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El trabajo en equipo dificulta el ascenso: interacciones en equipo y movilidad social*

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Resumen

Este documento examina cómo las habilidades sociales y las interacciones en equipo moldean la movilidad intergeneracional. Utilizando datos colombianos vinculados a los requisitos de habilidades ocupacionales, documentamos que las carreras administrativas académicas asociadas con mayores demandas de habilidades sociales exhiben sistemáticamente una movilidad social menor. Un aumento de una desviación estándar en los requisitos de habilidades sociales corresponde a un aumento de 0,046 puntos en el coeficiente de persistencia del ingreso intergeneracional. Implementamos experimentos de laboratorio en el campo con 604 estudiantes universitarios, variando aleatoriamente la composición socioeconómica del equipo y la información que los participantes observaron sobre los antecedentes de los compañeros de equipo. Los participantes de bajos ingresos reciben un reconocimiento de liderazgo significativamente menor en equipos de ingresos mixtos cuando se revelan señales de estatus socioeconómico (como la afiliación a la escuela secundaria o los nombres), a pesar de un desempeño comparable en la tarea. Estas brechas surgen tanto en las nominaciones de pares como en las autoevaluaciones y están acompañadas por percepciones reducidas de la calidad del trabajo en equipo y las contribuciones individuales. Nuestros hallazgos sugieren que los entornos basados en equipos pueden amplificar la desigualdad a través de mecanismos de evaluación social en lugar de complementariedades productivas, lo que proporciona una explicación a nivel micro de la menor movilidad observada en ocupaciones socialmente intensivas y resalta la importancia de las políticas de integración social temprana.

Palabras clave: movilidad social, movilidad intergeneracional, habilidades sociales, trabajo en equipo, liderazgo, discriminación, educación superior, segregación educativa.

*Las ideas, opiniones, tesis y argumentos expresados son de propiedad exclusiva de los autores y no representan el punto de vista del Icfes.Agradecemos al Icfes por brindarnos el acceso a los datos en este artículo a través del proyecto de investigación interna "Movilidad - DNP"; también agradecemos a Isabella Becerra, Catalina Leal y María Alejandra Páez por su excelente asistencia en la investigación.

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Teaming Up Hinders Moving Up:
Team Interactions and Social Mobility

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Abstract

This document examines how social skills and team interactions shape intergenerational mobility. Using Colombian administrative data linked to occupational skill requirements, we document that academic majors associated with higher social-skill demands exhibit systematically lower social mobility. A one standard deviation increase in social-skill requirements corresponds to a 0.046-point increase in the intergenerational income persistence coefficient. We implement lab-in-the-field experiments with 604 undergraduate students, randomly varying team socioeconomic composition and the information participants observe about teammates' backgrounds. Low-income participants receive significantly lower leadership recognition in mixed-income teams when signals of socioeconomic status (such as high school affiliation or names) are revealed, despite comparable task performance. These gaps emerge in both peer nominations and self-assessments and are accompanied by reduced perceptions of teamwork quality and individual contributions. Our findings suggest that team-based environments may amplify inequality through social evaluation mechanisms rather than productive complementarities, providing a micro-level explanation for the lower mobility observed in socially intensive occupations and highlighting the importance of early social integration policies.

Keywords: social mobility, intergenerational mobility, social skills, teamwork, leadership, discrimination, higher education, educational segregation

Contents

1 Introduction

A large literature documents a rising importance of social and noncognitive skills in modern labor markets. Deming (2017a) shows that employment and wage growth have been strongest in occupations requiring intensive interaction and teamwork, while Edin et al. (2022) find that returns to non-cognitive skills—such as leadership and teamwork—have increased substantially over time. At the same time, recent evidence indicates that high-income students obtain markedly higher returns from attending elite colleges than low-income students, with social capital and peer networks playing a central role in shaping access to top jobs and leadership positions (Zimmerman, 2019; Michelman et al., 2021). Together, these patterns point to social capital and peer dynamics within educational environments as potential mechanisms behind persistent inequalities in long-run outcomes.

This paper connects these two facts by studying how teamwork and the recognition of leadership abilities shape social mobility. We ask whether social mobility varies by the requirements for social skills, such as teamwork and leadership, and explore whether such differences could be explained by students from different socioeconomic backgrounds being perceived and evaluated differently when working in teams. To address these questions, we combine administrative records from Colombia with a set of lab-in-the-field experiments implemented through a virtual collaboration platform. The platform allows us to measure performance across different tasks and to randomly vary teams' socioeconomic composition and the information participants learn about their teammates' backgrounds. This design enables us to distinguish whether differences in performance and leadership recognition reflect productive complementarities—teams functioning better with certain types of peers—or biased beliefs about the abilities of students from different socioeconomic groups.

We proceed in three steps. First, we document patterns of socioeconomic segregation across educational institutions in Colombia. Second, we examine whether social mobility varies systematically with the social-skill requirements of different academic majors. Third, we implement lab-in-the-field experiments to investigate the mechanisms behind these patterns.

Understanding segregation is critical, as limited interaction across socioeconomic groups affects both teamwork skill development and network formation. We begin by documenting socioeconomic segregation across Colombian schools and higher education institutions using ICFES administrative data. Applying variance decomposition methods, we find substantial segregation at the secondary level: 68% of socioeconomic variance occurs between schools, far exceeding international benchmarks. Private schools show higher segregation than public schools and have become increasingly selective over time. In contrast, higher education exhibits considerably lower segregation (26% of variance between institutions), suggesting that socioeconomic sorting attenuates as students progress through the education system.

Then, in the second part, we test the extent to which the level of required social skills in the labor market influences social mobility. We classify Colombian majors—coded using the country's CINE (Clasificación Internacional Normalizada de la Educación) (Departamento Administrativo Nacional de Estadística (DANE), 2023) system—according to the social-skill demands of the occupations typically associated with each field of study. This classification relies on ONET (National Center for O*NET Development, 2025), a comprehensive U.S. occupational database that reports detailed, standardized measures of the skills, abilities, and interpersonal competencies required in each occupation. By linking CINE majors to their corresponding ONET occupational profiles, we construct a measure of each major's social-skill intensity, which we then use to examine whether students from different socioeconomic backgrounds systematically sort into fields with different levels of required social skills.

Moreover, our analysis also estimates the relationship between social skills and social mobility. Following Chetty et al. (2014), we examine this relationship by estimating the association between students' socioeconomic rank in their last year of high school and their labor-income rank eight years after graduation. We find a baseline slope of approximately 0.170. We then explore whether majors with higher social-skill requirements exhibit lower social mobility. Our results indicate that majors associated with occupations requiring one standard deviation higher social-skill levels display a slope that is roughly 0.046 points higher, consistent with lower mobility among these fields. In addition, majors in the top quartile of the distribution of social-skill requirements have a slope about 11.8 points higher than majors in the bottom quartile.

Motivated by these facts, and to complement the suggestive evidence from administrative data, we implement lab-in-the-field experiments varying the socioeconomic composition of teams and the information participants learn about their teammates. These experiments allow us to directly test whether differences in team performance and leadership recognition stem from productive complementarities or from systematic biases in how abilities are perceived across socioeconomic groups.

The experimental results indicate that these differences are not primarily driven by productive complementarities in team composition. Low-income participants receive lower leadership recognition and exert less influence in mixed-income teams when information that signals socioeconomic background—such as high school or names—is revealed. These gaps emerge both in peer nominations and self-nominations for leadership roles and are not explained by differences in task performance. Instead, they are consistent with systematic differences in how teammates perceive communication, teamwork, and individual contributions once socioeconomic signals become salient.

These patterns suggest that team-based environments may amplify background-based differences through social evaluation rather than through underlying productivity. When leadership and influence are determined within groups, individuals from disadvantaged backgrounds may face barriers to recognition even in settings where formal skills are comparable. Such dynamics provide a plausible micro-level mechanism linking socioeconomic segregation and the lower social mobility observed in academic fields and occupations that place a premium on teamwork, communication, and interpersonal influence.

2 Evidence from Administrative Data

2.1 Data

For our analysis, we use administrative data that allow us to follow multiple cohorts of students from their participation in the Saber 11° examination, the standardized exit exam from upper secondary education in Colombia, through their transition into higher education and their subsequent insertion into the formal labor market.

Data on the Saber 11° exam are obtained from the Colombian Institute for the Evaluation of Education (ICFES) and cover cohorts of students who took the exam between 2014 and 2019. To construct the analytical sample, we first remove repeated test takings and retain only the first time each individual sat for the exam. In addition, we restrict the sample to students with complete socioeconomic information and exclude observations with missing values in test scores or other key variables.

Information on enrollment, persistence, and graduation in higher education is drawn from the National Higher Education Information System (SNIES), administered by the Ministry of National Education (MEN), for the period 2014–2024. These records allow us to observe students' trajectories longitudinally across university and technical or technological programs, as well as characteristics of higher education institutions and academic programs. Using this information, we construct indicators of access to, continuation in, and graduation from higher education.

To measure outcomes at the end of higher education, we incorporate administrative records from the Saber Pro and Saber TyT standardized exit exams, administered by ICFES, for the period 2014–2023. These datasets include scores in the assessed competencies, along with sociodemographic information reported by students at the time of the exam.

Finally, we use data from the Integrated Contribution Settlement Form (PILA), administered by the Ministry of Health and Social Protection (MINSALUD), which contains administrative records on individuals' affiliation with the social security system. This source allows us to identify participation in the formal labor market, contribution-based earnings, and selected job characteristics. We link these records to cohorts of students who took the Saber 11° exam between 2014 and 2019, enabling the analysis of labor market outcomes several years after the completion of upper secondary education.

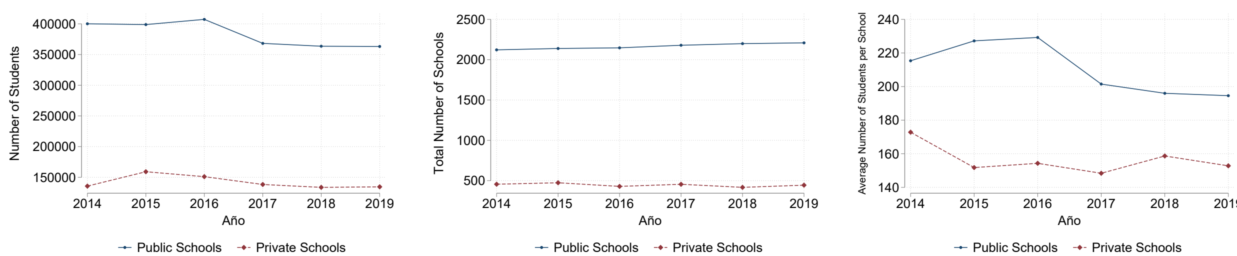
Combining information from the upper secondary exit exam (Saber 11°), higher education exit exams (Saber Pro and Saber TyT), longitudinal higher education records (SNIES), and administrative labor market data (PILA) allows us to reconstruct complete educational and labor market trajectories.

