Class differences in social networks: Evidence from a referral experiment

1-hour presentation

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

[1]Luxembourg Institute of Socioeconomic Research

[2]NYU Abu Dhabi

[3]University of Luxembourg

16 May 2025

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**

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**

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; 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)

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; 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)

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; 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)

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; 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)

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; 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)

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; 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)

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; 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)

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

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

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

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?*

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?*

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?*

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**

Setting

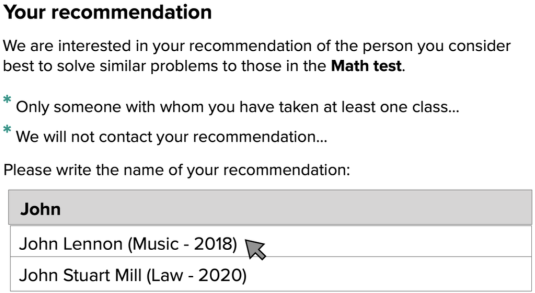
- Universidad Autónoma de Bucaramanga (UNAB)
- Approx. 6000 students across all social classes
- Administrative data including **SES**, age, program, GPA, **courses attended**, year of entry, and the **entry exam scores**

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**

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...

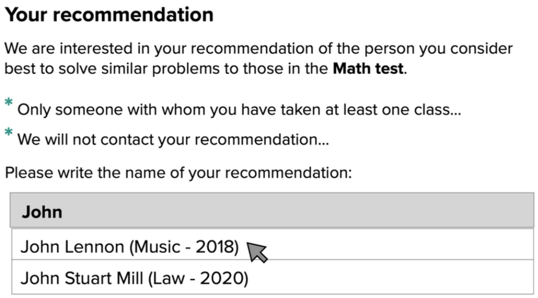
* We will not contact your recommendation...

Please write the name of your recommendation:

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

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...

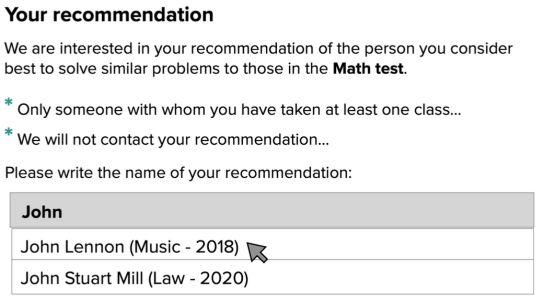
* We will not contact your recommendation...

Please write the name of your recommendation:

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

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...

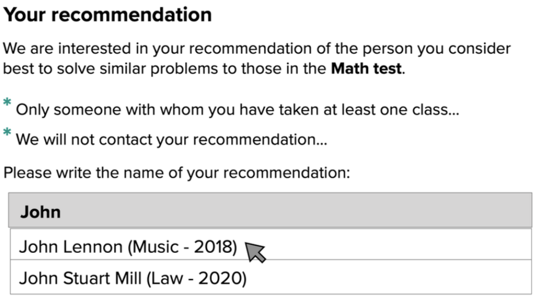
* We will not contact your recommendation...

Please write the name of your recommendation:

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

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:

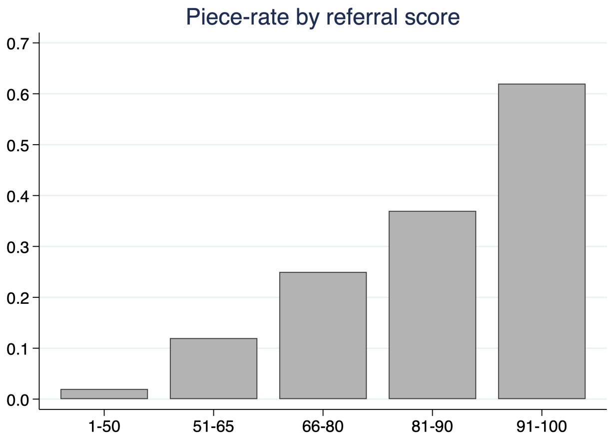
John

John Lennon (Music - 2018)

John Stuart Mill (Law - 2020)

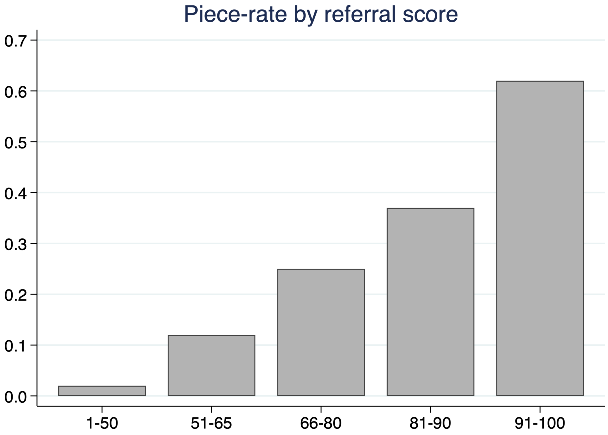
Design II: Incentives

- 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 (+)
- Not a real job opportunity (−)



