

1 Class differences in social networks: Evidence from a referral 1
2 experiment 2

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5 **Abstract** 5

6 Lorem Ipsum ([Beaman, Keleher, & Magruder, 2018](#)) 6

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9 class 9

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1 Introduction

Equally qualified individuals face different labor market outcomes depending on their socioeconomic status (Stansbury & Rodriguez, 2024). A key driver of this inequality is due to differences in social capital.¹ Because it correlates strongly with labor market income, the most important facet of social capital is the share of high-SES connections among low-SES individuals (Chetty et al., 2022b). A lack of social capital means lack of access to individuals with influential (higher paid) jobs and job opportunities. In economic terms, it implies having worse outcomes when using one’s network to find jobs conditional on the capacity on leveraging 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 which makes evident the role of differences in social capital. As 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, Smith-Lovin, & Cook, 2001), making across SES (low-to-high) connections less likely than same-SES connections (Chetty et al., 2022b). Referrals will thus reflect similarities in socio-demographic characteristics present in networks even in the absence of biases in the referral procedure, i.e., referring at random from one’s network according to some productivity criteria.

Yet, experimental evidence shows referrals can be biased even under substantial pay-for-performance incentives beyond what is attributable to differences in network compositions, at least for the case of gender (Beaman et al., 2018; Hederros, Sandberg, Kvissberg, & Polano, 2025). A similar bias against low-SES may further exacerbate outcomes of low-SES individuals: If job information are in the hands of a select few high-SES which

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

²See for example Lin, Ensel, and Vaughn (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.

low-SES have already limited network access to (social capital hypothesis), and high-SES referrers are biased against low-SES, referring other high-SES at higher rates than their network composition, we should expect referral hiring to further disadvantage low-SES.

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

In this study, we study inequalities related to SES combining a university-wide cross-sectional network data set comprising over 4,500 students in which 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 in a Colombian university. Participants were instructed to refer a qualified student for tasks similar to the math and reading parts of the national university entry exam (equivalent of SAT in US system). To incentivize participants to refer qualified candidates, we set earnings dependent 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). As 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 the need for the referred candidate to take any action and without revealing the identity of the referrer. This eliminates reputational concerns as there is no hiring firm, and puts a lower bound on the expected reciprocity for the referrer in combination with pay-for-performance incentives (Bandiera, Barankay, & Rasul, 2009; Witte, 2021). At the same time, referring based on university entry exam scores are still an objective, widely accepted measure of ability, and we show evidence that referrers in our setting not only possess accurate information about these signals but are also able

to screen more productive individuals from their university network.

In a university setting, class attendance provides essential opportunities for face-to-face interaction between students. On the one hand, this reduces network segregation by providing ample opportunities to meet across-SES, because of the exposure to an equal or higher level of high-SES compared to the population (Chetty et al., 2022a).³ On the other hand, as students take more and more classes together, their similarities across all observable characteristics tend to increase (Kossinets & Watts, 2009), which should drive the high- and low-SES networks to segregate. Our setting is ideal to study these opposing forces: First, The very high level of income inequality and existence of deeply rooted historical groups in Colombia makes SES differences extremely visible in access to tertiary education, where the rich and poor typically select into different institutions (Jaramillo-Echeverri & Álvarez, 2023). Yet, thanks to the particular standing of the institution we have chosen for this study (Figure 1), all SES groups including both low- and high-SES mix together in this university. Second, using administrative data, we are able to reconstruct 734 participants’ complete university network based on the number of common courses they have taken together with other students. This allows directly identifying the individual characteristics of those getting referrals among all possible candidates, as well as descriptive characterizations of similarity (e.g., in same-SES share) in student networks as a function of the number of classes taken.

We find strong evidence that networks of high- and low-SES participants exhibit same-SES bias. Both groups are connected at higher rates with their own SES group than what would be at random given actual group shares at the university (Figure 7). As students take more courses together within the same program, their networks dwindle in size (Figures 8a and 8b), and become more homogenous in SES-shares (Figure 9). We identify selection into academic programs as a key mechanism. The private university where our study took place implements exogenous cost-based program pricing and does

³In a different sample from the same university population, Díaz, Munoz, Reuben, and Tuncer (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 and Flórez (2021a).

not offer SES-based price reductions. These result in programs with very large cost differences within the same university (Figure 10). We find that average yearly fee paid per student increases with SES, and the high-SES share in the most expensive program at the university, medicine, drives the network segregation across SES (Figure 11).

Do segregated networks account for all the differences in SES referral rates across SES groups? Although same-SES referrals are 17% more common than is suggested by referrer networks, controlling for these, we find no general SES-bias against beyond what is attributable to network composition. Regardless of SES, participants refer productive individuals, and referred candidates are characterized by a very high number of courses taken together. The latter underlies the impact of program selection, where smaller and more homogenous parts of the networks are activated for referrals made in our setting. Our treatment randomized participants across two different incentive schemes by adding a substantial monetary bonus (\$25) for the referred candidate on top of the pay-for-performance incentives. We provide evidence that treatment incentives did not change the referral behavior across the same-SES referral rate, the number of courses taken together with the referral candidate, and the candidate’s exam scores.

This paper contributes to the literature on referral experiments by solving the challenge of observing the entire referral network. Earlier research could only compare referrals made across different incentive structures or experimental instructions and make according conclusions. For example, when participants are paid on the basis of their referred candidate’s productivity instead of receiving a fixed finder’s fee (Beaman & Magruder, 2012), or when participants are restricted to refer either a male or female candidate instead of freely (Beaman et al., 2018). Pallais and Sands (2016) recruited a random sample of nonreferred workers to compare with referred ones, but none of the previous studies could provide a direct comparison of the referral choice set with those who were selected by participants. Closest to our work is the work of Hederos et al. (2025), who elicited friendship networks by asking referrers to name 5 friends. Their findings suggest only half of those who were referred were from the elicited friendship network, and thus is not a complete observation of the referral choice set. Although

commonplace, censored elicitation methods also result in underestimating network effects (Griffith, 2022) and may suffer from biases in recall. We are able to take our analysis one step further by asking for referrals from the enrollment network, where we have complete information on every single connection that may or may not get a referral. This allows us to neatly separate the effect of the network composition from any potential biases stemming from the referral procedure itself.

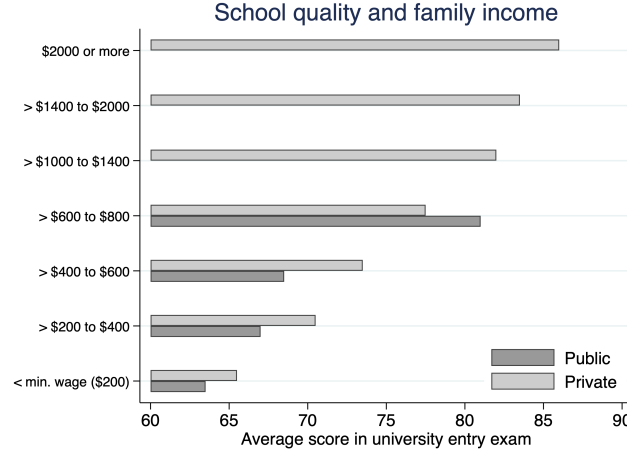
Second, we build upon to the earlier work on SES-biases in referrals. To our knowledge, the first to study SES-biases in referrals are Díaz et al. (2025), and our study is conceptually the closest to theirs. Drawing from a similar sample from the same institution, Díaz et al. (2025) focus on referrals from first year students made within mixed-program classrooms, and find no evidence for an aggregate bias against low-SES. We also find no aggregate bias against low-SES in referrals. Our setup differs as we sample from students who completed their first year and impose no limits on referring from a classroom. This has several implications: We find that referrals in our setup go to individuals within the same program, and that programs have different SES-shares which become more even more accentuated as students take more courses together. While networks drive inequality in referral outcomes because of the institutional environment in our sample, we have no reason to believe first year student networks in Díaz et al. (2025) have similar levels of segregation to begin with. Following the recent evidence, implementing more mixed-program courses which allow for across-SES mixing can be a clear policy goal (Alan, Duysak, Kubilay, & Mumcu, 2023; Rohrer, Keller, & Elwert, 2021).

