Class differences in social networks: Evidence from a referral experiment

8-min presentation

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

[1]Luxembourg Institute of Socioeconomic Research

[2]NYU Abu Dhabi

[3]University of Luxembourg

24 April 2025

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]
  - Refferals 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?

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]
  - Refferals 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?

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]
  - Refferals 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?

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]
  - Refferals 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?

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]
  - Refferals 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?

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]
  - Refferals 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?

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

Setting

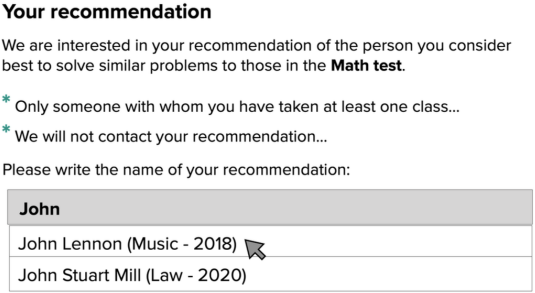
- Universidad Autónoma de Bucaramanga (UNAB)
- Approx. 6000 students across all social classes
- Administrative data including gender, age, program, GPA, classes attended, year of entry, and the entry exam scores

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

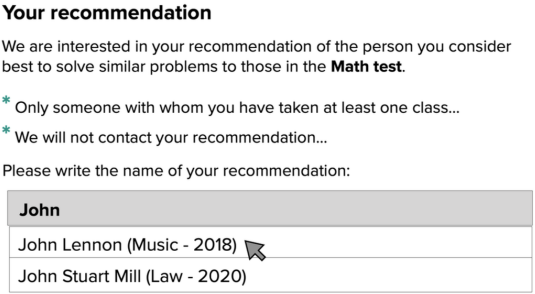
Design

- 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 refferals by increasing reward as referral score goes higher



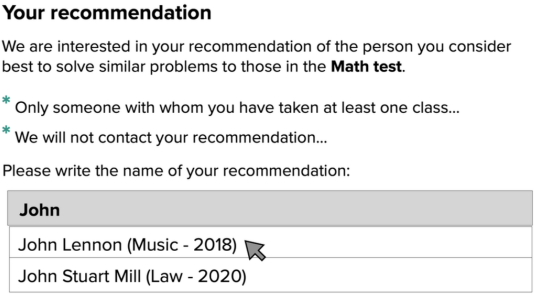
Design

- 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 refferals by increasing reward as referral score goes higher



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 refferals by increasing reward as referral score goes higher



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

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

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

Procedures

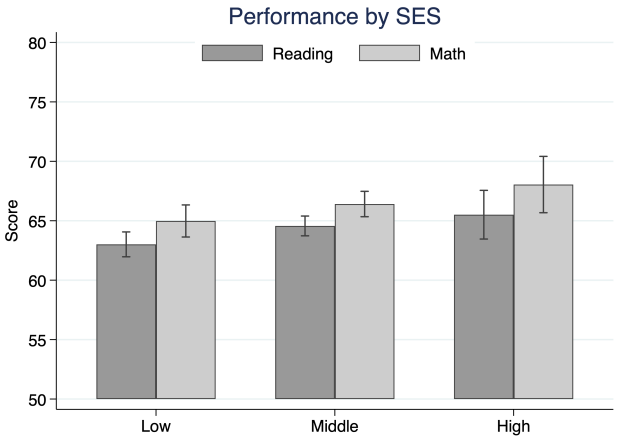
- Recruited participants by emailing 4500 students (>1st year)
- 30 minute online experiment in Qualtrics
- Average payment of 80 USD (lottery for 1 out of 10 participants)
- 840 complete responses
- Final sample 734 participants who referred someone they took a class with