2.2 Educational Segregation in Colombia

2.2.1 Socioeconomic Segregation in Secondary Education

Our analysis draws on data from students who presented the Saber 11 standardized exam during the 2014-2019 period, which provides comprehensive information on secondary education completion in Colombia. As shown in Figure 1, the public school sector serves substantially more students than the private sector, with approximately 350,000-400,000 students taking the Saber 11 exam each year from public schools compared to 150,000 from private schools during this period. Despite serving fewer students overall, the private sector operates a larger number of schools (approximately 2,000) compared to the public sector (approximately 500 schools), resulting in considerably smaller average school sizes. Public schools average 200-230 students per school taking the exam, while private schools average 140-180 students per school. These structural differences between sectors, with public schools serving more students in fewer, larger institutions and private schools operating through a more fragmented network of smaller institutions, provide important context for interpreting the segregation patterns documented in the following sections.

FIGURE 1: Descriptive statistics of the Colombian secondary education system (2014-2019)



(A) Number of students (B) Number of schools (C) Students per school

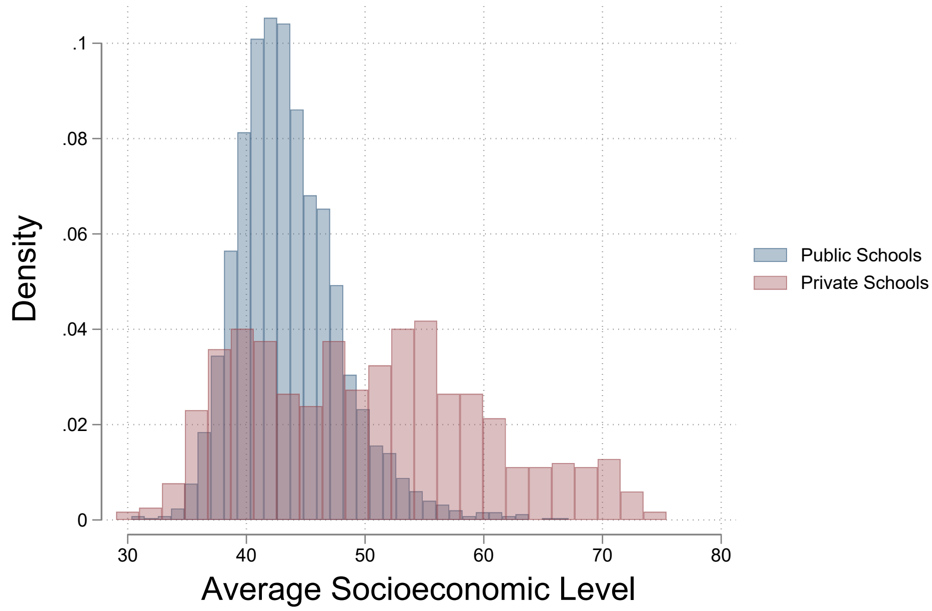
Note: Panel (a) displays the total number of students taking the Saber 11 exam by school type (public and private) over time. Panel (b) presents the total number of schools represented in the Saber 11 exam data by sector. Panel (c) shows the average number of students per school for each sector. The horizontal axis in all panels shows years from 2014 to 2019. Authors' calculations based on ICFES Saber 11 data.

Socioeconomic Status Index (INSE)

The Socioeconomic Index (INSE) employed by ICFES since 2012 is calculated using Item Response Theory (IRT) methodology, which ensures comparability across assessment periods through a stable measurement scale (ICFES, 2019). Following the capital-based framework proposed by Coleman (1988), the INSE captures three core dimensions of socioeconomic status: parental educational attainment, parental occupation, and household resources measured through ownership of assets and access to services as a proxy for family income (National Center for Education Statistics, 2012). Items selected for the index are validated through Principal Component Analysis to ensure unidimensionality and through psychometric analysis to confirm adequate discrimination properties. For dichotomous items (e.g., ownership of specific goods), a two-parameter logistic model (2PL) is applied, while polytomous items (e.g., parental education levels) are modeled using graded response or nominal response models depending on whether response categories are ordered (DeMars, 2010; ICFES, 2019). To maintain comparability over time, item parameters are anchored across periods through Differential Item Functioning (DIF) analysis, and the resulting latent trait scores are rescaled to a range of 0-100, centered at 50 with a standard deviation of 10, facilitating interpretation and longitudinal analysis of socioeconomic segregation patterns in the Colombian education system.

Figure 2 displays the distribution of average INSE scores across schools, separately for the public and private sectors. Public schools show a concentrated distribution centered around INSE values of 40-45, indicating relatively limited variation in the socioeconomic composition of public institutions. In contrast, private schools exhibit a substantially wider and more dispersed distribution, spanning from approximately 35 to 75 on the INSE scale, with notable concentrations at both moderate (around 50) and higher (around 60) socioeconomic levels. This heterogeneity in the private sector suggests the presence of distinct segments within private education, ranging from institutions serving students with socioeconomic profiles similar to or below the national average to elite institutions serving predominantly high-socioeconomic-status students.

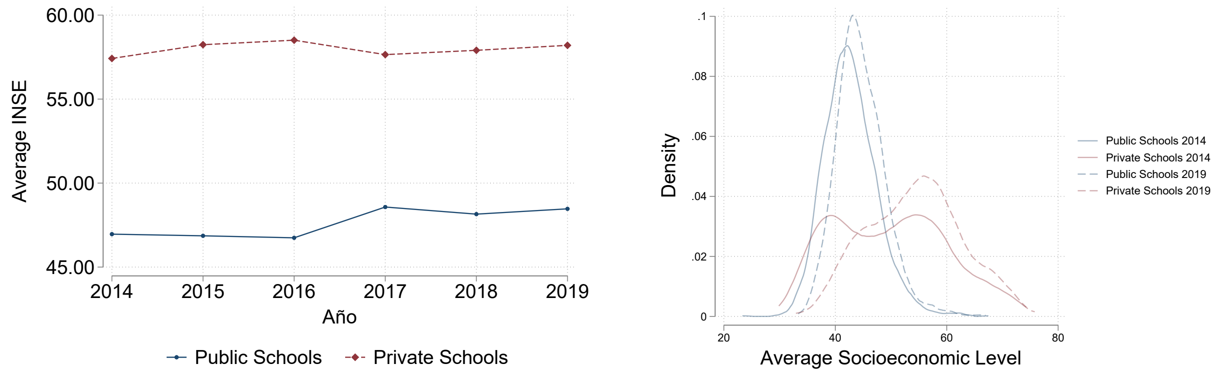
FIGURE 2: Distribution of average socioeconomic level (INSE) by school type



Note: The figure shows the distribution of average INSE scores across schools, differentiated by school type (public vs. private). INSE ranges from 0 to 100, centered at 50 with a standard deviation of 10. Data corresponds to the period 2016-2022. Authors' calculations based on ICFES Saber 11 data.

Figure 3 examines the temporal evolution of socioeconomic patterns across the 2014-2019 period. Panel (a) shows that the average INSE gap between public and private schools remains stable over time, with private schools consistently averaging approximately 57 compared to 47 for public schools. This persistent 10-point gap demonstrates that socioeconomic stratification between sectors is a structural feature of the Colombian education system. Panel (b) presents the kernel density distributions for both sectors in 2014 and 2019. Public schools show stability, maintaining a concentrated distribution around 45-50 in both years. Private schools, however, display a notable shift: the 2014 distribution shows pronounced bi-modality spanning from 35 to 70, while the 2019 distribution exhibits reduced bi-modality with greater concentration at higher INSE values. This pattern suggests that private schools have become more socioeconomically selective over time, with a relative decline in lower-socioeconomic-status students.

Figure 3: Socioeconomic index between public and private schools over time



(a) Evolution of average INSE, 2014-2019

(b) INSE distribution in 2014 and 2019

Note: Panel (a) displays the temporal evolution of average INSE scores for students in public and private schools from 2014 to 2019. Panel (b) shows the kernel density distributions of INSE for both school types in 2014 and 2019. INSE ranges from 0 to 100, centered at 50 with a standard deviation of 10. Authors' calculations based on ICFES Saber 11 data.

Methodology: Segregation Indices

To measure socioeconomic segregation across schools, we employ two complementary methodologies that allow us to decompose total inequality into within-school and between-school components. Both approaches provide consistent measures of segregation, capturing the extent to which students are sorted into schools based on their socioeconomic background.

Variance Decomposition with Random Effects Following the standard approach in the economics of education literature (Hanushek and Wössmann, 2006; Raudenbush and Bryk, 2002; Owens et al., 2016), we use variance decomposition as our benchmark measure of socioeconomic segregation. This method explicitly accounts for the hierarchical structure of students nested within schools through a random-effects model. The model specification is:

$$\text{INSE}_{ij} = \alpha + \beta_1 \text{Year}_t + \beta_2 \text{Official}_j + u_j + e_{ij}$$

where INSE_{ij} is the socioeconomic index of student i in school j, Year_t controls for temporal trends, Official_j is an indicator for public schools, u_j is the school-level random effect capturing unobserved school characteristics, and e_{ij} is the individual-level error term.

Under standard assumptions, $u_j \sim N(0, \sigma_u^2)$ and $e_{ij} \sim N(0, \sigma_e^2)$.

From this model, we compute the intraclass correlation coefficient (ICC):

$$\rho = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2}$$

The ICC provides an intuitive measure of segregation: it represents the proportion of total variance in socioeconomic status that is attributable to differences between schools rather than differences among students within the same school. An ICC close to zero indicates that schools are socioeconomically integrated (most variation occurs within schools), while an ICC close to one indicates strong segregation (most variation occurs between schools). This interpretation makes the ICC particularly useful for communicating the degree of segregation to policymakers and the public. International evidence from PISA assessments shows that highly tracked education systems exhibit ICCs of 50-60%, while comprehensive systems typically display ICCs under 15% (Hanushek and Wössmann, 2011).

Theil Index As a complementary approach, we also calculate the Theil index, an entropy-based measure of inequality that has the desirable property of being additively decomposable (Theil, 1967). This decomposition allows us to separate total socioeconomic inequality into inequality between schools (due to sorting of students across schools) and inequality within schools (due to socioeconomic diversity within each school). The total Theil index is computed as:

$$T = \frac{1}{N} \sum_{i=1}^{N} \frac{\text{INSE}_i}{\overline{\text{INSE}}} \cdot \ln\left(\frac{\text{INSE}_i}{\overline{\text{INSE}}}\right)$$

where N is the total number of students, INSE_i is the socioeconomic index of student i, and $\overline{\text{INSE}}$ is the mean INSE across all students. This total inequality can be decomposed into two components. The between-school component captures inequality arising from differences in average socioeconomic status across schools:

$$T_B = \frac{1}{M} \sum_{j=1}^{M} \frac{P_j}{P_{\text{total}}} \cdot \frac{\overline{\text{INSE}}_j}{\overline{\text{INSE}}} \cdot \ln\left(\frac{\overline{\text{INSE}}_j}{\overline{\text{INSE}}}\right)$$

where M is the number of schools, P_j is the population of school j, and $\overline{\text{INSE}}_j$ is the average INSE in school j. The within-school component captures inequality among students attending the same school:

$$T_W = \frac{1}{N} \sum_{i=1}^{N} \frac{\text{INSE}_{i,j}}{\overline{\text{INSE}}_j} \cdot \ln \left(\frac{\text{INSE}_{i,j}}{\overline{\text{INSE}}_j} \right)$$

By construction, $T = T_B + T_W$. A higher ratio of T_B to T indicates that a larger share of total socioeconomic inequality is attributable to segregation between schools rather than diversity within schools (Reardon and Firebaugh, 2002; Hutchens, 2004). Perfect integration would imply $T_B = 0$, while complete segregation would approach $T_B = T$. The Theil index provides a useful complement to the ICC by offering an alternative decomposition framework that does not rely on distributional assumptions about the random effects.

