# 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

8 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**

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# Research Questions

- *Are class differences in labor market 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** |
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| John Lennon (Music - 2018) |
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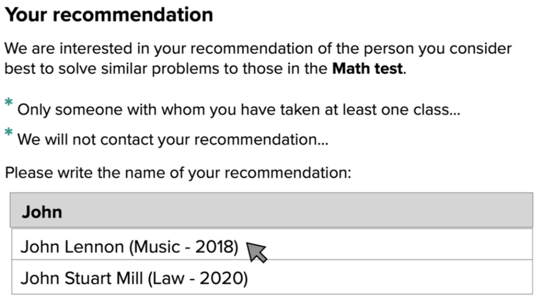

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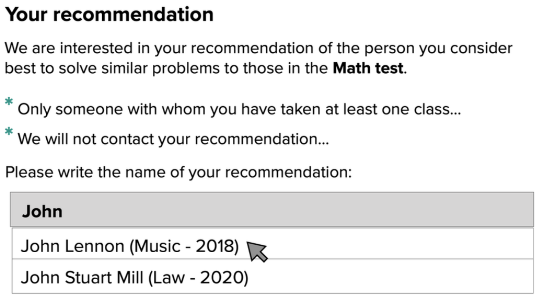

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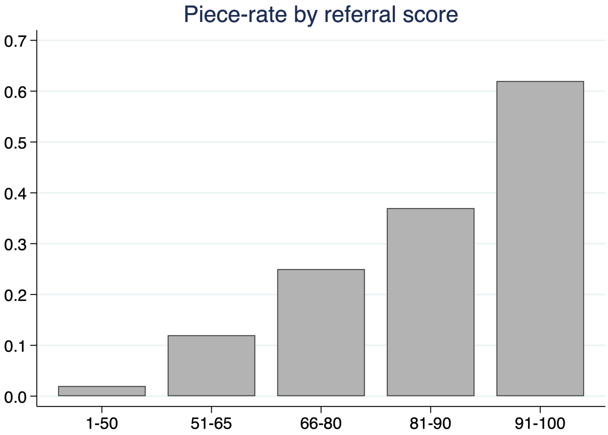
# Design II: Incentives

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



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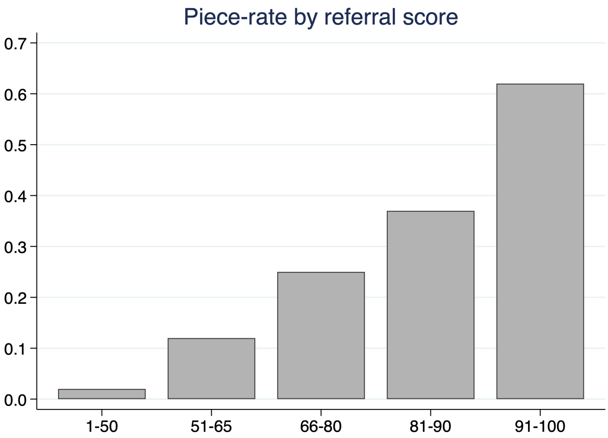

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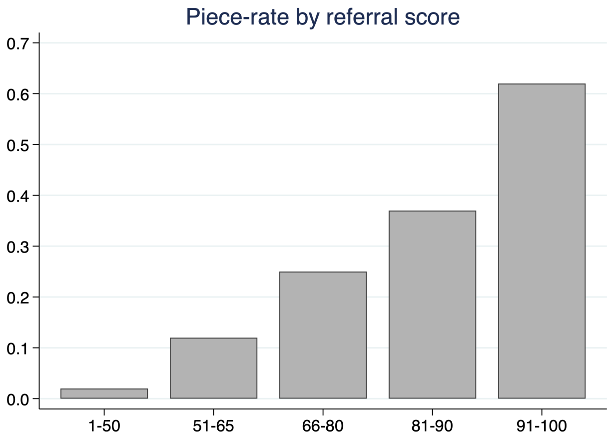

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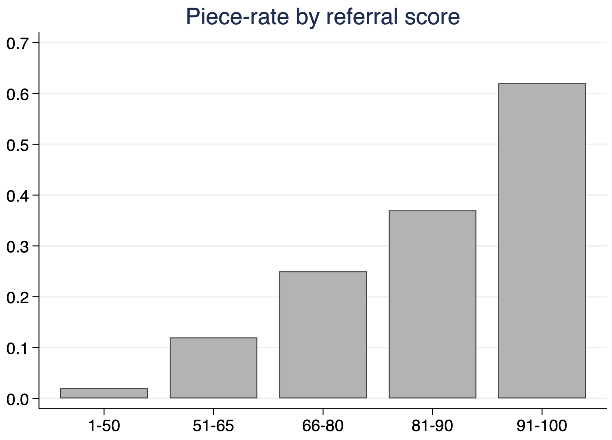

