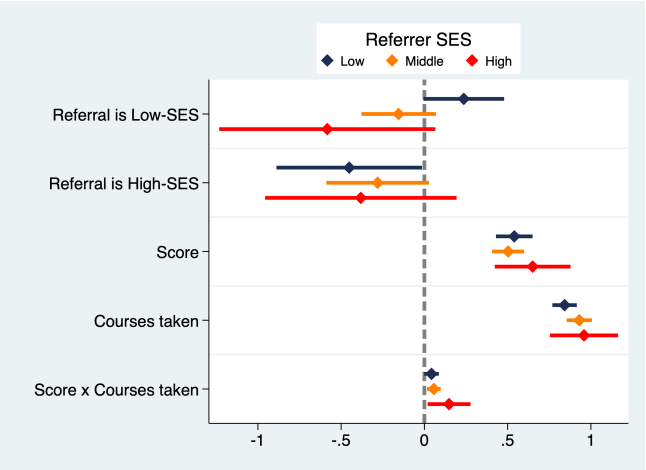
High-SES referrers are not biased

- 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 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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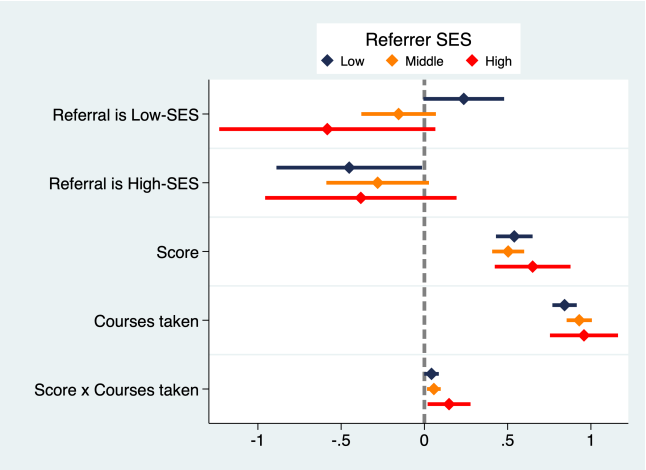

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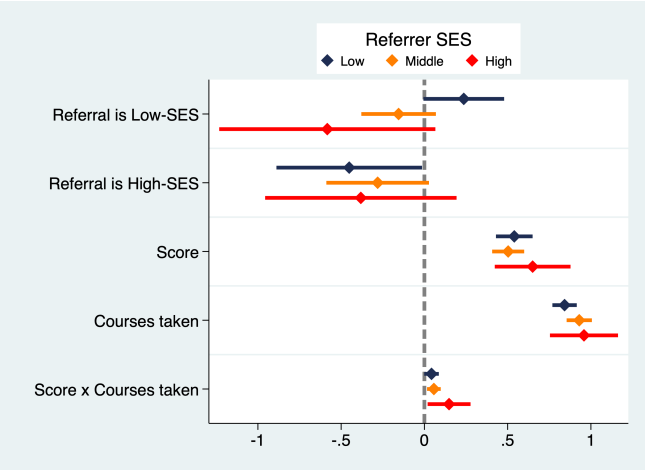

Summary

- 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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References I

Beaman, L., Keleher, N., and Magruder, J. (2018). Do job networks disadvantage women? evidence from a recruitment experiment in malawi. *Journal of labor economics*, 36(1):121–157.

Beaman, L. and Magruder, J. (2012). Who gets the job referral? evidence from a social networks experiment. *American economic review*, 102(7):3574–3593.

Brown, M., Setren, E., and Topa, G. (2016). Do informal referrals lead to better matches? evidence from a firm's employee referral system. *Journal of Labor Economics*, 34(1):161–209.

Calvó-Armengol, A. and Jackson, M. O. (2004). The effects of social networks on employment and inequality. *American Economic Review*, 94(3):426–454.

Calvó-Armengol, A., Patacchini, E., and Zenou, Y. (2009). Peer effects and social networks in education. *The Review of Economic Studies*, 76(4):1239–1267.

References II

Chetty, R., Jackson, M. O., Kuchler, T., Stroebel, J., Hendren, N., Fluegge, R. B., Gong, S., Gonzalez, F., Grondin, A., Jacob, M., et al. (2022). Social capital i: measurement and associations with economic mobility. *Nature*, 608(7921):108–121.

