Class differences in social networks: Evidence from a referral experiment

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Abstract

Lorem Ipsum (Beaman, Keleher, & Magruder, 2018)

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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; Hederos, 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

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

[2]See 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 disadvantagee 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 compositon. 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 4), 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 1a). As students take more courses together within the same program, their networks dwindle in size (Figures 2a and 2b), and become more homogenous in SES-shares (Figure 1b). 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

[3] In 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 3a). 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 3b).

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 attribuable 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.

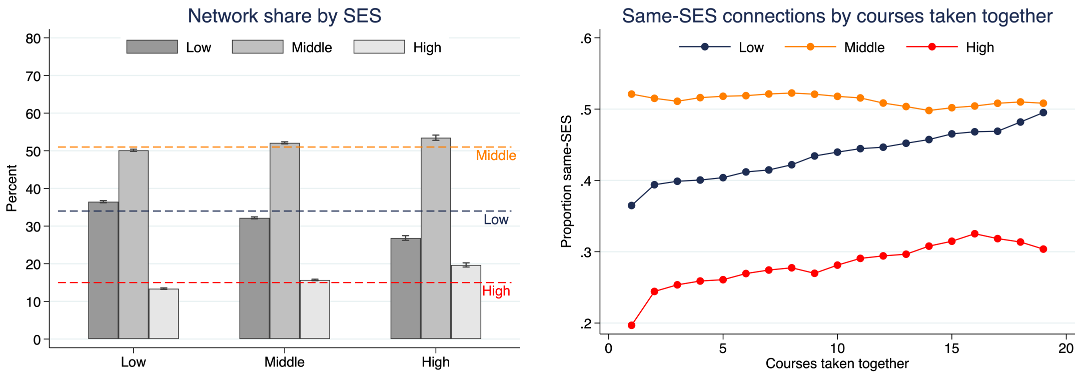
This paper contributes to the literature on referral experiments by solving the challenge of observing the entire referral network. Earlier research could only compare referrals made across different incentive structures or experimental instructions and make according conclusions. For example, when participants 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 restrictred 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 referals 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 institional 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 experiment. Section 6 concludes. The Appendix presents additional tables and figures as well as the experiment instructions.

Figure 1: Networks of SES groups and same-SES segregation

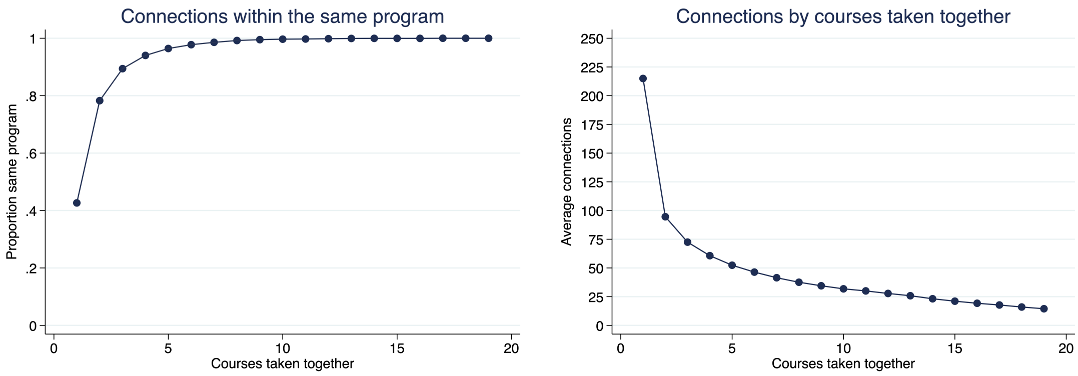


(a) SES networks

(b) Same-SES share

Note: The left panel compares the network shares of SES groups in the networks of low-, middle-, and high-SES. 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. The right panel shows the average share 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.