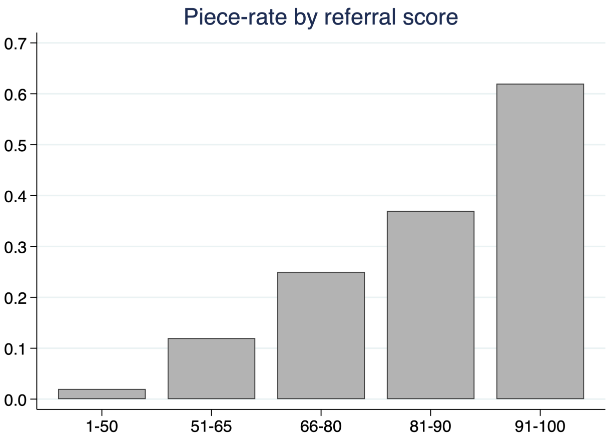
Design II: Incentives

- 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 (+)
- Not a real job opportunity (−)



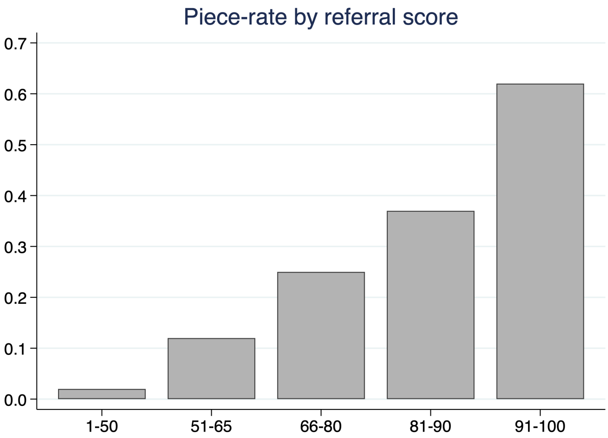
Design II: Incentives

- 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 (+)
- Not a real job opportunity (−)



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 (+)
- Not a real job opportunity (−)



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)

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)

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

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

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

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

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

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

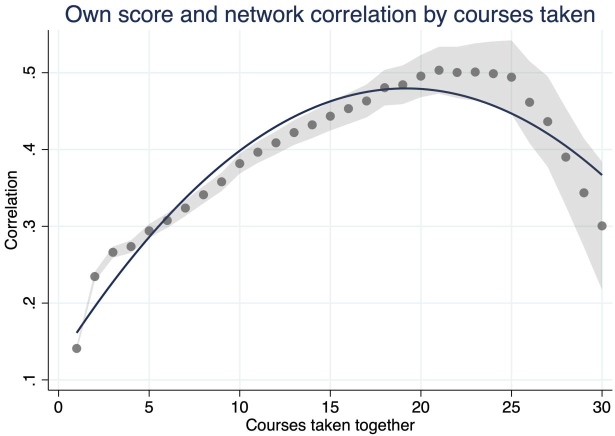
- Connections peak around 7 semesters and decline as students change majors or graduate
- Courses taken with peers increase over time

