

# Class differences in social networks: Evidence from a referral experiment

8-min presentation

Manu Munoz <sup>1</sup> Ernesto Reuben <sup>1,2</sup> Reha Tuncer <sup>3</sup>

<sup>1</sup>Luxembourg Institute of Socioeconomic Research

<sup>2</sup>NYU Abu Dhabi

<sup>3</sup>University of Luxembourg

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# Motivation and Research Question

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- 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

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- 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

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- 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:

<b>John</b>
John Lennon (Music - 2018) 
John Stuart Mill (Law - 2020)

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# Procedures

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- Recruited participants by emailing 4500 students ( $>1$ st 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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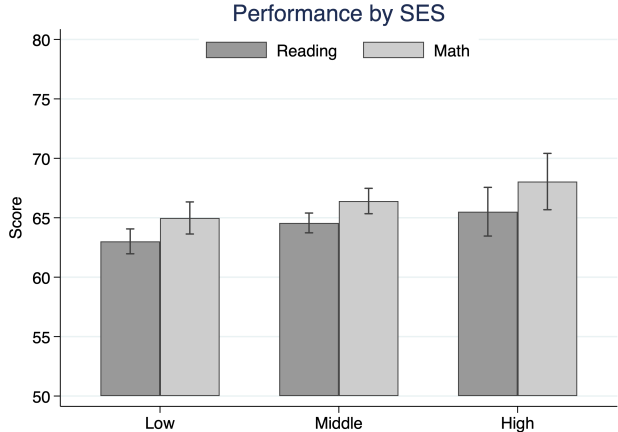
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# Entry exam performance across SES

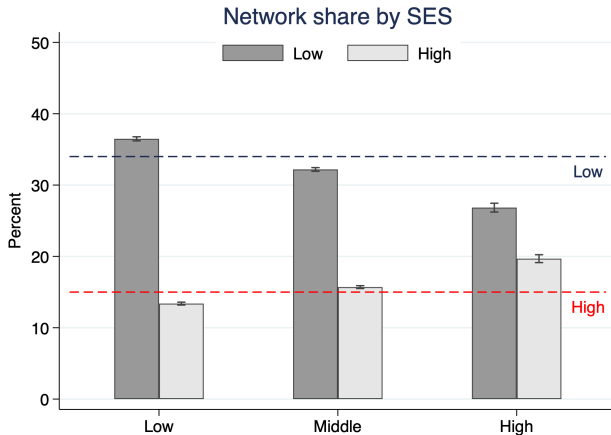
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- Very close distribution of entry exam scores in the sample



