Social and Academic Peer Effects: Experimental Evidence from Selective High Schools in Peru

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Abstract

This paper estimates peer effects on social and academic outcomes using a large-scale field experiment at selective public boarding schools in Peru. I use a new experimental design that generates substantial variation in peer characteristics. The experiment randomizes two types of neighbors into dormitories: (1) less or more sociable (identified by the social network) and (2) lower- or higher-achieving (determined by admission scores). Boys with more sociable neighbors have more connections, a better network position, and more advanced social skills. There are no effects on social outcomes for girls. Academic peer effects are, on average, a precise zero, with some negative impacts on lower-achieving girls. Differences in how peers affect boys' and girls' beliefs about their own abilities explain these findings. I also rule out friendships as the ultimate driver of peer effects.

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1 Introduction

Understanding how peers influence the formation of skills is crucial for education policies (Benabou, 1993; Allende, 2019). Yet, there is no consensus on which factors determine the direction and size of peer effects. The extensive literature on the topic has focused on the formation of academic skills, where the evidence remains inconclusive.[1] We know less about peer effects on social skills, where interactions with peers are intuitively more relevant and are also crucial for later-life outcomes. Skills such as teamwork, collaboration, and leadership are in high demand by firms in the US (Casner-Lotto and Barrington, 2006; Jerald, 2009) and developing countries (Novella et al., 2019). Furthermore, recent empirical evidence shows that in the era of automation, the labor market increasingly rewards social skills (Deming, 2017). However, economics studies have largely overlooked how social skills are formed; whether peer characteristics affect the formation of social skills in schools is an open question.

Studying peers' influence on social skills can also shed light on the mechanisms that operate behind peer effects. The size and nature of peer effects on academic outcomes are highly context-specific, and we still do not know why they are prominent in some cases and absent in others (Sacerdote, 2014). An intuitive explanation for the wide range of results is the formation of friendships, as friends should be more relevant than other peers in shaping our behavior (Calvó-Armengol et al., 2009; Carrell et al., 2013). An alternative explanation for the variation in peer effects estimates relies on students' beliefs about their own abilities (Marsh and Parker, 1984; Benabou and Tirole, 2002). As individuals compare themselves to their peers, they can change their levels of self-confidence, affecting students' performance (Compte and Postlewaite, 2004). Studying peers' influence across social and academic skills under the same setting will help us understand the mechanisms that explain the link between peer effects and skill formation in schools.

In this paper, I estimate social and academic peer effects and study the driving forces behind both. I conduct a large-scale field experiment at selective public boarding schools in Peru using a new experimental design to generate large exogenous variation in peers' skills. I assign students to two cross-randomized treatments when allocating them to beds in dormitories: (1) less or more sociable neighbors and (2) lower- or higher-achieving neighbors. To study the driving forces behind peers' influence, I rely on a comprehensive survey that measures students' beliefs about themselves and others, and different types of social interactions in schools. The results show that while boys benefit from having more sociable neighbors, lower-achieving girls perform worse when assigned to higher-achieving neighbors. Both results are consistent with the differences I observe in how peer interactions influence boys' and girls' beliefs in their own abilities. The formation of new friendships and study groups does not explain the main effects. All students are more likely to befriend and study with their new neighbors, but estimates of peer effects vary widely across outcomes, student characteristics, and peer type.

My finding that peer effects differ by gender is consistent with previous studies, which also report differences in how men and women form beliefs about their abilities. For instance, gender and stereotypes influence the formation of beliefs about oneself and others (Bordalo et al., 2019). A rich literature emphasizes the tendency of men to be more overconfident than women (Barber and Odean,

[1] See Epple and Romano (2011), Sacerdote (2011) and Sacerdote (2014) for recent reviews. In general, the evidence shows that peers have mixed results on standardized test scores and positive impacts on criminal behaviors, career decisions, and attitudes toward minorities (Boisjoly et al., 2006; Carrell et al., 2015; Rao, 2019).

2001; Niederle and Vesterlund, 2007; Croson and Gneezy, 2009; Sarsons and Xu, 2016), and there is evidence of gender differences in the updating of beliefs about personal abilities. Men are more likely than women to overestimate positive signals about their abilities (Mobius et al., 2014), and people react more to good news when it arrives in a gender-congruent domain (Coffman and Kulkarni., 2020). In schools, boys and girls also differ in the set of peers they consider as reference groups. Female students tend to make more upward social comparisons and fewer downward comparisons than male students (Pulford et al., 2018).

My analysis starts by describing the experimental design, which surmounts many of the challenges with traditional approaches that estimate peer effects. Most prior studies have examined students' random assignment to either dormitories or classrooms. Although this procedure generates exogenous peers, the variation in peer characteristics is weak by construction (Manski, 1993). Moreover, under these designs, multiple peer attributes (test scores, demographic characteristics, unobservables) vary at the same time. The use of numerous variables and non-linear functional forms in peer effects models aggravates these concerns.[2] The fact that different peer attributes all vary at the same time in a random assignment can become uninformative for policy recommendations. For example, Isphording and Zölitz (2019) estimate the value of a peer and find that while this value is substantial, observable characteristics are unable to predict it. My experiment ensures substantial differences in sociability and academic achievement only. Hence, my research design alleviates concerns about weak variation and minimizes the impact of other observed and unobserved peer characteristics that are not part of the treatments.

My experimental design involves three steps: (1) categorize students into types, (2) assign them to treatments, and (3) allocate them to dormitory beds. To classify students according to their level of sociability, I collected data on their social networks the year before the intervention. In the survey, students answered who were their preferred roommates, their friends, and with whom they studied or played games. I construct a general network aggregating the answers to these four questions and use the eigenvector centrality as a measure of sociability.[3] To classify students based on their academic achievement, I use the results of their admissions tests, which include math and reading scores. I perform a stratified randomization of students to the treatments and organize them into groups. The schools use these groups to allocate students to specific beds in the dormitories. This procedure ensures that the type of neighbor coincides with the assigned treatment. I show that the schools followed this protocol since the treatments predict the characteristics of students' neighbors. This allocation also affects social interactions. Students befriend, study, and play more with peers who, based on the assigned treatment, should be in nearby beds.

I estimate the impact of each treatment on social and academic outcomes. I consider three types of social outcomes: (1) the number of connections and the centrality in the social network after the intervention, (2) a social skills index based on an array of psychological tests that measure social skills.[4], (3) an index based on the perceptions of others—the number of peers who perceive

[2]For example, Angrist (2014) relates weak variation to weak-instrument bias and argues that this can explain the failure of optimal policies based on peer effects estimates (Carrell et al., 2013):"The disappointing Carrell et al. (2013) results seem to me more likely to originate in the spurious nature of econometric estimates of peer effects than in endogenous social stratification."

[3]Eigenvector centrality measures a student's influence within his or her social network. High values indicate that a student is connected to many other individuals, who themselves have high scores.

[4]These include openness to experience, extraversion, and agreeableness of the "Big Five" (McCrae and John, 1992; John and Srivastava, 1999; Almlund et al., 2011), altruism, empathy, leadership, emotional intelligence, intercultural sensitivity, and the "Reading the Mind in the Eyes" test.

the student as a leader, or as a popular, friendly, or shy person. To measure academic outcomes, I use grades and standardized test scores in math and reading.

To account for imperfect compliance between the assignment to treatments and actual neighbors in the dormitories, I exploit the experimental variation in a two-stage least-square (2SLS) model. I consider a linear-in-means peer effects model that jointly estimates the impact of neighbors' sociability and academic achievement on students' outcomes but allows for heterogeneity by gender and baseline characteristics.

Sociable peers improve the social outcomes of boys. Boys assigned to more sociable neighbors end up with a higher centrality (0.10σ, p-value 0.011) and higher scores in the social skills index (0.12σ, p-value 0.000). The effects on the less sociable boys are larger; they also have 0.8 more connections (p-value 0.006) and are perceived to be more sociable by their peers. The estimates of the 2SLS model show that a one-standard-deviation increase in the sociability of neighbors increases an index of all social outcomes by 0.337σ for all boys, and 0.470σ for the less sociable boys (both estimates are statistically significant at the 1% level). These results are robust to multiple checks, including randomization inference and multiple-hypotheses testing. I do not find that more sociable neighbors improve social outcomes for girls nor average academic achievement.

The improvement of social skills also affects later-life outcomes. The positive impacts for less sociable boys translate into lower dropout rates (2.3 p.p., p-value 0.007) and higher enrollment in better colleges. In Peru, higher education institutions use face-to-face interviews in the college admission process. Hence, an improvement in students' social skills would be consistent with enrolling at better colleges. The estimates show positive effects on attending a certified college by the government (5.1 p.p., p-value 0.045), and a top 20 college (4.4 p.p., p-value 0.062).

By contrast, I find that higher-achieving peers have no impact on social outcomes or average academic achievement. The 2SLS estimates show that a one-standard-deviation increase in the admission score of a student's neighbors reduces math scores by 0.039σ (s.e. 0.031) and reading scores by 0.038σ (s.e. 0.040), ruling out even the smallest positive peer effects estimated in the literature (Table A.1 shows a review). In fact, higher-achieving peers harm lower-achieving students—especially lower-achieving girls. For them, I find a negative treatment effect of -0.062σ (s.e. 0.030) for math and -0.124σ (s.e. 0.046) for reading. I also find consistent evidence for math grades and (non-significant) negative estimates for reading grades.

Next, I explore what determines the magnitude and direction of the peer effects estimates. I consider two potential mechanisms: (1) the formation of beliefs (self-confidence), and (2) friendship and study networks (social interactions). For this analysis, I rely on a comprehensive survey that measures beliefs and social interactions, with a response rate above 95%. As in Pop-Eleches and Urquiola (2013), my goal is not to estimate the causal impact of these mechanisms, but instead to establish evidence consistent with the influence of peers on students' outcomes.

The empirical evidence suggests that self-confidence is a valid mechanism. To measure beliefs about one's own abilities, I use two sets of variables: self-reported rankings of popularity and academic skills, and self-nominations among the most skilled and popular students in the class. The idea that peer interactions can affect self-confidence dates back to the big-fish–little-pond effect (Marsh and Parker, 1984), whereby equally able students have lower academic self-concept in high-ability schools than in low-ability schools. Recent evidence also shows that this mechanism might differ by gender due to social comparisons; female students tend to make more upward social comparisons and fewer downward comparisons than male students (Pulford et al., 2018).

I find that boys are more confident than girls in their social and academic abilities. Male students self-report a higher ranking in both popularity and academic skills within their cohorts. They are also more likely to nominate themselves among the most skilled and popular students in their class. These gender differences remain after controlling for observable characteristics such as personality, number of connections, and baseline test scores.

More interestingly, I find that peers affect the beliefs of boys and girls differently. While having more sociable neighbors increases less sociable boys' confidence in their social abilities, it has the opposite effect on girls. Boys are 14.9 points (p-value 0.014) more likely to report themselves as sociable. The effect for girls is negative (10 points, p-value 0.031). The estimates on a self-reported ranking of popularity within the dorm, classroom, and school show a similar pattern. Less sociable girls (but not boys) report a lower popularity ranking when assigned to more sociable neighbors.

I also explore whether the formation of beliefs can explain the social versus academic differences in peer effects. I argue that students have more information about their academic performance than their social abilities. I present two formal tests to support this argument. First, peers affect more students' beliefs about their social skills than their academic skills. Second, only first-year students respond to the intervention by changing their beliefs in their academic abilities. This change is consistent with the fact that first-year students have less information about their academic skills relative to their peers than older students. The formation of first-year students' beliefs also varies by gender; only lower-achieving girls lose confidence in their academic skills when assigned to higher-achieving peers.

By contrast, I rule out social interactions between students and their neighbors as a driving force of my empirical findings. The social network analysis shows that students form friendships and study groups with their new neighbors regardless of gender, or student/peer type. I study whether the formation of friendships between less sociable students and their neighbors depends on either gender or the more sociable peers treatment status; I cannot reject that gender or the treatment affects the formation of friendships. Analogously, I test whether study partnerships between lower-achieving students and their neighbors depend on gender or the higher-achieving peers treatment. Again, I find no evidence that either of these affect the formation of new study groups. Taken together, these results suggest that friendships and study partnerships are not sufficient for peers to influence students' outcomes.

Related literature: This paper builds on and contributes to four strands of the literature.

First, my conclusions add to the broader literature on peer effects (Epple and Romano, 2011; Sacerdote, 2011). While the literature is not conclusive about the effects of peers on test scores (Sacerdote, 2014), the research design appears to play a role in explaining the magnitude of the estimates. Most studies find small positive peer effects when schools randomly allocate students to small groups such as dormitories (Epple and Romano, 2011; Sacerdote, 2001), and sizable significant estimates in large groups such as classrooms (Duflo et al., 2011), squadrons (Carrell et al., 2009), or large dormitories (Garlick, 2018). While my results contradict this evidence, they are consistent with quasi-experimental research designs that generate substantial variation in peer characteristics (Abdulkadiroğlu et al., 2014; Duflo et al., 2011). I cannot disentangle whether these differences are due to the context or the research design. However, these differences highlight the methodological concerns that a random allocation might have, as other researchers have pointed out (Manski, 1993;

Angrist, 2014; Caeyers and Fafchamps, 2016). Still, my results are not aligned with Booij et al. (2017), who manipulate the composition of groups to achieve a wide range of support and find positive peer effects for low- and middle-skilled students.

I also find that, contrary to previous evidence (Carrell et al., 2013; Bandiera et al., 2010), high-skilled peers can harm low-skilled students, even when they befriend each other. This evidence suggests that further studies are needed to understand the differences between the effects of friends and other peers. My results are also consistent with peers decreasing students' outcomes due to rank concerns and social comparisons. For example, recent evidence shows that students have a lower self-concept in schools with higher-achieving peers (Fabregas, 2017). Via this mechanism, peers can also affect later-life outcomes since a lower ranking can reduce high school completion, college enrollment (Elsner and Isphording, 2017) and earnings (Ribas et al., 2018; De Roux and Riehl, 2019).

Second, my results also explore how peer characteristics affect the development of social skills in schools, extending the literature on the formation of social skills. While a substantial body of evidence documents the positive and increasing returns to social skills in the labor market (Deming, 2017) and their importance for communication within organizations, team productivity, and management practices (Woolley et al., 2010; Hoffman and Tadelis, 2018), little is known about how social skills are formed. There are a few exceptions: Rao (2019) shows that rich students are more altruistic when they are exposed to poor peers. Falk et al. (2018) and Alan et al. (2020) find that a mentorship program in Germany and an educational curriculum in Turkey increase children's pro-sociality. Adhvaryu et al. (2018) find that an on-the-job soft skills training program in India improves female workers' extraversion and communication.

Third, the paper builds on the literature on social networks. Previous evidence highlights the role of eigenvector centrality for the diffusion of microfinance (Banerjee et al., 2013) and the monitoring of savings decisions (Breza and Chandrasekhar, 2019). Calvó-Armengol et al. (2009) develop a model that shows that in equilibrium, the outcome of an individual embedded in a network is proportional to her Katz-Bonacich centrality. Hahn et al. (2015) find that among randomly formed groups, those that perform better in group assignments have members with high Katz-Bonacich centrality. This paper extends these findings by using a similar measure of the influence of a node, eigenvector centrality. This measure is highly correlated with social skills, such as extraversion and agreeableness of the Big Five. Moreover, my results show that having more central peers can have a positive effect on social skills, but does not affect students' academic achievement.

Lastly, my results relate to the literature on gender differences in the formation of beliefs. Gender stereotypes influence the formation of beliefs about oneself and others (Bordalo et al., 2019). Cools et al. (2019) find that while having high-achieving boys as peers reduces girls' high school completion rate and later labor force participation, high-achieving female peers have the opposite effect. My results suggest that even peers of the same gender can have a detrimental effect on the human capital of girls. Moreover, I find that peer interactions cause boys and girls to update their beliefs about their own academic and social skills differently.

The rest of the paper is organized as follows. Section 2 describes the research setting. Section 3 presents the experimental design. Section 4 shows the balance and the first stage. Section 5 describes the outcomes and outlines the empirical strategy. Section 6 documents the results on skill formation. Section 7 discusses potential mechanisms. Section 8 concludes.

2 Setting: Exam Schools in Peru

The Peruvian government runs a series of exam schools, *Colegios de Alto Rendimiento* (known as the COAR Network), to provide a high-quality education for the most talented low-income students during the last three years of secondary school. The COAR Network is composed of 25 schools spread across every region of Peru and enrolls approximately 3,000 students every year. It is also one of the largest programs in the national budget for education. The first exam school opened near Lima, the capital, in 2010. As of 2017, there is now a COAR school in each region of the country. For every cohort, there are 100 slots per school, except for the school in Lima, which serves 300.

The COAR Network meets the standards of elite private high schools in Latin America, where students have access to all the required inputs for a high-quality education. COAR are boarding schools, deliberately located close to the capital city of each region to reduce the daily transportation costs for both families and the government. Upon admission, students receive school materials, uniforms, and a personal laptop for school use. All of the schools have a high-quality infrastructure, including a library and excellent scientific laboratories. Students have the option of obtaining an International Baccalaureate (IB) degree. Teachers are hired outside the public school system and receive higher salaries. The government covers all the necessary operating expenses, including laundry service and food.

Applicants are eligible for admission to COAR if they ranked in the top 10 of their public school cohort in the previous academic year. The admissions process consists of two rounds. In the first round, applicants take a written test in reading comprehension and mathematics. The highest-scoring applicants move onto a second round, during which psychologists rate them based on two activities: a one-to-one interview, and the observation of peer interactions during a set of tasks. I refer to these as the *interview* and *social fit* scores, respectively. Admissions decisions are determined by a composite score of all three tests, the region of origin, and the applicant's school preferences.

Before the experiment, school directors implemented their own individual systems to allocate students to dormitories and classrooms. Most schools attempted to foster multi-cultural diversity by mixing students from different regions within the same dormitory. There was also variation across schools in how they allocated first-year students to classrooms. Classroom assignments for students in the upper cohorts depended on whether students applied for the IB degree and the track they chose for this program.

3 Experimental Design

The objective of the experiment is to estimate the impact of neighbors' sociability and academic achievement on students' outcomes. To ensure systematic variation in peer characteristics across treatments, I classify students into types according to sociability and academic achievement. Then, I randomize them into groups with systematic variation in the type of peer. These groups, therefore, have substantial variation in peer characteristics, overcoming the weak variation problem pointed out by Angrist (2014) in other peer effects studies.

Next, I describe the data that was available before the intervention. I then explain how I used this data to classify students according to their sociability and academic achievement. In a final step, I describe how students were randomized into groups with different types of peers, and how I used this assignment to allocate students to dormitories in the schools. Figure 1 shows the timeline of the project.

3.1 Data

3.1.1 Administrative Data

Administrative data on student demographics and baseline scores was collected as part of the admissions process or from existing government databases. For all students enrolled in the COAR Network in 2017, I have data on admissions test scores in three categories: (i) the written test in math and reading comprehension, (ii) the admissions interview, and (iii) the social fit score determined by a team of psychologists.

I also use socio-demographic data employed by the Government of Peru to determine households' eligibility for national social programs, which is available for 85% of COAR students. It includes whether a student comes from a household classified as poor or extremely poor, and whether they come from a rural area.

Column 1 of Table 1 reports descriptive statistics for students in the COAR Network. Although these schools target students from the public school system, admitted students have diverse social and economic backgrounds. For example, 36% of the students come from poor households, and 18% from extremely poor households. Likewise, 26% of students come from rural households, and 50% of them have public health insurance.

For the 2015 and 2016 cohorts, the Ministry of Education also administered psychological tests. Some of these tests incorporate measures of social skills, including emotional intelligence (Law et al., 2004) and the "Reading the Mind in the Eyes" test (Declerck and Bogaert, 2008). Appendix C describes these tests in detail.

3.1.2 Surveys

I partnered with the Ministry of Education to administer an online survey to measure social interactions and non-cognitive skills for students in the 2015 and 2016 cohorts. The survey was conducted in class and on a computer, with a compliance rate above 95% for each school. A team of psychologists in each school was in charge of monitoring the survey.

The survey asked students to list the names of their peers in four distinct categories of social interactions: (i) roommate preferences (students were told that their answers to this question could affect their dormitory assignment), (ii) friends , (iii) study partners, and (iv) people with whom they interact in social activities such as playing sports or games. Appendix Table A.2 shows three statistics for each category of the network: total degree, mutual degree, and eigenvector centrality. The average mutual degree is half of (or lower than) the average total degree. For example, when we consider a broad social network that aggregates all four questions about social interactions, students report having 11.06 connections on average, of which only 3.34 are mutual.