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

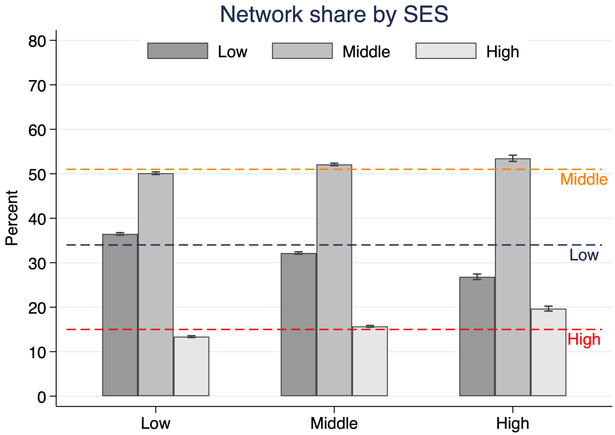
Courses taken together and performance

- Network homophily in terms of performance



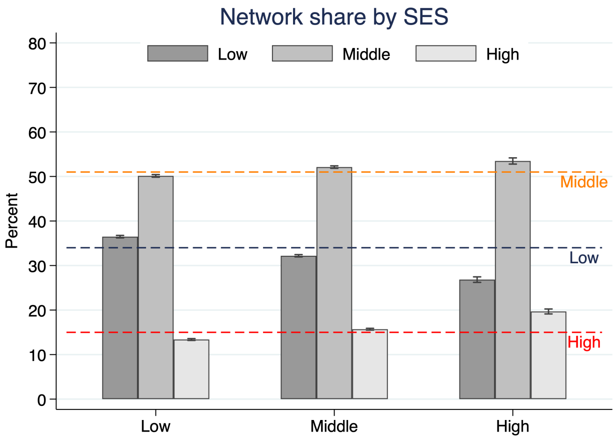
Network-level SES shares

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



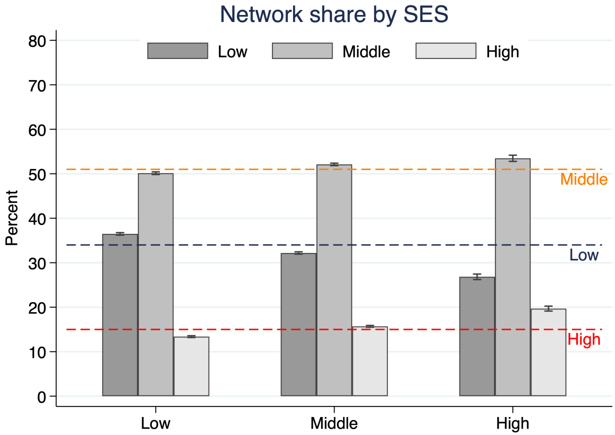
Network-level SES shares

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



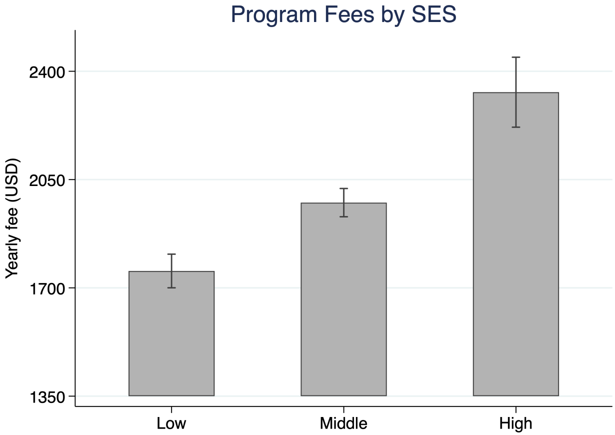
Network-level SES shares

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



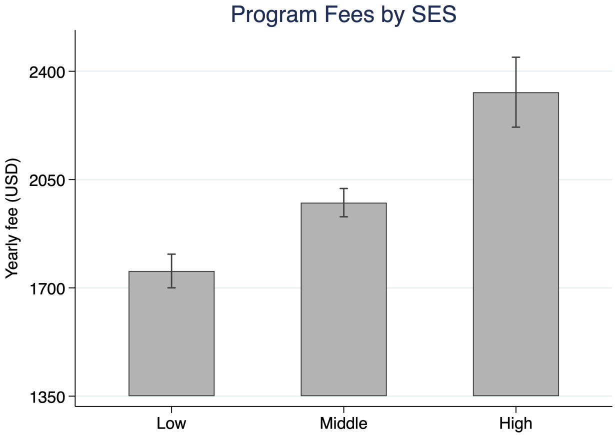
Selection into programs

- UNAB prices each program differently based on its cost
- Low-SES study in more affordable programs and is general knowledge
- Large difference as net average monthly salary around $350



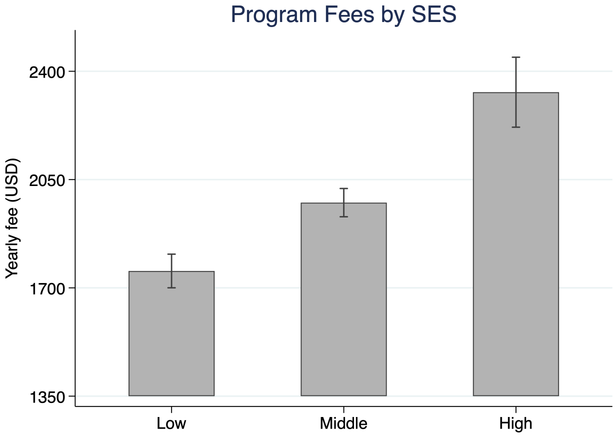
Selection into programs

- UNAB prices each program differently based on its cost
- Low-SES study in more affordable programs and is general knowledge
- Large difference as net average monthly salary around $350