Finally, we contribute to the growing literature on SES differences in the labor market, expliciting the role of networks as a driver of inequality. Stansbury and Rodriguez (2024) find that low-SES researchers coauthor more often with other low-SES, and have networks that have lower values which can explain why

The remainder of the paper is organized as follows. Section 2 begins with the background and setting in Colombia. In Section 3 we present the design of the experiment. In Section 4 we describe the data and procedures. Section 5 discusses the results of the

147 experiment. Section 6 concludes. The Appendix presents additional tables and figures 147
 148 as well as the experiment instructions. 148

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



Note: This figure shows the average score national university entry exam by 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 \(2021b\)](#).

149 2 Background and Setting 149

150 Our study takes place at UNAB, a medium-sized private university in Bucaramanga, 150
 151 Colombia with approximately 6,000 enrolled students. The university’s student body 151
 152 is remarkably diverse with about 35% of the students classified as low-SES, and 15% 152
 153 high-SES. Diversity at this institution provides a unique research setting as Colombian 153
 154 society is highly unequal and generally characterized by limited interaction between 154
 155 social classes, with different socioeconomic groups separated by education and geographic 155
 156 residence.⁴ Despite significant financial barriers, many lower and middle-SES families 156

⁴Colombia has consistently ranked as one of the most unequal countries in Latin America ([World Bank, 2024](#)), with the richest decile earning 50 times more than the poorest decile ([United Nations, 2023](#)). This economic disparity is reflected by a highly stratified society with significant class inequalities and

157 prioritize university education for their children ([Hudson & Library of Congress, 2010](#), 157
158 p. 103), and UNAB represents one of the few environments in Colombia where sustained 158
159 inter-SES contact occurs naturally (see Figure 1). 159

160 In 1994, Colombia introduced a nationwide classification system dividing the popu- 160
161 lation into 6 strata based on housing characteristics and neighborhood amenities.⁵ We 161
162 use this classification as the measure of SES in our experiment: Students in strata 1 to 162
163 2 are categorized as low-SES, strata 3 to 4 as middle-SES and those in strata 5 to 6 as 163
164 high-SES. 164

165 We invited via email all 4,417 UNAB undergraduate students who had at the time of 165
166 recruitment completed their first year at the university to participate in our experiment. 166
167 837 students who joined (19%) vary in terms of their academic programs, SES, and 167
168 progress in their studies. This setup provides a unique opportunity for collaborative 168
169 inter-class contact on equal status, whose positive effects on reducing discrimination are 169
170 casually documented ([Lowe, 2021](#); [Mousa, 2020](#); [Rao, 2019](#)). 170

171 Undergraduate programs at UNAB are spread across two semesters, with each indi- 171
172 vidual course lasting one semester. Students take between 5 to 7 courses per semester, 172
173 with programs lasting anywhere between 4 to 12 semesters (2 to 6 years). Medicine, 173
174 the largest program by size at UNAB, lasts for 12 semesters, followed by engineering 174
175 programs at 10 semesters. Most remaining programs lasting for about 8 to 10 semesters, 175
176 with specialized programs for immediate entry into the workforce lasting only 4. 176

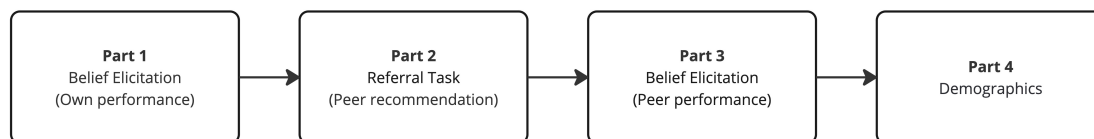
limited class mobility ([Angulo, Gaviria, Pérez, & Azevedo, 2012](#); [García, Rodríguez, Sánchez, & Bedoya, 2015](#)).

⁵Initially designed for utility subsidies from higher strata (5 and 6) to support lower strata (1 to 3), it now extends to university fees and social program eligibility. Stratum 4 neither receives subsidies nor pays extra taxes. This stratification system largely aligns with and potentially reinforces existing social class divisions ([Guevara S & Shields, 2019](#); [Uribe-Mallarino, 2008](#)).

3 Design

We designed an experiment to assess peer referral behavior from an SES perspective and to causally evaluate the effect of different incentive structures on referrals. The study design consists of a single online experiment organized at the university level (see Figure 2). The instructions are provided in Appendix B.

Figure 2: Experiment Timeline



Note: Participants first report beliefs about their own national university entry exam performance, then recommend peers for each academic area. In the final part, they report beliefs about their recommendations' performance and provide demographic information. This order is implemented for all participants.

3.1 Productivity measures

To establish an objective basis for referral productivity, we use national university entry exam scores (SABER 11). These scores provide pre-existing, comparable measures of ability across two domains relevant for the labor market. By using existing administrative data, we eliminate the need for additional testing and ensure that all eligible students have comparable productivity measures. The scores we use in this experiment comprise of critical reading and mathematics parts.

Critical reading evaluates competencies necessary to understand, interpret, and evaluate texts found in everyday life and broad academic fields (e.g., history). This measures students' ability to comprehend and critically evaluate written material. Mathematics assesses students' competency in using undergraduate level mathematical tools (e.g., reasoning in proportions, financial literacy). This captures quantitative reasoning and problem-solving abilities.

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

3.2 Referral task

After eliciting beliefs about their own performance, participants engage in incentivized peer recommendations. For both test areas (critical reading and mathematics), participants recommend one peer they believe excels in that domain. We first present an example question from the relevant test area to clarify what skills are being assessed. Participants then type the name of their recommended peer, with the system providing autocomplete suggestions from enrolled students who have taken the test (see Figure 3).

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)

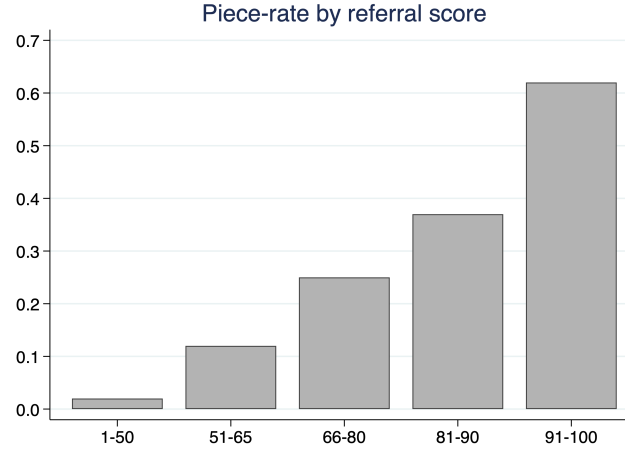
Note: This illustration shows how the system provides suggestions from enrolled students with their program and year of study from the administrative database.

Participants can only recommend students with whom they have taken at least one class during their university studies. This requirement ensures that referrals are based on actual peer interactions and overlap with the enrollment network that we construct. The order in which participants make recommendations across the two areas is randomized.

We incentivize referrals using a productivity-based payment scheme. Referrers earn increasing monetary rewards as the percentile ranking of their recommendation increases (see Figure 4). We multiply the piece rate coefficient associated to the percentile rank

with the actual test scores of the recommendation to calculate earnings. This payment structure provides strong incentives to screen for highly ranked peers, with potential earnings up to \$60 per recommendation.⁶

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.

3.3 Treatment variation

We implement a between-subjects treatment that varies whether the recommended peer also receives payment. In the **Baseline** treatment, only the referrer can earn money based on their recommendation's productivity. The **Bonus** treatment adds an additional fixed payment of \$25 to any peer who is recommended in the randomly selected area for payment. This payment is independent of the peer's actual productivity (see Figure 1).

