

Class differences in social networks: Evidence from a referral experiment

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Abstract

Economic connectivity, defined as the share of high-SES connections in one's network, is a strong correlate of labor market income. Yet, low-SES individuals are typically at a disadvantage when it comes to knowing the right people. Referral hiring leverages networks and make explicit the role of economic connectivity where taste-based biases could further exacerbate low-SES outcomes. We conduct a field experiment with 734 university students to study the network compositions of different SES groups. We leverage enrollment networks to identify all potential referral candidates and conduct an incentivized referral exercise to reveal SES biases within these choice sets. We find that the university enrollment networks are highly segregated, with low-SES and high-SES individuals having a higher share of same-SES connections in their networks due to program selection (12% and 31% respectively). When considering ex post actualized choice sets for the observed referrals, the segregation becomes worse: Low-SES individuals connect with other low-SES individuals at rates 30% higher than the university share, while high-SES individuals connect with other high-SES individuals at rates 55% higher

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20 than the university share. Yet, we find no bias against low-SES individuals once we 20
21 account for network structures. We randomly assign half of the participants to a condi- 21
22 tion where their referral candidate receives a fixed bonus on top of pay-for-performance 22
23 referral incentives. We find that additional incentives for the referral candidate do not 23
24 change social proximity with the referral nor the referral quality. Our findings suggest 24
25 that systematic segregation patterns in networks that alter choice sets matter more than 25
26 taste-based SES biases in referrals, and highlight the potential for institutional action 26
27 in promoting SES diversity. 27

28 **JEL Classification:** C93, J71, D85, Z13 28

29 **Keywords:** social capital, social networks, referral hiring, socioeconomic status, field 29
30 experiment 30

1 Introduction

Equally qualified individuals in terms of productivity face different labor market outcomes based on their socioeconomic status (Stansbury & Rodriguez, 2024). This persistent inequality undermines meritocratic ideals and represents a substantial barrier to economic mobility. A key driver of SES-based inequality in the labor market stems from differences in social capital.¹ Economic connectivity, defined as the share of high-SES connections among low-SES individuals, is the most important facet of social capital because it correlates strongly with labor market income (Chetty et al., 2022a). In this sense, a lack of social capital means lack of access to individuals with influential (higher paid) jobs and job opportunities. It implies having worse outcomes when using one’s network to find jobs conditional on the capacity to leverage one’s social network.²

Referral hiring—the formal or informal process where firms ask workers to recommend qualified candidates for job opportunities—is a common labor market practice that makes differences in social capital evident.³ Since referrals originate from the networks of referrers, the composition of referrer networks becomes a crucial channel that propagates inequality. Similar individuals across socio-demographic characteristics form connections at higher rates (McPherson et al., 2001), making across-SES (low-to-high) connections less likely than same-SES connections (Chetty et al., 2022a). Referrals will thus reflect similarities in socio-demographic characteristics present in networks even in the absence of biases in the referral procedure—that is, even when referring randomly from one’s network according to some productivity criteria.

Yet, experimental evidence shows referrals can be biased even under substantial

¹See for example Bourdieu (1986); Loury (1977) for pioneering work on the relationship between social position and human capital acquisition.

²See for example Lin et al. (1981); Mouw (2003) for differential outcomes while using contacts in job search, and Pedulla and Pager (2019); Smith (2005) specifically for the effects of race conditional on network use.

³Referrals solve some frictions in the search and matching process and benefit both job-seekers and employers. As a consequence, referral candidates get hired more often, have lower turnover, and earn higher wages (Brown et al., 2016; Dustmann et al., 2016; Friebe et al., 2023).

pay-for-performance incentives beyond what is attributable to differences in network compositions, at least in the case of gender (Beaman et al., 2018; Hederos et al., 2025). A similar bias against low-SES individuals may further exacerbate their outcomes. If job information is in the hands of a select few high-SES individuals to whom low-SES individuals already have limited network access due to their lack of economic connectivity, and high-SES referrers are biased against low-SES individuals—referring other high-SES individuals at higher rates than their network composition would suggest—we should expect referral hiring to further disadvantage low-SES individuals.

The empirical question we answer in this paper is whether referrers exhibit bias against low-SES peers after accounting for differences in network SES composition. We also evaluate the causal impact of two different incentive structures on referral behavior.

In this study, we examine inequalities related to SES by curating a university-wide network dataset comprising over 4,500 students for whom classroom interactions are recorded along with individual attributes. We focus on the role of SES in referrals by experimentally investigating whether individuals who are asked to refer a peer tend to refer a same-SES candidate. We also explore potential mechanisms behind referral patterns by randomizing participants into two different incentive structures. To this end, we conducted a lab-in-the-field experiment with 734 students at a Colombian university. We instructed participants to refer a qualified student for tasks similar to the math and reading parts of the national university entry exam (equivalent to the SAT in the US system). To incentivize participants to refer qualified candidates during the experiment, we set earnings to depend on referred candidates’ actual university entry exam scores.

Referral hiring in the labor market can range from firm-level formal referral programs asking employees to bring candidates to simply passing on job opportunities between network members (Topa, 2019). Since our participants are students at the university and refer based on exam scores, we abstract away from formal referral programs with defined job openings. Our setting instead resembles situations where contacts share opportunities with each other without requiring the referred candidate to take any action and without revealing the referrer’s identity. This eliminates reputational concerns since

there is no hiring employer. It also establishes a lower bound on the expected reciprocity for the referrer when combined with pay-for-performance incentives (Bandiera et al., 2009; Witte, 2021). At the same time, referring based on university entry exam scores is still an objective, widely accepted measure of ability. We show evidence that referrers in our setting not only possess accurate information about these signals but can also screen more productive individuals from their university network.

In a university setting, class attendance provides essential opportunities for face-to-face interaction between students. This is a powerful force that reduces network segregation by providing ample opportunities to meet across SES groups, because of exposure to an equal or higher level of high-SES individuals compared to the general population (Chetty et al., 2022b).⁴ The very high level of income inequality in Colombia makes SES differences extremely visible in access to tertiary education, where rich and poor typically select into different institutions (Jaramillo-Echeverri & Álvarez, 2023). However, in the particular institutional setting we have chosen for this study, different SES groups mix at this university, allowing us to focus on SES diversity within the institution. At the same time, as students take more classes together, their similarities across all observable characteristics tend to increase (Kossinets & Watts, 2009). This is an opposite force that drives high- and low-SES networks to segregate. We observe the net effect of these two opposing forces using administrative data and construct class attendance (enrollment) networks for 734 participants based on the number of common courses they have taken together with other students. This allows us to directly identify aggregate characterizations of different SES groups' network compositions as a function of courses taken (e.g., in same-SES share), as well as the individual characteristics of network members who receive referrals among all possible candidates.

We find strong evidence that networks of high- and low-SES participants exhibit same-SES bias. On average, both groups connect with their own SES group at higher

⁴In a different sample from the same university population, Díaz et al. (2025) show this holds true for the highest-SES individuals at this institution, accounting for about 6% of their sample but less than 5% of Colombian high-school graduates (Fergusson & Flórez, 2021a).

108 rates than would occur randomly given actual group shares at the university (12% for 108
 109 low-SES and 31% for high-SES). As students take more courses together within the 109
 110 same program, their networks dwindle in size and become even more homogeneous in 110
 111 SES shares. At 12 courses together (the median number of courses taken together among 111
 112 referrals), the same-SES share increases to 30% above the university share for low-SES 112
 113 students and 55% above for high-SES students. We identify selection into academic 113
 114 programs as a key mechanism explaining this phenomenon: The private university where 114
 115 our study took place implements exogenous cost-based program pricing and does not offer 115
 116 SES-based price reductions. This results in programs with very large cost differences 116
 117 within the same university, with some programs costing up to six times the cheapest 117
 118 one. We find that the average yearly fee paid per student increases with SES, and the 118
 119 high-SES share in the most expensive program at the university—medicine—drives a 119
 120 large part of the network segregation across SES groups. 120

121 Do segregated networks account for the differences in SES referral rates across SES 121
 122 groups? Same-SES referrals are 17% more common than referrer networks suggest. 122
 123 Controlling for differences in network compositions, we find that the entirety of the bias 123
 124 is driven by low-SES referrers. We find no bias against low-SES peers beyond what is 124
 125 attributable to differences in network composition. Regardless of SES, participants refer 125
 126 productive individuals, and referred candidates are characterized by a very high number 126
 127 of courses taken together. The latter underlies the impact of program selection on the 127
 128 intensity of social interaction, where participants activate smaller and more homogeneous 128
 129 parts of their networks for making referrals. Our treatment randomized participants 129
 130 across two different incentive schemes by adding a substantial monetary bonus (\$25) 130
 131 for the referred candidate on top of the pay-for-performance incentives. We provide 131
 132 evidence that treatment incentives did not change referral behavior across the same-SES 132
 133 referral rate, the number of courses taken together with the referral candidate, and the 133
 134 candidate's exam scores. We interpret the lack of differences in the number of courses 134
 135 taken together as further evidence that referrals go to strong social ties across both 135

treatments regardless of the incentive structure.⁵

Our main empirical contribution to the experimental referral literature is our observation of the entire network that characterizes the referral choice set. Earlier research compares referrals made across different incentive structures and makes inferences about the counterfactual. For example, [Beaman and Magruder \(2012\)](#) compared referrers paid based on their referred candidate’s productivity instead of receiving a fixed finder’s fee, and [Beaman et al. \(2018\)](#) compared referrers who were restricted to refer either a male or female candidate instead of choosing freely. While [Pallais and Sands \(2016\)](#) recruited a random sample of non-referred workers for comparison with referred ones, none of the previous studies could identify the entire referral choice set and provide a direct comparison to those who were referred by the participants. Observing the entire network allows us to identify biases in referrals in a more natural way, without imposing restrictions on the choice sets. A similar approach to ours is [Hederos et al. \(2025\)](#), who elicited friendship networks by asking referrers to name 5 close friends. Their findings suggest only half of those who were referred were from the elicited friendship network, and thus represent an incomplete observation of the entire referral choice set. We take our analysis one step further by requesting referrals from the enrollment network, where we have complete information on every single connection that may or may not receive a referral. This allows us to neatly separate the effect of network composition from any potential biases stemming from the referral procedure itself.

Second, we build upon the earlier work on inequalities in referrals and the role of SES differences. The reliance of labor markets on referrals, coupled with homophily in social networks, can lead to persistent inequalities in wages and employment ([Bolte et al., 2021](#); [Calvo-Armengol & Jackson, 2004](#); [Montgomery, 1991](#)). The premise of these models is that referrals exhibit homophily, so that employees are more likely to refer workers of their own race, gender, SES, etc. Supporting evidence shows that low-SES individuals have networks with lower shares of high-SES individuals, which partly explains why they

⁵This follows directly from earlier evidence showing that referrals tend to go to strong ties, i.e., close friends and/or family members ([Gee et al., 2017](#); [Kramarz & Nordström Skans, 2014](#); [Wang, 2013](#)).