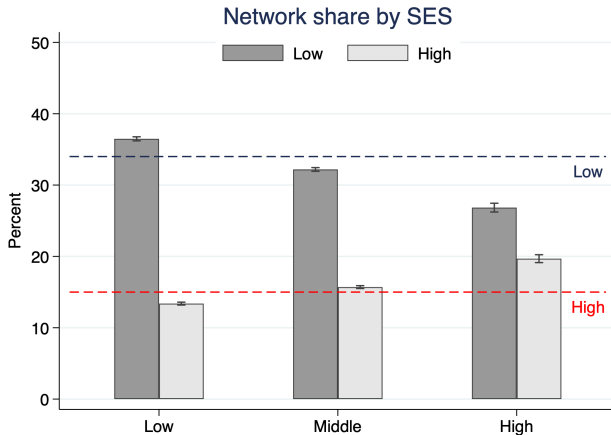
# Network-level SES shares

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



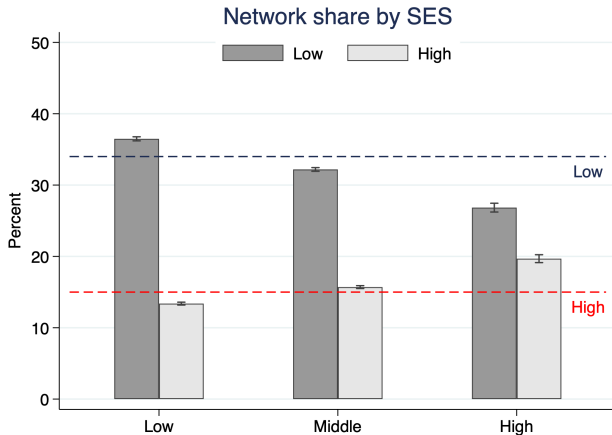
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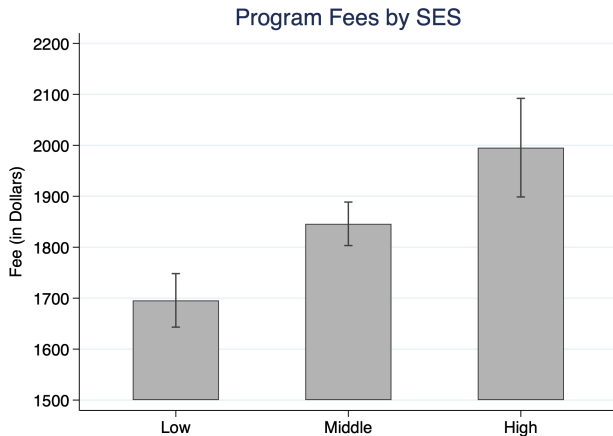
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# Selection into programs

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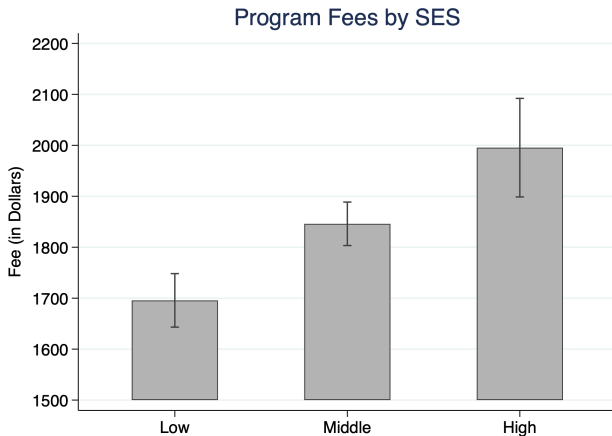
- Low-SES study in more affordable programs
- Large difference as net average monthly salary around \$350



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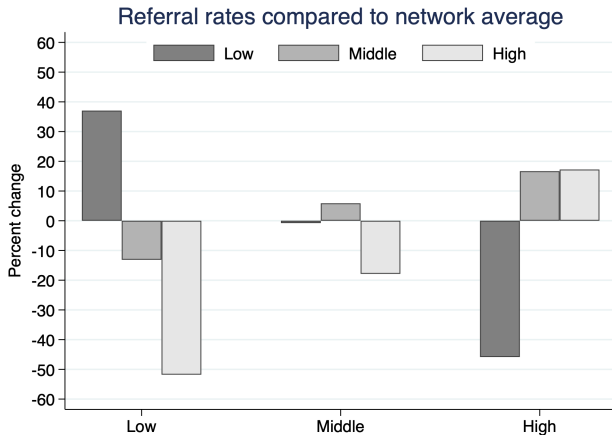
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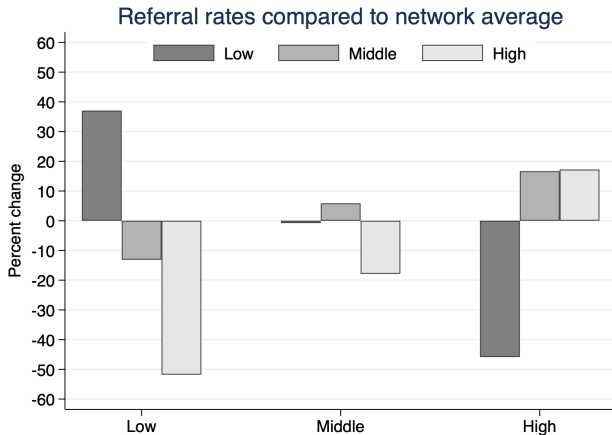
# Referral SES composition