Results: Segregation Across Schools

Table 1 presents the variance decomposition of socioeconomic status across schools in Colombia. The overall ICC of 0.675 indicates that approximately 68% of total socioeconomic variance occurs between schools rather than within schools. This level exceeds the OECD average of 29% reported in international assessments (Hanushek and Wössmann, 2011), reflecting substantial sorting of students across schools by socioeconomic background.

The analysis reveals important differences between public and private sectors. Private schools exhibit an ICC of 0.639, indicating that nearly two-thirds of socioeconomic variance occurs between institutions, suggesting that these schools tend to serve distinct student populations with limited socioeconomic mixing across institutions. This pattern is consistent with the wide dispersion in average INSE values across private schools shown in Figure 2. Public schools show a lower ICC of 0.428, though this still represents a considerable level of between-school variation. The within-school variance remains relatively stable across sectors ($\sigma_e \approx 6.2$), while the between-school variance component differs substantially ($\sigma_u = 8.330$ for private versus 5.352 for public schools). These patterns indicate that students with different socioeconomic backgrounds tend to attend different schools, with this sorting being more prevalent in the private sector.

Table 1: Variance decomposition of INSE across schools by sector

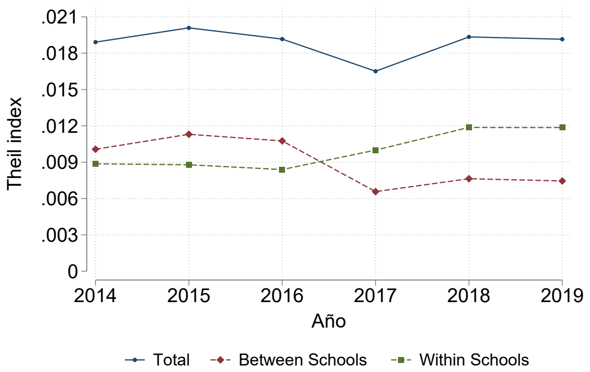
	(1) All Schools	(2) Public Schools	(3) Private Schools
σ_u (Between schools)	8.978	5.352	8.330
σ_e (Within schools)	6.230	6.190	6.256
ρ (ICC)	0.675	0.428	0.639
Observations	3,197,771	2,340,518	857,253

Note: This table presents the variance decomposition from random effects models of INSE at the school level. σ_u represents the between-school variance, σ_e represents the within-school variance, and ρ is the intraclass correlation coefficient (ICC), which indicates the proportion of total variance explained by differences between schools. Higher ICC values indicate greater segregation between schools. Authors' calculations based on ICFES Saber 11 data.

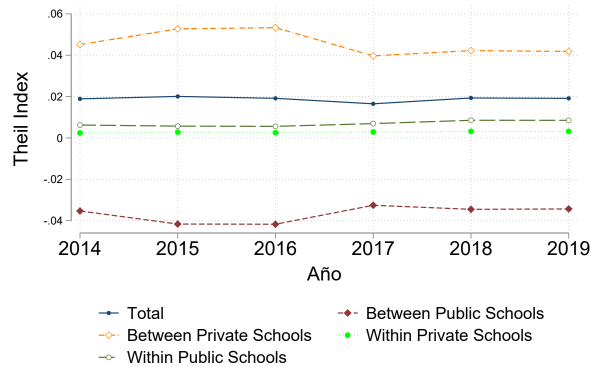
The Theil index decomposition presented in Figure 4 provides complementary evidence on the structure of socioeconomic segregation in Colombian schools. Panel (a) shows that the between-school and within-school components each contribute approximately half of the total socioeconomic inequality during the 2014-2019 period, indicating that segregation occurs both through sorting of students across schools and through socioeconomic diversity within individual schools. The total Theil index remains relatively stable over time, though this stability partly reflects the standardized scaling of the INSE measure (rescaled to a mean of 50 and standard deviation of 10 in each period), which mechanically limits temporal variation in inequality measures.

Panel (b) reveals important sectoral differences when decomposing the index into four components. The between-private-schools component (orange line) represents the largest positive contributor to total inequality, indicating substantial socioeconomic differentiation across private institutions. The between-public-schools component (blue line) shows a smaller positive contribution, while the within-private-schools component (green line) remains relatively stable. Notably, the within-public-schools component (red line) displays negative values, reflecting that public school students have, on average, lower socioeconomic status than the overall mean; because the Theil formula uses logarithmic ratios relative to this mean, groups with below-average values contribute negatively to the decomposition. These patterns confirm the findings from the variance decomposition analysis: socioeconomic sorting between schools accounts for a substantial portion of total inequality, with particularly pronounced stratification in the private sector.

FIGURE 4: Theil index decomposition of socioeconomic inequality, 2016-2022



(A) Three-component decomposition

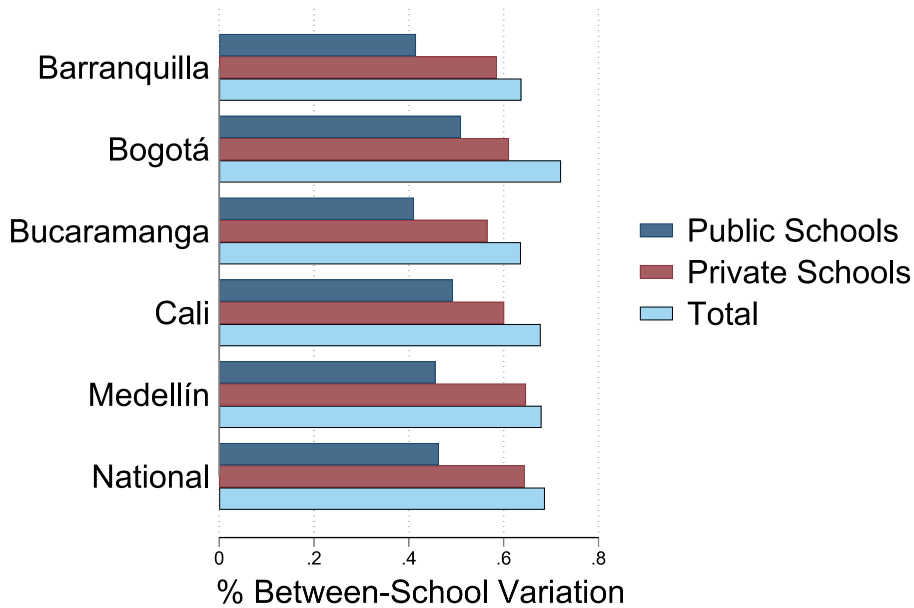


(B) Four-component decomposition by sector

Note: Panel (a) shows the decomposition of the total Theil index into between-school and within-school components over time. Panel (b) presents a four-component decomposition that separates between-school and within-school variance for public and private schools separately. The vertical axis represents the Theil index value, and the horizontal axis shows years from 2016 to 2022. Authors' calculations based on ICFES Saber 11 data.

Variation Across Cities Figure 5 presents the average ICC values across major Colombian cities, revealing consistent patterns of socioeconomic segregation throughout the country. All cities display substantial ICC values above 0.6, indicating that over 60% of socioeconomic variance occurs between schools rather than within them. In every city, private schools exhibit higher ICC values than public schools, confirming that socioeconomic stratification is more pronounced in the private sector. This consistency across diverse urban contexts suggests that segregation reflects systemic features of the Colombian education system rather than city-specific factors, pointing to a nationwide phenomenon that warrants policy attention at the national level. The temporal evolution of these patterns across cities is presented in Appendix Figure A.1, which shows that these patterns remain stable over the 2016-2022 period.

FIGURE 5: Average intraclass correlation coefficient (ICC) by school sector across cities

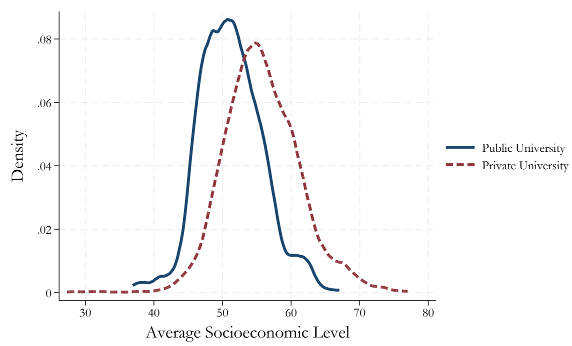


Note: The figure displays the average ICC values for public schools, private schools, and total, for different cities, and the overall national average. Each horizontal bar represents the proportion of total socioeconomic variance explained by differences between schools. Authors' calculations based on ICFES Saber 11 data.

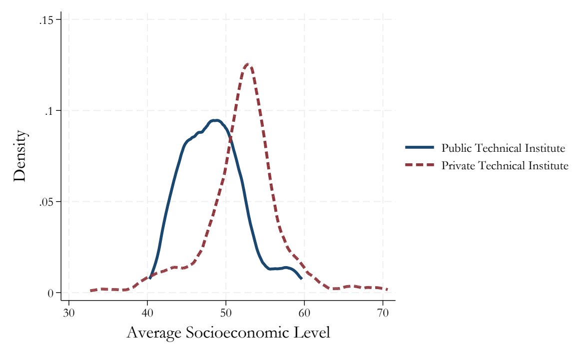
2.2.2 Segregation in Higher Education

Figure 6 displays the distribution of average INSE across higher education institutions by type and sector. Both public universities and public technical institutions show similar average INSE values centered around 50-52, while their private counterparts average approximately 55-57, representing a socioeconomic gap of 5-7 points between sectors. This gap is notably smaller than the 10-point difference observed between public and private secondary schools. The distributions reveal considerably less dispersion in higher education compared to secondary education. Public institutions in both categories show concentrated, unimodal distributions with limited spread, while private institutions display somewhat wider distributions but without the pronounced bi-modality or extended tails observed in private secondary schools. The similarity in INSE distributions between universities and technical institutions, particularly within each sector, suggests that institutional level (university vs. technical) is less determinative of socioeconomic composition than sector (public vs. private). Overall, these patterns indicate that while socioeconomic stratification persists in higher education, it is substantially attenuated compared to the pronounced segregation documented at the secondary level.

FIGURE 6: Distribution of average INSE by higher education institution type and sector



(A) Universities



(B) Technical institutions

Note: Panel (a) shows the kernel density distribution of average INSE for public and private universities. Panel (b) displays the distribution for public and private technical and technological institutions. INSE ranges from 0 to 100, centered at 50 with a standard deviation of 10. Authors' calculations based on ICFES-SNIES data (2014-2024).