163 have worse labor market outcomes ([Chetty et al., 2022a](#); [Stansbury & Rodriguez, 2024](#)). 163
164 We contribute by separately identifying the role of network homophily (the tendency 164
165 to connect with similar others) and referral homophily (the tendency to refer similar 165
166 others). Our results suggest that network homophily, rather than referral homophily, 166
167 drives SES inequality in our setting. 167

168 To our knowledge, [Díaz et al. \(2025\)](#) are the first to study SES biases in referrals, 168
169 and our study is conceptually the closest to theirs. Drawing from a similar sample at 169
170 the same institution, [Díaz et al. \(2025\)](#) focus on referrals from first-year students made 170
171 within mixed-program classrooms and find no evidence for an aggregate bias against low- 171
172 SES individuals. We also find no aggregate bias against low-SES individuals in referrals 172
173 beyond what is attributable to differences in network structure. Our setup differs as we 173
174 sample from students who completed their first year and impose no limits on referring 174
175 from a classroom. This has several implications: We find that referrals in our setup go to 175
176 individuals within the same program, and that programs have different SES shares which 176
177 become even more accentuated as students take more courses together. While networks 177
178 drive inequality in referral outcomes because of the institutional environment in our 178
179 sample, we have no reason to believe first-year student networks in [Díaz et al. \(2025\)](#) 179
180 have similar levels of segregation to begin with. Our findings suggest that implementing 180
181 more mixed-program courses that allow for across-SES mixing should be a clear policy 181
182 goal to reduce segregation ([Alan et al., 2023](#); [Rohrer et al., 2021](#)). 182

183 The remainder of the paper is organized as follows. Section 2 begins with the back- 183
184 ground and setting in Colombia. In Section 3 we present the design of the experiment. 184
185 In Section 4 we describe the data and procedures. Section 6 discusses the results of 185
186 the experiment and Section 7 introduces robustness checks. Section 8 concludes. The 186
187 Appendix presents additional tables and figures as well as the experiment instructions. 187

2 Background and Setting

Our experiment took place in Colombia, a country that consistently ranks highly in terms of economic inequality. The richest decile of Colombians earn 50 times more than the poorest decile (United Nations, 2023; World Bank, 2024). This economic disparity creates profound differences in outcomes across SES groups in terms of education, geographic residence, language, manners, and social networks (Angulo et al., 2012; García et al., 2015; García Villegas & Cobo, 2021). While these patterns are not atypical and exist elsewhere, Colombia’s pronounced inequality makes economic, educational, and cultural differences across SES particularly visible and thus provides an ideal setting to study SES biases in referral selection.

We rely on Colombia’s established estrato classification system to measure SES in our study. In 1994, Colombia introduced a nationwide system that divides the population into six strata based on “similar social and economic characteristics” (Hudson & Library of Congress, 2010, p. 102). Designed for utility subsidies from higher strata to support lower strata, the system aligns with and reinforces existing social class divisions (Guevara S & Shields, 2019; Uribe-Mallarino, 2008). It is widely used by policymakers and in official statistics (Fergusson & Flórez, 2021a). Using the estrato system, we categorize students in strata 1-2 as low-SES, strata 3-4 as middle-SES, and strata 5-6 as high-SES.

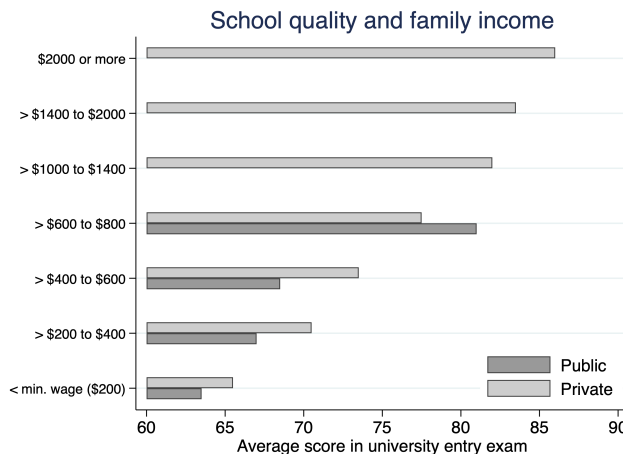
Colombia’s educational segregation typically prevents meaningful interaction between socioeconomic groups, as wealthy families attend exclusive private schools while poorer families access lower-quality public or “non-elite” private institutions (see Figure 1). Our study takes place in a non-elite private university which attracts students across the socioeconomic spectrum: The university’s student body comprises 35% low-SES, 50% middle-SES, and 15% high-SES students.⁶ This diversity provides opportunities for different SES groups to meet and interact within the same institutional framework.

The partner university creates conditions for contact on equal status. All students

⁶Government statistics reveal less than 5% of the population is high-SES (Hudson & Library of Congress, 2010, p. 103).

215 pay the same fees based on their program choices, and less than 5% of students receive 215
 216 scholarships. The student body is mostly urban and has comparable university entry 216
 217 exam scores due to the entrance exam **ADD NUMBERS**. These additional factors make 217
 218 our setting appropriate to study the effects of contact on intergroup discrimination. 218

Figure 1: Income, performance, and university choice in Colombia



Note: This figure shows the average score national university entry exam by monthly family income and type of higher education institution. With average student score in the 65-70 band, the private university where we conducted this experiment caters to low- and high-SES students. Figure reproduced from [Fergusson and Flórez \(2021b\)](#).

219 We construct enrollment networks using administrative data to map social connec- 219
 220 tions at the university. For each participant, we identify all other undergraduate students 220
 221 with whom they have taken at least one course and create their individual network of 221
 222 university connections. The size of this network depends on how many different students 222
 223 a participant has encountered through coursework, while the intensity of connection is 223
 224 measured by the number of courses taken together. This approach provides a complete 224
 225 picture of each participant's social environment at the university, including detailed 225
 226 characteristics (i.e., SES, academic program, performance) for both the participant and 226
 227 every person in their network. 227

228 **why don't we introduce number of programs and student count here as background?** 228

3 Empirical Specification

To formally test for SES bias, we use a choice modeling approach. We observe a single referral outcome from mutually exclusive candidates. Our design leverages the enrollment network to generate a dataset which includes alternative-specific variables for each referral decision, i.e., SES, courses taken together with the participant making the referral, as well as entry exam scores for not just the chosen alternative but all referral candidates. Using a conditional logit model, we can identify whether an SES group has an aggregate bias controlling for each individual's unique enrollment network composition.

We follow an additive random utility model framework where individual i and alternative j have utility U_{ij} that is the sum of a deterministic component, V_{ij} , that depends on regressors and unknown parameters, and an unobserved random component ε_{ij} :

We observe the outcome $y_i = j$ if alternative j has the highest utility of the alternatives. The probability that the outcome for individual i is alternative j , conditional on the regressors, is:

$$p_{ij} = \Pr(y_i = j) = \Pr(U_{ij} \geq U_{ik}), \quad \text{for all } k \quad (1)$$

The conditional logit model specifies that the probability of individual i choosing alternative j from choice set C_i is given by:

$$p_{ij} = \frac{\exp(x'_{ij}\beta)}{\sum_{l \in C_i} \exp(x'_{il}\beta)}, \quad j \in C_i \quad (2)$$

where x_{ij} are alternative-specific regressors, i.e., characteristics of potential referral candidates that vary across alternatives. In our context, individual i chooses to refer candidate j from their enrollment network C_i . The alternative-specific regressors include SES and entry exam scores of the referral candidate, and the number of courses taken together with the participant making the referral. Conditional logit structure eliminates participant-specific factors that might influence both network formation and referral decisions, allowing us to identify preferences within each participant's realized network.

252 For causal identification of SES bias, we require two identifying assumptions. Specif- 252
253 ically: 253

254 1. **Conditional exogeneity.** SES and the number of courses taken together could 254
255 be endogenous due to program selection. High-SES students sort into expensive 255
256 programs while low-SES students choose affordable programs, creating systematic 256
257 SES variation across enrollment networks. Similarly, the number of courses taken 257
258 together reflects program selection decisions that may correlate with unobserved 258
259 referral preferences. However, conditional on the realized enrollment network, the 259
260 remaining variation in both SES and the number of courses taken together across 260
261 referral candidates must be independent of unobserved factors affecting referral 261
262 decisions. In the robustness checks, we show that being in the same program 262
263 with the referrer does not impact our SES bias estimates, although it reduces the 263
264 coefficient on the number of courses taken together. 264

265 2. **Complete choice sets and independence of irrelevant alternatives.** Ad- 265
266 ministrative data captures the complete enrollment network, with all peers who 266
267 took at least one course with individual i and represent the true choice set for re- 267
268 ferral decisions (unless participants have potential referral candidates with whom 268
269 they never took classes). The independence of irrelevant alternatives (IIA) as- 269
270 sumption requires that choices between any two alternatives be independent of 270
271 other options in the choice set, which could be problematic if, e.g., peers within 271
272 the same SES group are viewed as close substitutes. This concern does not apply 272
273 to our setting because the design of our experiment ensures that choice sets are 273
274 fixed by enrollment rather than arbitrary inclusion/exclusion of alternatives that 274
275 create IIA violations. 275

276 Under these assumptions, the conditional logit framework controls for individual het- 276
277 erogeneity in program selection (absorbed by conditioning on choice sets), selection into 277
278 programs based on observable characteristics (through alternative-specific variables), and 278
279 choice set composition effects (through the multinomial structure). Therefore, β should 279

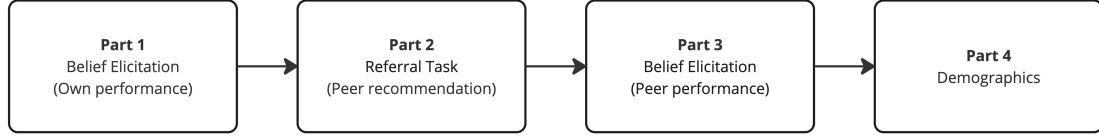
identify the causal effect of referral candidate SES on referral probability, holding constant the number of courses taken together and the entry exam scores of candidates. A significant coefficient will then indicate taste-based discrimination.

We pool participants by their SES group, and estimate the above described conditional fixed effects logit model once for low-, middle-, and high-SES referrers. We standardize entry exam scores and the number of courses taken together at the individual network level. For each referrer’s network, we first calculate the mean and standard deviation for both measures. We then compute the average of these means and standard deviations across all 734 referrers. Each referral candidate’s entry exam score and the number of courses they have taken with the referrer is standardized using these network-level statistics. The standardization formula is $z_i = (x - \bar{X}_i)/\sigma_i$, where \bar{X}_i and σ_i are the average of network means and standard deviations for C_i .

4 Design

We designed an online experiment to assess peer referral selection from an SES perspective and to evaluate the causal effect of providing a bonus to referral candidates. The experimental design consisted of two incentivized tasks administered in the following sequence: First, participants completed belief elicitation tasks about their own performance on the national university entry exam. Second, they completed the main referral task, nominating peers based on exam performance in two academic areas. Finally, participants reported beliefs about their referrals’ performance and provided demographic information. This structure allowed us to measure both the accuracy of participants’ beliefs and their referral behavior under controlled incentive conditions. Figure 2 shows the experimental timeline, and detailed instructions are provided in Appendix B.

Figure 2: Experimental Timeline



Note: Participants first reported beliefs about their own university entry exam performance, then made referrals for each academic area, and finally reported beliefs about their referrals' performance and provided demographics.

