An Experimental Approach to Peer Effects: Evidence on Social and Academic Skills

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Abstract

Researchers often exploit random allocation to groups to estimate peer effects. As groups get larger, estimates become imprecise and amplify bias due to weak variation. I show that classifying individuals by quantiles and randomizing the type of peer improves precision and bias. I apply this design in a large-scale field experiment at selective boarding schools in Peru, focusing on social skills. Peer effects are more pronounced for social skills than academic outcomes and largely depend on gender. While boys benefit from sociable peers, higher-achieving peers reduce the academic performance of lower-achieving girls. Gender differences in self-confidence can explain these findings.

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1 Introduction

Social skills and connections are essential determinants of individuals' well-being and labor market success. Recent empirical evidence shows that having five more friends during adolescence raises wages as much as an additional year of schooling (Lleras-Muney et al., 2020). The labor market also increasingly rewards social skills (Deming, 2017), and these are becoming more complementary to cognitive skills (Weinberger, 2014). Empirical evidence within organizations shows that individuals' capacity to interact with others increases firms' productivity, as team performance and management practices heavily depend on social abilities (Woolley et al., 2010; Adhvaryu et al., 2018; Hoffman and Tadelis, 2018). However, economics studies have not thoroughly explored the question of how social skills are formed.

Socialization with others is an essential input for the formation of social skills. As childhood and adolescence are crucial for the malleability of personality and non-cognitive skills (Heckman and Mosso, 2014), schools play a pivotal role in shaping how individuals socialize and interact with others. Intuitively, the characteristics of peers with whom students interact in schools can have short- and long-term consequences on their social capital. While the literature of peer effects in education is extensive, most of it has focused on academic performance, and the evidence remains inconclusive. We know less about peer effects on social skills, where interactions with peers are reasonably more relevant and are also crucial for later-life outcomes.

This paper studies how peers' sociability and academic achievement affect students' social skills, academic performance, and college outcomes. I conduct a novel and large-scale field experiment at the COAR Network —a group of elite public boarding high schools in every region of Peru. The COAR Network is designed for the most talented low-income students in the country. I depart from the traditional research design which exploits random allocation to groups. My experimental design generates large variation in peers' skills by assigning 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. I also study the driving forces behind peers' influence by relying on a comprehensive survey that measures students' beliefs about themselves and others, as well as different types of social interactions in the schools.

The results show three main findings. First, social skills are malleable during high school as boys paired with more sociable neighbors have more connections and develop more social skills. These effects appear to affect later life outcomes, as they also drop out less and enroll more at better colleges. By contrast, peers' sociability does not affect girls' outcomes. Second, consistent with the idea that peer influences are more pronounced for social abilities, academic peer effects are, on average, a precisely estimated zero, with some negative estimates on lower-achieving girls. Third, there is no

evidence of cross-skill peer effects; neither the sociability of peers affect achievement, nor higher-achieving peers influence social skills outcomes.

These findings are explained by how boys' and girls' beliefs in their abilities respond to peer interactions. My results on the formation of beliefs support the existing evidence from laboratory studies on gender differences in self-confidence (Niederle and Vesterlund, 2007; Mobius et al., 2014; Bordalo et al., 2019). By contrast, peer effects in this study are not explained by the formation of friendships or study groups. Even though students are befriending and studying with their new neighbors, there is no influence of peers in either academic outcomes or girls' social outcomes. From a policy perspective, these findings suggest that peer allocation policies need to account for their impact on beliefs in addition to social interactions.

My experimental design surmounts many of the challenges with traditional approaches that estimate peer effects. Most prior studies have exploited students' random assignment to groups such as dormitories or classrooms. However, as groups get larger, estimates of peer effects become imprecise and amplify bias due to weak variation. Angrist (2014) shows that factors unrelated to social influences such as weak-instrument bias and measurement error can be confounded with peer effects when the identification relies on variation in peer characteristics across groups.[1] The use of numerous variables and non-linear functional forms can further aggravate these concerns due to multiple hypotheses testing.

I propose an experimental approach to estimate peer effects. In my design, the researcher predetermines the relevant peer characteristics of interest. Participants are classified by types based on the quantiles of the distribution of those characteristics. Rather than randomly allocating students to groups, these are randomly assigned to a treatment arm defined by the type of peer. Students are matched to peers of their treatment, and this match determines the final allocation to groups. I show that this design generates a large variation in peer characteristics, improving precision, and limiting bias amplification concerns. Furthermore, my identification strategy relies on the variation across treatments rather than variation in peer characteristics across groups. As students in the same group belong to different treatment arms, this design overcomes the econometric concerns pointed out by Manski (1993) and Angrist (2014). An experimental approach also generates an ex-ante commitment to study a prespecified set of peer characteristics and functional forms, improving transparency in this type of research.

I apply this design in the COAR Network in Peru to study how peers' sociability and academic achievement affect students' outcomes. To classify students as less or more

[1] Acemoglu and Angrist (2000) show that whether peer effects exist is econometrically identical to whether a 2SLS estimator that uses group dummies to instrument individual characteristics differs from OLS estimates of the effect of these characteristics.

sociable, I use the eigenvector centrality[2] of a social network that aggregates links of preferred roommates, friendships, study groups, and social activities such as team sports. Likewise, I use the admissions test score to the COAR Network to classify students as higher- or lower-achieving. I perform a stratified randomization of students to the treatments and organize them into groups. The schools used these groups to allocate students to specific beds in the dormitories, ensuring that the neighbors' type coincides with the assigned treatment.

I estimate the impact of each treatment on social and academic outcomes. I consider three types of social outcomes:[3] (1) the social network after the intervention, (2) psychological tests that measure social skills (see Appendix D for details), (3) the number of peers who perceive the student as a leader or as a popular, friendly, or shy person. To measure academic outcomes, I use grades and standardized tests. I also exploit the experimental variation in a two-stage least-square (2SLS) model to account for imperfect compliance between the assignment to treatments and actual neighbors in the dormitories. 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 have more social connections and a better network position. They also have higher scores in psychological tests of social skills and are also perceived by their peers to be more social. The impact on the less sociable students is the main driver of these positive effects. The 2SLS model shows that a one-standard-deviation increase in neighbors' sociability increases the number of connections by about 1.25 (p-value 0.016) for all boys and by 2.4 for the less sociable boys (p-value 0.001). The sociability peer effect on an index of all social outcomes is about 0.219σ (p-value 0.007) for all boys. 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.

Peer effects on social skills persist in later life as less sociable boys with more sociable neighbors drop out less of the COAR Network and enroll more at better colleges. In Peru, higher education institutions use face-to-face interviews as part of the college admission process. Hence, an improvement in students' social skills would be consistent with enrolling at better colleges. The estimates reveal a reduction in the dropout rate (2.1 p.p, p-value 0.012), and a positive effect on the attendance rate of government-certified colleges (6.6 p.p., p-value 0.034), as well as the top 20 colleges (5.2 p.p., p-value

[2]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.

[3]These outcomes follow the definition in Glaeser et al. (2002) of social capital: an individual's social skills, and an individual's connections.

0.058). Within-school correlations between social skills and college outcomes are consistent with these findings.

By contrast, 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 0.042σ (p-value 0.144) and reading scores by 0.059σ (p-value 0.094), ruling out even small positive peer effects. In fact, higher-achieving peers harm lower-achieving girls. For them, the estimates reveal a negative treatment effect of -0.070σ (p-value 0.015) on math and -0.084σ (p-value 0.046) on reading scores.

Understanding how peers influence the formation of skills is crucial for education policies (Benabou, 1993; Allende, 2019). Hence, I characterize optimal policies based on the above estimates. As the estimates reveal differences between boys and girls, optimal allocation policies should be mindful of gender. In an optimal allocation, boys should be mixed by their initial sociability, and girls should be separated by their initial academic performance.

While policy recommendations are insightful, their implementation can fail without a full understanding of the mechanisms that drive peer effects (Carrell et al., 2013). Therefore, I explore the forces behind the main results of this paper. I consider two potential mechanisms: (1) the formation of beliefs (self-confidence), and (2) friendships and study networks (social interactions).

To study these mechanisms, I rely on a comprehensive survey that measures beliefs and social interactions. The survey has two advantages compared to previous studies. First, I have high-quality information on the social networks within the schools. The response rate is above 95% in all schools, and I measure different types of social interactions with no restrictions on the number of peers that students can list. These factors are essential to observe all direct and indirect links and measure network statistics like centrality. Second, the survey elicits students' beliefs about their abilities. While some papers on the peer effects literature have addressed ranking concerns (Elsner and Isphording, 2017; Fabregas, 2017; Tincani, 2017; Murphy and Weinhardt, 2020), the measurement of beliefs is a cornerstone to explain how self-confidence can drive heterogeneous peer effects.

I observe changes in self confidence that are consistent with belief formation being a driver of the main results in this paper. 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 indicates that this mechanism might differ by gender during high school, as adolescence is a period when girls, but not boys, experience a dramatic decline in 'social confidence' (Alan et al., 2019). Social comparisons

can also drive gender differences as female students tend to make more upward and fewer downward social 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. These gender differences remain after controlling for observable characteristics such as personality, number of connections, and baseline test scores.

Peers also affect the self-confidence of boys and girls differently. While more sociable neighbors increase less sociable boys' confidence in their social abilities —they are more likely to nominate themselves as sociable and report a higher popularity ranking— it has the opposite impact on girls. The estimates show that girls experience declines in their self-reported popularity when exposed to more sociable peers. Differences in self-confidence in academic abilities by gender are also consistent with the main effects on grades and test scores.

I also find that social interactions do not explain the patterns observed in this paper. Students form friendships and study groups with their new neighbors regardless of gender, student, or peer type, and yet some of their outcomes remain unaffected. For instance, while students befriend their higher-achieving neighbors, they do not experience gains in academic performance. Similarly, even though girls befriend their more sociable neighbors, their social skills do not improve. Furthermore, although lower-achieving girls study with their higher-achieving neighbors, their academic performance declines. Overall, friendships or study groups are not sufficient for peers to influence students' outcomes.

Related literature: The paper has four contributions to the literature.

First, social skills are malleable during high school, and peers' sociability can improve 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 team productivity and management practices (Woolley et al., 2010; Hoffman and Tadelis, 2018), less is known about the formation of social skills. My findings extend the evidence in early childhood (Falk et al., 2018) and primary schools (Rao, 2019; Alan et al., 2020), which has mainly focused on prosociality. I show that a larger set of social abilities, including social connections and personality, are also malleable during high school and that these can improve by interacting with more sociable peers.

Second, the paper contributes to the broader literature on academic peer effects. Most of the existing evidence has focused on the impact of higher-achieving peers on test scores, but the results here suggest that peer effects are more pronounced for social skills. The experimental design also adds to the understanding of how research designs affect peer effects estimates. While the literature is not conclusive about the size of peer effects on test scores (Sacerdote, 2014), the research design appears to play a role in explaining

the differences. Most studies find small positive peer effects when schools randomly allocate students to small groups such as small dorms (Epple and Romano, 2011; Sacerdote, 2001), and sizable significant estimates in large groups such as classrooms (Duflo et al., 2011; Carrell et al., 2009; Garlick, 2018). My results contradict this evidence, but the findings align with quasi-experimental research designs that do not exploit variation across groups to estimate peer effects (Abdulkadiroğlu et al., 2014; Duflo et al., 2011).[4]

The third contribution is that there are no cross-skill peer effects; sociable peers do not affect academic performance, and higher-achieving peers do not affect social abilities. From the perspective of peer allocation policies and a social planner who is aiming to maximize both social skills and academic achievement among students, there are no trade-offs between the two sets of abilities. Before the experiment, it was theoretically unclear how peers' sociability might affect academic performance. On the one hand, recent evidence documents that students underinvest in education due to social image concerns (Bursztyn and Jensen, 2015; Bursztyn et al., 2018). Intuitively, these effects should be more pronounced when interacting with more sociable peers, who have more influence on other students. On the other hand, Calvó-Armengol et al. (2009) develop a model that shows how the performance of each student embedded in a network is proportional to her centrality, and Hahn et al. (2015) presents empirical evidence consistent with this result. My findings are inconsistent with social image concerns being more pronounced when students interact with more influential peers and are somehow incompatible with the theoretical conclusions in Calvó-Armengol et al. (2009). More sociable peers do not affect academic achievement —even when they increase the centrality of other students.

The final contribution is studying the mechanisms that underpin peer effects; I show that self-confidence and beliefs play a more prominent role than social interactions in the results. First, the findings here are consistent with peers changing self-confidence (Marsh and Parker, 1984) and self-confidence affecting performance (Compte and Postlewaite, 2004). The differences in how peers affect boys' and girls' perceptions of their abilities in this field experiment complement the evidence, mainly from laboratory studies, on gender differences in belief formation (Mobius et al., 2014; Bordalo et al., 2019; Coffman and Kulkarni., 2020). These differences are also consistent with the findings of Murphy and Weinhardt (2020) on the effects of ordinal ranking in self-confidence. Second, while the findings in Carrell et al. (2013) show that the endogenous formation of friendships can change the direction of peer effects, my results establish that social links are not enough for peers to improve students' outcomes. Moreover, even when they befriend and study with each other, high-skilled peers can harm low-skilled students.

[4]The research design in Duflo et al. (2011) combines an experiment on tracking, random allocation of students to classrooms in schools without tracking, and a regression discontinuity for the marginal student between the bottom and the top sections in tracked schools.

The rest of the paper is organized as follows. Section 2 presents the experimental design and its advantages. Section 3 describes the research setting. Section 4 details the implementation of the experiment in the COAR Network. Section 5 shows the balance and the first stage. Section 6 describes the outcomes and outlines the empirical strategy. Section 7 documents the results on skill formation. Section 8 discusses potential mechanisms. Section 9 concludes.

2 Estimation of Peer Effects

In this section, I present my experimental design and describe how it addresses methodological concerns of exploiting random allocation to groups for the identification of peer effects.

2.1 Random Allocation to Groups

A widely used research method to estimate contextual peer effect —the impact of ex-ante peer characteristics on individual outcomes (Manski, 1993)— is to exploit random allocation to groups. In settings where schools and colleges apply this method, there is no self-selection of peers, and ex-ante individual and peer characteristics are unrelated. Hence, the random allocation to groups allows researchers to estimate the causal impact of predetermined peer characteristics on individual outcomes. The estimates of contextual peer effects are also informative to policymakers, who can use them to design and implement policies to optimize students' outcomes.

However, there are some concerns with exploiting random allocation to groups to estimate peer effects. By construction, the variation in peer characteristics from random groups is small. As groups get larger, this problem aggravates. For instance, Manski commented Epple and Romano (2011), pointing out that "random assignment will not work well in a large group setting, because all groups will have essentially the same distribution of types". Angrist (2014) argues that "the interpretation of results from models that rely solely on chance variation in peer groups is therefore complicated by bias from weak instruments".

I will build on Angrist (2014) to establish the methodological concerns of random allocation to groups. I will then relate this to the existing literature and explain the advantages of my experimental design. Succinctly, the design has three advantages relative to random allocation to groups: (i) it guarantees a strong variation in peer characteristics, (ii) it exploits variation across types of peers rather than across groups, and (iii) it improves transparency by ex-ante specifying a set of peer characteristics and functional forms.

To introduce the problem, let us consider the following peer effects model:

$$y_{ig} = \alpha + \pi_0 x_i + \pi_1 \overline{x}_g + \varepsilon_{ig} \tag{1}$$

where y_{ig} is the outcome of individual i when assigned to group g, x_i is a pre-specified exogenous characteristic of i and $\overline{x}_g$ the mean of the exogenous characteristic x among those in group g.

The parameter π_1 is the causal effect of a change in the group average of x over students' outcomes. Acemoglu and Angrist (2000) show that equation 1 relates to whether a 2SLS estimator using group dummies to instrument individual characteristics differs from OLS estimates of the effect of these characteristics. Specifically,

$$\pi_1 = \frac{\psi_1 - \psi_0}{1 - \tau^2}, \tag{2}$$

where ψ_0 is the OLS estimator of the parameter ψ in the model:

$$y_{ig} = \alpha + \psi x_i + \varepsilon_i, \tag{3}$$

and ψ_1 is the 2SLS estimator of this model, using the vector of group dummies g as instruments for x_i. The parameter τ^2 is the first stage R-squared associated to this 2SLS estimate —the variation in x_i explained by the group dummies.

Angrist (2014) argues that due to the relationship in equation 2, the estimation of peer effects using random allocation to groups can suffer from weak instruments. Furthermore, even with systematic variation in group composition, the 2SLS estimates can exceed the OLS estimates due to other reasons unrelated to social effects such as measurement error. The use of variation across groups to estimate peer effects can confound peer effects with factors unrelated to social influences.

Nevertheless, as pointed out by Feld and Zölitz (2017), Angrist (2014) does not explicitly show under what conditions an upward bias would exist and how it depends on the underlying parameters of the model. In fact, under regular conditions, 2SLS estimates with weak instruments are biased towards OLS, which implies that π_1 will tend to zero. Feld and Zölitz (2017) also show that with classical measurement error in the exogenous characteristics x, and a random group assignment, peer effects estimates are biased towards zero. In this vein, exploiting random allocation to groups seems to underestimate rather than overestimate peer effects.

Still, the evidence in the literature suggests that estimates of peer effects increase with group size when the variation of peer characteristics weakens. For instance, with an average classroom size of 44 students (range 19-91), Duflo et al. (2011) find that a one-standard-deviation increase in average peer test scores would increase the test score of a student by 0.445 standard deviations, an effect they claim is comparable to previous work. Similarly, in Carrell et al. (2009), a 100-points increase in peer SAT verbal

scores has negligible peer effects on grades when roommates are the relevant peer group– 0.003 (0.019)–, but sizable and significant effects when peers are other freshmen in the squadron –0.338 (0.107)– where group size is larger.[5] Carrell et al. (2013) use the last set of estimates in a posterior experiment that estimates the effect of optimal groups. Contrary to the prediction, they find a negative treatment effect. While the authors attribute this disappointing result to the endogenous patterns of social interactions, Angrist (2014) argues that it might be driven in part by the imprecision of a 2SLS without a real first stage.