Results: Segregation Across Higher Education Institutions

Table 2 presents the variance decomposition of socioeconomic status across higher education institutions in Colombia. The overall ICC of 0.257 indicates substantially lower segregation compared to secondary education, with approximately one-quarter of socioeconomic variance occurring between institutions rather than within them. Unlike the pronounced sectoral differences observed in secondary schools, public and private institutions show modest ICC differences in both universities and technical institutions, with within-institution variance consistently dominating between-institution variance across all categories. This pattern, consistent with the overlapping distributions shown in Figure 6, indicates that while socioeconomic sorting persists in higher education, it operates at considerably lower intensity than in secondary schools, with institutional diversity being the primary source of socioeconomic variation.

Table 2: Variance decomposition of INSE by institution type

	(1) All	(2) Public University	(3) Private University	(4) Public Technical	(5) Private Technical
σ_u (Between institutions)	4.855	3.972	4.334	3.300	4.451
σ_e (Within institutions)	8.252	8.137	8.448	7.304	7.414
ρ (ICC)	0.257	0.192	0.208	0.170	0.265
Observations	1,333,044	541,330	698,239	45,541	47,934

Note: This table presents the variance decomposition from random effects models of INSE at the higher education level. σ_u represents the between-institution variance, σ_e represents the within-institution variance, and ρ is the intraclass correlation coefficient (ICC), which indicates the proportion of total variance explained by differences between institutions. Authors' calculations based on ICFES-SNIES data (2014-2024).

3 Social Skills and Social Mobility

3.1 Social skills requirements and Colombian academic programs

To characterize the skill content of Colombian higher-education programs, we link detailed occupational skill measures from ONET to academic majors observed in SNIES using a multi-step crosswalk that harmonizes international education and occupation taxonomies. The target academic classification is UNESCO's CINE-F (ISCED-F), which is the reference field-of-study system used to categorize Colombian programs in SNIES. Because ONET is organized around U.S. occupations, we rely on occupational and instructional-program bridges that allow us to translate between education fields and occupations in a consistent and replicable way.

Our integration uses five classification systems and two administrative sources. First, we use SNIES to identify Colombian programs and to assign each program a CINE-F code at the appropriate level of aggregation (e.g., 2-digit broad fields and 4-digit detailed fields). Second, we employ an education crosswalk from CINE-F to the Canadian 2016 Classification of Instructional Programs (CIP), which provides a standardized intermediate representation of majors that is widely used in North American education datasets. Third, we map CIP codes to U.S. Standard Occupational Classification (SOC) codes using existing CIP–SOC linkages. Finally, we connect SOC occupations to O*NET, which provides harmonized measures of tasks and skills for each occupation.

Because the SOC system undergoes periodic revisions, we incorporate an explicit correspondence between SOC 2018 and SOC 2019 to ensure compatibility between the CIP–SOC linkage and the SOC version used in our ONET extract. This step reduces mechanical mismatches that can arise from changes in occupation definitions or code splits/merges across SOC vintages. The result is a single integrated crosswalk—CINE → CIP → SOC → ONET—that yields, for each Colombian CINE field, a set of linked occupations and their associated O*NET skill measures.

Using the integrated crosswalk, we assign to each CINE-coded program a vector of occupational skill requirements derived from O*NET. The central idea is that an academic program can be characterized by the occupational bundle it prepares students for, and therefore by the skills those occupations require. For each skill dimension, we aggregate across the set of linked occupations to obtain a program-level measure, and we report results at the 4-digit CINE level.

To characterize the social-skill content of academic programs, we rely on a broad set of occupational descriptors from O*NET that capture interpersonal interaction, coordination, communication, persuasion, and conflict resolution. Consistent with Deming (2017a), we treat social skills as a multidimensional construct rather than isolating a single task or role (e.g., leadership). Specifically, we draw on O*NET measures related to developing and building teams, communication with individuals outside the organization, communication with supervisors, peers, and subordinates, coordinating the work and activities of others, establishing and maintaining interpersonal relationships, resolving conflicts and negotiating, and selling or influencing others.

For each of these underlying dimensions, we summarize the distribution of occupational requirements using multiple moments and percentiles—including the mean as well as the 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentiles—computed across the occupations linked to a given CINE field. This approach allows us to capture not only average skill intensity but also heterogeneity within fields, reflecting the fact that graduates from the same academic program may sort into occupations with varying degrees of social interaction and coordination demands.

We aggregate the full set of social-skill moments using principal component analysis

(PCA) to construct a single summary index of social-skill intensity at the academic-field level. The PCA is estimated using all percentile-based and mean measures across the selected O*NET social-skill descriptors, and the first principal component is retained as our baseline social-skill score. This component captures the common variation across interpersonal, coordination, communication, and influence-related tasks and closely aligns with the concept of "social skills" emphasized in Deming (2017a).

The resulting index is standardized to have mean zero and unit variance and is assigned at the CINE field level. To facilitate interpretation and comparisons across programs, we additionally construct percentile ranks and discrete quartiles of the social-skill distribution. These alternative representations allow us to present results using both continuous measures (e.g., regressions) and categorical groupings (e.g., low- vs. high-social-skill fields).

Our construction uses O*NET measures that reflect the intensity of occupational requirements rather than individual-level skill endowments. As such, the social-skill index should be interpreted as capturing the skill demands of the occupations associated with each academic field, not the skills directly taught or acquired within programs. By incorporating multiple percentiles rather than relying solely on mean values, the index is less sensitive to outlier occupations and better reflects the range of potential labor-market trajectories linked to each field of study.

Because the social-skill measures are derived through a multi-step mapping from CINE to O*NET, we implement systematic coverage and merge diagnostics at each stage. These diagnostics document the share of academic fields with valid occupational links, identify fields where mappings are sparse or highly dispersed, and allow us to define robustness samples that restrict attention to CINE fields with reliable occupational coverage. All main results are robust to excluding fields with limited or low-quality mappings.

Using the program-level social-skill index, we rank Colombian academic fields according to their overall social-skill intensity and examine the distribution of scores across CINE 4-digit classifications. We report top and bottom segments of the distribution as well as quartile-based groupings to highlight systematic differences across fields. This descriptive analysis reveals substantial heterogeneity in social-skill demands across majors, with some broad areas consistently associated with higher interpersonal, coordination, and communication requirements, while others are characterized by lower social-skill intensity and greater emphasis on routine or task-specific work.

Tables 3.a and 3.B report the PCA-based social skill index for all academic majors, together with mean values of the underlying O*NET social-skill components. Majors in management and administration, education, psychology, law, and architecture rank highest in social-skill intensity, reflecting strong requirements in communication with supervisors and external actors, interpersonal relations, coordination of work, and conflict resolution. In contrast, majors in engineering, natural sciences, mathematics, information technologies, and agriculture are characterized by substantially lower social-skill scores and lower mean values across most interpersonal dimensions. These patterns reveal large and systematic heterogeneity in social-skill demands across fields of study, even within broadly defined disciplinary groups, underscoring the importance of occupation-based measures for characterizing academic programs.

Table 3.a: Social score (PCA) and Mean O*NET Social-Skill Components by Major

Major	Social score (PCA)	Build teams	Comm. outside	Comm. supervisors	Coord. work	Interpersonal	Conflict res.	Selling
Management and Administration	1.697	3.922	4.655	5.214	4.411	5.293	4.650	3.304
Education Sciences	1.583	4.078	4.919	5.311	4.233	5.243	4.190	3.377
Social and Behavioral Sciences (n.e.c.)	1.533	3.903	4.900	5.268	4.601	5.292	4.536	3.160
Psychology	1.489	3.716	4.909	5.277	4.336	5.408	4.596	3.013
Architecture and Urban Planning	1.449	3.890	4.931	5.015	4.624	5.123	4.421	3.446
Sociology, Anthropology, and Cultural Studies	1.422	3.853	4.911	5.241	4.518	5.289	4.639	2.920
Health (n.e.c.)	1.381	3.806	4.900	5.199	4.438	5.176	4.477	3.190
Marketing and Advertising	1.356	3.507	4.739	5.026	4.044	5.059	4.259	4.239
Political Science and Civic Education	1.319	3.758	4.862	5.190	4.392	5.219	4.605	3.056
Journalism and Information	1.311	3.744	4.873	5.203	4.406	5.249	4.559	3.042
Industrial, Fashion, and Interior Design	1.253	3.790	4.845	4.963	4.559	5.047	4.302	3.613
Economics	1.203	3.721	4.703	5.059	4.242	5.078	4.317	3.438
Statistics	1.184	3.709	4.650	5.019	4.380	5.019	4.250	3.226
Pharmacy	1.159	3.740	4.727	5.110	4.280	5.140	4.250	3.130
Religion and Theology	1.156	3.821	4.706	4.952	4.453	5.073	4.451	2.814
Library, Information, and Archival Studies	1.129	3.683	4.735	5.059	4.265	5.138	4.279	3.043
Environmental Protection Technology	1.104	3.635	4.738	5.065	4.247	5.101	4.282	3.020
Arts and Humanities	1.053	3.729	4.616	4.900	4.345	4.974	4.223	2.954
Nursing and Midwifery	1.016	3.776	4.657	4.979	4.231	5.126	4.081	2.683
Journalism, Communication, and Reporting	0.996	3.575	4.755	5.002	4.111	5.045	4.224	3.295
Wholesale and Retail Sales	0.947	3.473	4.608	4.941	4.017	5.004	4.109	4.124
Agricultural and Livestock Production	0.892	3.563	4.519	4.871	4.061	4.905	4.046	3.011
Computer Use	0.864	3.414	4.589	4.892	4.022	4.911	4.016	3.039
Forestry	0.830	3.512	4.465	4.820	4.018	4.849	3.981	2.858
Law	0.826	3.678	4.781	5.109	4.291	5.184	4.879	3.723
Medicine	0.816	3.720	4.607	4.950	4.187	5.090	4.017	2.629
Veterinary Medicine	0.781	3.621	4.510	4.822	4.066	4.901	3.954	2.808
Financial Management, Banking, and Insurance	0.767	3.466	4.515	4.891	3.998	4.955	4.075	3.810
Music and Performing Arts	0.755	3.624	4.444	4.761	4.154	4.822	4.036	2.788
Biochemistry	0.734	3.563	4.453	4.815	4.055	4.851	3.972	2.694
Network and Database Design and Administration	0.709	3.310	4.488	4.762	4.003	4.788	3.862	2.831
Hotels, Restaurants, and Catering	0.692	3.375	4.560	4.865	3.972	4.930	4.041	3.896
Physics	0.677	3.521	4.376	4.738	4.019	4.774	3.860	2.545
Fine Arts	0.664	3.560	4.346	4.704	4.001	4.742	3.875	2.612
Biology	0.642	3.471	4.401	4.744	3.978	4.792	3.885	2.620

Notes: This table reports, by academic major, a composite index of social-skill intensity and the mean values of its underlying components. The social score corresponds to the standardized first principal component of O*NET measures capturing communication, coordination, interpersonal interaction, persuasion, and conflict resolution. Occupational measures are linked to majors using a CINE–CIP–SOC–O*NET crosswalk and aggregated at the major level. Higher values indicate majors associated with occupations requiring greater social skills.