4.1 Performance measures

To establish an objective basis for referral performance, we use national university entry exam scores (SABER 11). All Colombian high school students take the SABER 11 exam at the end of their final year as a requirement for university admission. The scores from this exam provide pre-existing, comparable measures of performance. By using existing administrative data, we also ensure that all eligible students have comparable performance measures.

The exam consists of five areas (critical reading, mathematics, natural sciences, social sciences, and English). We focus on critical reading and mathematics as these represent two independent and fundamental skills. Critical reading evaluates competencies necessary to understand, interpret, and evaluate texts found in everyday life and broad academic fields (e.g., history). Mathematics assesses students' competency in using undergraduate level mathematical tools (e.g., reasoning in proportions, financial literacy). These together capture performance in comprehending and critically evaluating written material as well as reasoning and problem-solving abilities.

For each area, we calculate percentile rankings based on the distribution of scores among all currently enrolled students, providing a standardized measure of relative performance within the university population.

321 **4.2 Referral task** 321

322 The main task involves making referrals among peers. For both exam areas (critical 322
 323 reading and mathematics), participants refer one peer they believe excels in that area. 323
 324 We provide an example question from the relevant exam area to clarify the skills that 324
 325 are being assessed. Participants type the name of their preferred candidate to make 325
 326 a referral. To avoid issues with recall, the interface provides autocomplete name and 326
 327 program suggestions from the administrative database (see Figure 3). 327


Figure 3: Referral task interface

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:

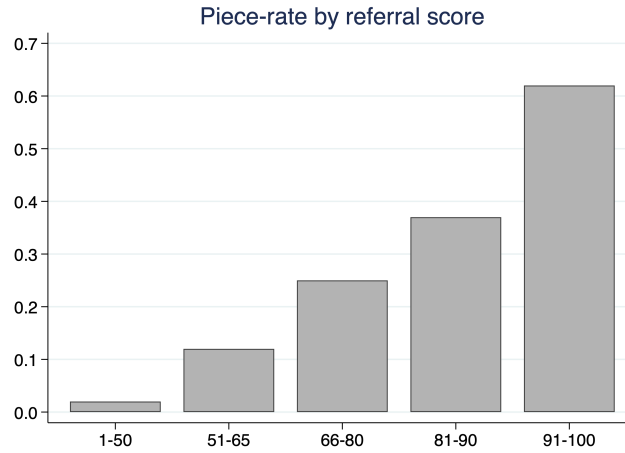
John
John Lennon (Music - 2018) 
John Stuart Mill (Law - 2020)

Note: This illustration shows how the system provides suggestions from enrolled students with their program and year of study from the administrative database.

328 Participants can only refer students with whom they have taken at least one class 328
 329 during their university studies. This requirement ensures that referrals are based on 329
 330 actual peer interactions. We randomize the order in which participants make referrals 330
 331 across the two exam areas. 331

332 We incentivize referrals using a piece rate payment structure. Referrers earn in- 332
 333 creasing payments as the percentile ranking of their referral increases (see Figure 4). We 333
 334 multiply the piece rate coefficient associated with the percentile rank by the actual exam 334
 335 scores of the referral to calculate earnings. This payment structure provides strong in- 335
 336 centives to refer highly ranked peers with potential earnings going up to \$60 per referral. 336

Figure 4: Referral incentives



Note: This figure shows how the piece rate coefficient increases as a function of the referral ranking in the university, providing incrementally higher rewards for higher ranked peers.

4.3 Bonus Treatment

To examine how different incentive structures affect referral selection, we randomly assign a fixed bonus payment for students who get a referral. In the **Baseline** treatment, only the participants can earn money based on their referral's performance. The **Bonus** treatment adds an additional fixed payment of \$25 to the peer who gets the referral. This payment is independent of the referral's actual performance (see Table 1).

Table 1: Incentive structure by treatment

	Baseline	Bonus
Referrer (sender)	Performance-based	Performance-based
Referral (receiver)	No payment	Fixed reward

⁷Note that due to the selection into the university, the actual exam score distribution has limited variance. Below a certain threshold students cannot qualify for the institution and choose a lower ranked university, and above a certain threshold they have better options to choose from.

344 We use a between-subjects design and randomly assign half our participants to the 344
345 **Bonus** treatment. This allows us to causally identify the effect of the bonus on referral 345
346 selection. Participants learn whether their referral gets the fixed bonus before making 346
347 referral decisions. 347

348 4.4 Belief elicitation 348

349 We collect two sets of incentivized beliefs to assess the accuracy of participants' knowl- 349
350 edge about exam performance. Participants first report beliefs about their own percentile 350
351 ranking in the university for each exam area. After making referrals, participants report 351
352 their beliefs about their referrals' percentile ranking in the university. For both belief 352
353 elicitation tasks, participants earn \$5 per correct belief if their guess is within 7 per- 353
354 centiles of the true value. This margin of error is designed to balance precision with the 354
355 difficulty of the task. 355

356 5 Sample, Incentives, and Procedure 356

357 We invited all 4,417 undergraduate students who had completed their first year at the 357
358 university at the time of recruitment to participate in our experiment. A total of 837 358
359 students participated in the data collection (19% response rate). Our final sample con- 359
360 sists of 734 individuals who referred peers with whom they had taken at least one class 360
361 together (88% success rate). We randomly allocated participants to either **Baseline** or 361
362 **Bonus** treatments. 362

363 Table 2 presents key demographic characteristics and academic performance indi- 363
364 cators across treatments (see Appendix Table A.1 for selection). The sample is well- 364
365 balanced between the **Baseline** and **Bonus** conditions and we observe no statistically 365
366 significant differences in any of the reported variables (all p values > 0.1). Our sample is 366
367 characterized by a majority of middle-SES students with about one-tenth of the sample 367
368 being high-SES students. The test scores and GPA distributions are balanced. On av- 368
369 erage, participants had taken 3.8 courses together with members of their network, and 369

the average network consisted of 175 peers.

370

Table 2: Balance between treatments

	Baseline	Bonus	<i>p</i>
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
Middle-SES	0.492	0.506	0.714
High-SES	0.089	0.094	0.824
Observations	382	352	734

Note: This table presents balance tests between **Baseline** and **Bonus** conditions. *p*-values for binary outcomes are from two-sample tests of proportions; for continuous variables, from two-sample *t*-tests with unequal variances. All reported *p*-values are two-tailed. Reading and math scores are in original scale units out of 100. GPA is grade point average out of 5. Connections refers to the average number of network members. Low-SES, Med-SES, and High-SES indicate SES categories based on strata.

The experiment was conducted online through Qualtrics, with participants recruited from active students. To ensure data quality while managing costs, we randomly selected one in ten participants for payment. Selected participants received a fixed payment of \$17 for completion. They also received potential earnings from one randomly selected belief question (up to \$5) and one randomly selected referral question (up to \$60). This structure resulted in maximum total earnings of \$82. The average time to complete the survey was 30 minutes, with an average compensation of \$80 for the one in ten participants randomly selected for payment. Payment processing occurred through bank transfer within 15 business days of participation.

6 Results

6.1 Network characteristics

We begin by describing the key features of the enrollment networks. On average, participants connect with 175 other students, and take an average of 3.62 courses together. Figure 5 shows how network characteristics vary by students' time at the university: both the number of connections (network size) and the number of courses taken together (connection intensity) change as participants progress through their studies.

Figure 5: Network size and courses taken together by time spent at the university

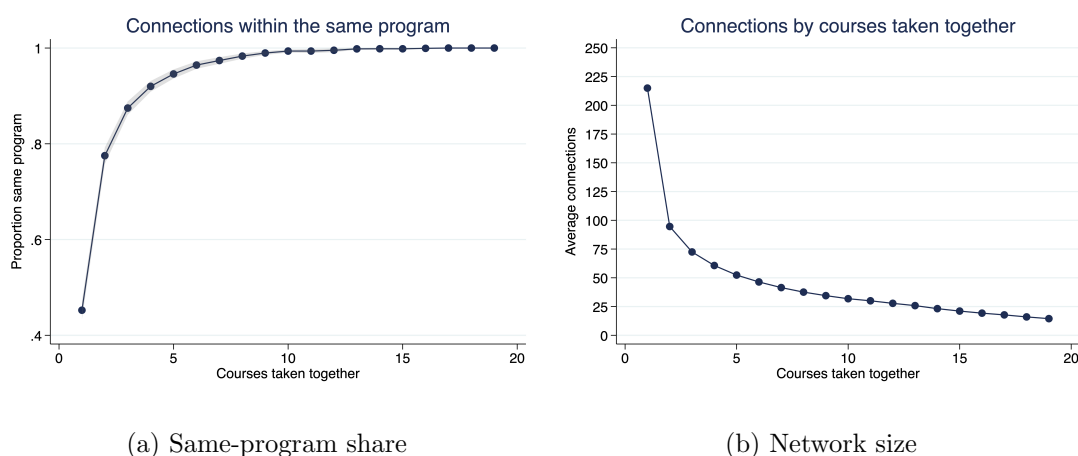


Note: This figure displays the average number of connections in blue and the average number of courses taken together with connections in grey across semesters completed. Network size (nb. of connections) peaks around 7 semesters before declining as students graduate. Connection intensity (nb. of courses taken) has an increasing trend.

We now examine how connection intensity relates to network size and composition. First, if two students take more courses together, it is very likely that they are in the same academic program. We plot this relationship in Figure 6a: As students take more than 5 courses together, the share of students in their enrollment network from the same academic program quickly exceeds 90%. Second, because students sort into specialized

academic programs, increases in courses taken together should result in decreases in connections. We plot this relationship in Figure 6b: As students take more than 5 courses together, the size of their enrollment network drops dramatically from above 210 to below 50. These patterns reveal that while participants' overall networks are large with relatively few courses taken together on average, they spend most of their time at the university within smaller, more intensive groups of peers from the same academic program.

Figure 6: Network characteristics and courses taken together



Note: The left panel illustrates the share of connections within the same program as a function of the number of courses taken together. The right panel shows the average network size as a function of the number of courses taken together. Taking more than 5 courses together with a network member means on average 90% chance to be in the same program. Similarly, past 5 courses together, the average network size dwindles by 80%, from more than 210 individuals to below 50.

6.2 Referral characteristics

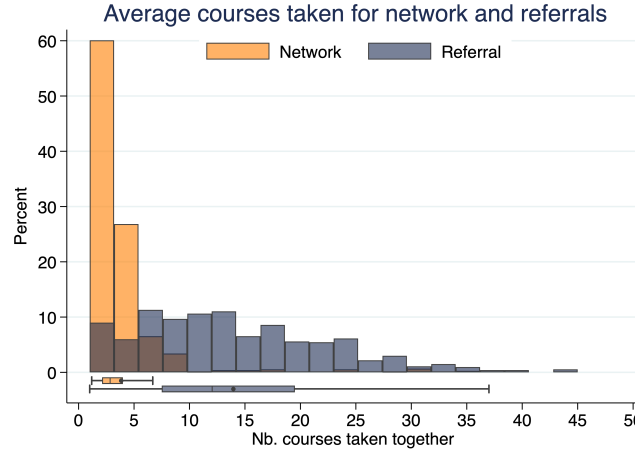
Participants made one referral for math and one referral for the reading part of the university entry exam from their enrollment networks. We observe 1,342 referrals from 734 participants in our final dataset. More than 90% of these consist of participants

referring for both exam areas (see Appendix Table A.2). About 70% of these referrals go to two separate individuals. We compare the outcomes across exam areas for referrals only going to separate individuals in Appendix Table A.3 and all referrals in Appendix Table A.4. In both cases, we find no meaningful differences between referrals made for Math or Reading areas of the entry exam. As referrals in both exam areas come from the same enrollment network, we pool referrals per participant and report their averages in our main analysis to avoid inflating statistical power in our comparisons.