The survey also included questions on students' perceptions of their peers. Students were asked to rank up to five peers in the categories of leadership, friendliness, popularity, and shyness. Table A.2 shows descriptive statistics for these variables. On average, a student was named by 2.6 of her peers as a leader, by 2.7 as the most friendly, by 2.4 as the most popular, and by 2.0 as the shyest.

3.2 Classifying Students by Academic and Social Skills

I use data from the admissions process and a baseline social network survey to identify more sociable and higher-achieving students.

I use the math and reading comprehension test scores from the admissions process to characterize students as lower- or higher-achieving at baseline. Students took this test before they had any interaction between them. For each school-by-grade-by-gender cell, students above the cell-specific median are classified as higher-achieving, and those below the median as lower-achieving.

To identify more and less sociable students, I rely on the baseline network survey described in the previous section. I use the eigenvector centrality of an aggregate undirected social network that groups the four categories of social interactions described above. Banerjee et al. (2013) and Banerjee et al. (2014) perform a similar aggregation. Other studies have shown that in other contexts, individuals with high centrality are better at diffusing information (Banerjee et al., 2014; Beaman and Dillon, 2018) and monitoring savings decisions (Breza and Chandrasekhar, 2019). I use the same strategy as above: students with an eigenvector centrality above the cell-specific median are classified as more sociable, and those below the cell-specific median as less sociable. Appendix Figure A.1 shows that centrality and admissions test scores are positively correlated.

Table A.2 (columns 2 to 5) presents descriptive statistics of the baseline social networks by student type. More sociable students have a better position in the schools' social networks, with a larger average degree, mutual degree, and eigenvector centrality for the four social networks reported (roommate preferences, friends, study connections, and social connections). For example, in the general network more sociable students have, on average, 5.7 more connections and 1.5 more mutual connections than less sociable students. More sociable students are also perceived as friendly by 3.5 peers on average, while only 1.9 peers perceive less sociable students as friendly.

More interestingly, I also find a large statistically significant correlation between eigenvector centrality and my set of indicators of social skills. Appendix Table A.3 reports standardized coefficients of an ordinary least squares (OLS) regression of social skills measures[5] on the three admissions test scores, and on the eigenvector centrality of the baseline social network, controlling for school$\times$grade$\times$gender fixed effects. For most of my social skills indicators, eigenvector centrality has a stronger correlation than admissions test scores. These results confirm that individuals who are assessed as very central in the schools' social networks at baseline also have highly developed social skills.

Since first-year students did not complete the baseline survey in 2016, eigenvector centrality at baseline is not available for this cohort. However, in an attempt to identify *sociable* students in this cohort, I use the *social-fit* test from the admissions process. In theory, this score comprises measures of empathy, leadership, and teamwork. However, in contrast to the eigenvector centrality, the correlations between the *social-fit* score and more traditional social skills measures are weak. For this reason, I focus on the higher-achieving peers treatment for the first years. In all the estimations I also include the social-fit treatment, although I do not report the effects in the main tables.[6]

[5] Some of these variables were collected before or after the intervention. They are described in detail in Section 5.1 and Appendix C.

[6] These results are available upon request.

3.3 Randomization

To estimate the impact of peers' sociability and academic achievement on students' outcomes, I randomized students into two treatments: (1) more sociable peers and (2) higher-achieving peers. In the previous section, I explained how students were classified as more/less sociable and higher/lower-achieving. Here I explain the details of the randomization.

3.3.1 Peer Group Types

By randomizing the type of peers that students have, instead of simply randomizing them to groups, I assure that they are exposed to peers with different levels of skills. This novel approach is central to my study. It differs from the more traditional approach that exploits random assignments to groups, where, by virtue of the randomization, peer characteristics are the same in expectation—although there will be small variations across groups in the realized sample.

My experimental design accounts for the fact that a student not only *receives* a treatment, but also serves as a treatment for her peers. Students were allocated to *peer group types* in which they were matched with peers in their respective treatments. In each *peer group type*, half of the peers are of the same type as the student, and the other half are of the type of her assigned treatment.

Consider the simple case of two types of students: high and low. The researcher is interested in identifying the average treatment effect (ATE) of having high-type peers. With two types of students, there are three *peer group types*: two homogenous groups, each composed of individuals of a single type, and a heterogeneous group composed of individuals of both types. The following matrix shows the composition of *peer group types*:

	High	Low
High	Group A	Group B
Low	Group B	Group C

In this case, there are three potential *peer group types*:

a) Group A: a group composed of the high type only.

b) Group B: a mixed group, in which half are high-type students, and the other half are low-type students.

c) Group C: a group composed of the low type only.

Notice that, conditional on a student's type, she can be assigned to either a homogeneous group (Group A or C) or to a mixed group (Group B). To show how this generates systematic variation across treatments, compare a high-type student in Group A to a high-type student in Group B. In Group A, all peers are high types, while in Group B, half are high types, and the other half are low types. Hence, the difference in the proportion of high-type peers in Group A versus B equals 0.5. The conditional average treatment effect (CATE) of having high-type peers conditional on being a high-type student ($\tau_i = H$) can be identified as the difference between high-type students in Group A and high-type students in Group B.

$$CATE_H = \mathbf{E}\left[Y_i|\tau_i = H, A\right] - \mathbf{E}\left[Y_i|\tau_i = H, B\right] \tag{1}$$

Similarly, consider a low-type student in Group B versus a low-type student in Group C. In Group B, half the peers are high types, and the other half are low types, while in Group C, all peers are low-type students. Hence, the difference in the proportion of high-type peers in Group B versus C equals 0.5. The CATE of having high-type peers conditional on being a low-type student ($\tau_i = L$) can be identified as the difference between low-type students in Group B and low-type students in Group C.

$$CATE_L = \mathbf{E}\left[Y_i|\tau_i = L, B\right] - \mathbf{E}\left[Y_i|\tau_i = L, C\right] \tag{2}$$

Considering the above, the ATE of high-type peers is a weighted average of the CATE in equations 1 and 2, where weights capture the proportion of high- and low-type students in the data, respectively. Since I am using the cell-specific median to classify students, the weights are equal.

$$ATE = 0.5 * CATE_H + 0.5 * CATE_L \tag{3}$$

Notice that the statistical power to estimate this average effect is maximized when all peer group types —Groups A, B and C— are of the same size. The number of students who are treated (high-type students in Group A and low-type students in Group B) and the number of students who are not treated (high-type students in Group B and low-type students in Group C) would be the same.

The fact that all three groups are the same size implies that students are twice as likely to be assigned peers of their same type. Hence, high-type students are twice as likely to receive the treatment (high-type peers) as low-type students. Given that the propensity score of receiving the treatment will vary by student type, we need to account for this in the empirical analysis.

The randomization in my field experiment is analogous to this example, with just one difference. In my randomization I use two treatments instead of one, so rather than two types of students, I have four types: (i) more sociable and higher-achieving, (ii) more sociable and lower-achieving, (iii) less sociable and higher-achieving, and (iv) less sociable and lower-achieving. This implies that instead of the three *peer group types* A, B, and C from my previous example, there are ten potential *peer group types* in my experimental strategy.[7]

Figure 2 shows the ten possible combinations of types of peers and student types. Each row corresponds to the student type, each column to the type of peer to whom she was assigned, and each cell to the combination of student type and type of of peer, namely a *peer group type*.[8] Each group takes a different cell color in the symmetrical matrix of Figure 2.

I performed the randomization by stratifying at the school-by-grade-by-gender level and at the student's type. The first stratification (school-by-grade-by-gender) is performed because the allocation to dormitories is specific to these strata. The second stratification (student type) is necessary because students were assigned to *peer group types* based on their type, as described in the classification above.

This design generates a larger variation in peers' sociability and academic achievement than a random allocation to groups. Figure 3 plots the distribution of students' sociability and academic achievement, as well as the distribution of peer characteristics for students assigned to each treatment group. As a benchmark, the figure also plots the variation in peer characteristics under a

[7]With four types of students there would be 16 possible combinations, but 6 of them are redundant.

[8]Group 1, for example, is composed of only more sociable and higher-achieving students. Group 3 is composed of less sociable and higher-achieving with more sociable and lower-achieving students.

simple randomization to groups, the traditional research design in the peer effects literature. Unsurprisingly, the distribution of peer characteristics under this benchmark (the black line) collapses the distribution of the respective skill in the students' population (grey-dashed line). My experimental design, rather than exploiting the variation within the black distribution, compare students assigned to either the colored left- or right-sided distributions in the plot. Overall, the comparison across these two extreme distributions guarantees a strong first stage to identify peer effects.

3.3.2 Assigning Students to Dormitories

This subsection describes how I implement my experimental strategy. After randomizing students into *peer group types*, as described above, I used these groups to allocate students to the dormitories of the COAR Network.

There is vast heterogeneity in the structure of dormitories across the COAR Network. For example, while the school in Lima has dormitories of three to five students, its counterpart in Cusco has a total of four dormitories, with approximately 80 students per dormitory. Figure 4 shows a picture of the dormitories in the schools in Lima, Piura, and Cusco. To reconcile my *peer group types* with the widely varying number of dorm sizes across schools, I sorted the names of the students on a list based on the ten *peer group types* mentioned in the previous subsection. This list was later used to allocate students to specific beds in the dormitories. The *peer group types* were randomly ordered on the list,[9] and for mixed groups composed of more than one student type, the names of students of different types were alternated. Appendix B describes in detail how the lists determined the allocation to dormitories and classrooms.

The order on the list is directly linked to the physical distance between two students in a dormitory. Students who are adjacent on the list are more likely to be near each other in the dormitories. In small dorms, the assigned peers will likely share the same room. In bigger dorms, students and assigned peers will be placed either in the same bunk bed or in beds next to each other.

Most of the schools (23 out of 25) in the COAR Network used my lists to allocate students to dormitories. There were logistical coordination problems with the other two schools. In some cases, the school directors sent the allocation they used, and I checked whether it was done based on the lists. In most cases, I performed the assignment to dorms using information that the principals sent me about the dorm structure in their schools.

School administrators generally followed the design protocol, but in some cases, there was not perfect compliance between the order of students on the list and the actual assignment to dormitories. For example, in some schools, students were assigned to other beds for health reasons. Likewise, since there is a natural mismatch between the size of dormitories and the size of the peer group types from my randomization, some students did not have their assigned peers as neighbors in the dormitories. I account for this below by considering three relevant groups:

1. Assigned peers: Students assigned to the same *peer group types*.

2. Neighbors: For small dormitories (less than five students), I define neighbors as roommates. For larger dormitories (more than five students), neighbors are students assigned either to the same or the adjacent bunk bed.

[9] The order was specific to each school×grade×gender.

3. Friends: Peers with whom the student reports a social connection after the intervention.

I now show that the distance on the list predicts neighbors and friends. First, schools sent me the exact locations of students' beds, which allows me to test whether they followed the experimental design empirically. Second, I administered two network surveys after the intervention (as shown in the timeline in Figure 1). The first survey took place four months after the intervention in August 2017. In this survey, students identified their friends, study partners, and people with whom they engaged in social activities such as playing games or dancing. The second survey took place in December 2017, using the same set of questions. I constructed a general network that aggregates the answers from both surveys. I estimate the following equation to test how the distance on the list affects the likelihood of being neighbors and interacting socially:

$$y_{ij} = \gamma_0 + \sum_{k=1}^{9} \gamma_k \mathbf{1}_{d=k_{ij}} + \nu_{ij}, \tag{4}$$

where y_{ij} is a dummy variable equal to 1 when students i and j are neighbors or friends, and $\mathbf{1}_{d=k_{ij}}$ are dummies for a distance k between students i and j on the list. The equation includes nine dummy variables, each of which represents a distance of 1–9 on the list.

Panel A of Figure 5 shows that the distance between students on the list predicts neighbors in dormitories. The plots show the estimates of γ_k with the respective 95% confidence intervals. A distance of one on the list increases the likelihood of being neighbors by 72 percentage points (p-value 0.000). A distance of two or three is also large and statistically significant, with an increase of 62 p.p. (p-value 0.000) and 48 p.p. (p-value 0.000), respectively. Overall, Panel A of Figure 5 shows a monotonous decreasing effect of the distance on the list and the likelihood of being neighbors. From a distance of four onward, all the estimates are weaker, and a very precise zero at a distance of six.

Furthermore, the distance on the list has a substantial effect on social interactions. Panel B of Figure 5 shows the likelihood that two students will form a social connection as a function of their position on the list. Being at a distance of one on the list increases the likelihood of becoming friends, engaging in social activities together, or studying together by approximately 23 percentage points (p-value 0.000). I also find a decreasing pattern with distance: the physical location of beds in the dormitories predicts social interactions. This evidence shows that the experimental design was successfully implemented.

4 Balance and First Stage

This section shows that the randomization is balanced in characteristics at baseline and that the experiment ensures substantial variation in peer characteristics across treatments. This variation translates into neighbors with different academic skills and levels of sociability at baseline. I also show that the intervention led to the formation of new friendships, influencing the social networks in the schools.

4.1 Balance of Baseline Characteristics

I use the following equation to estimate the correlation of the higher-achieving peers treatment and the more sociable peers treatment on students' outcomes and baseline characteristics:

$$y_{i\tau} = \alpha + \lambda_s s_{i\tau} + \lambda_c c_{i\tau} + \gamma_\tau + \nu_{i\tau} \tag{5}$$

Equation 5 explores how the treatment of more sociable peers, $s_{i\tau}$, and the treatment of higher-achieving peers, $c_{i\tau}$, correlate with the characteristics of individual i of type τ, $y_{i\tau}$. We include student type fixed effects, denoted by γ_τ since the propensity score of receiving the treatment varies by student type. The parameters of interest are λ_s and λ_c, which represent the correlation of more sociable and higher-achieving peers, respectively.

In addition to the type fixed effect, all of my estimations control for the stratification variables of my randomization: the strata are cells by school-by-grade-by-gender-by-student type. For the 2017 cohort, I used a similar procedure to the one described in Section 3.3.2 to assign students to classrooms. To exploit the same type of variation as with dorm assignments, I include a classroom-gender fixed effect for students in their first year when I estimate equation 5. The magnitude of peer effects from roommates could be different to the magnitude of peer effects from classmates. For example, prior studies have found that teachers change their behavior based on the composition of the classroom (Duflo et al., 2011). Hence, I make sure that the variation in peer characteristics is only coming from the sociability and academic achievement of neighbors in the dormitories.

I estimate equation 5 on social skills and academic outcomes at baseline for all students, and for all subgroups of sociability, academic achievement, and gender. Table 2 reports these estimates. In general, I find that the treatments are not correlated with social skills or academic outcomes at baseline. Furthermore, Tables A.4 and A.5 present balance tests on all other variables available at baseline. Overall, and as expected from a randomized controlled trial, I do not reject a zero correlation of the treatments with baseline characteristics. The table also reports the F-statistic of multivariate regressions, which shows that for both treatments and across all subgroups of students, treatments are not correlated with baseline characteristics.

4.2 First Stage

Next, I explore the impact of the randomization on the number of assigned peers of each type and their average characteristics. First, I estimate equation 5 on the number of more sociable and higher-achieving assigned peers. I also estimate these impacts on the average peer characteristics; this corresponds to the first stage and is depicted in equations 6a and 6b. I also estimate the same set of equations for *neighbors* and *friends* as described above.

$$\bar{s}_{p_{i\tau}} = \theta_s + \delta_s s_{i\tau} + \phi_s c_{i\tau} + \gamma_\tau + \xi_{i\tau}, \tag{6a}$$

$$\bar{c}_{p_{i\tau}} = \theta_c + \delta_c s_{i\tau} + \phi_c c_{i\tau} + \gamma_\tau + \nu_{i\tau}, \tag{6b}$$

where δ_s and δ_c are the effects of the more sociable peers treatment on the average sociability and academic achievement of peers, respectively. ϕ_s and ϕ_c represent the effects of the higher-achieving peers treatment on the same variables.

As expected from the randomization, the assignment to treatments leads to differences in the type of assigned peers. Table 3 reports the impact of both treatments on the type of peers that students have and on the average characteristics of these peers. Columns 1 and 2 of Table 3 show how each treatment changed the number of more sociable and higher-achieving peers assigned to each group. As a general rule, being assigned to more sociable peers increases the number of more sociable peers in a student's group by 3, and the same holds for higher-achieving peers. That is, students have three additional peers associated with the type of treatment.

The impacts on the number of peers translate into substantial variation in their average characteristics. Columns 3 and 4 of Table 3 show the impact of the treatments on the average characteristics of the assigned peers. The more sociable peers treatment increases the average sociability of the assigned peers by 0.93 standard deviations. Likewise, the higher-achieving peers treatment raises the average academic achievement of the assigned peers by 0.94 standard deviations. The results also show that sociability and academic achievement are positively correlated at baseline. The higher-achieving peers treatment has a positive impact on peers' average sociability, and the more sociable peers treatment raises peers' average academic achievement.

Notice that the experimental design aims to change the mean and not other moments of the peers' skills distribution. For instance, other peer effects studies have also examined the impact of the variance on students' outcomes (Hoxby and Weingarth, 2006; Duflo et al., 2011; Booij et al., 2017). By construction, under a symmetric distribution, and conditional on the change in the mean, the allocation to treatments should not have predictive power on the variance. Non-reported results show that, after controlling for average peer skills, the treatments do not predict the variance of peer academic achievement. The more sociable peers treatment has a small negative impact on the variance of neighbors' sociability due to the asymmetry in the distribution (see Figure 3.) However, this impact is not substantial compared to the change in the mean.

In some cases, there is no perfect compliance between the randomly assigned peers and actual neighbors. Hence, I estimate the same set of equations on actual neighbors rather than the peers in the peer group types. For small dormitories (less than 5 students), I defined neighbors as roommates. For larger dormitories (more than 5 students), neighbors are students in either the same or the adjacent bunk bed.

The data shows that the treatments predict the neighbors' characteristics, which confirms that the schools followed the implementation procedures described in the previous section. The impact on the treatments in columns 5 to 8 of Table 3 show the effect of each treatment on students' actual neighbors. Columns 5 and 6 show the estimation of equation 5 on more sociable and higher-achieving neighbors. Overall, both treatments, more sociable and higher-achieving peers, increase the number of neighbors of their respective type by 1.6. Columns 7 and 8 show the effect on average neighbors' characteristics. Being assigned to more sociable peers increases the average sociability of neighbors by 0.56 standard deviations. Likewise, the higher-achieving peers treatment increases the average academic achievement of neighbors by 0.58 standard deviations. As expected, due to the non-compliance reasons mentioned above, these effects are smaller than those reported in columns 1 to 4 of Table 3 on assigned peers, but are still very strong and highly significant.

As the intervention had an impact on the schools' social networks, I also estimate equation 5 on the number of connections of each type and average connections' characteristics. Columns 9–12 of Table 3 present the results. More sociable neighbors increase the number of more sociable connections by 0.47, and higher-achieving neighbors increase the number of higher-achieving connections by 0.36. These effects translate into an increase in the average sociability and academic achievement of friends of 0.062 and 0.055 standard deviations, respectively. All of these estimates are statistically significant at the 1% level.

5 Outcomes and Empirical Strategy

5.1 Outcomes

The principal outcomes are grouped into two broad categories according to the type of skill affected: social skills and academic outcomes. Social skills outcomes are network degree and centrality, psychological self-reported instruments, and peers' perceptions of students. Academic outcomes are school grades and test scores collected by the Ministry of Education.

5.1.1 Social Skills Outcomes

The first set of outcomes corresponds to measures of social skills. Finding reliable measures of social skills is a big challenge. My first outcome is the one that I used to classify students by sociability: the social network's centrality level after the intervention. I also look at the number of connections. As described above, I collected two waves of network surveys after the intervention in which students listed their friends, study partners, and who they play sports and games with. I constructed a global network aggregating all the questions from both waves. Like other network studies (Breza and Chandrasekhar, 2019; Banerjee et al., 2013, 2014), I consider an undirected network, but my results are robust to mutual connections.

I also measure social skills using self-reported psychological tests. My primary outcome is a social skills index that uses the first component of a principal component analysis on the entire set of tests. These tests include extraversion and agreeableness of the "Big Five" (altruism, empathy, leadership, emotional intelligence, intercultural sensitivity) and the "Reading the Mind in the Eyes" test. Appendix C describes the details of these tests.