Epple and Romano (2011) reach a similar conclusion with respect to group size. Their handbook chapter concludes that a one-unit increase in peer average ability increases a student's achievement by 0.2 to 0.6 points. Epple and Romano (2011) also consider it surprising that studies that exploit randomization tend to find larger peer effects than those typically found with other identification strategies. For instance, studies using quasi-experimental variation such as Dobbie and Fryer (2014) and Abdulkadiroğlu et al. (2014) find little evidence of peer effects on test scores and college outcomes. Likewise, in the same context of the large peer effects mentioned above, Duflo et al. (2011) find little evidence of peer effects when exploiting an RD on the median student of a tracking system.

This pattern is not limited to classrooms or groups of very large size. Garlick (2018) estimates an impact of 0.216 s.d. when students are assigned to dorms with an average size of 128 students in a South African university. Glaeser et al. (2003) finds that the impact of the average fraction of peers that drink in high school on fraternity participation increases with the size of the reference group —even when the differences are small (see Table 1 in Angrist (2014)). While the estimated effect is of 0.098 at the dorm level (average size of 2.3 students), it increases by 50% to 0.145 at the floor level (average size of 8.0 students). The impact is even larger at the building level (0.232), where the average group size is 28 students.

There are two explanations to this phenomenon that can be extracted from equation 2. The first one is that as groups get larger, and the variation in peer characteristics is weaker, estimates of peer effects would become more imprecise. To see this, notice that the variance of the estimator of π_1 in equation 1 is given by

$$var(\hat{\pi}_1) = \frac{1}{N_s} \frac{N_g}{N_g - 1} \frac{\sigma_\varepsilon^2}{var(\overline{x}_g)} \tag{4}$$

where N_s is the sample size, $var(\overline{x}_g) = \frac{\sigma_x^2}{N_g}$, and N_g is the group size. The variance of π_1 (equation 4) is an increasing function in $N_g \geq 2$. Intuitively, as groups get larger the variation in peer characteristics is lower and hence the precision of the estimate decreases. This argument has been previously explored by Angrist (2014) as an explanation for the

[5] A squadron comprises approximately 120 students (freshmen through seniors).

estimates in Glaeser et al. (2003) and the differences between Carrell et al. (2009) and Carrell et al. (2013).

The second and less explored explanation of positive peer effects that increase with group size is the amplification of bias when the variation in peer characteristics is weak. This is a similar situation to the one encountered when instruments explain little of the variation in the endogenous variables. A very small violation of the exclusion restriction can lead to a large (asymptotic) bias. Following equation 2, it would imply that estimates of peer effects grow with group size, as the difference between 2SLS and OLS estimates is increasing.

The probability limit of ψ_1 is:

$$plim\ \psi_1 = \pi_0 + \frac{cov(\varepsilon_{ig}, \overline{x}_g)}{var(\overline{x}_g)}.$$

As groups get larger and the variance of $\overline{x}_g$ decreases, any correlation between the error term and the average peer characteristics will be amplified. Notice that this is the case even if the covariance between the error term and $\overline{x}_g$ also decreases with group size, but at a lower rate than the decrease in the variance of $\overline{x}_g$. Any model with this feature will amplify the bias with group size much like weak instruments do.

Figure 1 introduces simulations of the linear-in-means peer effects model (equation 1), illustrating both problems. In particular, the left column in Panel A presents the distribution of the estimates of π_1 in equation 1, assuming that $\pi_1 = 0$. In general, and as expected from equation 4, estimates become imprecise as the group size increases. However, these losses in precision would imply observing both large positive and large negative estimates across studies, which is inconsistent with the empirical evidence.

A second explanation for the increase in peer effects estimates when group size is larger is the amplification of bias. The right plot in Panel A of Figure 1 illustrates this concern. For this plot, I consider a small non-linear peer effect in the error term. In particular, all groups with an average score above the median receive a positive shock of 0.1 –a relatively small non-linearity. As the plot shows, the misspecification of the functional form amplifies the bias of the linear-in-means estimate when the group size increases.[6] While the average bias is only about 0.056 when the groups are pairs, it rapidly grows to 0.082 when the group size is 4. The increase in magnitude of the bias is explosive. With a group size of 7 students, the bias is twice as large as the one with 2. A larger group size of 25 students quadruples the bias, with an average and median estimate of 0.20.

A final problem of exploiting random allocation to groups is that multiple peer attributes such as test scores, demographic characteristics, and other unobservable characteristics vary simultaneously. From a research design perspective, it is unclear which of

[6]In an individual model, this correlation with the error term would generate a bias of π_1 of 0.05. However, as illustrated by the plot, the bias amplifies with the group size.

these peer attributes are the relevant ones as all of them change across random groups. This can also be 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. The use of numerous variables and non-linear functional forms in peer effects models can also aggravate the weak variation concerns due to multiple hypotheses testing.

2.2 Experimental Approach

I propose an experimental approach to estimate peer effects as in equation 1. The approach comes as a solution to an allocation problem, where a set of students is assigned to a set of groups while generating exogenous and strong variation in peer characteristics. Let $\mathcal{S} = \{s_1, \cdots, s_n\}$ denote the set of students, and $\mathcal{G} = \{g_1, g_2, \cdots, g_m\}$ denote the set of groups. Let ς_{g_k} denote the group size of group g_k.

I will describe how the design generates large variation and explain my identification strategy using treatments rather than variation across groups. For illustration, I consider the simplest possible case of a single peer characteristic and one treatment. Appendix C describes how this procedure can be extended to multiple variables and treatment groups. The method is as follows:

1. Define the students' characteristics of interest, x. Traditionally, researchers have looked at measures of academic achievement.

2. Classify students into two types $\{h, l\}$ based on the sample median of x. Students with a value above the median would be classified as high h, and those with a value below the median would be classified as low l. The type τ_i of student i is defined as follows:

$$\tau_i(x_i) = \begin{cases} l & \text{if} \quad x_i \leq x_{med} \\ h & \text{if} \quad x_i > x_{med} \end{cases}$$

3. Conditional on each student's type, randomly assign the type of peer, where each type of peer represents a different treatment group. In this case, the treatment is having high-type peers, and the control is having low-type peers. Let $t_i = \{l, h\}$ denote the treatment arm of student i.

   Assigning a type of peer to each student is equivalent to allocating students to *peer group types*, where a *peer group type* represents the combination of a student's type and the type of peer. Let ρ_i denote the *peer group type* of student i. 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 with both types of students. The following matrix shows these combinations:

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

Each row in this matrix represents the type of student and each column the treatment or type of peer. In this simple example with only one treatment (high-type peers), there are three *peer group types*:

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

b) Group B: a mixed group with half of its members high-type and half of its members low-type.

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

As depicted by the matrix, ρ_i is a function of student's type and their assigned type of peer $\rho_i = \rho(\tau_i, t_i)$. Notice that the diagonal of the matrix shows all combinations of a single type of student. Outside of the diagonal, the matrix is symmetric, as students are matched to peers of their treatment and therefore assigned to the same *peer group type*. This implies that ρ_i is a symmetric function in τ and t: $\rho(\tau_i, t_i) = \rho(t_i, \tau_i)$.

4. Use the allocation to *peer group types* to organize the students on a list. Take the list to create a partition of the students into the set of groups $\mathcal{G}$ using the group size vector ς.

   The order of the *peer group types* is random on the list, and within each *peer group type*, the students' order is also random. The one condition that needs to hold on the list is alternating high- and low-type students in the mixed group which guarantees contact with their treatment peers.

   More formally, let us call the order of student i on the list as o_i. Then, the group that the student i is assigned to is a function of o_i and defined as:

$$\varrho(o_i) = g_k \quad \text{if} \quad \sum_{l=1}^{k-1} \varsigma_{g_l} < o_i \leq \sum_{l=1}^{k} \varsigma_{g_l}.$$

   Appendix B develops the full method that is used to generate the list of students and an application to different types of dorms.

My experimental design has three major advantages relative to other identification strategies. First, by randomizing the type of peers that students have, instead of simply randomizing them to groups, I assure that students are exposed to peers with different skill levels. This feature differs from the more traditional approach of random assignments to

groups. Theoretically, by virtue of the randomization, peer characteristics are the same in expectation for all groups, with small variations in the realized assignment.

To show how the design generates systematic variation across treatments, we can compare a treated high-type student in Group A to a control 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 that we find in the proportion of high-type peers in Group A versus B equals 0.5. The same difference applies to the comparison between a treated low-type student in Group B and a control low-type student in Group C. This difference in the proportion of high-type peers generates large variation in peer characteristics regardless of group size.

The second advantage is that the identification of peer effects relies on the variation across treatments rather than the variation across groups. The design accounts for the fact that a student receives and provides the treatment by allocating students to the *peer group types*, in which half of the peers are of the same type as the student and the other half are of the type of the assigned treatment. Rather than using all peers in a group, I only use the random variation from the half of peers that provide the treatment.[7]

Notice that with this design, some students in different treatment arms will belong to the same group. Likewise, students who share the same treatment arm would end up allocated to various groups. For these reasons, peer effects estimates are no longer proportional to the difference between IV and OLS estimates, as in equation 2. Hence, the design eliminates concerns of measurement error or other factors unrelated to social influences, which could end up driving differences between IV and OLS estimates.[8]

While students are allocated to three groups, please remember that there is only one treatment in our simple example. As students can be assigned to all combinations of the student's and peers' type (the treatment), there are differences in the treatment arm of students within the same group. In our simple example, students in the mixed group (Group B) belong to different treatment arms. As the variation in peers' skills comes from the treatment status, this allows me to identify the parameter π_1 in equation 1 without comparing peer characteristics across groups. In particular, being assigned to high-type peers predicts average peer characteristics in a student's group. The following equation represents the first stage of this model:

$$\overline{x}_g = \mu_0 + \lambda H_{i\tau} + \mu_1 x_{i\tau} + \gamma_\tau + \nu_{ig\tau} \tag{5}$$

where $H_{i\tau}$ takes the value of one when student i of type τ is assigned to the treatment

[7]One of the concerns pointed out in Angrist (2014), is that research designs that exploit random allocation to groups confound subjects of the study with peers that provide the treatment. Notice that with this design, it is straightforward to identify the peers providing the treatment without losses in statistical power. For instance, the first version of this design implied splitting the sample into two, but this implies losing half of the sample for the experiment.

[8]For example, Booij et al. (2017) manipulate the composition of groups to achieve a wide range of support in academic skills, but still exploit the variation across groups to estimate peer effects.

group and zero otherwise. The parameter of interest in this first stage is λ, which captures the impact of the treatment on average peer characteristics $\overline{x}_g$. The model includes variation in student's type τ, and type-fixed effects as the randomization is performed at this level.[9] The model also controls for individual characteristic $x_{i\tau}$, and $\nu_{ig\tau}$ is an error term.

The third advantage of my experimental design is that it increases transparency in the study of peer effects. The design generates an ex-ante commitment from the researcher to study a set of pre-specified characteristics. This contrasts with the traditional approach where researchers could potentially study multiple characteristics that vary by chance when individuals are randomly allocated to groups. My experimental design can be adapted to include multiple treatment arms beyond the two that I consider in this paper. It could also be adapted to study non-linear peer effects by adding more quantiles. However, as in any other experimental study, there is a trade-off between statistical power and additional treatments.

It is also important to acknowledge how peer effects studies can suffer from a correlation between the variables of interest and other observed or unobserved peer characteristics. This makes it hard for traditional studies to isolate the effect of treatments. While the variables that define my treatments might be correlated with other characteristics, the variation of these other traits across treatment arms is still lower by construction in my design. Let us recall that the treatment arms in my experimental design are defined by the median or other quantiles. Hence, the design minimizes the role of other variables that are not part of the treatments.

Overall, my experimental design does not lose precision or increase bias with group size. This occurs since there is substantial variation in peer characteristics by virtue of the treatment arms and because the identification strategy does not rely on variation across groups. The parameter π_1 is estimated via a 2SLS model with a single instrument and a strong first stage. Simulations on Panel B of Figure 1 numerically illustrate how my experimental design preserves precision and limits the bias of estimates with different group sizes. On the left panel, I assume that $\pi_1 = 0$ and plot the corresponding peer effects estimates. The precision of the estimates remains constant with group size and only varies with the sample size. Similarly, I consider a non-linear correlation with the error term on the right panel, but the positive bias still remains constant regardless of group size. Both plots sharply contrast with the findings from a random allocation to groups, which is the traditional approach in the peer effects literature.

I further show how this design can be extended to multiple peer characteristics and

[9] The type-fixed effects also allow for the propensity score of receiving the treatment to vary across students' types. Notice that if all groups are of the same size, the high-type students are twice as likely to be in the treatment group than low-type students. Given that the propensity score of receiving the treatment varies by student type, we need to account for this in the empirical analysis.

allow for non-linearities by including other quantiles beyond the median in Appendix C. The following two sections detail how I applied this experimental design to study peer effects on academic outcomes and social skills at selective high schools in Peru. In the next section, I describe the setting and Section 4 expands on the implementation.

3 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 multicultural 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.

4 Implementation of the Experimental Design

This section explains how I applied the experimental design described before to study the impact of sociability and academic achievement of peers at the COAR Network. First, I describe what measures of sociability and achievement I use to classify students into types. Second, I explain the design in this context, including the assignment to treatments and *peer group types*, and the allocation to dormitories in the schools. Appendix Figure A.1 presents the timeline of the project.

4.1 Data

4.1.1 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, and whether they come from a rural area.

Column 1 of Table 1 reports descriptive statistics for students in the COAR Network. Despite these schools target students from the public school system, there is diversity in the socio-economic composition. For example, 41% of the students come from poor households, and 26% of students come from rural households. Around 50% of them have subsidized health insurance.

Students enrolled at the COAR Network also have higher test scores than the average student in the country. Although the scores in a national standardized test before applying are not available for all cohorts[10], it is clear that these students have high levels of academic achievement; they have average scores 1.81σ higher than the average student in the country.

4.1.2 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%

[10]The Ministry implemented a middle school test since 2015. Hence, the scores are not available for the 2015 cohort.

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, (ii) friends, (iii) study partners, and (iv) people with whom they interact in social activities such as playing sports or games. The social networks questions had a drop-down list of all the students enrolled at the school-cohort, and there were no restrictions on the number of peers students could list.

Column 1 of Table 1 shows that, on average, students have 14.7 connections with a standard deviation of 6.49. 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. I construct a peers' perception index that aggregates the four questions using principal component analysis (PCA). On average, between 2 and 3 peers rank a student in each of these social categories.

The Ministry of Education also collects administrative data on different 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). This latter measure is not self-reported as it is a multiple-choice questionnaire with correct answers. It also predicts teamwork abilities at both the group(Woolley et al., 2010) and the individual level (Weidmann and Deming, 2020). Appendix D describes these tests in detail. As with the peers' perception measures, I construct a social skills index at baseline using this information.

4.2 Classifying Students by Academic and Social Skills

I use data from the baseline social network survey to identify more sociable students and the admission test's performance to identify higher-achieving students.

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.2 shows that centrality and admissions test scores are positively correlated in this setting.

Columns 2 to 9 of Table 1 present descriptive statistics of demographics and baseline characteristics by student type and gender. More sociable students are less likely to

be from a poor or rural household. They are also less likely to have subsidized health insurance. As expected, there is also a large gap in measures of social skills between the two groups. More sociable students have more connections, a higher social skills index, and better peers' perception than less sociable students. Except for the number of connections, women have higher social skills than men.

I also find a large statistically significant correlation between eigenvector centrality and my set of indicators of social skills. Appendix Table A.1 reports standardized coefficients of an ordinary least squares (OLS) regression of social skills measures[11] on the three admissions test scores, and on the eigenvector centrality of the baseline social network, controlling for school×grade×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 weaker and similar in magnitude to the correlation with academic achievement. For this reason, I focus on the higher-achieving peers treatment for the first years.[12]

I use the admission test score to characterize students as lower- or higher-achieving at baseline. The test assesses students' skills in math and reading comprehension. Students took this test before they had any interaction between each other. 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.

It is important to point out that in a national standardized test before the application, high-achieving students have scores of 0.7σ higher than lower-achieving students. This fact shows that despite the COAR Network targeting very talented students, there is still a wide variation in students' achievement within the schools.[13]

4.3 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)

[11] Some of these variables were collected before or after the intervention. They are described in detail in Section 6.1 and Appendix D.

[12] All the results are robust to including the social-fit treatment. These models are available upon request.

[13] I did not have access to this data at the moment of the experiment. This test is also not available for the 2015 cohort. For these reasons, I defined the academic treatment with the admission test scores.

higher-achieving peers. In the previous section, I explained how students were classified as more/less sociable and higher/lower-achieving. Next, I explain how I applied the experimental design from section 2.2 to my particular setting.

4.3.1 Peer Group Types

The randomization in my field experiment is analogous to the design in Section 2.2, with two variables, sociability and academic achievement, and one treatment for each of them. With this design, rather than two types of students, there are four types of students. The four types of students are also the type of peers that define the treatment groups:

1. Less sociable and lower-achieving peers.
2. Less sociable and higher-achieving peers.
3. More sociable and lower-achieving peers.
4. More sociable and higher-achieving peers.

Notice that this design is equivalent to two treatments: (1) more sociable peers, (2) higher-achieving peers, and (3) an interaction between the two.

Analogously, instead of the three *peer group types* A, B, and C of the simplest case, there are ten potential *peer group types*.[14] 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 peer, namely a *peer group type*.[15] 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 design.