What are the characteristics of the individuals who receive referrals, and how do they compare to others in the enrollment network? Because we have an entire pool of potential candidates with one referral chosen from it, we compare the distributions for our variables of interest between the referred and non-referred students.

First, referrals go to peers with whom the referrer has taken around 14 courses with on average, compared to almost 4 on average with others in their network (see Figure 7). This difference of 10.1 courses is significant ($t = 34.98$, $p < 0.001$), indicating that referrers choose individuals with whom they have stronger ties. While the median referral recipient has taken 12 courses together with the referrer, the median network member has shared only 2.8 courses. The interquartile range for referrals spans from 7.5 to 19.5 courses, compared to just 2.1 to 4.0 courses for the broader network, highlighting the concentration of referrals among peers with high social proximity. In addition, 93% of referrals go to students within same program.

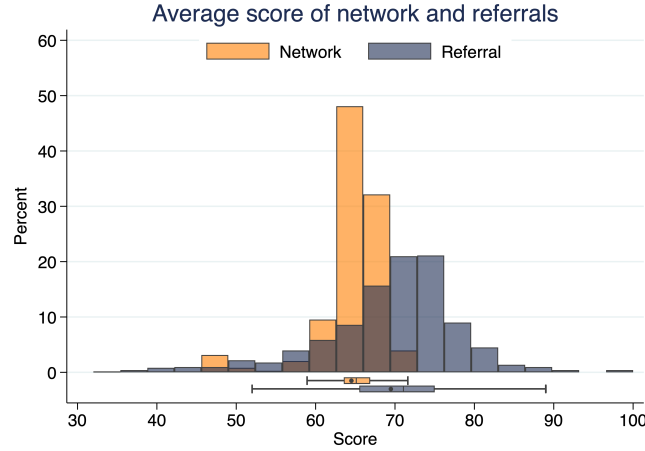
Figure 7: Courses taken together with network members and referrals



Note: This figure compares the distributions of the number of courses taken together between referrers and their network members (orange) versus referrers and their chosen referral recipients (dark blue) for all 734 participants. 75% of referral recipients take more than 7.5 courses together with the referrer, compared to only 25% of network members. The distributions are significantly different (Kolmogorov-Smirnov test $D = 33.37$, $p < 0.001$).

Second, we examine entry exam score differences between referred students and the broader network. Referrals go to peers with an average score of 69.5 points, compared to 64.5 points for other network members (see Figure 8). This difference of 5 points is significant ($t = 18.97$, $p < 0.001$), indicating that referrers choose higher-performing peers. While the median referral recipient scores 71 points, the median network member scores 65.1 points. The interquartile range for referrals spans from 65.5 to 75 points, compared to 63.5 to 66.9 points for the broader network, highlighting the clear concentration of referrals among higher performing peers.

Figure 8: Entry exam scores of network members and referrals



Note: This figure compares the distributions of entry exam scores (Math and Reading average) between referrers' network members (orange) versus their chosen referral recipients (dark blue) for all 734 participants. 75% of referral recipients score above 65.5 points compared to only 25% of network members scoring above 66.9 points. The distributions are significantly different (Kolmogorov-Smirnov test $D = 71.16$, $p < 0.001$).

6.3 Effect of the Bonus treatment

Do referred individuals have different outcomes across treatments? We compare the performance, number of courses taken together, and SES shares of referred individuals between the **Baseline** and **Bonus** treatments in Table 3. While performance of referrals across Reading, Math, and GPA are similar across treatments, middle- and high-SES shares have significant differences. We find that referrals under the **Bonus** condition referred a higher proportion of high-SES individuals (13.5% vs 8.8%, $p = 0.041$) and a lower proportion of middle-SES individuals on average (47.0% vs 53.7%, $p = 0.072$). The similarities in academic performance and number of courses taken together suggest that performance and contact intensity drive referrals regardless of treatment. For this reason, in the remainder of the paper, we report pooled results combining the averages of referral outcomes across treatments.

Table 3: Characteristics of referrals by treatment condition

	Baseline Referred	Bonus Referred	p
Reading score	67.806	67.210	0.308
Math score	70.784	70.155	0.406
GPA	4.155	4.149	0.799
Courses taken	13.840	14.065	0.723
Low-SES	0.376	0.395	0.593
Middle-SES	0.537	0.470	0.072
High-SES	0.088	0.135	0.041
Observations	382	352	

Note: This table compares the characteristics of network members who were referred under baseline vs bonus treatment conditions. p -values for binary outcomes are from two-sample tests of proportions; for continuous variables, from two-sample t -tests with unequal variances. All reported p -values are two-tailed. Reading and math scores are raw test scores out of 100. GPA is grade point average out of 5. Courses taken is the number of courses participant has taken with their referral. Low-SES, Med-SES, and High-SES are binary variables indicating the share of participants in estrato 1-2, 3-4, or 5-6, respectively. Both columns include only network members who were actually nominated for referral in each treatment condition.

6.4 Identifying the SES bias in referrals

We now present our empirical findings and describe our first set of findings in Table 4. To begin with, the variance explained by all three models are extremely low, suggesting the role of potential SES biases in referrals that go beyond the network structure must be limited. Regardless, controlling for network composition, low-SES participants are more likely to refer other low-SES, and are less likely to refer high-SES relative to the probability of referring middle-SES peers. In contrast, we find that high-SES participants are less likely to refer other low-SES, relative to the probability of referring middle-SES peers.

Table 4: SES bias in referral decisions by referrer SES group

	Referrer SES		
	Low	Middle	High
	(1)	(2)	(3)
Low-SES referral	0.453*** (0.109)	-0.019 (0.098)	-0.710** (0.333)
High-SES referral	-0.584*** (0.211)	-0.255* (0.145)	0.001 (0.261)
χ^2	33.47	3.18	4.94
Observations	110,142	127,088	19,767
Individuals	301	366	67

Note: Individual-level clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column represents a separate conditional logit regression estimated on the subsample of referrers from the indicated SES group. Coefficients represent log-odds of referring from the specified SES group relative to referring middle-SES candidates. All models include individual fixed effects that control for each referrer's choice set composition.

Next, we include social proximity controls in our analysis. We proceed by adding the standardized number of courses taken together as a control in our specification and describe the results in Table 5. A one standard deviation increase in the number of courses taken together proves to be highly significant across all models, with coefficients ranging from 0.856 to 1.049, indicating that intensity of contact substantially increase the probability of referral. The high χ^2 statistics suggest that these models explain considerably more variance than specifications without this control, highlighting the predictive power of courses taken together in referral decisions. Nevertheless, low-SES participants still show a strong same-SES bias relative to referring middle-SES peers at the average number of courses taken together. This same-SES bias is not observed among middle-SES or high-SES referrers, who also display no statistically significant

463 bias toward low-SES candidates. No referrer group shows a positive bias for high-SES 463
464 candidates relative to middle-SES candidates. 464

Table 5: SES bias in referral decisions by referrer SES group

	Referrer SES		
	Low (1)	Middle (2)	High (3)
Low-SES referral	0.348*** (0.123)	-0.064 (0.115)	-0.489 (0.337)
High-SES referral	-0.366 (0.223)	-0.165 (0.157)	-0.140 (0.286)
Courses taken (z-score)	0.856*** (0.035)	0.931*** (0.037)	1.049*** (0.126)
χ^2	626.15	636.10	71.43
Observations	110,142	127,088	19,767
Individuals	301	366	67

Note: Individual-level clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column represents a separate conditional logit regression estimated on the subsample of referrers from the indicated SES group. Coefficients represent log-odds of referring from the specified SES group relative to referring middle-SES candidates. All models include individual fixed effects that control for each referrer's choice set composition.

465 We add standardized entry exam scores (Math and Reading average) as a second 465
466 control variable and describe our results in Table 6. A one standard deviation increase 466
467 in the entry exam score proves highly significant across all models, with coefficients 467
468 ranging from 0.587 to 0.883. This shows merit-based considerations due to the incentive 468
469 structure of the experiment remained central to referral decisions. The slightly higher χ^2 469
470 statistics compared to the earlier specification suggests that entry exam scores improve 470
471 model fit. The inclusion of standardized entry exam scores strengthens SES biases. Low- 471

SES referrers maintain their same-SES bias, with now a significant negative bias against high-SES. Middle-SES referrers, previously showing no SES bias, now show marginal negative bias against high-SES. Finally, high-SES referrers exhibit marginal negative bias against low-SES candidates.

The evidence of a bias becoming significant when controlling for entry exam scores has a nuanced interpretation. While at the university-level, low-SES typically score lower in the entry exam, low-SES students appearing in high-SES networks are positively selected, scoring about 0.14 standard deviations higher than middle-SES students (see Appendix Table A.5). Controlling for performance thus removes this positive selection and reveals the “pure” SES bias that was previously underestimated by above average performance of low-SES. Vice versa, high-SES in low-SES networks perform 0.12 standard deviations better than middle-SES students. The same bias was underestimated as high-SES candidates’ better performance relative to middle-SES in the same networks provided a meritocratic justification for getting more referrals. Controlling for exam scores reveal that both high- and low-SES referrers have negative SES bias towards one another that operates independently of - and counter to - performance-based considerations. What makes interpretation difficult is that while biased against low-SES, high-SES referrers do not (under any specification) display a positive bias towards their in-group. For this final reason, we do not dig any further in this direction.