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

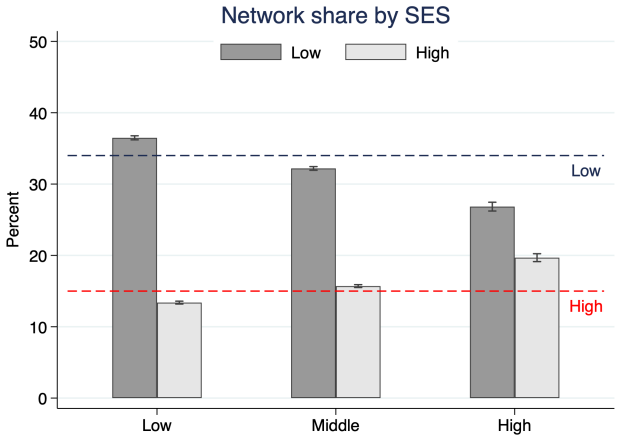
Entry exam performance across SES

- Very close distribution of entry exam scores in the sample



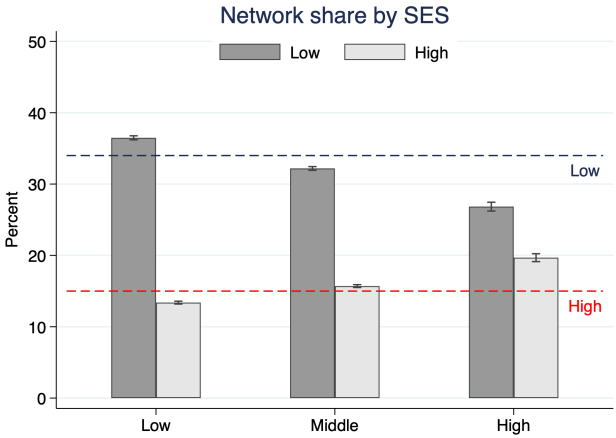
Network-level SES shares

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



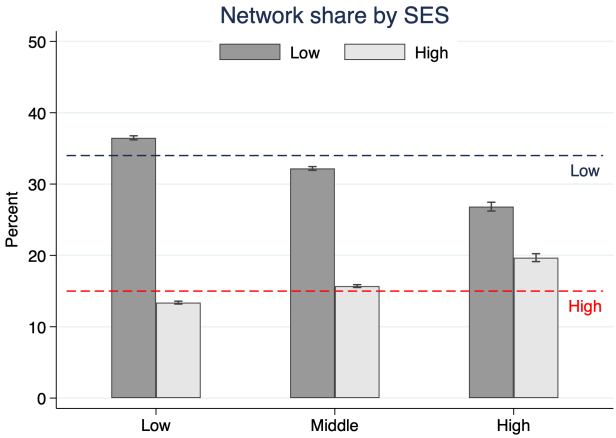
Network-level SES shares

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



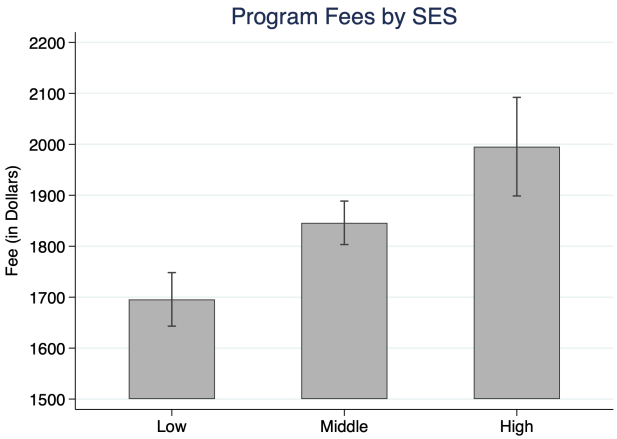
Network-level SES shares

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



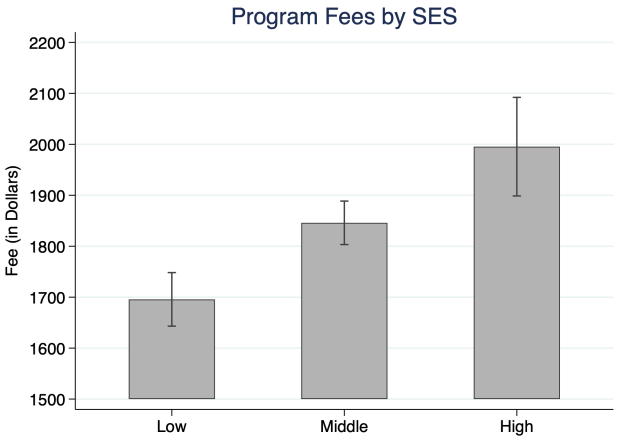
Selection into programs