The original design considered the impact of each type of peer separately. This strategy is equivalent to including the two treatments and the interaction. The original project had two main hypotheses: (1) whether sociable peers could improve social skills, and (2) whether the interaction of sociable and higher-achieving peers could drive positive academic peer effects and explain part of the heterogeneity in the literature. The main empirical strategy now does not include the interaction term, as this generates some gains

[14] With four types of students, there would be 16 possible combinations, but 6 of them are redundant as $\rho(\tau_i, t_i) = \rho(t_i, \tau_i)$.

[15] 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.

in precision. In general, the interaction term does not affect the main results on social skills, and the coefficient associated with it is a precise zero. For the estimates on academic skills, I cannot reject that the interaction term is equal to zero, but the estimates are less precise.

4.3.2 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 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 75 students per dormitory. Appendix Figure A.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*. This list was later used to allocate students to specific beds in the dormitories. As described in Section 2.2, the *peer group types* were randomly ordered on the list and the order was specific to each school$\times$grade$\times$gender. Within each *peer group type*, the student's order was also randomized with the only condition that in the mixed groups with two different types, the names of students of different types were alternated. Appendix B describes in detail how the lists determine the allocation to different dormitories.

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.

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 Appendix Figure A.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:

$$y_{ij} = \gamma_0 + \sum_{k=1}^{9} \gamma_k \mathbf{1}_{d=k_{ij}} + \nu_{ij}, \tag{6}$$

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 3 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 65 p.p. (p-value 0.000) and 48 p.p. (p-value 0.000), respectively. Overall, Panel A of Figure 3 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 3 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.[16] This evidence shows that the experimental design was successfully implemented.

5 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.

5.1 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:

$$y_{i\tau} = \alpha + \lambda_s s_{i\tau} + \lambda_c c_{i\tau} + \gamma_\tau + \nu_{i\tau} \tag{7}$$

Equation 7 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 4.3.2 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 7. 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 7 on social skills and academic outcomes at baseline for all students, and for all subgroups of sociability, academic achievement, and gender. Table 2

[16] There is an impact of distance on social interactions regardless of dorm size.

reports these estimates. In general, I find that the treatments are not correlated with social skills or academic outcomes at baseline. Furthermore, Tables A.2 and A.3 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.

5.2 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 7 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 8a and 8b. I also estimate the same set of equations for *neighbors* as described above.

$$\overline{s}_{p_{i\tau}} = \theta_s + \delta_s s_{i\tau} + \phi_s c_{i\tau} + \gamma_\tau + \xi_{i\tau}, \tag{8a}$$

$$\overline{c}_{p_{i\tau}} = \theta_c + \delta_c s_{i\tau} + \phi_c c_{i\tau} + \gamma_\tau + \nu_{i\tau}, \tag{8b}$$

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 effect 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 0.89 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 small positive impact on peers' average sociability, and the more sociable

peers treatment raises peers' average academic achievement. This indirect effect is small compared to the direct impact on the respective skill for each treatment.

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. Columns 5 to 8 of Table 3 show the effect of each treatment on students' neighbors in the dormitories. Columns 5 and 6 show the estimation of equation 7 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 about 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 0.54 standard deviations. Likewise, the higher-achieving peers treatment increases the average academic achievement of neighbors by 0.57 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.

6 Outcomes and Empirical Strategy

6.1 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. I also have data on longer-term outcomes that include dropping out of the COAR Network and college enrollment.

6.1.1 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 with whom they play sports and games. As in the baseline survey, these questions

had a drop-down list of all the students enrolled at the school-cohort, and there were no restrictions on the number of peers students could list. 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 all of my results are robust to the network of mutual connections.

I also measure social skills using 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 openness, extroversion, and agreeableness of the "Big Five", and altruism, empathy, leadership, emotional intelligence, intercultural sensitivity. The index also includes the "Reading the Mind in the Eyes" test that is a multiple-choice test that predicts team productivity abilities at both, the group (Woolley et al., 2010) and the individual level (Weidmann and Deming, 2020). Appendix D 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.[17] 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.

As a general outcome of social skills, I use an index that aggregates the four types of social outcomes described above: connections, centrality, psychological tests, and peers' perception. I reproduce a similar index of social skills with the available measures at baseline. Panel B in Appendix Figure A.2 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 0.41-standard-deviation increase in the social skills index after the intervention.

6.1.2 Academic Outcomes

The performance for students in 2016–17 cohorts is measured by standardized tests designed by the Ministry of Education. For the 2015 cohort, the Ministry relies on the performance on the IB degree. I combine these three outcomes to measure test scores as these are comparable across schools. I also have the grades assigned by teachers for

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

students in the 2016-17 cohorts. These are not available for the 2015 cohort as these students' primary assessment is the IB degree.

6.1.3 Longer-term Outcomes

In addition to social skills and academic scores, I also test the intervention's impact on longer-term outcomes. I consider two types of these outcomes. First, I observe whether students dropped out from the COAR Network. Second, I use administrative data of the Ministry of Education that tracks students into higher education. I consider three different college outcomes that include whether students enrolled at any university and its quality.

In Peru, there is a vast number of private universities with low-quality standards. As a result, in 2014, the Peruvian government issued the *Universities Law* and created the National Superintendence of Higher Education (SUNEDU) to regulate universities. As part of this law, all public and private universities needed to fulfill a minimum requirement of quality to receive a government's certification. By 2019, only 73 institutions had received this certification. I use whether a university has been or not certified as the first measure of college quality. The SUNEDU also has a ranking of higher education institutions to inform families about the best universities. I use whether a university belongs to the top 20 of this ranking as the second measure of college quality.

6.2 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 6.1. The following equation estimates the impact of each treatment:

$$y_{i\tau} = \alpha + \lambda_s s_{i\tau} + \lambda_c c_{i\tau} + X'_{i\tau}\delta + \gamma_\tau + \varepsilon_{i\tau}. \tag{9}$$

Equation 9 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, as the propensity score of receiving the treatments varies by student type. Rosenbaum and Rubin (1983) show that adjusting for the scalar propensity score is sufficient to remove bias due to all observed covariates. The inclusion of students' type fixed effects accounts for the differences in the propensity score of being assigned to the treatment.

The parameters of interest in equation 9, 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×peer-group-type* level, since all the students within this unit share the same treat-

ment 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 9 including the interaction of the two treatments with a *boy* dummy variable. The following equation describes this model:

$$y_{i\tau} = \alpha + \lambda_s s_{i\tau} + \lambda_c c_{i\tau} + \phi_s s_{i\tau} \times boy_i + \phi_c c_{i\tau} \times boy_i + X'_{i\tau}\delta + \gamma_\tau + \varepsilon_{i\tau}, \tag{10}$$

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

Estimates of equation 9 and equations 8a and 8b are of independent interest. They are also 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:

$$y_{i\tau} = \theta + \beta_s \overline{s}_{n_{i\tau}} + \beta_c \overline{c}_{n_{i\tau}} + X'_{i\tau}\delta + \gamma_\tau + \varepsilon_{i\tau}, \tag{11}$$

where $\overline{s}_{n_{i\tau}}$ and $\overline{c}_{n_{i\tau}}$ 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 8a and 8b. It represents the impact of the assignment to treatment on neighbors' characteristics.

As described in Section 5, columns 7 and 8 of Table 3 display the estimates of equations 8a and 8b. Being assigned to live with more sociable peers increases the average sociability of neighbors by 0.54 standard deviations, and the higher-achieving peers treatment increases the average academic achievement of neighbors by 0.57 standard deviations.

7 Main Results

7.1 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 9 and 10 for all students on all of my social outcomes indicators.

The results reveal that having more sociable peers improves social outcomes, but only for boys. Columns 1 and 2 in Panel A report the post-intervention effects on the number of connections. The impact of more sociable peers on the number of links for all students is close to zero (-0.001, p-value 0.989). However, column 2 shows that this average impact masks some heterogeneity by gender. While the impact is negative for girls (-0.334, s.e. 0.183), the effect is large and positive for boys, who end up having 0.48 (p-value 0.031) more connections after the intervention. The results for the network centrality (columns 3 and 4) reveal a similar pattern; boys with more sociable peers have a better network position after the intervention (0.10σ, p-value 0.009), but for girls, the point estimate is -0.048 (s.e. 0.031).

I also find that more sociable neighbors increase the social outcomes of boys only, as captured by their psychological tests (columns 5 and 6). The estimates in column 5 show an ATE of 0.071σ (s.e 0.027) on the psychological tests. This positive impact is mainly driven by boys for whom more sociable neighbors increase the social skills index by 0.144σ (p-value 0.001). Although the results on peers' perception (columns 7 and 8) are weaker, the conclusion is similar. While the ATE of more sociable neighbors on peers' perception in column 7 is 0.030σ (s.e. 0.020), the impact for boys is larger with a magnitude of 0.052σ (p-value 0.099).

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 0.011σ, s.e. 0.019), the social skills index (column 5, effect of -0.017σ, s.e. 0.021), and the peers' perceptions (column 7, effect of 0.017σ, 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 9 and 10 by subgroups: less and more sociable students at baseline (Panels B and C, respectively). I then compare these results to the estimates of equation 9 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 0.956 (p-value 0.001). 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 0.000 and 0.012. By contrast, I do not find robust evidence that more sociable neighbors affect the social

outcomes of the less sociable girls. Likewise, having higher-achieving neighbors does not appear to change the social outcomes of less sociable students. While I observe some negative effects on peers' perceptions of less sociable students (column 7), I do not over-interpret this result as it is inconsistent with the impact 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 longer-term outcomes such as lower dropout rates and higher enrollment rates at better colleges. Appendix Table A.4 shows that the measures of social skills have predictive power on dropout, college enrollment, and college quality. Column 1 shows that social skills have the largest predictive power on dropping out of the COAR Network. A one-standard-deviation increase in the social skills index is correlated with a decrease of 0.8 percentage points on the dropout rate. The three types of skills —social skills, math, and reading scores— are also correlated with college enrollment and college quality.[18] In general, the best predictor is math scores, but social skills also play a significant role with a larger magnitude than reading scores for college enrollment and enrollment at a certified college.

Furthermore, the results in Panel B of Table 5 show that more sociable neighbors also influence the longer-term outcomes of the less sociable boys. Column 2 shows a negative effect of 2.1 p.p. (p-value 0.012) on the dropout rate. Columns 4 and 6 show an increase of 6.6 p.p. (p-value 0.034) and 5.2 p.p. (p-value 0.058), 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.

7.1.1 Robustness Checks

The improvement of the social skills for the less sociable boys remains after multiple robustness checks. Appendix Figure A.5 presents the effect of the more sociable peers treatment on all the individual outcomes that are related to social skills. These social outcomes were measured at different moments after the implementation of the experi-

[18] A one-standard-deviation in social skills correlates with a 2.4-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 college, where the correlation with social skills is about 45% of the correlation with math scores.

ment (see the timeline in Appendix Figure A.1). Yet, the results are consistently positive regardless of the moment of measurement. These outcomes include:

1. The degree and the centrality of the friendship, study, and play network.
2. Openness, extroversion, 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.

Panel A displays the point estimates and 90% confidence intervals for the less sociable boys. The point estimate is positive for 38 out of the 39 outcomes, and in 29 cases, statistically different from zero.

Moreover, Table A.5 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.6 presents p-values for multiple hypotheses across different groups by gender and sociability at baseline.[19]

7.1.2 2SLS Estimates

To account for imperfect compliance between assigned peers and actual neighbors, and to provide more comparable estimates to other peer effects studies, I estimate equation 11. Table 6 presents the results of the 2SLS two-endogenous model described in equation 11 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 6 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 6 show the results for all students, boys, and girls. A one-standard-deviation increase in neighbors' sociability has an impact of 0.033σ impact (s.e. 0.046) on the average student's social skills index (column 1). This slightly positive impact comes from the effect on boys in column 2, with an estimate of 0.219σ (s.e. 0.081). By contrast, column 3 shows that the social peer effects estimate on girls is small (-0.076) and relatively precise (s.e. 0.054). Social outcomes are also not affected by the academic achievement of students' neighbors.

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

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 0.475σ (p-value 0.000). By contrast, the results in columns 7 to 9 show that peers' sociability and achievement do not affect the social skills of the more sociable students.

7.2 Academic Outcomes

Next, I estimate treatment effects on academic outcomes. Table 7 reports the estimates of equations 9 and 10. Columns 1 and 2 report the effects on grades in math and reading comprehension. These outcomes are only available for the 2016-17 cohorts. 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 7 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 0.006σ. For reading (column 7), it ranges between -0.072 and 0.006σ. 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 0.073σ (p-value 0.007).

I also examine treatment effects heterogeneity by academic achievement. I estimate equations 9 and 10 for two subgroups of academic achievement: lower- and higher-achieving students. Panels B and C of Table 7 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 7 show that the higher-achieving peers treatment has a negative effect on both math and reading grades, although these are marginally significant. Higher-achieving neighbors reduce students' math grades by 0.060σ (p-value 0.101) and reading grades by 0.066σ (p-value 0.078). The treatment effects on test scores are also negative. Columns 5 and 7 of Table 7 show that the effects of higher-achieving peers on lower-achieving students are -0.041σ (p-value 0.101) on

math scores and -0.046σ (p-value 0.145) on reading scores. 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 7 report the estimates of equation 10 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, -0.112σ, p-value 0.021), math test scores (column 6, -0.070σ, p-value 0.014), and reading test scores (column 8, -0.084σ, p-value 0.047). For reading grades (column 2), the point estimate is also negative (-0.056σ, p-value 0.242), 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.

These results are also robust to randomization inference (Panel B of Table A.5). However, the effects are weaker than those on social skills once we account for multiple hypotheses testing (Panel B of Table A.6). Under the traditional multiple hypotheses tests, the treatment effects on math for lower-achieving girls are significant at the 10% level. Conversely, the estimates are not statistically significant for reading scores.

I do not find that more sociable or higher-achieving neighbors affect the academic performance of higher-achieving students. Panel C in Table 7 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 7). Neighbors' characteristics do not appear to affect the academic achievement of the strongest students. If anything, higher-achieving peers reduce the performance in reading for girls by -0.071σ (column 8).

7.2.1 2SLS Estimates

Table 8 reports the 2SLS estimates of equation 11 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 -0.042 (s.e. 0.029) on math and -0.059 (s.e. 0.035, p-value 0.094) on reading scores. My estimates rule out small positive peer effects; the upper limit of the 95% confidence interval is 0.016 for math and 0.001 for reading scores. I also find fairly precise estimates of neighbors' sociability on academic outcomes. Estimates in columns 2 and 3 show that while peer effects on math are similar for boys and girls, a one-standard-deviation increase in neighbors' academic achievement reduces girls' performance in reading by 0.119 σ (s.e. 0.044).

The results in columns 4 and 6 of Table 8 show that academic peer effects are negative for lower-achieving students, but statistically indistinguishable from zero. However, column 6 shows that girls drive these negative point estimates. For them a one-standard-deviation increase in peers' achievement at baseline reduces math performance by 0.112σ (p-value 0.017) and reading performance by 0.144σ (p-value 0.047). On the other hand, for boys (column 5), the estimates on academic peer effects are very close and indistinguishable from zero.

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.

7.3 Optimal Policies

In this section, I discuss policy recommendations based on the reported impact of peers' sociability and achievement on students' outcomes. Any peer effects study has an underlying optimization problem of a social planner that can use allocation policies to maximize students' outcomes. Much of the empirical evidence has focused on achievement, where the objective function commonly maximizes average grades or test scores.

This paper looks at two dimensions of skills affecting later life outcomes: social skills and academic performance. For this reason, my analysis focuses on a single outcome that depends on both sets of skills. For instance, Appendix Table A.4 reports how social skills, math, and reading scores predict college outcomes. Similarly, previous research shows that wages depend positively on both academic performance c_i and social skills s_i (Lleras-Muney et al., 2020; Deming, 2017).

Consider a social planner that needs to decide how to allocate students across dorms to maximize their future wages w_i. The results in this paper show that: (1) more sociable peers improve social outcomes only for less sociable boys, (2) higher-achieving peers reduce the performance of lower-achieving girls, (3) there are no trade-offs between social and academic abilities. Based on these results, the optimal policies can be characterized as follows:

1. The social planner can maximize social and academic skills separately as there is no evidence of cross-skill peer effects.

2. The optimal policy in terms of social abilities should only be targeted to boys. To maximize the average level of social outcomes and reduce inequality in social skills, the social planner should 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 remain unchanged by their sociable peers, optimal allocation to dorms should not target their sociability.

3. The optimal policy in terms of academic achievement should only target girls. As the results show that higher-achieving neighbors decrease the performance of lower-achieving girls, the social planner should separate girls by their initial academic achievement. While there is also a negative treatment effect on reading scores for higher-achieving girls, these effects are smaller than the estimates for lower-achieving girls. They also do not experience losses in math. As the academic treatment does not affect boys' outcomes, optimal policies should not target their academic abilities.

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.

8 Mechanisms

8.1 Self-confidence

In this section, I examine whether beliefs about one's abilities (self-confidence) explain my findings. In Appendix E, I present 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. Overall, there are three arguments to explain the link between self-confidence and the main results.

First, there are two channels through which beliefs could affect performance. On the one hand, through complementarities between effort and abilities. When effort and abilities are complements, more self-confident individuals would exert more effort Benabou and Tirole (2002). On the other hand, as argued by (Compte and Postlewaite, 2004), self-confidence could also have a direct effect on performance.

Second, by interacting with peers, students would receive signals about their skills that could change their beliefs. While it is beyond this paper's scope to study how these signals are produced, a natural example is the big-fish–little-pond effect; students could lose self-confidence in their abilities due to social comparisons. 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.

Third, the interpretation of a signal might depend on gender. Men and women differ in how they form beliefs about themselves and others (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). 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).

Next, I study these factors to explore whether self-confidence can be a valid mechanism of my main results. This analysis is divided into two subsections. First, following the results in Section 7, I study to what extent male and female students differ in their beliefs. Second, I estimate treatment effects on self-reported measures of ability.

8.1.1 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 4 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.