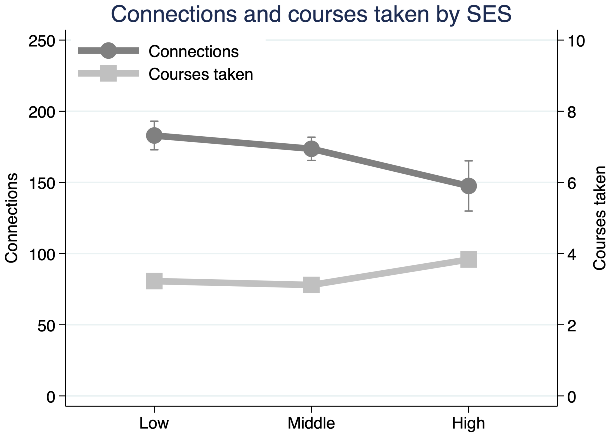
Selection into programs

- UNAB prices each program differently based on its cost
- Low-SES study in more affordable programs and is general knowledge
- Large difference as net average monthly salary around $350



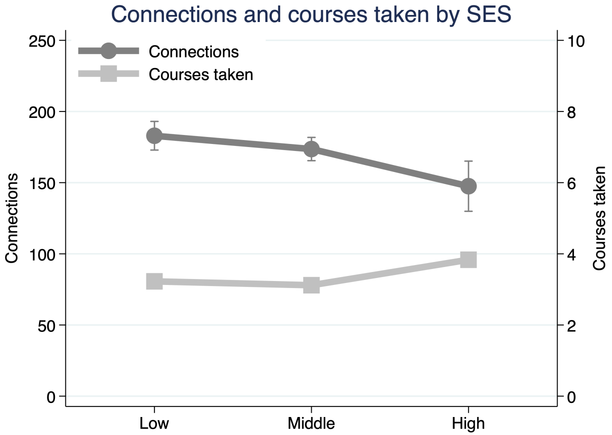
Network dynamics by SES

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



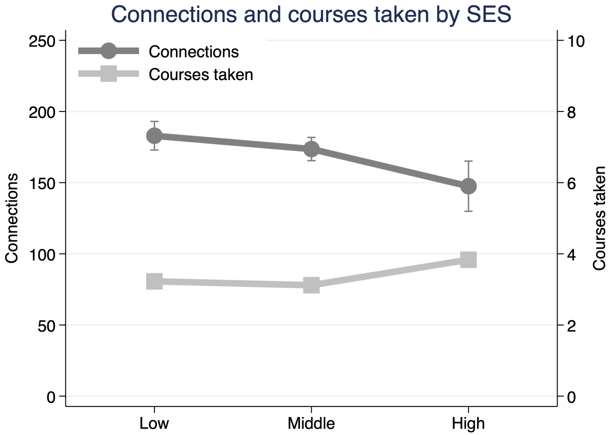
Network dynamics by SES

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



Network dynamics by SES

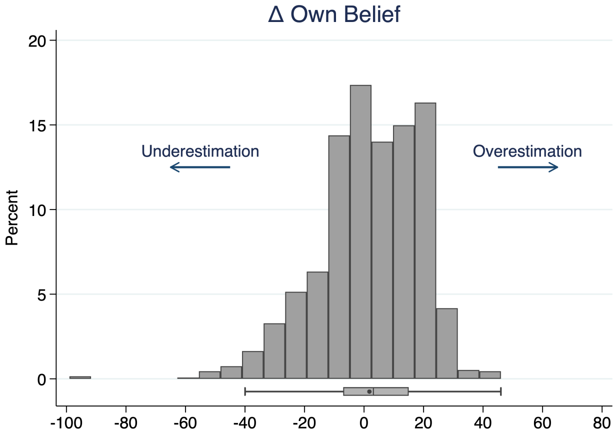
- Connections decrease with SES
- Courses taken with peers increases with SES
- High-SES take more courses with their own See



