

Class differences in social networks: Evidence from a referral experiment

8-min presentation

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Motivation and Research Question

- Understand persistent class differences in labor the market, like the underrepresentation of Low-SES researchers in top academic institutions [Stansbury and Rodriguez, 2024]
- Focus on class biases in referrals
 - Most jobs are found through referrals [Topa, 2011]
 - Referrals depend on social networks, which exhibit homophily [McPherson et al., 2001]
- Are there social class biases in referrals?
- If so, what are the potential drivers of these biases?

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Setting

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



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Design

- Ask students to refer someone they have taken at least one class with
- Pay according to the student's math and verbal scores in the national entry exam
- Incentivize better referrals by increasing reward as referral score goes higher

Your recommendation

We are interested in your recommendation of the person you consider best to solve similar problems to those in the **Math test**.

- * Only someone with whom you have taken at least one class...
- * We will not contact your recommendation...

Please write the name of your recommendation:

John

John Lennon (Music - 2018) 

John Stuart Mill (Law - 2020)

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Procedures

- Recruited participants by emailing 4500 students (>1st year)
- 30 minute online experiment in Qualtrics
- Average payment of 80 USD (lottery for 1 out of 10 participants)
- 840 complete responses
- Final sample 734 participants who referred someone they took a class with

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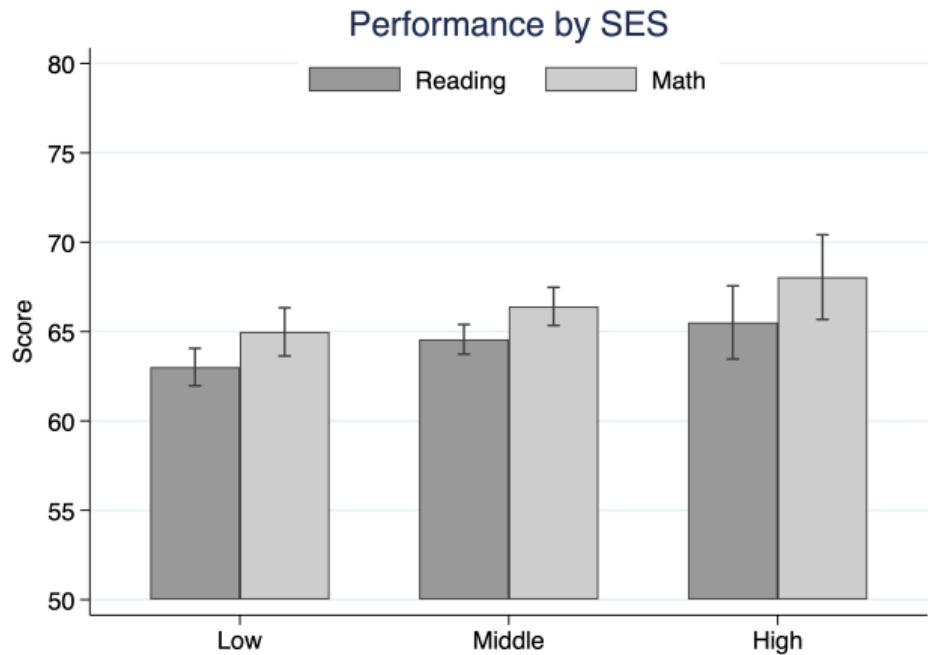
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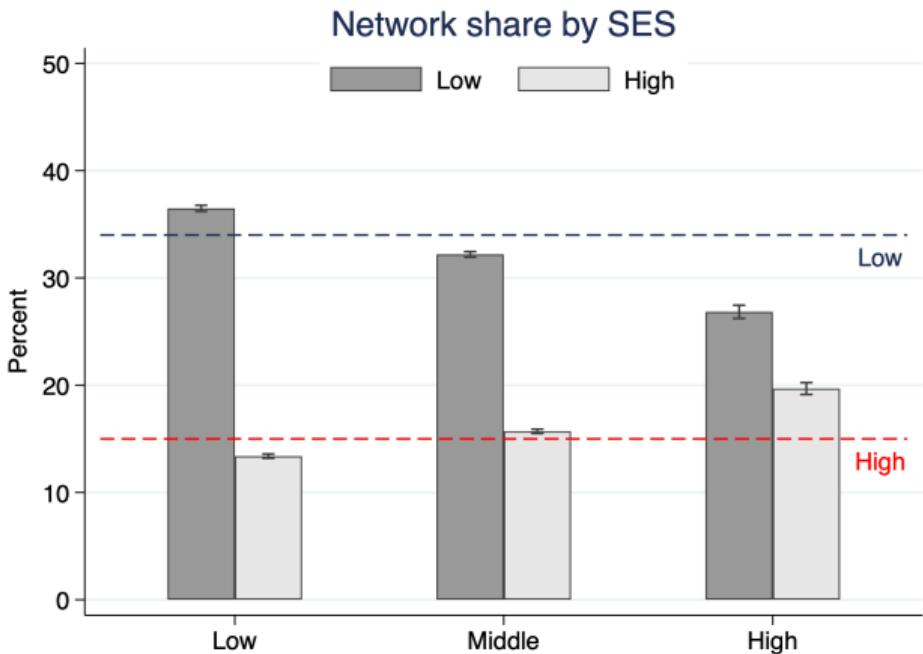
Entry exam performance across SES