Figure 2: Network characteristics and courses taken together

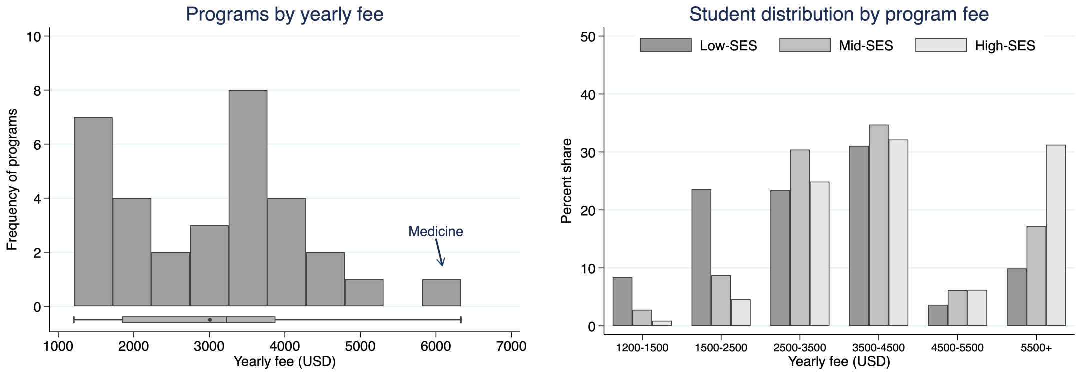


(a) Same-program share

(b) Network size

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 220 individuals to below 50.

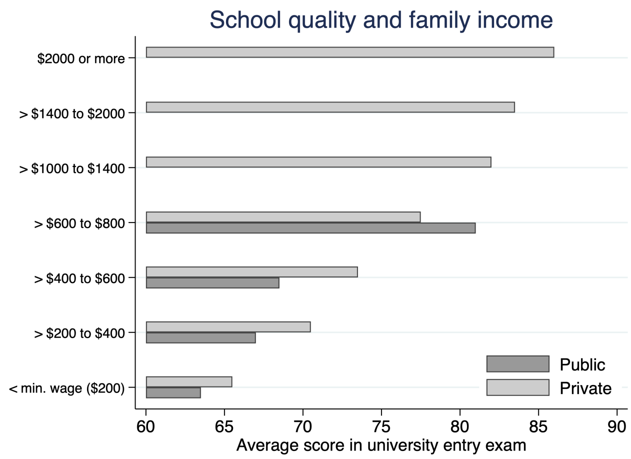
Figure 3: University programs by yearly fee and SES distribution



(a) Programs sorted by fee (b) SES distribution by program fee

Note: The left panel shows the distribution of programs at the university by their average yearly fee. The right panel illustrates the distribution of each SES group across programs sorted by fee. As of 2025 net average monthly wage is around \$350 and the minimum legal wage is at \$200. The average yearly fee of programs stands at \$3000, and medicine is an extreme outlier at \$6000. Distributions of SES groups across programs show 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.

Figure 4: 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 instition. 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).

2 Background and Setting

Our study takes place at UNAB, a medium-sized private university in Bucaramanga, Colombia with approximately 6,000 enrolled students. The university's student body is remarkably diverse with about 35% of the students classified as low-SES, and 15% high-SES. Diversity at this institution provides a unique research setting as Colombian society is highly unequal and generally characterized by limited interaction between social classes, with different socioeconomic groups separated by education and geographic residence.[4] Despite significant financial barriers, many lower and middle-SES families prioritize university education for their children (Hudson & Library of Congress, 2010,

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

p. 103), and UNAB represents one of the few environments where sustained inter-SES contact occurs naturally (see Figure 4).

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

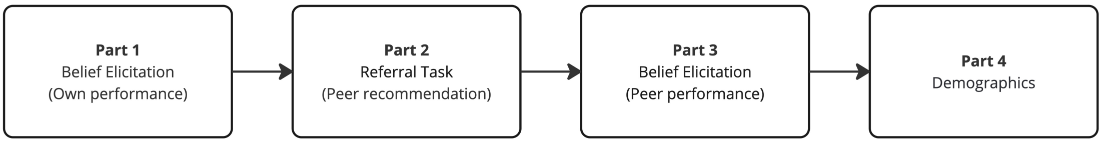
We invited via email all 4,417 UNAB students who had at the time of recruitment completed their first year at the university to participate in our experiment. 837 students who joined (19%) vary in terms of their academic programs, SES, and progress in their studies. This setup provides a unique opportunity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

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 5). The instructions are provided in Appendix B.

[5]Initially 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).

Figure 5: 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.