Table 3.B: Social score (PCA) and Mean O*NET Social-Skill Components by Major

Major	Social score (PCA)	Build teams	Comm. outside	Comm. supervisors	Coord. work	Interpersonal	Conflict res.	Selling
Construction and Civil Engineering	0.615	3.395	4.389	4.712	3.990	4.753	3.821	2.702
Audiovisual Techniques and Media Production	0.590	3.402	4.454	4.770	3.962	4.835	3.854	2.985
Philosophy and Ethics	0.571	3.491	4.315	4.625	3.998	4.694	3.857	2.451
Accounting and Taxation	0.545	3.255	4.315	4.662	3.889	4.704	3.806	3.058
Mathematics	0.514	3.336	4.254	4.591	3.871	4.665	3.746	2.393
Teacher Training (with Subject Specialization)	0.491	3.539	4.497	4.816	3.887	4.888	3.724	2.800
Chemistry	0.454	3.310	4.244	4.570	3.842	4.625	3.692	2.351
Electronics and Automation	0.421	3.189	4.247	4.580	3.829	4.641	3.662	2.449
Agriculture (n.e.c.)	0.401	3.242	4.210	4.547	3.812	4.612	3.643	2.392
Software and Application Development and Analysis	0.375	3.101	4.239	4.559	3.790	4.631	3.602	2.401
Physiotherapy and Speech Therapy, Occupational Therapy	0.362	3.222	4.327	4.641	3.821	4.741	3.632	2.274
Teacher Training (without Subject Specialization)	0.338	3.412	4.399	4.704	3.801	4.812	3.542	2.628
Literature and Linguistics	0.324	3.395	4.305	4.626	3.807	4.734	3.575	2.392
Mining and Extraction	0.312	3.098	4.128	4.477	3.780	4.561	3.631	2.530
Sports	0.297	3.244	4.284	4.617	3.782	4.718	3.503	2.460
Electricity and Energy	0.279	3.110	4.162	4.512	3.756	4.609	3.521	2.488
Engineering (General)	0.262	3.010	3.980	4.210	3.690	4.180	3.410	2.510
Natural Sciences (General)	0.246	2.910	3.760	4.050	3.550	4.020	3.280	2.360
Mathematics and Statistics (General)	0.233	2.780	3.620	3.940	3.420	3.890	3.110	2.220
Information and Communication Technologies (General)	0.221	2.650	3.510	3.820	3.330	3.760	2.940	2.180
Health Sciences (General)	0.205	2.490	3.440	3.710	3.190	3.620	2.880	2.050
Agriculture and Veterinary Sciences (General)	0.190	2.330	3.280	3.540	3.010	3.410	2.690	1.980
Services (General)	0.178	2.210	3.110	3.380	2.890	3.270	2.550	1.840
Fishing	-1.906	2.180	3.040	3.300	2.820	3.190	2.480	1.790
Language Acquisition	-2.066	2.100	2.980	3.220	2.750	3.120	2.420	1.720
Physical Sciences (n.e.c.)	-2.111	2.060	2.940	3.180	2.720	3.080	2.390	1.690
Mechanics and Metalworking Trades	-2.243	1.990	2.880	3.120	2.660	3.020	2.340	1.640
Languages (n.e.c.)	-2.294	1.950	2.840	3.080	2.620	2.990	2.310	1.610

Notes: This table reports, by academic major, a composite index of social-skill intensity and the mean values of its underlying components. The social score corresponds to the standardized first principal component of O*NET measures capturing communication, coordination, interpersonal interaction, persuasion, and conflict resolution. Occupational measures are linked to majors using a CINE–CIP–SOC–O*NET crosswalk and aggregated at the major level. Higher values indicate majors associated with occupations requiring greater social skills.

3.2 Linking social skills to social mobility

3.2.1 Empirical Strategy

To study how the social-skill content of academic majors relates to social mobility, we combine program-level measures of social-skill intensity with individual-level data on students' socioeconomic background and labor market outcomes. Social mobility is measured as the relationship between students' socioeconomic rank at the end of high school and their labor income rank observed approximately eight years after high school graduation. Socioeconomic rank is constructed from administrative records, while labor income rank is defined within cohort and academic-field cells to ensure comparability across time and programs.

Our baseline specification follows the inter-generational mobility literature (Chetty et al., 2014) allows the degree of inter-generational persistence to vary with the social-skill intensity of the academic major. We estimate the following equation:

$$\mathrm{Rank}^{\mathrm{inc}}_{i,f,c} = \alpha + \beta\,\mathrm{Rank}^{\mathrm{HS}}_{i} + \gamma\,\mathrm{SocialSkill}_f + \delta\left(\mathrm{Rank}^{\mathrm{HS}}_{i} \times \mathrm{SocialSkill}_f\right) + \mu_{f\times c} + \varepsilon_{i,f,c}, \quad (1)$$

where $\mathrm{Rank}^{\mathrm{inc}}_{i,f,c}$ denotes the labor income rank of individual i from academic field f and cohort c, measured approximately eight years after high school graduation, and $\mathrm{Rank}^{\mathrm{HS}}_{i}$ is the individual's socioeconomic rank at the end of high school. $\mathrm{SocialSkill}_f$ is the PCA-based social-skill index associated with academic major f. The term $\mu_{f\times c}$ represents academic-field-by-cohort fixed effects, which absorb time-invariant differences across fields and cohort-specific shocks. Standard errors are computed robustly.

The coefficient β captures the average degree of income persistence across majors, while δ measures how this persistence varies with the social-skill intensity of the major. A positive value of δ implies that socioeconomic background is a stronger predictor of adult outcomes in majors associated with higher social-skill demands, and therefore there is less social mobility for these fields.

To assess robustness, we estimate alternative versions of equation (1) using different parameterizations of social skills. First, we replace the continuous social-skill index with its percentile rank $Q(\mathrm{SocialSkill}_f)$:

$$\text{Rank}^{\text{inc}}_{i,f,c} = \alpha + \beta \, \text{Rank}^{\text{HS}}_i + \gamma \, Q(\text{SocialSkill}_f) + \delta \left(\text{Rank}^{\text{HS}}_i \times Q(\text{SocialSkill}_f) \right) + \mu_{f \times c} + \varepsilon_{i,f,c}. \quad (2)$$

Second, we discretize majors into quartiles based on the social-skill index and estimate a fully interacted specification:

$$\text{Rank}^{\text{inc}}_{i,f,c} = \alpha + \beta \, \text{Rank}^{\text{HS}}_i + \sum_{q=2}^{4} \delta_q \left(\text{Rank}^{\text{HS}}_i \times \mathbb{1} \{ \text{SocialSkill}_f \in q \} \right) + \mu_{f \times c} + \varepsilon_{i,f,c}, \qquad (3)$$

where the first quartile of the social-skill distribution serves as the omitted category. This specification allows the slope of intergenerational persistence to vary flexibly across social-skill groups.

In addition to the regression-based approach, we present nonparametric evidence using local polynomial regressions. For each social-skill quartile q, we estimate:

$$\mathbb{E} \left[\text{Rank}^{\text{inc}}_{i,f,c} \;\middle|\; \text{Rank}^{\text{HS}}_i, \; \text{SocialSkill}_f \in q \right] = g_q \left(\text{Rank}^{\text{HS}}_i \right), \qquad q = 1, 2, 3, 4, \qquad (4)$$

where $g_q(\cdot)$ is estimated using local polynomial smoothing. This approach imposes minimal functional-form assumptions and allows both the shape and slope of the mobility relationship to differ across social-skill groups.

Finally, we replicate the main specifications using alternative definitions of labor income rank that assign zero ranks to individuals without formal earnings records and include controls for standardized test scores at the end of secondary school. Across all specifications, the interaction between socioeconomic rank and social-skill intensity remains positive and statistically significant.

3.2.2 Results

We begin by quantifying the relationship between the requirements for social skills and social mobility. Table 4 reports estimates of equations (1) and (2), separately for individuals observed in formal employment and for the full sample.

Across all specifications, high school socioeconomic rank is a strong and precisely estimated predictor of labor income rank eight years after high school graduation. The estimated coefficients on high school rank range from 0.10 to 0.18, indicating substantial persistence in earnings outcomes compared to the socioeconomic score at high school graduation.

More importantly, the interaction between high school socioeconomic rank and the social-skill content of the academic major is positive and statistically significant in all specifications. In column (1), which uses the continuous social-skill index and restricts attention to employed individuals, the interaction coefficient implies that the relationship between parental background and adult income rank becomes steeper as the social-skill intensity of the major increases. Columns (2) and (4), which instead use the percentile rank of the social-skill index, yield qualitatively similar results, confirming that the findings are not sensitive to the scale or parameterization of the social-skill measure.

The magnitude of the interaction effects is economically meaningful. Moving from a low–social-skill major to a high–social-skill major substantially increases the sensitivity of adult income rank to initial socioeconomic position. This pattern holds both when focusing on individuals with observed labor income and when expanding the sample to include all individuals, assigning zero ranks to those without formal earnings. Taken together, the regression results provide strong evidence that majors associated with higher social-skill requirements exhibit lower social mobility.

We next examine the relationship between socioeconomic background and adult labor income rank using a flexible, nonparametric approach. Figure 7 plots local polynomial estimates of equation (4), separately by quartiles of the social-skill index.

The figure reveals systematic differences in mobility patterns across social-skill groups. For majors in the lowest quartile of social-skill intensity, the relationship between high school socioeconomic rank and adult labor income rank is relatively flat, indicating greater mobility. In contrast, for majors in the highest quartile of social-skill intensity, the slope of the mobility curve is substantially steeper, reflecting stronger intergenerational persistence.

These differences are particularly pronounced at the top and bottom of the socioeconomic distribution. Students from disadvantaged backgrounds who enroll in high–social-skill majors experience more limited upward mobility, while students from advantaged backgrounds achieve disproportionately higher income ranks. As a result, income rank gaps between high- and low-background students widen in majors associated with greater social-skill demands.