# Design III: Treatment

- **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

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- 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 |

# Descriptive Statistics I: Network

# Network size and tie strength

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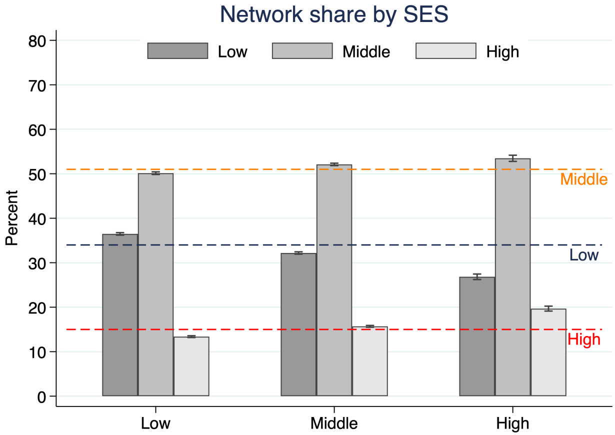
# Network-level SES shares

- 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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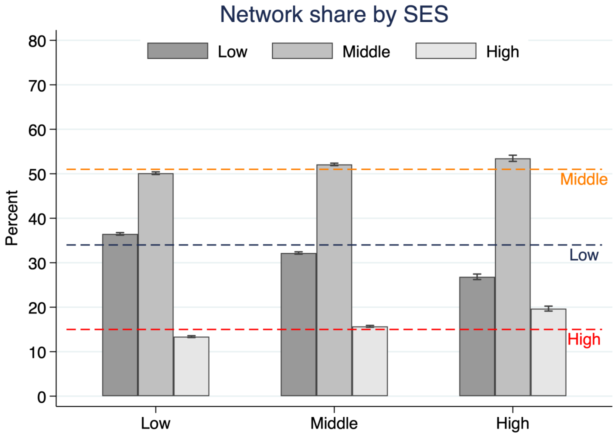

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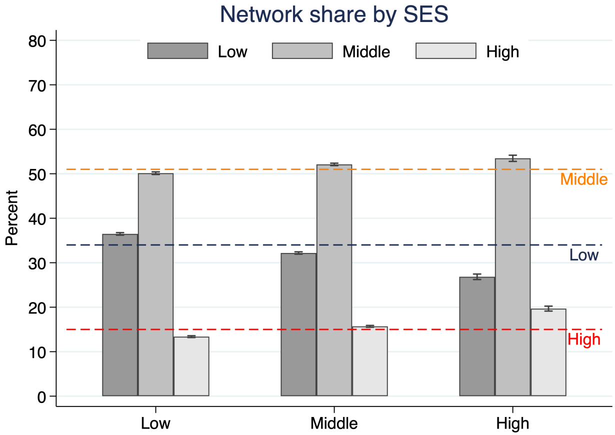
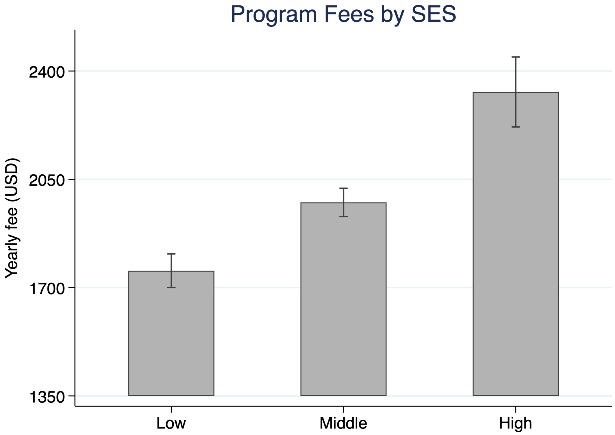


# Selection into programs

- 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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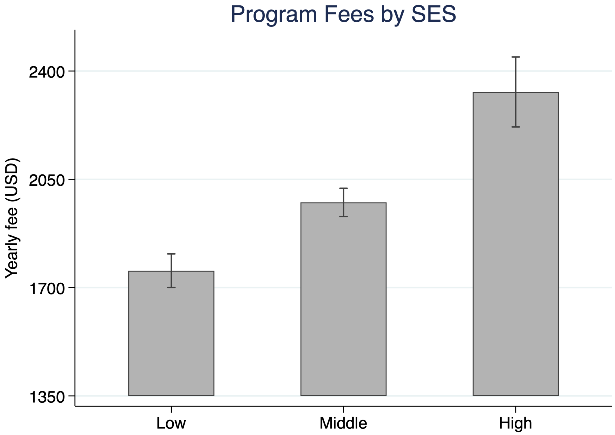