Results II: Referrals

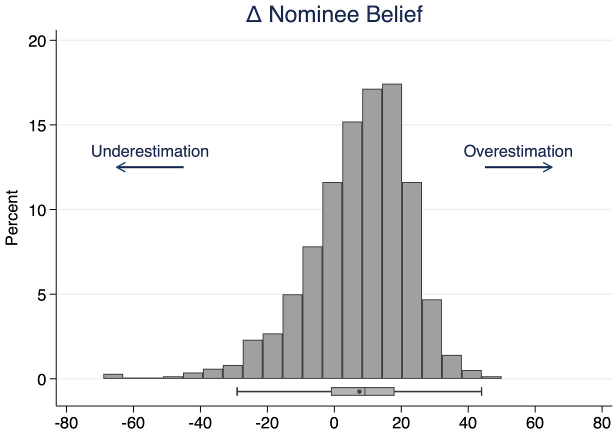
Referrers know their own scores

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



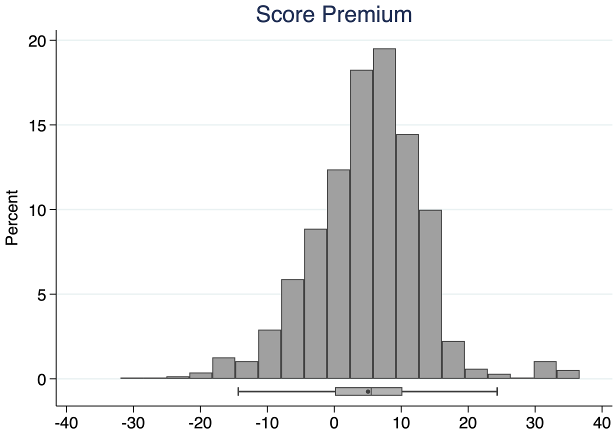
Referrers know their nominees' scores

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



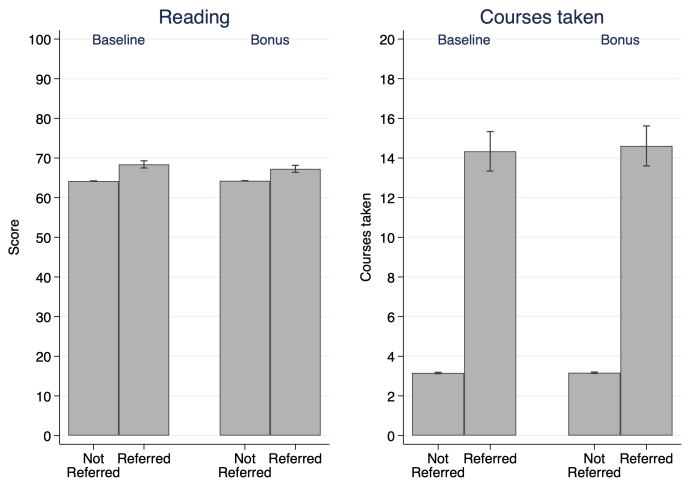
Referrals are better than network average

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



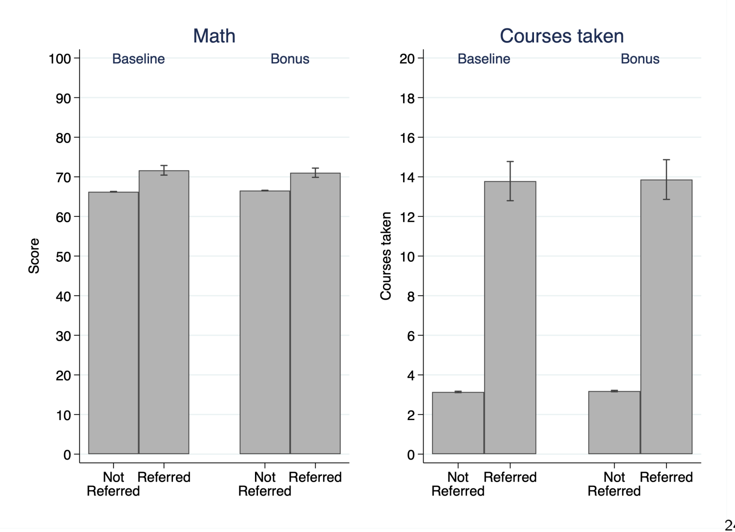
Referrals for Reading

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



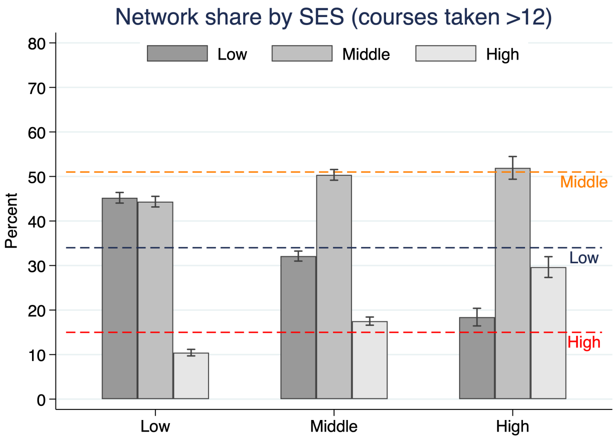
Referrals for Math

- Referrals have higher math scores (.5 SD) and much higher tie strength (2.5 SD)
- No treatment effect on the referred (t-tests, $p > 0.1$)