Table 4: Social Mobility and Social Skills Requirements

	Employed		All sample	
	(1)	(2)	(3)	(4)
hs rank	0.143***	0.101***	0.176***	0.134***
	(0.002)	(0.005)	(0.002)	(0.005)
hs rank × social skills index	0.027***	0.009***	0.027***	0.009***
	(0.002)	(0.001)	(0.002)	(0.001)
Cont. measure	Yes	No	Yes	No
Major perc.	No	Yes	No	Yes
N	272,233	272,233	408,097	408,097

Notes: This table reports estimates of equations (1) and (2). The dependent variable is labor income rank measured approximately eight years after high school graduation. High school rank denotes students' socioeconomic rank at the end of secondary school. Social skills are measured using a PCA-based index constructed from O*NET occupational descriptors and assigned at the academic-major level. Columns labeled "Employed" restrict the sample to individuals with observed labor income, while columns labeled "All sample" include all individuals, assigning zero ranks to those without formal earnings. All specifications include academic-field-by-cohort fixed effects. Robust standard errors are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

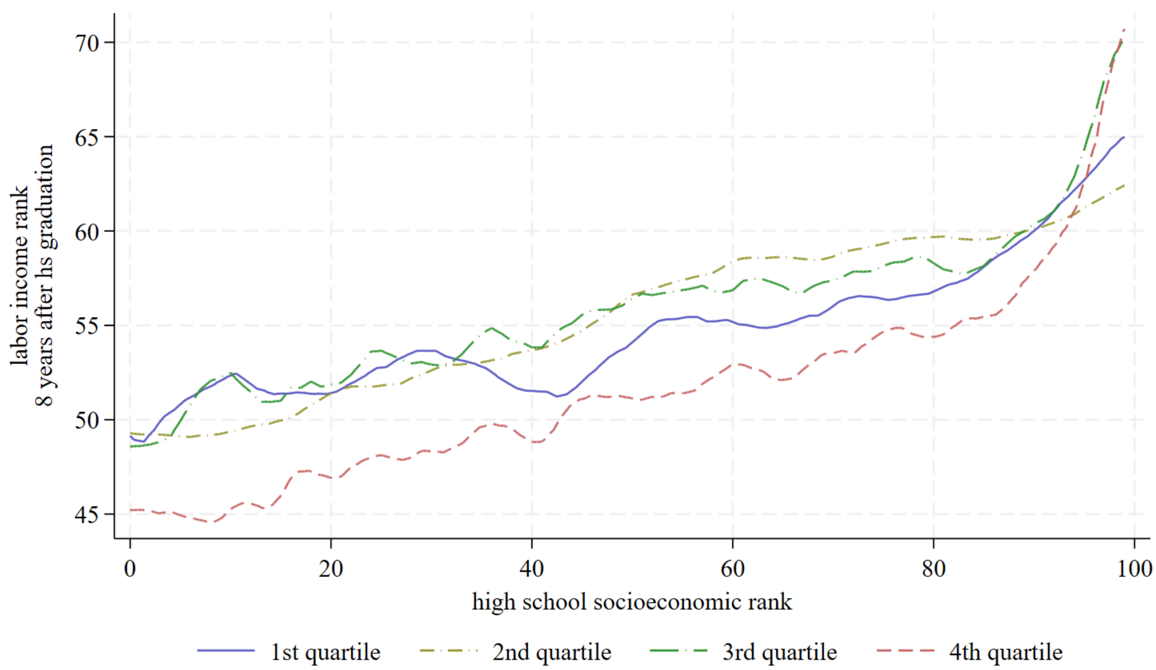
Overall, the nonparametric evidence reinforces the regression results by showing that the lower mobility associated with high–social-skill majors is not driven by functional-form assumptions. Instead, the relationship between background and outcomes is consistently steeper across the distribution for majors linked to occupations emphasizing communication, coordination, and interpersonal interaction.

Taken together, the evidence from Table 4 and Figure 7 indicates that majors associated with occupations requiring higher levels of social skills exhibit lower intergenerational mobility. While social skills are highly rewarded in the labor market, access to the occupations that value them appears to depend more strongly on pre-existing socioeconomic advantages.

4 Experimental Evidence

Recent empirical evidence shows the growing importance of social skills in the labor market. In 2019, teamwork was deemed "very" or"extremely" important in 78% of jobs in the US. Likewise, occupations requiring high levels of social skills have increased as a share of the US labor force in the last four decades (Deming, 2017b), and these are becoming more complementary to cognitive skills (Weinberger, 2014). This evidence is not exclusive to the

FIGURE 7: Non-parametric Regressions of Social Mobility



Notes: The figure plots local polynomial estimates of equation (4), showing labor income rank eight years after high school graduation as a function of high school socioeconomic rank. Estimates are shown separately by quartiles of the academic major's social-skill index, constructed from O*NET occupational data. Each curve represents a nonparametric fit within a social-skill quartile and is estimated using local polynomial smoothing.

US, as it is also a phenomenon in low- and middle-income countries. For example, (Novella et al., 2019) find that employers list teamwork, communication, and leadership among the scarcest skills in the workforce in Peru.

Despite the increasing importance of social skills in the labor market, educational assessment tools have lagged behind. Most current evaluation instruments prioritize conventional competencies like quantitative and verbal reasoning, leaving a conspicuous void in assessing crucial non-cognitive skills. While there have been attempts to innovate in this arena, many of these innovations rely on self-reported data, introducing a measure of uncertainty due to potential social desirability bias and misperception.

This section explores the relationship between team interactions and social mobility in Latin America. While the existing economic literature highlights the potential role of higher-education to increase social mobility (Restuccia and Urrutia, 2004; Chetty et al., 2020), recent empirical evidence from Chile (Zimmerman, 2019) and the US (Michelman et al., 2021) casts doubts on whether access to higher education, even to elite colleges, can increase social mobility. In particular, only students from more advantaged backgrounds benefit from attending elite colleges. Existing evidence documents that low-income students, even those who manage to graduate from university, do not access leadership positions or to the top percentiles of the income distribution. Furthermore, only male students graduating from elite high schools benefit from enrolling at elite universities (Zimmerman, 2019).

One potential explanation for this phenomenon is the relationships built between peers with similar socioeconomic characteristics and their interactions when they work in teams. There is evidence in other contexts showing that having bosses with similar characteristics to your own improves job promotions (Cullen and Perez-Truglia, 2019) and that peers of the same ethnicity (Hjort, 2014) or caste (Lowe, 2021) have higher team productivity.

These differences in team productivity may be due to two factors with different policy implications for promoting social mobility. On the one hand, it may be because people are more productive with leaders or teammates similar to them. On the other hand, it may be because of biases in the perception of the abilities of coworkers with whom they do not share similar characteristics. Differentiating between these two mechanisms is difficult as it requires a context that can generate sufficient diversity in the formation of groups and tools that allow hiding or revealing information about the characteristics of leaders or teammates to understand the impact on team interactions.

Our study aims to understand to what extent team interactions when individuals work in groups can explain these findings. In particular, we test whether individuals are more or less productive working in teams with people of a similar socioeconomic background. Furthermore, our experimental design aims to separately identify the differences in productivity that come from cultural and communication differences and the ones related to prejudice and discrimination. In particular, by randomly hiding or revealing information that signal the income level of teammates, we are able to differentiate between underlying productivity differences in teamwork of individuals from different income levels from differences that emerge when such information is available.

We conducted a laboratory experiment with undergraduate students at an elite Colombian university with socioeconomic diversity in its student body. There are two levels of randomization. The first level is at the individual level and corresponds to whether the participant is assigned to an income-segregated team, only composed of high- or low-income individuals, or to a mixed team, where half of the participants come from a low-income background and half from a high-income background. The second level of randomization is at the team level and corresponds to the information participants learn about their team members. The design considers three treatment arms: one in which all the tasks are completed anonymously, one in which the graduating high school is revealed, and one in which the identity (names) of the participants is revealed.

High school is an important signal of income as most education systems in Latin America are highly segregated, and high school is an important income background signal and predictor of success (García Villegas et al., 2021; Zimmerman, 2019). While names can also signal income background (Bertrand and Mullainathan, 2004), they may also signal other characteristics as students are in the same course. Yet, understanding whether revealing names has a differential effect depending on the income background of a participant can shed some light on the relationship between team interactions and social mobility.

The results from this study reveal that Low-income participants receive a lower leadership recognition in mixed-income teams compared to income-segregated teams, but that gap emerges as more information that signals income is revealed to the participants. In particular, the gap is higher when the participants' high school is revealed to other team members and is even higher when names (identities) are revealed to them. Interestingly, that gap emerges both for peer nominations as well as for self-nominations to the top leadership position in the team. Such effects are not aligned with performance. Still, they are consistent with the effects on the perception of low-income participants on the quality of teamwork, communication, and their contributions to the team.

The rest of the section is organized as follows. Section 4.1 presents the experimental design to assess teamwork and leadership skills. Section 4.2 reports the results of a lab experiment we run to explore how teamwork can affect social mobility in Latin America. Finally, Section 4.3 concludes.

4.1 Design

Play Together[1] is a virtual platform designed to measure teamwork and leadership skills. Using this tool, a total of 604 undergraduate students (389 participants recruited through the Universidad de Los Andes Mobile Experimental Lab (Greiner, 2015) and 215 first-year undergraduates from economics) were invited to complete a battery of psychological instruments and collaboration tasks with other individuals.

To ensure the reliability and validity of measurement of teamwork and leadership skills, subjects face performance tests aligned with standardized exams in Latin America (such as Saber 11 and Saber Pro in Colombia) to study how participants collaborate when solving them as teams. These tests cover various subjects, including math and reading comprehension. While previous research has employed some of these tasks to assess individual abilities, our methodology aligns with studies that investigate contributions within a team dynamic beyond individual abilities (Weidmann and Deming, 2020).

Participants face two different stages on the platform. First, participants register with their basic information and solve some of the tasks individually, allowing us to measure individual abilities. In the second stage, participants solve the tasks in teams. Team members need to agree on their answers to proceed on the platform.

During this group stage, participants can communicate with their teammates via chats. The interaction space in both tools is limited to chats for three reasons. First, using chats

[1] This video shows the platform at the different stages of the games, and the interactions space between participants.

to study group dynamics has been validated in other contexts, such as the PISA assessment of collaborative problem-solving abilities (OECD, 2017). Second, an additional advantage of using chats is that it allows the research team to control what information is revealed to the participants in the game about their teammates' characteristics. Third, it reduces the costs of developing these tools as including video interactions is too expensive.

The individual and group phases of the experiment took place during the same session, and we provided as incentives based on performance in their individual or team tasks. For subjects recruited through Uniandes ME-Lab the incentive is monetary (ranging from $\$18,000$ to $\$63,000$ COP) while the incentive in the lab-in-the-field experiment is a higher score in the final grade of an introductory course to economics. The input of the final incentive is randomly chosen between the participant's performance in the individual or the team phase of the experiment.

4.1.1 Treatments

We implement two different types of random variation when participants solve the tasks in teams:

1. Team composition: Based on the demographic characteristics of the participants we computed an income composite index and randomly vary the socieconomic composition of the team. To characterize students as low- or high-income, participants answered a survey where we collected different sociodemographic information, including the characteristics of their graduating high school, their parents' education level, and the socioeconomic level (or estrato) of the Colombian system classification of residential properties used to determine subsidies to pay for utilities. We used such information to construct a socioeconomic index and used the index's median to classify participants into high- and low-income groups. While for some teams, all members have either a low income index or a high income (i.e. *segregated group*), other participants are assigned to an income-mixed team (i.e. *mixed group*).