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



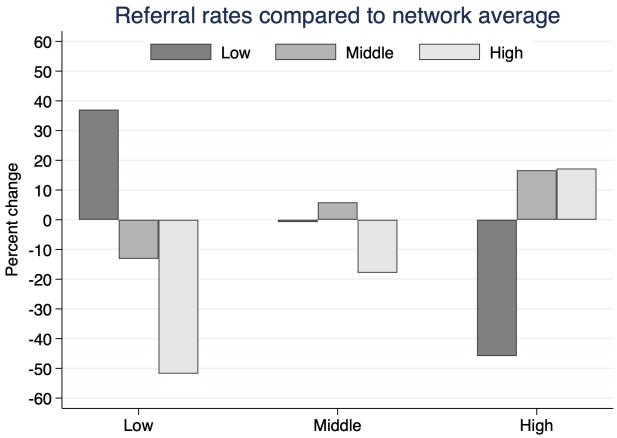
Selection into programs

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



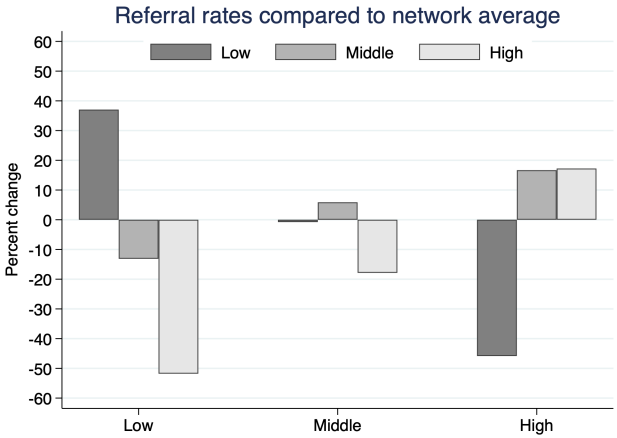
Referral SES composition

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



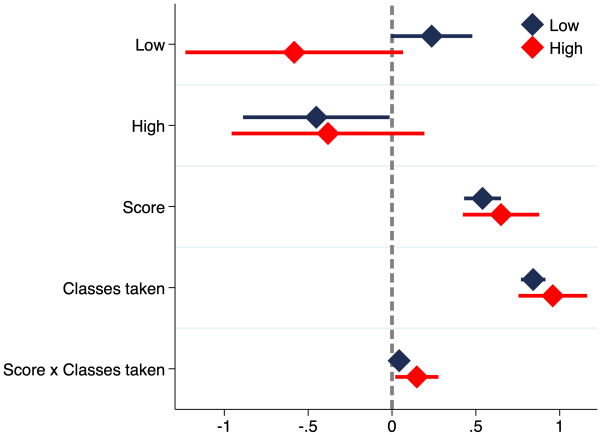
Referral SES composition

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



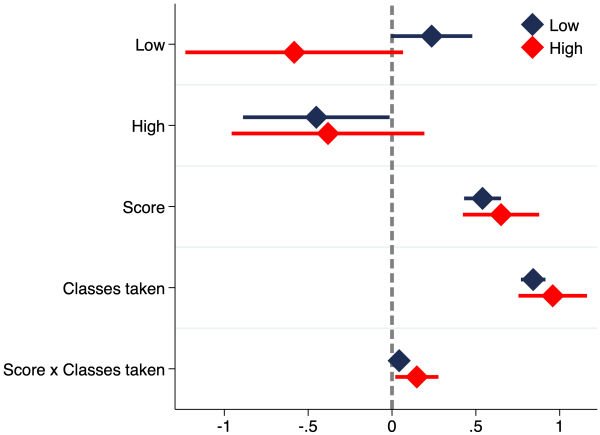
Is there a SES bias in referrals?

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



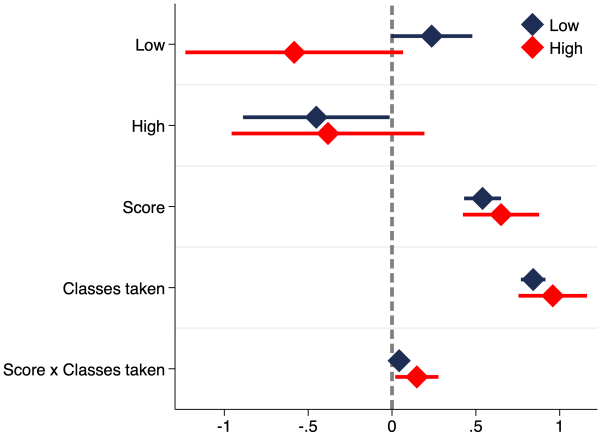
Is there a SES bias in referrals?