DiTomaso, N. (2013). *The American Non-dilemma: Racial Inequality Without Racism*. Russell Sage Foundation.

Dustmann, C., Glitz, A., Schönberg, U., and Brücker, H. (2016). Referral-based job search networks. *The Review of Economic Studies*, 83(2):514–546.

Fergusson, L. and Flórez, S. A. (2021). Distinción escolar. In Cárdenas, J. C., Fergusson, L., and García-Villegas, M., editors, *La Quinta Puerta: De cómo la educación en Colombia agudiza las desigualdades en lugar de remediarlas*, Ariel Ciencias Sociales, pages 81–114. Ariel, Bogotá.

Friebel, G., Heinz, M., Hoffman, M., and Zubanov, N. (2023). What do employee referral programs do? measuring the direct and overall effects of a management practice. *Journal of Political Economy*, 131(3):633–686.

References III

Granovetter, M. (1995). Getting a job: A study of contacts and careers chicago.

Hederos, K., Sandberg, A., Kvissberg, L., and Polano, E. (2025). Gender homophily in job referrals: Evidence from a field study among university students. *Labour Economics*, 92:102662.

Kramarz, F. and Skans, O. N. (2014). When strong ties are strong: Networks and youth labour market entry. *The Review of Economic Studies*, 81(3):1164–1200.

Lin, N., Ensel, W. M., and Vaughn, J. C. (1981). Social resources and strength of ties: Structural factors in occupational status attainment. *American Sociological Review*, 46(4):393–405.

McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 27:415–444.

Mouw, T. (2003). Social capital and finding a job: Do contacts matter? *American Sociological Review*, 68(6):868–898.

References IV

Smith, S. S. (2005). Don't put my name on it: Social capital activation and job-finding assistance among the black urban poor. *American Journal of Sociology*, 111(1):1–57.

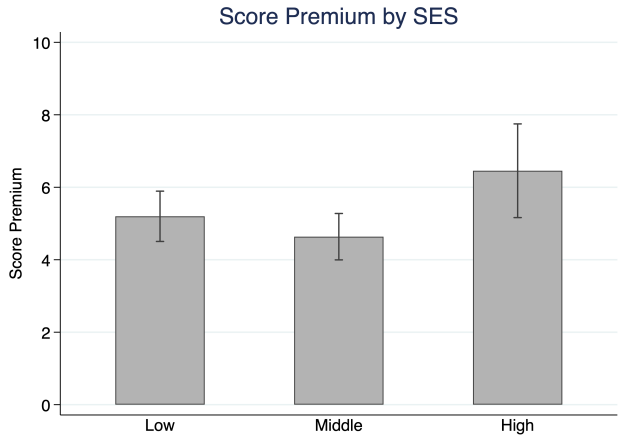
Stansbury, A. and Rodriguez, K. (2024). The class gap in career progression: Evidence from academia. *Econometrica*. Revise & Resubmit.

Topa, G. (2019). Social and spatial networks in labour markets. *Oxford Review of Economic Policy*, 35(4):722–745.

No differences for Score Premium by SES

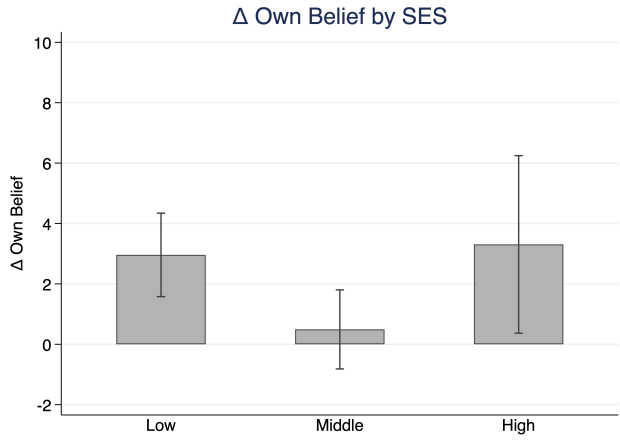
- Middle-SES refer slightly worst (joint F-test, $p < 0.1$)