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



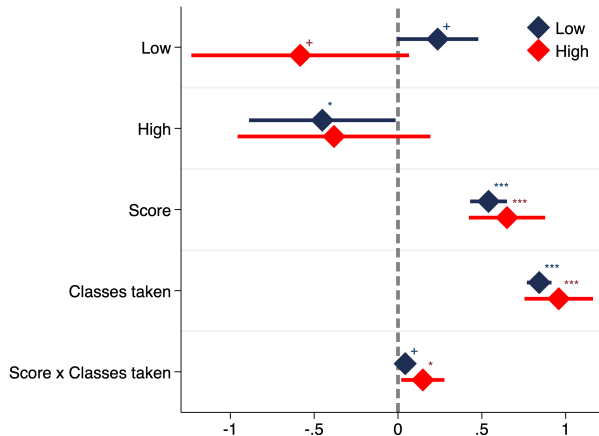
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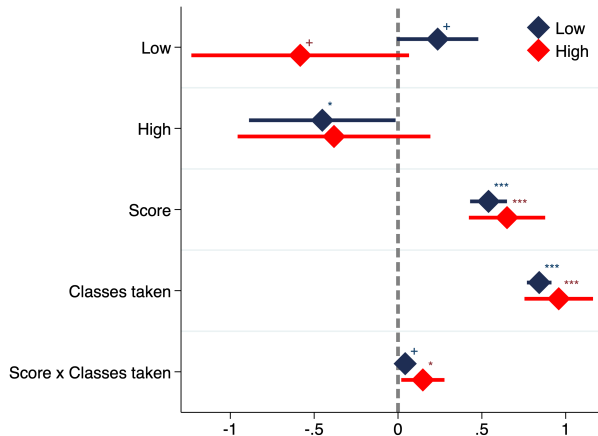
# Is there a SES bias in referrals?

- 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?



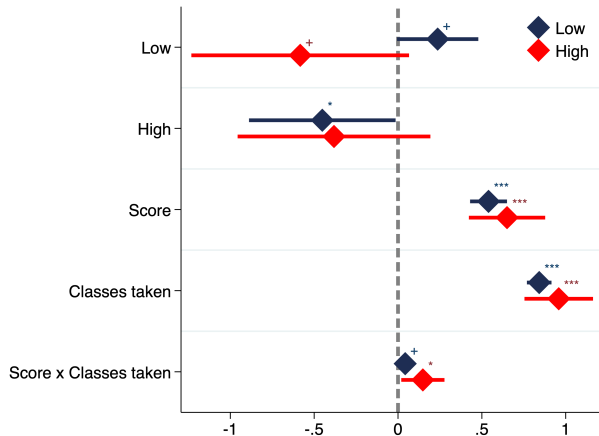
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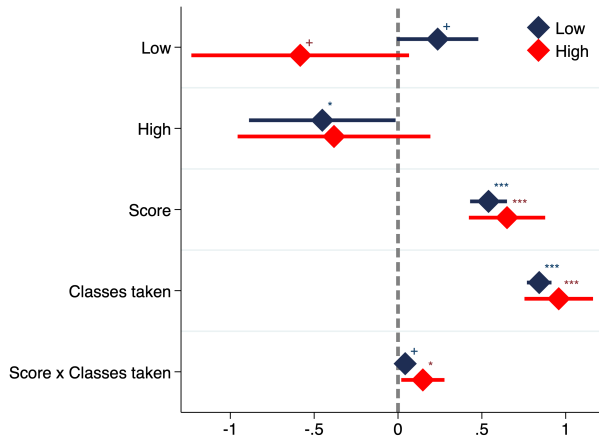
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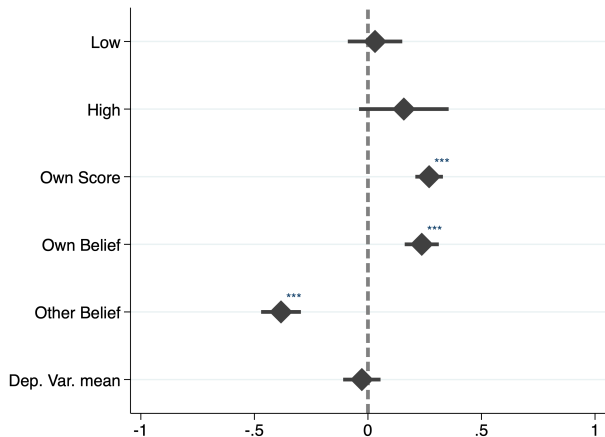
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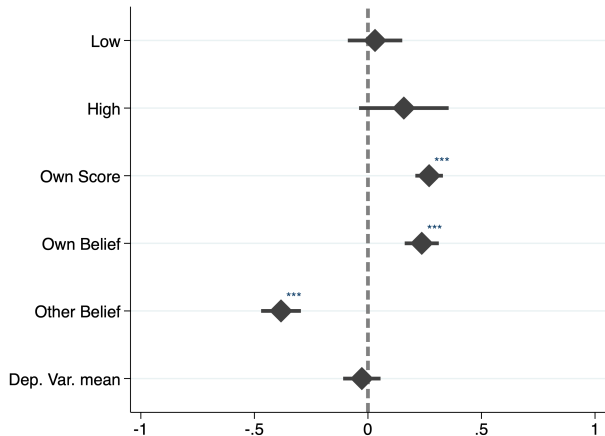
# Who makes better referrals?