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



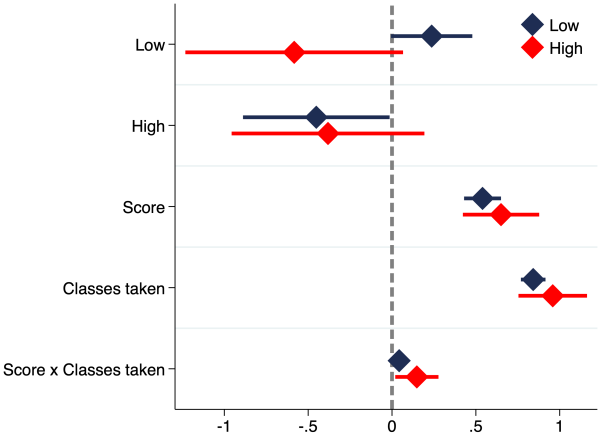
Is there a SES bias in referrals?

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



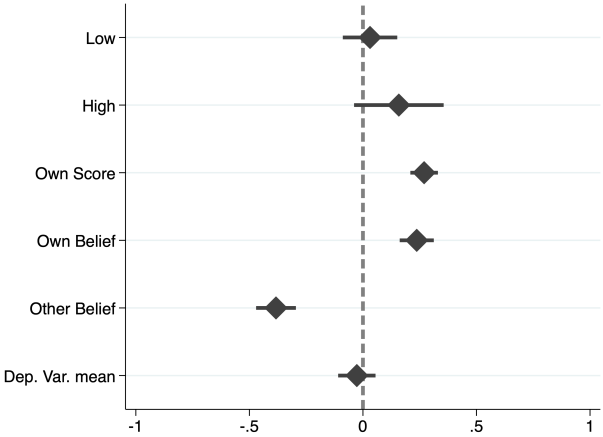
Is there a SES bias in referrals?

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



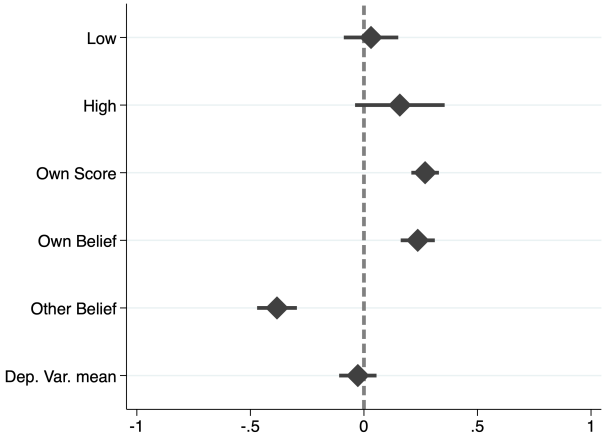
Who makes better referrals?

- No effect of SES on how well referrals score compared to referrer's network average
- Referrer own score increases premium
- Accuracy on own scores increases premium
- Accuracy on nominee beliefs increases premium
- All 3 factors are equal across SES



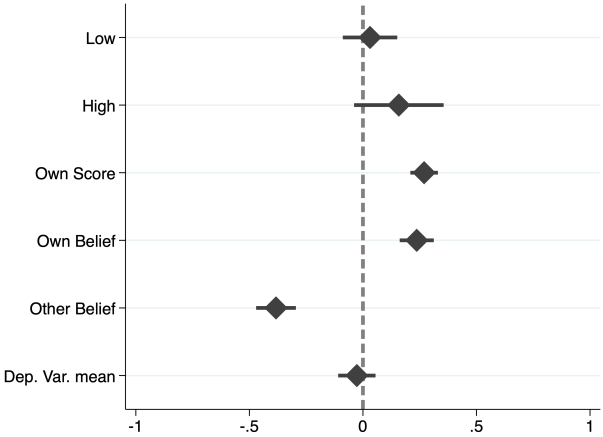
Who makes better referrals?