Participants are informed about their treatment condition before making recommendations through both video and text instructions. The treatment is assigned at the individual level, allowing us to compare referral outcomes across conditions.

⁶Due to the selection into the university, the actual test 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.

Table 1: Incentive structure by treatment

	Baseline	Bonus
Referrer (sender)	Productivity-based	Productivity-based
Recommendation (receiver)	No payment	Fixed reward

3.4 Belief elicitation

We elicit incentivized beliefs at two points in the experiment. First, before making referrals, participants report their beliefs about their own percentile ranking in each test area. Second, after making each referral, participants report their beliefs about their recommendedation’s percentile ranking. For both belief elicitation tasks, participants earn \$5 if their guess is within 7 percentiles of the true value. This tolerance level is expected to balance precision with the difficulty of the task.

4 Sample, Incentives, and Procedure

We invited all 4,417 UNAB undergraduate students who had at the time of recruitment completed their first year at the university to participate in our experiment. A total of 837 students took part in the data collection with a 19% response rate. Our final sample consists of 734 individuals who referred peers with whom they have taken at least one class together, resulting in an 88% success rate for the sample. We randomly allocated half of the participants into either **Baseline** or **Bonus** treatments. Table 2 presents key demographic characteristics and academic performance indicators across treatments (see Appendix Table A.1 for selection). The sample is well-balanced between the **Baseline** and **Bonus** conditions and we observe no statistically significant differences in any of the reported variables (all p values > 0.1). Our sample is characterized by a majority of middle-SES students with about one-tenth of the sample being high-SES students. The test scores and GPA distributions are balanced. On average, participants took 3.8 courses together with their network, and the average network consisted of 175 peers.

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
Med-SES	0.492	0.506	0.714
High-SES	0.089	0.094	0.824
N	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.

245 The experiment was conducted online through Qualtrics, with participants recruited 245
246 from active UNAB students. To manage budget constraints while maintaining sufficient 246
247 incentives, we randomly selected one in ten participants for payment. Selected partici- 247
248 pants received a fixed payment of \$17 for completion, plus potential earnings from one 248
249 randomly selected belief question (up to \$5) and one randomly selected recommendation 249
250 question (up to \$60), for maximum total earnings of \$82. The average time to complete 250
251 the survey was 30 minutes, with an average compensation of \$80 for one in ten par- 251
252 ticipants randomly selected for payment. Payment processing occurred through online 252
253 banking platform Nequi within 15 business days of participation. 253

5 Results

5.1 Network characteristics

We begin by describing the characteristic features of the “enrollment network” for all participants. This data set pairwise associates every participant in our sample with another university student if they have taken at least one course together at the time of the data collection. By doing so, we construct the entire referral choice set for participants. We include in this data set both the participant’s and their potential candidate’s individual characteristics, as well as the number of common courses they have taken together. In Figure 5, we describe the evolution of the enrollment network across the average number of network connections in network and the number of common courses taken with network members as participants progress through semesters.

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

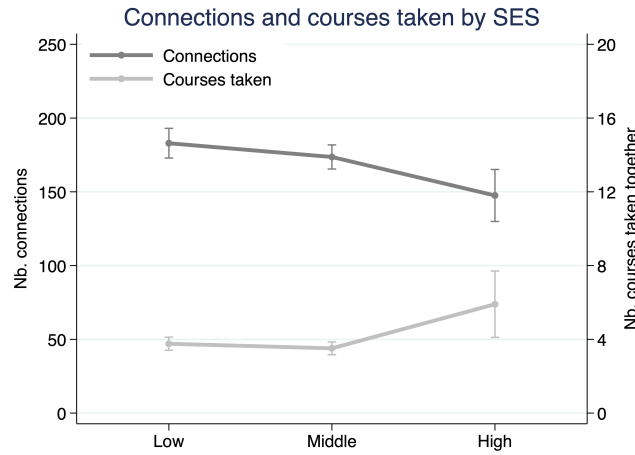


Note: This figure displays the average number of connections in blue and the average number of classes they have taken together with their connections in grey across semesters spent. The data shows an increase in the number of classes taken together as students progress in their programs, with the connections peaking around 7 semesters and dropping as certain students finish their bachelor’s.

Are enrollment networks different across SES groups? We look at how the number of

connections (network size) and number of courses taken together (tie strength) change across SES groups in Figure 6. 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 ($t = 3.03, p = .003$ and $t = 2.49, p = .013$, respectively), but high-SES 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 6: Network size and courses taken together by time spent at UNAB



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.

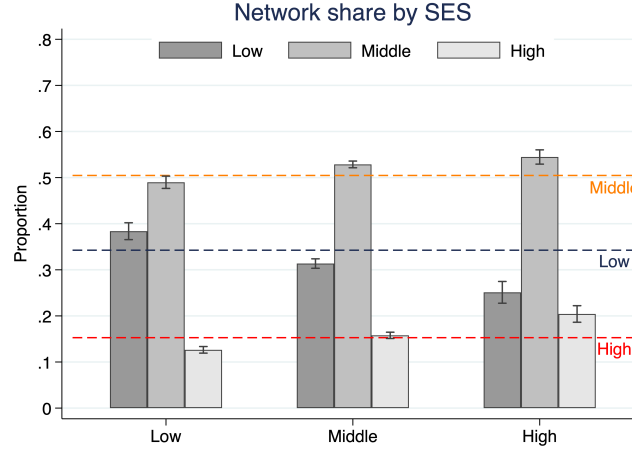
5.2 SES diversity in networks

What are diversity related consequences of SES-driven differences across networks? In terms of network compositions, SES groups may connect at different rates with other SES groups than at random (Figure 7).⁷ Our results reveal modest deviations from university-wide SES composition across groups. Low-SES students have networks with

⁷Because we estimate the share of SES groups in every individual network, we get very precise estimates of the actual means in networks. However, it is important to note that these are not independent

278 38.4% low-SES peers compared to the university average of 34.3%, middle-SES students 278
 279 connect with 52.9% middle-SES peers versus the university average of 50.5%, and high- 279
 280 SES students show 20.4% high-SES connections compared to the university average of 280
 281 15.3%. 281

Figure 7: 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. 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.

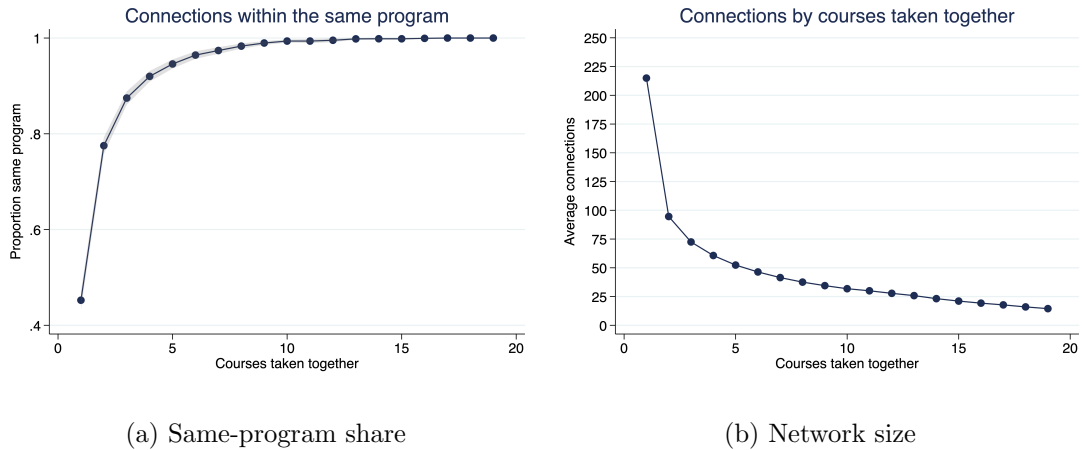
282 At the same time, we observe much larger differences between SES groups in how 282
 283 they connect on average with others. Low-SES students connect with other low-SES stu- 283
 284 dents at higher rates than middle-SES students (38.4% vs 31.4%) and high-SES students 284
 285 (38.4% vs 25.1%). Conversely, high-SES students connect more with other high-SES stu- 285
 286 dents than both low-SES students (20.4% vs 12.6%) and middle-SES students (20.4% vs 286
 287 15.8%). Middle-SES students are in between the two extreme patterns, connecting with 287
 288 middle-SES peers at higher rates than low-SES students (52.9% vs 49.0%) but lower rates 288

observations across the network - the reason these estimates are so precise is because most people are seemingly connected with similar others, creating systematic patterns that reduce variance. For this reason we choose not reporting test results in this section and focus on describing the relationships between SES groups.

than high-SES students (52.9% vs 54.5%). These findings indicate SES-based network segregation, with same-SES homophily patterns across groups.