- 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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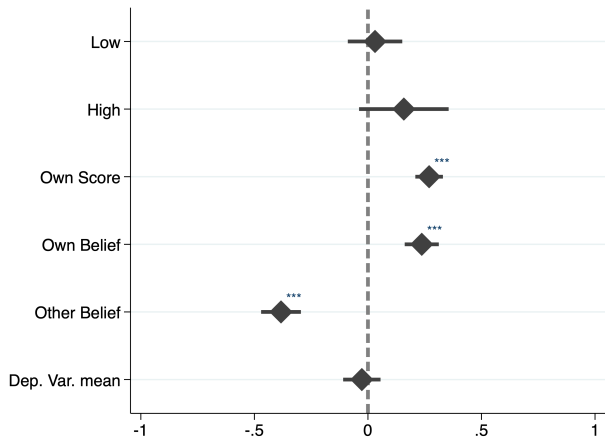
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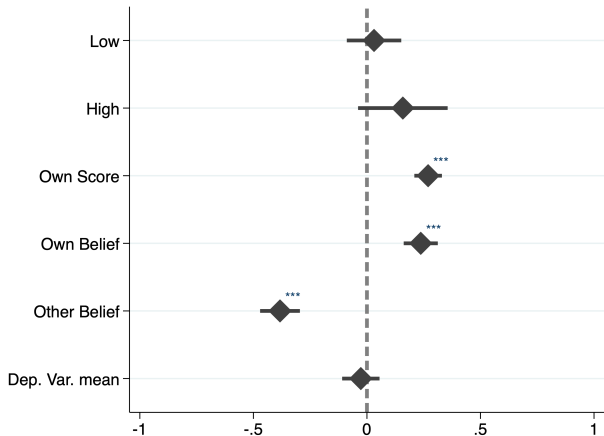
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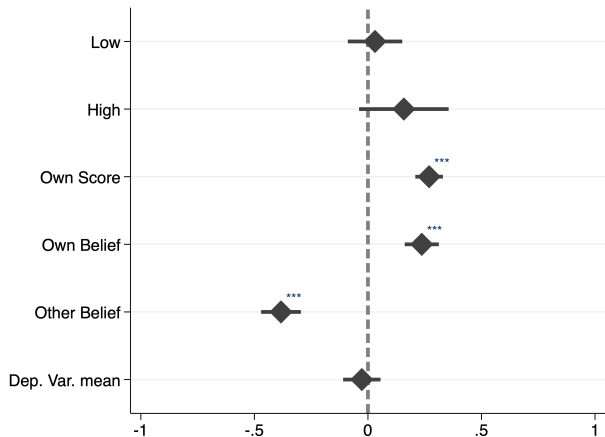
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# Conclusion