To account for potential biases in self-reported answers, I include peers' perceptions of their personal social skills as the third type of social outcome. While self-reported psychological tests are frequently used to measure social skills, they are subject to social desirability bias and can be manipulated by the respondent. Since social skills are important for interactions with peers, we also included questions about how peers perceive the students.[10] Previous studies have found that relying on the perceptions of other community members relaxes information asymmetries (Hussam et al., 2017). Students were asked to rank up to five of their peers in four dimensions of social skills: leadership, friendliness, popularity, and shyness (reversed). I construct an index of peers' perceptions using the number of peers that nominated the student in each category.

I reproduce similar measures of social skills with the available social skills measures at baseline. Panel B in Appendix Figure A.1 displays a scatter plot of the two general measures of social skills before and after the intervention. There is a large, positive correlation between the two measures. An OLS regression shows that a one-standard-deviation in the social skills index at baseline correlates with a 0.42-standard-deviation increase in the social skills index after the intervention.

[10] This was also the case in the baseline survey, as described in Appendix A.

5.1.2 Academic Outcomes

Teachers assign grades to students for each subject based on their homework and test scores during the first three quarters of the year. These variables are only available for the 2016–17 cohorts. The Ministry of Education relies on the grades of the IB degree for the 2015 cohort, and I do not have access to the final scores.

Students in 2016–17 cohorts were also assessed via standardized tests designed by the ministry. These tests determine the students' grades for their final quarter at school. For the 2015 cohort, these test scores are not available since the ministry only used the IB grades.

As described in Section 3, the more sociable peers treatment is only available for the 2015–16 cohorts. Likewise, test scores and grades are only available for the 2016–17 cohorts. Appendix Table A.6 reconciles both sets of information and indicates which cohorts were used for each treatment–outcome combination. I still use all the cohorts to estimate the impact of the higher-achieving peers treatment on social skills.

5.2 Empirical Strategy

I begin by estimating the effect of my two treatments—more sociable and higher-achieving peers—on the social skills and academic outcomes described in Section 5.1. The following equation estimates the impact of each treatment:

$$y_{i\tau} = \alpha + \lambda_s s_{i\tau} + \lambda_c c_{i\tau} + X'_{i\tau}\delta + \gamma_\tau + \varepsilon_{i\tau}. \tag{7}$$

Equation 7 shows how the more sociable peers treatment, $s_{i\tau}$, and the higher-achieving peers treatment, $c_{i\tau}$, affect the outcome, $y_{i\tau}$, of individual i of student type τ. I include student type fixed effects, γ_τ, because the likelihood of receiving the treatments varies by student type. The parameters of interest in this equation, λ_s and λ_c, denote the causal impact of the more sociable and higher-achieving peers treatments, respectively. The vector $X'_{i\tau}$ is a set of baseline characteristics chosen via the "post-double-selection" Lasso method developed by Belloni et al. (2014a,b). The standard errors are clustered at the student *type*$\times$*group of peer* level, since all the students within this unit share the same treatment peers (Abadie et al., 2017). I also report the randomization inference p-values for my main results (Athey and Imbens, 2017; Young, 2018).

To estimate heterogeneous effects by gender, I also estimate equation 7 including the interaction of the two treatments with a *boy* dummy variable. The following equation describes this model:

$$y_{i\tau} = \alpha + \lambda_s s_{i\tau} + \lambda_c c_{i\tau} + \phi_s s_{i\tau} \times boy_i + \phi_c c_{i\tau} \times boy_i + X'_{i\tau}\delta + \gamma_\tau + \varepsilon_{i\tau}, \tag{8}$$

where ϕ_s and ϕ_c are the differentiated impacts of each treatment for boys.

Estimates of equation 7 and equations 6a and 6b are of independent interest. They also are the reduced form and the first stage of an instrumental variables estimate of the effect of peers' abilities. I estimate the effect of a one-standard-deviation in peers' average characteristics (i.e. neighbors' sociability and academic achievement) on students' outcomes. I use the experimental variation in my study in a two-endogenous model, and jointly estimate the effect of peers' characteristics on students' social skills and academic outcomes. The following equation introduces my two-endogenous model:

$$y_{i\tau} = \theta + \beta_s \bar{s}_{n_{i\tau}} + \beta_c \bar{c}_{n_{i\tau}} + X'_{i\tau}\delta + \gamma_\tau + \varepsilon_{i\tau}, \tag{9}$$

where $\bar{s}_{n_{i\tau}}$ and $\bar{c}_{n_{i\tau}}$ denote the average baseline sociability and academic achievement of student i of type τ. For small dormitories (less than 5 students), I define neighbors as peers in the same room. For larger dormitories (more than 5 students), neighbors are defined as having the same or the adjacent bunk bed. The parameters of interest are β_s and β_c; the effect of a one-standard-deviation in the average sociability and academic achievement of neighbors on students' outcomes. The first stage of this model is depicted in equations 6a and 6b. It represents the impact of the assignment to treatment on neighbors' characteristics.

As described in Section 4, columns 7 and 8 of Table 3 display the estimates of equations 6a and 6b. Being assigned to live with more sociable peers increases the average sociability of neighbors by 0.56 standard deviations, and the higher-achieving peers treatment increases the average academic achievement of neighbors by 0.58 standard deviations.

6 Main Results

6.1 Social Skills Outcomes

My description of the results starts by reporting the impact of my two treatments—the more sociable peers treatment and the higher-achieving peers treatment—on network measures, social-psychological tests, and peers' perceptions. Panel A of Table 4 reports the reduced-form estimates of equations 7 and 8 for all students on all of my social outcomes indicators.

The results reveal that having more sociable peers has a positive impact on social outcomes, but only for boys. Columns 1 and 2 in Panel A report the post-intervention effects on the number of connections for all students. The impact of more sociable peers on the number of links for all students is a zero (-0.038, p-value 0.995). However, column 2 shows that this average impact masks some heterogeneity by gender. While the impact is negative for girls, the effect is large and positive for boys, who end up having 0.357 (p-value 0.112) more connections after the intervention. The results for the network centrality (columns 3 and 4) reveal that boys have a better network position after the intervention (0.10σ, p-value 0.011). Having more sociable neighbors thus reduces the centrality of girls (-0.050, s.e. 0.032) and increases it for boys (0.100, p-value 0.011).

I also find that more sociable neighbors increase the social outcomes of boys only, as captured by their psychological tests (columns 5 and 6) and their peers' perceptions (columns 7 and 8). Columns 5 and 7 show an ATE of 0.073σ (p-value 0.007) on the psychological tests, and of 0.031σ (p-value 0.126) on peers' perceptions. However, these positive effects are mainly driven by boys, for whom sociable neighbors increase the social skills index by 0.124σ (p-value 0.000) and the peers' perception index by 0.050σ (p-value 0.114).

By contrast, I do not find that higher-achieving peers affect social outcomes for either boys or girls. Overall, the estimates for all the students in Panel A are precise zeros. This is true for the network centrality measure (column 3, effect of 0.001σ, s.e. 0.019), the social skills index (column 5, effect of -0.008σ, s.e. 0.021), and the peers' perceptions (column 7, effect of 0.021σ, s.e. 0.017). Both the point estimates and standard errors are small for every single social measure. I also find no differences by gender when I test for heterogeneous impacts in the even columns of Table 4.

Next, I explore whether these effects vary according to students' sociability at baseline by estimating equations 7 and 8 by subgroups: less and more sociable students at baseline (Panels B and C, respectively). I then compare these results to the estimates of equation 7 for all students, presented in Panel A.

The positive effects of having more sociable neighbors on boys' social skills mainly come from the impact on students who were less sociable at baseline (Panels A and B of Table 4). More sociable peers increase the connections of less sociable students by 0.80 (p-value 0.005). The estimates on network centrality, psychological tests, and peers' perceptions are all consistent with this conclusion. All of the point estimates are larger than those reported in Panel A, and the p-values range between 0.001 and 0.013. By contrast, I do not find robust evidence that more sociable neighbors affect the social outcomes of less sociable girls. Nor does having higher-achieving neighbors appear to affect the social outcomes of less sociable students. While I observe some marginal negative effects on peers' perceptions of less sociable girls, I do not over-interpret this result as it is inconsistent with the effect on other social outcomes.

The more sociable peers treatment does not affect the formation of social skills for students assessed as more sociable at baseline. Panel C supports this general conclusion by showing the reverse side of the story. In general, I cannot reject a zero treatment effect for most of the outcomes in this table for both boys and girls. Higher-achieving peers, however, appear to increase the social perceptions of lower-achieving girls. As this effect is not aligned with other social outcomes, I refrain from drawing general conclusions from these estimates.

The positive impacts on social skills for the less sociable boys translate into hard outcomes such as lower dropout rates and higher enrollment rates at better colleges. Panel A of Table A.7 shows that the measures of social skills have predictive power on college enrollment and quality. Social skills, math scores, and reading scores do not affect the dropout rate (column 1). However, social skills and math scores predict both college enrollment (column 2) and college quality (columns 3 and 4).[11] Furthermore, the results in Panel B show that more sociable neighbors also influence the hard outcomes of the less sociable boys. Column 1 shows a negative effect of 2.3 p.p. (p-value 0.007) on the dropout rate. Columns 3 and 4 show an increase of 5.2 p.p. (p-value 0.028) and 4.8 p.p. (p-value 0.062), respectively, on the likelihood of enrolling at a certified or top 20 college. This is consistent with the evidence that social skills affect later-life outcomes and the fact that Peruvian universities use interviews as part of their admissions process.

6.1.1 Robustness Checks

The improvement of the social skills for less sociable boys remains after multiple robustness checks. Figure 6 presents the effect of the more sociable peers treatment on all the individual outcomes that are related to social skills. These include:

1. The degree and the centrality of the friendship, study and play network.
2. Openness, extraversion, and agreeableness of the Big Five, as well as other psychological tests.
3. The number of peers who perceive the student as a leader or as a friendly, popular, or shy person.

[11] A one-standard-deviation in social skills correlates with a 1.6-percentage-point increase in college enrollment. This is one-quarter of the correlation between college enrollment and math scores. The results are more noteworthy for enrollment at a certified and a top 20 college, where the correlation with social skills is about 45% of the correlation with math scores. By contrast, reading scores are weakly correlated with college outcomes except for enrollment at a top 20 college.

Panel A displays the point estimates and 90% confidence intervals for the less sociable boys. The point estimate is positive for 34 out of the 36 outcomes, and in 27 cases, statistically different from zero. Moreover, Table A.8 presents the p-values of Young (2018), showing that these results are robust to randomization inference. Likewise, I can also reject a zero effect after accounting for multiple-hypotheses testing. Table A.9 presents p-values for multiple hypotheses across different groups by gender and sociability at baseline.[12]

6.1.2 2SLS Estimates

To account for imperfect compliance between assigned peers and actual neighbors, and to provide more compatible estimates to other peer effects studies, I estimate equation 9. Table 5 presents the results of the 2SLS two-endogenous model described in equation 9 on social and academic outcomes for different groups. The table reports the estimates of parameters β_s and β_c, the impact of neighbors' average sociability, and academic achievement on students' outcomes. There are two endogenous variables: neighbors' sociability and neighbors' academic achievement (both calculated at baseline). I instrument for these variables using indicators for whether the student was assigned to the more sociable or higher-achieving peers treatment. Table 5 reports peer effects on a social skills index constructed using all the measures of social outcomes.

The results of the 2SLS model summarize the treatment effects (the reduced form) described above. I find that neighbors' sociability has a positive impact on social skills, but only for boys. Columns 1 to 3 of Table 5 show the results for all students, boys, and girls. A one-standard-deviation increase in neighbors' sociability has a 0.138σ impact (p-value 0.004) on the social skills index for the average student (column 1). This positive impact comes from the effect on boys in column 2, with an estimate of 0.337σ (p-value 0.000). By contrast, column 3 shows that the social peer effects estimate on girls is small (0.029) and precise (s.e. 0.055). Social outcomes are also not affected by the academic achievement of students' neighbors.

These positive social peer effects on boys are driven by the impact on the students assessed as less sociable at baseline. Columns 4 to 6 show the results for the less sociable students. For every group, the estimates are larger than for the combined sample in columns 1 to 3. Less sociable boys benefit the most from more sociable neighbors. A one-standard-deviation in neighbors' sociability increases the social skills index of the less sociable boys by 0.470σ (p-value 0.000). I also find that among more sociable students (columns 7 to 9), boys benefit more from sociable peers than girls, but the effect is small compared to the estimate in column 5.

Taken together, these results show that having more sociable peers can enhance the formation of social skills for boys—especially those with lower levels of sociability at baseline. Based on these estimates, the optimal policy recommendation to maximize the average level of social outcomes and reduce inequality in social skills is to mix boys according to their initial level of sociability. While less sociable boys would benefit from this policy, more sociable boys would remain unaffected. As girls' social skills are also unchanged by the sociable peers, optimal allocation to dorms should not target their levels of sociability.

[12] To perform this test, I use the *wyoung* command developed by Jones et al. (2019).

6.2 Academic Outcomes

Next, I estimate treatment effects on academic outcomes. Table 6 reports the estimates of equations 7 and 8. Columns 1 and 2 report the effects on grades in math and reading comprehension. Analogously, columns 3 and 4 show the impact of each treatment on math and reading test scores.

Consistent with the peer effects estimates reported by previous quasi-experimental studies (Angrist and Lang, 2004; Duflo et al., 2011; Abdulkadiroğlu et al., 2014) that generate large variation in peers' skills, I find that the impact of higher-achieving peers on students' academic achievement is a precise zero. The odd columns in Panel A of Table 6 present the ATEs for all students in my sample. These are precise estimates in the context of my study. The 95% confidence interval for math test scores (column 5) ranges between -0.056 and 0.014σ. For reading (column 7), it ranges between -0.066 and 0.024σ. Overall, these confidence intervals allow me to rule out positive peer effects on the average student. Likewise, I do not find evidence that having more sociable peers affects the academic achievement of the average student. Nor can I reject the possibility of homogeneous treatment effects by gender, except for reading test scores. In column 8, I find a negative effect on girls of 0.067 (p-value 0.042).

I also examine treatment effects heterogeneity by academic achievement. I estimate equations 7 and 8 for two subgroups of academic achievement: lower- and higher-achieving students. Panels B and C of Table 6 report the reduced-form estimates for lower- and higher-achieving students at baseline.

Higher-achieving peers have heterogeneous treatment effects on academic achievement. Columns 1 and 3 in Panel B of Table 6 show that the higher-achieving peers treatment has a negative effect on both math and reading grades. Higher-achieving neighbors reduce students' math grades by 0.084σ (p-value 0.018) and reading grades by 0.072σ (p-value 0.049). Results on test scores show a similar impact. Columns 5 and 7 of Table 6 show that the effects of higher-achieving peers on lower-achieving students are negative and significant for both math (-0.050, p-value 0.058) and reading (-0.063, p-value 0.069). For the more sociable peers treatment, there is no consistent evidence that it affects academic performance.

The negative academic peer effects on lower-achieving students are starker for girls. The even columns in Panel B of Table 6 report the estimates of equation 8 for lower-achieving students. These results show that for lower-achieving girls, the treatment academic effect is particularly negative, as reflected in math grades (column 2, -0.145 s.d., p-value 0.002), math test scores (column 6, -0.062 s.d., p-value 0.036), and reading test scores (column 8, -0.124 s.d., p-value 0.007). These results are robust to randomization inference (Panel B of Table A.8) and multiple-hypotheses testing (Panel B of Table A.9) —although the latter is weaker for math test scores. For reading grades (column 2), the point estimate is also negative, but it is more negative for boys. This evidence suggests that higher-achieving neighbors can harm the academic performance of lower-achieving girls. For lower-achieving boys, I cannot reject the null hypothesis of a zero impact.

For the higher-achieving students at baseline, I do not find that more sociable or higher-achieving neighbors affect their academic performance. Panel C in Table 6 reports these estimates. Overall, in most cases, the estimates are small and fairly precise. This is true for grades and test scores, as well as for boys and girls (even columns in Table 6). Neighbors' characteristics do not appear to affect the academic achievement of the strongest students.

6.2.1 2SLS Estimates

Table 7 reports the 2SLS estimates of equation 9 for both math and reading test scores (Panels A and B, respectively). These estimates account for imperfect compliance and are comparable to other peer effects studies. Panel A presents the results for math, and Panel B displays the results for reading test scores. Column 1 shows a precise zero estimate of average academic peer effects. The impact of a one-standard-deviation in neighbors' academic achievement at baseline is -0.039 (s.e. 0.031) on math and -0.038 (s.e. 0.040) on reading scores. Table A.1 presents estimates of peer effects in other studies. The 95% confidence intervals of my estimates rule out even the smallest significant effects reported in the table (0.072 in Carrell et al. (2009)), and both the point estimates and standard errors are very similar to Abdulkadiroğlu et al. (2014). I also find fairly precise estimates of neighbors' sociability on academic outcomes, and columns 2 and 3 do not reveal differences by gender, except for reading test scores.

The results in columns 4 and 6 of Table 7 show that academic peer effects are negative for lower-achieving students, particularly for girls. Column 4 reports that a one-standard-deviation increase in the academic achievement of neighbors decreases math scores by 0.086σ (Panel A, p-value 0.063) and reading scores by 0.118σ (Panel B, p-value 0.065). Column 6 shows that academic peer effects are more negative for lower-achieving girls, for whom a one-standard-deviation increase in the admission scores of neighbors reduces math scores by 0.103σ (p-value 0.034) and reading scores by 0.223σ (p-value 0.006).

In summary, higher-achieving peers have, on average, a zero effect on students' academic outcomes. However, higher-achieving peers appear to be detrimental to the performance of lower-achieving students, and especially lower-achieving girls. As higher-achieving neighbors decrease the performance of lower-achieving girls, optimal policies based on these estimates would be geared towards tracking girls by academic achievement in the allocation to dormitories.

These optimal policy recommendations are exclusively based on peer effects estimates and ignore other potential drivers of the results. In the next section, I explore these mechanisms and test whether gender differences in beliefs and social interactions can explain my findings.

7 Mechanisms

7.1 Self-confidence

In this section I examine whether beliefs about one's own abilities (self-confidence) explain my findings. I use a simple framework based on previous theoretical results to illustrate how beliefs would affect student's outcomes and the impact of peer characteristics on beliefs.

There are two mechanisms for self-confidence to improve students' outcomes. First, if ability and effort are complements in the education production function, students with higher confidence will exert more effort (Benabou and Tirole, 2002).

To illustrate this, let's consider the following education production function that depends on effort e_i and ability a_i.

$$y_i = a_i + \theta e_i + \gamma a_i e_i, \tag{10}$$

with $\theta > 0$ (effort improves the output) and $\gamma > 0$ (effort and ability are complements). The utility of student i is $u_i = y_i - \frac{c}{2}e_i^2$, where c parametrizes the marginal cost of effort. The optimal effort level of the student would be given by: $e_i^* = \frac{\theta + \gamma a_i}{c}$. When students have imperfect information then students take expectation over the ability distribution, such that:

$$e_i^* = \frac{\theta + \gamma \mathbb{E}[a_i]}{c}.$$

Hence, two students with the same level of ability (a_i) but different beliefs ($\mathbb{E}[a_i]$) would have different outcomes. By having higher self-confidence, students are incentivized to exert more effort, and this can improve their performance.

The second mechanism for self-confidence to affect performance is a direct one. Compte and Postlewaite (2004) introduce a model that explains how a person's psychological state can affect performance. In their model, the probability of success depends on a person's level of confidence, captured by her perception of success in previous cases. For example, a student who is more confident about her chances of making friends is more likely to make these friendships, and a student who is more confident in her math skills would have a higher score in a test.

A simple way of introducing the direct effect into the education production function is by including a parameter of self-confidence, $\kappa(\cdot)$ in equation 10:

$$y_i = \kappa(\mathbb{E}[a_i])(a_i + \theta e_i), \tag{11}$$

with $0 \leq \kappa(\cdot) \leq 1$, and $\kappa'(\cdot) > 0$. Notice that in equation 11, I set $\gamma = 0$. The idea behind this production function is that even without complementarity between effort and ability, higher self-confidence can increase output.

The next question to tackle down is: how do peer characteristics affect these beliefs in oneself? By interacting with peers, students receive signals about their skills. It is beyond the scope of this paper to study how these signals are produced. However, it is useful to introduce some examples. For instance, according to the big-fish–little-pond effect, students lose self-confidence due to social comparisons. In the context of the intervention, a student may feel less popular by comparing herself to a more sociable neighbor. However, students could also receive positive signals such as friendships. For example, the same student might feel more popular if she befriends the most sociable students in her class.