So far we have looked at the entire network without considering the intensity of connections between students. In our network data set, this variable amounts to the number of classes taken together with peers. As we will see in the next section, referrals go to peers with whom participants have taken on average 14 courses with, implying the intensity of the connection matters. We begin by dissecting what the intensity means in our context. As students take more courses together, the proportion of peers from the same academic program quickly goes beyond 95% (see Figure 8a). Similarly, the average network size drops very quickly from above 210 to below 50 (see Figure 8b). Both results indicate that actual referral considerations originate from a much smaller pool of individuals from the same academic program.

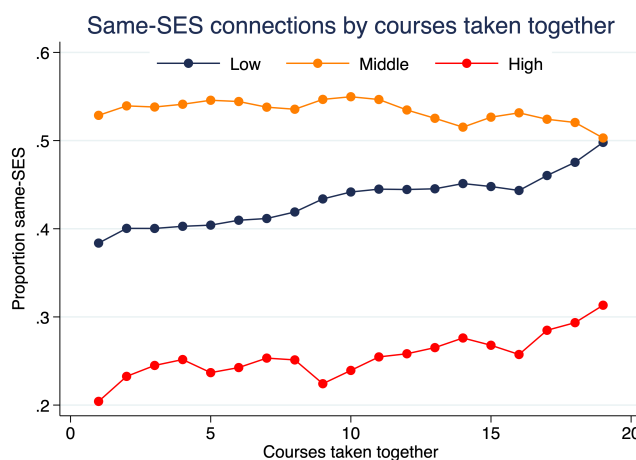
Figure 8: Network characteristics and courses taken together



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.

What are the diversity implications of increasing the intensity of connections 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 9). 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 9: 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.

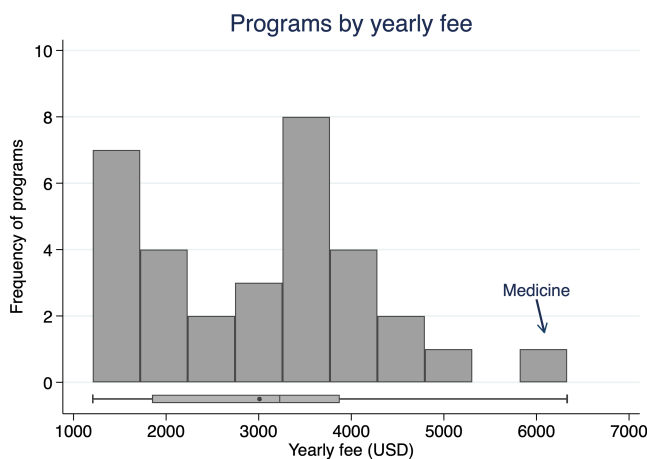
5.3 Program selection and SES diversity

Academic programs at this university are priced based on how much they cost, and typically less than 5% of students receive any kind of scholarship (Díaz et al., 2025). Based on these, we first calculate how much every program at the university is expected to cost students per year (see Figure 10). Considering that net minimum monthly wage stands at \$200 and the average Colombian salary around \$350, the cost difference between programs are large enough to make an impact of program selection. Is it the case

315 that SES groups select into programs with financial considerations?

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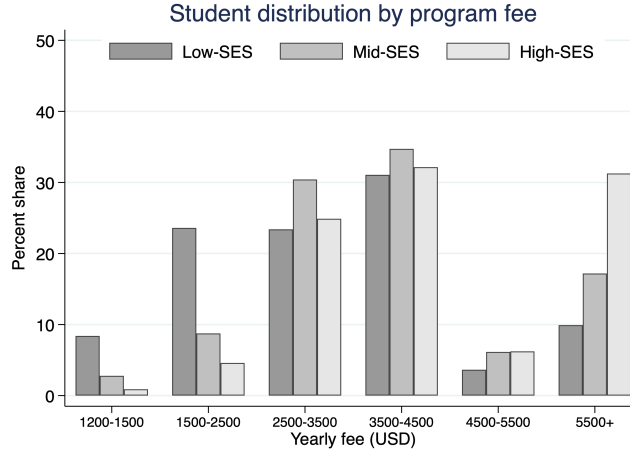
Figure 10: Programs sorted by fee



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.

316 We look at how SES groups are distributed across programs to see evidence of SES- 316
 317 based selection (see Figure 11). Indeed, low-SES students select into more affordable 317
 318 programs, followed by middle-SES students. High-SES students sort almost exclusively 318
 319 into above-average costing programs, with a third selecting into medicine and creating a 319
 320 very skewed distribution. The distributions are significantly different across all pairwise 320
 321 comparisons: low-SES vs. middle-SES (Kolmogorov-Smirnov test $D = 33.89$, $p < 0.001$), 321
 322 low-SES vs. high-SES ($D = 31.31$, $p < 0.001$), and middle-SES vs. high-SES ($D = 31.31$, 322
 323 $p < 0.001$). With this finding, program selection could be the reason why low- and high- 323
 324 SES networks tend to segregate as the number of courses taken increases. The next 324
 325 section characterizes the referrals, and we will return to the diversity implications of 325
 326 program selection once we propose an understanding of how referrals were made. 326

Figure 11: 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.

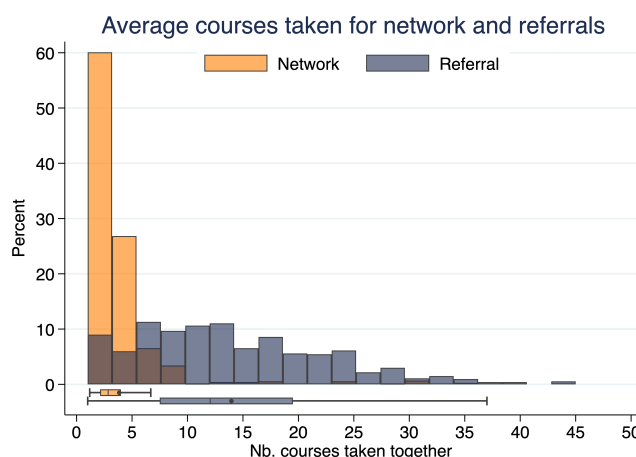
5.4 Characterizing referrals

We observe 1342 referrals from our 734 participants in our final data set. More than 90% of these consist from participants referring for both areas of the national entry exam (see Appendix Table A.2). While each participant made one referral for Math and Reading parts of the exam, we pool these referrals in our main analysis and look at averages as there is no difference in terms of referral SES compositions between the two exam areas (see Appendix Table A.3).

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 12). 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 within same program (93%).

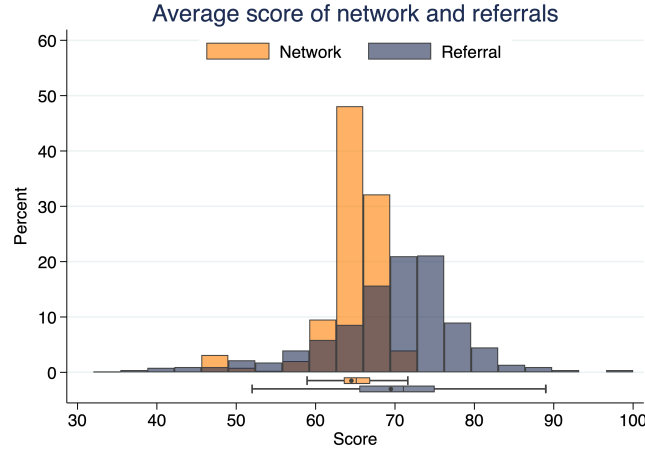
Figure 12: Courses taken together with network members and referrals



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 having taken 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 13). 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.