To conclude, we conduct joint significance tests, testing whether low- and high-SES regression coefficients are jointly different from middle-SES for each regression specification. For low-SES referrers, the joint test remains highly significant across all three specifications ($\chi^2 = 10.20$, $p = 0.006$ in the final model), indicating persistent SES bias across all specifications. In contrast, middle-SES referrers display no significant joint SES bias in any specification, with the test becoming increasingly non-significant as controls are added ($\chi^2 = 4.13$, $p = 0.127$ in the final model). High-SES referrers similarly show no significant joint SES bias across all three models ($\chi^2 = 4.28$, $p = 0.118$ in the final model). These results suggest that SES bias in referrals is primarily driven by low-SES. There is no sufficient evidence to conclude that middle- and high-SES referrers

501 systematically discriminate against other-SES peers. Naturally, this null result occurs 501
502 once we take into account the potential differences in the network compositions of each 502
503 SES group. In the next section, we explore the differences in the network compositions 503
504 of different SES groups. 504

Table 6: SES bias in referral decisions by referrer SES group with academic performance controls

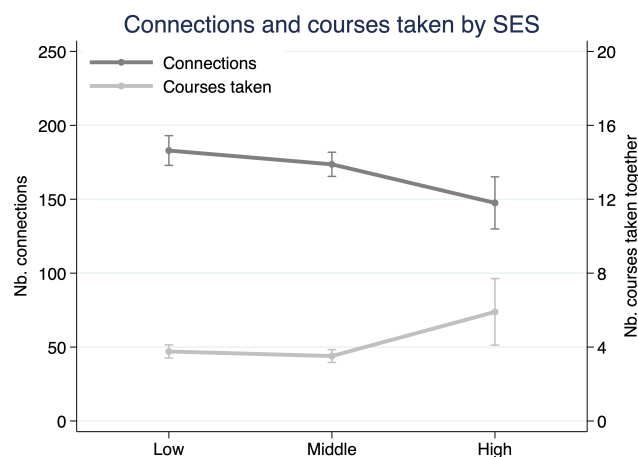
	Referrer SES		
	Low	Middle	High
	(1)	(2)	(3)
Low-SES referral	0.242** (0.123)	-0.159 (0.114)	-0.600* (0.327)
High-SES referral	-0.445** (0.222)	-0.274* (0.157)	-0.345 (0.287)
Courses taken (z-score)	0.859*** (0.036)	0.948*** (0.038)	1.043*** (0.118)
Entry exam (referral z-score)	0.607*** (0.052)	0.587*** (0.047)	0.883*** (0.111)
χ^2	789.87	756.06	120.54
Observations	110,142	127,088	19,767
Individuals	301	366	67

Note: Individual-level clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column represents a separate conditional logit regression estimated on the subsample of referrers from the indicated SES group. Coefficients represent log-odds of referring candidates from the specified SES group relative to referring middle-SES candidates. All models include individual fixed effects that control for each referrer's choice set composition.

6.5 SES diversity in networks

How do enrollment networks differ across SES groups? We look at how the number of connections (network size) and number of courses taken together (contact intensity) change across SES groups in Figure 9. Low- and middle-SES students have larger networks but take fewer courses together with network members, while high-SES students have smaller, denser networks. Specifically, both low- and middle-SES students have significantly larger networks than high-SES students ($t = 3.03$, $p = 0.003$ and $t = 2.49$, $p = 0.013$, respectively), but high-SES students take significantly more courses with their network members than both low- ($t = -3.70$, $p < .001$) and middle-SES ($t = -4.20$, $p < .001$).

Figure 9: Network size and courses taken together by SES



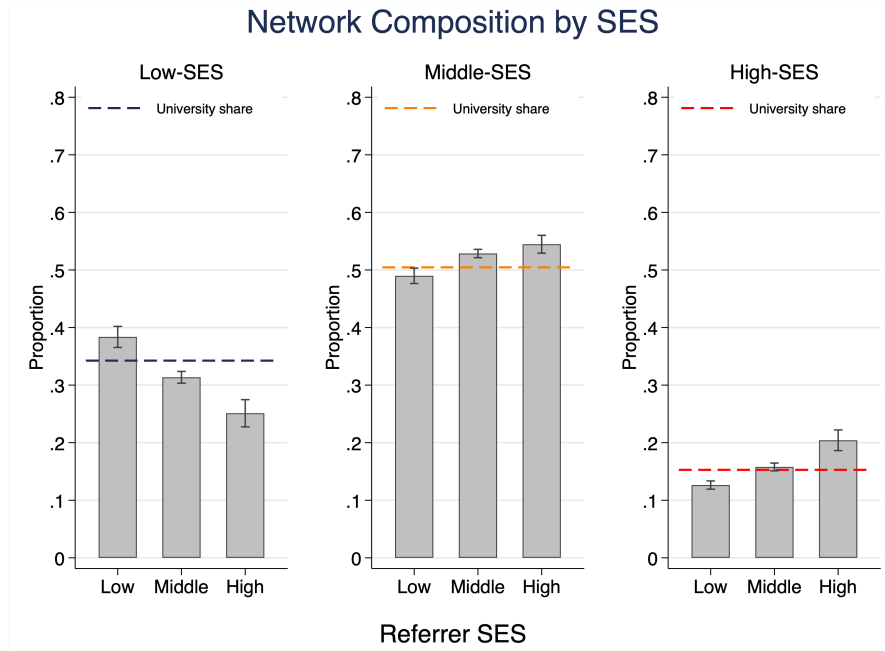
Note: This figure displays the average number of connections and the average number of classes taken together across SES groups. The data shows a decrease in the number of connections with SES, and an associated increase in the number of classes taken together.

What are the diversity-related consequences of SES-driven differences across networks? In terms of network compositions, SES groups may connect with other SES groups at different rates than would occur randomly (Figure 10).⁸ Our results reveal

⁸Because we estimate the share of SES groups in every individual network, we get very precise esti-

modest deviations from university-wide SES composition across groups. Low-SES students have networks with 38.4% low-SES peers compared to the university average of 34.3%, middle-SES students connect with 52.9% middle-SES peers versus the university average of 50.5%, and high-SES students show 20.4% high-SES connections compared to the university average of 15.3%.

Figure 10: Network shares of SES groups



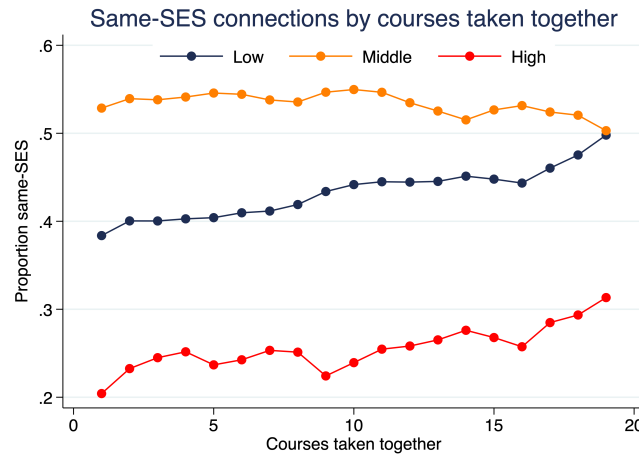
Note: This figure compares the network shares of SES groups in the networks of low-, middle-, and high-SES participants. Horizontal lines plot the university-wide shares of each SES group (Low: 35%, Mid: 51%, High: 14%). While the share of low-SES peers in the network decreases as the SES of the group increases, the share of high-SES peers in the network increases.

mates of the actual means. However, it is important to note that these are not independent observations for each network. Estimates are precise because each network is a draw with replacement from the same pool of university population, from which we calculate the proportion of SES groups per individual network, and take the average over an SES group. Pooling over SES groups who are connected with similar others systematically reduces variance (similar to resampling in bootstrapping). For this reason we choose not reporting test results in certain sections including this one and focus on describing the relationships between SES groups.

We observe larger differences between SES groups in their connection patterns with other groups. Low-SES students connect with other low-SES students at higher rates than middle-SES students (38.4% vs 31.4%) and high-SES students (38.4% vs 25.1%). Conversely, high-SES students connect more with other high-SES students than both low-SES students (20.4% vs 12.6%) and middle-SES students (20.4% vs 15.8%). Middle-SES students are in between the two extreme patterns, connecting with middle-SES peers at higher rates than low-SES students (52.9% vs 49.0%) but lower rates than high-SES students (52.9% vs 54.5%). These findings indicate SES-based network segregation, with same-SES homophily patterns across groups.

This raises an important question: What are the diversity implications of increased connection intensity between students? As students take more courses together with peers, the share of same-SES peers in the networks of low- and high-SES increases while the share of middle-SES declines (see Figure 11). Both increases are substantial, amounting to 50% for high-, and 30% for low-SES. Combining these with the earlier result that beyond 5 courses taken together network members are almost entirely within the same program, these suggest program selection may have strong consequences for SES diversity in our setting.

Figure 11: Network size and courses taken together by courses taken

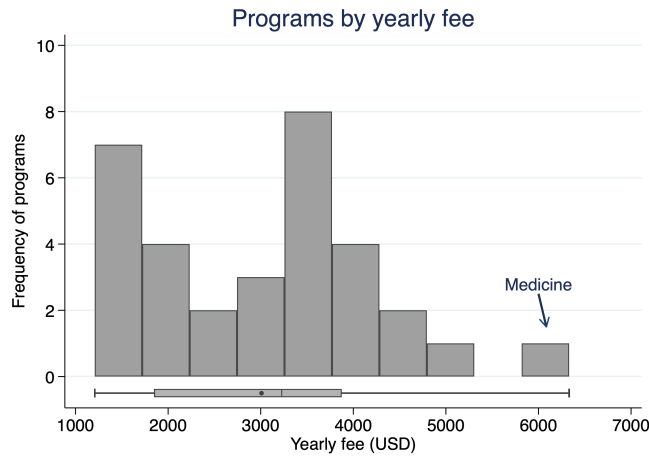


Note: This figure illustrates the shares of same-SES connections for low-, middle-, and high-SES as a function of the average number of courses taken together with network members. Low- and high-SES networks both become more homogenous as the average number of courses taken together with their connections increase.

6.6 Program selection and SES diversity

To understand the mechanisms driving these patterns, we examine program selection. Academic programs at this university use cost-based pricing, and typically less than 5% of students receive any kind of scholarship. Based on this, we first calculate how much every program at the university is expected to cost students per year (see Figure 12). Considering that net minimum monthly wage stands at \$200 and the average Colombian salary around \$350, the cost differences between programs are large enough to make an impact on program selection. Is it the case that SES groups select into programs with financial considerations?

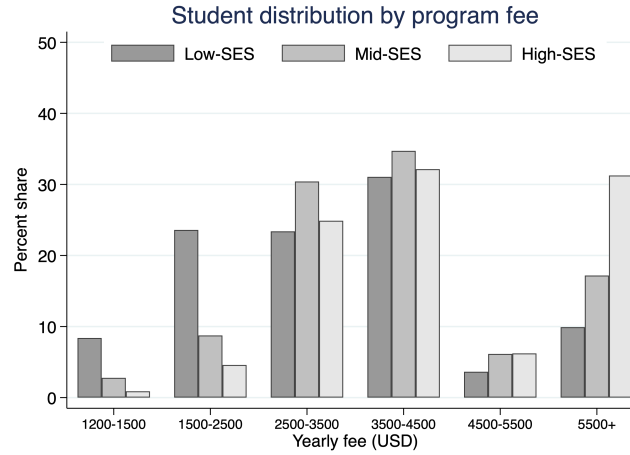
Figure 12: Programs sorted by fee



Note: This figure illustrates the distribution of programs at the university by their average yearly fee. The average yearly fee stands at \$3000, and medicine is an outlier at \$6000.

We examine how SES groups are distributed across programs to identify evidence of SES-based selection (see Figure 13). Indeed, low-SES students select into more affordable programs, followed by middle-SES students. High-SES students sort almost exclusively into above-average costing programs, with a third selecting into medicine and creating a very skewed distribution. The distributions are significantly different across all pairwise comparisons: low-SES vs. middle-SES (Kolmogorov-Smirnov test $D = 33.89$, $p < 0.001$), low-SES vs. high-SES ($D = 31.31$, $p < 0.001$), and middle-SES vs. high-SES ($D = 31.31$, $p < 0.001$). With this finding, program selection could be the reason why low- and high-SES networks tend to segregate as the number of courses taken increases. The next section characterizes the referrals, and we will return to the diversity implications of program selection once we propose an understanding of how referrals were made.