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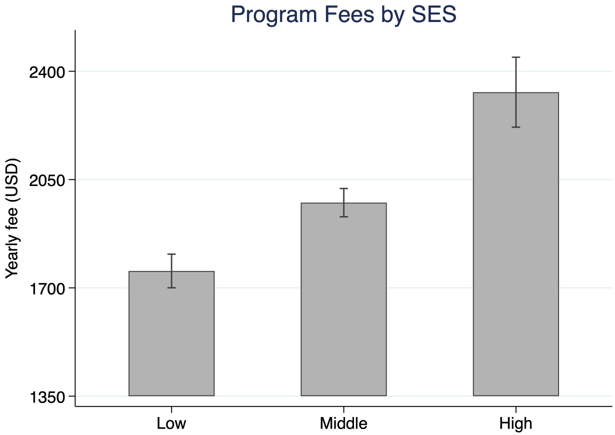
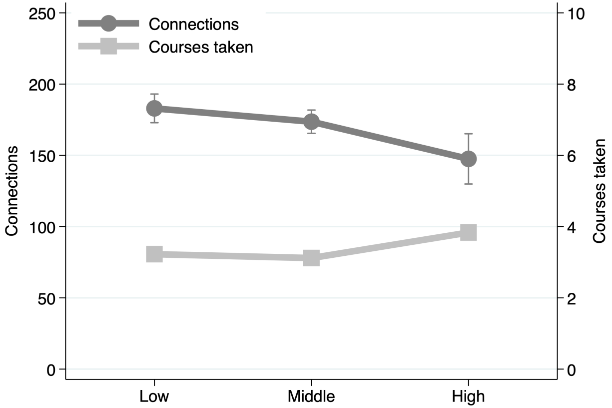


# Network dynamics by SES

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

Connections and courses taken by SES



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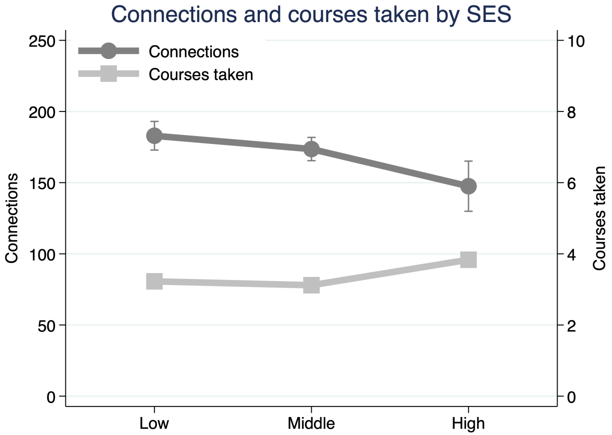

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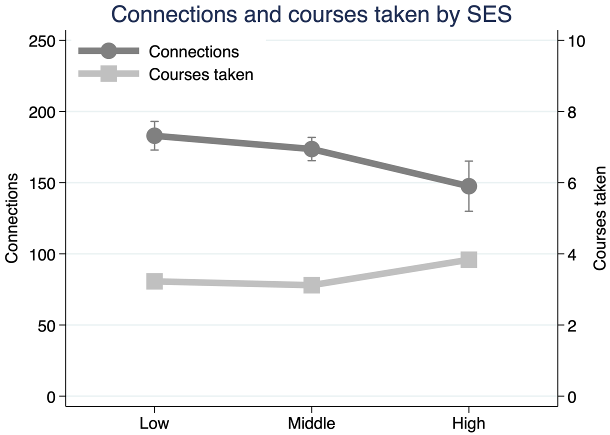
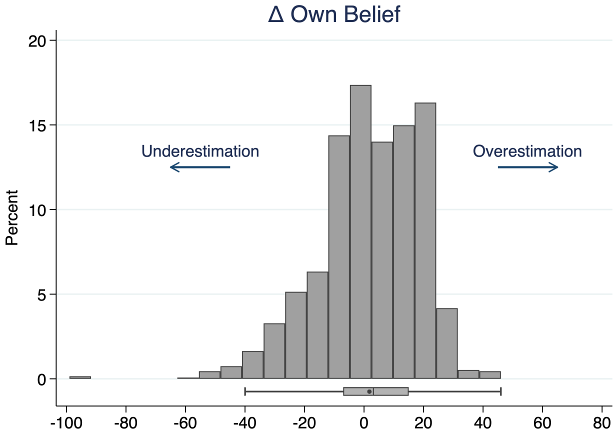