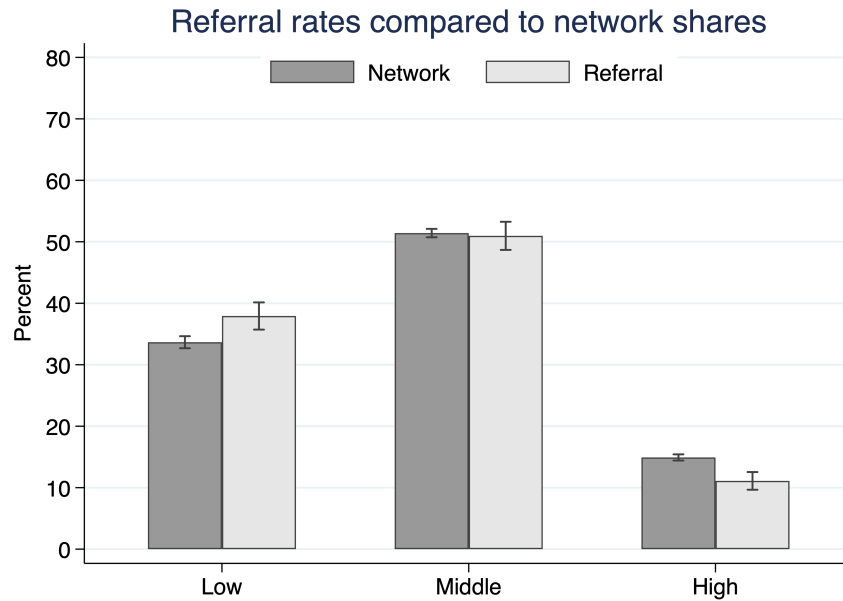
Figure 13: Entry exam scores of network members and referrals



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 $D = 71.16$, $p < 0.001$).

Third, we 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



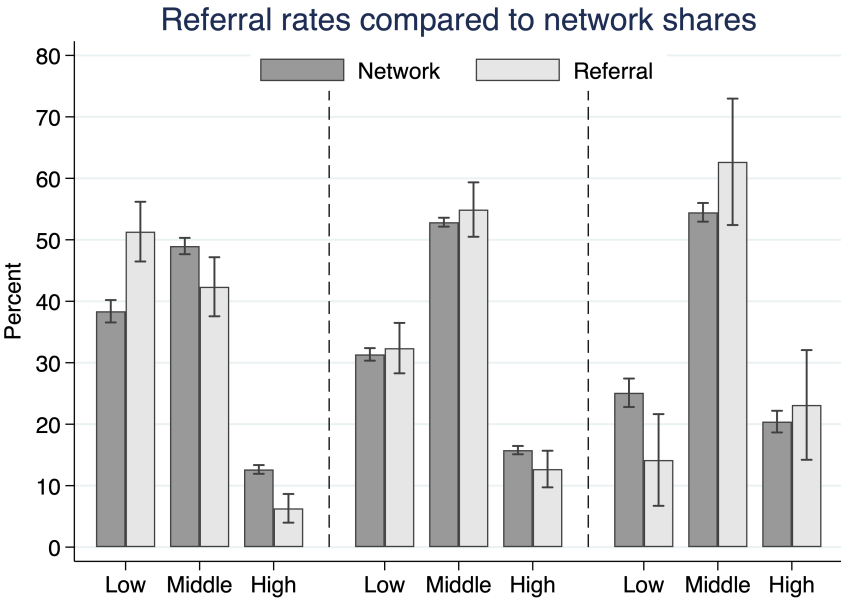
Note: This figure compares the average SES composition of referrers' networks (dark gray) to the SES composition of referrals (light gray). Error bars represent 95% confidence intervals.

365 to do: 1- SES composition by SES, 2- expost choice sets 3- effect of the bonus 4- bias 365
 366 regression 366

367 Fourth, we examine referral patterns by referrer SES to identify potential SES biases 367
 368 across groups. Figure 15 reveals mixed patterns of deviation from network composition 368
 369 that vary by referrer SES. Most patterns show modest deviations from network composi- 369
 370 tion, with differences typically ranging from 1-6 percentage points. However, at the very 370
 371 extremes, meaning low-SES to high-SES connections and vice versa, we observe the the 371
 372 largest discrepancies between network share (which were already biased toward same- 372
 373 SES connections to begin with) and referral rates. Low-SES referrers show the strongest 373
 374 same-SES preference, referring 12.9 percentage points more to low-SES students than 374
 375 their network composition would suggest, while under-referring to high-SES recipients 375
 376 by 6.3 percentage points. Conversely, high-SES referrers under-refer to low-SES stu- 376
 377 dents by 10.9 percentage points compared to their network composition. Middle-SES 377

378 referrers show the most balanced patterns, with deviations generally under 3 percent- 378
 379 age points across all recipient groups. These findings indicate that cross-SES referral 379
 380 patterns - particularly between the most socioeconomically distant groups - show the 380
 381 largest departures from network availability, suggesting that when SES differences are 381
 382 most pronounced, referral behavior diverges most from underlying network structure. 382

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.

383 5.5 Effect of the Bonus treatment 383

384 Table 3 384

Table 3: Summary statistics for network members by referral status

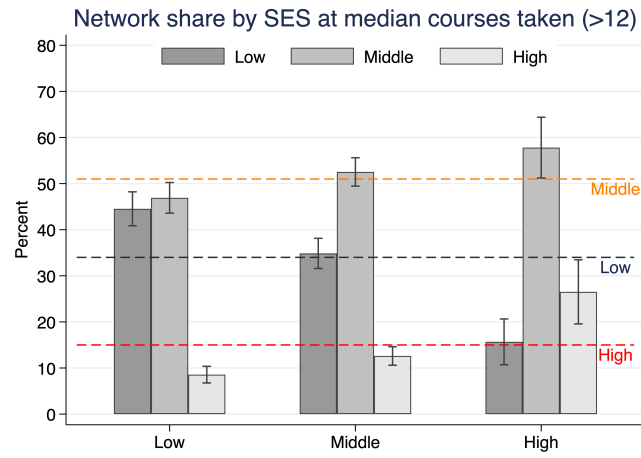
	Not Referred - to remove	Baseline Referred	Bonus Referred	<i>p</i>
Reading score	64.212	68.044	67.180	0.063
Math score	66.361	71.119	70.240	0.143
GPA	3.909	4.158	4.148	0.583
Tie strength	3.162	14.062	14.236	0.732
Low-SES	0.336	0.366	0.393	0.304
Med-SES	0.514	0.548	0.468	0.004
High-SES	0.150	0.086	0.138	0.002
Observations	255,655	699	643	

Note: P-values are from two-sample t-tests with unequal variances for continuous variables and two-sample tests of proportions for binary variables, comparing Baseline Referred vs Bonus Referred groups. Reading and math scores are raw test scores. GPA is the grade point average. Tie strength measures the weighted frequency of contact between individuals. Low-SES, Med-SES, and High-SES are binary variables indicating the share of participants in estrato 1 and 2, 3 and 4, or 5 and 6, respectively. Not Referred includes all network members who were not nominated for referral. Baseline Referred and Bonus Referred include only those network members who were actually nominated for referral in each treatment condition.