Figure 13: Programs sorted by fee

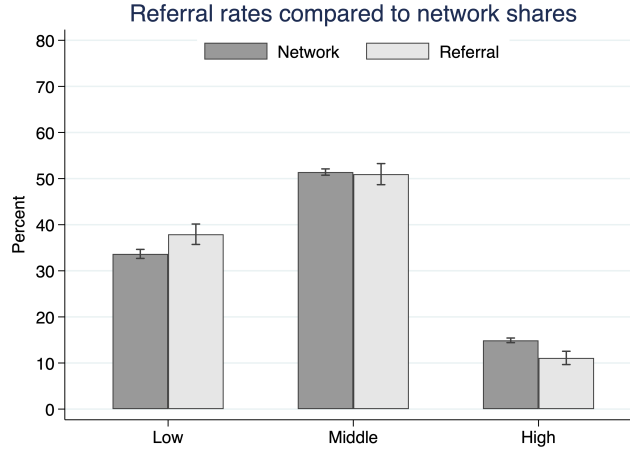


Note: This figure illustrates the distribution of each SES group across programs sorted by fee. the majority of low-SES select into programs with below average cost, while high-SES select into programs with above average cost. Medicine accounts for a third of all high-SES students at this university.

6.7 Referral SES composition

We now examine the overall SES compositions in referral selection. Referrals to low-SES peers constitute 37.9% of all referrals, compared to 33.7% low-SES representation in individual networks (see Figure 14). This represents a modest over-representation of 4.3 percentage points. For middle-SES students, referrals constitute 51.0% versus 51.4% network representation, showing virtually no difference (-0.5 pp.). High-SES referrals account for 11.1% compared to 14.9% network share, an under-representation of 3.8 percentage points. While these patterns suggest some deviation from proportional representation—with slight over-referral to low-SES peers and under-referral to high-SES peers—the magnitudes are relatively modest. Overall, referral compositions are largely balanced and closely mirror the underlying network structure, with the largest deviation being less than 5 percentage points for any SES group.

Figure 14: Referral patterns compared to network composition



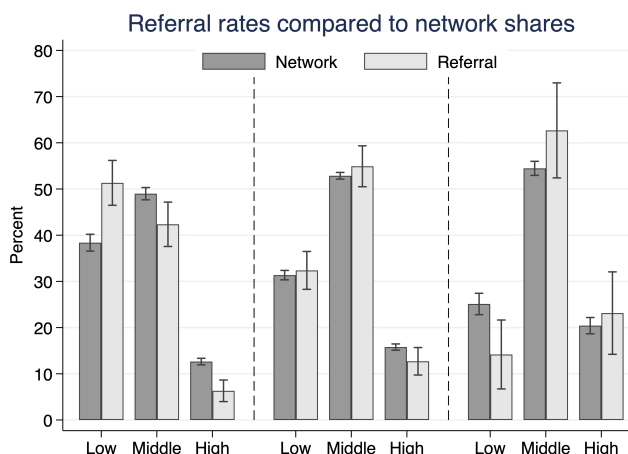
Note: This figure compares the average SES composition of referrers' networks (dark gray) to the SES composition of referrals (light gray). Error bars represent 95% confidence intervals.

Then, we examine referral patterns by referrer SES to identify potential SES biases across groups. Figure 15 reveals mixed patterns of deviation from network composition that vary by referrer SES. Most patterns show modest deviations from network composition, with differences typically ranging from 1-6 percentage points. However, at the very extremes—low-SES to high-SES connections and vice versa—we observe the largest discrepancies between network share (which were already biased toward same-SES connections to begin with) and referral rates. Low-SES referrers show the strongest same-SES preference, referring 12.9 percentage points more to low-SES students than their network composition would suggest, while under-referring to high-SES recipients by 6.3 percentage points. Conversely, high-SES referrers under-refer to low-SES students by 10.9 percentage points compared to their network composition. Middle-SES referrers show the most balanced patterns, with deviations generally under 3 percentage points across all recipient groups. Cross-SES referral patterns, particularly between the most socioeconomically distant groups, show the largest departures from network availability. These results suggest that referral behavior diverges most from underlying network

structure when SES differences are most pronounced.

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Figure 15: Referral patterns by referrer SES compared to network composition



Note: This figure compares the average SES composition of referrers' networks (dark gray) to the SES composition of referrals (light gray) for each SES group. The panels show referral patterns for low-SES (left), middle-SES (center), and high-SES referrers (right). Error bars represent 95% confidence intervals.

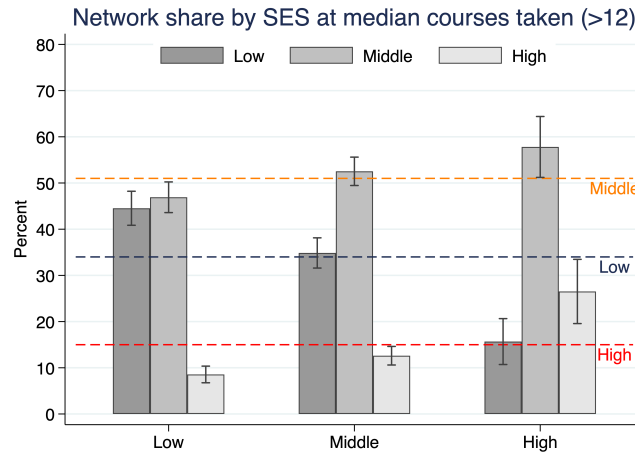
6.8 Ex post referral choice sets

588

We now shed more light on the referral behavior after having characterized how referrals were made. Particularly interesting is that referrals go to peers with whom the median participant took 12 courses, with an average of 14. By restricting the networks for courses taken above the median, we can get a snapshot of how the referral choice set actually looked for participants before making referral decisions. As discussed in Section 6.5, taking more courses with network members increases the share of same-SES individuals for both low- and high-SES students, and we had explored program selection as a potential mechanism. In Figure 16, we show the effects of network segregation on *ex post* referral choice sets for each SES group. Network compositions above the median number of courses taken reveal strong segregation effects: Low-SES networks

599 contain 44.5% low-SES peers, higher than the 35% university-wide share by 9.5 percent- 599
 600 age points. Conversely, high-SES students are under-represented in low-SES networks at 600
 601 only 8.6% average share, compared to the 14% population share (-5.4 pp.). At the other 601
 602 extreme, high-SES networks show the reverse pattern with average low-SES share drop- 602
 603 ping to just 15.7%, a 19.3 percentage point decrease relative to the university average. 603
 604 High-SES students have a same-SES concentration at 26.5%, doubling their 14% popu- 604
 605 lation share ($+12.5$ pp.). Middle-SES networks remain relatively balanced and closely 605
 606 track population proportions across all SES groups. Taken together, these confirm that 606
 607 the observed referral rates of SES groups follow the network compositions above median 607
 608 number of courses taken together, except for the low-SES. We conclude that the referral 608
 609 choices in our setting are mainly driven by availability and performance. 609

Figure 16: Network size and courses taken together by courses taken



Note: This figure compares the network shares of SES groups in the networks of low-, middle-, and high-SES participants above the median number of courses taken together with peers. Horizontal lines plot the university-wide shares of each SES group (Low: 35%, Mid: 51%, High: 14%). Low- and high-SES networks both become same-SES dominated at the expense of each other while middle-SES networks remain balanced. Error bars represent 95% confidence intervals.

7 Robustness check

Does the number of courses taken together have an independent effect that goes beyond identifying peers in the same academic program? To evaluate this question we leverage our administrative data, and identify peers within the same program: In each individual network we observe the participant-specific academic program for the participant making the referral and alternative-specific academic program for each referral candidate. We add this new variable in our specification and describe our findings in Table 7. Being in the same academic program has a substantial positive effect on referral likelihood, with coefficients ranging from 1.257 to 2.198 across all referrer SES groups. This confirms that program affiliation serves as a strong predictor of referral decisions, reflecting increased familiarity. Our comparison of interest is the point estimate for the standardized number of courses taken. Across all three referrer groups, the standardized number of courses taken together maintains its statistical significance after controlling for same program membership. The coefficient magnitudes are expectedly smaller compared to specifications without program controls (ranging from 0.688 to 0.930) as the newly added variable is a moderator: Matching academic programs leads to taking more courses together. The remaining estimates in our model remain robust to the inclusion of the same-program variable with little change in point estimates. The persistence of statistical significance (all $p < 0.001$) suggests that the number of courses taken together has an independent effect on referral decisions. To sum, our measure of contact intensity seems to capture meaningful social interaction patterns that lead to referrals, and go beyond simply identifying matching academic programs.

Table 7: SES bias in referral decisions by referrer SES group with program controls

	Referrer SES		
	Low (1)	Middle (2)	High (3)
Low-SES referral	0.236** (0.119)	-0.140 (0.111)	-0.567* (0.331)
High-SES referral	-0.421* (0.220)	-0.249 (0.158)	-0.383 (0.281)
Entry exam (referral z-score)	0.623*** (0.054)	0.590*** (0.048)	0.892*** (0.114)
Courses taken (z-score)	0.688*** (0.032)	0.760*** (0.035)	0.930*** (0.119)
Same program	2.074*** (0.215)	2.198*** (0.185)	1.257*** (0.467)
χ^2	865.35	981.99	135.47
Observations	110,142	127,088	19,767
Individuals	301	366	67

Note: Individual-level clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column represents a separate conditional logit regression estimated on the subsample of referrers from the indicated SES group. Coefficients represent log-odds of referring candidates from the specified SES group relative to referring middle-SES candidates. All models include individual fixed effects that control for each referrer's choice set composition.

8 Conclusion

In this paper, we study whether SES groups are biased toward one another beyond what is attributable to differences in their networks, and the effects of different incentive structures on referral behavior. Through a lab-in-the-field experiment that leverages enrollment networks at a socially diverse university, we find that the SES biases in referrals originate mostly from network structures, and referrals under performance-pay incentives do not exacerbate existing SES inequalities.

Our findings reveal that enrollment networks are surprisingly segregated and referrals from these networks reflect closely the choice sets of the referrers. We identify program selection as the key mechanism driving this segregation. Low-SES students select into more affordable programs, and program selection plays a major part in segregating SES groups where low- and high-SES take more courses with their own SES group. Consequently, referrals come almost exclusively from the same academic program as the referrer, limiting the SES-diversity of their choice sets. Regardless of the bonus for the referral candidate, participants also pick higher performing peers with whom they have taken many courses together. We find that only low-SES referrers exhibit a same-SES bias. These findings suggest that the underlying network structure plays a crucial role in referrals, where institutional action can remedy the network segregation.