Return



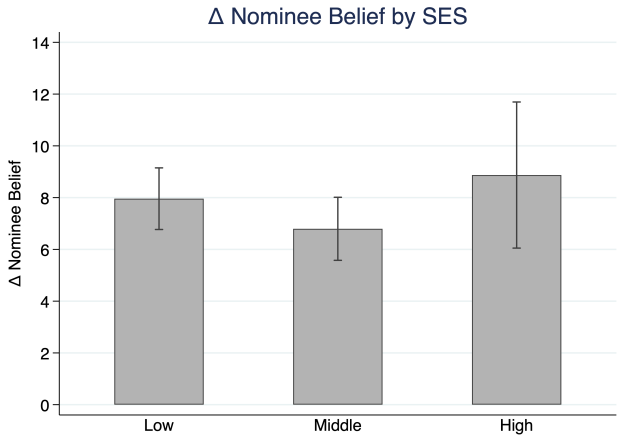
No differences for own ranking beliefs by SES

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



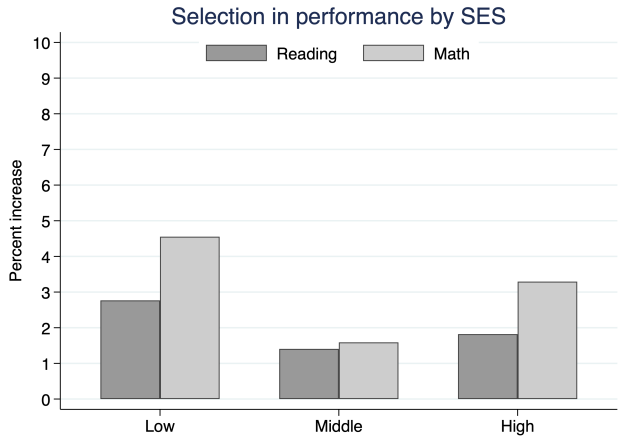
No differences for nominee score beliefs by SES

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



Strong selection by Low-SES

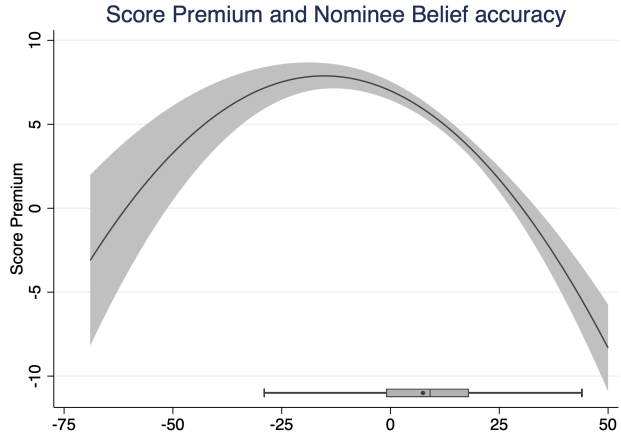
- Significant Low-SES selection (t-tests, $p < 0.01$)
- Other SES groups do select less (t-tests, $p > 0.05$) Return



Nominee Beliefs are rewarded for accuracy

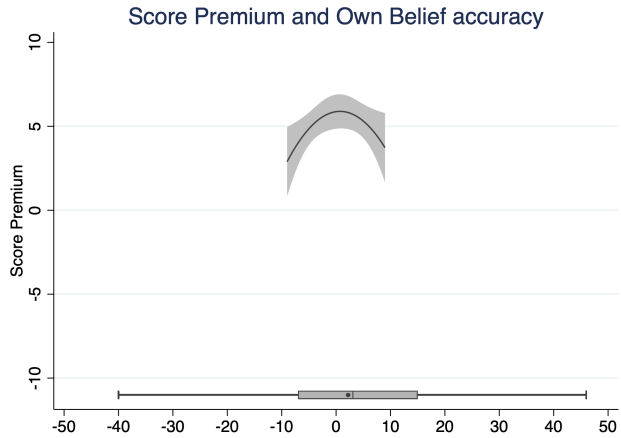
- Negative coeffient is explained by quadratic shape

Return



Own score beliefs are rewarded for accuracy

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



Courses taken by SES

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

Return