5.6 SES diversity in ex post referral choice sets

At the median number of courses taken together for referrals, the effects of network segregation on SES diversity becomes clear (see Figure 16)

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



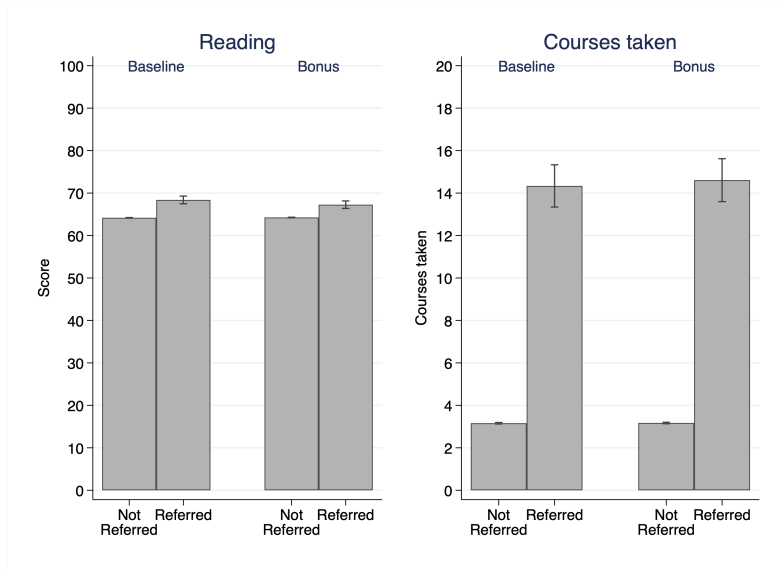
Note: This figure illustrates the shares of same-SES connections for low-, middle-, and high-SES as a function of the average number of courses taken together with network members. Low- and high-SES networks both become more homogenous as the average number of courses taken together with their connections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

Table 4: Comparison of math and verbal scores by SES group and data source

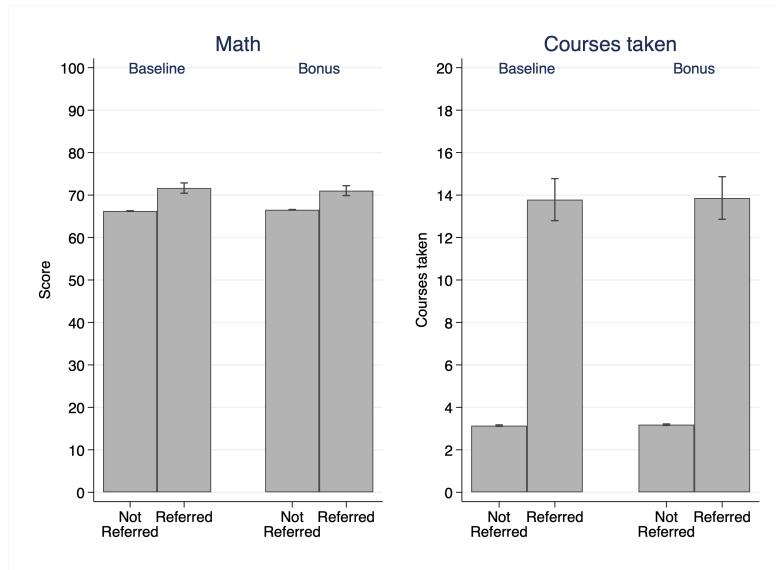
	Math			Verbal		
	Network	Admin	Sample	Network	Admin	Sample
Low-SES	66.976 (0.052)	61.653 (0.346)	67.813 (0.694)	64.738 (0.043)	60.974 (0.274)	66.058 (0.574)
Mid-SES	65.627 (0.039)	64.531 (0.224)	66.859 (0.580)	63.685 (0.032)	63.154 (0.183)	64.779 (0.436)
High-SES	67.781 (0.077)	67.330 (0.416)	70.610 (1.295)	64.966 (0.063)	64.892 (0.341)	66.397 (1.214)
Observations	128,150	4,415	669	128,847	4,403	673

Note: Standard errors in parentheses. The table presents mean scores with standard errors for math and verbal tests across the entire network, the admin data, and the sample. Admin data consistently shows lower scores than both network and the sample across all SES groups consistent with selection, with the largest gaps occurring for the Low-SES. Differences between network and sample scores are generally smaller than those between either and the admin data.

Figure 17: Effect of the Bonus on Referrals



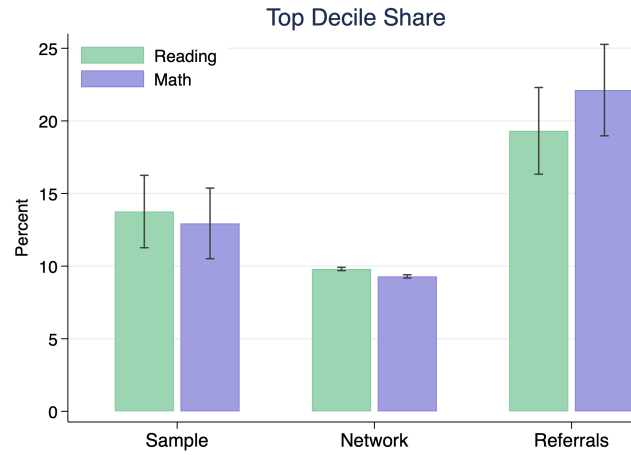
(a) Reading



(b) Math

Note: The top panel compares the reading scores and tie strength of referrals across conditions. The bottom panel shows the average standardized math and tie strength of referrals across conditions. We test differences in across conditions using two-sample t -tests and find no meaningful differences. For both math and reading, treatment causes no significant changes in referral performance or tie strength.

Figure 18: Top decile performer share across the sample, network and referrals



Note: This figure displays the percentage share of top decile individuals according to the admin data across three dimensions. First bar shows referrers in the sample of participants. Second bar is the share of top decile individuals in their networks. Third column shows the share of top decile among the referrals made. We test differences between proportions across these three groups using two-sample tests of proportions. For both math and reading scores, the differences between Sample and Network ($p < 0.001$), Sample and Referrals ($p < 0.005$), and Network and Referrals ($p < 0.001$) are all statistically significant.

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490 **A Additional Figures and Tables**

490

491 **Additional Figures**

491

Table A.1: Selection into the experiment

	University	Sample	<i>p</i>
Reading score	62.651	65.183	0.000
Math score	63.973	67.477	0.000
GPA	3.958	4.012	0.000
Low-SES	0.343	0.410	0.000
Med-SES	0.505	0.499	0.763
High-SES	0.153	0.091	0.000
Female	0.567	0.530	0.060
Age	21.154	20.651	0.000
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 academic area

	Reading	Math	<i>p</i>
Reading score	67.85	67.41	0.348
Math score	70.04	71.36	0.029
Low-SES	37%	38%	0.714
Med-SES	51%	51%	0.829
High-SES	11%	11%	0.824
N	673	669	

Note: This table compares characteristics of referred students by referrer's academic area (verbal vs. math). p -values are from two-sample t-tests with unequal variances. Math area participants refer peers with significantly higher math performance ($p = 0.029$), while no significant differences exist for reading scores or SES composition across areas.