# Descriptive Statistics II: Referrals

# 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

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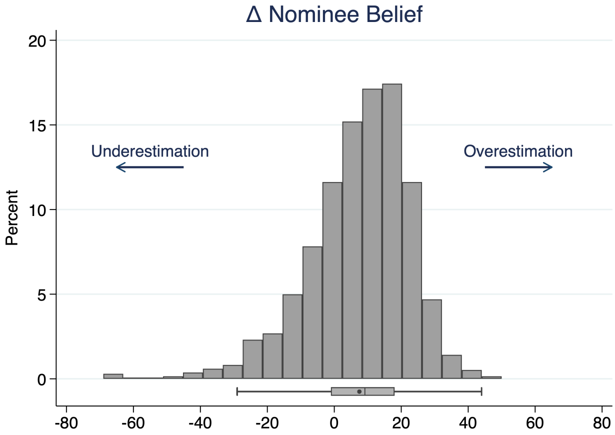
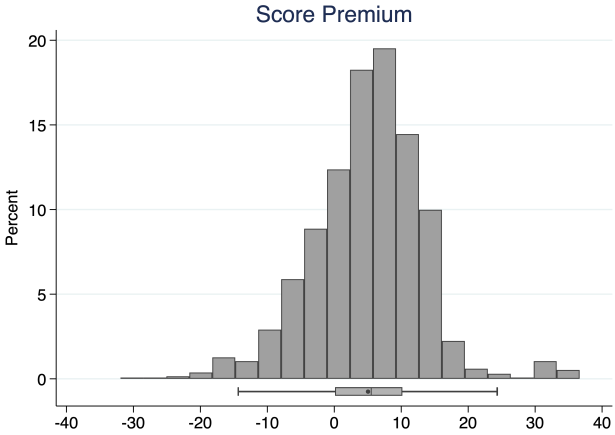


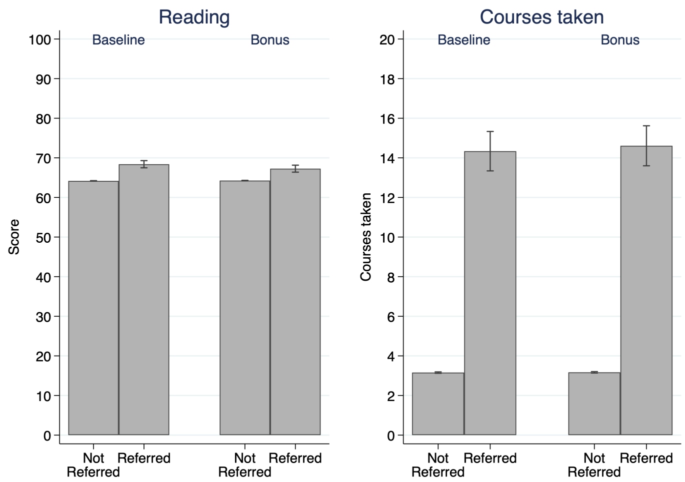
# Referrals are better than network average

- 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

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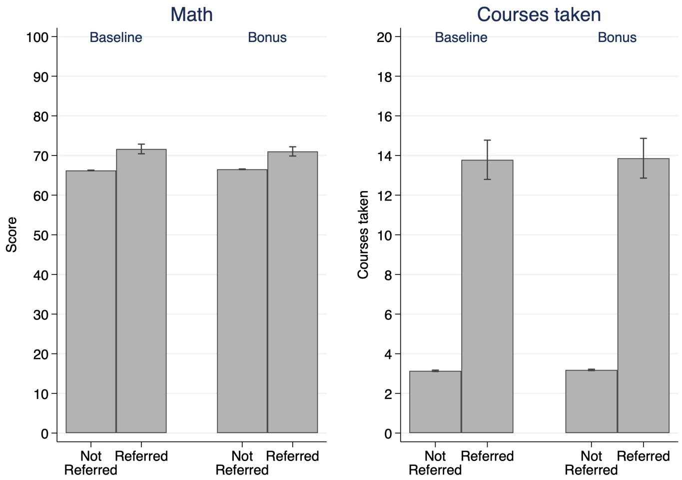
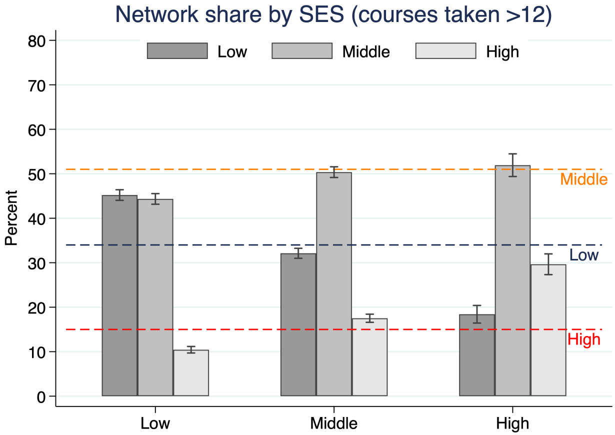