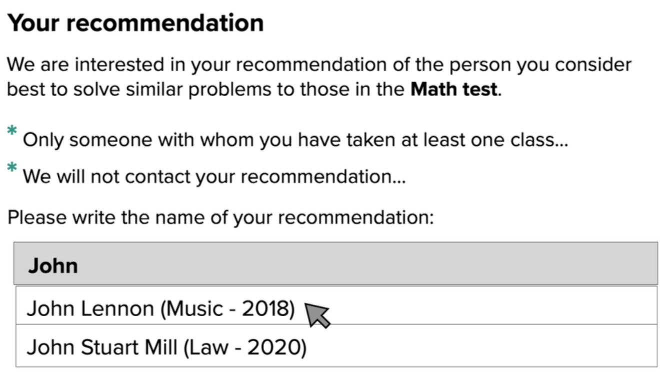
Critical reading evaluates competencies necessary to understand, interpret, and evaluate texts found in everyday life and broad academic fields (e.g., history). This measures students' ability to comprehend and critically evaluate written material. Mathematics assesses students' competency in using undergraduate 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 6).

Figure 6: Referral task interface

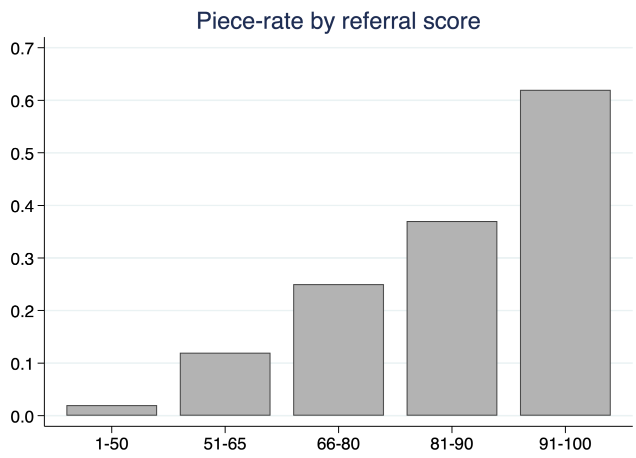


Note: This illustration shows how the system provides suggestions from enrolled students with their program and year of study from the administrative database.

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 7). 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 7: 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.

[6] Due 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: Payment 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 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 **Quota** 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. Participants have taken on average 3.8 courses together with their connections and the average network consists of 175 peers.

Table 2: Balance between treatments

	Baseline	**Bonus**	***p***
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.

The experiment was conducted online through Qualtrics, with participants recruited from active UNAB students who have SABER 11 scores in the administrative records. To manage budget constraints while maintaining sufficient incentives, we randomly selected one in ten participants for payment. Selected participants received a fixed payment of $17 for completion, plus potential earnings from one randomly selected belief question (up to $5) and one randomly selected recommendation question (up to $60), for maximum total earnings of $82. The random selection of payment part ensured that participants had incentives to exert effort across all tasks rather than focusing on a single part. Payment processing occured through online banking platform Nequi within 15 business days of participation.

Data collection occurred during the last two weeks of April 2024. Our local partner at UNAB coordinated scheduled classroom visits and recruited research assistants to administer the experiment. Students present in class on the scheduled visit dates participated. Each classroom visit constituted a separate session. There were in total 35 sessions. Participants accessed the Qualtrics-based experiment using their smartphones during these visits. The median time to complete the survey was 20 minutes, with a compensation of $26 for 117 lottery winners.

5 Results

5.1 Descriptives

Table 3: Distribution of referrals by area

Area	Only one referral	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 referral” indicates individuals who made referrals exclusively in that area. “Both areas” shows individuals who made referrals in both verbal and math areas. The majority of referrers (608) made referrals in both areas.

Table 4: Summary statistics for network members by nomination status

	Verbal		Math	
	Not Referred	Referred	Not Referred	Referred
Reading z-score	0.070	0.509	0.079	0.465
	(0.003)	(0.039)	(0.003)	(0.040)
Math z-score	0.079	0.452	0.087	0.590
	(0.003)	(0.042)	(0.003)	(0.043)
GPA z-score	-0.066	0.705	-0.069	0.711
	(0.003)	(0.041)	(0.003)	(0.041)
Tie strength z-score	-0.153	2.690	-0.184	2.488
	(0.003)	(0.091)	(0.003)	(0.090)
Low-SES	0.334	0.374	0.338	0.384
	(0.001)	(0.019)	(0.001)	(0.019)
Med-SES	0.515	0.513	0.513	0.507
	(0.001)	(0.019)	(0.001)	(0.019)
High-SES	0.151	0.113	0.149	0.109
	(0.001)	(0.012)	(0.001)	(0.012)
Observations	128,174	673	127,481	669