These results complement the broader literature where much of the bias in referrals can be attributable to the “practical” choice sets of the referrers. While previous work demonstrates that about half of referrals come from a smaller, elicited network of close friends (Hederos et al., 2025), we go the other way and use administrative data to construct a complete network which presumably includes close social relationships at the institutional level. Having access to the complete network thus eliminates any potential for under or overestimating taste-based biases (Griffith, 2022). Under performance-pay incentives, referrers identify productive others regardless of additional financial rewards for the referral candidate. Still, the lack of a treatment effect suggests that in both incentive structures referrers pick close ties, shifting the responsibility to institutional

660 actors to create diverse environments where cross-SES social interaction can take place 660
661 more frequently and allow more diversity in networks. 661

662 These findings have policy implications. Looking forward, institutions can play a 662
663 crucial role in achieving SES equality of opportunity in higher education. Universities 663
664 are already a setting in which low-SES get exposed to typically a higher than population 664
665 share of higher-SES individuals than at other settings ([Chetty et al., 2022b](#)). Yet, 665
666 segregation within the higher education institutions remain a source for SES inequality. 666
667 If low-SES peers never get to interact in meaningful ways with higher-SES, e.g., by 667
668 taking courses together, the premise of social mobility through social channels remains 668
669 severely underexploited. Future studies should work on ways to reduce SES segregation 669
670 in collaboration with institutions, where having access to complete enrollment networks 670
671 in addition to the typical friendship elicitation methods could help identifying the exact 671
672 overlap between the two distinct approaches. 672

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792 **A Additional Figures and Tables**

792

793 **Additional Figures**

793

Table A.1: Selection into the experiment

	University	Sample	<i>p</i>
Reading score	62.651	65.183	< 0.001
Math score	63.973	67.477	< 0.001
GPA	3.958	4.012	< 0.001
Low-SES	0.343	0.410	< 0.001
Middle-SES	0.505	0.499	0.763
High-SES	0.153	0.091	< 0.001
Female	0.567	0.530	< 0.001
Age	21.154	20.651	< 0.001
Observations	4,417	734	

Note: This table compares characteristics between the university and the experimental sample. *p*-values for binary outcomes (Low-SES, Med-SES, High-SES, Female) are from two-sample tests of proportions; for continuous variables, from two-sample *t*-tests with unequal variances. All reported *p*-values are two-tailed.

Table A.2: Distribution of referrals by area

Area	Only one area	Both areas	Total
Verbal	65	608	673
Math	61	608	669
Total	126	1,216	1,342

Note: The table shows how many referrers made referrals in only one area versus both areas. “Only one area” indicates individuals who made referrals exclusively for one area of the exam. “Both areas” shows individuals who made referrals in both verbal and math areas. The majority of referrers (608) made referrals in both areas.

Table A.3: Referral characteristics by exam area (unique referrals only)

	Reading	Math	<i>p</i>
Reading score	67.733	67.126	0.252
Math score	69.339	71.151	0.008
GPA	4.136	4.136	0.987
Courses taken	13.916	13.019	0.123
Low-SES	0.372	0.385	0.666
Med-SES	0.526	0.518	0.801
High-SES	0.103	0.097	0.781
Observations	487	483	

Note: This table compares characteristics of uniquely referred students by entry exam area for the referral (verbal vs. math). p -values are from two-sample t-tests with unequal variances. Referrals in Math area go to peers with significantly higher math scores ($p = 0.008$), while we find no significant differences for Reading scores, GPA, courses taken, or SES composition for referrals across the two areas. Excluding referrals going to the same individuals does not change the outcomes for referrals compared to Appendix Table [A.4](#)

Table A.4: Referral characteristics by academic area

	Reading	Math	<i>p</i>
Reading score	67.85	67.41	0.348
Math score	70.04	71.36	0.029
GPA	4.153	4.153	0.984
Courses taken	14.467	13.822	0.206
Low-SES	37%	38%	0.714
Middle-SES	51%	51%	0.829
High-SES	11%	11%	0.824
Observations	673	669	

Note: This table compares characteristics of referred students by entry exam area for the referral (verbal vs. math). *p*-values are from two-sample t-tests with unequal variances. Referrals in Math area go to peers with significantly higher math scores ($p = 0.029$), while we find no significant differences for Reading scores, GPA, courses taken, or SES composition for referrals across the two areas.

Table A.5: Average entry exam z-scores by SES network connections

Referrer SES	Network average for SES group		
	Low	Middle	High
Low	0.086	-0.018	0.144
Middle	0.186	0.023	0.215
High	0.204	0.064	0.285
All	-0.361	-0.078	0.169

Note: This table shows average (Math and Reading) standardized entry exam scores for individuals of different SES levels (rows) when connected to peers of specific SES levels (columns). The “All” row shows the overall average scores across all participant SES levels when connected to each network SES type. Higher values indicate better academic performance in SD’s.

795 B Experiment 795

796 *We include the English version of the instructions used in Qualtrics. Participansts saw* 796
797 *the Spanish version. Horizontal lines in the text indicate page breaks and clarifying* 797
798 *comments are inside brackets.* 798

799 Consent 799

800 You have been invited to participate in this decision-making study. This study is directed 800
801 by [omitted for anonymous review] and organized with the support of the Social Bee Lab 801
802 (Social Behavior and Experimental Economics Laboratory) at UNAB. 802

803 In this study, we will pay **one (1)** out of every **ten (10)** participants, who will be 803
804 randomly selected. Each selected person will receive a fixed payment of **70,000** (seventy 804
805 thousand pesos) for completing the study. Additionally, they can earn up to **270,000** 805
806 (two hundred and seventy thousand pesos), depending on their decisions. So, in total, 806
807 if you are selected to receive payment, you can earn up to **340,000** (three hundred and 807
808 forty thousand pesos) for completing this study. 808

809 If you are selected, you can claim your payment at any Banco de Bogotá office by 809
810 presenting your ID. Your participation in this study is voluntary and you can leave the 810
811 study at any time. If you withdraw before completing the study, you will not receive 811
812 any payment. 812

813 The estimated duration of this study is 20 minutes. 813

814 The purpose of this study is to understand how people make decisions. For this, we will 814
815 use administrative information from the university such as the SABER 11 test scores of 815
816 various students (including you). Your responses will not be shared with anyone and your 816
817 participation will not affect your academic records. To maintain strict confidentiality, the 817
818 research results will not be associated at any time with information that could personally 818

819 identify you. 819

820 There are no risks associated with your participation in this study beyond everyday risks. 820

821 However, if you wish to report any problems, you can contact Professor [omitted for 821

822 anonymous review]. For questions related to your rights as a research study participant, 822

823 you can contact the IRB office of [omitted for anonymous review]. 823

824 By selecting the option “I want to participate in the study” below, you give your con- 824

825 sent to participate in this study and allow us to compare your responses with some 825

826 administrative records from the university. 826

827 • I want to participate in the study [advances to next page] 827

828 • I do not want to participate in the study 828

829

 829

830 **Student Information** 830

831 Please write your student code. In case you are enrolled in more than one program 831

832 simultaneously, write the code of the first program you entered: 832

833 [Student ID code] 833

834 What semester are you currently in? 834

835 [Slider ranging from 1 to 11] 835

836

 836

837 [Random assignment to treatment or control] 837

838	Instructions	838
839	The instructions for this study are presented in the following video. Please watch it	839
840	carefully. We will explain your participation and how earnings are determined if you are	840
841	selected to receive payment.	841
842	[Treatment-specific instructions in video format]	842
843	If you want to read the text of the instructions narrated in the video, press the “Read	843
844	instruction text” button. Also know that in each question, there will be a button with	844
845	information that will remind you if that question has earnings and how it is calculated,	845
846	in case you have any doubts.	846
847	<ul style="list-style-type: none"> • I want to read the instructions text [text version below] 	847
848	<hr/>	848
849	In this study, you will respond to three types of questions. First, are the belief questions.	849
850	For belief questions, we will use as reference the results of the SABER 11 test that you	850
851	and other students took to enter the university, focused on three areas of the exam:	851
852	mathematics, reading, and English.	852
853	For each area, we will take the scores of all university students and order them from	853
854	lowest to highest. We will then group them into 100 percentiles. The percentile is a	854
855	position measure that indicates the percentage of students with an exam score that is	855
856	above or below a value.	856
857	For example, if your score in mathematics is in the 20th percentile, it means that 20	857
858	percent of university students have a score lower than yours and the remaining 80 percent	858
859	have a higher score. A sample belief question is: “compared to university students, in	859
860	what percentile is your score for mathematics?”	860
861	If your answer is correct, you can earn 20 thousand pesos. We say your answer is correct	861

862 if the difference between the percentile you suggest and the actual percentile of your 862
863 score is not greater than 7 units. For example, if you have a score that is in the 33rd 863
864 percentile and you say it is in the 38th, the answer is correct because the difference is 864
865 less than 7. But if you answer that it is in the 41st, the difference is greater than 7 and 865
866 the answer is incorrect. 866

867 The second type of questions are recommendation questions and are also based on the 867
868 mathematics, reading, and English areas of the SABER 11 test. We will ask you to think 868
869 about the students with whom you have taken or are taking classes, to recommend from 869
870 among them the person you consider best at solving problems similar to those on the 870
871 SABER 11 test. 871

872 When you start typing the name of your recommended person, the computer will show 872
873 suggestions with the full name, program, and university entry year of different students. 873
874 Choose the person you want to recommend. If the name doesn't appear, check that you 874
875 are writing it correctly. Do not use accents and use 'n' instead of 'ñ'. If it still doesn't 875
876 appear, it may be because that person is not enrolled this semester or because they did 876
877 not take the SABER 11 test. In that case, recommend someone else. 877

878 You can earn up to 250,000 pesos for your recommendation. We will multiply your 878
879 recommended person's score by 100 pesos if they are in the first 50 percentiles. We will 879
880 multiply it by 500 pesos if your recommended person's score is between the 51st and 880
881 65th percentile. If it is between the 66th and 80th percentile, we will multiply your 881
882 recommended person's score by 1000 pesos. If the score is between the 81st and 90th 882
883 percentile, you earn 1500 pesos multiplied by your recommended person's score. And if 883
884 the score is between the 91st and 100th percentile, we will multiply your recommended 884
885 person's score by 2500 pesos to determine the earnings. 885

886 The third type of questions are information questions and focus on aspects of your 886
887 personal life or your relationship with the people you have recommended. 887

888 Earnings 888

889 Now we will explain who gets paid for participating and how the earnings for this study 889
890 are assigned. The computer will randomly select one out of every 10 participants to pay 890
891 for their responses. For selected individuals, the computer will randomly choose one of 891
892 the three areas, and from that chosen area, it will pay for one of the belief questions. 892

893 Similarly, the computer will randomly select one of the three areas to pay for one of the 893
894 recommendation questions. 894

895 **Additionally, if you are selected to receive payment, your recommended per-** 895
896 **son in the chosen area will receive a fixed payment of 100 thousand pesos.** 896
897 [Only seen if assigned to the treatment] 897

898 Each person selected to receive payment for this study can earn: up to 20 thousand pesos 898
899 for one of the belief questions, up to 250 thousand pesos for one of the recommendation 899
900 questions, and a fixed payment of 70 thousand pesos for completing the study. 900

901 Selected individuals can earn up to 340 thousand pesos. 901

902

 902

903 [Participants go through all three Subject Areas in randomized order] 903

904 Subject Areas 904

905 Critical Reading 905

906 For this section, we will use as reference the Critical Reading test from SABER 11, which 906
907 evaluates the necessary competencies to understand, interpret, and evaluate texts that 907
908 can be found in everyday life and in non-specialized academic fields. 908