# Ex post referral choice sets

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



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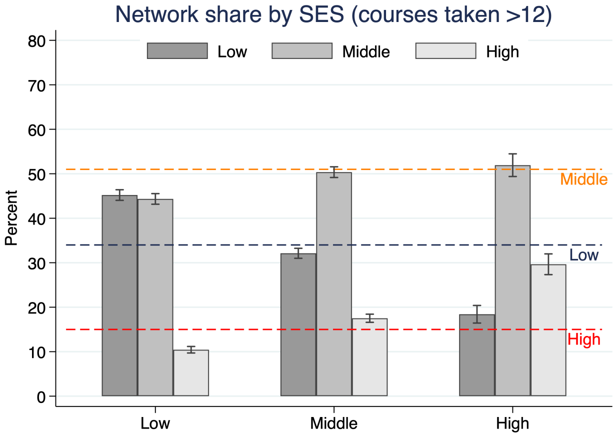
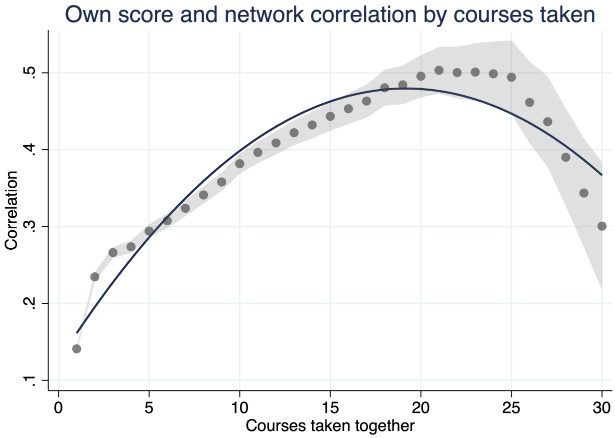


# Referral choice sets and performance

- Sweet spot for referring closest performing peers to one's own around 15
- Network homophily in terms of performance



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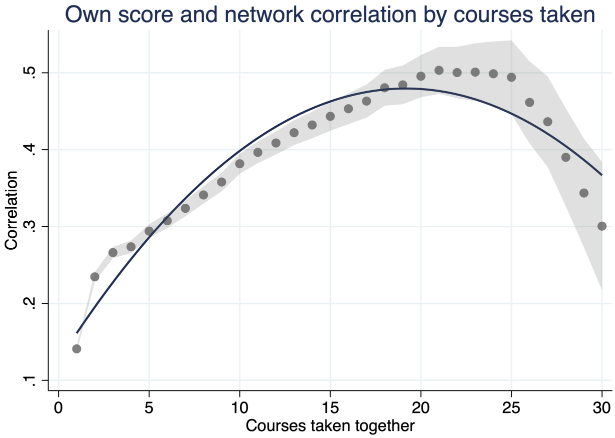
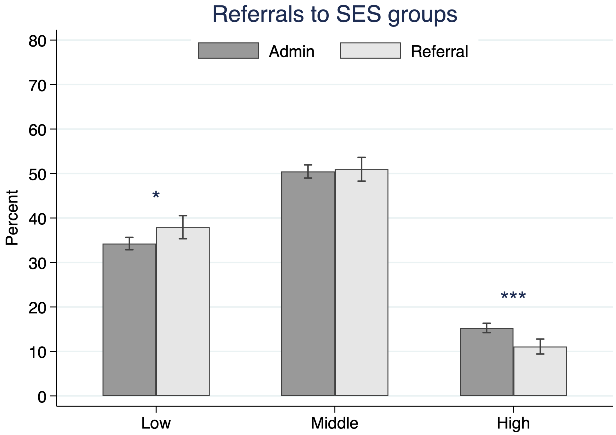