8.1.2 Peers and Beliefs

Social Skills: In this subsection, I examine whether having more sociable peers affects students' perception of their own social skills. Panel A of Figure 5 presents average

self-confidence indexes in social skills by baseline sociability, the more sociable peers treatment status, and gender. The index is constructed by adding self-reported rankings (all between 0 and 100) in the dorm[20], the classroom, and the cohort. The index also includes whether the student nominated herself when asked to name up to five students on leadership, friendliness, popularity, and shyness (reversed).

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. The bar plot shows that while the treatment effect is positive for the less sociable boys ($\approx 0.16\sigma$), it is negative for the less sociable girls ($\approx 0.10\sigma$). Appendix Table A.7 formally tests whether the effects are different from zero. It reports the estimates of equation 10 on the index and all the individual measures. Panel A presents the results for the less sociable students at baseline and Panel B for the more sociable. The results in column 8 show a treatment effect for the less sociable boys on the index of about 0.135σ (p-value 0.031). Less sociable girls, on the contrary, have a negative treatment effect of about 0.128σ (p-value 0.007).

The table also presents the effects on the individual measures used for the index. Columns 1 to 3 show the effect on the different self-reported rankings and columns 4 to 8 on self-nominations. 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 2.74 points lower (p-value 0.062). By contrast, we cannot reject a zero effect for boys. The interaction term of the treatment with the boy dummy is positive and marginally non-statistically significant (p-value 0.116).

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. I 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 4.9 and 5.3 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 2.61 positions (p-value 0.102). This result suggests that men believe they are more popular after interacting with more sociable neighbors in the dormitories.

The estimates on self-nominations (columns 4 to 7) are consistent with these results. The positive impact on the beliefs of the less sociable boys is driven by their self-

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

perceived levels of leadership and popularity, but especially shyness. In general, less sociable boys are 4.3 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 similar interactions with their assigned neighbors.

Academic Achievement: Changes in beliefs about academic skills are also a valid mechanism to explain the results for the academic peer effects. The evidence in Table 7 shows that higher-achieving peers decrease the academic scores of lower-achieving students, especially of lower-achieving girls. Here, I measure whether these changes are aligned with changes in self-confidence.

Panel B of Figure 5 presents a bar plot of average self-confidence index in academic skills by initial achievement level, the higher-achieving peers treatment status, and gender. I use three types of measures to construct the index. The first type are self-reported beliefs on academic rankings within the dorm, classroom, and cohort. The second type is whether a student nominates herself among the five most skilled students in their cohort. The third type are two factors of the Achievement Goals Questionnaire: (i) the performance-approach goal that measures whether a student wants to do better than their peers, and (ii) the performance-avoidance goal that measures whether a student avoids doing worse than their peers.

As the bar plot shows, there is a negative effect on lower-achieving girls' self-confidence of about 0.11σ. Appendix Table A.8 presents the estimates of equation 10 on this index and formally test whether it is equal to zero. Overall, the results show a negative effect of 0.093σ (p-value 0.030).

The table also reports treatment effects on individual measures. In the first column, the results show that while lower-achieving girls report a ranking within the dorm 1.48 positions lower (p-value 0.117), the effects for boys are around -0.054 positions and statistically indistinguishable from zero. The results on relative performance goals are more striking with a negative impact on the performance-approach goal of 0.187σ (p-value$<$0.001), and a negative impact on the performance-avoidance goal of 0.132σ (p-value 0.018). By contrast, the impact on boys is slightly positive and indistinguishable

from zero.[21]

Panel B of Appendix Table A.8 presents the results for higher-achieving students. Although the estimates are, in general, indistinguishable from zero, there is some evidence of gender differences in the formation of beliefs. Columns 1 to 3 show that while higher-achieving peers reduce the self-reported academic rankings within the dorm, classroom, and cohort, this is not the case for boys. This impact is aligned with the negative effects on reading scores. However, estimates in column 7 on the self-confidence index show no statistically significant effects neither for higher-achieving girls or boys.

Overall, gender differences in self-confidence are consistent with the results in Section 7. 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 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.

8.2 Social Interactions

I also study whether social connections with neighbors explain the results in Section 7. 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 10) 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 6 presents the average number of connections with neighbors by distance on the list for different groups. Appendix Table A.9 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

[21]The results on rankings and self-confidence are more negative for first-year students who have less information about their academic abilities relative to their peers.

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 6 shows that less sociable boys form connections with their neighbors in a similar way to comparable groups. For all the groups of less sociable students, the distance on the list reduces the average number of connections. The number of links is also relatively similar at all values of distance, including odd ones, where the peers that provide the treatment are located. I formally test whether the treatment or its interaction with gender, predict connections in Panel A of Appendix Table A.9. 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 nor 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 6 reports the average number of connections by distance with neighbors for lower-achieving students.[22] The figure shows a similar pattern to Panel A and Figure 3, 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 in Appendix Table A.9 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 8 reveal negative academic peer effects for lower-achieving girls.

Taken together, the 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 widely across outcomes, student characteristics and peer type.

9 Conclusion

This paper presents the results of a field experiment designed to estimate causal peer effects on social and academic skills. The study was conducted in 23 out of 25 exam schools in Peru, covering a sample of approximately 6,000 students. The experimental

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

design surmounts recent concerns with the traditional approach to estimating peer effects, which exploits random allocation to groups. The experiment guarantees strong variation in peer characteristics by randomizing the type of peer. Students were classified by baseline sociability and academic achievement using centrality measures of social networks and test scores. Furthermore, the identification strategy relies on the variation in peer characteristics across treatments rather than groups.

I found that more sociable peers positively impact boys in their development of social skills. The effects are mainly driven by the impact on boys who were assessed as less sociable at baseline. This group of boys ends 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. I also find that some effects translate into longer-term outcomes. Having more sociable neighbors helps to 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 experimental design can be adapted to include non-linearities, but as in other experimental studies, there is a trade-off between more treatments and statistical power.

I also rule out social interactions as a mechanism behind the main effects. For example, although lower-achieving girls befriend and study 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). 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 inter-

acting with more sociable neighbors. These results are consistent with a broad literature studying how men and women form 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.

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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)
Demographics									
Female (%)	0.57	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00
Poor (%)	0.41	0.46	0.47	0.39	0.39	0.47	0.46	0.36	0.37
Rural (%)	0.26	0.31	0.30	0.25	0.22	0.31	0.29	0.22	0.21
Subsidized health insurance (%)	0.50	0.51	0.57	0.44	0.47	0.52	0.55	0.44	0.49
Baseline characteristics									
National standardized score*	1.81	1.51	1.26	1.79	1.61	1.52	1.42	2.23	2.08
	(0.95)	(0.96)	(0.98)	(0.93)	(0.95)	(0.83)	(0.84)	(0.85)	(0.97)
Connections	14.70	12.73	11.49	16.41	14.49	15.35	13.82	15.65	14.32
	(6.49)	(5.45)	(5.08)	(5.74)	(5.65)	(6.57)	(6.30)	(6.47)	(6.47)
Social skills index	-0.00	-0.14	-0.07	0.06	0.13	-0.07	0.00	-0.02	0.06
	(1.00)	(1.00)	(1.00)	(0.97)	(0.99)	(0.99)	(0.98)	(0.99)	(1.01)
Peers' perception	0.00	-0.29	-0.27	0.23	0.31	-0.14	-0.09	0.07	0.14
	(1.00)	(0.76)	(0.69)	(1.11)	(1.18)	(0.86)	(0.91)	(1.05)	(1.11)
Treatments									
Sociability	-0.00	-0.73	-0.75	0.75	0.75	-0.06	-0.04	0.06	0.04
	(0.99)	(0.40)	(0.40)	(0.84)	(0.83)	(0.96)	(0.98)	(1.02)	(1.01)
Academic achievement	0.00	-0.06	-0.08	0.07	0.08	-0.79	-0.78	0.80	0.77
	(0.99)	(0.96)	(0.95)	(1.01)	(1.03)	(0.48)	(0.47)	(0.68)	(0.74)

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. *Scores in the national standardized test before the application to the COAR Network is not available for the 2015 cohort as this was the first year of this test. The table includes a set of students' demographic characteristics 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	0.000	0.031	-0.031	0.027	0.012	0.042	-0.001	0.006	-0.008
	(0.030)	(0.033)	(0.051)	(0.023)	(0.030)	(0.035)	(0.021)	(0.030)	(0.030)
Higher-achieving	-0.019	0.017	-0.055	0.007	-0.023	0.028	-0.014	-0.033	0.006
	(0.030)	(0.033)	(0.050)	(0.019)	(0.026)	(0.030)	(0.018)	(0.027)	(0.027)
Control mean	-0.18	-0.76	0.71	-0.11	-0.38	0.29	-0.06	-0.27	0.24
N	3,654	1,832	1,822	6,031	3,000	3,019	6,029	2,999	3,018
				Panel B: Boys					
More sociable	-0.040	-0.045	-0.036	0.000	-0.026	0.025	0.011	0.005	0.018
	(0.046)	(0.052)	(0.076)	(0.037)	(0.049)	(0.056)	(0.032)	(0.047)	(0.044)
Higher-achieving	-0.068	-0.022	-0.114	0.015	-0.011	0.042	-0.016	-0.012	-0.023
	(0.046)	(0.052)	(0.076)	(0.030)	(0.043)	(0.047)	(0.027)	(0.040)	(0.040)
Control mean	-0.26	-0.81	0.59	0.01	-0.29	0.45	-0.15	-0.39	0.20
N	1,490	753	737	2,614	1,304	1,299	2,613	1,303	1,299
				Panel C: Girls					
More sociable	0.028	0.084	-0.028	0.046	0.038	0.054	-0.009	0.007	-0.025
	(0.040)	(0.042)	(0.068)	(0.029)	(0.037)	(0.044)	(0.028)	(0.040)	(0.041)
Higher-achieving	0.015	0.044	-0.016	0.001	-0.031	0.019	-0.012	-0.049	0.026
	(0.040)	(0.043)	(0.067)	(0.024)	(0.032)	(0.039)	(0.025)	(0.036)	(0.037)
Control mean	-0.12	-0.73	0.79	-0.20	-0.45	0.16	0.01	-0.17	0.28
N	2,164	1,079	1,085	3,417	1,696	1,720	3,416	1,696	1,719

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-student-type level.

TABLE 3: First Stage on Assigned Peers and Neighbors

	Assigned peers				Neighbors			
	Number		Baseline characteristics		Number		Baseline characteristics	
	More sociable	Higher-achieving	Sociability	Academic achievement	More sociable	Higher-achieving	Sociability	Academic achievement
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
More sociable	3.177	-0.009	0.886	0.088	1.575	0.060	0.544	0.087
	(0.107)	(0.105)	(0.016)	(0.017)	(0.049)	(0.048)	(0.019)	(0.020)
Higher-achieving	0.016	2.984	0.036	0.943	-0.031	1.527	0.022	0.570
	(0.067)	(0.081)	(0.010)	(0.013)	(0.032)	(0.038)	(0.013)	(0.015)
Control mean	0.38	0.92	-0.22	-0.53	0.59	1.39	-0.13	-0.36
N	6,079	6,079	6,079	6,079	6,079	6,079	6,079	6,079

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 and neighbors, 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-student-type level.

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	-0.001	-0.334	0.012	-0.048	0.071	0.021	0.030	0.014
	(0.142)	(0.183)	(0.024)	(0.031)	(0.027)	(0.034)	(0.020)	(0.025)
Higher-achieving	-0.020	-0.118	0.011	-0.010	-0.017	-0.010	0.017	0.040
	(0.127)	(0.169)	(0.019)	(0.025)	(0.021)	(0.028)	(0.017)	(0.022)
More sociable × boy		0.817		0.147		0.123		0.038
		(0.290)		(0.049)		(0.055)		(0.040)
Higher-achieving × boy		0.231		0.050		-0.017		-0.054
		(0.255)		(0.038)		(0.044)		(0.036)
mean control	13.79	13.79	-0.05	-0.05	-0.03	-0.03	-0.05	-0.05
p-val ms boys		0.031		0.009		0.001		0.099
p-val ha boys		0.554		0.161		0.424		0.623
N	6,079	6,079	6,079	6,079	6,079	6,079	6,079	6,079
Panel B: Less sociable students at baseline								
More sociable	0.307	-0.149	0.056	-0.043	0.128	0.056	0.039	0.003
	(0.195)	(0.262)	(0.032)	(0.041)	(0.039)	(0.047)	(0.022)	(0.027)
Higher-achieving	-0.162	-0.217	0.003	-0.014	-0.028	-0.078	-0.063	-0.048
	(0.194)	(0.257)	(0.032)	(0.041)	(0.038)	(0.047)	(0.023)	(0.029)
More sociable × boy		1.105		0.239		0.175		0.087
		(0.392)		(0.065)		(0.079)		(0.045)
Higher-achieving × boy		0.122		0.039		0.118		-0.036
		(0.381)		(0.064)		(0.078)		(0.046)
mean control	11.24	11.24	-0.25	-0.25	-0.16	-0.16	-0.29	-0.29
p-val ms boys		0.001		0.000		0.000		0.012
p-val ha boys		0.740		0.602		0.510		0.019
N	1,832	1,832	1,832	1,832	1,832	1,832	1,832	1,832
Panel C: More sociable students at baseline								
More sociable	-0.357	-0.574	-0.037	-0.060	0.014	-0.013	0.015	0.021
	(0.201)	(0.250)	(0.035)	(0.044)	(0.037)	(0.047)	(0.031)	(0.040)
Higher-achieving	0.166	0.129	0.053	0.034	-0.012	0.068	0.082	0.112
	(0.205)	(0.261)	(0.035)	(0.046)	(0.037)	(0.047)	(0.031)	(0.039)
More sociable × boy		0.535		0.057		0.066		-0.012
		(0.414)		(0.072)		(0.074)		(0.063)
Higher-achieving × boy		0.088		0.049		-0.198		-0.076
		(0.424)		(0.072)		(0.075)		(0.064)
mean control	14.28	14.28	0.27	0.27	0.04	0.04	0.21	0.21
p-val ms boys		0.906		0.958		0.356		0.867
p-val ha boys		0.511		0.133		0.025		0.478
N	1,822	1,822	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 gender-by-classroom fixed effects. The control group is defined as being assigned to less sociable and lower-achieving peers. The sample in Panel A includes students from all the cohorts. The sample in Panels B and C include students from the 2015-16 cohorts as there is no information on sociability at baseline for the 2017 cohort. Standard errors are clustered at the peer-group-type-by-student-type level.

TABLE 5: Reduced-Form Estimates on Longer-term Outcomes

Dependent variable:	Dropout		College enrollment		Certified college		Top 20 college	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Panel A: All students					
More sociable	-0.001	0.005	-0.026	-0.045	-0.011	-0.031	-0.013	-0.030
	(0.004)	(0.006)	(0.014)	(0.019)	(0.014)	(0.017)	(0.013)	(0.017)
Higher-achieving	0.004	0.002	-0.015	-0.022	-0.015	-0.016	-0.016	-0.022
	(0.004)	(0.006)	(0.014)	(0.019)	(0.014)	(0.017)	(0.013)	(0.016)
More sociable × boy		-0.014		0.045		0.049		0.041
		(0.008)		(0.028)		(0.028)		(0.026)
Higher-achieving × boy		0.006		0.018		0.002		0.013
		(0.008)		(0.028)		(0.028)		(0.026)
mean control	0.02	0.02	0.62	0.62	0.32	0.32	0.26	0.26
p-val ms boys		0.068		0.974		0.428		0.585
p-val ha boys		0.149		0.838		0.549		0.686
N	3,654	3,654	3,654	3,654	3,654	3,654	3,654	3,654
			Panel B: Less sociable students at baseline					
More sociable	-0.001	0.012	-0.010	-0.010	0.014	-0.021	-0.001	-0.038
	(0.006)	(0.009)	(0.020)	(0.027)	(0.019)	(0.023)	(0.018)	(0.022)
Higher-achieving	0.017	0.017	-0.024	-0.039	-0.010	-0.011	-0.017	-0.025
	(0.006)	(0.009)	(0.021)	(0.028)	(0.019)	(0.024)	(0.018)	(0.022)
More sociable × boy		-0.033		0.001		0.087		0.090
		(0.012)		(0.041)		(0.039)		(0.036)
Higher-achieving × boy		-0.000		0.037		0.001		0.019
		(0.013)		(0.041)		(0.040)		(0.036)
mean control	0.02	0.02	0.58	0.58	0.26	0.26	0.22	0.22
p-val ms boys		0.012		0.749		0.034		0.058
p-val ha boys		0.075		0.947		0.750		0.828
N	1,832	1,832	1,832	1,832	1,832	1,832	1,832	1,832
			Panel C: More sociable students at baseline					
More sociable	0.000	-0.002	-0.043	-0.077	-0.037	-0.041	-0.028	-0.024
	(0.005)	(0.008)	(0.019)	(0.026)	(0.020)	(0.025)	(0.019)	(0.025)
Higher-achieving	-0.008	-0.013	-0.007	-0.005	-0.021	-0.022	-0.018	-0.022
	(0.005)	(0.007)	(0.019)	(0.026)	(0.020)	(0.025)	(0.019)	(0.024)
More sociable × boy		0.006		0.085		0.010		-0.008
		(0.009)		(0.038)		(0.041)		(0.039)
Higher-achieving × boy		0.011		-0.004		0.002		0.009
		(0.009)		(0.038)		(0.041)		(0.039)
mean control	0.03	0.03	0.68	0.68	0.41	0.41	0.33	0.33
p-val ms boys		0.401		0.773		0.345		0.282
p-val ha boys		0.715		0.734		0.532		0.684
N	1,822	1,822	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 gender-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-student-type level.