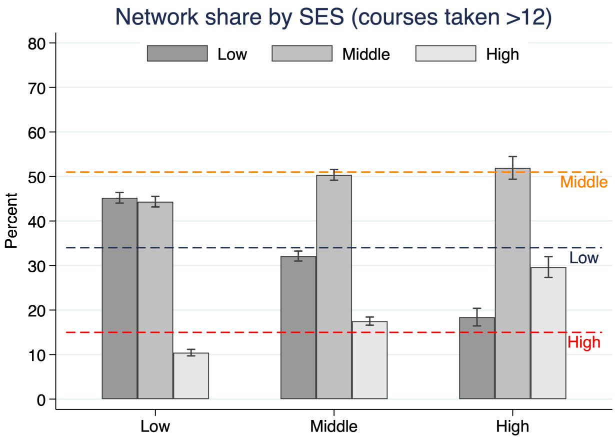
Ex post referral choice sets

- 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



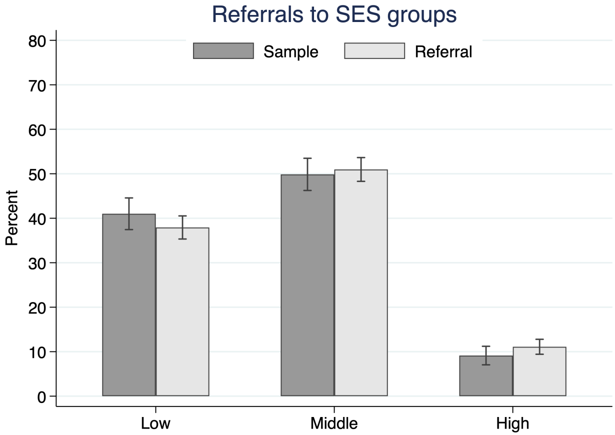
Ex post referral choice sets

- 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



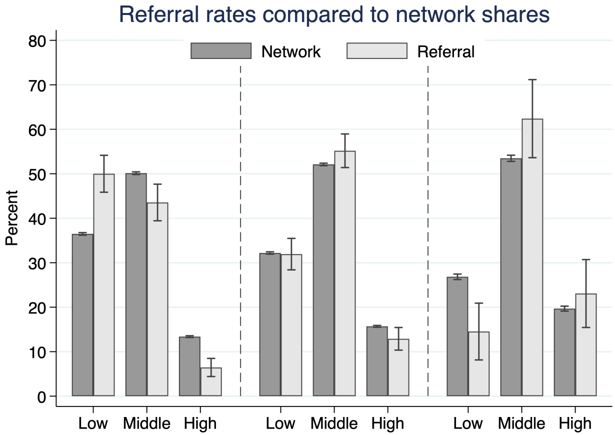
Referrals are balanced

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



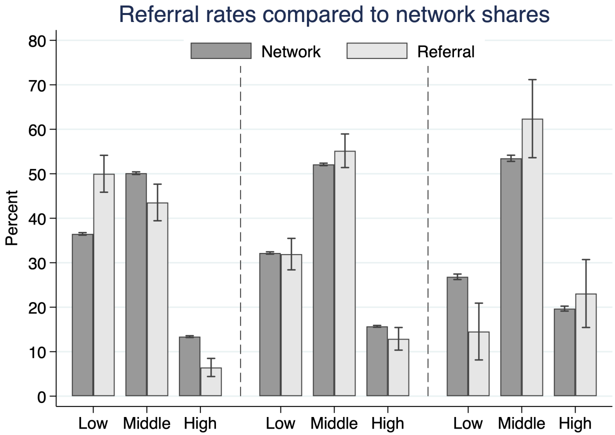
Referral SES composition

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



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?



Is there a SES bias in referrals?

Conditional FE Logit:

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

- 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
- 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**	-0.013	-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)
Courses taken		0.916***	0.894***
		(0.026)	(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

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**	-0.013	-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)
Courses taken		0.916***	0.894***
		(0.026)	(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

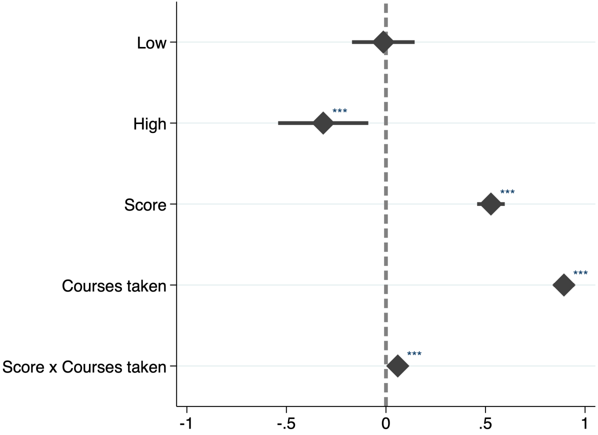
Is there a SES bias in referrals?