493 B Experiment 493

494 *We include the English version of the instructions used in Qualtrics. Participansts saw* 494
495 *the Spanish version. Horizontal lines in the text indicate page breaks and clarifying* 495
496 *comments are inside brackets.* 496

497 Consent 497

498 You have been invited to participate in this decision-making study. This study is directed 498
499 by [omitted for anonymous review] and organized with the support of the Social Bee Lab 499
500 (Social Behavior and Experimental Economics Laboratory) at UNAB. 500

501 In this study, we will pay **one (1)** out of every **ten (10)** participants, who will be 501
502 randomly selected. Each selected person will receive a fixed payment of **70,000** (seventy 502
503 thousand pesos) for completing the study. Additionally, they can earn up to **270,000** 503
504 (two hundred and seventy thousand pesos), depending on their decisions. So, in total, 504
505 if you are selected to receive payment, you can earn up to **340,000** (three hundred and 505
506 forty thousand pesos) for completing this study. 506

507 If you are selected, you can claim your payment at any Banco de Bogotá office by 507
508 presenting your ID. Your participation in this study is voluntary and you can leave the 508
509 study at any time. If you withdraw before completing the study, you will not receive 509
510 any payment. 510

511 The estimated duration of this study is 20 minutes. 511

512 The purpose of this study is to understand how people make decisions. For this, we will 512
513 use administrative information from the university such as the SABER 11 test scores of 513
514 various students (including you). Your responses will not be shared with anyone and your 514
515 participation will not affect your academic records. To maintain strict confidentiality, the 515
516 research results will not be associated at any time with information that could personally 516

517 identify you. 517

518 There are no risks associated with your participation in this study beyond everyday risks. 518

519 However, if you wish to report any problems, you can contact Professor [omitted for 519

520 anonymous review]. For questions related to your rights as a research study participant, 520

521 you can contact the IRB office of [omitted for anonymous review]. 521

522 By selecting the option “I want to participate in the study” below, you give your con- 522

523 sent to participate in this study and allow us to compare your responses with some 523

524 administrative records from the university. 524

525 • I want to participate in the study [advances to next page] 525

526 • I do not want to participate in the study 526

527

 527

528 **Student Information** 528

529 Please write your student code. In case you are enrolled in more than one program 529

530 simultaneously, write the code of the first program you entered: 530

531 [Student ID code] 531

532 What semester are you currently in? 532

533 [Slider ranging from 1 to 11] 533

534

 534

535 [Random assignment to treatment or control] 535

536	Instructions	536
537	The instructions for this study are presented in the following video. Please watch it	537
538	carefully. We will explain your participation and how earnings are determined if you are	538
539	selected to receive payment.	539
540	[Treatment-specific instructions in video format]	540
541	If you want to read the text of the instructions narrated in the video, press the “Read	541
542	instruction text” button. Also know that in each question, there will be a button with	542
543	information that will remind you if that question has earnings and how it is calculated,	543
544	in case you have any doubts.	544
545	<ul style="list-style-type: none"> • I want to read the instructions text [text version below] 	545
546	<hr/>	546
547	In this study, you will respond to three types of questions. First, are the belief questions.	547
548	For belief questions, we will use as reference the results of the SABER 11 test that you	548
549	and other students took to enter the university, focused on three areas of the exam:	549
550	mathematics, reading, and English.	550
551	For each area, we will take the scores of all university students and order them from	551
552	lowest to highest. We will then group them into 100 percentiles. The percentile is a	552
553	position measure that indicates the percentage of students with an exam score that is	553
554	above or below a value.	554
555	For example, if your score in mathematics is in the 20th percentile, it means that 20	555
556	percent of university students have a score lower than yours and the remaining 80 percent	556
557	have a higher score. A sample belief question is: “compared to university students, in	557
558	what percentile is your score for mathematics?”	558
559	If your answer is correct, you can earn 20 thousand pesos. We say your answer is correct	559

560 if the difference between the percentile you suggest and the actual percentile of your 560
561 score is not greater than 7 units. For example, if you have a score that is in the 33rd 561
562 percentile and you say it is in the 38th, the answer is correct because the difference is 562
563 less than 7. But if you answer that it is in the 41st, the difference is greater than 7 and 563
564 the answer is incorrect. 564

565 The second type of questions are recommendation questions and are also based on the 565
566 mathematics, reading, and English areas of the SABER 11 test. We will ask you to think 566
567 about the students with whom you have taken or are taking classes, to recommend from 567
568 among them the person you consider best at solving problems similar to those on the 568
569 SABER 11 test. 569

570 When you start typing the name of your recommended person, the computer will show 570
571 suggestions with the full name, program, and university entry year of different students. 571
572 Choose the person you want to recommend. If the name doesn't appear, check that you 572
573 are writing it correctly. Do not use accents and use 'n' instead of 'ñ'. If it still doesn't 573
574 appear, it may be because that person is not enrolled this semester or because they did 574
575 not take the SABER 11 test. In that case, recommend someone else. 575

576 You can earn up to 250,000 pesos for your recommendation. We will multiply your 576
577 recommended person's score by 100 pesos if they are in the first 50 percentiles. We will 577
578 multiply it by 500 pesos if your recommended person's score is between the 51st and 578
579 65th percentile. If it is between the 66th and 80th percentile, we will multiply your 579
580 recommended person's score by 1000 pesos. If the score is between the 81st and 90th 580
581 percentile, you earn 1500 pesos multiplied by your recommended person's score. And if 581
582 the score is between the 91st and 100th percentile, we will multiply your recommended 582
583 person's score by 2500 pesos to determine the earnings. 583

584 The third type of questions are information questions and focus on aspects of your 584
585 personal life or your relationship with the people you have recommended. 585

586 Earnings 586

587 Now we will explain who gets paid for participating and how the earnings for this study 587
588 are assigned. The computer will randomly select one out of every 10 participants to pay 588
589 for their responses. For selected individuals, the computer will randomly choose one of 589
590 the three areas, and from that chosen area, it will pay for one of the belief questions. 590

591 Similarly, the computer will randomly select one of the three areas to pay for one of the 591
592 recommendation questions. 592

593 **Additionally, if you are selected to receive payment, your recommended per-** 593
594 **son in the chosen area will receive a fixed payment of 100 thousand pesos.** 594
595 [Only seen if assigned to the treatment] 595

596 Each person selected to receive payment for this study can earn: up to 20 thousand pesos 596
597 for one of the belief questions, up to 250 thousand pesos for one of the recommendation 597
598 questions, and a fixed payment of 70 thousand pesos for completing the study. 598

599 Selected individuals can earn up to 340 thousand pesos. 599

600

 600

601 [Participants go through all three Subject Areas in randomized order] 601

602 Subject Areas 602

603 Critical Reading 603

604 For this section, we will use as reference the Critical Reading test from SABER 11, which 604
605 evaluates the necessary competencies to understand, interpret, and evaluate texts that 605
606 can be found in everyday life and in non-specialized academic fields. 606

607 [Clicking shows the example question from SABER 11 below] 607

608 Although the democratic political tradition dates back to ancient Greece, political 608
609 thinkers did not address the democratic cause until the 19th century. Until then, democ- 609
610 racy had been rejected as the government of the ignorant and unenlightened masses. 610
611 Today it seems that we have all become democrats without having solid arguments in 611
612 favor. Liberals, conservatives, socialists, communists, anarchists, and even fascists have 612
613 rushed to proclaim the virtues of democracy and to show their democratic credentials 613
614 (Andrew Heywood). According to the text, which political positions identify themselves 614
615 as democratic? 615

- 616 • Only political positions that are not extremist 616
- 617 • The most recent political positions historically 617
- 618 • The majority of existing political positions 618
- 619 • The totality of possible political currents 619

620

 620

621 **Mathematics** 621

622 This section references the Mathematics test from SABER 11, which evaluates people's 622
623 competencies to face situations that can be resolved using certain mathematical tools. 623

624 [Clicking shows the example question from SABER 11 below] 624

625 A person living in Colombia has investments in dollars in the United States and knows 625
626 that the exchange rate of the dollar against the Colombian peso will remain constant 626
627 this month, with 1 dollar equivalent to 2,000 Colombian pesos. Their investment, in 627
628 dollars, will yield profits of 3% in the same period. A friend assures them that their 628
629 profits in pesos will also be 3%. Their friend's statement is: 629

- 630 • Correct. The proportion in which the investment increases in dollars is the same 630
631 as in pesos. 631

632	• Incorrect. The exact value of the investment should be known.	632
633	• Correct. 3% is a fixed proportion in either currency.	633
634	• Incorrect. 3% is a larger increase in Colombian pesos.	634
635	<hr/>	635
636	English	636
637	This section uses the English test from SABER 11 as a reference, which evaluates that	637
638	the person demonstrates their communicative abilities in reading and language use in	638
639	this language.	639
640	[Clicking shows the example question from SABER 11 below]	640
641	Complete the conversations by marking the correct option.	641
642	• Conversation 1: I can't eat a cold sandwich. It is horrible!	642
643	– I hope so.	643
644	– I agree.	644
645	– I am not.	645
646	• Conversation 2: It rained a lot last night!	646
647	– Did you accept?	647
648	– Did you understand?	648
649	– Did you sleep?	649
650	<hr/>	650
651	[Following parts are identical for all Subject Areas and are not repeated here for brevity]	651