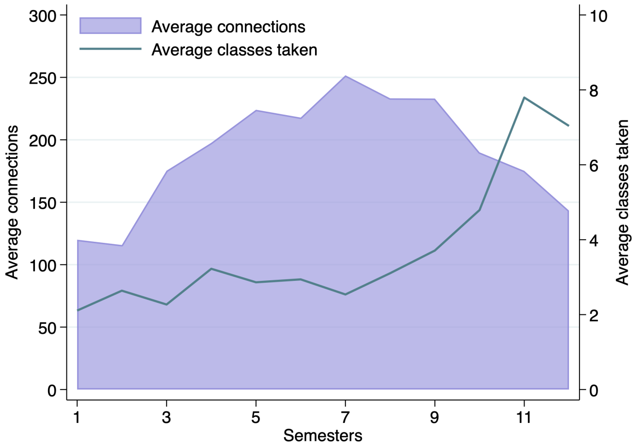
Note: Standard errors in parentheses. GPA, test scores, and tie strength are standardized at the network level. For each referrer's network, we first calculated the mean and standard deviation of each measure. We then computed the average of these means and standard deviations across all referrers. Each individual's score was standardized using these network-level statistics. The standardization formula is $z = (x - \bar{x}_{network})/\sigma_{network}$, where $\bar{x}_{network}$ and $\sigma_{network}$ are the average of network means and standard deviations, respectively. 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. Tie strength measures the number of connections between individuals.

Table 5: Comparison of math and verbal scores by SES group and data source

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

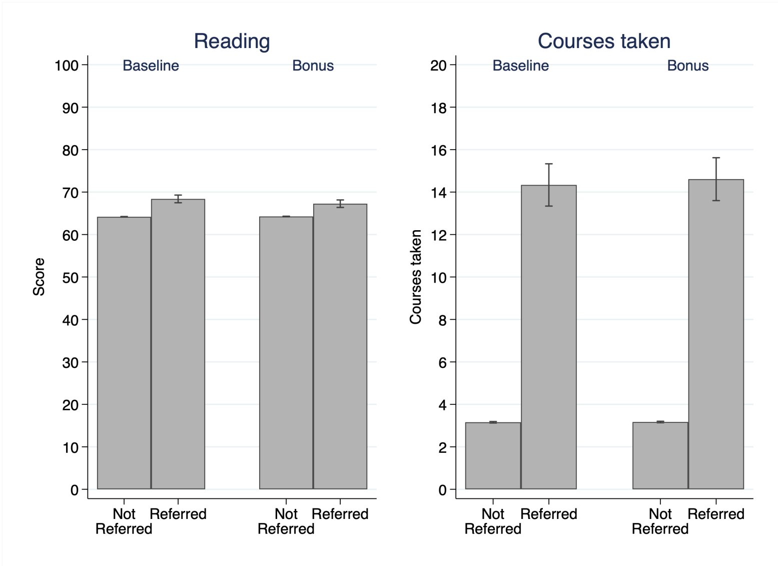
Note: Standard errors in parentheses. The table presents mean scores with standard errors for math and verbal tests across the entire network, the admin data, and the sample. Admin data consistently shows lower scores than both network and the sample across all SES groups consistent with selection, with 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 8: Participant network size and tie strength by time spent at UNAB