- Very close distribution of entry exam scores in the sample



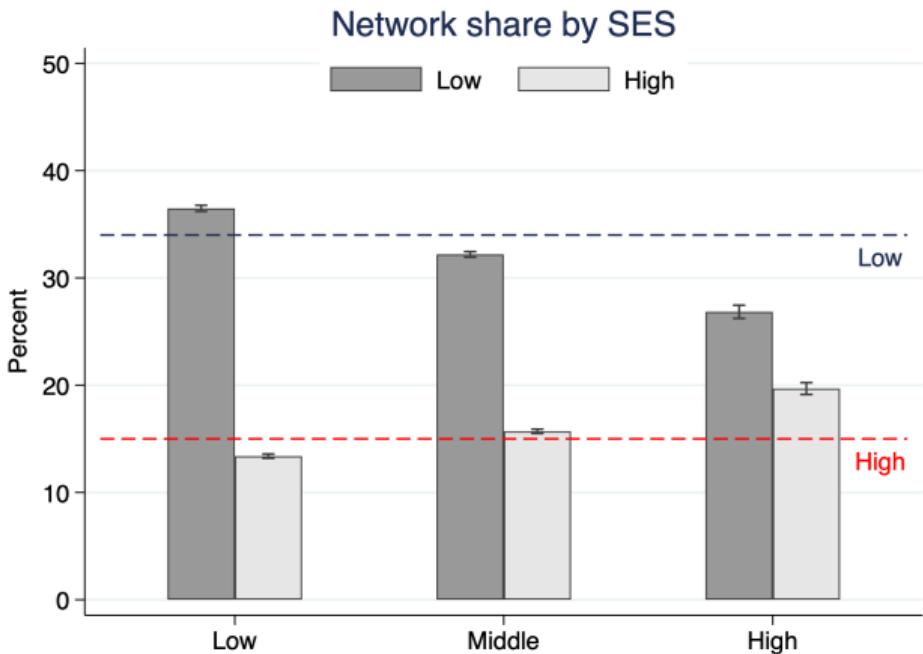
Network-level SES shares

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



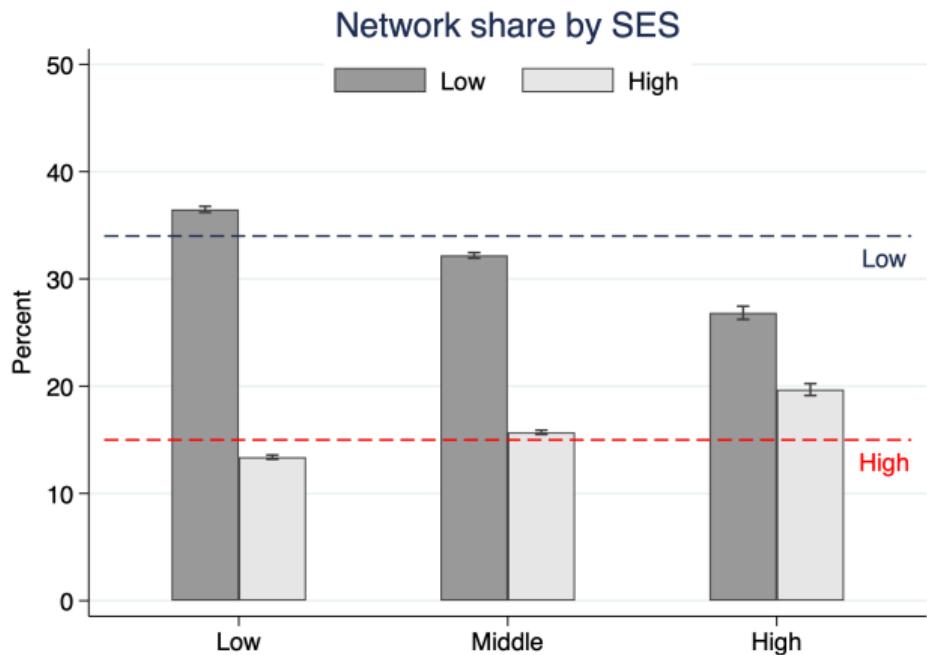
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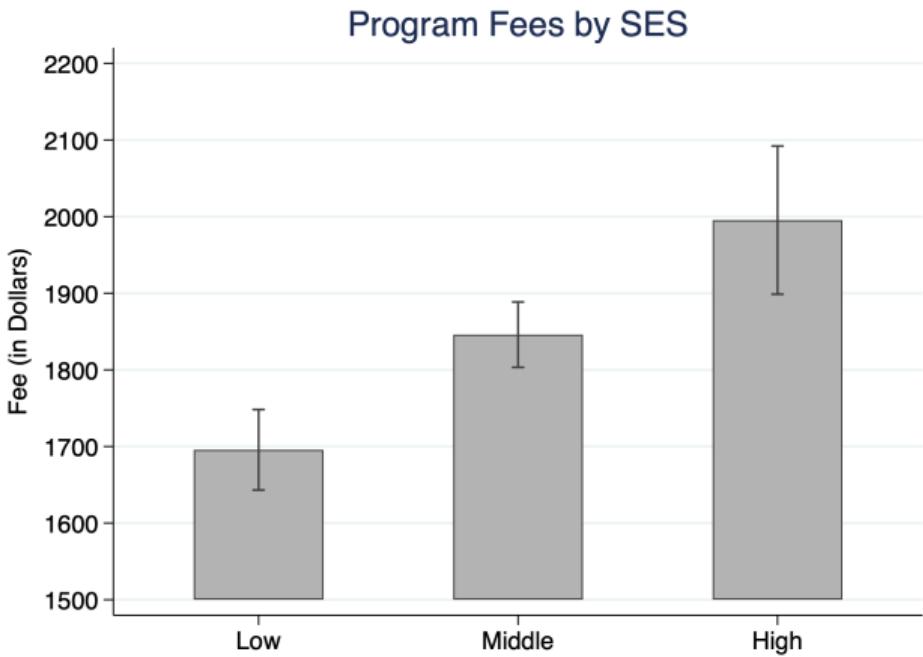
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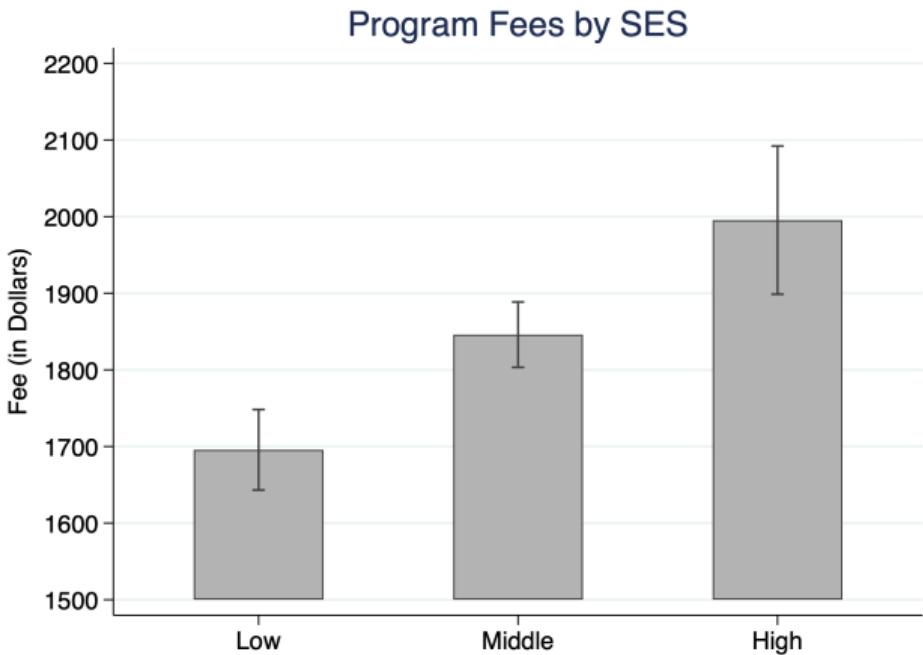
Selection into programs