In general, it is unclear how signals depend on peer characteristics and how students interpret them. However, two factors are relevant for this analysis: gender differences and the precision of information about abilities.

Prior studies have found that men and women differ in how they form beliefs about themselves (Bordalo et al., 2019). For instance, recent evidence in psychology shows that female students tend to make more upward social comparisons and fewer downward comparisons than male students in math (Pulford et al., 2018). Furthermore, downward social comparisons negatively affect confidence. Likewise, an extensive literature in economics shows that men and women differ in their levels of confidence (Sarsons and Guo, 2016), how they respond to feedback (Mobius et al., 2014), as well as in their preferences for competition (Gneezy et al., 2003; Buser and Yuan, 2019) and approaches to self-promotion (Exley and Kessler, 2019). This evidence illustrates why we care about gender differences in the formation of beliefs and peer effects.

Similarly, the quality of the information that a person has about her abilities can play an equally meaningful role. As students have more information about their skills, they put less weight on signals, including those from peer interactions. To illustrate this, lets consider again the education production function in 10 and 11, and a simple Bayesian updating for a normal distribution, where the prior of ability $a_i \sim \mathcal{N}\left(\overline{a}, \frac{1}{\tau_a}\right)$. When a students receive a signal of the form $x_i = a_i + \varepsilon_i$, where $\varepsilon_i \sim \mathcal{N}\left(0, \frac{1}{\tau_\varepsilon}\right)$ the posterior is given by:

$$a_i|x_i \sim \mathcal{N}\left(\frac{\tau_a \overline{a} + \tau_\varepsilon x_i}{\tau_a + \tau_\varepsilon}, \frac{1}{\tau_a + \tau_\varepsilon}\right).$$

Higher values of precision (τ_a) reduce the weight that students put in the signal as part of the updating process. Hence, as students learn more about their skills, their priors are more precise, and the effect of peer characteristics on beliefs should be lower.

Next, I take this conceptual framework and the forces of gender differences and the precision of information to study whether self-confidence can be a valid mechanism for my experimental results. This analysis is divided into three subsections. First, following the results in Section 6, I study to what extent male and female students differ in their beliefs. Second, I estimate treatment effects on self-reported measures of ability. Third, I examine whether the effect of peer characteristics on beliefs is lower when students know more about their skills.

7.1.1 Gender Differences

To determine if gender differences are affecting students' beliefs and ultimately driving the results reported above, I start by studying whether boys and girls report different beliefs in their skills. In the endline survey, we asked students to rank their own academic skills and popularity from 0 (lowest) to 100 (highest). I also measure beliefs by considering whether a student identifies herself in her cohort's top 5 of the most academically skilled, leadership, friendliness, popularity, and shyness (reversed).

Figure 7 presents the cumulative distribution of the self-reported academic and popularity rankings by gender (Panels A and B, respectively). The left column displays quantile regressions for the gender gap of these self-reports after controlling for observable characteristics including test scores, number of friends and centrality, as well as peers' perceptions of academic skills and popularity.

In general, boys report higher self-confidence in both academic skills and popularity. The left column of both panels shows that the distribution of boys' self-reported academic and popularity rankings has first-order stochastic dominance over the distribution of the same variables for girls. Furthermore, the estimates of the quantile regressions in the right column show that these differences remain even after controlling for observable characteristics. Hence, the estimates suggest that men are more confident than women. The male-female gap is positive across the entire distribution, and in most cases, it is statistically significant at the 95% level. At the median of the distributions, for example, the difference in the ranking is approximately five positions —0.25 standard deviations of the academic ranking and 0.20 standard deviations of the popularity ranking.

This subsection shows that male students are more confident than comparable female students. Next, I explore whether these differences translate into treatment effects on beliefs in their own abilities.

7.1.2 Peers and Beliefs

In this subsection, I examine whether having more sociable peers affects students' perception of their own social skills. Table 8 reports the impact of more sociable neighbors on beliefs in one's own social skills. Panel A presents the results for the less sociable students at baseline and Panel B for the more sociable. I hereafter focus my analysis in Panel A, as less sociable boys benefit the most from sociable neighbors (Table 4). Columns 1 to 3 show the effect on three different self-reported rankings (all of them between 0 and 100): (i) in the dorm,[13] (ii) in the classroom, and (iii) in the cohort. Columns 4 to 8 report estimates on whether the student nominated herself when asked to name up to five peers based on different personal features. Column 4 shows whether the student considers herself a leader, column 5 among the most popular, column 6 among the friendliest, and column 7 among the shyest (reversed). Column 8 presents an index that combines the four categories.

While the less sociable girls negatively updated their beliefs about their own social skills, the less sociable boys believed they were more social after the intervention. As students were placed in dormitories with more sociable neighbors, we would expect a negative report on the popularity ranking within their dorms. However, column 1 shows that we only find this effect for girls, who generally report a ranking that is 2.9 points lower (p-value 0.049). By contrast, we cannot reject a zero effect for boys. The interaction term of the treatment with male is positive, although not statistically significant.

The results also show that beyond the negative mechanic effect within the dorm, girls also report a lower ranking in the classroom and in their cohort when assigned to more sociable peers (columns 2 and 3, respectively). Hence, the intervention caused them to believe less in their own popularity. This result is aligned with previous evidence that women tend to make more upward social comparisons than men. We also find that the impact of the treatment on self-reported rankings varies by gender. The treatment effect on the ranking in the classroom and the dorm is 5.01 and 5.35 ranking positions higher for men than for women. Both differences are statistically significant at the 95% level. Furthermore, the estimate in column 3 shows that the treatment effect is positive for men, with an increase in the ranking by 2.6 positions (0.1σ, p-value 0.106). This result suggests that men believe they are more popular after interacting with more sociable neighbors in the dormitories.

The estimates in column 8 show that less sociable boys indeed believe themselves to be more social after interacting with more sociable peers. The more sociable peers treatment increases this self-recognition for boys by approximately 15 points (p-value 0.014). By contrast, the effect is negative (-10 points, p-value 0.015) for girls. The results in columns 4 to 7 show that the positive impact on the beliefs of the less sociable boys is driven by their self-perceived levels of leadership and popularity, but especially shyness. In general, less sociable boys are 5.1 percentage points (p-value 0.005) less likely to report themselves among the shyest in the school after the intervention.

This evidence suggests that more sociable neighbors affect boys' and girls' beliefs in their abilities differently. It is important to point out that I cannot disentangle whether these effects are explained by differences in the updating process or the type of signal that students receive. On the one hand, boys and girls may receive different signals due to gender-specific peer interactions. On the other hand, boys and girls who receive the same signal may update differently due to social comparisons or other biases that influence the belief-formation process. As I will discuss later, I cannot reject that social interactions between less sociable students and more sociable neighbors differ by gender. Hence, this suggests that less sociable boys and girls respond differently to having

[13]For large dormitories, the dorm is defined as the students in nearby bunk beds.

similar interactions with their assigned neighbors.

7.1.3 The Role of Information

Changes in beliefs about academic skills are also a valid mechanism to explain the results for the academic peer effects. The evidence in Table 6 shows that higher-achieving peers decrease the academic scores of lower-achieving students, especially of lower-achieving girls. Furthermore, the results in Table A.10 show that these negative effects are mainly driven by first-year students. Here I show that, consistent with the idea that students have more information about their academic skills relative to their social skills, students in the upper cohorts do not change their beliefs about their academic abilities. However, first-year students have less information about their abilities relative to their peers and are therefore more likely to change these beliefs.

Students in the upper cohort do not change their beliefs in their academic abilities due to peer interactions. Table A.11 presents these results. Column 1 shows the impact on self-nominations for the top 5 most skilled students in the cohort. Columns 2 to 4 show the results of the self-reported academic rankings: in the dorm, classroom, and cohort. Overall, the results indicate that the higher-achieving peers treatment does not affect students' perceptions of their own skills. The only impact that is statistically different from zero is self-nomination for girls (column 1). Although this effect can be observed in both panels, the results are inconsistent with the impact on self-reported rankings and test scores.

By contrast, first-year students do change their perception after their assignment to higher-achieving peers. Table 9 presents these results. Column 1 shows the treatment effect on the self-nominations among the most skilled in the cohort, and columns 2 to 4 present the results of the self-reported rankings. The results show that the higher-achieving peers treatment has a negative effect on lower-achieving students' perceptions of their own academic skills, especially for lower-achieving girls. Column 1 shows a negative treatment effect of 5.5 percentage points (p-value 0.040) for girls, with a larger treatment effect for boys of 8.4 percentage points (p-value 0.059). However, I cannot reject that the treatment effect is different for men and women. Furthermore, in all the ranking measures, only lower-achieving girls respond negatively. Column 9 shows that higher-achieving peers reduces their self-reported ranking by about 3.9 positions (p-value 0.026).

Overall, gender differences in self-confidence are consistent with the results in Section 6. While less sociable boys think of themselves as sociable people when paired with more sociable neighbors, the opposite result holds for girls. Lower-achieving girls in their first-year also lose self-confidence in their academic skills due to peer interactions. Hence, gender differences in psychological factors are an important mediator of peer effects.

7.2 Social Interactions

I also study whether social connections with neighbors explain the results in Section 6. Intuitively, the effects of friends should be different from those of other peers. For example, Carrell et al. (2013) find that peers who were supposed to increase the performance of low-skilled students end up harming them due to changes in social and study networks. When low-skilled students are in groups with high-skilled peers, there is segregation by the level of academic achievement, and the performance of the low-skilled students worsens. Given this evidence on the importance of social interactions for the direction and magnitude of peer effects, I test whether this is a valid mechanism driving my results.

To study the role of social interactions, I estimate the impact of each treatment (equation 8) on the number of connections students made with neighbors of their treatment groups. Under a scenario where social interactions are a major driver of peer effects, we would expect that less sociable boys and more sociable neighbors form more connections than other groups. Likewise, we would expect that lower-achieving girls study less with their neighbors when these are higher-achieving.

In general, I do not find that different patterns of social interactions explain my estimates of peer effects. Figure 8 presents the average number of connections with neighbors by distance on the list for different groups. Table 10 reports the treatment effects on the number of connections with assigned neighbors. The table considers the following networks: friendships (column 1), study partnerships (column 2), social activities (column 3), and any of these links (column 4). In the endline survey, we also asked students from whom they have received support to deal with academic (column 5) or personal problems (column 6).

I find no evidence that social interactions explain the positive impacts on social skills for male students. The first panel of Figure 8 shows that less sociable boys form connections with their neighbors in a similar way to comparable groups. The three groups of less sociable students show that the distance on the list reduces the average number of connections. The number of links is also relatively similar at odd values of distance, where peers that provide the treatment are located, and also even ones. I formally test whether the treatment or its interaction with gender, predict connections in Panel A of Table 10. The estimates show that I cannot reject that less sociable boys form more social connections with more sociable neighbors than other groups. In particular, column 1 shows that neither the more sociable peers treatment status or the gender explains social connections with neighbors. Other than a marginally significant effect in column 6, I cannot reject that these parameters are equal to zero. Overall, these results suggest that other groups for which there is no evidence of an improvement in social skills also formed similar connections with their neighbors.

Changes in social interactions are also not consistent with the findings on academic peer effects. Panel B of Figure 8 reports the average number of connections by distance with neighbors for lower-achieving students.[14] The figure shows a similar pattern to Panel A and Figure 5, where increases in distance are associated with lower social interactions for the three groups, and a similar average number of connections for all the values of distance. The estimates in Panel B of Table 10 confirm this, as neither the higher-achieving peers treatment nor its interaction with gender predicts social connections (column 1). Strikingly enough, this result also holds for study partnerships (column 3). Indeed, the results also show that contrary to intuition, lower-achieving girls receive more support from their neighbors in academic and personal problems (columns 5 and 6, respectively), when these are higher-achieving. By contrast, the estimates in Table 7 reveal negative academic peer effects for lower-achieving girls.

Taken together, this evidence rules out social connections as the ultimate driver of peer effects. All students are equally likely to befriend their neighbors, and yet, estimates of peer effects vary

[14]The numbers are higher compared to less sociable students because first-year students form on average more links.

widely across outcomes, student characteristics and peer type.

8 Conclusion

This paper presents the results of a field experiment designed to estimate causal academic and social peer effects. The study was conducted in 23 out of 25 exam schools in Peru, covering a sample of approximately 6,000 students. Students were classified according to baseline sociability and academic achievement using centrality measures of social networks and test scores. Unlike previous experimental designs, my experiment guarantees strong variation in peer characteristics by randomizing the type of peer and matching students to peers of their treatment groups.

I found that more sociable peers have a positive impact on the development of social skills, but only for boys. These effects are mainly driven by the impact on boys who were assessed as less sociable at baseline. My results show that they end up with more connections and a higher centrality or influence in their networks. These results are consistent with the impact on psychological tests and peers' perceptions of their social skills. Furthermore, I find that some of these effects translate into hard outcomes. Having more sociable neighbors helps prevent less sociable boys from dropping out of the COAR network, and makes them more likely to enroll in better colleges.

By contrast, I reject positive academic peer effects on academic achievement. For students who were lower achieving at baseline, the evidence suggests that higher-achieving peers have a negative effect. This result is stronger for lower-achieving girls. My results are not consistent with peer effects estimates from other studies, especially those that use random allocation to groups (Sacerdote, 2011; Epple and Romano, 2011). I cannot determine whether these differences are due to specific conditions of my research setting or methodological differences in the empirical design. However, my conclusions are similar to the evidence on peer effects from quasi-experimental studies (Angrist and Lang, 2004; Abdulkadiroğlu et al., 2014; Duflo et al., 2011) that also ensure substantial variation in peers' skills.

A potential limitation of this paper is that it does not allow for non-linearities in peer effects. However, while the main estimation is based on a linear-in-means peer effects model, I do allow for heterogeneity by gender and baseline characteristics. Furthermore, the main objective of the experimental design was to generate a strong variation in peers' skills. While it would be possible to estimate non-linearities by including more treatment groups—for example, by dividing the sample by terciles—this would be costly in terms of statistical power.

I also rule out social interactions as a mechanism behind the main effects. The impact on less sociable boys is not because they interact more with their sociable neighbors than with other groups. Likewise, although lower-achieving girls are interacting and studying with their higher-achieving neighbors, they experience a decline in academic achievement. This result contradicts previous evidence in the literature, which suggests that students only benefit from higher-achieving peers when they are interacting with them (Carrell et al., 2013). Hence, further studies are needed to understand the differences between peer effects from friends and others.

Overall, the results show that policies that affect peer characteristics need to account for gender differences in psychological factors. Less sociable boys and less sociable girls experience different impacts on their beliefs in their own social skills after interacting with more sociable neighbors. These results are consistent with a broad literature studying how men and women formulate beliefs about themselves and others differently.

To answer the motivating question of this study, I find evidence that social skills can be enhanced by interacting with more sociable people. However, this positive impact depends on how boys and girls respond to peer interactions and form beliefs about their abilities. Further studies are needed to assess whether these results are valid in other contexts.

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Table 1: Summary Statistics

	All Students	By Sociability				By Academic Achievement			
		Less Sociable		More Sociable		Lower-achieving		Higher-achieving	
		Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatments									
Sociability	-0.00	-0.59	-0.68	0.68	0.62	-0.01	-0.06	0.09	0.00
(centrality at baseline)	(1.00)	(0.54)	(0.49)	(0.97)	(0.95)	(0.99)	(0.99)	(1.02)	(1.00)
Academic achievement	0.00	-0.06	-0.08	0.07	0.08	-0.79	-0.78	0.80	0.77
(score in the admission test)	(0.99)	(0.96)	(0.95)	(1.01)	(1.03)	(0.48)	(0.47)	(0.68)	(0.74)
Demographics									
Female (%)	0.57	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00
	(0.50)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Poor (%)	0.36	0.39	0.39	0.34	0.37	0.39	0.38	0.31	0.35
	(0.48)	(0.49)	(0.49)	(0.47)	(0.48)	(0.49)	(0.49)	(0.46)	(0.48)
Extremely poor (%)	0.18	0.20	0.23	0.18	0.19	0.21	0.21	0.16	0.16
	(0.39)	(0.40)	(0.42)	(0.39)	(0.39)	(0.41)	(0.41)	(0.37)	(0.37)
Rural (%)	0.26	0.31	0.30	0.25	0.22	0.31	0.29	0.22	0.21
	(0.44)	(0.46)	(0.46)	(0.44)	(0.41)	(0.46)	(0.46)	(0.42)	(0.41)
Public health insurance (%)	0.50	0.51	0.57	0.44	0.47	0.52	0.55	0.44	0.49
	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
N	6,136	753	1,079	737	1,085	1,332	1,725	1,329	1,750

Notes: This table reports summary statistics by type of student. Standard deviations are in parentheses. Column 1 shows statistics for all students, columns 2 to 5 by sociability and columns 6 to 9 by academic achievement. Columns 2 to 5 excludes the 2017 cohort because there is no available measure of sociability. The table includes a set of demographic characteristics of students, including gender, poverty, extreme poverty, whether the student comes from a rural household, and public health insurance. These demographic variables come from government administrative data.

Table 2: Balance on Academic Performance and Social Skills at Baseline

Dependent variable:	Social skills index			Math score			Reading score		
	All students	Sociability		All students	Academic achievement		All students	Academic achievement	
		Less sociable	More sociable		Lower-achieving	Higher-achieving		Lower-achieving	Higher-achieving
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: All students									
More sociable	-0.019	-0.015	-0.024	0.019	0.019	0.019	0.010	0.022	-0.002
	(0.038)	(0.056)	(0.053)	(0.027)	(0.034)	(0.043)	(0.028)	(0.041)	(0.041)
Higher-achieving	0.032	0.062	0.001	0.014	-0.026	0.043	-0.000	-0.010	0.010
	(0.038)	(0.055)	(0.052)	(0.021)	(0.029)	(0.035)	(0.022)	(0.033)	(0.034)
Control mean	-0.06	-0.18	0.12	-0.11	-0.39	0.31	-0.08	-0.31	0.25
N	3,654	1,832	1,822	4,523	2,243	2,268	4,523	2,243	2,268
Panel B: Boys									
More sociable	-0.071	-0.094	-0.047	-0.004	0.014	-0.022	0.009	-0.019	0.037
	(0.059)	(0.085)	(0.080)	(0.044)	(0.056)	(0.070)	(0.040)	(0.059)	(0.056)
Higher-achieving	-0.102*	-0.072	-0.133	0.028	-0.017	0.076	0.006	0.025	-0.016
	(0.059)	(0.085)	(0.082)	(0.032)	(0.046)	(0.055)	(0.031)	(0.046)	(0.047)
Control mean	-0.05	-0.18	0.16	0.01	-0.31	0.48	-0.16	-0.42	0.22
N	1,490	753	737	2,029	1,013	1,005	2,029	1,013	1,005
Panel C: Girls									
More sociable	0.016	0.040	-0.007	0.035	0.022	0.048	0.011	0.052	-0.030
	(0.050)	(0.073)	(0.069)	(0.034)	(0.044)	(0.054)	(0.039)	(0.055)	(0.057)
Higher-achieving	0.124**	0.156**	0.093	0.004	-0.032	0.020	-0.005	-0.037	0.030
	(0.049)	(0.072)	(0.067)	(0.027)	(0.037)	(0.046)	(0.031)	(0.046)	(0.047)
Control mean	-0.07	-0.19	0.10	-0.20	-0.46	0.17	-0.01	-0.21	0.28
N	2,164	1,079	1,085	2,494	1,230	1,263	2,494	1,230	1,263

Notes: This table reports balance checks of being assigned to more sociable and higher-achieving peers on social skills and academic performance for all students and subgroups by sociability and academic achievement at baseline. All regressions include strata fixed effects and control for the baseline value of the dependent variable. For the 2017 cohort all regressions include strata-by-classroom fixed effects. Standard errors are clustered at the peer group type-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table 3: First Stage on Assigned Peers, Neighbors, and Friends