TABLE 6: 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	0.033	0.219	-0.076	0.141	0.475	-0.047	-0.076	-0.048	-0.098
	(0.046)	(0.081)	(0.054)	(0.068)	(0.113)	(0.083)	(0.061)	(0.115)	(0.070)
Neighbors' achievement	0.018	0.020	0.004	-0.086	-0.078	-0.097	0.120	0.123	0.116
	(0.042)	(0.069)	(0.052)	(0.056)	(0.092)	(0.070)	(0.062)	(0.105)	(0.076)
F sociability	809.60	222.86	644.97	332.67	81.79	288.64	476.53	141.15	376.75
F achievement	822.02	331.67	509.31	374.69	203.47	196.19	466.31	143.56	337.57
N	3,654	1,490	2,164	1,832	753	1,079	1,822	737	1,085

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). The sample includes students from the 2015-16 cohorts as there is no information on sociability at baseline for the 2017 cohort. Standard errors are clustered at the peer-group-type-by-student-type level.

TABLE 7: Reduced-Form Estimates on Test Scores

Dependent variable:	Grades (2016-17 cohorts)				Test scores			
	Math		Reading		Math		Reading	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: All Students							
More sociable	0.029	0.008	0.040	0.045	-0.020	-0.015	0.023	-0.007
	(0.035)	(0.046)	(0.036)	(0.050)	(0.021)	(0.026)	(0.026)	(0.035)
Higher-achieving	0.011	-0.008	-0.012	0.004	-0.025	-0.027	-0.033	-0.073
	(0.023)	(0.030)	(0.024)	(0.032)	(0.016)	(0.020)	(0.020)	(0.027)
More sociable × boy		0.049		-0.011		-0.011		0.070
		(0.072)		(0.073)		(0.044)		(0.053)
Higher-achieving × boy		0.043		-0.037		0.005		0.091
		(0.046)		(0.048)		(0.034)		(0.040)
mean control	-0.06	-0.06	-0.05	-0.05	-0.05	-0.05	-0.04	-0.04
p-val ms boys		0.304		0.516		0.458		0.109
p-val ha boys		0.318		0.361		0.428		0.529
N	4,419	4,419	4,418	4,418	5,681	5,681	5,796	5,796
	Panel B: Lower-achieving students at baseline							
More sociable	0.019	-0.001	0.057	0.051	-0.017	-0.063	0.036	0.014
	(0.050)	(0.066)	(0.051)	(0.069)	(0.030)	(0.035)	(0.038)	(0.051)
Higher-achieving	-0.060	-0.112	-0.066	-0.056	-0.041	-0.070	-0.046	-0.084
	(0.036)	(0.048)	(0.037)	(0.048)	(0.025)	(0.028)	(0.032)	(0.042)
More sociable × boy		0.046		0.015		0.107		0.050
		(0.101)		(0.101)		(0.062)		(0.076)
Higher-achieving × boy		0.117		-0.023		0.065		0.089
		(0.072)		(0.073)		(0.052)		(0.063)
mean control	-0.27	-0.27	-0.21	-0.21	-0.29	-0.29	-0.11	-0.11
p-val ms boys		0.554		0.373		0.381		0.257
p-val ha boys		0.925		0.164		0.925		0.929
N	2,196	2,196	2,196	2,196	2,779	2,779	2,861	2,861
	Panel C: Higher-achieving students at baseline							
More sociable	0.053	0.032	0.021	0.031	-0.019	0.030	0.010	-0.028
	(0.052)	(0.065)	(0.053)	(0.073)	(0.031)	(0.039)	(0.037)	(0.048)
Higher-achieving	0.054	0.073	0.042	0.055	-0.025	-0.010	-0.032	-0.071
	(0.035)	(0.045)	(0.038)	(0.049)	(0.025)	(0.031)	(0.030)	(0.039)
More sociable × boy		0.049		-0.023		-0.118		0.091
		(0.105)		(0.106)		(0.063)		(0.075)
Higher-achieving × boy		-0.046		-0.032		-0.033		0.093
		(0.071)		(0.075)		(0.051)		(0.060)
mean control	0.25	0.25	0.18	0.18	0.30	0.30	0.07	0.07
p-val ms boys		0.332		0.918		0.078		0.274
p-val ha boys		0.633		0.685		0.280		0.621
N	2,210	2,210	2,209	2,209	2,889	2,889	2,922	2,922

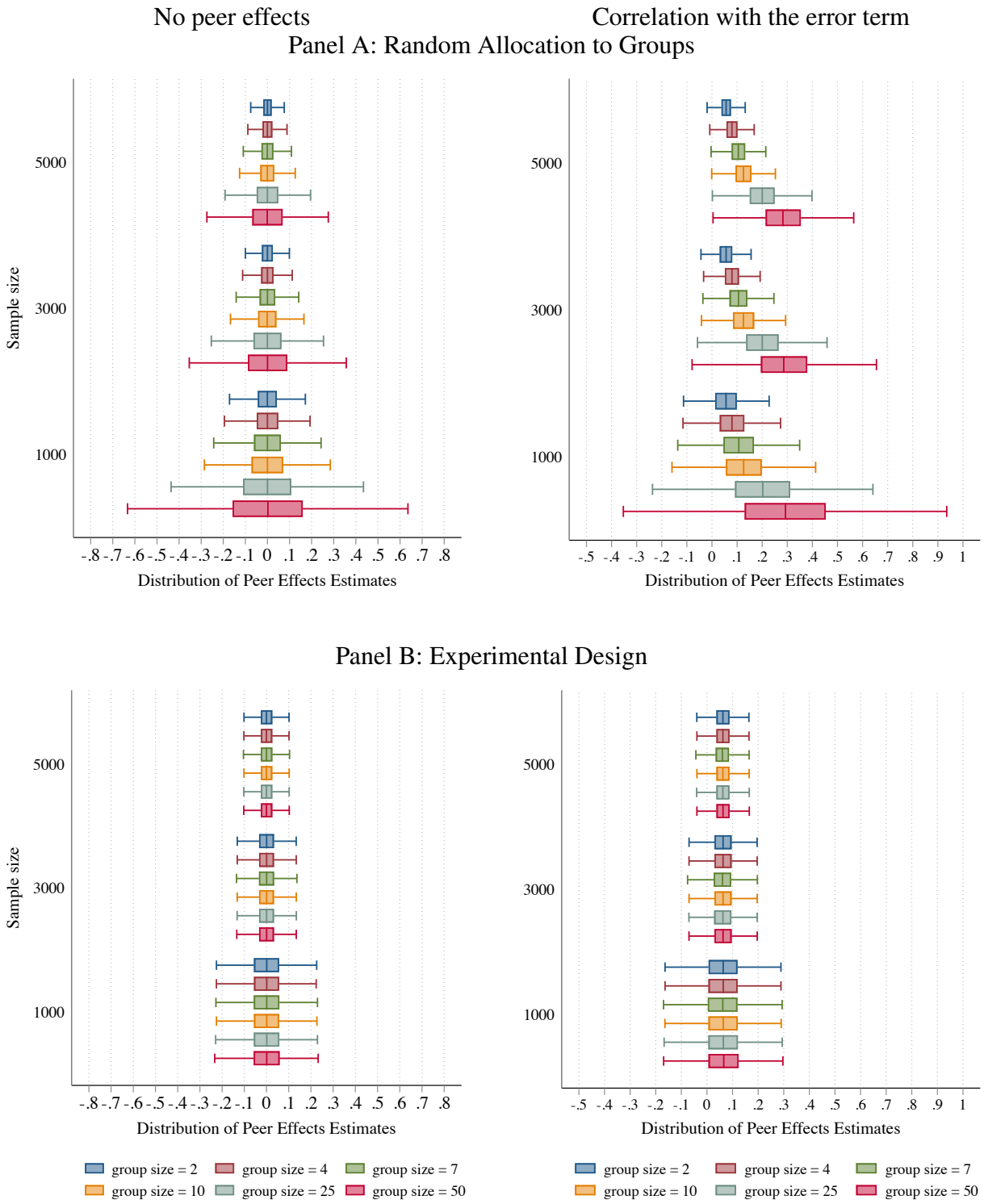
Notes: This table reports the effect of being assigned to more sociable and higher-achieving peers identified at baseline on grades and test scores. All regressions include strata fixed effects and control for selected covariates using the "post-double-selection" Lasso method (Belloni et al., 2014b). For the 2017 cohort, all regressions include gender-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-student-type level.

TABLE 8: 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	-0.029	-0.049	-0.019	-0.017	0.073	-0.079	-0.030	-0.177	0.050
	(0.039)	(0.075)	(0.043)	(0.053)	(0.102)	(0.056)	(0.058)	(0.118)	(0.064)
Neighbors' achievement	-0.042	-0.033	-0.040	-0.073	-0.012	-0.112	-0.039	-0.055	-0.014
	(0.029)	(0.053)	(0.033)	(0.045)	(0.086)	(0.047)	(0.041)	(0.073)	(0.048)
F sociability	768.18	221.16	607.64	463.99	141.71	349.51	310.32	82.02	260.97
F achievement	1,238.91	530.55	736.57	466.98	186.97	286.00	638.35	281.73	382.82
N	5,681	2,505	3,176	2,779	1,236	1,543	2,889	1,259	1,630
Panel B: Dependent variable reading scores									
Neighbors' sociability	0.051	0.122	0.008	0.077	0.119	0.048	0.026	0.132	-0.029
	(0.048)	(0.085)	(0.058)	(0.068)	(0.115)	(0.086)	(0.070)	(0.133)	(0.082)
Neighbors' achievement	-0.059	0.028	-0.119	-0.084	0.003	-0.144	-0.053	0.034	-0.111
	(0.035)	(0.058)	(0.044)	(0.057)	(0.092)	(0.072)	(0.049)	(0.084)	(0.061)
F sociability	817.35	224.66	666.56	475.70	138.63	365.58	333.83	83.37	292.26
F achievement	1,275.60	542.20	769.15	512.66	202.13	318.93	630.79	278.50	379.75
N	5,796	2,540	3,256	2,861	1,260	1,601	2,922	1,270	1,652

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 gender-by-classroom fixed effects. Standard errors are clustered at the peer-group-type-by-student-type level.

FIGURE 1: Simulations of Peer Effects



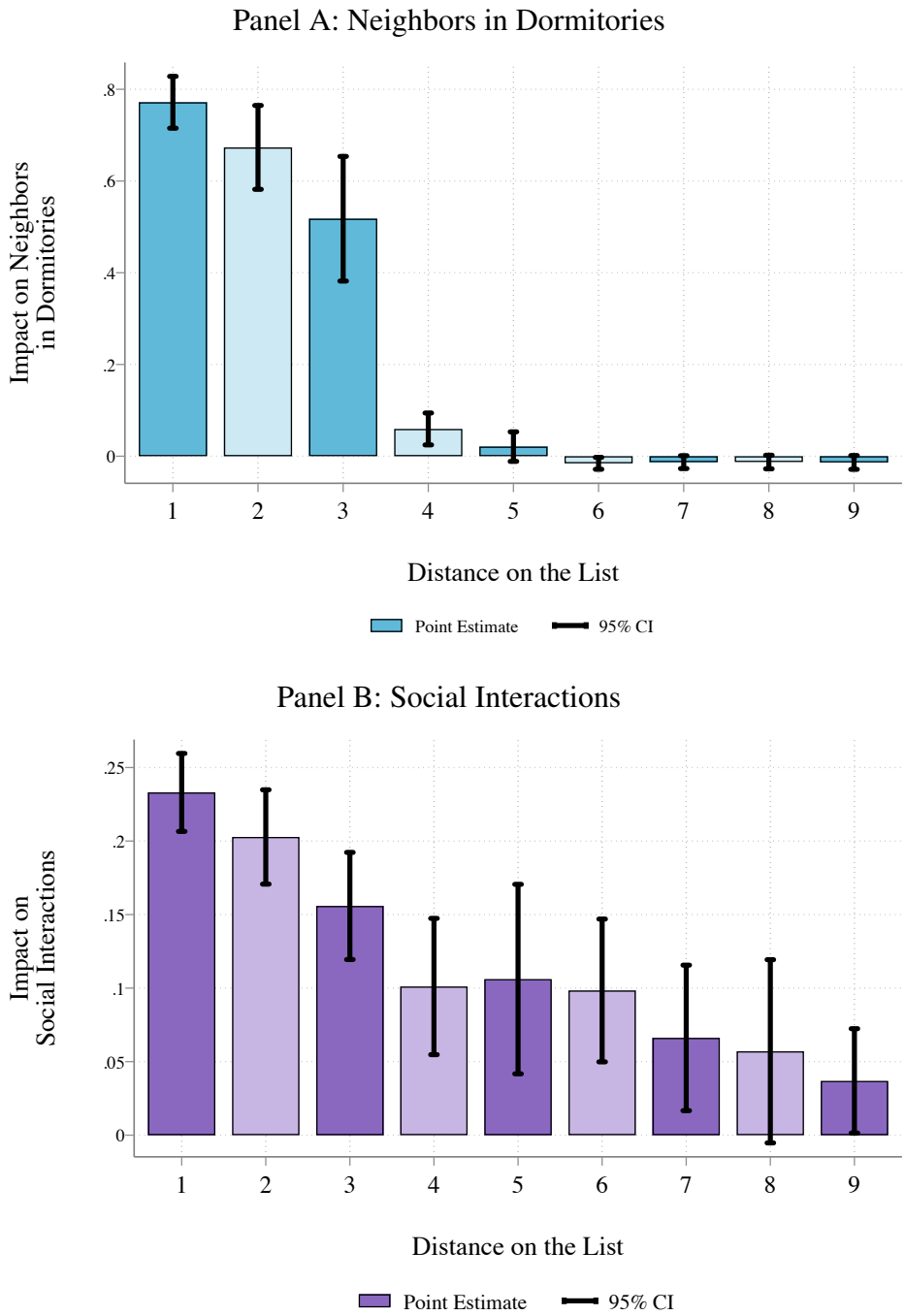
Notes: Monte Carlo simulations based on 10,000 repetitions of the estimate of parameter π_1 in equation 3. The simulations assume that $x_i \sim N(0,1)$, and $\nu_{ig} \sim N(0,1)$. In the left column, $\pi_0 = 1$, $\pi_1 = 0$, and $\varepsilon_{ig} = \nu_{ig}$. In the right column, $\pi_0 = 1$, $\pi_1 = 0$, and $\varepsilon_{ig} = 0.1 \times I(\overline{x}_g \geq 0) + \nu_{ig}$.

FIGURE 2: Groups of Peers in the Experimental Design

Student Type \ Type of Peers	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.

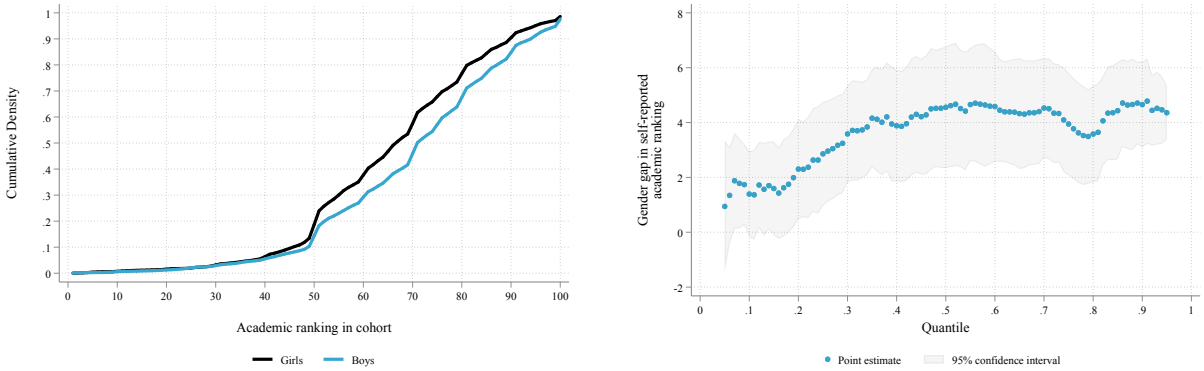
FIGURE 3: Effects of Proximity on the List on Neighbors and Social Interactions



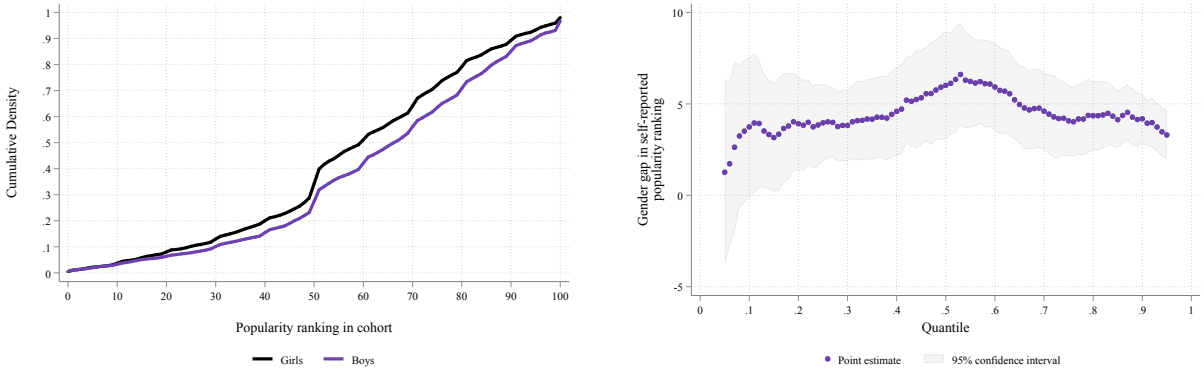
Notes: This figure shows the impact of distance between a pair of students on the likelihood of being neighbors and social interaction (friends, study, and playing games or sports). Distance is captured by five distance dummies, and 95% confidence intervals are displayed for all proximity effects. Students 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 4: Gender Differences in Self-reported Rankings