- Low-SES study in more affordable programs
- Large difference as net average monthly salary around \$350



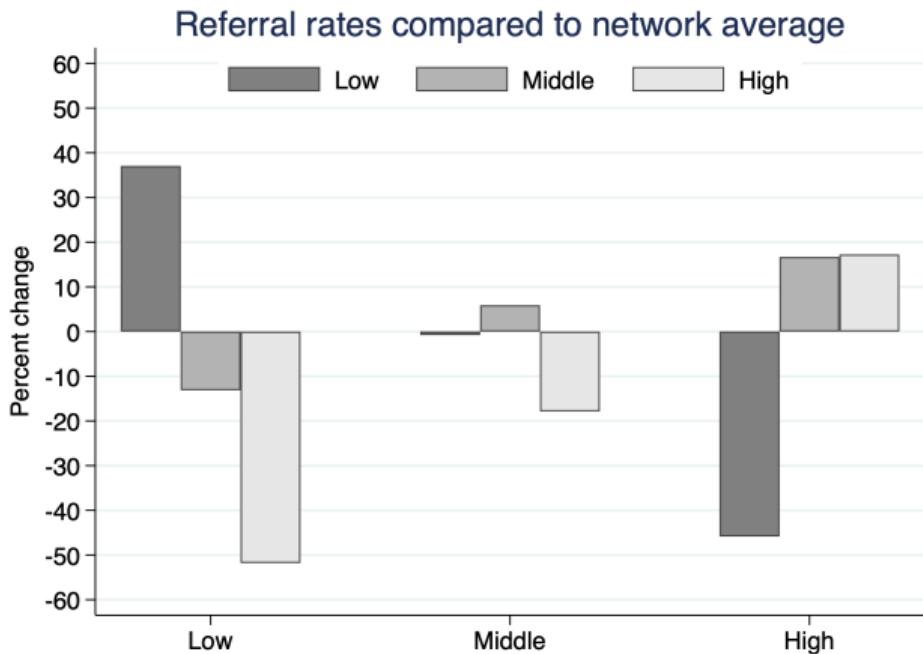
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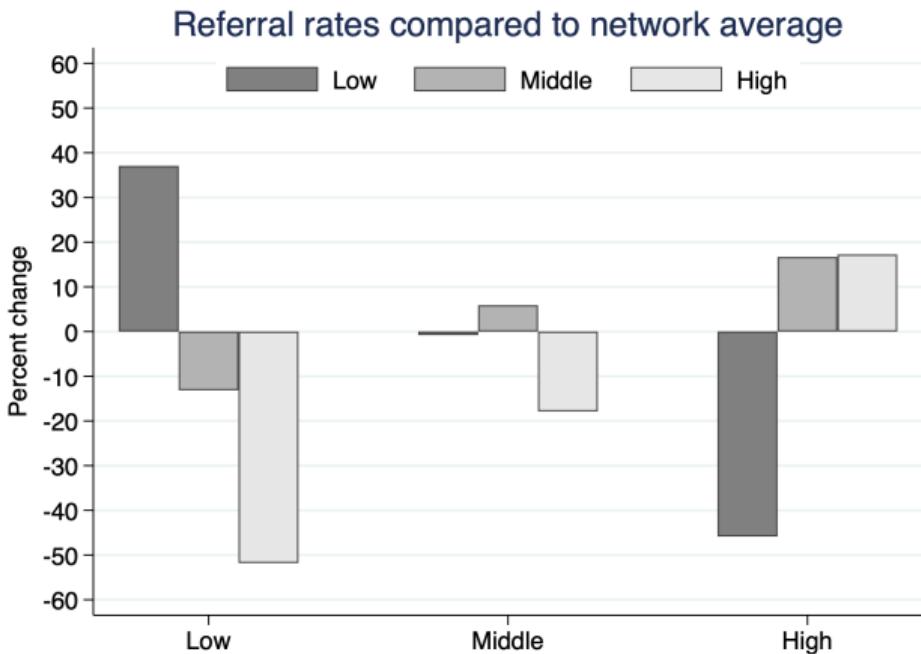
Referral SES composition