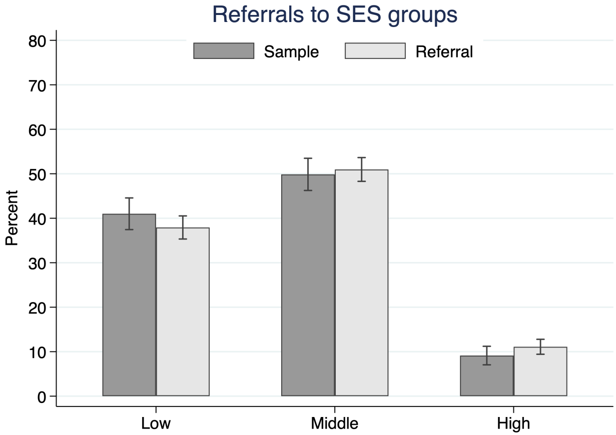
# Referrals are balanced

- More referrals for Low-SES and less for High-SES compared to the admin data
- No differences at the sample-level (all $p > 0.1$)



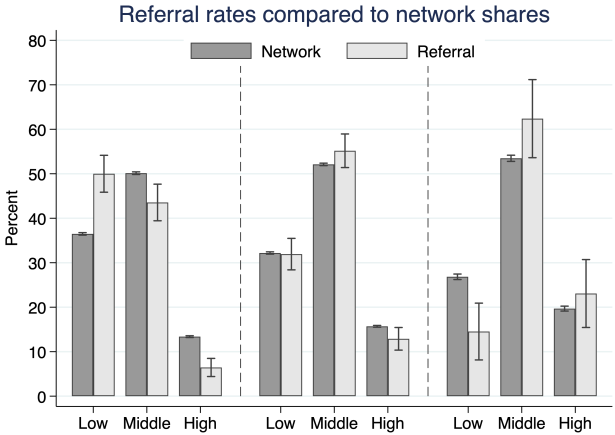
# Referrals are balanced

- More referrals for Low-SES and less for High-SES compared to the admin data
- 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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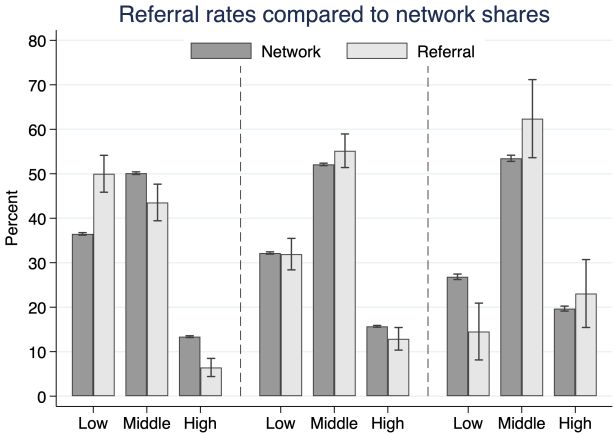

# Is there a SES bias in referrals?

**Conditional FE Logit:**

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

- $\text{Refer}_{ij}$: Binary outcome indicating whether individual $i$ refers individual $j$
- $\text{SES}_j$: Referral $j$ is Low, Middle, or High SES
- $\text{Score}_j$: Standardized Math or Reading score of referral $j$
- $\text{Courses}_{ij}$: Standardized number of courses taken together for $i$ and $j$
- $\alpha_i$: 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 |

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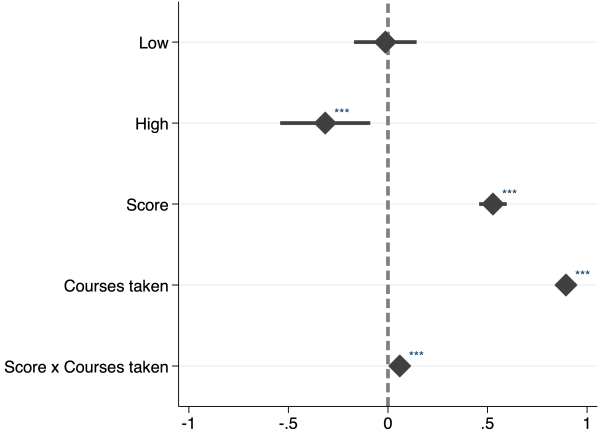


# Low-SES referrers are biased

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

| | (1) | (2) | (3) |
|---|---|---|---|
| Low | 0.453*** | 0.242** | 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 $\times$ 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 × Courses taken | | | 0.057*** |
| | | | (0.021) |
| Observations | 127088 | 127088 | 127088 |
| Ind. | 366 | 366 | 366 |
| Chi-test | 3.18 | 756.06 | 766.33 |