2. Information participants learn about team members: In general, in-person assessments cannot differentiate biases from other factors that could explain how team composition affects performance (for example, students might communicate better with other same-

major studetns when working in teams). To differentiate between biases and other factors that could explain team composition effects on performance, we follow a standard procedure to measure discrimination in experiments (Bertrand and Duflo, 2017): varying the information that participants learn about their team members. The platform is flexible enough to reveal or hide any information about participants: the most extreme case we implement is a completely anonymous interaction, where participants are only tagged as Player 1, Player 2, etc. (*blind group*), versus a case where participants' identities (*names revealed group*) are revealed. As documented by previous empirical evidence (Zimmerman, 2019; García Villegas et al., 2021), high school is an important signal of income in Latin America. Likewise, there is wide evidence documenting that name-revealing can benefit certain individuals due to race (Bertrand and Mullainathan, 2004) or immigration status (Oreopoulos, 2011), with similar phenomena pertaining to income.[2].

4.1.2 Outcomes

The primary outcomes are performance measures and participants' perceptions of teammates' skills in the games. Moreover, the platform also collects all the chats, allowing the research team to study how team interactions respond to team composition, information, and leadership assignments.

The platform collects data on performance across all the different available tasks. At the end of the team session, the platform also collects a survey where participants answer questions regarding preferences for teammates in a future session on the platform, the perception of leadership and social influence, and they rate their teammates across different domains, including teamwork and communication.

In addition, as we can measure individual and team answers for the same tasks, we can calculate the social influence of each member on the teams' final answers, following the methodology of (Weidmann and Deming, 2020). Finally, we can use the chats to measure how individuals interact with each other when solving the team tasks, including the number of interventions of each participant and the sentiment they evoke with these interactions.

[2]We acknowledge that name can signal other characteristics besides income, such as gender and that participants may have more information about each other if they attend the same school

4.2 Results on Leadership Nominations and Team Interactions

We are interested in studying the relationship between teamwork and social mobility in Latin America. In particular, we explore whether there are differences in performance between income-segregated and mixed-income teams and whether revealing variables that signal income background to teammates reduces peer- and self-leadership recognition.

Following this experimental design, we separate the sample between low- and high-income participants and estimate the following equation to assess the income composition and information effects on participants' outcomes:

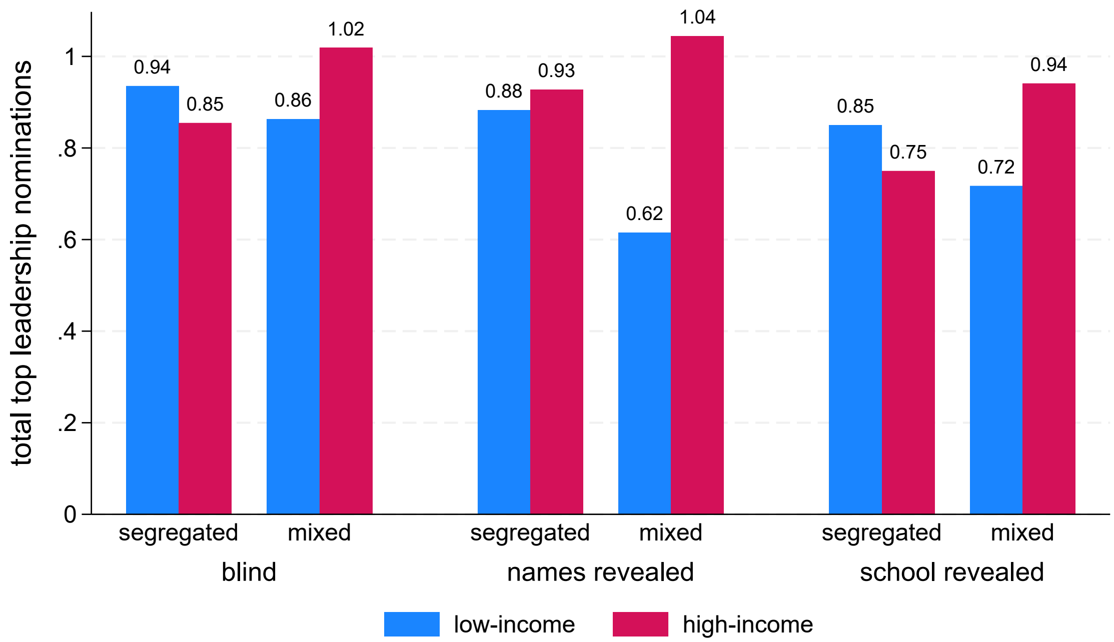
$$\begin{aligned} y_{itr} = \; & \alpha + \beta \; mixed_{itr} + \delta_s \; school_{tr} + \delta_n \; names_{tr} + \\ & \gamma_s \; mixed_{itr} \times school_{tr} s + \gamma_n \; mixed_{itr} \times names_{tr} + \\ & \phi_{s,r} + \varepsilon_{itr}, \end{aligned} \tag{5}$$

the variable $mixed_{itr}$ is a binary variable indicating whether individual i is assigned to a mixed-income team t. $school_{tr}$ is a binary variable indicating whether the graduating high school is revealed to the members of team t and $names_{tr}$ is an indicator on whether personal names were revealed.

The parameters of interest in equation 5 are β, the effect of being assigned to a mixed-income team, δ_s and δ_n, the effects of revealing the graduating high school and the identities, respectively, and γ_s and γ_n, the differential effect of such information depending on whether the team is composed of participants of the same income level or whether is a mixed-income team. Appendix Table A.1 reports balance tests of the experimental design separating the samples between low-income (Panel A) and high-income (Panel B) participants. Overall, while some of the variables present some imbalance due to statistical chance, the treatment assignment doesn't predict participants' characteristics before the experimental sessions.

Our primary outcomes are total-leadership recognition. Figure 8 presents a graph bar of our primary outcomes by income levels and treatment arms for the two levels of randomization. It reports the raw means for total top leadership nominations. The figure shows that for total leadership nominations, under the blind condition, there are no differences in top-leadership nominations between low- and high-income individuals in both segregated and mixed-income teams. However, as information is revealed, an income gap emerges in

FIGURE 8: Information and Income Composition on Leadership Perception



Notes: This figure presents averages of total leadership nominations by income level and treatment arm status of team composition and information. Table 5 reports these differences in a regression form.

mixed-income teams. In the most extreme case, when participants learn their teammates' identities (names), there is a difference of about half a leadership nomination between low- and high-income individuals in mixed-income teams.

Table 5 reports the estimates of equation 5 on leadership perception. Columns 1 reports the results for the pooled sample while adding treatment-level indicator variables, and columns 2 and 3 report the results for low-income and high-income participants, respectively. Column 4 adds the interaction between randomization level and an dummy for high income, while column 5 includes a rich set of controls. The estimates show that revealing names decreases by about 0.265 (p-value < 0.1) the total leadership nominations low-income participants receive. The point estimate of the effect of revealing high schools is also negative, but it is not statistically significant at the conventional levels. For high-income participants, the estimates in column 3 also show a negative effect of revealing names; the estimate is only -0.007 and is not statistically significant.

Tables 6 and 7 report the estimates of equation 5 on individual performance and team

TABLE 5: Information and Income Composition on Leadership Perception

	(1) All	(2) Low-income	(3) High-income	(4) All	(5) All
mixed_group	-0.112	-0.001	0.152	-0.060	-0.011
	(0.070)	(0.107)	(0.127)	(0.107)	(0.106)
school_rev	-0.095	-0.007	-0.153	-0.062	-0.037
	(0.064)	(0.084)	(0.127)	(0.071)	(0.085)
names_rev	0.010	0.001	0.076	-0.010	0.005
	(0.047)	(0.101)	(0.072)	(0.071)	(0.091)
mixed_school_rev	-0.007	-0.068	0.130	-0.053	-0.086
	(0.075)	(0.166)	(0.186)	(0.160)	(0.166)
mixed_names_rev	-0.129*	-0.223	-0.014	-0.238	-0.265*
	(0.069)	(0.159)	(0.186)	(0.149)	(0.153)
mixed_income	0.308**			0.208	0.173
	(0.123)			(0.214)	(0.208)
Constant	0.895***	-0.592	-2.849	0.895***	-1.088
	(0.032)	(3.479)	(5.201)	(0.033)	(2.582)
Observations	604	296	300	604	596
R2	.032	.081	.083	.034	.061

Notes: This table presents treatment effects on total leadership nominations. All estimations include experimental round and school-grade fixed effects. Additionally, columns 2, 3, and 5 include a rich set of controls: socioeconomic strata, social ladder, parents schooling levels, high-school calendar type (A or B), and interactions between a high income indicator and these variables. Standard errors double-clustered at the team and individual levels are presented in parentheses; * p-value< 0.1; ** p-value< 0.05; *** p-value< 0.01.

perception measures, respectively. The results in Table 6 show that the differences in leadership recognition are not correlated with effects on performance. In general, the results seem to show there is no clear pattern of the effects of team composition and information on performance for participant from either income level.

The results on team interaction perceptions (Table 7 appear to be consistent with an income team composition effect on team interactions perception, with such effect varying by the information available about other team members. Overall, low-income participants perceive lower-quality teamwork (column 1) when assigned to mixed-income teams. A similar result is found for their perception of their contribution to their teams specially when the name of their high-school is revealed (column 3). By contrast, for high-income participants such perceptions do not change irrespectively of the team-composition or the information revelation treatment, apart from a lower perception of communication skills when their names are revealed and they are in a mixed-income group.

Table 6: Information and Income Composition on Math and Reading Individual Performance

	Low-income		High-income	
	Math	Reading	Math	Reading
	(1)	(2)	(3)	(4)
mixed_group	0.006	-0.006	-0.025	0.026
	(0.020)	(0.020)	(0.021)	(0.021)
school_rev	-0.023	0.026	0.002	-0.002
	(0.018)	(0.018)	(0.027)	(0.026)
names_rev	0.028	-0.029	-0.005	0.004
	(0.028)	(0.028)	(0.021)	(0.021)
mixed_school_rev	0.032	-0.034	0.043	-0.045
	(0.028)	(0.028)	(0.037)	(0.037)
mixed_names_rev	-0.055	0.055	0.017	-0.018
	(0.038)	(0.037)	(0.033)	(0.033)
Observations	295	294	299	297
R2	0.78	0.78	0.83	0.79

Notes: This table presents treatment effects on math and reading team performance. All estimations include experimental round and school-grade fixed effects, and additionally, they include a rich set of controls: socioeconomic strata, social ladder, parents' schooling levels, high-school calendar type (A or B), and interactions between a high income indicator and these variables. Standard errors double-clustered at the team and individual levels are presented in parentheses; * p-value< 0.1; ** p-value< 0.05; *** p-value< 0.01.

Overall, the results are consistent with the hypothesis that team interactions may hinder the social mobility of low-income individuals in the labor market. In particular, low-income participants receive fewer top leadership nominations when assigned to mixed-income teams than high-income individuals. This income gap is not present when teams complete group tasks in a completely blind condition and only starts to emerge as more information that signals income level, including high schools and names, is revealed to all team members.