- No effect of SES on how well referrals score compared to referrer's network average
- Referrer own score increases premium
- Accuracy on own scores increases premium
- Accuracy on nominee beliefs increases premium
- All 3 factors are equal across SES



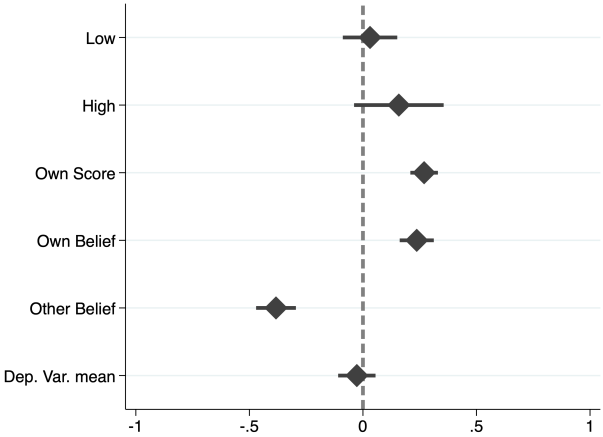
Who makes better referrals?

- No effect of SES on how well referrals score compared to referrer's network average
- Referrer own score increases premium
- Accuracy on own scores increases premium
- Accuracy on nominee beliefs increases premium
- All 3 factors are equal across SES



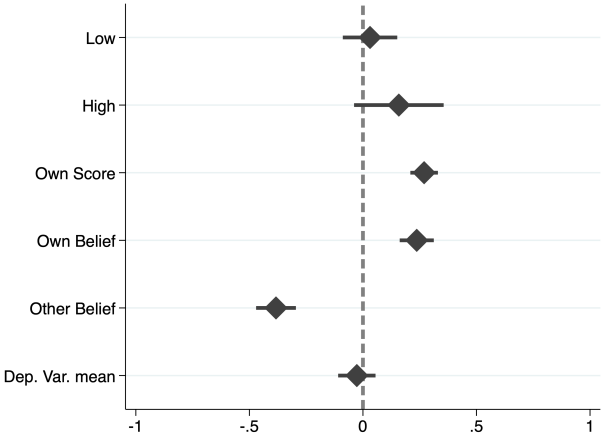
Who makes better referrals?

- No effect of SES on how well referrals score compared to referrer's network average
- Referrer own score increases premium
- Accuracy on own scores increases premium
- Accuracy on nominee beliefs increases premium
- All 3 factors are equal across SES



Who makes better referrals?

- No effect of SES on how well referrals score compared to referrer's network average
- Referrer own score increases premium
- Accuracy on own scores increases premium
- Accuracy on nominee beliefs increases premium
- All 3 factors are equal across SES



Conclusion

- Networks are separated by SES
- Low and High-SES exhibit bias against one another and worsen the network effect in referrals
- All referrers pick those with whom they take a lot of courses and better performers from network
- All referrers uniformly 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

Conclusion

- Networks are separated by SES
- Low and High-SES exhibit bias against one another and worsen the network effect in referrals
- All referrers pick those with whom they take a lot of courses and better performers from network
- All referrers uniformly 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

Conclusion

- Networks are separated by SES
- Low and High-SES exhibit bias against one another and worsen the network effect in referrals
- All referrers pick those with whom they take a lot of courses and better performers from network
- All referrers uniformly 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

Conclusion

- Networks are separated by SES
- Low and High-SES exhibit bias against one another and worsen the network effect in referrals
- All referrers pick those with whom they take a lot of courses and better performers from network
- All referrers uniformly 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

Conclusion

- Networks are separated by SES
- Low and High-SES exhibit bias against one another and worsen the network effect in referrals
- All referrers pick those with whom they take a lot of courses and better performers from network
- All referrers uniformly 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

Conclusion

- Networks are separated by SES
- Low and High-SES exhibit bias against one another and worsen the network effect in referrals
- All referrers pick those with whom they take a lot of courses and better performers from network
- All referrers uniformly 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