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



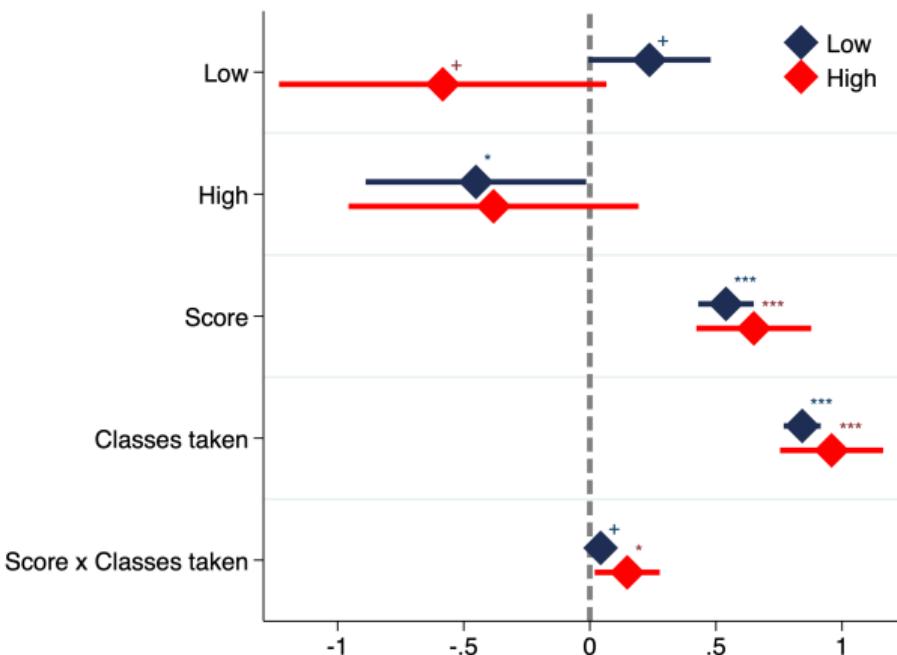
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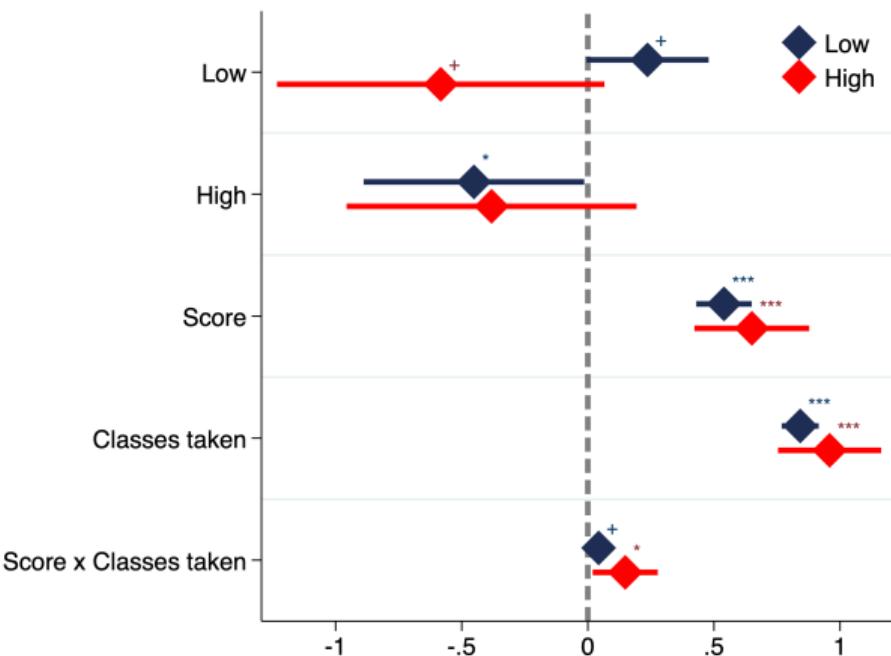
Is there a SES bias in referrals?

- Nominee score and classes taken together are strong predictors of referrals
- **High-SES** referrers are biased against Low-SES
- **Low-SES** referrers are biased against High-SES
- Do these biases impact referral performance?