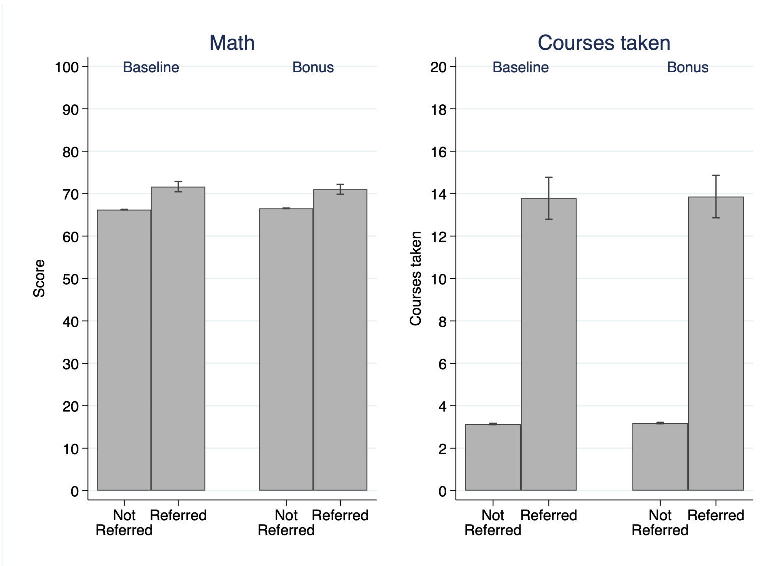


Note: This figure displays the average number of connections for referrers in blue and the average number of classes they have taken together with their connections in green across semesters spent at UNAB. The data shows an increase in the number of classes taken together as students progress in their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

Figure 9: Effect of the Bonus on Referrals



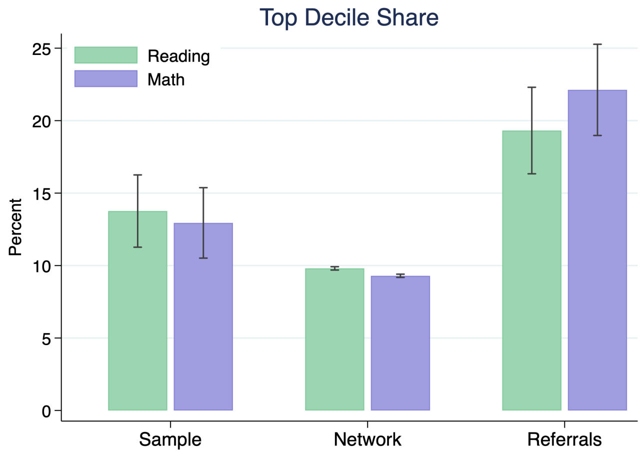
(a) Reading



(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 10: Top decile performer share across the sample, network and referals



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.

6 Conclusion

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A Additional Figures and Tables

Additional Figures

Additional Tables

Table A.1: Selection into the experiment

	University	**Sample**	***p***
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	5,151

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.

B Experiment

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

Consent

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

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

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

The estimated duration of this study is 20 minutes.

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

There are no risks associated with your participation in this study beyond everyday risks. However, if you wish to report any problems, you can contact Professor [omitted for anonymous review]. For questions related to your rights as a research study participant, you can contact the IRB office of [omitted for anonymous review].

By selecting the option "I want to participate in the study" below, you give your consent to participate in this study and allow us to compare your responses with some administrative records from the university.

- I want to participate in the study [advances to next page]
- I do not want to participate in the study

Student Information

Please write your student code. In case you are enrolled in more than one program simultaneously, write the code of the first program you entered:

[Student ID code]

What semester are you currently in?

[Slider ranging from 1 to 11]

[Random assignment to treatment or control]

Instructions

The instructions for this study are presented in the following video. Please watch it carefully. We will explain your participation and how earnings are determined if you are selected to receive payment.

[Treatment-specific instructions in video format]

If you want to read the text of the instructions narrated in the video, press the "Read instruction text" button. Also know that in each question, there will be a button with information that will remind you if that question has earnings and how it is calculated, in case you have any doubts.

- I want to read the instructions text [text version below]

In this study, you will respond to three types of questions. First, are the belief questions. For belief questions, we will use as reference the results of the SABER 11 test that you and other students took to enter the university, focused on three areas of the exam: mathematics, reading, and English.

For each area, we will take the scores of all university students and order them from lowest to highest. We will then group them into 100 percentiles. The percentile is a position measure that indicates the percentage of students with an exam score that is above or below a value.

For example, if your score in mathematics is in the 20th percentile, it means that 20 percent of university students have a score lower than yours and the remaining 80 percent have a higher score. A sample belief question is: "compared to university students, in what percentile is your score for mathematics?"

If your answer is correct, you can earn 20 thousand pesos. We say your answer is correct if the difference between the percentile you suggest and the actual percentile of your score is not greater than 7 units. For example, if you have a score that is in the 33rd percentile and you say it is in the 38th, the answer is correct because the difference is less than 7. But if you answer that it is in the 41st, the difference is greater than 7 and the answer is incorrect.