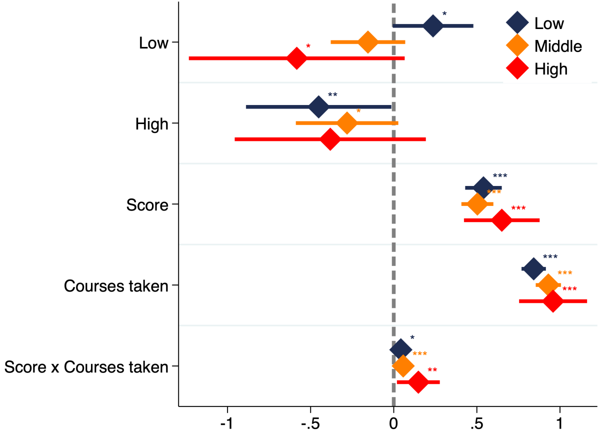
# High-SES referrers are not biased

- 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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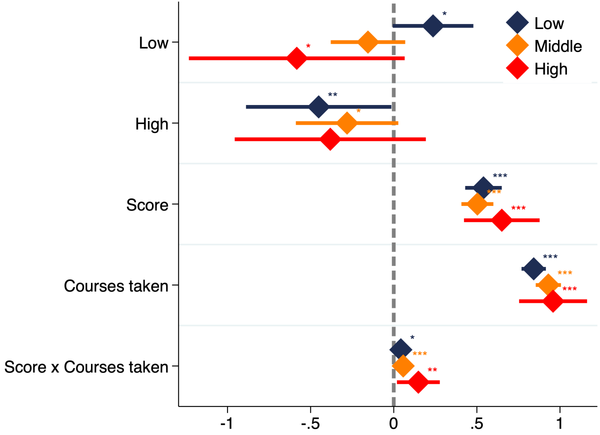

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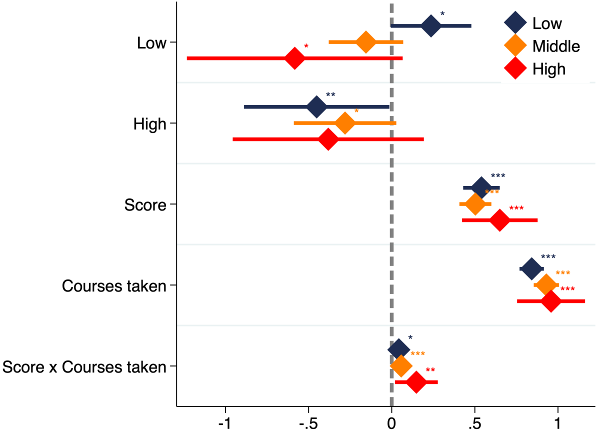

# Summary

- 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
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# Reading

- Reading score and tie strength are strong predictors of referrals
- No interaction between reading score and tie strength
- No evidence for a Low-SES bias Alt. Specification

| | (1) | (2) | (3) |
|---|---|---|---|
| Low-SES | 0.143* | -0.007 | -0.007 |
| | (0.086) | (0.101) | (0.102) |
| High-SES | -0.293** | -0.271* | -0.275** |
| | (0.128) | (0.139) | (0.139) |
| Nominee score | | 0.566*** | 0.513*** |
| | | (0.044) | (0.048) |
| Tie | | 0.949*** | 0.939*** |
| | | (0.031) | (0.032) |
| Score x Tie | | | 0.030 |
| | | | (0.018) |
| Observations | 128847 | 128847 | 128847 |
| Ind. | 673 | 673 | 673 |
| Chi-test | 10.81 | 1117.46 | 1145.58 |

# 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.

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.

# References III


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.

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

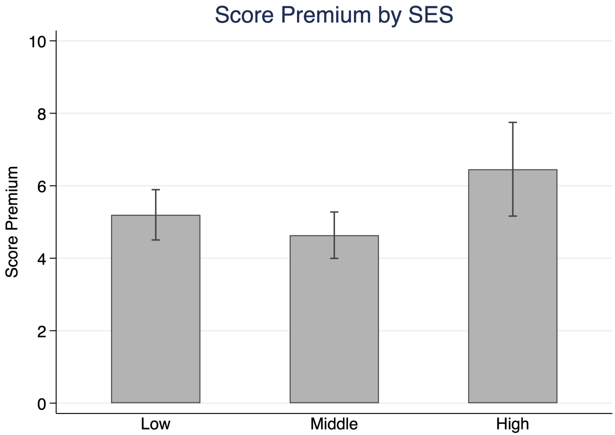
Return

| | Low-SES<br>(1) | Other-SES<br>(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