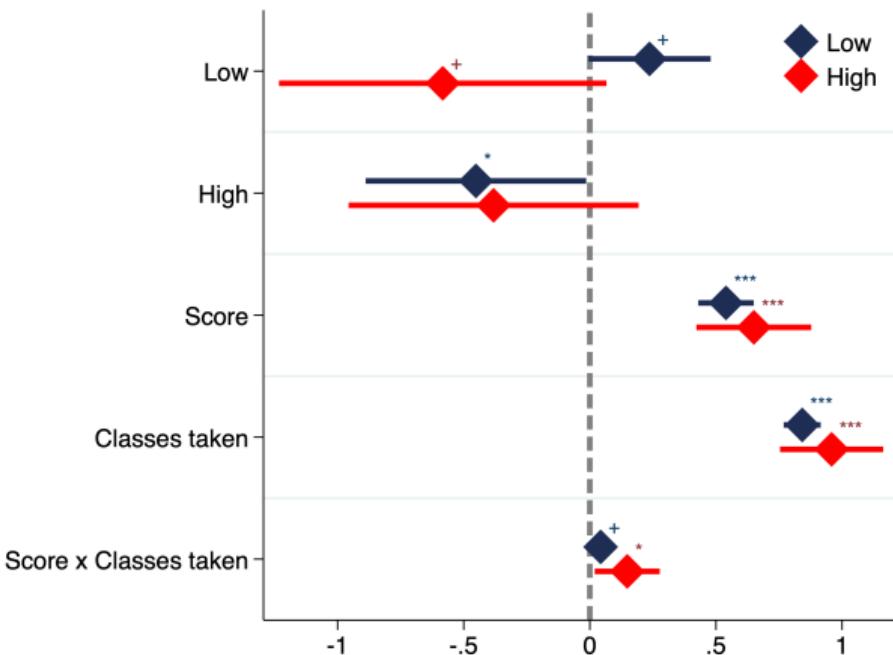
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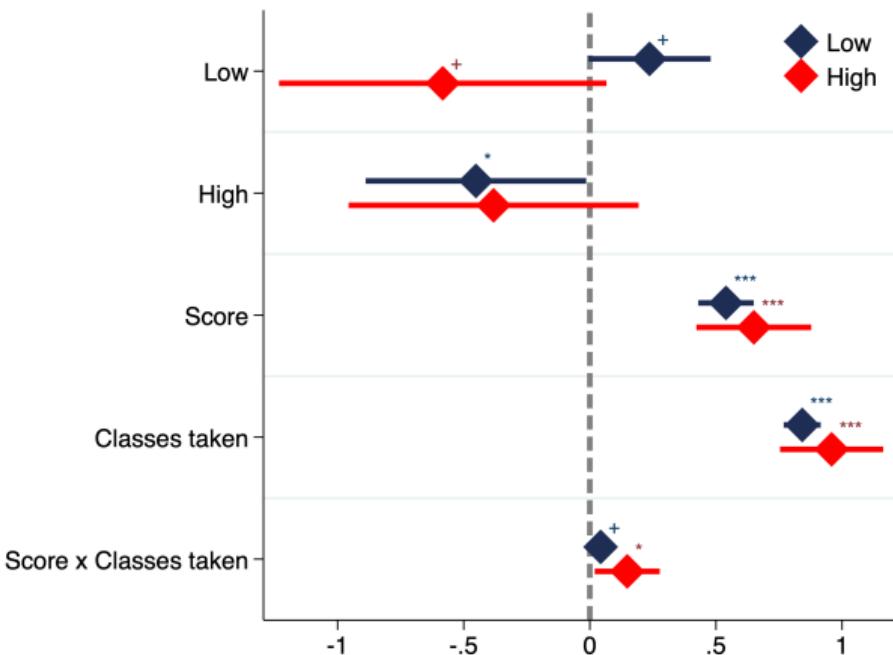
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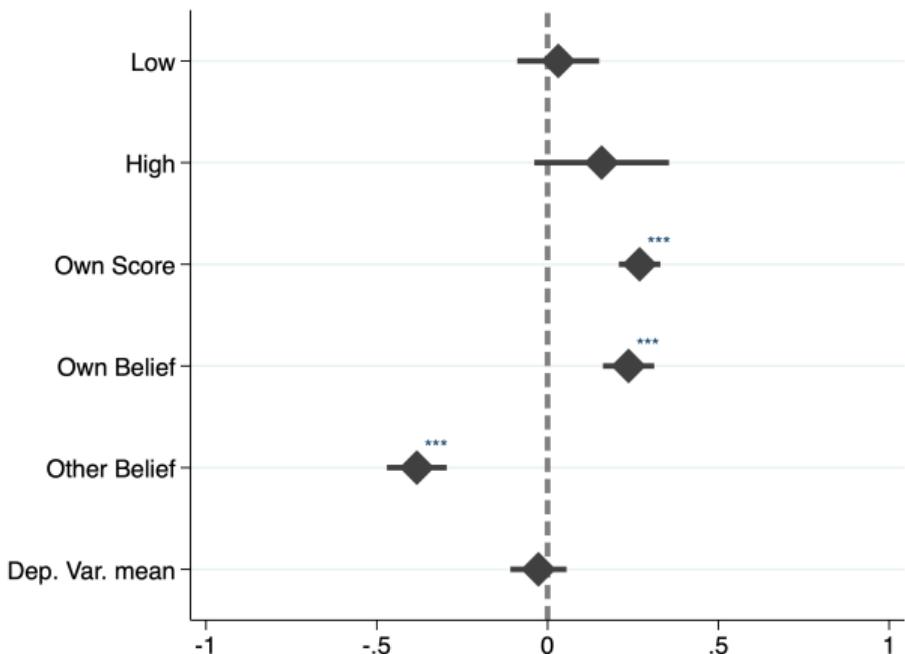
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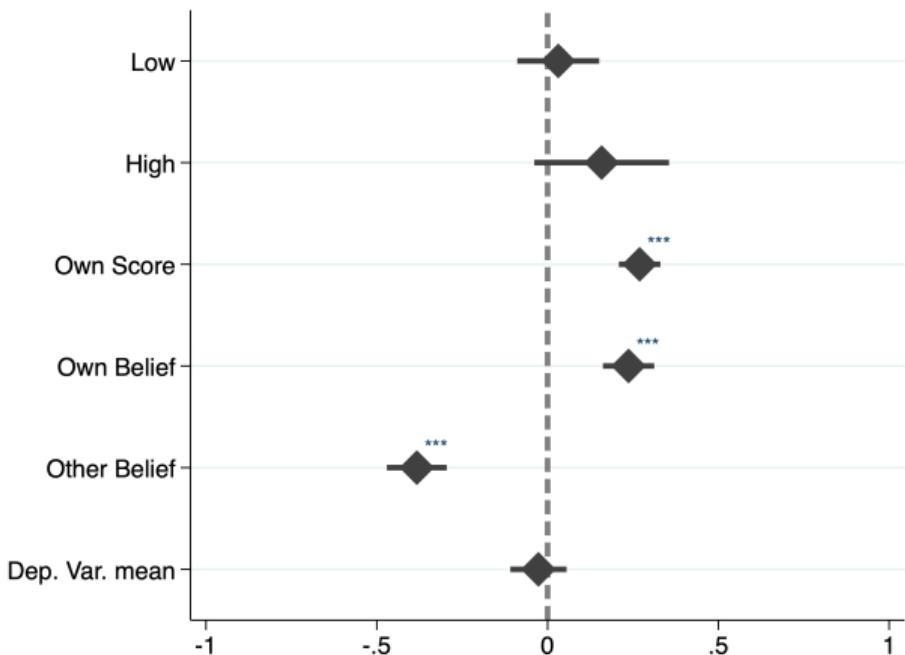
Who makes better referrals?

- No effect of SES on referral score
- Referrer's own score increases premium
- Referrer's knowledge of own scores increases premium
- Referrer's knowledge of nominee's score increases premium
- All 3 factors are equal across SES