	Assigned peers				Neighbors				Friends			
	Number		Baseline characteristics		Number		Baseline characteristics		Number		Baseline characteristics	
	More sociable	Higher-achieving	Sociability	Academic achievement	More sociable	Higher-achieving	Sociability	Academic achievement	More sociable	Higher-achieving	Sociability	Academic achievement
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
More sociable	3.175***	-0.010	0.929***	0.088***	1.632***	0.004	0.556***	0.081***	0.472***	-0.009	0.062***	-0.009
	(0.107)	(0.105)	(0.016)	(0.017)	(0.051)	(0.049)	(0.019)	(0.020)	(0.107)	(0.095)	(0.011)	(0.010)
Higher-achieving	0.015	2.979***	0.037***	0.943***	-0.046	1.603***	0.017	0.583***	-0.105	0.356***	-0.004	0.055***
	(0.067)	(0.083)	(0.010)	(0.013)	(0.033)	(0.038)	(0.013)	(0.015)	(0.073)	(0.080)	(0.008)	(0.007)
Control mean	0.38	0.93	-0.23	-0.53	0.61	1.38	-0.13	-0.36	2.84	6.28	0.03	-0.06
N	6,068	6,068	6,068	6,068	6,068	6,068	6,068	6,068	6,068	6,068	6,068	6,068

Notes: This table reports the effect of being assigned to more sociable and higher-achieving peers identified at baseline on the number of more sociable and higher-achieving assigned peers, neighbors, and friends, and on the average sociability and academic achievement for each of these groups. Assigned peers are students in the *groups of peers* to which the student was assigned, neighbors are students in the same dormitory for small dorms and students in the same or adjacent bunk bed for large dorms. All regressions include strata fixed effects and control for the baseline value of the dependent variable. For the 2017 cohort all regressions include strata-by-classroom fixed effects. The control group is defined as being assigned to less sociable and lower-achieving peers. Standard errors are clustered at the peer group type-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table 4: Reduced-Form Estimates on Social Skills

Dependent variable:	Connections		Centrality		Psychological tests		Peers' perception	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: All students				
More sociable	-0.038	-0.320*	0.011	-0.050	0.073***	0.016	0.031	0.018
	(0.143)	(0.183)	(0.025)	(0.032)	(0.027)	(0.033)	(0.020)	(0.027)
Higher-achieving	0.061	-0.111	0.001	-0.018	-0.008	0.003	0.021	0.042*
	(0.127)	(0.175)	(0.019)	(0.026)	(0.021)	(0.027)	(0.017)	(0.023)
More sociable × boy		0.678**		0.150***		0.140**		0.032
		(0.290)		(0.050)		(0.056)		(0.041)
Higher-achieving × boy		0.396		0.044		-0.027		-0.047
		(0.252)		(0.039)		(0.043)		(0.035)
mean control	14.55	14.55	-0.05	-0.05	-0.01	-0.01	-0.05	-0.05
p-val ms boys		0.112		0.011		0.000		0.114
p-val ha boys		0.115		0.378		0.472		0.834
N	5,818	5,818	6,068	6,068	6,068	6,068	6,068	6,068
				Panel B: Less sociable students at baseline				
More sociable	0.237	-0.171	0.035	-0.073*	0.105***	0.039	0.035	0.000
	(0.195)	(0.260)	(0.033)	(0.041)	(0.039)	(0.048)	(0.022)	(0.028)
Higher-achieving	-0.094	-0.192	-0.025	-0.047	0.024	-0.022	-0.068***	-0.061**
	(0.192)	(0.251)	(0.033)	(0.042)	(0.038)	(0.046)	(0.023)	(0.030)
More sociable × boy		0.971**		0.263***		0.161**		0.085*
		(0.389)		(0.066)		(0.078)		(0.044)
Higher-achieving × boy		0.220		0.052		0.111		-0.017
		(0.381)		(0.066)		(0.077)		(0.044)
mean control	11.65	11.65	-0.25	-0.25	-0.25	-0.25	-0.31	-0.31
p-val ms boys		0.006		0.000		0.001		0.013
p-val ha boys		0.924		0.918		0.154		0.021
N	1,749	1,749	1,832	1,832	1,832	1,832	1,832	1,832
				Panel C: More sociable students at baseline				
More sociable	-0.288	-0.441*	-0.010	-0.026	0.040	-0.007	0.030	0.038
	(0.203)	(0.252)	(0.036)	(0.046)	(0.037)	(0.044)	(0.033)	(0.042)
Higher-achieving	0.301	0.302	0.056	0.045	-0.005	0.067	0.113***	0.143***
	(0.207)	(0.263)	(0.036)	(0.047)	(0.037)	(0.044)	(0.033)	(0.042)
More sociable × boy		0.373		0.040		0.117		-0.020
		(0.421)		(0.074)		(0.076)		(0.067)
Higher-achieving × boy		-0.007		0.027		-0.179**		-0.074
		(0.427)		(0.074)		(0.076)		(0.069)
mean control	14.68	14.68	0.27	0.27	-0.01	-0.01	0.19	0.19
p-val ms boys		0.841		0.821		0.077		0.732
p-val ha boys		0.378		0.203		0.073		0.203
N	1,785	1,785	1,822	1,822	1,822	1,822	1,822	1,822

Notes: This table reports the effect of being assigned to more sociable and higher-achieving peers on social skills outcomes. All regressions include strata fixed effects and control for selected covariates using the "post-double-selection" Lasso method (Belloni et al., 2014b). For the 2017 cohort all regressions include strata-by-classroom fixed effects. The control group is defined as being assigned to less sociable and lower-achieving peers. Standard errors are clustered at the peer group type-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table 5: 2SLS Estimates on Social Skills

Group:	All students			Less sociable			More sociable		
	All	Boys	Girls	All	Boys	Girls	All	Boys	Girls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Neighbors' sociability	0.138***	0.337***	0.029	0.223***	0.470***	0.086	0.068	0.286**	-0.032
	(0.049)	(0.094)	(0.055)	(0.075)	(0.133)	(0.090)	(0.063)	(0.139)	(0.065)
Neighbors' achievement	0.010	-0.061	0.040	0.006	0.071	-0.055	0.007	-0.223*	0.125*
	(0.044)	(0.082)	(0.051)	(0.062)	(0.107)	(0.075)	(0.062)	(0.126)	(0.069)
F sociability	857.33	236.43	709.60	381.72	94.59	341.37	492.22	142.96	412.59
F achievement	942.96	366.97	586.85	449.01	231.39	240.21	515.59	157.20	371.36
N	3,572	1,487	2,085	1,792	752	1,040	1,780	735	1,045

Notes: This table reports 2SLS estimates of average sociability and academic achievement of neighbors on students' social outcomes, using treatment assignment as instruments. All regressions include strata fixed effects and control for selected covariates using the "post-double-selection" Lasso method (Belloni et al., 2014b). For the 2017 cohort, all regressions include strata-by-classroom fixed effects. Standard errors are clustered at the group of peers-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table 6: Reduced-Form Estimates on Academic Performance

Dependent variable:	Grades				Test scores			
	Math		Reading		Math		Reading	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All Students								
More sociable	0.012	0.010	0.043	0.052	-0.027	-0.013	0.020	-0.009
	(0.034)	(0.042)	(0.036)	(0.049)	(0.024)	(0.030)	(0.032)	(0.044)
Higher-achieving	-0.010	-0.034	-0.014	0.005	-0.021	-0.015	-0.021	-0.067**
	(0.022)	(0.029)	(0.024)	(0.031)	(0.018)	(0.021)	(0.023)	(0.031)
More sociable × boy		0.003		-0.021		-0.033		0.067
		(0.069)		(0.072)		(0.048)		(0.065)
Higher-achieving × boy		0.054		-0.044		-0.014		0.105**
		(0.045)		(0.048)		(0.037)		(0.045)
mean control	-0.05	-0.05	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
p-val ms boys		0.801		0.564		0.229		0.219
p-val ha boys		0.565		0.281		0.326		0.247
N	4,404	4,404	4,407	4,407	4,412	4,412	4,434	4,434
Panel B: Lower-achieving students at baseline								
More sociable	-0.008	-0.025	0.079	0.074	-0.048	-0.072*	0.024	0.017
	(0.048)	(0.061)	(0.051)	(0.070)	(0.032)	(0.040)	(0.045)	(0.060)
Higher-achieving	-0.084**	-0.145***	-0.072**	-0.054	-0.050*	-0.062**	-0.063*	-0.124***
	(0.036)	(0.046)	(0.037)	(0.048)	(0.026)	(0.030)	(0.035)	(0.046)
More sociable × boy		0.040		0.012		0.055		0.016
		(0.099)		(0.102)		(0.066)		(0.089)
Higher-achieving × boy		0.137*		-0.042		0.027		0.136*
		(0.072)		(0.074)		(0.055)		(0.069)
mean control	-0.26	-0.26	-0.20	-0.20	-0.29	-0.29	-0.10	-0.10
p-val ms boys		0.845		0.250		0.746		0.624
p-val ha boys		0.883		0.092		0.450		0.816
N	2,180	2,180	2,181	2,181	2,182	2,182	2,195	2,195
Panel C: Higher-achieving students at baseline								
More sociable	0.049	0.059	0.015	0.035	0.002	0.046	0.018	-0.033
	(0.049)	(0.060)	(0.052)	(0.070)	(0.035)	(0.044)	(0.048)	(0.065)
Higher-achieving	0.028	0.054	0.051	0.065	-0.010	0.011	0.009	-0.021
	(0.033)	(0.043)	(0.037)	(0.049)	(0.028)	(0.035)	(0.035)	(0.048)
More sociable × boy		-0.023		-0.045		-0.103		0.119
		(0.098)		(0.103)		(0.071)		(0.096)
Higher-achieving × boy		-0.060		-0.032		-0.048		0.070
		(0.068)		(0.074)		(0.057)		(0.070)
mean control	0.26	0.26	0.18	0.18	0.32	0.32	0.05	0.05
p-val ms boys		0.645		0.892		0.300		0.224
p-val ha boys		0.909		0.564		0.407		0.330
N	2,212	2,212	2,214	2,214	2,218	2,218	2,227	2,227

Notes: This table reports the effect of being assigned to more sociable and higher-achieving peers identified at baseline on grades and test scores. All regressions include strata fixed effects and control for selected covariates using the "post-double-selection" Lasso method (Belloni et al., 2014b). For the 2017 cohort all regressions include strata-by-classroom fixed effects. The control group is defined as being assigned to less sociable and lower-achieving peers. Grades are standardized at the school-by-grade level and test scores at the grade level. Standard errors are clustered at the peer group type-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table 7: 2SLS Estimates on Academic Achievement

Group:	All students			Lower-achieving			Higher-achieving		
	All	Boys	Girls	All	Boys	Girls	All	Boys	Girls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Dependent variable math scores									
Neighbors' sociability	-0.048	-0.087	-0.020	-0.073	-0.032	-0.099	0.002	-0.109	0.081
	(0.043)	(0.076)	(0.050)	(0.054)	(0.102)	(0.062)	(0.069)	(0.121)	(0.079)
Neighbors' achievement	-0.039	-0.051	-0.021	-0.086*	-0.065	-0.103**	-0.011	-0.030	0.029
	(0.031)	(0.055)	(0.036)	(0.047)	(0.088)	(0.049)	(0.046)	(0.077)	(0.056)
F sociability	460.82	148.43	339.28	297.83	116.68	184.68	169.08	48.04	145.42
F achievement	1,069.14	521.05	566.56	391.58	185.47	215.61	528.50	266.83	276.34
N	4,413	1,991	2,422	2,182	991	1,191	2,218	990	1,228
Panel B: Dependent variable reading scores									
Neighbors' sociability	0.044	0.095	0.009	0.057	0.040	0.062	0.045	0.213	-0.045
	(0.059)	(0.095)	(0.075)	(0.075)	(0.123)	(0.094)	(0.097)	(0.155)	(0.124)
Neighbors' achievement	-0.038	0.062	-0.114**	-0.118*	0.023	-0.223***	0.022	0.079	-0.030
	(0.040)	(0.062)	(0.052)	(0.062)	(0.100)	(0.078)	(0.060)	(0.089)	(0.080)
F sociability	466.77	151.66	340.83	306.02	121.83	187.80	168.38	47.57	145.10
F achievement	1,074.77	522.00	570.73	396.43	188.26	217.16	528.01	263.67	278.15
N	4,435	2,000	2,435	2,195	997	1,198	2,227	993	1,234

Notes: This table reports 2SLS estimates of average sociability and academic achievement of neighbors on students' academic outcomes, using treatment assignment as instruments. All regressions include strata fixed effects and control for selected covariates using the "post-double-selection" Lasso method (Belloni et al., 2014b). For the 2017 cohort, all regressions include strata-by-classroom fixed effects. Standard errors are clustered at the group of peers-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table 8: Self-confidence in Social Skills

Dependent variable:	Popularity Ranking			Self-nomination (in the top 5)				
	Dorm	Classroom	Cohort	Leader	Popular	Friendly	No shy	Sum
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Less sociable students at baseline								
More sociable	-2.881**	-3.208**	-2.765**	-0.072***	-0.020	0.014	-0.007	-0.100**
	(1.458)	(1.388)	(1.402)	(0.023)	(0.025)	(0.017)	(0.016)	(0.041)
Higher-achieving	0.047	0.637	-0.873	0.022	0.026	-0.001	0.021	0.040
	(1.474)	(1.441)	(1.450)	(0.022)	(0.025)	(0.016)	(0.016)	(0.040)
More sociable × boy	3.752	5.010**	5.352**	0.112***	0.072*	0.009	0.051**	0.249***
	(2.304)	(2.171)	(2.119)	(0.038)	(0.038)	(0.032)	(0.022)	(0.073)
Higher-achieving × boy	2.262	2.344	1.518	-0.078**	-0.066*	0.006	-0.049**	-0.141**
	(2.266)	(2.149)	(2.125)	(0.037)	(0.038)	(0.031)	(0.022)	(0.070)
mean control	67.29	64.85	58.77	0.28	0.22	0.14	0.91	0.51
p-val ms boys	0.625	0.284	0.106	0.174	0.071	0.406	0.005	0.014
p-val ha boys	0.181	0.062	0.679	0.062	0.164	0.842	0.078	0.081
N	1,663	1,667	1,666	1,681	1,681	1,681	1,681	1,832
Panel B: More sociable students at baseline								
More sociable	0.940	1.257	0.837	-0.002	-0.010	0.006	0.011	-0.000
	(1.366)	(1.160)	(1.260)	(0.023)	(0.025)	(0.019)	(0.014)	(0.046)
Higher-achieving	-1.044	-0.051	-0.781	0.036	0.011	-0.011	0.004	0.053
	(1.346)	(1.154)	(1.228)	(0.025)	(0.024)	(0.020)	(0.013)	(0.047)
More sociable × boy	0.017	-0.007	0.121	-0.033	-0.020	-0.008	-0.016	-0.077
	(2.064)	(1.870)	(1.950)	(0.038)	(0.038)	(0.032)	(0.021)	(0.074)
Higher-achieving × boy	1.700	-0.539	-0.517	0.002	-0.013	0.009	0.030	0.003
	(2.015)	(1.858)	(1.885)	(0.040)	(0.038)	(0.032)	(0.021)	(0.076)
mean control	72.22	70.75	65.26	0.30	0.25	0.16	0.92	0.58
p-val ms boys	0.536	0.395	0.521	0.243	0.287	0.943	0.783	0.180
p-val ha boys	0.663	0.688	0.367	0.220	0.943	0.914	0.033	0.346
N	1,701	1,700	1,702	1,710	1,710	1,710	1,710	1,822

Notes: This table reports the effect of being assigned to more sociable and higher-achieving peers identified at baseline on self-confidence in social skills. All regressions include strata fixed effects and control for selected covariates using the "post-double-selection" Lasso method (Belloni et al., 2014b). For the 2017 cohort, all regressions include strata-by-classroom fixed effects. The control group is defined as being assigned to less sociable and lower-achieving peers. Standard errors are clustered at the group of peers-by-type level; *** p-value$<$0.01, ** p-value$<$0.05, * p-value$<$0.1.

Table 9: Self-confidence in Academic Skills (First-years)

Dependent variable:	Self-nomination (top 5) skilled	Academic Ranking		
		Dorm	Classroom	Cohort
	(1)	(2)	(3)	(4)
Panel A: Lower-achieving students at baseline				
Higher-achieving	-0.055**	-3.277	-3.004*	-3.854**
	(0.026)	(2.232)	(1.630)	(1.719)
Higher-achieving × boy	-0.029	3.901	3.975	3.443
	(0.051)	(3.265)	(2.848)	(2.732)
mean control	0.16	71.70	68.97	64.63
p-val ha boys	0.059	0.793	0.680	0.846
N	1,132	1,119	1,119	1,119
Panel B: Higher-achieving students at baseline				
Higher-achieving	0.006	-0.176	-0.981	-0.696
	(0.036)	(1.589)	(1.624)	(1.344)
Higher-achieving × boy	0.033	1.144	1.833	2.430
	(0.055)	(2.633)	(2.430)	(2.140)
mean control	0.22	74.90	73.42	69.03
p-val ha boys	0.371	0.647	0.638	0.298
N	1,157	1,153	1,154	1,153

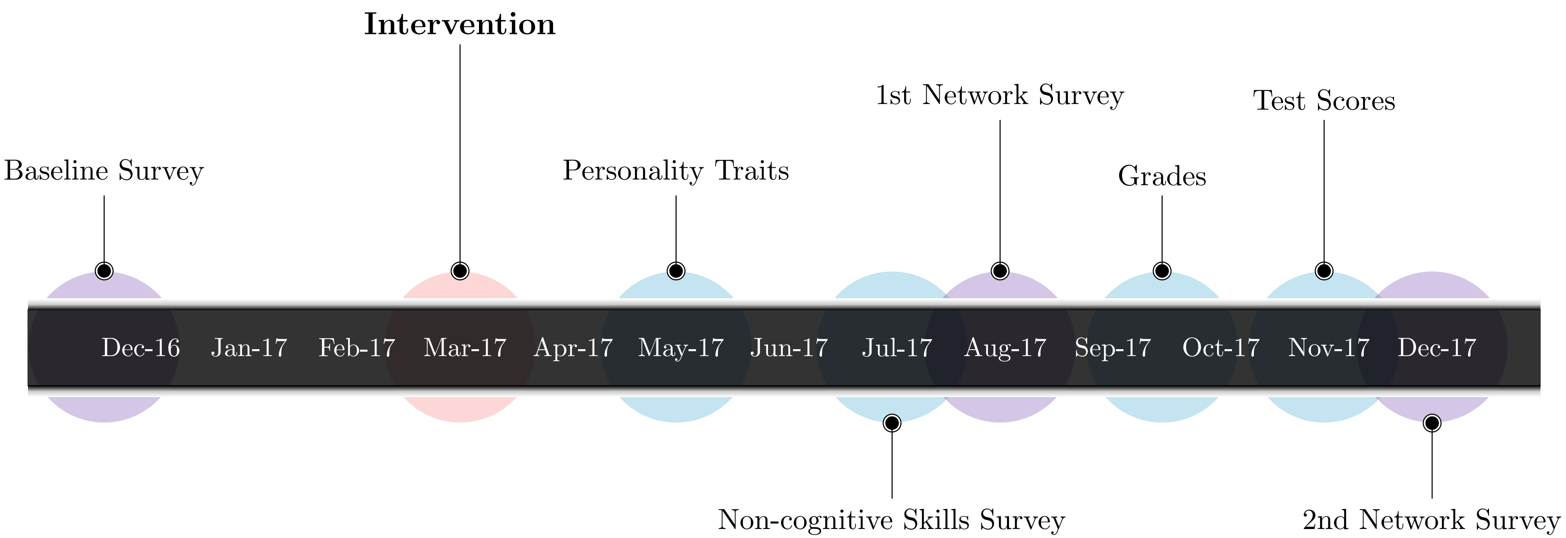
Notes: This table reports the effect of being assigned to more sociable and higher-achieving peers identified at baseline on self-confidence in social skills. All regressions include strata fixed effects and control for selected covariates using the "post-double-selection" Lasso method (Belloni et al., 2014b). For the 2017 cohort, all regressions include strata-by-classroom fixed effects. The control group is defined as being assigned to less sociable and lower-achieving peers. Standard errors are clustered at the group of peers-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table 10: Social Connections with Neighbors

Dependent variable: (network)	Friend	Study	Social	Any	Help academic	Help personal
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Less sociable students at baseline						
More sociable	0.002	-0.010	-0.026	0.015	-0.000	-0.037
	(0.046)	(0.033)	(0.042)	(0.053)	(0.032)	(0.034)
Higher-achieving	-0.048	-0.018	-0.062	-0.025	0.059*	0.028
	(0.043)	(0.033)	(0.041)	(0.050)	(0.033)	(0.035)
More sociable × boy	0.030	0.005	0.063	0.055	0.033	0.076*
	(0.065)	(0.050)	(0.062)	(0.072)	(0.046)	(0.044)
Higher-achieving × boy	0.053	0.009	0.070	0.019	-0.017	-0.020
	(0.065)	(0.050)	(0.060)	(0.072)	(0.045)	(0.044)
mean control	0.57	0.39	0.54	0.74	0.20	0.28
p-val ms boys	0.476	0.901	0.403	0.143	0.317	0.154
p-val ha boys	0.921	0.825	0.864	0.902	0.180	0.735
N	1,829	1,829	1,829	1,829	1,829	1,829
Panel B: Lower-achieving students at baseline						
More sociable	-0.122*	-0.053	-0.105	-0.059	0.009	-0.021
	(0.064)	(0.050)	(0.067)	(0.078)	(0.048)	(0.054)
Higher-achieving	0.043	0.048	-0.011	0.039	0.087**	0.102**
	(0.052)	(0.045)	(0.054)	(0.058)	(0.038)	(0.046)
More sociable × boy	0.184**	0.029	0.139	0.109	0.008	0.036
	(0.091)	(0.074)	(0.090)	(0.105)	(0.068)	(0.063)
Higher-achieving × boy	0.009	-0.045	-0.120	-0.028	-0.021	-0.150***
	(0.083)	(0.067)	(0.076)	(0.086)	(0.055)	(0.055)
mean control	1.15	0.83	1.04	1.44	0.46	0.50
p-val ms boys	0.342	0.667	0.585	0.473	0.742	0.673
p-val ha boys	0.422	0.959	0.015	0.855	0.098	0.134
N	2,258	2,258	2,258	2,258	2,258	2,258

Notes: This table reports the effect of being assigned to more sociable and higher-achieving peers identified at baseline on social links with neighbors who are the treatment. All regressions include strata fixed effects and control for selected covariates using the "post-double-selection" Lasso method (Belloni et al., 2014b). For the 2017 cohort, all regressions include strata-by-classroom fixed effects. The control group is defined as being assigned to less sociable and lower-achieving peers. Standard errors are clustered at the group of peers-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Figure 1: Timeline of the Project



Notes: This figure presents the timeline of the project. The purple circles represent data collection with surveys, the blue circles collection of administrative data through the Ministry of Education, and the red circle the implementation of the intervention.