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

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

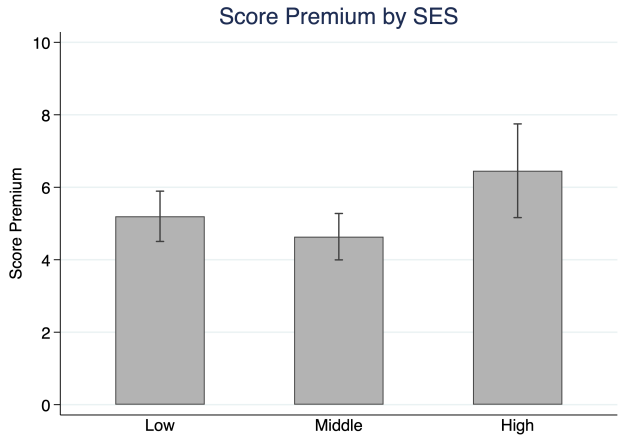
Return

	Low-SES (1)	Other-SES (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

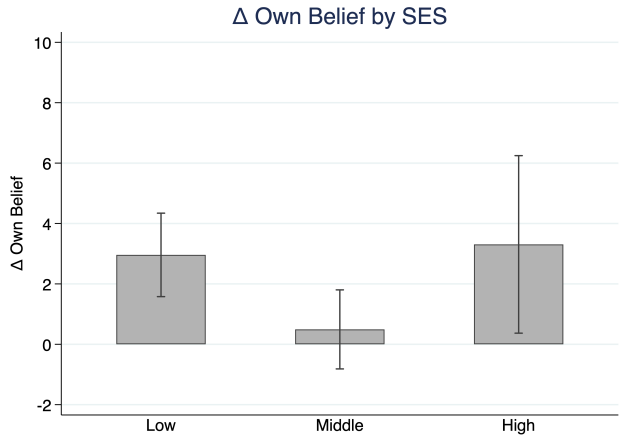
- Middle-SES refer slightly worst (joint F-test, $p < 0.1$)

Return



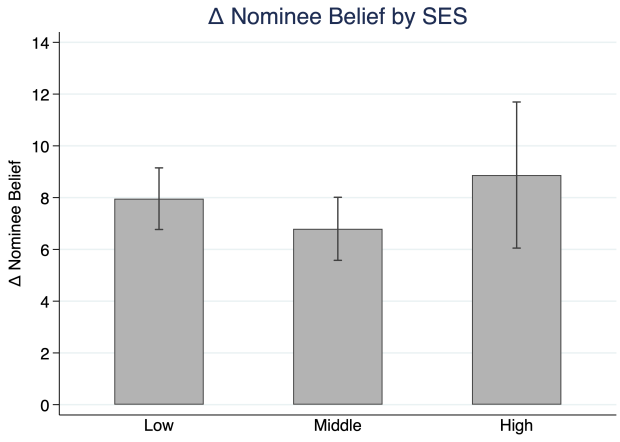
No differences for own score beliefs by SES

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



No differences for nominee score beliefs by SES

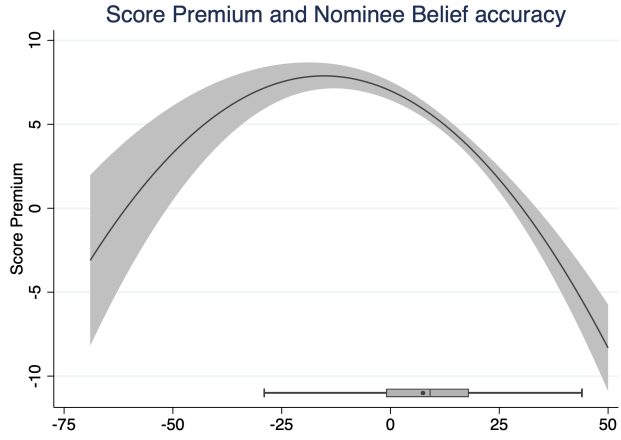
- No difference (joint F-test, $p = 0.41$) Return

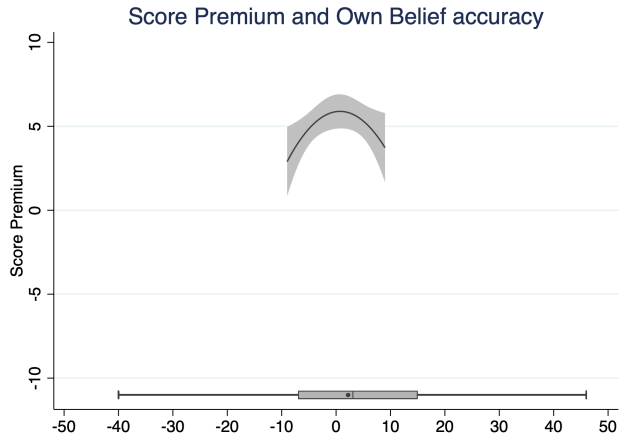


Nominee Beliefs are rewarded for accuracy

- 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