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- 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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	(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)

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	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

# 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
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	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

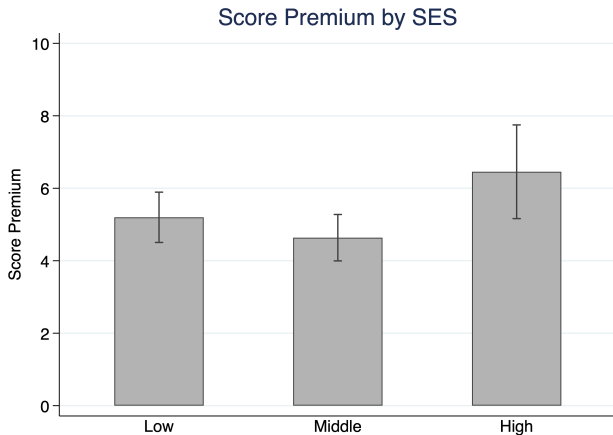


# No differences for Score Premium by SES

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

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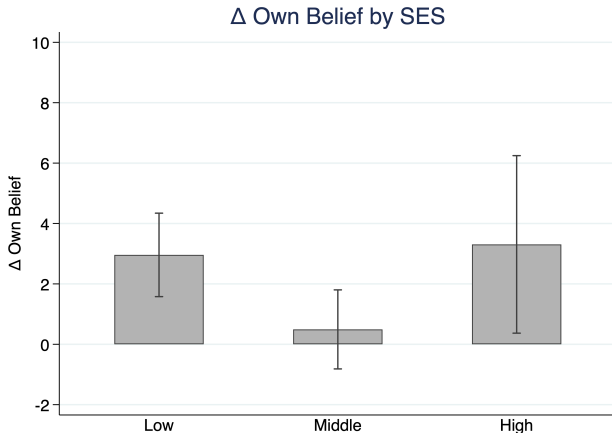


# No differences for own score beliefs by SES

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

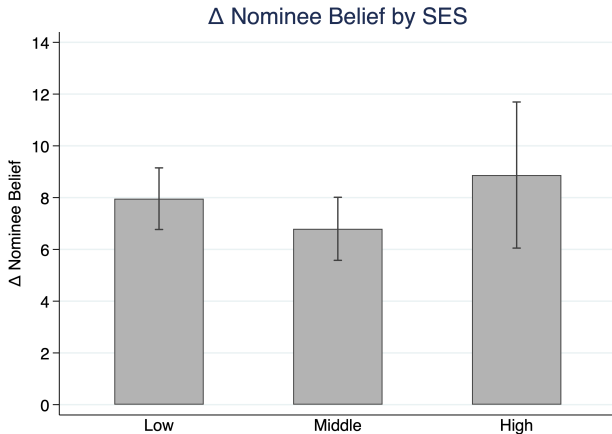
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# No differences for nominee score beliefs by SES

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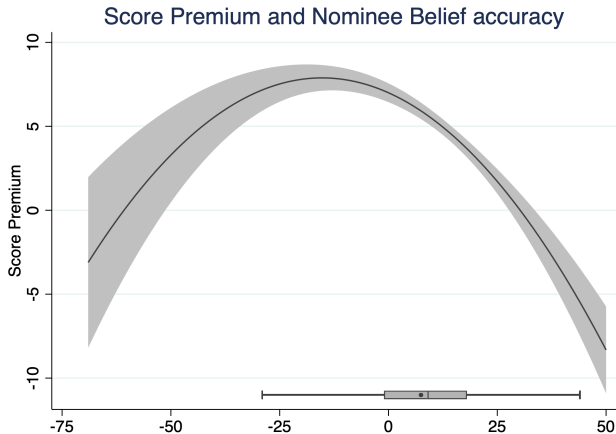
- No difference (joint F-test,  $p = 0.41$ ) [Return](#)



# Nominee Beliefs are rewarded for accuracy

- Negative coefficient is explained by quadratic shape

Return



# Own score beliefs are rewarded for accuracy

- Positive coefficient is explained by quadratic shape and extreme outliers

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