- 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**	-0.013	-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)
Courses taken		0.916***	0.894***
		(0.026)	(0.026)
Score × Courses taken			0.059***
			(0.015)
Observations	256997	256997	256997
Ind.	734	734	734
Chi-test	17.44	1602.42	1640.06

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



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)
Nominee score		0.607***	0.540***
		(0.052)	(0.056)
Courses taken		0.859***	0.842***
		(0.036)	(0.037)
Score × 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 $\times$ Courses taken			0.057***
			(0.021)
Observations	127088	127088	127088
Ind.	366	366	366
Chi-test	3.18	756.06	766.33

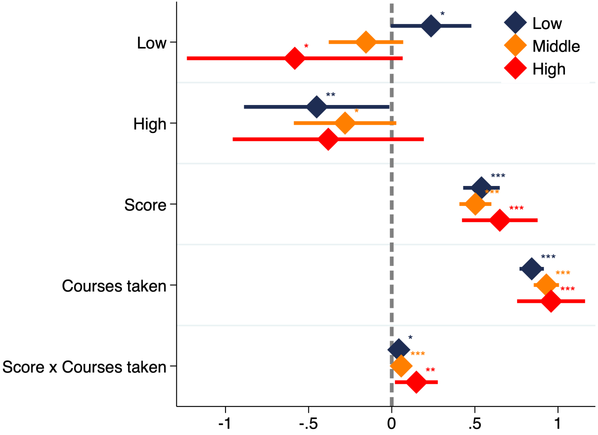
High-SES referrers are not biased

- 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 $\times$ Courses taken			0.148**
			(0.066)
Observations	19767	19767	19767
Ind.	67	67	67
Chi-test	4.94	120.54	144.77

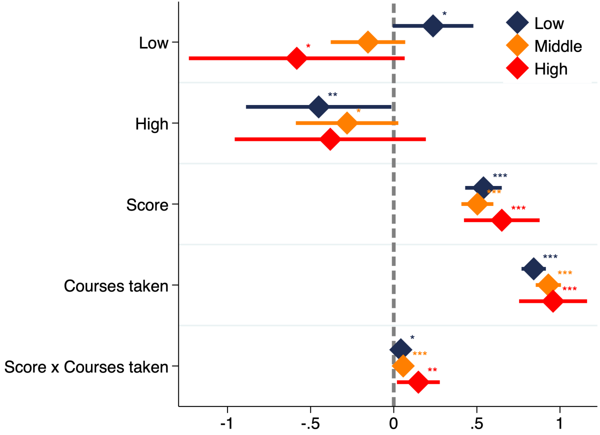
No bias against Low-SES in referrals

- **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



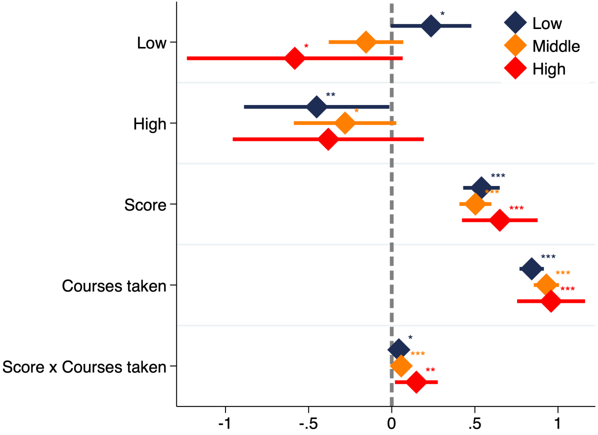
No bias against Low-SES in referrals

- **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



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



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

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

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

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

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

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

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.

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.

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.

References III

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.

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.

References IV

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

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	Middle-SES	High-SES
	(1)	(2)	(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 (1)	Middle-SES (2)	High-SES (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