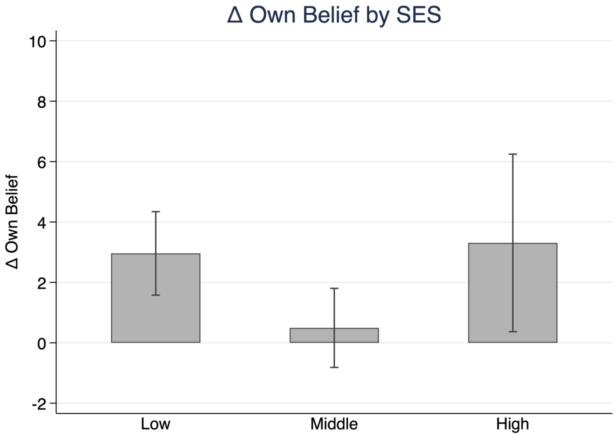
- Middle-SES refer slightly worst (joint F-test, $p < 0.1$)

Return



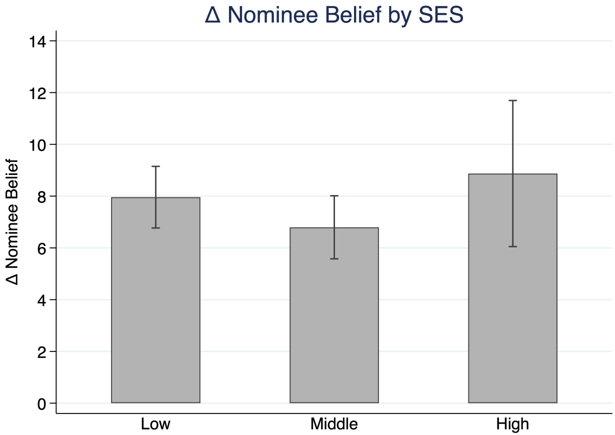
# No differences for own score beliefs by SES

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



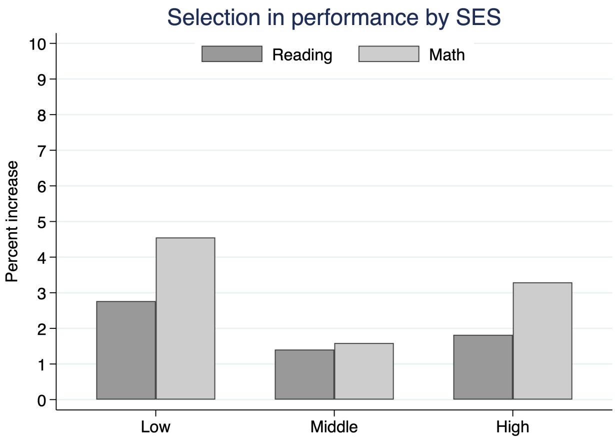
# No differences for nominee score beliefs by SES

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



# Strong selection by Low-SES

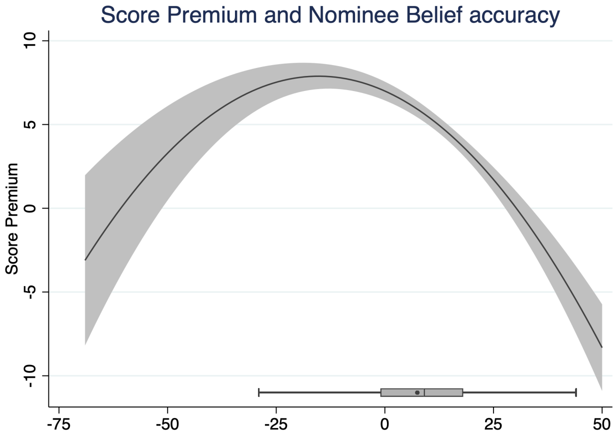
- Significant Low-SES selection ($t$-tests, $p < 0.01$)
- Other SES groups do select less ($t$-tests, $p > 0.05$) Return



# Nominee Beliefs are rewarded for accuracy

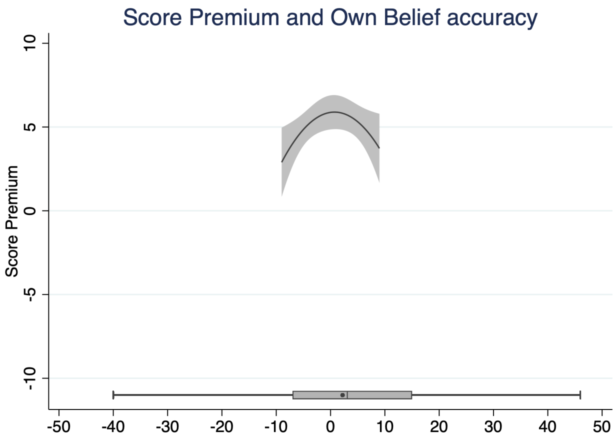
- Negative coeffient is explained by quadratic shape

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