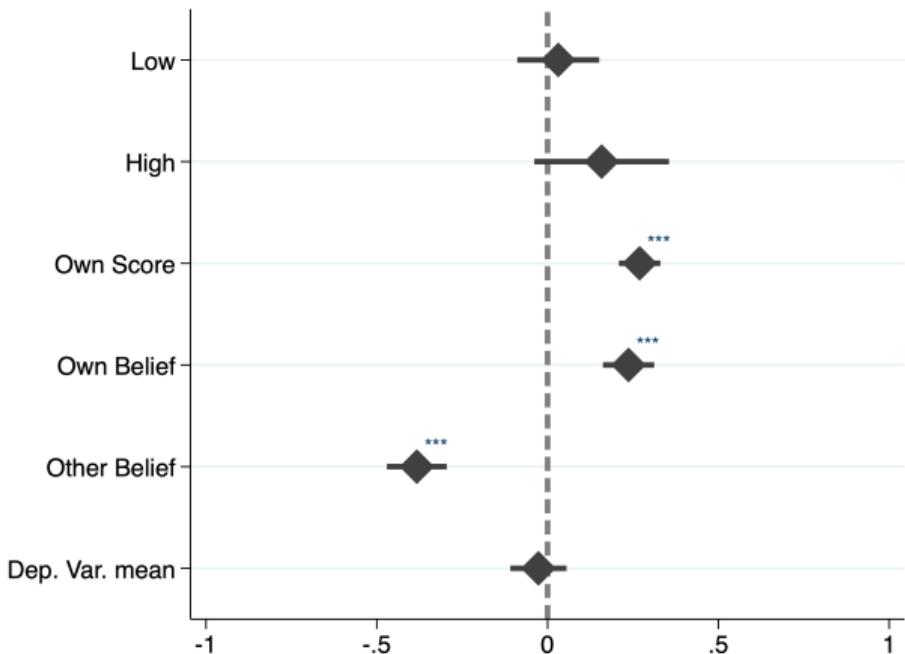
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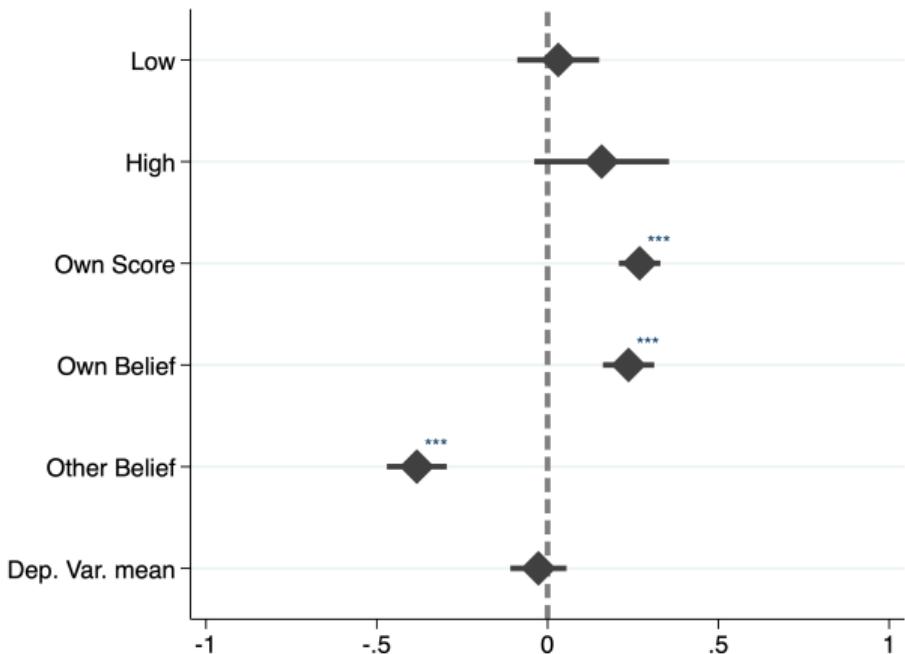
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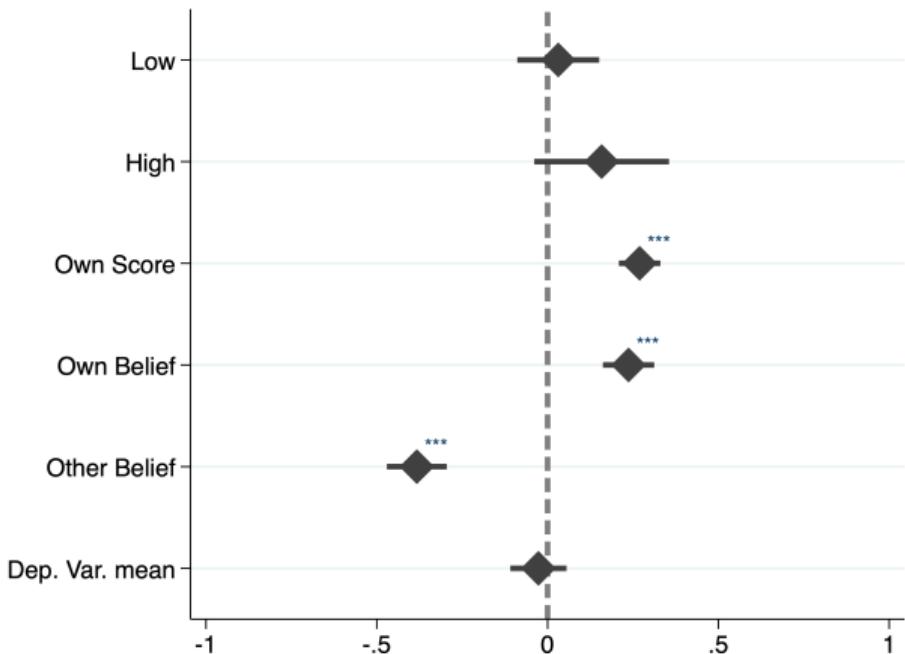
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Conclusion

- Networks are separated by SES
- Low and High-SES exhibit bias against one another when referring
- Referrers nominate better as their own scores get higher, have more accurate beliefs about own and nominee scores
- Individuals across SES refer equally well ...
- ... but prefer nominating similar others in SES

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Reading

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

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

Math

- Math score and tie strength are strong predictors of referrals
- Significant but small interaction between math score and tie strength
- No evidence for a Low-SES bias Alt. Specification

	(1)	(2)	(3)
Low-SES	0.161* (0.086)	-0.013 (0.099)	-0.015 (0.100)
High-SES	-0.309** (0.131)	-0.343** (0.142)	-0.361** (0.144)
Nominee score		0.662*** (0.040)	0.546*** (0.042)
Tie		0.885*** (0.029)	0.851*** (0.029)
Score x Tie			0.089*** (0.019)
Observations	128150	128150	128150
Ind.	669	669	669
Chi-test	12.38	1122.75	1154.40

Reading (Low-SES vs others)

- Alternative specification with binary Low-SES
- No evidence for a Low-SES bias
- Consistent with main model