Panel A: Academic ranking in cohort



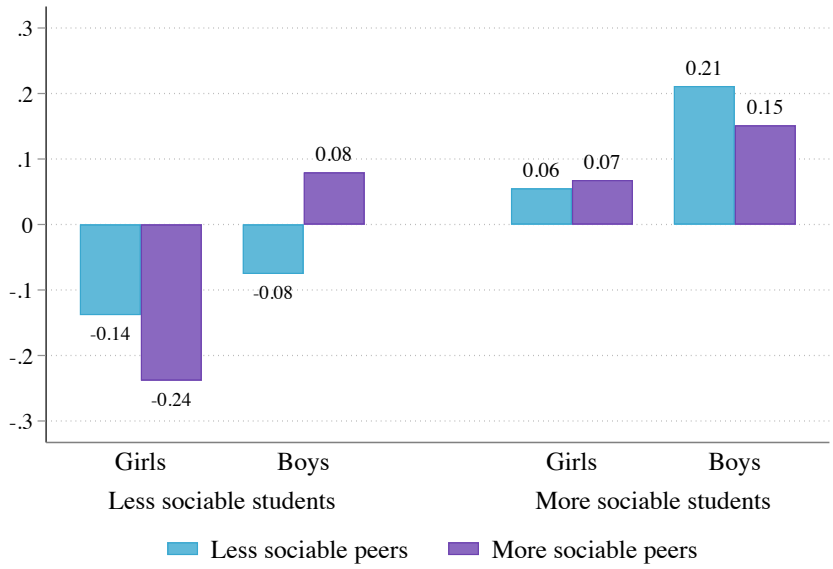
Panel B: Popularity ranking in cohort



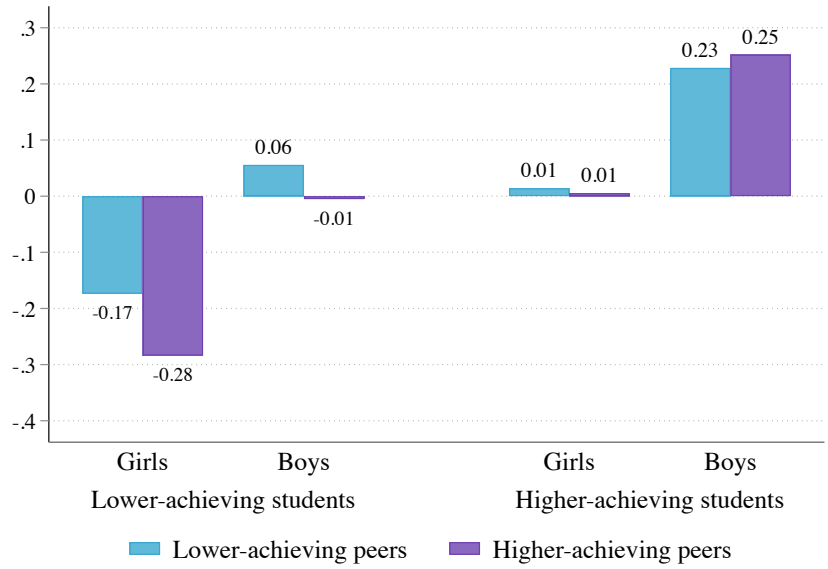
Notes: This figure plots differences by gender in self-reported academic and popularity ranking within the cohort. The left column presents the cumulative distribution function and the right column the estimates from quantile regressions of the gender gap after controlling for observable characteristics. 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 5: Peer Effects on Self-confidence

Panel A: Self-confidence in social skills

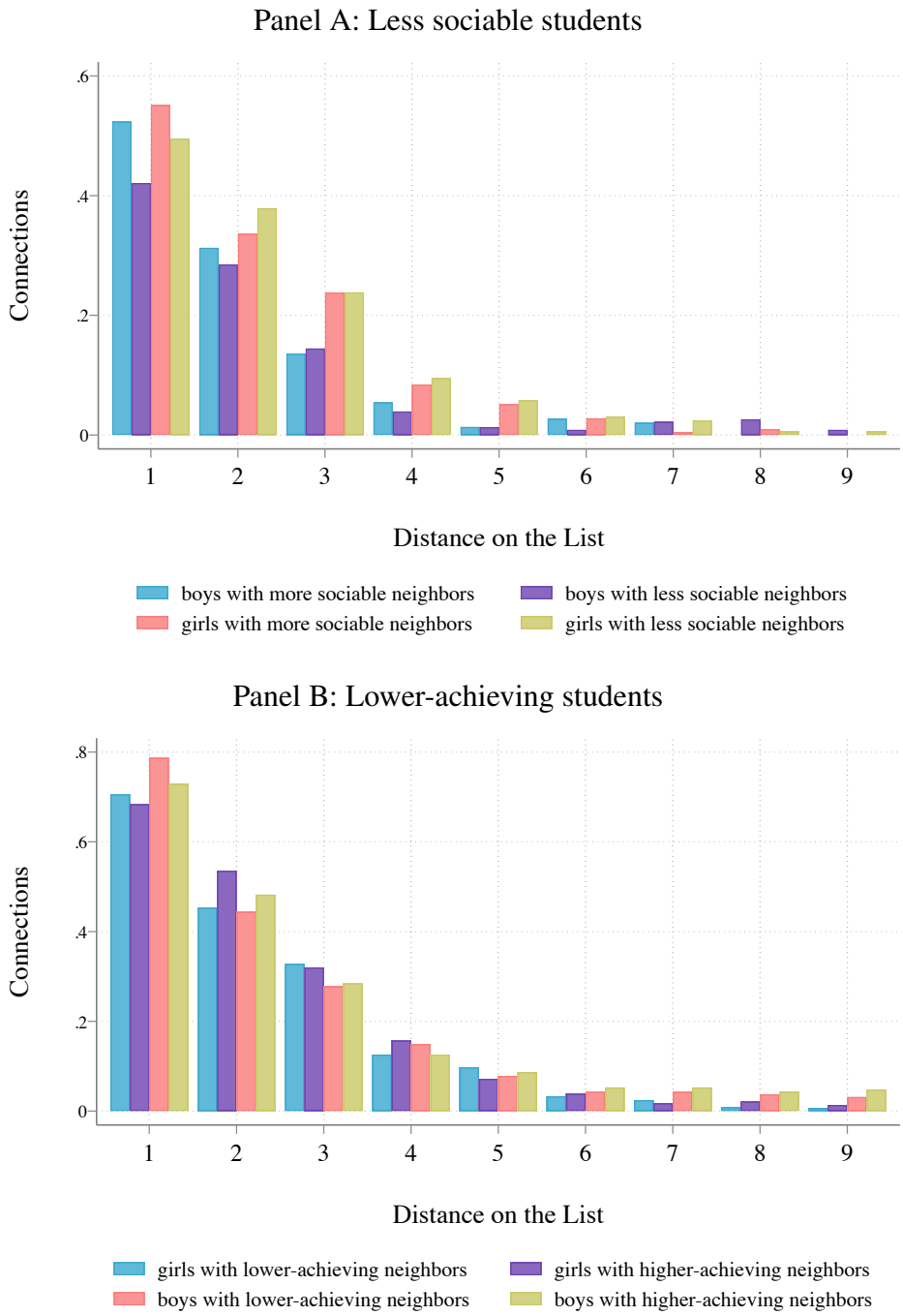


Panel B: Self-confidence in academic skills



Notes: This figure plots average self-confidence indexes by gender, baseline characteristics, and treatment groups. The indexes are standardized at the school-cohort level. Panel A reports average indexes for social skills and panel B for academic skills. Appendix Tables A.7 and A.8 present treatment effects (estimates of equation 10) on the indexes and the individual measures I used to construct each of them.

FIGURE 6: Social Interactions of Most Affected vs. Comparable Groups



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.

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A Supplementary Material

TABLE A.1: Correlation of Sociability and Social Skills Outcomes

	Big Five Personality Traits					Peers' Perception				Other measures of social skills	Social Skills Index at baseline	Social Skills Index at endline
	Openness	Conscientiousness	Emotional Stability	Extroversion	Agreeableness	Leadership	Friendliness	Popularity	Shyness			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Academic achievement	0.090	-0.001	0.065	-0.015	-0.015	0.217	0.044	0.105	-0.066	0.040	0.056	0.040
	(0.021)	(0.022)	(0.022)	(0.019)	(0.020)	(0.020)	(0.016)	(0.022)	(0.019)	(0.016)	(0.017)	(0.017)
Sociability	0.103	0.062	0.032	0.142	0.121	0.230	0.360	0.215	-0.103	0.092	0.125	0.117
	(0.024)	(0.025)	(0.017)	(0.021)	(0.017)	(0.021)	(0.020)	(0.029)	(0.021)	(0.019)	(0.019)	(0.020)
Social-fit score	0.072	0.022	0.001	0.063	0.027	0.136	0.075	0.103	-0.112	0.027	0.057	0.042
	(0.018)	(0.020)	(0.020)	(0.019)	(0.020)	(0.015)	(0.016)	(0.017)	(0.020)	(0.018)	(0.018)	(0.019)
Interview score	0.092	0.072	0.072	0.090	0.048	0.069	0.058	0.050	-0.036	0.066	0.118	0.080
	(0.019)	(0.016)	(0.016)	(0.018)	(0.018)	(0.015)	(0.015)	(0.017)	(0.017)	(0.016)	(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. Academic achievement and sociability are measured at baseline. 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. In columns 1 to 5, the dependent variables are personality traits from the Big Five. In columns 6 to 9, the dependent variables are the number of peers who perceive the student as part of the top 5 of leadership, friendliness, popularity, and shyness. In column 10, the dependent variable is an index excluding social network outcomes, personality traits, and peers' perception. In columns 11 and 12, the dependent variable is a social skills index that excludes social networks outcomes. Column 11 presents the correlations on this index at baseline and column 12 at endline. All indexes are constructed using Principal Component Analysis (PCA) on all the variables that measure social skills (see Appendix D for details).

TABLE A.2: 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
	(1)	(2)	(3)	(4)	(5)	(6)
Admission test	-0.016	0.002	-0.064	-0.024	0.058	0.028
		(0.019)		(0.027)		(0.026)
Interview score	-0.006	0.017	-0.006	0.041	-0.006	-0.006
		(0.030)		(0.042)		(0.042)
Social-fit score	-0.024	0.045	-0.028	0.027	-0.019	0.062
		(0.031)		(0.042)		(0.044)
Female (%)	0.591	0.000	0.589	0.000	0.594	0.000
		(0.000)		(0.000)		(0.000)
Poor (%)	0.431	0.014	0.460	0.026	0.389	0.003
		(0.014)		(0.021)		(0.019)
Rural household (%)	0.284	-0.018	0.314	-0.024	0.241	-0.013
		(0.014)		(0.020)		(0.019)
Subsidized health insurance	0.508	0.008	0.552	-0.011	0.443	0.027
		(0.016)		(0.022)		(0.022)
Math scores	-0.043	0.027	-0.141	0.048	0.103	0.007
		(0.023)		(0.032)		(0.031)
Reading scores	-0.029	-0.001	-0.128	0.038	0.120	-0.040
		(0.021)		(0.031)		(0.028)
Social skills	-0.108	-0.000	-0.522	0.023	0.515	-0.024
		(0.022)		(0.024)		(0.037)
Degree friends	7.331	0.230	5.609	0.163	9.918	0.295
		(0.130)		(0.113)		(0.234)
Centrality friends	-0.110	0.021	-0.521	0.032	0.505	0.011
		(0.025)		(0.023)		(0.044)
Degree study	4.560	-0.007	3.741	-0.060	5.789	0.046
		(0.069)		(0.081)		(0.111)
Centrality study	-0.071	-0.006	-0.350	-0.056	0.340	0.043
		(0.027)		(0.028)		(0.046)
Degree all	10.475	0.067	8.261	-0.060	13.802	0.193
		(0.135)		(0.127)		(0.238)
Centrality all	-0.152	0.023	-0.705	-0.010	0.679	0.056
		(0.018)		(0.016)		(0.031)
Reading the mind in the eyes	20.521	-0.060	20.224	0.184	20.960	-0.304
		(0.130)		(0.186)		(0.180)
Peers' perception leadership	2.499	-0.185	1.586	-0.111	3.874	-0.259
		(0.150)		(0.132)		(0.271)
Peers' perception friendliness	2.550	-0.008	1.836	0.195	3.625	-0.214
		(0.080)		(0.083)		(0.135)
Peers' perception popularity	2.201	0.108	1.465	0.127	3.310	0.089
		(0.159)		(0.142)		(0.285)
Peers' perception shyness	2.083	0.025	2.561	-0.137	1.364	0.189
		(0.144)		(0.226)		(0.178)
Total score Rosenberg Scale	32.991	0.101	32.777	0.119	33.306	0.081
		(0.154)		(0.224)		(0.212)
Total score Grit Scale	43.707	-0.248	43.340	-0.171	44.251	-0.325
		(0.198)		(0.285)		(0.274)
Multivariate F p-value		0.756		0.479		0.594

Notes: This table reports balance checks of being assigned to more sociable peers on baseline characteristics. All regressions include strata fixed effects and include the higher-achieving peers treatment. For the 2017 cohort, all regressions include gender-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-student-type level.

TABLE A.3: 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
	(1)	(2)	(3)	(4)	(5)	(6)
Admission test	-0.163	0.022	-0.787	0.004	0.764	0.036
		(0.015)		(0.018)		(0.026)
Interview score	0.049	-0.016	0.212	-0.031	-0.192	-0.015
		(0.024)		(0.031)		(0.041)
Social-fit score	0.045	-0.030	0.164	-0.014	-0.130	-0.050
		(0.022)		(0.029)		(0.039)
Female (%)	0.567	0.000	0.566	-0.000	0.567	0.000
		(0.000)		(0.000)		(0.000)
Poor (%)	0.418	0.010	0.456	0.015	0.362	-0.002
		(0.012)		(0.018)		(0.017)
Rural household (%)	0.267	0.004	0.308	-0.019	0.206	0.017
		(0.011)		(0.018)		(0.015)
Subsidized health insurance	0.504	0.013	0.517	0.045	0.485	-0.019
		(0.015)		(0.021)		(0.022)
Math scores	-0.081	0.007	-0.345	-0.023	0.310	0.028
		(0.019)		(0.026)		(0.030)
Reading scores	-0.047	-0.014	-0.234	-0.033	0.229	0.006
		(0.018)		(0.027)		(0.027)
Social skills	-0.015	-0.017	-0.090	-0.029	0.097	-0.006
		(0.022)		(0.030)		(0.032)
Degree friends	8.023	-0.438	7.787	-0.418	8.374	-0.457
		(0.134)		(0.183)		(0.195)
Centrality friends	0.029	-0.081	-0.025	-0.082	0.107	-0.080
		(0.025)		(0.033)		(0.037)
Degree study	4.719	0.012	4.609	-0.145	4.882	0.167
		(0.069)		(0.097)		(0.096)
Centrality study	-0.011	-0.004	-0.058	-0.028	0.059	0.020
		(0.027)		(0.034)		(0.042)
Degree all	11.125	-0.244	10.946	-0.394	11.392	-0.094
		(0.137)		(0.187)		(0.201)
Centrality all	-0.002	-0.012	-0.031	-0.036	0.041	0.011
		(0.018)		(0.025)		(0.025)
Reading the mind in the eyes	20.602	-0.264	20.248	-0.231	21.127	-0.295
		(0.128)		(0.180)		(0.183)
Peers' perception leadership	2.487	0.011	1.923	-0.026	3.328	0.047
		(0.148)		(0.178)		(0.236)
Peers' perception friendliness	2.688	0.011	2.612	-0.002	2.801	0.024
		(0.078)		(0.112)		(0.109)
Peers' perception popularity	2.361	-0.018	2.006	-0.025	2.890	-0.014
		(0.158)		(0.185)		(0.255)
Peers' perception shyness	2.017	0.038	2.108	0.162	1.881	-0.086
		(0.146)		(0.211)		(0.203)
Total score Rosenberg Scale	33.013	0.138	32.854	0.127	33.249	0.153
		(0.154)		(0.221)		(0.215)
Total score Grit Scale	43.568	0.160	43.330	0.431	43.921	-0.108
		(0.196)		(0.271)		(0.282)
Multivariate F p-value		0.256		0.889		0.232

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 gender-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-student-type level level.

TABLE A.4: Correlations between Types of Skills and Longer-term Outcomes

Dependent variable:	Dropout	College	Certified	Top 20
	(1)	(2)	(3)	(4)
Social skills	-0.008	0.024	0.036	0.026
	(0.001)	(0.008)	(0.008)	(0.008)
Math scores	-0.002	0.069	0.079	0.090
	(0.001)	(0.010)	(0.010)	(0.010)
Reading scores	0.002	0.019	0.025	0.036
	(0.001)	(0.009)	(0.009)	(0.009)
mean control	0.02	0.62	0.33	0.27
N	6,147	3,654	3,654	3,654

Notes: This table reports the correlation of social skills with longer-term outcomes. All models include school-by-cohort-by-gender fixed effects. Column 1 presents the results on the dropout rate with data available for all cohorts. Columns 3 to 4 present the estimates on college outcomes only available for the 2015-16 cohorts. Robust standard errors in parentheses.