909 [Clicking shows the example question from SABER 11 below] 909

910 Although the democratic political tradition dates back to ancient Greece, political 910
911 thinkers did not address the democratic cause until the 19th century. Until then, democ- 911
912 racy had been rejected as the government of the ignorant and unenlightened masses. 912
913 Today it seems that we have all become democrats without having solid arguments in 913
914 favor. Liberals, conservatives, socialists, communists, anarchists, and even fascists have 914
915 rushed to proclaim the virtues of democracy and to show their democratic credentials 915
916 (Andrew Heywood). According to the text, which political positions identify themselves 916
917 as democratic? 917

- 918 • Only political positions that are not extremist 918
- 919 • The most recent political positions historically 919
- 920 • The majority of existing political positions 920
- 921 • The totality of possible political currents 921

922

 922

923 **Mathematics** 923

924 This section references the Mathematics test from SABER 11, which evaluates people's 924
925 competencies to face situations that can be resolved using certain mathematical tools. 925

926 [Clicking shows the example question from SABER 11 below] 926

927 A person living in Colombia has investments in dollars in the United States and knows 927
928 that the exchange rate of the dollar against the Colombian peso will remain constant 928
929 this month, with 1 dollar equivalent to 2,000 Colombian pesos. Their investment, in 929
930 dollars, will yield profits of 3% in the same period. A friend assures them that their 930
931 profits in pesos will also be 3%. Their friend's statement is: 931

- 932 • Correct. The proportion in which the investment increases in dollars is the same 932
933 as in pesos. 933

934	• Incorrect. The exact value of the investment should be known.	934
935	• Correct. 3% is a fixed proportion in either currency.	935
936	• Incorrect. 3% is a larger increase in Colombian pesos.	936
937	<hr/>	
938	English	938
939	This section uses the English test from SABER 11 as a reference, which evaluates that	939
940	the person demonstrates their communicative abilities in reading and language use in	940
941	this language.	941
942	[Clicking shows the example question from SABER 11 below]	942
943	Complete the conversations by marking the correct option.	943
944	• Conversation 1: I can't eat a cold sandwich. It is horrible!	944
945	– I hope so.	945
946	– I agree.	946
947	– I am not.	947
948	• Conversation 2: It rained a lot last night!	948
949	– Did you accept?	949
950	– Did you understand?	950
951	– Did you sleep?	951
952	<hr/>	
953	[Following parts are identical for all Subject Areas and are not repeated here for brevity]	953

954	Your Score	954
955	Compared to university students, in which percentile do you think your [Subject Area]	955
956	test score falls (1 is the lowest percentile and 100 the highest)?	956
957	[Clicking shows the explanations below]	957
958	How is a percentile calculated?	958
959	A percentile is a position measurement. To calculate it, we take the test scores for all	959
960	students currently enrolled in the university and order them from lowest to highest. The	960
961	percentile value you choose refers to the percentage of students whose score is below	961
962	yours. For example, if you choose the 20th percentile, you're indicating that 20% of	962
963	students have a score lower than yours and the remaining 80% have a score higher than	963
964	yours.	964
965	What can I earn for this question?	965
966	For your answer, you can earn 20,000 (twenty thousand) PESOS , but only if the	966
967	difference between your response and the correct percentile is less than 7. For example, if	967
968	the percentile where your score falls is 33 and you respond with 38 (or 28), the difference	968
969	is 5 and the answer is considered correct. But if you respond with 41 or more (or 25 or	969
970	less), for example, the difference would be greater than 7 and the answer is incorrect.	970
971	Please move the sphere to indicate which percentile you think your score falls in:	971
972	[Slider with values from 0 to 100]	972
973	<hr/>	973

974 **Recommendation** 974

975 Among the people with whom you have taken any class at the university, who is your 975
976 recommendation for the [Subject Area] test? Please write that person's name in the 976
977 box below: 977

978 **Important:** You will not be considered for payment unless the recommended 978
979 person is someone with whom you have taken at least one class during your 979
980 studies. 980

981 Your response is only a recommendation for the purposes of this study and we will **not** 981
982 contact your recommended person at any time. 982

983 [Clicking shows the explanations below] 983

984 Who can I recommend? 984

985 Your recommendation **must** be someone with whom you have taken (or are taking) a 985
986 class. If not, your answer will not be considered for payment. The person you recommend 986
987 will not be contacted or receive any benefit from your recommendation. 987

988 As you write, you will see up to 7 suggested student names containing the letters you 988
989 have entered. The more you write, the more accurate the suggestions will be. Please 989
990 write **without** accents and use the letter 'n' instead of 'ñ'. If the name of the person 990
991 you're writing doesn't appear, it could be because you made an error while writing the 991
992 name. 992

993 If the name is correct and still doesn't appear, it could be because the student is not en- 993
994 rolled this semester or didn't take the SABER 11 test. In that case, you must recommend 994
995 someone else. 995

996 My earnings for this question? 996

For your recommendation, you could receive earnings of up to 250,000 (two hundred and fifty thousand) PESOS. The earnings are calculated based on your recommendation's score and the percentile of that score compared to other UNAB students, as follows:

- We will multiply your recommendation's score by \$100 (one hundred) pesos if it's between the 1st and 50th percentiles
- We will multiply your recommendation's score by \$500 (five hundred) pesos if it's between the 51st and 65th percentiles
- We will multiply your recommendation's score by \$1000 (one thousand) pesos if it's between the 66th and 80th percentiles
- We will multiply your recommendation's score by \$1500 (one thousand five hundred) pesos if it's between the 81st and 90th percentiles
- We will multiply your recommendation's score by \$2500 (two thousand five hundred) pesos if it's between the 91st and 100th percentiles

This is illustrated in the image below:

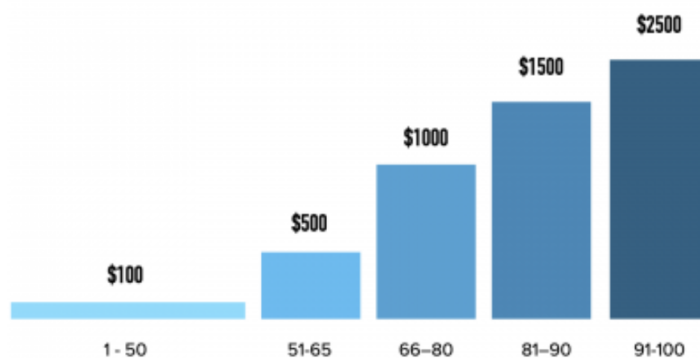


Figure B.1: Earnings for recommendation questions

For example, if your recommendation got 54 points and the score is in the 48th percentile,

1012 you could earn $54 \times 100 = 5400$ PESOS. But, if the same score of 54 points were in the 1012
1013 98th percentile, you could earn $54 \times 2500 = 135,000$ PESOS. 1013

1014 [Text field with student name suggestions popping up as participant types] 1014

1015

 1015

1016 **Relationship with your recommendation** 1016

1017 How close is your relationship with your recommendedation: “[Name of the student 1017
1018 selected from earlier]”? (0 indicates you are barely acquaintances and 10 means you are 1018
1019 very close) 1019

1020 [Slider with values from 0 to 10] 1020

1021

 1021

1022 **Your recommendation’s score** 1022

1023 Compared to university students, in which percentile do you think [Name of the student 1023
1024 selected from earlier]’s score falls in the [Subject Area] test (1 is the lowest percentile 1024
1025 and 100 the highest)? 1025

1026 [Clicking shows the explanations below] 1026

1027 How is a percentile calculated? 1027

1028 A percentile is a position measurement. To calculate it, we take the test scores for all 1028
1029 students currently enrolled in the university and order them from lowest to highest. The 1029
1030 percentile value you choose refers to the percentage of students whose score is below 1030
1031 yours. For example, if you choose the 20th percentile, you’re indicating that 20% of 1031
1032 students have a score lower than yours and the remaining 80% have a score higher than 1032
1033 yours. 1033

1034 What can I earn for this question? 1034

1035 For your answer, you can earn **20,000 (twenty thousand) PESOS**, but only if the 1035
1036 difference between your response and the correct percentile is less than 7. For example, 1036
1037 if the percentile where your recommended person's score falls is 33 and you respond with 1037
1038 38 (or 28), the difference is 5 and the answer is considered correct. But if you respond 1038
1039 with 41 or more (or 25 or less), for example, the difference would be greater than 7 and 1039
1040 the answer is incorrect. 1040

1041 Please move the sphere to indicate which percentile you think your recommended per- 1041
1042 son's score falls in: 1042

1043 [Slider with values from 0 to 100] 1043

1044 _____ 1044

1045 Demographic Information 1045

1046 What is the highest level of education achieved by your father? 1046

1047 [Primary, High School, University, Graduate Studies, Not Applicable] 1047

1048 What is the highest level of education achieved by your mother? 1048

1049 [Primary, High School, University, Graduate Studies, Not Applicable] 1049

1050 Please indicate the socio-economic group to which your family belongs: 1050

1051 [Group A (Strata 1 or 2), Group B (Strata 3 or 4), Group C (Strata 5 or 6)] 1051

1052 _____ 1052

1053	UNAB Students Distribution	1053
1054	Thinking about UNAB students, in your opinion, what percentage belongs to each socio-	1054
1055	economic group? The total must sum to 100%:	1055
1056	[Group A (Strata 1 or 2) percentage input area]	1056
1057	[Group B (Strata 3 or 4) percentage input area]	1057
1058	[Group C (Strata 5 or 6) percentage input area]	1058
1059	[Shows sum of above percentages]	1059
1060	<hr/>	1060
1061	End of the Experiment	1061
1062	Thank you for participating in this study.	1062
1063	If you are chosen to receive payment for your participation, you will receive a confirma-	1063
1064	tion to your UNAB email and a link to fill out a form with your information. The process	1064
1065	of processing payments is done through Nequi and takes approximately 15 business days,	1065
1066	counted from the day of your participation.	1066
1067	[Clicking shows the explanations below]	1067
1068	Who gets paid and how is it decided?	1068
1069	The computer will randomly select one out of every ten participants in this study to be	1069
1070	paid for their decisions.	1070
1071	For selected individuals, the computer will randomly select one area: mathematics,	1071
1072	reading, or English, and from that area will select one of the belief questions. If the	1072
1073	answer to that question is correct, the participant will receive 20,000 pesos.	1073

1074 The computer will randomly select an area (mathematics, critical reading, or English) to 1074
1075 pay for one of the recommendation questions. The area chosen for the recommendation 1075
1076 question is independent of the area chosen for the belief question. The computer will 1076
1077 take one of the two recommendations you have made for the chosen area. Depending on 1077
1078 your recommendation's score, you could win up to 250,000 pesos. 1078

1079 Additionally, people selected to receive payment for their participation will have a fixed 1079
1080 earnings of 70,000 pesos for completing the study. 1080

1081 _____ 1081

1082 **Participation** 1082

1083 In the future, we will conduct studies similar to this one where people can earn money 1083
1084 for their participation. The participation in these studies is by invitation only. Please 1084
1085 indicate if you are interested in being invited to other studies similar to this one: 1085

1086 [Yes, No] 1086