Figure 2: Groups of Peers in the Experimental Design

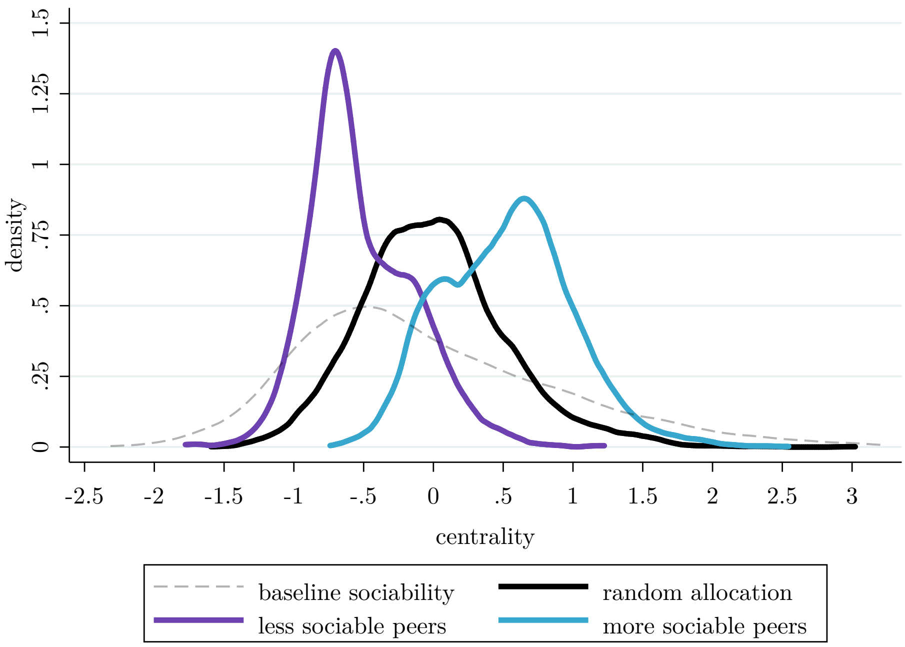
Type of Peers

Student Type	higher-achieving more sociable	higher-achieving less sociable	lower-achieving more sociable	lower-achieving less sociable
higher-achieving more sociable	Group 1	Group 2	Group 3	Group 4
higher-achieving less sociable	Group 2	Group 5	Group 6	Group 7
lower-achieving more sociable	Group 3	Group 6	Group 8	Group 9
lower-achieving less sociable	Group 4	Group 7	Group 9	Group 10

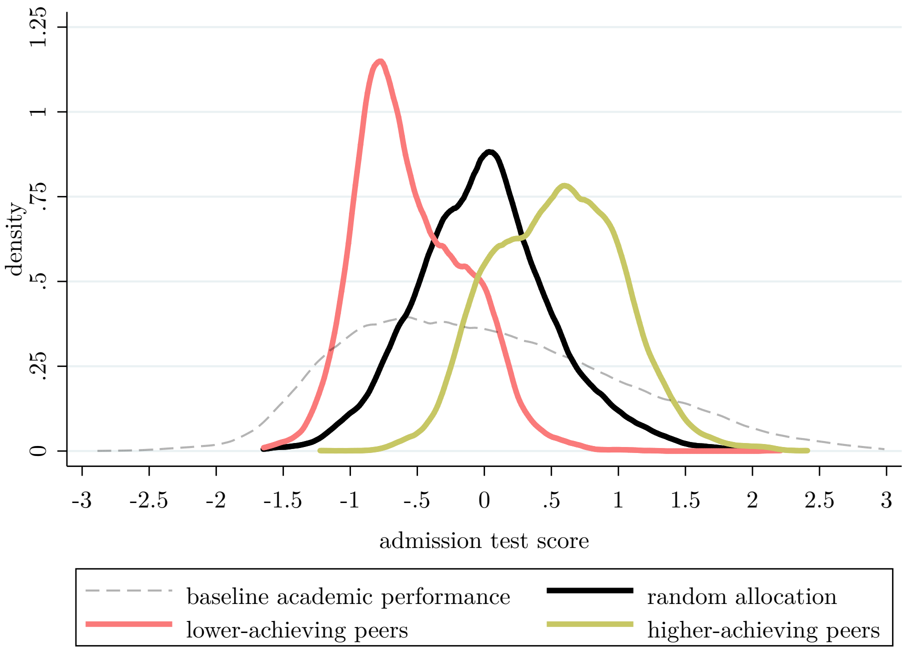
Notes: this figure shows the ten *groups of peers* in my experimental design. It represents all possible combinations between student type and type of peers. Rows are described by student types, and columns show the types of peers to which they were randomly assigned. The diagonal of the matrix is composed by groups of a single type. The matrix is symmetric by virtue of the fact that students are matched with peers of the assigned type.

Figure 3: Distribution of Baseline and Peer Characteristic

Panel A: Sociability



Panel B: Academic Achievement



Notes: This figure plots the distribution of baseline and peer characteristics in the allocation to the *peer group types*. It also shows the distribution of peer characteristics using random assignment to groups for comparison. .

Figure 4: Dorm Structure

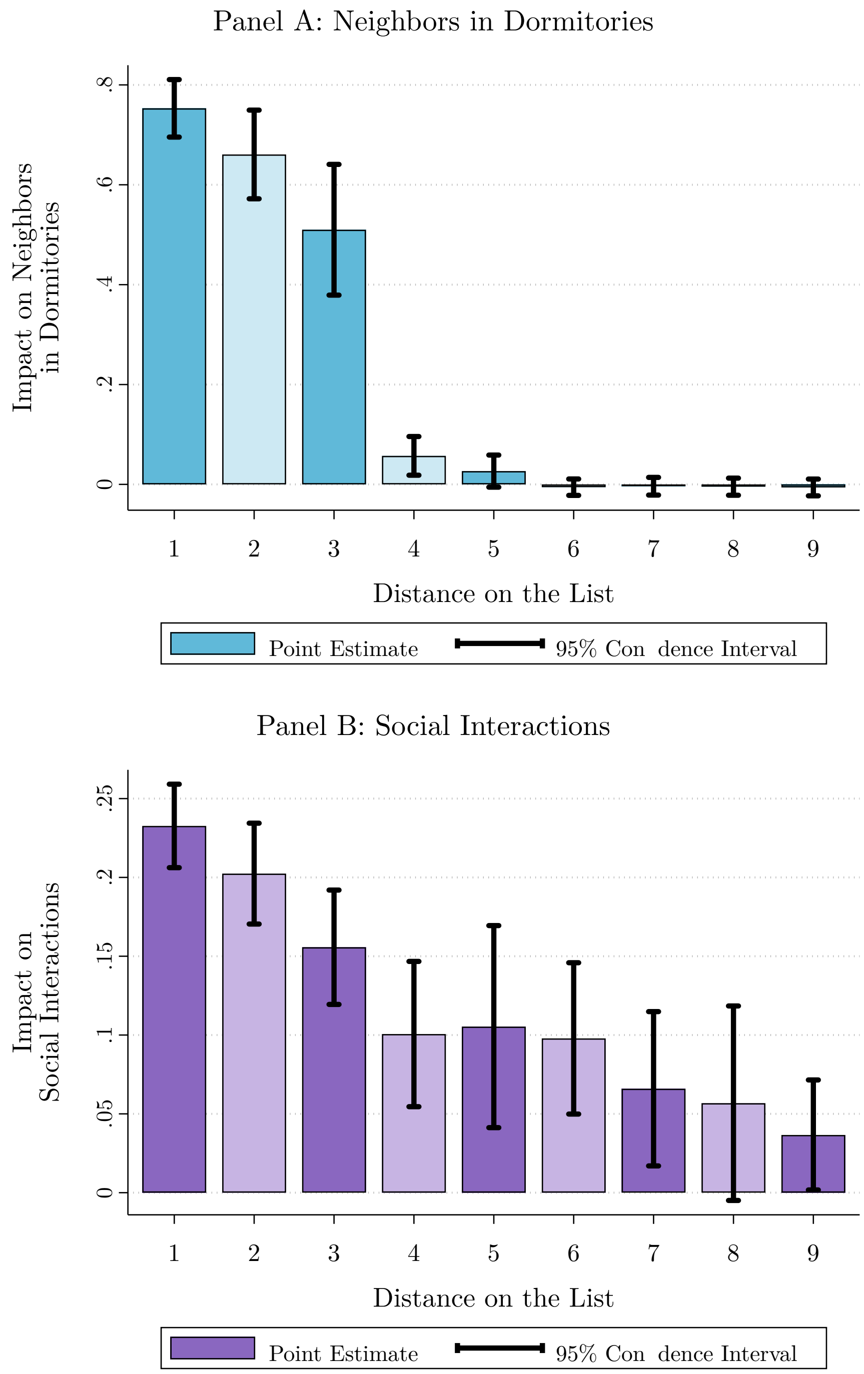
School in Lima

School in Piura

School in Cusco

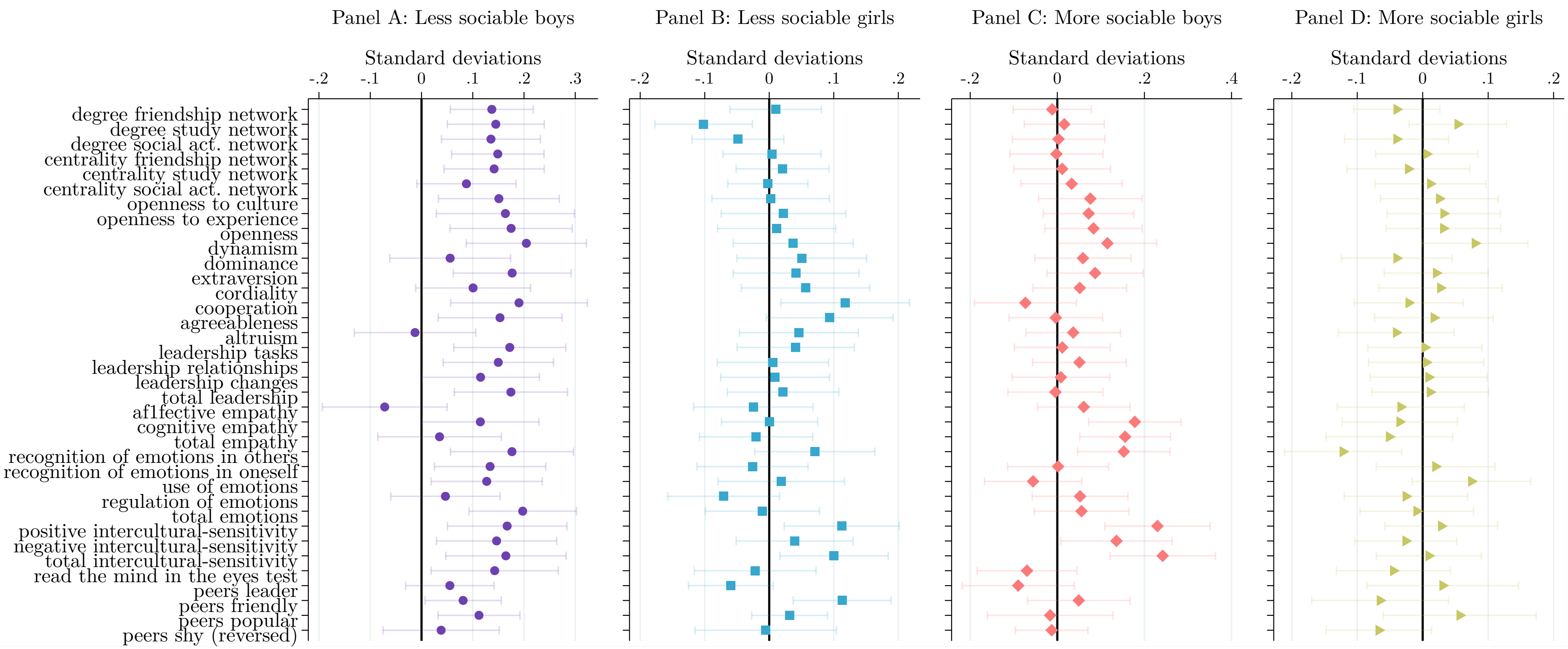
Notes: This figure displays pictures of the dorms for the schools in Lima, Piura, and Cusco. It shows the vast heterogeneity in the type of rooms across the schools.

Figure 5: Effects of Proximity on the List on Neighbors and Social Interactions



Notes: This figure shows the impact of distance between a pair of students on the likelihood of being neighbors and social interaction (friends, study, and playing games or sports). Distance is captured by five distance dummies, and 95% confidence intervals are displayed for all proximity effects. Students are at an odd distance from their treatment peers, and at an even distance from the peers of their type, by construction of the experimental design. All estimations control for strata fixed effects. Standard errors are clustered at the school-by-cohort level.

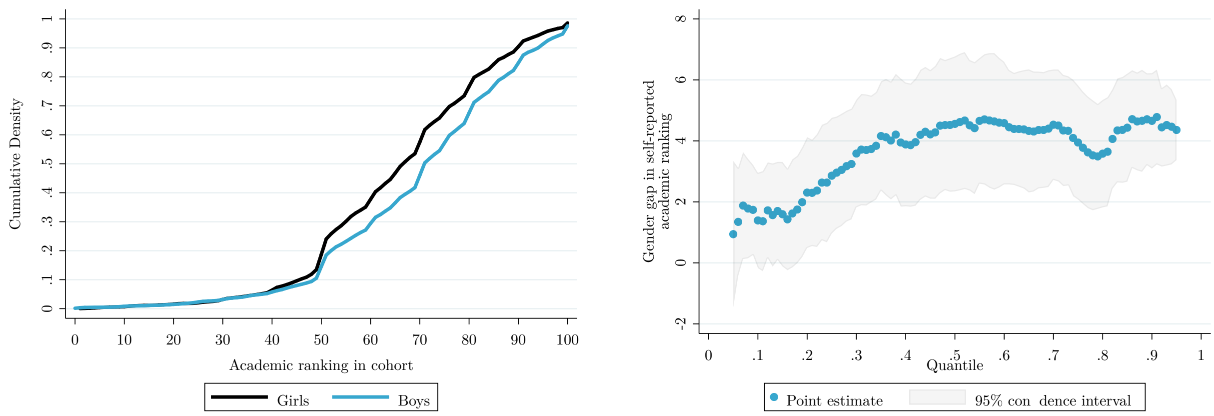
Figure 6: Effects of More Sociables Peers on Social Skills



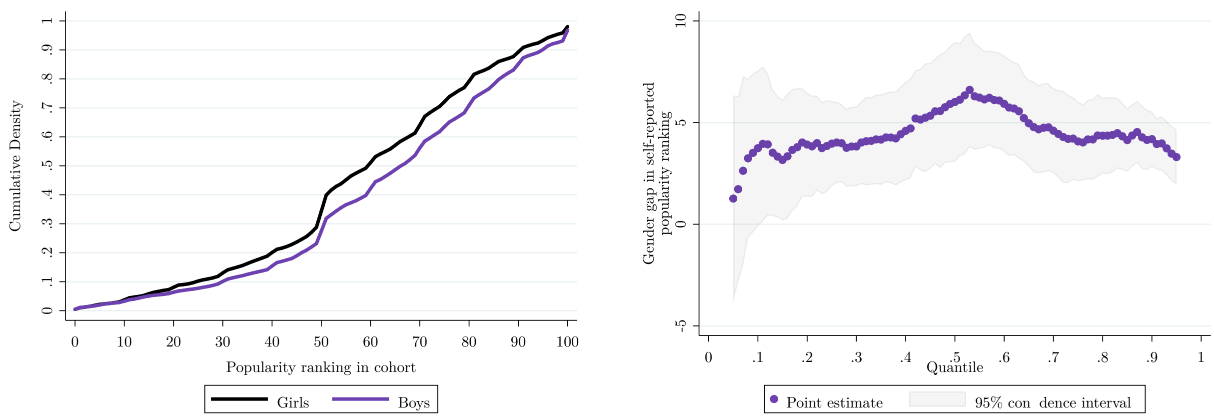
Notes: This figure reports treatment effects and 90% confidence intervals of being assigned to more sociable peers on social skills outcomes. All regressions include strata fixed effects and control for the baseline value of the dependent variable. The control group is defined as being assigned to less sociable peers. Standard errors are clustered at the peer group type-by-type level.

Figure 7: Gender Differences in Self-reported Rankings

Panel A: Academic ranking in cohort



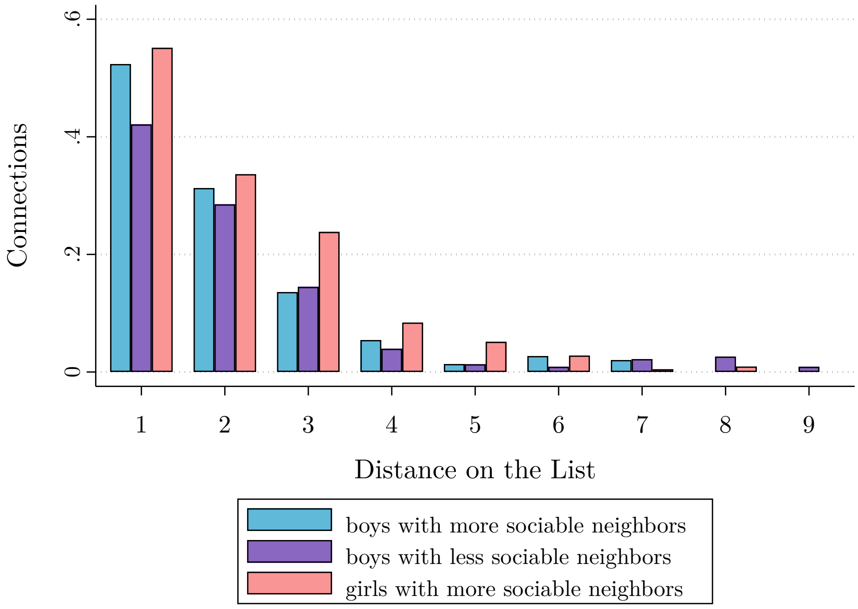
Panel B: Popularity ranking in cohort



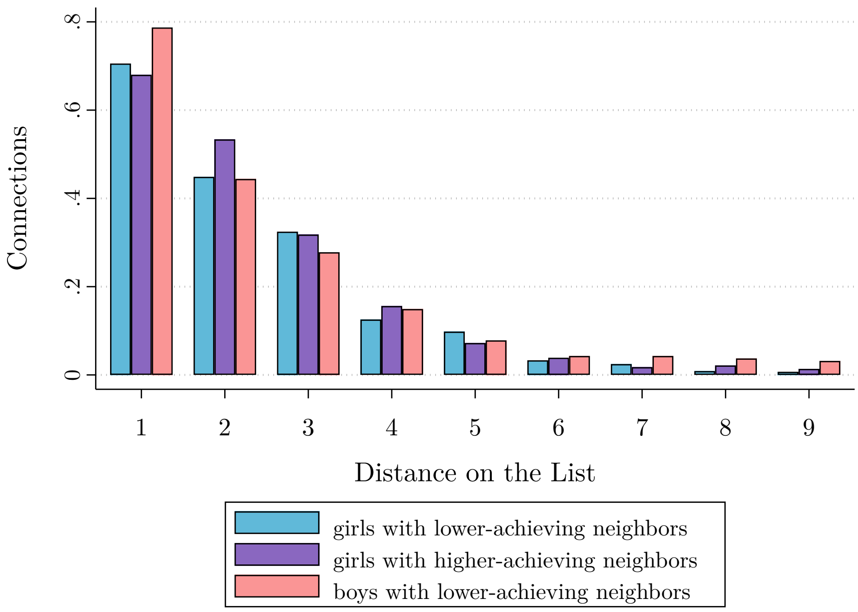
Notes: This figure plots differences by gender in self-reported academic and popularity ranking within the cohort. The left column presents the cumulative distribution function and the right column estimates from quantile regressions of the gender gap after controlling for observable characteristics. These covariates include scores in mathematics and reading tests, network degree and centrality, and peers' perception of social and academic skills. Standard errors are clustered at the school-by-cohort level.