652	Your Score	652
653	Compared to university students, in which percentile do you think your [Subject Area]	653
654	test score falls (1 is the lowest percentile and 100 the highest)?	654
655	[Clicking shows the explanations below]	655
656	How is a percentile calculated?	656
657	A percentile is a position measurement. To calculate it, we take the test scores for all	657
658	students currently enrolled in the university and order them from lowest to highest. The	658
659	percentile value you choose refers to the percentage of students whose score is below	659
660	yours. For example, if you choose the 20th percentile, you're indicating that 20% of	660
661	students have a score lower than yours and the remaining 80% have a score higher than	661
662	yours.	662
663	What can I earn for this question?	663
664	For your answer, you can earn 20,000 (twenty thousand) PESOS , but only if the	664
665	difference between your response and the correct percentile is less than 7. For example, if	665
666	the percentile where your score falls is 33 and you respond with 38 (or 28), the difference	666
667	is 5 and the answer is considered correct. But if you respond with 41 or more (or 25 or	667
668	less), for example, the difference would be greater than 7 and the answer is incorrect.	668
669	Please move the sphere to indicate which percentile you think your score falls in:	669
670	[Slider with values from 0 to 100]	670
671	<hr/>	671

672 **Recommendation** 672

673 Among the people with whom you have taken any class at the university, who is your 673
674 recommendation for the [Subject Area] test? Please write that person's name in the 674
675 box below: 675

676 **Important:** You will not be considered for payment unless the recommended 676
677 person is someone with whom you have taken at least one class during your 677
678 studies. 678

679 Your response is only a recommendation for the purposes of this study and we will **not** 679
680 contact your recommended person at any time. 680

681 [Clicking shows the explanations below] 681

682 Who can I recommend? 682

683 Your recommendation **must** be someone with whom you have taken (or are taking) a 683
684 class. If not, your answer will not be considered for payment. The person you recommend 684
685 will not be contacted or receive any benefit from your recommendation. 685

686 As you write, you will see up to 7 suggested student names containing the letters you 686
687 have entered. The more you write, the more accurate the suggestions will be. Please 687
688 write **without** accents and use the letter 'n' instead of 'ñ'. If the name of the person 688
689 you're writing doesn't appear, it could be because you made an error while writing the 689
690 name. 690

691 If the name is correct and still doesn't appear, it could be because the student is not en- 691
692 rolled this semester or didn't take the SABER 11 test. In that case, you must recommend 692
693 someone else. 693

694 My earnings for this question? 694

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:

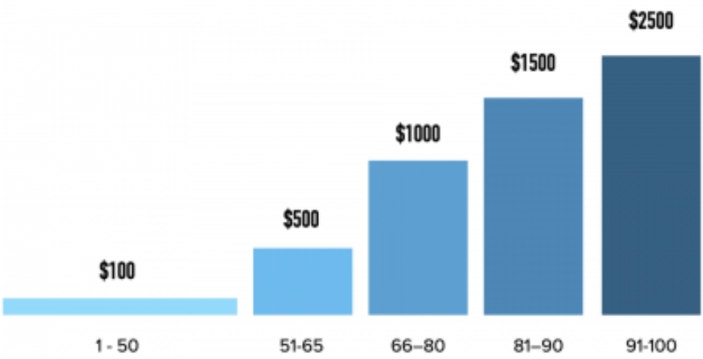


Figure B.1: Earnings for recommendation questions

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

710 you could earn $54 \times 100 = 5400$ PESOS. But, if the same score of 54 points were in the 710
711 98th percentile, you could earn $54 \times 2500 = 135,000$ PESOS. 711

712 [Text field with student name suggestions popping up as participant types] 712

713

 713

714 **Relationship with your recommendation** 714

715 How close is your relationship with your recommendedation: “[Name of the student 715
716 selected from earlier]”? (0 indicates you are barely acquaintances and 10 means you are 716
717 very close) 717

718 [Slider with values from 0 to 10] 718

719

 719

720 **Your recommendation’s score** 720

721 Compared to university students, in which percentile do you think [Name of the student 721
722 selected from earlier]’s score falls in the [Subject Area] test (1 is the lowest percentile 722
723 and 100 the highest)? 723

724 [Clicking shows the explanations below] 724

725 How is a percentile calculated? 725

726 A percentile is a position measurement. To calculate it, we take the test scores for all 726
727 students currently enrolled in the university and order them from lowest to highest. The 727
728 percentile value you choose refers to the percentage of students whose score is below 728
729 yours. For example, if you choose the 20th percentile, you’re indicating that 20% of 729
730 students have a score lower than yours and the remaining 80% have a score higher than 730
731 yours. 731

732 What can I earn for this question? 732

733 For your answer, you can earn **20,000 (twenty thousand) PESOS**, but only if the 733
734 difference between your response and the correct percentile is less than 7. For example, 734
735 if the percentile where your recommended person's score falls is 33 and you respond with 735
736 38 (or 28), the difference is 5 and the answer is considered correct. But if you respond 736
737 with 41 or more (or 25 or less), for example, the difference would be greater than 7 and 737
738 the answer is incorrect. 738

739 Please move the sphere to indicate which percentile you think your recommended per- 739
740 son's score falls in: 740

741 [Slider with values from 0 to 100] 741

742 _____ 742

743 Demographic Information 743

744 What is the highest level of education achieved by your father? 744

745 [Primary, High School, University, Graduate Studies, Not Applicable] 745

746 What is the highest level of education achieved by your mother? 746

747 [Primary, High School, University, Graduate Studies, Not Applicable] 747

748 Please indicate the socio-economic group to which your family belongs: 748

749 [Group A (Strata 1 or 2), Group B (Strata 3 or 4), Group C (Strata 5 or 6)] 749

750 _____ 750

751	UNAB Students Distribution	751
752	Thinking about UNAB students, in your opinion, what percentage belongs to each socio-	752
753	economic group? The total must sum to 100%:	753
754	[Group A (Strata 1 or 2) percentage input area]	754
755	[Group B (Strata 3 or 4) percentage input area]	755
756	[Group C (Strata 5 or 6) percentage input area]	756
757	[Shows sum of above percentages]	757
758	<hr/>	758
759	End of the Experiment	759
760	Thank you for participating in this study.	760
761	If you are chosen to receive payment for your participation, you will receive a confirma-	761
762	tion to your UNAB email and a link to fill out a form with your information. The process	762
763	of processing payments is done through Nequi and takes approximately 15 business days,	763
764	counted from the day of your participation.	764
765	[Clicking shows the explanations below]	765
766	Who gets paid and how is it decided?	766
767	The computer will randomly select one out of every ten participants in this study to be	767
768	paid for their decisions.	768
769	For selected individuals, the computer will randomly select one area: mathematics,	769
770	reading, or English, and from that area will select one of the belief questions. If the	770
771	answer to that question is correct, the participant will receive 20,000 pesos.	771

772 The computer will randomly select an area (mathematics, critical reading, or English) to 772
773 pay for one of the recommendation questions. The area chosen for the recommendation 773
774 question is independent of the area chosen for the belief question. The computer will 774
775 take one of the two recommendations you have made for the chosen area. Depending on 775
776 your recommendation's score, you could win up to 250,000 pesos. 776

777 Additionally, people selected to receive payment for their participation will have a fixed 777
778 earnings of 70,000 pesos for completing the study. 778

779 _____ 779

780 **Participation** 780

781 In the future, we will conduct studies similar to this one where people can earn money 781
782 for their participation. The participation in these studies is by invitation only. Please 782
783 indicate if you are interested in being invited to other studies similar to this one: 783

784 [Yes, No] 784