[Return](#)

	(1)	(2)	(3)
Low-SES	0.199** (0.083)	0.041 (0.100)	0.042 (0.100)
Nominee Score		0.561*** (0.044)	0.509*** (0.048)
Tie		0.951*** (0.031)	0.941*** (0.032)
Score x Tie			0.029 (0.018)
Observations	128,847	128,847	128,847
Ind.	673	673	673
Chi-test	5.73	1100.40	1127.92

Math (Low-SES vs others)

- Alternative specification with binary Low-SES
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- Consistent with main model

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	(1)	(2)	(3)
Low-SES	0.220*** (0.083)	0.049 (0.097)	0.050 (0.098)
Nominee Score		0.653*** (0.040)	0.538*** (0.041)
Tie		0.887*** (0.029)	0.854*** (0.030)
Score x Tie			0.088*** (0.019)
Observations	128,150	128,150	128,150
Ind.	669	669	669
Chi-test	7.02	1124.24	1156.08

Reading across SES

- Restrict sample by referrer SES
- Low-SES bias against other SES
- No evidence for a bias against Low-SES

Alt. Specification

	Low-SES (1)	Middle-SES (2)	High-SES (3)
Low-SES	0.266* (0.155)	-0.202 (0.149)	-0.275 (0.369)
High-SES	-0.307 (0.268)	-0.254 (0.186)	-0.511 (0.377)
Nominee score	0.548*** (0.076)	0.483*** (0.067)	0.553*** (0.179)
Tie	0.873*** (0.046)	0.991*** (0.046)	0.986*** (0.128)
Score x Tie	0.019 (0.027)	0.021 (0.027)	0.145** (0.072)
Observations	54611	64596	9640
Ind.	275	340	58
Chi-test	531.49	553.06	97.57

Reading across SES (Low-SES vs others)

- Alternative specification with binary Low-SES
- Low-SES bias against other SES
- No evidence for a bias against Low-SES
- Consistent with main model

	Low-SES (1)	Other-SES (2)
Low-SES	0.312** (0.153)	-0.160 (0.137)
Nominee score	0.545*** (0.076)	0.486*** (0.062)
Tie	0.876*** (0.046)	0.996*** (0.044)
Score x Tie	0.019 (0.027)	0.036 (0.025)
Observations	54611	74236
Ind.	275	398
Chi-test	517.41	627.40

[Return](#)

Math across SES

- Restrict sample by referrer SES
- Low-SES bias against High-SES
- High-SES bias against Low-SES

Alt. Specification

	Low-SES (1)	Middle-SES (2)	High-SES (3)
Low-SES	0.208 (0.150)	-0.101 (0.145)	-0.986** (0.469)
High-SES	-0.619** (0.283)	-0.313 (0.195)	-0.269 (0.381)
Nominee score	0.540*** (0.064)	0.526*** (0.060)	0.730*** (0.128)
Tie	0.814*** (0.041)	0.870*** (0.043)	0.929*** (0.128)
Score x Tie	0.067** (0.028)	0.096*** (0.029)	0.160 (0.097)
Observations	55531	62492	10127
Ind.	283	327	59
Chi-test	525.71	561.64	110.76

Math across SES (Low-SES vs others)

- Alternative specification with binary Low-SES
- Low-SES bias against other SES
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- Consistent with main model

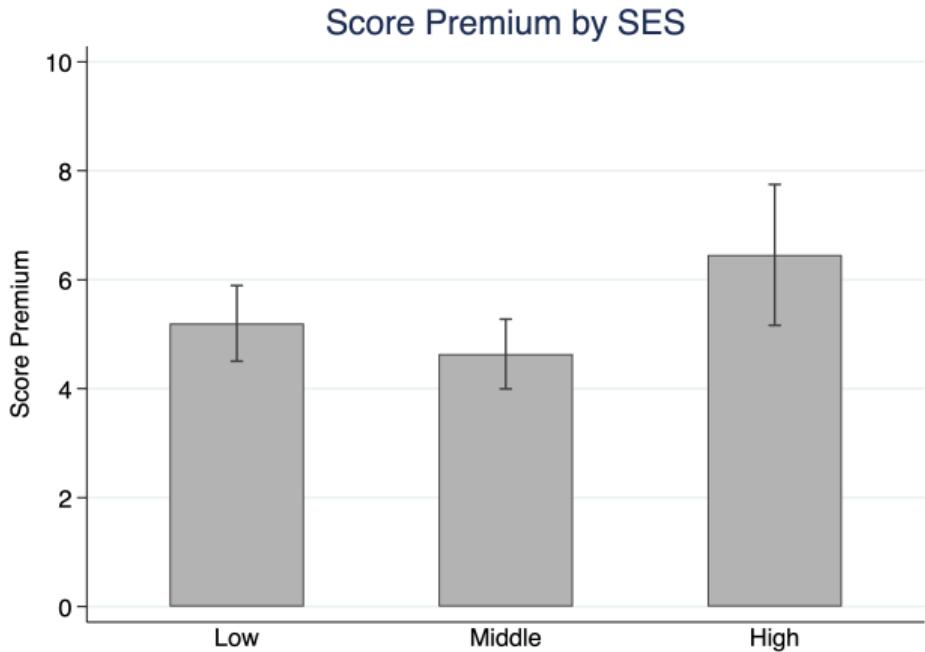
	Low-SES (1)	Other-SES (2)
Low-SES	0.296** (0.147)	-0.138 (0.136)
Nominee score	0.533*** (0.063)	0.541*** (0.055)
Tie	0.820*** (0.042)	0.882*** (0.042)
Score x Tie	0.064** (0.028)	0.106*** (0.027)
Observations	55531	72619
Ind.	283	386
Chi-test	523.84	647.99

[Return](#)