4.3 Concluding Remarks

The report presents the results of an experiment where we use the platform to explore the relationship between leadership recognition and how team interactions can affect social mobility. The experimental design has two phases: randomly varying the composition of teams and the information that participants learn about their team members. Our results show that team composition and information that participants learn about their team members affect the leadership recognition of low-income participants. While income gaps are absent in mixed teams when participants complete the tasks in an anonymous setting where they

Table 7: Information and Income Composition on the Perception of Team Interactions

	Low-income			High-income		
	Teamwork	Communication	Own-contribution	Teamwork	Communication	Own-contribution
	(1)	(2)	(3)	(4)	(5)	(6)
mixed_group	-0.518**	-0.303	-0.160	0.086	-0.043	-0.052
	(0.216)	(0.259)	(0.146)	(0.191)	(0.240)	(0.169)
school_rev	-0.330	0.013	-0.401**	-0.138	-0.310	-0.193
	(0.252)	(0.290)	(0.159)	(0.292)	(0.374)	(0.197)
names_rev	0.091	0.098	-0.021	0.196	0.333	-0.072
	(0.212)	(0.253)	(0.154)	(0.187)	(0.228)	(0.177)
mixed_school_rev	0.975***	0.604	0.492**	-0.164	-0.057	0.118
	(0.332)	(0.375)	(0.248)	(0.336)	(0.418)	(0.261)
mixed_names_rev	0.253	0.182	-0.073	-0.246	-0.653*	0.017
	(0.300)	(0.361)	(0.238)	(0.259)	(0.338)	(0.260)
Observations	296	296	293	300	300	298
R2	0.10	0.10	0.09	0.12	0.13	0.14

Notes: This table presents treatment effects on the perception of teamwork, communication, and contribution to the team. All estimations include experimental round and school-grade fixed effects and additionally they include a rich set of controls: socioeconomic strata, social ladder, parents schooling levels, high-school calendar type (A or B), and interactions between a high income indicator and these variables. Standard errors double-clustered at the team and individual levels are presented in parentheses; * p-value< 0.1; ** p-value< 0.05; *** p-value< 0.01.

don't have information about their teammates, such differences emerge when identities or other variables that signal income (i.e., personal names) are revealed to other team members.

5 Policy Recommendations

The findings in this report point to a central tension in modern education systems. Social skills—such as teamwork, communication, and leadership—are increasingly valued in the labor market, yet access to careers that rely heavily on these skills appears to depend more strongly on students' socioeconomic background. Majors associated with higher social-skill requirements exhibit systematically lower social mobility, and experimental evidence suggests that social interactions and leadership recognition within teams are shaped by socioeconomic signals rather than performance alone. These patterns imply that inequalities in social mobility are not driven solely by academic preparation, but also by differences in social integration, peer interactions, and the formation of social capital over the life course.

5.1 Early Social Integration as a Complement to Academic Policy

A key implication of our findings is that policies aimed at increasing social mobility should intervene *before* students reach higher education or the labor market. Because social skills are exercised, recognized, and rewarded in interactive environments, inequalities in exposure to diverse peers during childhood and adolescence may compound over time. Highly segregated school systems—such as the Colombian secondary education system documented in this report—limit opportunities for students from different socioeconomic backgrounds to develop shared norms, communication styles, and leadership experiences.

Social integration interventions during school years can therefore be seen as a complement to traditional policies focused on access, funding, or academic achievement. Rather than targeting skills in isolation, these interventions aim to shape the *social environments in which skills are formed and evaluated*.

5.2 Participatory and Deliberative Programs: The Case of SIMONU Bogotá

One promising example of such an intervention is *SIMONU Bogotá*, a city-wide Model United Nations program organized by the Secretaría de Educación del Distrito. SIMONU brings together students from public and private schools across Bogotá to participate in structured deliberation, negotiation, and collective problem-solving exercises. Importantly, the program explicitly mixes students from different socioeconomic backgrounds and schools, creating repeated opportunities for interaction under shared rules and common objectives.

Programs like SIMONU are well aligned with the mechanisms highlighted in this report for several reasons. First, they expose students to diverse peers in settings where leadership, persuasion, and teamwork are salient and observable. Second, they provide low-stakes environments in which students can practice and display social skills without the high returns or gatekeeping mechanisms present in elite educational or labor-market contexts. Third, by normalizing interaction across socioeconomic lines at earlier ages, such programs may reduce the salience of background-based signals that later shape leadership recognition and peer evaluations.

While rigorous causal evidence on the long-term impacts of SIMONU-like programs remains limited, our results suggest that such interventions may help weaken the link between socioeconomic background and access to socially intensive career paths. As a policy strategy, they are relatively low-cost, scalable, and compatible with existing school curricula.

5.3 Directions for Policy Design and Evaluation

Based on the evidence presented in this report, we highlight three guiding principles for policymakers:

- **Start early**: Social integration policies are likely to be more effective when implemented during primary and secondary education, before social hierarchies and networks become entrenched.
- **Focus on interaction, not only instruction**: Programs should emphasize collaborative tasks, deliberation, and collective decision-making rather than individual performance alone.
- **Embed evaluation**: Given the growing importance of social skills and social capital, future expansions of integration programs should incorporate experimental or quasi-experimental evaluation designs to assess their medium- and long-run effects on educational trajectories and labor-market outcomes.

6 Conclusions

This report documents a robust and previously underexplored relationship between social skills, team interactions, and social mobility. Using administrative data from Colombia, we show that academic majors associated with higher social-skill requirements exhibit lower intergenerational mobility. Complementary experimental evidence demonstrates that leadership recognition and peer evaluations within teams are shaped by socioeconomic signals rather than performance, particularly when information about background is revealed.

Taken together, these findings suggest that social skills—while highly rewarded in the labor market—may also function as a channel through which inequality is reproduced. When access to socially intensive careers depends on early exposure to diverse peers, leadership opportunities, and favorable social perceptions, students from disadvantaged backgrounds face structural barriers that are not easily addressed through academic interventions alone.

Policies that promote social integration during school years, such as participatory and deliberative programs exemplified by SIMONU Bogotá, represent a promising avenue to address these barriers. By reshaping the social contexts in which skills are developed and recognized, such interventions may help ensure that the rising importance of social skills contributes to greater opportunity rather than deeper inequality.

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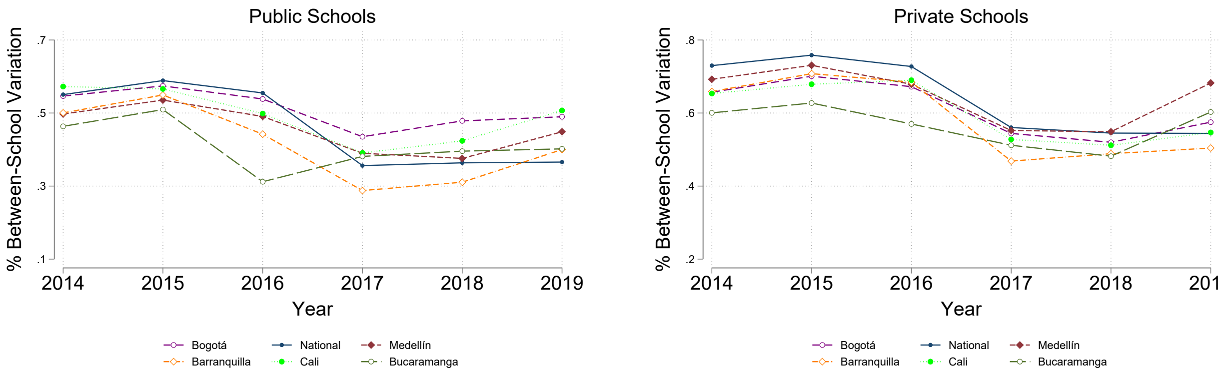
A Additional Tables and Figures

FIGURE A.1: Temporal variation in intraclass correlation coefficient (ICC) by school type



(A) Public schools

(B) Private schools

Note: Panel (a) displays the ICC values over time for public schools across different cities. Panel (b) shows the ICC values over time for private schools across different cities. Each line represents a different city, with the national average shown for comparison. The ICC represents the proportion of total socioeconomic variance explained by differences between schools. Authors' calculations based on ICFES Saber 11 data.

Table A.1: Balance Checks on Participants' Characteristics by Income Levels

Variable	N	Control Group Mean	sd	mixed group	se	school revealed	se	names revealed	se	school × mixed	se	names × mixed	se
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Panel A: Low-income participants													
edad	299	17.89	2.92	-0.825	0.575	-1.125*	0.616	-0.022	0.575	1.524*	0.869	0.198	0.829
male (%)	300	0.55	0.50	-0.035	0.096	-0.017	0.102	0.004	0.096	-0.002	0.145	0.103	0.138
private high school	297	0.58	0.49	0.071	0.093	0.124	0.099	0.032	0.093	-0.215	0.140	0.027	0.133
ses classification system	297	0.08	0.28	-0.046	0.048	0.015	0.052	-0.006	0.048	-0.010	0.073	0.026	0.069
perceived socio-economic	299	5.73	1.68	0.247	0.309	0.167	0.331	-0.184	0.309	-0.538	0.467	0.302	0.446
father's education	299	6.82	2.67	-0.209	0.502	0.758	0.538	0.497	0.502	-1.018	0.759	0.032	0.724
mother's education	299	7.62	2.02	-0.009	0.385	0.333	0.413	0.305	0.385	-0.485	0.582	0.048	0.555
rate correct math test	299	0.49	0.31	-0.017	0.050	-0.049	0.055	0.022	0.050	0.061	0.077	-0.054	0.073
rate correct reading test	299	0.49	0.31	-0.030	0.051	-0.005	0.055	-0.030	0.051	0.004	0.077	0.060	0.073
Panel B: High-income participants													
age	295	17.88	2.92	0.623	0.442	-0.001	0.495	0.483	0.436	0.221	0.683	-0.815	0.647
male (%)	302	1	0	-0.114	0.094	0.007	0.105	-0.112	0.093	0.108	0.144	0.300**	0.137
private high school	300	1	0	-	0.019	-0.057***	0.021	-	0.018	0.038	0.029	-	0.027
ses classification system	300	0.56	0.50	-0.067	0.093	0.071	0.105	0.024	0.092	0.066	0.143	0.129	0.136
perceived socio-economic	302	7.84	1.03	0.180	0.212	0.050	0.237	-0.057	0.210	-0.442	0.325	0.060	0.311
father's education	302	9.37	1.23	0.044	0.192	0.018	0.215	-0.098	0.190	0.038	0.294	0.128	0.281
mother's education	302	9.52	0.65	-0.063	0.135	0.067	0.152	-0.062	0.134	0.049	0.208	-0.102	0.199
rate correct math test	301	0.72	0.26	0.025	0.055	-0.064	0.062	-0.019	0.055	-0.003	0.085	-0.025	0.081
rate correct reading test	299	0.61	0.33	0.045	0.050	-0.060	0.056	-0.004	0.049	-0.053	0.076	-0.064	0.073

Notes: This table presents balance tests of pilot 2. Standard errors double-clustered at the team and individual levels are presented in parentheses; * p-value< 0.1; * p-value< 0.0.05; *** p-value< 0.01.