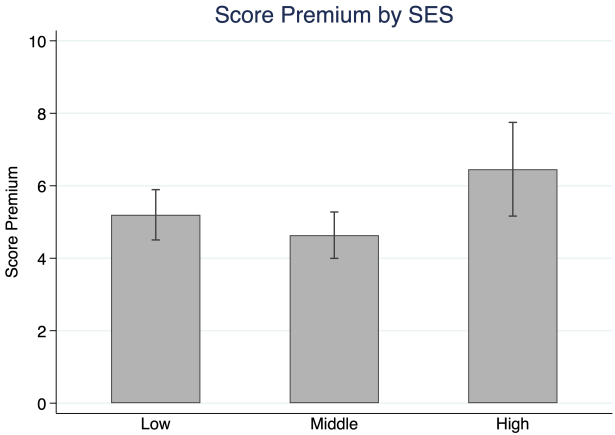
Return

	Low-SES	Other-SES
	(1)	(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

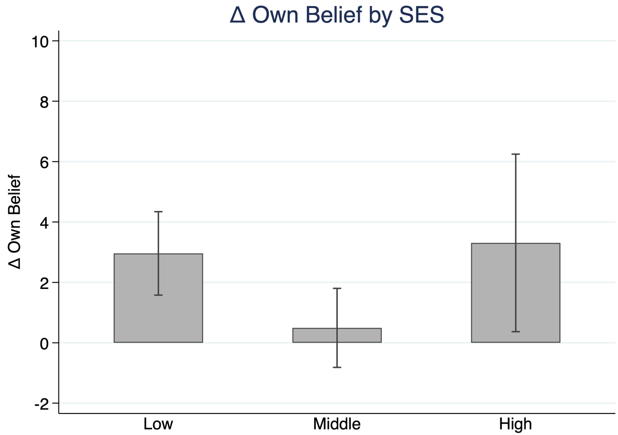
- Middle-SES refer slightly worst (joint F-test, $p < 0.1$)

Return



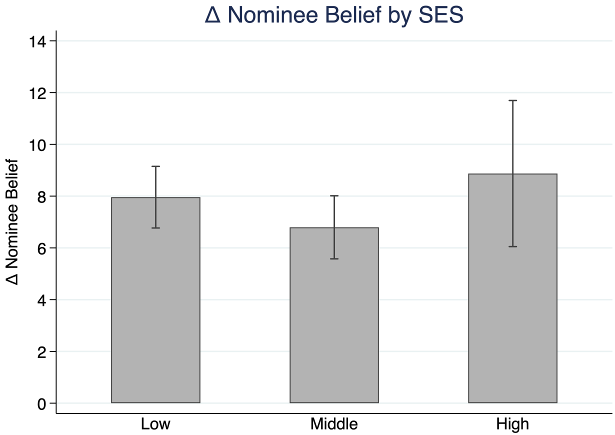
No differences for own score beliefs by SES

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



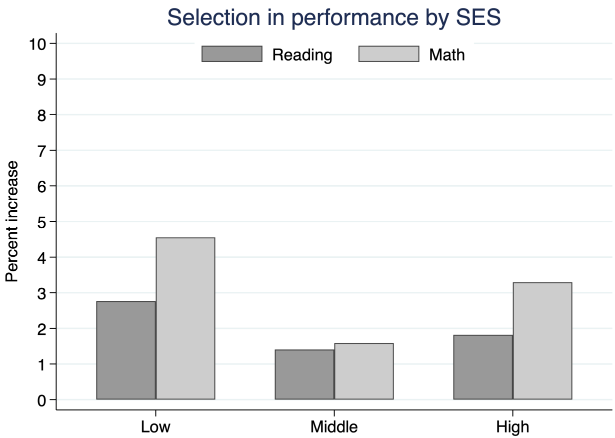
No differences for nominee score beliefs by SES

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



Strong selection by Low-SES

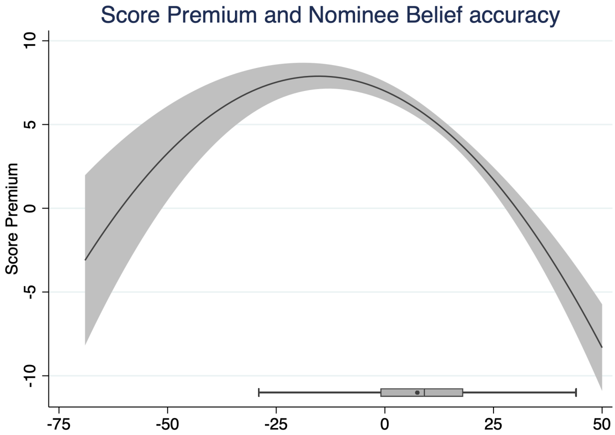
- Significant Low-SES selection (t-tests, $p < 0.01$)
- Other SES groups do select less (t-tests, $p > 0.05$) Return



Nominee Beliefs are rewarded for accuracy

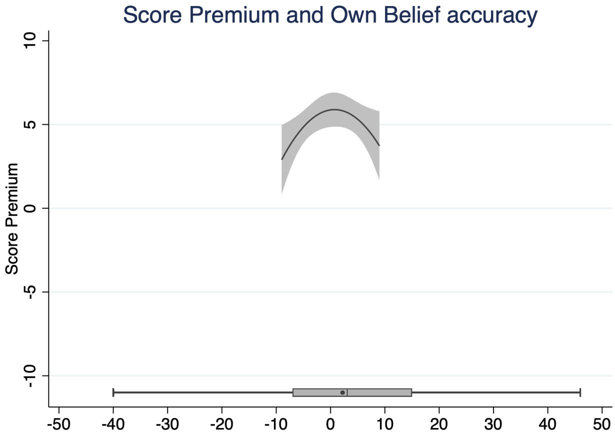
- Negative coeffient is explained by quadratic shape

Return



Own score beliefs are rewarded for accuracy

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



Courses taken by SES

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

Return