TABLE A.5: Randomization Inference p-values

Group	Treatment	Dependent variables			
(1)	(2)	(3)	(4)	(5)	(6)
		Panel A: Results on Social Skills			
		Connections	Centrality	Psychological Tests	Peers' perception
	More sociable peers	0.917	0.697	0.013	0.140
All students	Higher-achieving peers	0.429	0.979	0.466	0.372
	Joint test	0.726	0.921	0.031	0.197
	More sociable peers	0.033	0.009	0.001	0.095
Boys	Higher-achieving peers	0.755	0.269	0.472	0.603
	Joint test	0.100	0.026	0.002	0.255
	More sociable peers	0.002	0.002	0.001	0.014
Less sociable boys	Higher-achieving peers	0.512	0.788	0.524	0.015
	Joint test	0.002	0.001	0.001	0.005
		Panel B: Results on Academic Skills			
		Grades		Test Scores	
		Math	Reading	Math	Reading
	More sociable peers	0.405	0.255	0.390	0.359
All students	Higher-achieving peers	0.645	0.618	0.150	0.095
	Joint test	0.646	0.466	0.227	0.159
	More sociable peers	0.679	0.242	0.527	0.316
Lower-achieving	Higher-achieving peers	0.086	0.078	0.103	0.127
	Joint test	0.240	0.119	0.230	0.215
	More sociable peers	0.949	0.464	0.077	0.756
Lower-achieving girls	Higher-achieving peers	0.017	0.208	0.012	0.041
	Joint test	0.062	0.384	0.017	0.126

Notes: This table reports randomization inference p-values for social and academic outcomes by groups of students and treatments. The first column presents the group for which the p-value is calculated, and the second column the respective treatment. Columns 3 to 6 show the set of outcomes. In Panel A, these are social skills outcomes, and in Panel B, academic outcomes. The p-values were calculated using the procedure developed by Young (2018) with 1,000 randomization iterations.

TABLE A.6: Multiple-hypotheses Testing

Group	Test	Dependent variables			
(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Results on Social Skills				
		Connections	Centrality	Psychological Tests	Peers' perception
	Sidak and Holm	0.091	0.033	0.002	0.219
Boys	Bonferroni and Holm	0.093	0.033	0.002	0.233
	Westfall and Young	0.144	0.066	0.006	0.313
	Sidak and Holm	0.006	0.001	0.001	0.057
Less sociable boys	Bonferroni and Holm	0.006	0.001	0.001	0.058
	Westfall and Young	0.012	0.003	0.004	0.118
	Panel B: Results on Academic Skills				
		Grades		Test Scores	
		Math	Reading	Math	Reading
	Sidak and Holm	0.191	0.150	0.189	0.268
Lower-achieving	Bonferroni and Holm	0.201	0.156	0.198	0.289
	Westfall and Young	0.277	0.225	0.309	0.316
	Sidak and Holm	0.784	0.921	0.391	0.013
Girls	Bonferroni and Holm	0.784	0.921	0.440	0.013
	Westfall and Young	0.831	0.943	0.481	0.022
	Sidak and Holm	0.082	0.588	0.064	0.168
Lower-achieving girls	Bonferroni and Holm	0.085	0.796	0.066	0.180
	Westfall and Young	0.135	0.710	0.120	0.216

Notes: This table reports multiple-hypotheses testing p-values. The first column presents the group for which the test is performed among all the possible classifications of students. For instance, if the groups are boys, the reported test is on the treatment effect for boys of multiple hypotheses that considers the impact on both boys and girls. The second column corresponds to the respective test of multiple hypotheses. Columns 3 to 6 show the set of outcomes. In Panel A, these are social skills outcomes, and in Panel B, academic outcomes. Calculations were performed using the *wyoung* command developed by Jones et al. (2019).

TABLE A.7: Self-confidence in Social Skills

Dependent variable:	Popularity Ranking			Self-nomination (in the top-5)				Index
	Dorm	Classroom	Cohort	Leader	Popular	Friendly	No shy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Less sociable students at baseline								
More sociable	-2.742	-3.077	-2.661	-0.072	-0.020	0.013	-0.007	-0.128
	(1.465)	(1.395)	(1.408)	(0.023)	(0.025)	(0.017)	(0.016)	(0.048)
Higher-achieving	0.067	0.649	-0.893	0.022	0.023	-0.003	0.020	0.036
	(1.480)	(1.447)	(1.456)	(0.022)	(0.025)	(0.016)	(0.016)	(0.049)
More sociable × boy	3.633	4.897	5.274	0.113	0.075	0.009	0.050	0.263
	(2.308)	(2.175)	(2.122)	(0.038)	(0.038)	(0.032)	(0.022)	(0.078)
Higher-achieving × boy	2.260	2.330	1.530	-0.078	-0.061	0.007	-0.048	-0.054
	(2.270)	(2.154)	(2.128)	(0.037)	(0.038)	(0.031)	(0.022)	(0.078)
mean control	67.29	64.85	58.77	0.28	0.22	0.14	0.91	-0.12
p-val ms boys	0.618	0.279	0.102	0.166	0.055	0.416	0.005	0.031
p-val ha boys	0.178	0.062	0.682	0.061	0.186	0.887	0.074	0.776
N	1,662	1,666	1,665	1,682	1,682	1,682	1,682	1,832
Panel B: More sociable students at baseline								
More sociable	1.134	1.349	1.060	-0.001	-0.014	0.008	0.012	0.036
	(1.356)	(1.156)	(1.253)	(0.023)	(0.025)	(0.019)	(0.014)	(0.047)
Higher-achieving	-0.935	-0.087	-0.756	0.034	0.007	-0.009	0.004	-0.002
	(1.341)	(1.147)	(1.223)	(0.025)	(0.024)	(0.020)	(0.013)	(0.047)
More sociable × boy	-0.179	-0.064	-0.171	-0.037	-0.022	-0.010	-0.016	-0.053
	(2.049)	(1.861)	(1.941)	(0.038)	(0.038)	(0.032)	(0.021)	(0.071)
Higher-achieving × boy	1.574	-0.562	-0.478	0.006	-0.011	0.004	0.030	0.019
	(2.008)	(1.846)	(1.880)	(0.040)	(0.038)	(0.032)	(0.021)	(0.072)
mean control	72.22	70.75	65.26	0.30	0.25	0.16	0.92	0.09
p-val ms boys	0.534	0.381	0.551	0.213	0.216	0.924	0.769	0.750
p-val ha boys	0.669	0.657	0.390	0.201	0.893	0.852	0.033	0.759
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 gender-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-student-type level.

TABLE A.8: Self-confidence in Academic Skills

Dependent variable:	Academic Ranking			Competition		Self-nominate top-5 skilled	Index
	Dorm	Classroom	Cohort	Want to do better than peers	Avoid doing worse than peers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Lower-achieving students at baseline							
More sociable	-0.594	0.092	-0.552	-0.019	0.016	-0.010	-0.019
	(1.036)	(1.043)	(0.977)	(0.062)	(0.063)	(0.016)	(0.048)
Higher-achieving	-1.478	0.045	-0.743	-0.187	-0.132	0.016	-0.093
	(0.946)	(0.875)	(0.877)	(0.053)	(0.055)	(0.015)	(0.044)
More sociable × boy	-1.580	-1.388	-0.786	0.025	-0.001	-0.042	-0.094
	(1.639)	(1.606)	(1.541)	(0.093)	(0.098)	(0.027)	(0.077)
Higher-achieving × boy	1.424	-0.410	0.954	0.253	0.226	-0.057	0.087
	(1.415)	(1.348)	(1.288)	(0.079)	(0.085)	(0.025)	(0.068)
mean control	72.46	69.61	65.76	-0.01	-0.05	0.15	-0.09
p-val ms boys	0.086	0.288	0.261	0.925	0.847	0.019	0.063
p-val ha boys	0.959	0.723	0.823	0.260	0.144	0.039	0.915
N	2,801	2,805	2,805	2,673	2,673	2,831	3,026
Panel B: Higher-achieving students at baseline							
More sociable	-0.181	-0.716	-0.557	-0.058	0.011	-0.000	-0.027
	(0.969)	(0.864)	(0.863)	(0.061)	(0.055)	(0.019)	(0.046)
Higher-achieving	-0.740	-1.609	-1.247	-0.008	-0.011	0.028	-0.017
	(0.833)	(0.757)	(0.719)	(0.048)	(0.045)	(0.017)	(0.038)
More sociable × boy	1.773	3.172	1.583	-0.058	-0.135	-0.034	0.023
	(1.615)	(1.560)	(1.439)	(0.092)	(0.092)	(0.035)	(0.078)
Higher-achieving × boy	1.727	2.317	2.357	0.026	0.030	-0.028	0.084
	(1.352)	(1.282)	(1.181)	(0.073)	(0.072)	(0.029)	(0.064)
mean control	74.78	73.47	69.50	-0.04	0.05	0.19	0.09
p-val ms boys	0.221	0.060	0.376	0.090	0.091	0.233	0.951
p-val ha boys	0.355	0.494	0.237	0.745	0.739	0.997	0.193
N	2,848	2,851	2,850	2,764	2,764	2,867	3,040

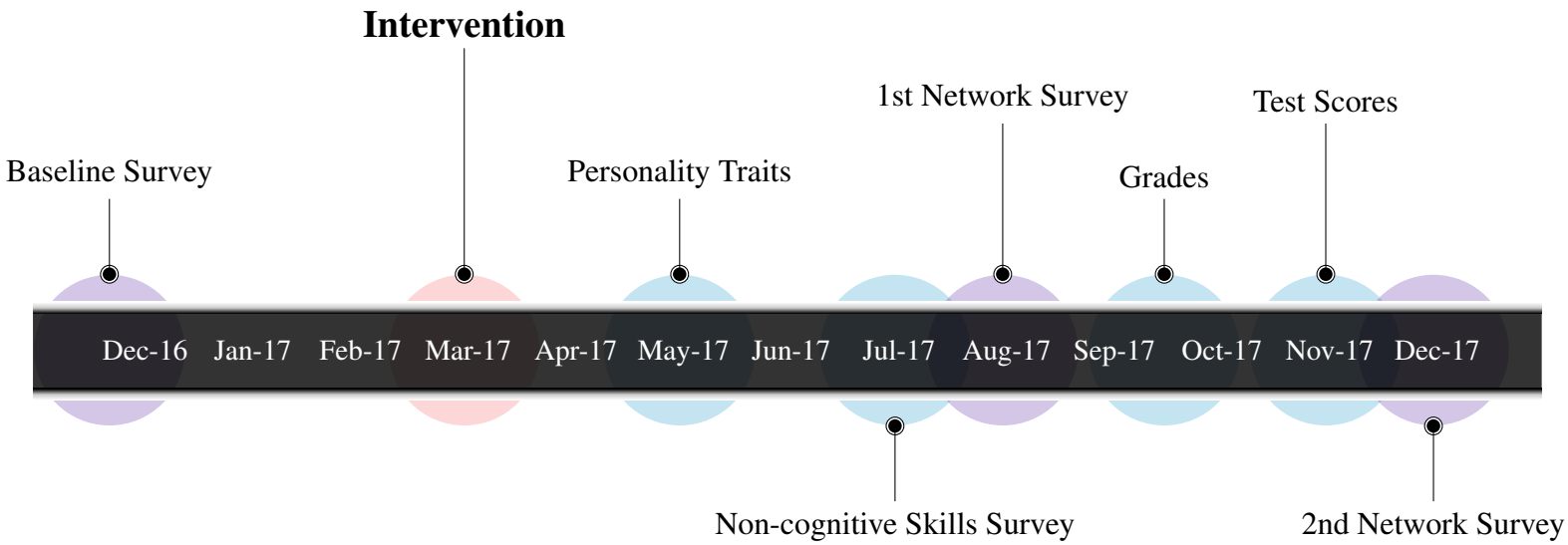
Notes: This table reports the effect of being assigned to more sociable and higher-achieving peers identified at baseline on self-confidence in social skills. All regressions include strata fixed effects and control for selected covariates using the "post-double-selection" Lasso method (Belloni et al., 2014b). For the 2017 cohort, all regressions include gender-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-student-type level.

TABLE A.9: 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	0.003	-0.005	-0.030	0.026	-0.000	-0.036
	(0.046)	(0.034)	(0.043)	(0.053)	(0.032)	(0.034)
Higher-achieving	-0.044	-0.010	-0.060	-0.010	0.059	0.027
	(0.043)	(0.033)	(0.041)	(0.050)	(0.033)	(0.035)
More sociable × boy	0.026	-0.009	0.071	0.024	0.033	0.075
	(0.065)	(0.051)	(0.062)	(0.072)	(0.046)	(0.044)
Higher-achieving × boy	0.049	0.008	0.065	0.018	-0.017	-0.017
	(0.064)	(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	0.518	0.712	0.355	0.306	0.317	0.156
p-val ha boys	0.919	0.965	0.895	0.876	0.180	0.721
N	1,829	1,829	1,829	1,829	1,829	1,829
Panel B: Lower-achieving students at baseline						
More sociable	-0.137	-0.037	-0.115	-0.044	0.009	-0.022
	(0.065)	(0.052)	(0.068)	(0.079)	(0.048)	(0.054)
Higher-achieving	0.049	0.078	-0.010	0.075	0.092	0.106
	(0.053)	(0.047)	(0.054)	(0.059)	(0.038)	(0.046)
More sociable × boy	0.195	0.002	0.140	0.069	0.008	0.041
	(0.091)	(0.076)	(0.089)	(0.108)	(0.068)	(0.064)
Higher-achieving × boy	0.007	-0.066	-0.119	-0.050	-0.026	-0.151
	(0.082)	(0.068)	(0.077)	(0.087)	(0.055)	(0.055)
mean control	1.15	0.84	1.04	1.45	0.47	0.51
p-val ms boys	0.369	0.534	0.685	0.730	0.743	0.613
p-val ha boys	0.370	0.816	0.017	0.696	0.103	0.147
N	2,270	2,270	2,270	2,270	2,270	2,270

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 peer-group-type-by-student-type level.

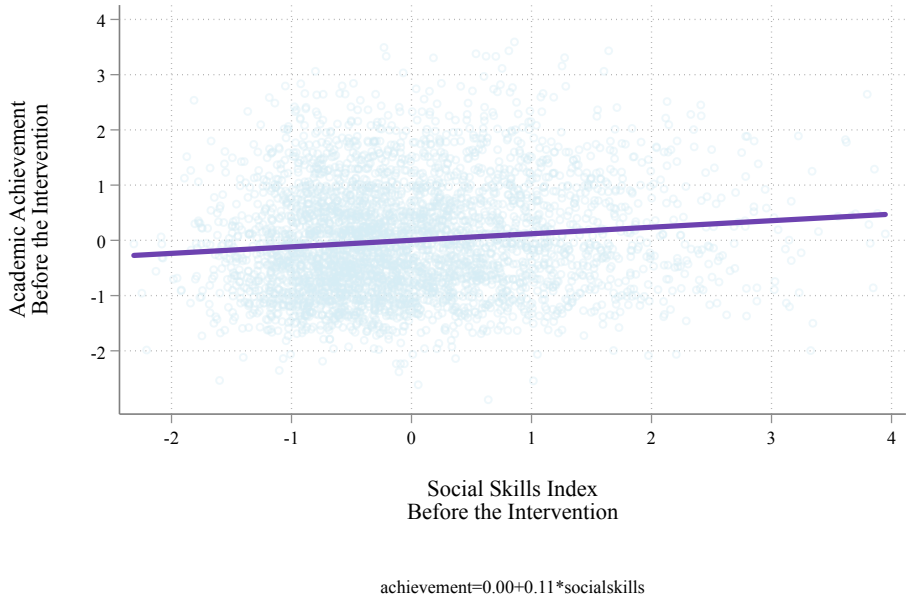
FIGURE A.1: Timeline of the Project



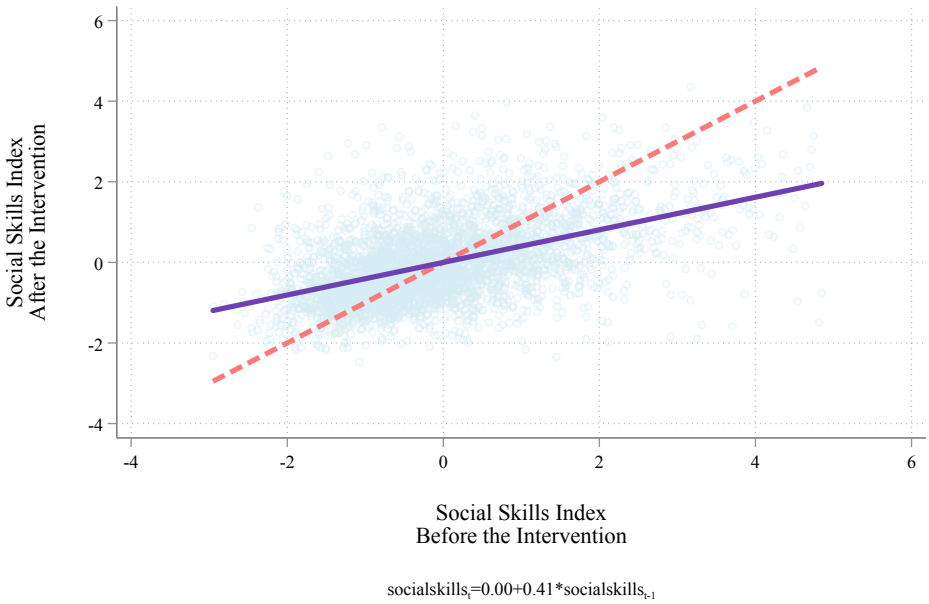
Notes: This figure presents the timeline of the project. The purple circles represent data collection with surveys, the blue circles the collection of administrative data through the Ministry of Education, and the red circle the implementation of the intervention.