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

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

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

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

Earnings

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

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

Additionally, if you are selected to receive payment, your recommended person in the chosen area will receive a fixed payment of 100 thousand pesos. [Only seen if assigned to the treatment]

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

Selected individuals can earn up to 340 thousand pesos.

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

Subject Areas

Critical Reading

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

[Clicking shows the example question from SABER 11 below]

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

- Only political positions that are not extremist
- The most recent political positions historically
- The majority of existing political positions
- The totality of possible political currents

Mathematics

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

[Clicking shows the example question from SABER 11 below]

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

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

- Incorrect. The exact value of the investment should be known.
- Correct. 3% is a fixed proportion in either currency.
- Incorrect. 3% is a larger increase in Colombian pesos.

English

This section uses the English test from SABER 11 as a reference, which evaluates that the person demonstrates their communicative abilities in reading and language use in this language.

[Clicking shows the example question from SABER 11 below]

Complete the conversations by marking the correct option.

- Conversation 1: I can't eat a cold sandwich. It is horrible!
  - I hope so.
  - I agree.
  - I am not.
- Conversation 2: It rained a lot last night!
  - Did you accept?
  - Did you understand?
  - Did you sleep?

[Following parts are identical for all Subject Areas and are not repeated here for brevity]

Your Score

Compared to university students, in which percentile do you think your [**Subject Area**] test score falls (1 is the lowest percentile and 100 the highest)?

[Clicking shows the explanations below]

How is a percentile calculated?

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

What can I earn for this question?

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

Please move the sphere to indicate which percentile you think your score falls in:

[Slider with values from 0 to 100]

Recommendation

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

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

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

[Clicking shows the explanations below]

Who can I recommend?

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

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

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

My earnings for this question?

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:

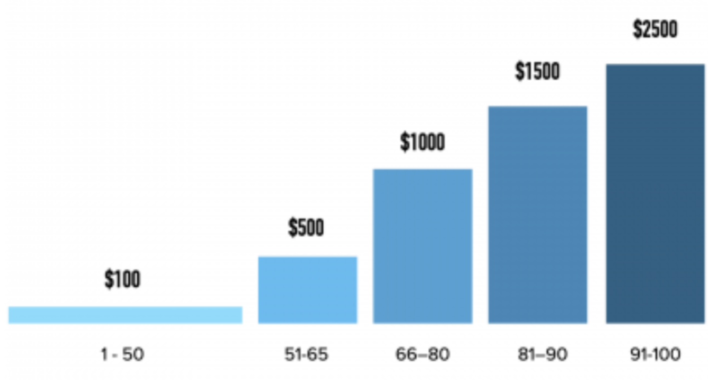

Figure B.1: Earnings for recommendation questions

For example, if your recommendation got 54 points and the score is in the 48th percentile, you could earn 54x100 = 5400 PESOS. But, if the same score of 54 points were in the 98th percentile, you could earn 54x2500 = 135,000 PESOS.

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

Relationship with your recommendation

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

[Slider with values from 0 to 10]

Your recommendation’s score

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

[Clicking shows the explanations below]

How is a percentile calculated?

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

What can I earn for this question?

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

Please move the sphere to indicate which percentile you think your recommended person's score falls in:

[Slider with values from 0 to 100]

Demographic Information

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

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

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

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

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

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

UNAB Students Distribution

Thinking about UNAB students, in your opinion, what percentage belongs to each socio-economic group? The total must sum to 100%:

[Group A (Strata 1 or 2) percentage input area]
[Group B (Strata 3 or 4) percentage input area]
[Group C (Strata 5 or 6) percentage input area]
[Shows sum of above percentages]

End of the Experiment

Thank you for participating in this study.

If you are chosen to receive payment for your participation, you will receive a confirmation to your UNAB email and a link to fill out a form with your information. The process of processing payments is done through Nequi and takes approximately 15 business days, counted from the day of your participation.

[Clicking shows the explanations below]

Who gets paid and how is it decided?

The computer will randomly select one out of every ten participants in this study to be paid for their decisions.

For selected individuals, the computer will randomly select one area: mathematics, reading, or English, and from that area will select one of the belief questions. If the answer to that question is correct, the participant will receive 20,000 pesos.

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

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

Participation

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

[Yes, No]