Figure 8: Social Interactions of Most Affected vs. Comparable Groups

Panel A: Less sociable students



Panel B: Lower-achieving students



Notes: This figure shows the average number of connections with neighbors by distance on the list. By construction of the experimental design, students are at an odd distance from their treatment peers, and at an even distance from peers of their type.

A Supplementary Material

Table A.1: Peer Effects Estimates on Academic Achievement in the Literature

Study	Sample	Identification	Peer characteristic	Outcome	Effect of one s.d. in peers' background	Source
Hoxby (2000)	Elementary school students in Texas.	Cohort variation within school.	Peer test scores	Girls reading score Boys reading score	0.34-0.52 0.31-0.50	Table 1, Sacerdote (2014)
Sacerdote (2001)	Undergraduate students at Dartmouth college.	Randomly assigned roommates.	Academic index	GPA	-0.030 (not significant)	Table 1, Sacerdote (2014)
Hanushek et al. (2003)	Texas public elementary students.	Student and school-by-grade fixed effects. Control for family and school characteristics.	Math test scores	Average math score in grade G-2	0.150 (0.025)	Table 2, column 3
Zimmerman (2003)	Undergraduate students at Williams college.	Randomly assigned roommates.	SAT	GPA	0.104 (not significant)	Table 1, Sacerdote (2014)
Stinebrickner and Stinebrickner (2006)	Female undergraduate students at Barea college.	Randomly assigned roommates.	SAT	GPA	0.017 (not significant)	Table 1, Sacerdote (2014)
			High school GPA	GPA	0.100	
Carrell et al. (2009)	Undergraduate students at the US Air Force Adademy.	Randomly assigned squadrons.	SAT verbal score	GPA	0.072	Table 1, Sacerdote (2014)
Ammermueller and Pischke (2009)	Primary school students in Europe.	Variation across classes within schools.	Peer background	Reading score	0.162	Table 8
Duflo et al. (2011)	Primary school students in Western Kenya.	Randomly assigned classmates.	Baseline test scores	Total score	0.346 (0.150)	Table 4, Panel A, column 1
				Math score	0.323 (0.160)	Table 4, Panel A, column 2
				Reading score	0.293 (0.131)	Table 4, Panel A, column 3
Imberman et al. (2012)	Elementary school students in Louisiana.	Hurricane-induced shock to peers.	Peer test scores	Math test scores Reading test scores	0.33 (0.15) 0.00 (0.27) (not significant)	Table 1, Sacerdote (2014)
	Middle- and high-school students in Louisiana	Hurricane-induced shock to peers.	Peer test scores	Math test scores Reading test scores	0.15 (0.08) 0.08 (0.08) (not significant)	Table 1, Sacerdote (2014)
Pop-Eleches and Urquiola (2013)	Students transitioning from middle to high school in Romania.	RDD for admission at a better school.	Peer transition grade	Baccalaureate grade	0.212 (0.034)	Table 4, Panel C, column 4
Abdulkadiroğlu et al. (2014)	Middle and high school students in Boston and NYC.	RDD for admission at exam schools.	Peer test scores	Math score	-0.038 (0.032)	Table 9, column 1
				Reading score	0.006 (0.030)	Table 9, column 6
Booij et al. (2017)	Undergraduate students in economics in a Dutch university.	Random composition of groups with a wide range of support.	GPA	GPA	0.148 (0.052)	Table 4, column 5
Garlick (2018)	Undergraduate students in South Africa.	Randomly assigned roommates to large dormitories.	High school GPA	GPA	0.216 (0.112)	Table 4, column 1

Notes: This table reports estimates of peer effects on academic outcomes in the literature.

Table A.2: Summary Statistics for the Networks Survey at Baseline

	All Students	By Sociability		By Academic Achievement	
		Less Sociable	More Sociable	Lower-achieving	Higher-achieving
Variable	(1)	(2)	(3)	(4)	(5)
Any connections degree	11.06	8.23	13.91	10.77	11.35
	(5.64)	(3.20)	(6.11)	(5.58)	(5.69)
Any connections mutual degree	3.34	2.60	4.09	3.20	3.49
	(2.18)	(1.67)	(2.37)	(2.20)	(2.16)
Any connections centrality	0.00	-0.71	0.71	-0.05	0.05
	(1.00)	(0.44)	(0.89)	(0.97)	(1.01)
Dorm preferences degree	6.55	5.20	7.91	6.32	6.77
	(3.53)	(2.71)	(3.73)	(3.57)	(3.47)
Dorm preferences mutual degree	1.71	1.35	2.07	1.58	1.84
	(1.55)	(1.27)	(1.71)	(1.51)	(1.58)
Dorm preferences centrality	-0.00	-0.23	0.23	-0.03	0.03
	(1.00)	(0.75)	(1.14)	(0.97)	(1.02)
Friendships degree	7.87	5.66	10.09	7.61	8.12
	(5.07)	(2.75)	(5.84)	(5.07)	(5.06)
Friendships mutual degree	2.11	1.65	2.57	1.98	2.24
	(1.69)	(1.37)	(1.84)	(1.70)	(1.66)
Friendships centrality	-0.00	-0.51	0.51	-0.06	0.06
	(1.00)	(0.57)	(1.07)	(0.98)	(1.00)
Study connections degree	4.77	3.72	5.83	4.55	4.99
	(2.67)	(1.95)	(2.87)	(2.54)	(2.78)
Study connections mutual degree	1.11	0.93	1.30	1.05	1.18
	(1.09)	(0.96)	(1.18)	(1.05)	(1.12)
Study connections centrality	0.00	-0.37	0.37	-0.07	0.07
	(1.00)	(0.66)	(1.13)	(0.92)	(1.06)
Social connections degree	5.68	4.45	6.91	5.62	5.74
	(3.12)	(2.29)	(3.35)	(3.20)	(3.05)
Social connections mutual degree	1.24	1.01	1.47	1.21	1.26
	(1.24)	(1.05)	(1.36)	(1.24)	(1.23)
Social connections centrality	0.00	-0.37	0.37	-0.01	0.01
	(1.00)	(0.69)	(1.11)	(1.01)	(0.98)
Peers who named the student as a leader	2.63	1.54	3.72	1.90	3.35
	(5.15)	(3.31)	(6.32)	(4.21)	(5.86)
Peers who named the student as friendly	2.70	1.91	3.51	2.61	2.80
	(2.81)	(1.90)	(3.32)	(2.76)	(2.86)
Peers who named the student as popular	2.43	1.51	3.35	1.99	2.86
	(5.31)	(3.43)	(6.57)	(4.47)	(6.01)
Peers who named the student as skilled	2.62	1.80	3.44	1.20	4.03
	(6.45)	(5.97)	(6.80)	(3.15)	(8.32)
Peers who named the student as shy	2.00	2.51	1.48	2.18	1.82
	(4.66)	(5.16)	(4.03)	(4.61)	(4.70)
N	3,654	1,832	1,822	1,822	1,832

Notes: This table reports summary statistics for the social networks survey at baseline by student's type. Standard deviations are reported in parentheses. Column 1 shows statistics for all the students and columns 2 to 5 according to the classification of students by social skills and academic achievement. The dorm preferences network is based on the question: "who would you like to have as roommates?". The friendship network is based on the question: "who are your friends?". The study connections network is based on the question: "with whom have you studied?". The social connections network is based on the question: "with whom have you engage in social activities with such as playing sports or dancing?". The any connections network aggregates the four questions.

Table A.3: Correlation of Sociability and Social Skills Outcomes

	Big Five Personality Traits					Peers' Perception				Other measures of social skills	Social Skills Index Before the Intervention	Social Skills Index After the Interventipn
	Openness	Conscientiousness	Emotional Stability	Extraversion	Agreeableness	Leadership	Friendliness	Popularity	Shyness			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Academic achievement at baseline	0.090***	-0.001	0.064***	-0.014	-0.013	0.217***	0.042**	0.105***	-0.066***	0.047***	0.064***	0.042**
	(0.021)	(0.022)	(0.022)	(0.019)	(0.020)	(0.020)	(0.016)	(0.022)	(0.019)	(0.016)	(0.017)	(0.016)
Sociability at baseline	0.103***	0.061**	0.032*	0.142***	0.120***	0.230***	0.359***	0.215***	-0.103***	0.099***	0.139***	0.142***
	(0.024)	(0.025)	(0.017)	(0.021)	(0.017)	(0.021)	(0.020)	(0.029)	(0.021)	(0.018)	(0.018)	(0.018)
Social-fit score	0.072***	0.022	0.001	0.063***	0.027	0.137***	0.073***	0.104***	-0.113***	0.027	0.066***	0.046**
	(0.018)	(0.020)	(0.020)	(0.019)	(0.020)	(0.015)	(0.016)	(0.017)	(0.020)	(0.018)	(0.017)	(0.019)
Interview score	0.092***	0.073***	0.071***	0.091***	0.049***	0.068***	0.057***	0.049***	-0.036**	0.074***	0.118***	0.088***
	(0.019)	(0.016)	(0.016)	(0.018)	(0.018)	(0.015)	(0.015)	(0.017)	(0.017)	(0.015)	(0.016)	(0.015)
N	3,106	3,106	3,106	3,106	3,106	3,637	3,637	3,637	3,637	3,654	3,654	3,654

Notes: This table reports standardized estimates of an OLS regression on social skills outcomes of sociability at baseline and the score in the three tests of the admission process to the COAR Network. All regressions include school-by-grade-by-gender fixed effects. Sociability at baseline is measured by the eigenvector centrality of an aggregate social network of dorm preferences, friendships, study, and social partnerships. Eigenvector centrality is a measure of the influence of a student in the network. Academic achievement at baseline is the score in the admission test to the COAR Network, which evaluates the applicants in math and reading comprehension. Personality traits correspond to the Big Five. Measures of peers' perception correspond to the number of peers who think the student is in the top 5 of leadership, friendliness, popularity, and shyness (school-by-grade). The table presents two social skills indexes for robustness. The first one is constructed using Principal Component Analysis (PCA) on all the variables that measure social skills (see Appendix C for details), excluding personality traits and measures of peers' perception. The second index is contructed using Principal Component Analysis (PCA) on all the variables that measure social skills (see Appendix C for details).

Table A.4: Balance Tests for the More Sociable Peers Treatment

Variable	All Students		Less Sociable at Baseline		More Sociable at Baseline	
	Control mean	Difference	Control mean	Difference	Control mean	Difference
Admission test	-0.016	0.002	-0.064	-0.024	0.058	0.028
		(0.019)		(0.027)		(0.026)
Interview score	14.065	0.009	14.053	0.019	14.082	-0.000
		(0.042)		(0.059)		(0.061)
Social-fit score	20.001	0.095	19.977	0.071	20.035	0.119
		(0.064)		(0.088)		(0.092)
Female	0.589	0.003	0.594	0.002	0.582	0.004
		(0.003)		(0.004)		(0.003)
Not poor	0.426	-0.014	0.393	-0.008	0.475	-0.020
		(0.014)		(0.021)		(0.020)
Poor	0.364	0.026*	0.378	0.034	0.344	0.019
		(0.015)		(0.022)		(0.020)
Extremely poor	0.210	-0.012	0.229	-0.026	0.182	0.001
		(0.012)		(0.018)		(0.017)
Rural	0.279	-0.014	0.315	-0.028	0.224	0.000
		(0.012)		(0.018)		(0.017)
Subsidized health insurance	0.508	0.008	0.552	-0.011	0.443	0.027
		(0.016)		(0.022)		(0.022)
Average math at baseline	-0.049	0.019	-0.157	0.012	0.115	0.027
		(0.027)		(0.037)		(0.038)
Average reading at baseline	-0.049	0.010	-0.169	0.041	0.134	-0.021
		(0.028)		(0.041)		(0.038)
Sociability index baseline	-0.042	-0.041	-0.293	-0.033	0.333	-0.050
		(0.080)		(0.117)		(0.111)
Indegree baseline network	-0.077	-0.021	-0.434	-0.003	0.460	-0.040
		(0.027)		(0.033)		(0.044)
Outdegree baseline network	-0.094	0.023	-0.419	0.016	0.395	0.029
		(0.026)		(0.027)		(0.046)
Centrality baseline network	0.303	0.003	0.203	-0.002	0.453	0.008
		(0.003)		(0.003)		(0.006)
Peers' perception leader	2.502	-0.184	1.587	-0.113	3.879	-0.257
		(0.151)		(0.132)		(0.272)
Peers' perception friendly	2.553	-0.009	1.837	0.200**	3.631	-0.221
		(0.080)		(0.083)		(0.136)
Peers' perception popular	2.203	0.110	1.466	0.126	3.313	0.093
		(0.159)		(0.142)		(0.285)
Peers' perception shy	2.083	0.029	2.560	-0.131	1.366	0.192
		(0.144)		(0.227)		(0.178)
Baseline grit	43.707	-0.248	43.340	-0.171	44.251	-0.325
		(0.198)		(0.285)		(0.274)
Baseline Rosenberg scale	32.991	0.101	32.777	0.119	33.306	0.081
		(0.154)		(0.224)		(0.212)
Baseline Read the Mind	20.521	-0.060	20.224	0.184	20.960	-0.304*
		(0.130)		(0.186)		(0.180)
Multivariate F p-value		0.785		0.571		0.726

Notes: This table reports balance checks of being assigned to more sociable peers on baseline characteristics. All regressions include strata fixed effects, control for the baseline value of the dependent variable, and include the higher-achieving peers treatment. For the 2017 cohort, all regressions include strata-by-classroom fixed effects. The control group is defined as being assigned to less sociable and lower-achieving peers. The "F p-value" correspond to the F-statistic of the more sociable peers treatment of multivariate regressions that include all the variables at baseline. Standard errors are clustered at the peer group type-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table A.5: Balance Tests for the Higher-Achieving Peers Treatment

Variable	All Students		Lower-achieving at Baseline		Higher-achieving at Baseline	
	Control mean	Difference	Control mean	Difference	Control mean	Difference
Admission test	-0.163	0.013	-0.787	-0.006	0.764	0.031
		(0.016)		(0.018)		(0.026)
Interview score	8.400	-0.013	8.589	-0.011	8.117	-0.015
		(0.033)		(0.042)		(0.052)
Social-fit score	11.973	-0.061	12.161	0.012	11.693	-0.131*
		(0.049)		(0.061)		(0.077)
Female	0.575	-0.000	0.575	0.004	0.575	-0.004
		(0.002)		(0.004)		(0.003)
Not poor	0.443	0.010	0.404	0.001	0.502	0.019
		(0.012)		(0.017)		(0.018)
Poor	0.369	-0.017	0.387	-0.005	0.342	-0.030*
		(0.013)		(0.018)		(0.017)
Extremely poor	0.188	0.007	0.209	0.003	0.156	0.011
		(0.011)		(0.016)		(0.014)
Rural	0.276	-0.003	0.319	-0.021	0.212	0.014
		(0.013)		(0.019)		(0.016)
Subsidized health insurance	0.504	0.013	0.517	0.045**	0.485	-0.019
		(0.015)		(0.021)		(0.022)
Average math at baseline	-0.093	0.016	-0.373	-0.023	0.319	0.053
		(0.023)		(0.030)		(0.034)
Average reading at baseline	-0.064	-0.000	-0.281	-0.012	0.256	0.011
		(0.023)		(0.032)		(0.033)
Sociability index baseline	-0.023	0.048	-0.065	0.060	0.040	0.038
		(0.059)		(0.083)		(0.083)
Indegree baseline network	0.008	-0.050*	-0.075	-0.032	0.131	-0.068*
		(0.027)		(0.038)		(0.039)
Outdegree baseline network	-0.001	-0.013	-0.016	-0.059	0.021	0.033
		(0.028)		(0.040)		(0.038)
Centrality baseline network	0.330	-0.003	0.324	-0.007	0.338	0.000
		(0.003)		(0.004)		(0.004)
Peers' perception leader	2.493	0.006	1.930	-0.036	3.331	0.050
		(0.148)		(0.178)		(0.236)
Peers' perception friendly	2.691	0.010	2.618	-0.001	2.801	0.021
		(0.078)		(0.112)		(0.109)
Peers' perception popular	2.362	-0.013	2.007	-0.024	2.890	-0.006
		(0.158)		(0.186)		(0.255)
Peers' perception shy	2.020	0.036	2.110	0.160	1.886	-0.089
		(0.146)		(0.211)		(0.203)
Baseline grit	43.568	0.158	43.330	0.431	43.921	-0.108
		(0.196)		(0.271)		(0.282)
Baseline Rosenberg scale	33.013	0.139	32.854	0.127	33.249	0.153
		(0.154)		(0.221)		(0.215)
Baseline Read the Mind	20.602	-0.265**	20.248	-0.231	21.127	-0.295
		(0.128)		(0.180)		(0.183)
Multivariate F p-value		0.810		0.857		0.625

Notes: This table reports balance checks of being assigned to higher-achieving peers on baseline characteristics. All regressions include strata fixed effects, control for the baseline value of the dependent variable, and include the more sociable peers treatment. For the 2017 cohort all regressions include strata-by-classroom fixed effects. The control group is defined as being assigned to less sociable and lower-achieving peers. The "F p-value" correspond to the F-statistic of the higher-achieving peers treatment of multivariate regressions that include all the variables at baseline. Standard errors are clustered at the peer group type-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table A.6: Treatments and Outcomes Available by Cohort

Treatments	**Outcomes**	
	Social Skills	Academic Outcomes
More sociable peers	2015, 2016	2016
Higher-achieving peers	2015, 2016, 2017	2016, 2017

Table A.7: Correlations and Effects on Hard Outcomes for Less Sociable Boys

Dependent variable:	Dropout	College	Certified	Top 20
	(1)	(2)	(3)	(4)
Panel A: Correlations				
Social skills	-0.001	0.016**	0.016***	0.014**
	(0.001)	(0.008)	(0.006)	(0.006)
Math score	-0.003	0.060***	0.034***	0.032***
	(0.002)	(0.010)	(0.008)	(0.008)
Reading score	-0.000	0.014	0.007	0.024***
	(0.002)	(0.010)	(0.008)	(0.007)
mean control	0.02	0.46	0.20	0.16
N	6,085	3,649	3,649	3,649
Panel B: Impact on less sociable boys				
More sociable	-0.023***	0.009	0.051**	0.044*
	(0.008)	(0.029)	(0.026)	(0.025)
Higher-achieving	0.020**	0.003	-0.012	-0.015
	(0.010)	(0.029)	(0.026)	(0.026)
mean control	0.02	0.46	0.20	0.16
N	753	753	753	753

Notes: This table reports correlation of social skills with hard outcomes (Panel A), and the effect of being assigned to more sociable and higher-achieving peers on hard outcomes for less sociable boys (Panel B). All regressions in Panel A include school-by-cohort-by-gender fixed effects. All regressions in Panel B include strata fixed effects and control for the dependent variable at baseline. Standard errors are clustered at the group of peers-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Table A.8: Randomization Inference p-values

Group	Treatment	Dependent variables			
		(1)	(2)	(3)	(4)
		Panel A: Results on Social Skills			
		Connections	Centrality	Psychological Tests	Peers' perception
	More sociable peers	0.791	0.629	0.002	0.105
All students	Higuer-achieving peers	0.603	0.980	0.673	0.208
	Joint test	0.838	0.891	0.022	0.118
	More sociable peers	0.109	0.007	0.000	0.099
Boys	Higuer-achieving peers	0.102	0.353	0.473	0.840
	Joint test	0.071	0.021	0.001	0.241
	More sociable peers	0.006	0.000	0.002	0.013
Less sociable boys	Higuer-achieving peers	0.925	0.979	0.147	0.020
	Joint test	0.025	0.003	0.003	0.005
		Panel B: Results on Academic Skills			
		Grades		Test Scores	
		Math	Reading	Math	Reading
	More sociable peers	0.720	0.205	0.284	0.551
All students	Higuer-achieving peers	0.579	0.471	0.137	0.302
	Joint test	0.817	0.366	0.221	0.519
	More sociable peers	0.743	0.135	0.123	0.601
Lower-achieving	Higuer-achieving peers	0.018	0.055	0.033	0.061
	Joint test	0.060	0.071	0.040	0.178
	More sociable peers	0.595	0.265	0.072	0.785
Lower-achieving girls	Higuer-achieving peers	0.002	0.260	0.022	0.010
	Joint test	0.004	0.331	0.024	0.017

Notes: This table reports randomization inference p-values.