No differences for Score Premium by SES

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

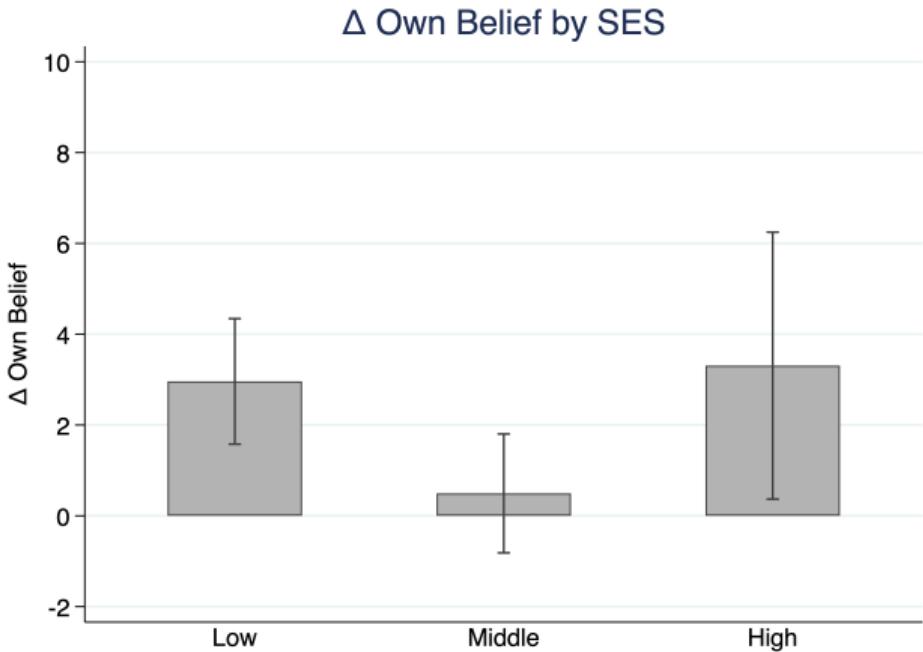
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No differences for own score beliefs by SES

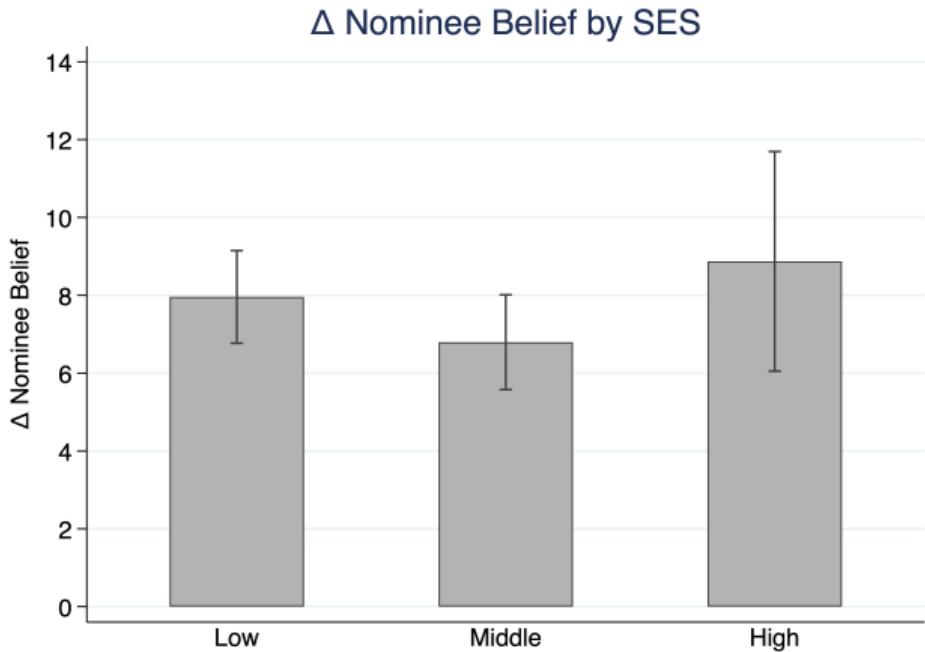
- Middle-SES are slightly more accurate (joint F-test, $p < 0.1$)

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No differences for nominee score beliefs by SES

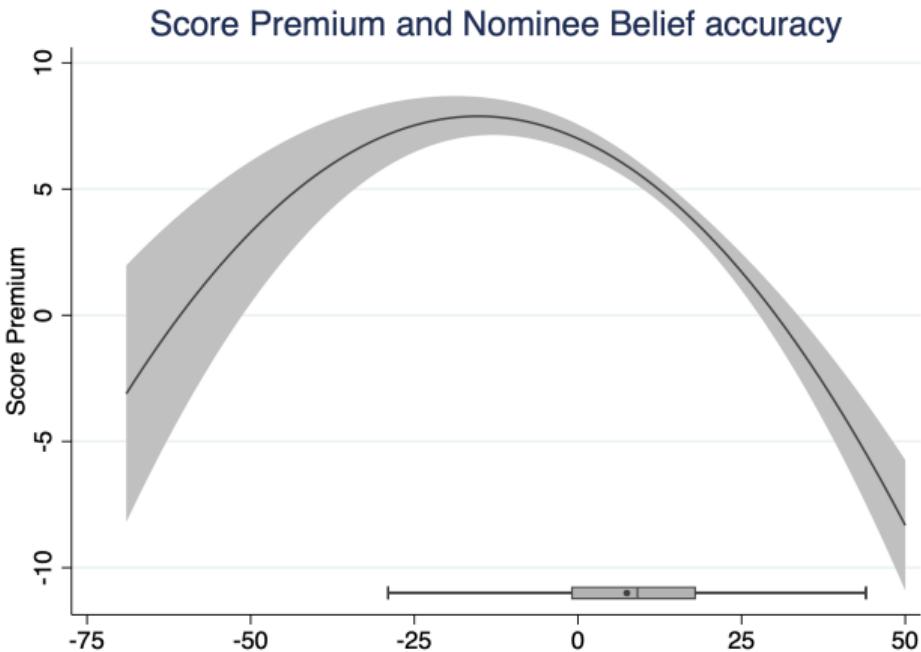
- No difference (joint F-test,
 $p = 0.41$) [Return](#)



Nominee Beliefs are rewarded for accuracy

- Negative coefficient is explained by quadratic shape

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Own score beliefs are rewarded for accuracy

- Positive coefficient is explained by quadratic shape and extreme outliers

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