FIGURE A.2: Social Skills Index

Panel A: Correlation with Academic Achievement

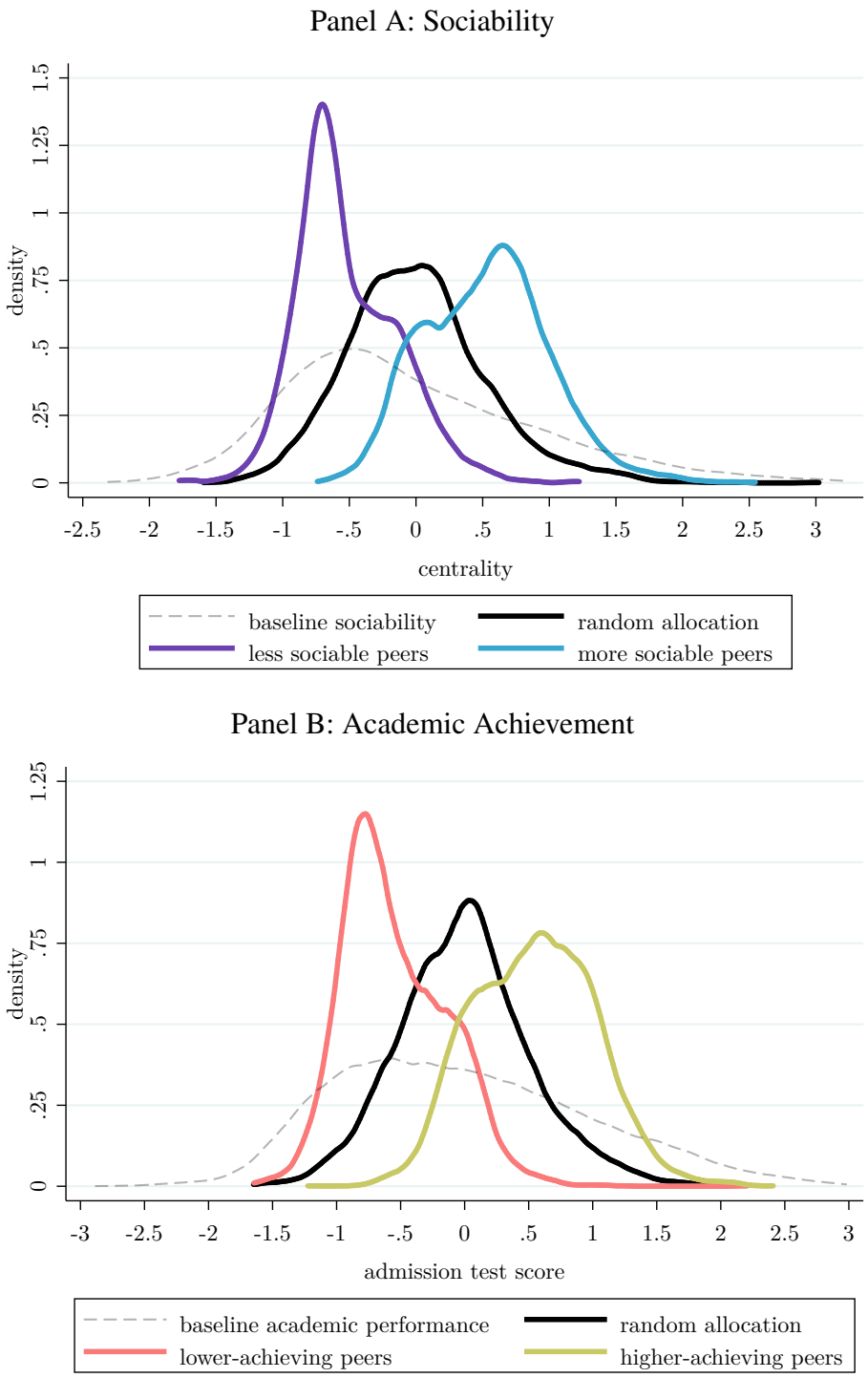


Panel B: Correlation over Time



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.

FIGURE A.3: Distribution of Baseline and Peer Characteristics



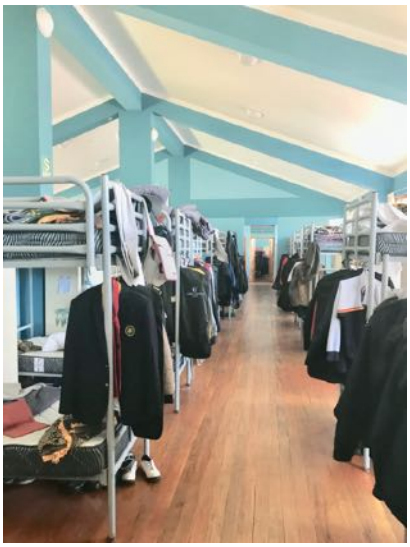
Notes: This figure plots the distribution of baseline and peer characteristics in the allocation to the *peer group types*. It also shows the distribution of peer characteristics using random assignment to groups for comparison. .

FIGURE A.4: Dorm Structure

School in Lima

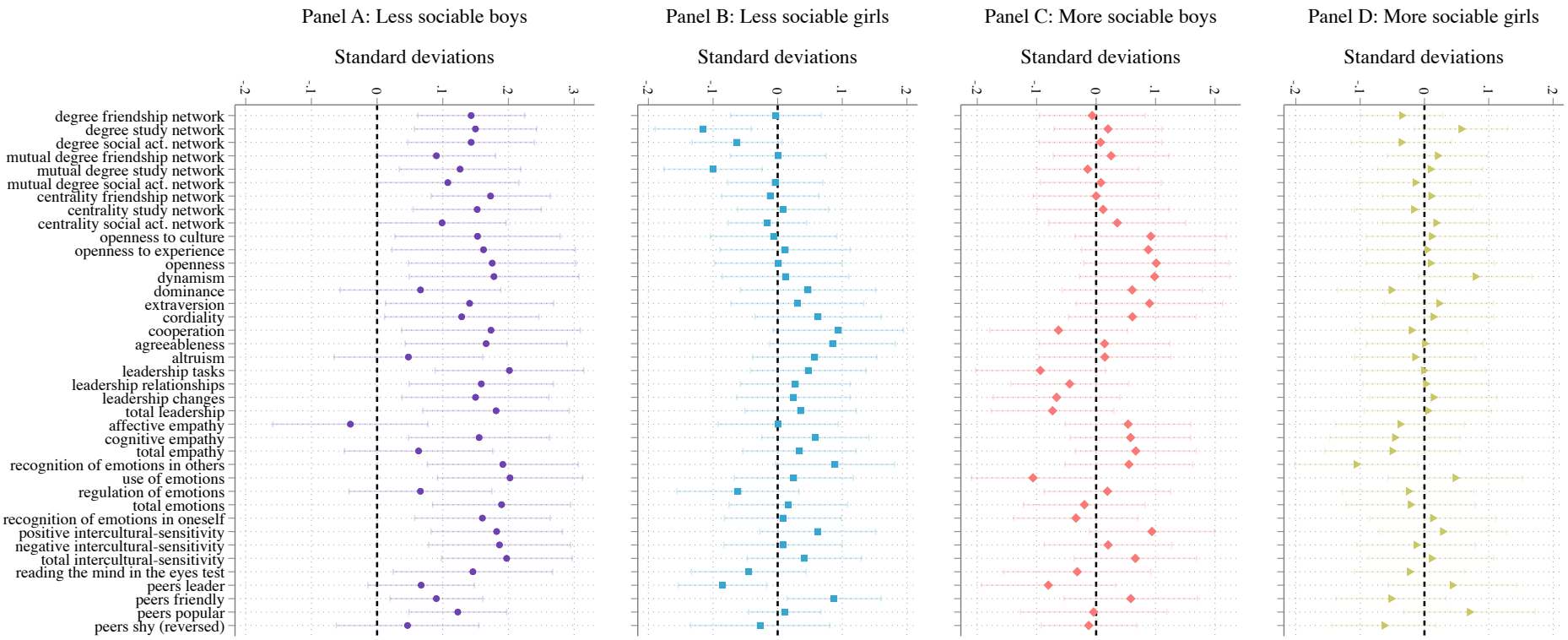
School in Piura

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 A.5: 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-student-type level.

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 2.2, this case allows for three *peer group types*: Group A (only hs), Group B (a mixed group of hs and ls), and Group C (only ls).

The design uses three random numbers to determine the order on the list as described in section 2.2.

1. A vector of random numbers at the *peer group type* level $r = r_A, r_B, r_C$. Let R_ρ denote the rank of *peer group type* ρ constructed from the vector r.

2. A vector of random numbers at the student level $s_i = s_1, \cdots, s_n$. Let $S_{i\tau\rho}$ denote the rank of student i among those of the same type τ in the *same peer group type* ρ constructed from the vector s. For instance, $S_{ihB} = 1$ for the high-type student with the largest s_i among all the high-type students in Group B.

3. A random number at the students type-*peer group type* level $u_{\tau\rho} = \{u_{hA}, u_{hB}, u_{lB}, u_{lC}\}$. Let $U_{\tau\rho}$ denote the ranking of type τ in *peer group type* ρ.

The order of student i, o_i is defined as the sequence of the lexicographic function of R_ρ, $S_{i\tau\rho}$, $U_{\tau\rho}$:

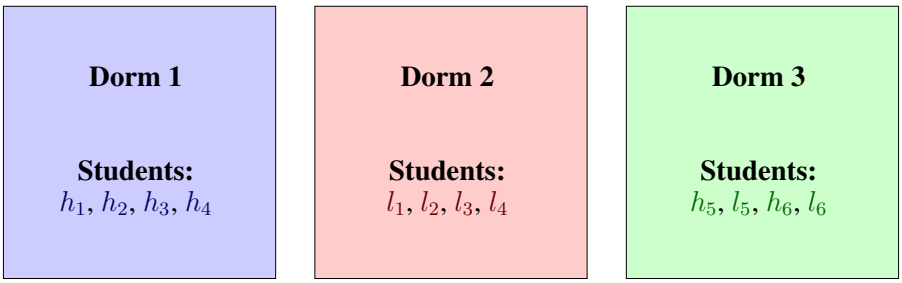
$$o_i = seq(R_\rho, S_{i\tau\rho}, U_{\tau\rho})$$

Let's assume that the random ordering of the *peer group types* on the list is: Group A-Group C-Group B. 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.

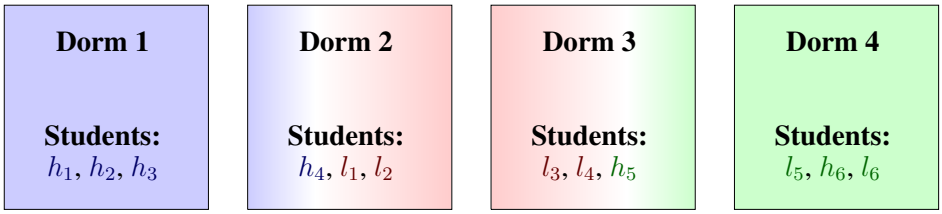
Figure B.1 shows an example of how the lists were used to allocate students to dorms and classrooms. Panel A describes the allocation when each room holds four students, Panel B when dorm rooms hold three students and Panel C for a big dorm room of 12 students. The order on the list is used to determine 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 A (only hs)—are allocated to room 1. The fourth student assigned to Group A 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

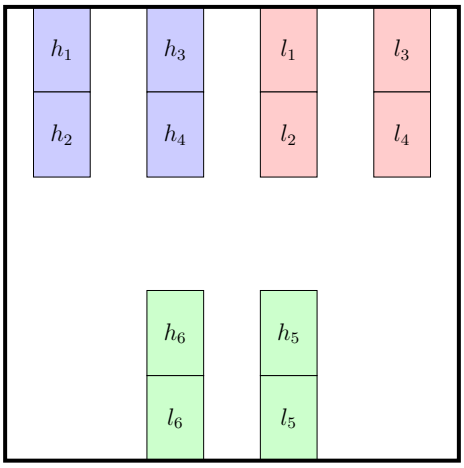
Panel A: Dorms of 4 Students



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 Experimental Design with Multiple Variables and Non-linearities

In this appendix, I show how the design in Section 2.2 can be extended to multiple characteristics and multiple treatments to allow for non-linearities. Assume that the researcher is interested in estimating peer effects on K characteristics with $x_i = \{x_{i1}, \cdots, x_{iK}\}$ denoting the vector of characteristics of student i. Each group g has a fixed size ς_g. The procedure is as follows:

1. Define the set of K characteristics (the vector x_i) relevant to the study.

2. Classify students by type based on a set of predetermined quantiles for each characteristic k. Each type of student represents a different treatment group.

   Let $\mathcal{Q}_k : \{q_{1,k}, \cdots, q_{L_k-1,k}\}$ denote the set of relevant quantiles for characteristic k. The type of a student i along characteristic k, τ_{ik} is given by the position of x_i in the distribution. Notice that with $L_k - 1$ quantiles there are L_k types of students.

   $$\tau_{ik} = \begin{cases} 1 & \text{if} \quad x_{ik} \leq q_{1,k} \\ l & \text{if} \quad q_{l-1,k} < x_{ik} \leq q_{l,k} \\ L_k & \text{if} \quad x_{ik} > q_{L-1,k} \end{cases}$$

   with $\mathcal{T}_k$ denoting the set of student's types for characteristic k, and $\mathcal{T} = \mathcal{T}_1 \times \cdots \times \mathcal{T}_K$ denoting the cartesian product of all types, with the general type of a student defined as: $\tau_i(x_{i1}, \cdots, x_{ik}) = \tau_{i1} \times \cdots \times \tau_{iK}$. The number of types of students T is $|\mathcal{T}| = \prod_{k=1}^{K} L_K$.

3. Conditional on the students' type, randomly assign the type of peer, where each type of peer represents a different treatment group. Let $t_i \in \mathcal{T}$ denote the treatment (type of peer) of student i.

   The randomization to the type of peer is equivalent to allocate students to *peer group types*: all the possible combinations of a student's and peer's type. Let ρ_i denote the *peer group type* of student i. As with two types of students, ρ_i is a function of student's type and their assigned type of peer $\rho_i = \rho(\tau_i, t_i)$, and is a symmetric function with $\rho(\tau_i, t_i) = \rho(t_i, \tau_i)$.

   To see how this works the following matrix shows all the possible combinations between student's and peer type. The diagonal of the matrix shows all the combinations of a single type of student. Outside of the diagonal, the matrix is symmetric, due to the fact that students are matched to peers of their treatment and therefore assigned to the same *peer group type*.

Type of Peers (treatment)

Student Type		$t_1 = (1, 1, \cdots, 1)$	$t_2 = (1, 1, \cdots, 2)$	$\cdots$	$t_T = (L_1, L_2, \cdots, L_K)$
	$\tau_1 = (1, 1, \cdots, 1)$	$\rho(\tau_1, t_1)$	$\rho(\tau_1, t_2)$	$\cdots$	$\rho(\tau_1, t_T)$
	$\tau_2 = (1, 1, \cdots, 2)$	$\rho(\tau_2, t_1)$	$\rho(\tau_2, t_2)$	$\cdots$	$\rho(\tau_2, t_T)$
	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
	$\tau_T = (L_1, L_2, \cdots, L_K)$	$\rho(\tau_T, t_1)$	$\rho(\tau_T, t_2)$	$\cdots$	$\rho(\tau_T, t_T)$

4. Use the allocation to *peer group types* to organize the students on a list. Use the list to create a partition of the students into the set of groups $\mathcal{G}$ using the vector of group size ς.

   On the list, the order of the *peer group types* is random, and within each *peer group type*, the students' order is also random. The only condition is that the list should alternate high- and low-type students in the mixed group to guarantee contact with their treatment peers.

   This order can be defined as a sequence of three random numbers:

   (a) A vector of random numbers at the *peer group type* level $r = r_{\rho_1}, \cdots, r_{\rho_{T^2}}$. Let R_ρ denote the rank of *peer group type* ρ constructed from the vector r.

   (b) A vector of random numbers at the student level $s_i = s_1, \cdots, s_n$. Let $S_{i\tau\rho}$ denote the rank of student i among those of the same type τ in the *same peer group type* ρ constructed from the vector s.

   (c) A random number at the students type-*peer group type* level $u_{\tau\rho} = \{u_{1\rho(1,1,)}, \cdots, u_{T\rho(T,T)}\}$. Let $U_{\tau\rho}$ denote the ranking of type τ in *peer group type* ρ.

   The order of student i, o_i is defined as the sequence of the lexicographic function of R_ρ, $S_{i\tau\rho}$, $U_{\tau\rho}$:

$$o_i = seq(R_\rho, S_{i\tau\rho}, U_{\tau\rho})$$

   Formally, let's denote by o_i the order of student i on the list. The group to which student i is assigned is a function of o_i and defined as:

$$\varrho(o_i) = g_k \quad \text{if} \quad \sum_{l=1}^{k-1} \varsigma_{g_l} < o_i \leq \sum_{l=1}^{k} \varsigma_{g_l}.$$

D 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 6.1, the tests used to construct the sociability index are:

D.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).[23] 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.

[23] 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.

2. Openness to Experience: the tendency to be open to new aesthetic, cultural, or intellectual experiences.

3. Extroversion: 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.

Two traits from the Big Five are linked to social skills: extroversion[24] agreeableness[25]. Empirical evidence shows that extroversion 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. I also include openness to experience[26] in the index as previous research shows that it is associated with leadership (Nieb and Zacher, 2015; Özbağ, 2016; Javed et al., 2020). In the COAR Network, it is also the trait with the largest predictive power on the number of peers that identify a student as a leader. The results are robust to excluding openness to experience from the index.

D.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).

D.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.

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

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

[26]Openness involves six facets or dimensions, including active imagination (fantasy), aesthetic sensitivity, attentiveness to inner feelings, preference for variety, and intellectual curiosity.

D.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.

D.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.

D.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.

D.7 The Reading the Mind in the Eyes Test

This test aims 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 relates to social value orientation (Declerck and Bogaert, 2008), a social intelligence factor, and performance in groups (Woolley et al., 2010), and individual teamwork abilities (Weidmann and Deming, 2020).

D.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 as part of self-confidence in academic skills.

E Theoretical Framework for the Role of Beliefs

In this section, I present a simple theoretical framework to understand how the formation of beliefs about abilities can drive peer effects. Overall, 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.

$$y_i = a_i + \theta e_i + \gamma a_i e_i, \tag{12}$$

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:

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

Hence, two students with the same level of ability (a_i) but different beliefs ($\mathbb{E}\left[a_i\right]$) 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 12:

$$y_i = \kappa\left(\mathbb{E}\left[a_i\right]\right)\left(a_i + \theta e_i\right), \tag{13}$$

with $0 \leq \kappa(\cdot) \leq 1$, and $\kappa'(\cdot) > 0$. Notice that in equation 13, 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.