Table A.9: Multiple-hypotheses Testing

Group	Test	Dependent variables			
		(1)	(2)	(3)	(4)
Panel A: Results on Social Skills					
		Connections	Centrality	Psychological Tests	Peers' perception
	Sidak and Holm	0.146	0.034	0.001	0.182
Boys	Bonferroni and Holm	0.151	0.034	0.001	0.191
	Westfall and Young	0.198	0.062	0.001	0.273
	Sidak and Holm	0.028	0.002	0.006	0.055
Less sociable boys	Bonferroni and Holm	0.028	0.002	0.006	0.057
	Westfall and Young	0.064	0.004	0.018	0.109
Panel B: Results on Academic Skills					
		Grades		Test Scores	
		Math	Reading	Math	Reading
	Sidak and Holm	0.044	0.108	0.106	0.130
Lower-achieving	Bonferroni and Holm	0.044	0.111	0.108	0.134
	Westfall and Young	0.080	0.168	0.175	0.200
	Sidak and Holm	0.008	0.461	0.119	0.026
Lower-achieving girls	Bonferroni and Holm	0.008	0.538	0.125	0.026
	Westfall and Young	0.019	0.597	0.204	0.056

Notes: This table reports multiple-hypotheses testing p-values. Calculations were performed using the *wyoung* command developed by Jones et al. (2019).

Table A.10: Reduced-Form Estimates on Academic Performance (Lower-achieving First-years)

Dependent variable:	Grades				Test scores			
	Math		Reading		Math		Reading	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Higher-achieving	-0.062	-0.151**	-0.056	-0.075	-0.044	-0.084**	-0.064	-0.207***
	(0.054)	(0.069)	(0.051)	(0.061)	(0.045)	(0.042)	(0.060)	(0.078)
Higher-achieving × boy		0.188*		0.039		0.084		0.303**
		(0.108)		(0.102)		(0.092)		(0.117)
mean control	-0.27	-0.27	-0.22	-0.22	-0.35	-0.35	-0.09	-0.09
p-val ha boys		0.654		0.663		0.999		0.274
N	1,168	1,168	1,169	1,169	1,169	1,169	1,170	1,170

Notes: This table reports the effect of being assigned to higher-achieving peers identified at baseline on grades and test scores for lower-achieving first-year students. All regressions include strata fixed effects and control for the baseline value of the dependent variable. For the 2017 cohort all regressions include gender-by-classroom fixed effects. The control group is defined as being assigned to lower-achieving peers. Grades are standardized at the school-by-grade level and test scores at the grade level. Standard errors are clustered at the peer group type-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

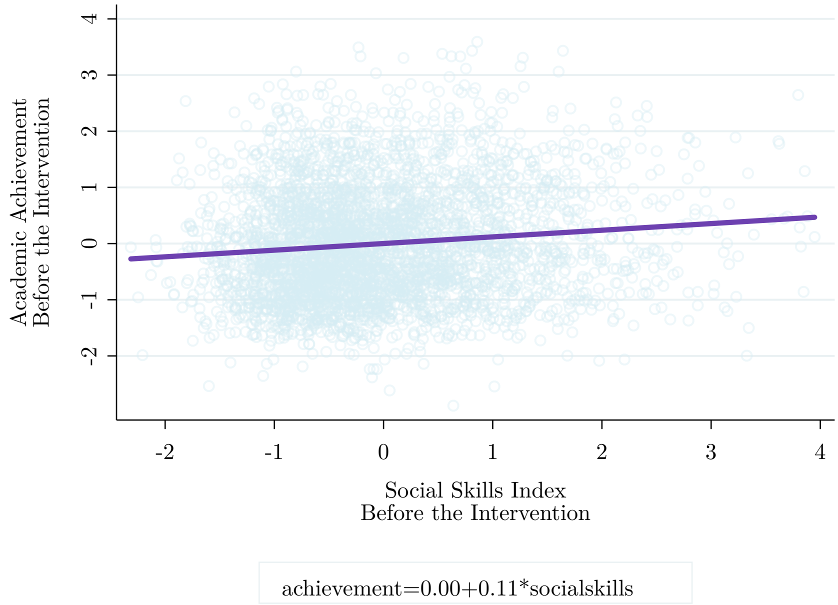
Table A.11: Self-confidence in Academic Skills

Dependent variable:	Self-nomination	Academic Ranking		
	(top 5) skilled	Dorm	Classroom	Cohort
	(1)	(2)	(3)	(4)
Panel A: Lower-achieving students at baseline				
More sociable	-0.012	-0.679	-0.077	-0.633
	(0.016)	(1.007)	(1.003)	(0.947)
Higher-achieving	0.037**	-1.071	0.883	0.174
	(0.017)	(1.013)	(0.997)	(0.977)
More sociable × boy	-0.041	-1.372	-0.938	-0.493
	(0.027)	(1.614)	(1.555)	(1.498)
Higher-achieving × boy	-0.061**	0.664	-2.039	0.205
	(0.028)	(1.540)	(1.503)	(1.453)
mean control	0.13	73.06	70.30	67.16
p-val ms boys	0.014	0.103	0.393	0.331
p-val ha boys	0.282	0.726	0.304	0.725
N	1,681	1,676	1,677	1,677
Panel B: Higher-achieving students at baseline				
More sociable	0.001	-0.291	-0.768	-0.707
	(0.018)	(0.947)	(0.853)	(0.850)
Higher-achieving	0.040**	-0.725	-1.720**	-1.331
	(0.018)	(0.970)	(0.832)	(0.846)
More sociable × boy	-0.036	1.899	2.912*	1.516
	(0.034)	(1.612)	(1.553)	(1.438)
Higher-achieving × boy	-0.058*	1.477	2.108	2.032
	(0.034)	(1.618)	(1.533)	(1.446)
mean control	0.16	74.17	73.34	69.91
p-val ms boys	0.212	0.220	0.100	0.488
p-val ha boys	0.543	0.560	0.762	0.550
N	1,710	1,701	1,702	1,701

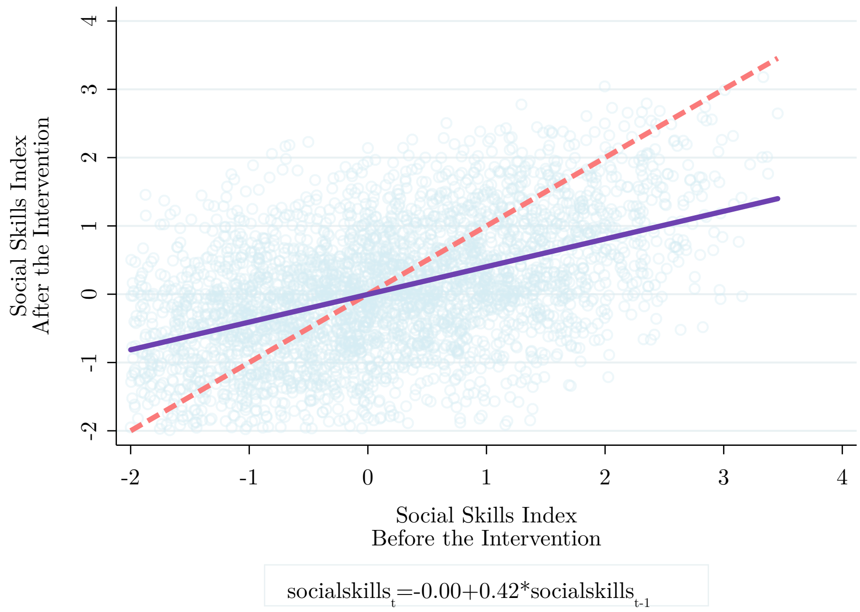
Notes: This table reports the effect of being assigned to more sociable and higher-achieving peers identified at baseline on self-confidence in social skills. All regressions include strata fixed effects and control for the dependent variable at baseline. For the 2017 cohort, all regressions include strata-by-classroom fixed effects. The control group is defined as being assigned to less sociable and lower-achieving peers. Standard errors are clustered at the group of peers-by-type level; *** p-value<0.01, ** p-value<0.05, * p-value<0.1.

Figure A.1: Social Skills Index

Panel A: Correlation with Academic Achievement



Panel B: Correlation over Time



Notes: Panel A shows a scatter plot of academic achievement and sociability at baseline for the 2015-16 cohorts by student type. A one-standard-deviation of the social skills index predicts an increase in 0.11 standard deviations of academic achievement at baseline. Panel B shows a scatter plot and the linear prediction of the sociability index before and after the intervention. A one-standard-deviation of the social skills index before the intervention predicts an increase of 0.42 in the social skills index after the intervention.

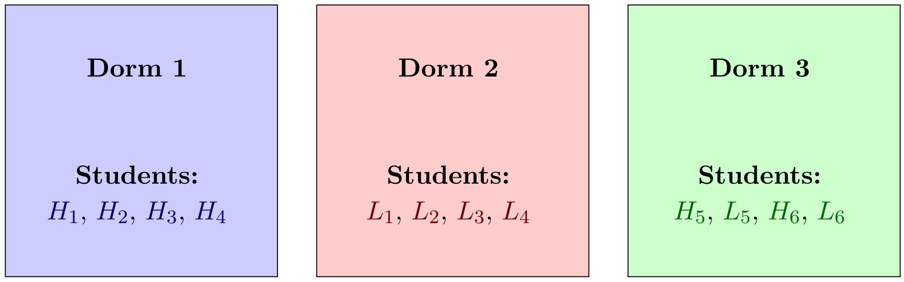
B Use of the Lists to Allocate Students to Dorms and Classrooms

This section explains in detail how the order of students on the lists determines their allocation to dormitories. To start, recall the simple two-type example in which students were either H and L. As described in section 3.3.2, this case allows for three groups of combined types: Group 1 (only Hs), Group 2 (a mixed group of Hs and Ls), and Group 3 (only Ls). Let us assume that the random ordering of the groups on the list is: Group 1-Group 3-Group 2. For simplicity, I will assume that there are 12 students, four in each group. After numbering the students by type, the order on the list would be the following: $H_1 - H_2 - H_3 - H_4 - L_1 - L_2 - L_3 - L_4 - H_5 - L_5 - H_6 - L_6$. Notice that on the list, the order of the students in Group 2 alternates the type of student in the form H-L.

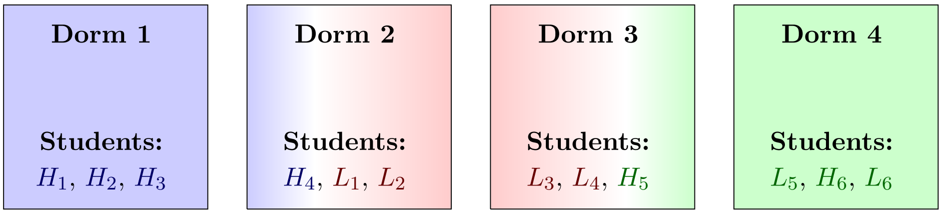
Figure B.1 shows an example of how the lists were used to allocate students to dorms and classrooms. Panel A describes the allocation when each room holds four students, Panel B when dorm rooms hold three students and Panel C for a big dorm room of 12 students. The order on the list is used to determine the allocation. When dorm rooms hold four students, dorms and *peer group types* have the same size so there is perfect compliance with the initial allocation. Yet, when dorm rooms hold three students, the first three students of type H –who were assigned to Group 1 (only Hs)—are allocated to room 1. The fourth student assigned to Group 1 is assigned to a room with two students who are type L. Notice that in this case there is no perfect compliance. In the big dorm, all students $H_1 - H_4$ are in beds close to each other. However, students H_3 and H_4 are also close to students of type L, while students H_1 and H_2 are surrounded only by peers who are type H.

FIGURE B.1: Examples of the Allocation to Dorms

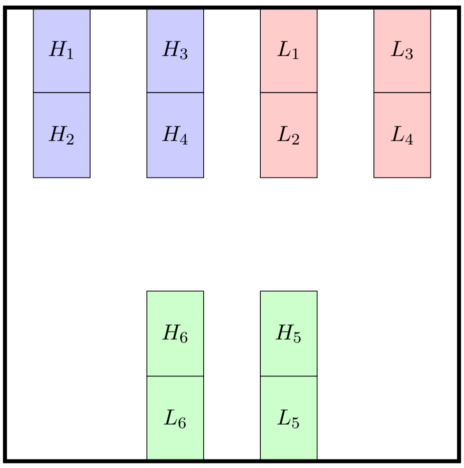
Panel A: Dorms of 4 Students



Panel B: Dorms of 3 Students



Panel C: Big Dorm of 6 Bunk Beds



Student:	H_1	H_2	H_3	H_4	L_1	L_2	L_3	L_4	H_5	L_5	H_6	L_6
3 dorms of 4 students:	D1	D1	D1	D1	D2	D2	D2	D2	D3	D3	D3	D3
4 dorms of 3 students:	D1	D1	D1	D2	D2	D2	D3	D3	D3	D4	D4	D4

Notes: This figure displays three examples of how the randomization to groups was used to allocate students to dorm rooms and classrooms.

C Psychological Tests

This section describes in detail the psychological tests that were used to construct the sociability index.

In addition to the Big Five personality traits and the peers' perceptions measures described in section 5.1, the tests used to construct the sociability index are:

C.1 The Big Five

The most widely accepted taxonomy of psychological traits, both in the literature and in my data, is the Big Five (McCrae and John, 1992; John and Srivastava, 1999).[15] The *American Psychology Association Dictionary* defines the Big Five personality traits as follows (Table 1.1 in Almlund et al. (2011)):

1. Conscientiousness: the tendency to be organized, responsible, and hardworking.
2. Openness to Experience: the tendency to be open to new aesthetic, cultural, or intellectual experiences.
3. **Extraversion**: an orientation of one's interests and energies toward the outer world of people and things rather than the inner world of subjective experience; characterized by positive affect and sociability.
4. **Agreeableness**: the tendency to act in a cooperative, unselfish manner.
5. Neuroticism or Emotional Stability: Emotional Stability is "predictability and consistency in emotional reactions, with absence of rapid mood changes." Neuroticism is a chronic level of emotional instability and proneness to psychological distress.

Only two traits from the Big Five are associated with social skills: extraversion[16] and agreeableness[17]. Empirical evidence shows that extraversion is associated with good labor market outcomes (Fletcher, 2013), and that agreeableness influences occupational decisions (Almlund et al., 2011; Cobb-Clark and Tan, 2011). These results are consistent with a study by Deming (2017) that concludes that the labor market increasingly rewards social skills.

C.2 Altruism

The altrusim self-reported scale was developed by Rushton et al. (1981). The test used in the COAR network is composed of 17 items. The score on the test is found to predict criteria such as peer ratings of altruism, completing an organ donor card, and paper-and-pencil measures of prosocial orientation (Rushton et al., 1981). More recent evidence shows that the score on the test is related to spontaneous smiles—which is an important signal in the formation and maintenance of cooperative relationships (Mehu et al., 2007). Likewise, there is evidence that the score in the test is related to charity giving but not to blood donor donation behavior (Otto and Bolle, 2011).

[15] Almlund et al. (2011) summarizes the Big Five personality traits and their application to economics. Likewise, Akee et al. (2018); Donato et al. (2017); Kranton and Sanders (2017) provide recent evidence of the Big Five in economics research.

[16] The facets of extraversion correspond to: warmth (friendly), gregariousness (sociable), assertiveness (self-confident), activity (energetic), excitement seeking (adventurous), and positive emotions (enthusiastic).

[17] The facets of agreeableness are: trust (forgiving), straight-forwardness (not demanding), altruism (warm), compliance (not stubborn), modesty (not show-off), tender-mindedness (sympathetic).

C.3 Leadership

The leadership scale corresponds to the leader behavior questionnaire developed in Spanish by Castro-Solano (2007). It is based on the theory of Yukl (2013). The scale measures three components of leadership: (1) behaviors guided towards tasks, (2) behaviors guided towards others, and (3) behaviors guided towards changes. In my data, there is a positive correlation between the score on the scale and the number of peers who perceived the subject as a leader.

C.4 Empathy

The empathy scale corresponds to the Basic Empathy Scale developed by Jolliffe and Farrington (2006). The scale is composed of two factors: cognitive and emotional empathy. The scale has been validated in other contexts: when applied to adults (Carre et al., 2013) and the Spanish version of it (Villadangos et al., 2016). It has also been affirmed that students who report higher scores in socially aversive personalities (psychopathy, narcissism, and Machiavellianism) have a low score on the scale (Wai and Tiliopoulos, 2012). Likewise, Gambin and Sharp (2018) show that a low score on the test is associated with guilt and depressive symptoms.

C.5 Intercultural Sensitivity

This 24-item scale of intercultural sensitivity was developed by Chen and Starosta (2000). The authors define intercultural sensitivity as: "*a person's ability to develop a positive emotion towards understanding and appreciating cultural differences that promotes appropriate and effective behavior in intercultural communication.*" The scale is composed of two factors: positive and negative reactions to intercultural interactions. Evidence shows that there is a positive correlation between intercultural sensitivity and compassion in nurses (Arli and Bakan, 2018), that American student scores depend on religious affiliation and the number of times they have traveled outside the US (Gordon and Mwavita, 2018), and that Iranian university students have demonstrated a strong relationship between intercultural sensitivity and ethnic background.

C.6 Emotional Intelligence

Emotional intelligence is defined as individuals' ability to recognize their own emotions and those of others, discern between different feelings and label them appropriately, use emotional information to guide thinking and behavior, and manage and/or adjust emotions to adapt to environments or achieve one's goal(s) (Colman, 2009). The emotional intelligence test corresponds to the scale developed by Law et al. (2004). The test is composed of 16 items and has four factors: self-emotional appraisal, uses of emotion, regulation of emotion, and others' emotional appraisal.

C.7 The Read the Mind in the Eyes Test

The objective of this test is to assess how well people can read others' emotions just by looking at pictures of their eyes. It is a multiple choice test with 36 items. For each item, the respondent has to identify the corresponding emotion expressed in a pair of eyes; four choices are given for each question. According to Deming (2017), this test is a reliable measure of social skills since it is positively correlated with performance in groups (Declerck and Bogaert, 2008). However, this measure could potentially have problems due to the cultural differences between the context where the test was developed and the context of my study. In particular, according to the website Lab in the Wild: socialintelligence.labinthewild.org, the test was developed in Great Britain and the images were taken from British magazines in the 1990s. Therefore, the test may not produce accurate results when administered to people who are not native speakers of English or those who come from cultures that are very different from Britain's.

C.8 Achievement Goals

While not part of the construction of the social skills index, students completed the *The Achievement Goal Questionnaire* (J. Elliot and Murayama, 2008). Achievement goals are conceptualized as cognitive–dynamic aims that focus on competence. The test is composed of 12 items and has four factors: mastery approach goal items, mastery avoidance goal items, performance-approach goal items, and performance-avoidance goal items. The last two items are related to goals in comparison with peers and are the ones I use to proxy for preferences for competition.