Homophily and Transmission of Behavioral Traits in Social Networks*

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Abstract

Social networks are a key factor of success in life, but they are also strongly segmented on gender, ethnicity, and other demographic characteristics (Jackson, 2010). We present novel evidence on an understudied source of homophily: behavioral traits. Based on unique data collected using incentivized experiments with more than 2,500 French high-school students, we find high levels of homophily across all behavioral traits that we study. Notably, the extent of homophily depends on similarities in demographics, particularly gender. Using network econometrics, we show that the observed homophily is not only an outcome of endogenous network formation, but is also a result of friends influencing each others' behavioral traits. Importantly, the transmission of traits is larger when students share demographic characteristics such as gender.

JEL-classification: D85, C91, D01, D90.

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1 Introduction

An individual's social network of friends, relatives and peers is a key factor of success in life (Jackson, 2021). A large body of research shows that social networks affect a wide range of outcomes such as the probability of finding a job (Rubineau and Fernandez, 2013; Zeltzer, 2020), teen pregnancy (Kearney and Levine, 2015), or the probability of being vaccinated (Banerjee et al., 2019). Even before adult age, networks shape important decisions and behaviors that may have long-lasting consequences. Friends in school affect student achievement (Epple and Romano, 2011; Sacerdote, 2014; Golsteyn et al., 2021), educational aspirations (Gagete-Miranda, 2020; Norris, 2020), disruptive classroom behavior, school dropout rates (Case and Katz, 1991; Gaviria and Raphael, 2001), and prosocial behavior (Rao, 2019; Alan et al., 2021).

Social networks are not only highly influential, they are also strongly segmented (Jackson, 2010, 2021). A large literature on homophily—a term that refers to people associating with others who are similar to themselves (Lazarsfeld et al., 1954)—shows that social networks are segregated by demographic factors, such as ethnicity, income, gender, age, profession, or religion (McPherson et al., 2001; Currarini et al., 2009; Chetty et al., 2022). For example, in the US in 2020, 56 percent of black Americans had social networks composed entirely of people who are also black (Cox et al., 2020). Using data on the social networks of 70.3 million Facebook users, Chetty et al. (2022) document large homophily by parental SES among high school friends. So, the existence of homophily based on demographic characteristics is a well-established fact.

However, we know surprisingly little on whether and to what extent homophily is also based on behavioral traits, even though the latter are important for success in life (Cunha and Heckman, 2007b, 2008; Borghans et al., 2011; Alan et al., 2019; Algan et al., 2022). For instance, risk and time preferences have been shown to affect educational achievements (Castillo et al., 2011, 2018; Golsteyn et al., 2014; Cadena and Keys, 2015) and financial success (Meier and Sprenger, 2010, 2012; Dohmen et al., 2011). Social preferences have a positive impact on one's professional career (Deming, 2017; Kosse et al., 2020; Kosse and Tincani, 2020). Competitiveness has a strong influence on educational choices, professional career paths, and wages (Buser et al., 2014; Flory et al., 2015). Educational aspirations matter for investments in both physical and human capital (Dalton et al., 2016; Genicot and Ray, 2017). Given the influence of a large set of behavioral traits on success in life, it seems important to investigate two key questions: Are people more likely to interact or befriend each other when they share similar behavioral traits (and does this happen on top of homophily with respect to demographic characteristics)? And, if such homophily on behavioral traits exists, do the behavioral traits of friends affect one's own behavioral traits?

We address both questions in this paper. We do so by collecting unique data on the behavioral traits of more than 2,500 French high school students, aged 15.8 years on average. We asked them to report up to five of their closest friends in the classroom, which allows us to identify the network of friends. Behavioral traits were elicited in an incentivized way to avoid social desirability concerns (Paulhus, 1984; Forsythe et al., 1994). We measure an encompassing set of behavioral traits: prosociality (covering altruism, trust, cooperation, generosity, morality, and preferences for redistribution), risk tolerance, coordination, depth of reasoning, competitiveness, and educational aspirations.[1] Then we merge the data on friendship networks with our data on behavioral traits and complement this with administrative data from the Ministry of Education in France, which provides us with rich information on student demographic characteristics, such as gender, parental occupation, place of residence, nationality, and ethnicity.

Our first main contribution is to provide novel evidence that homophily arises based on all behavioral traits we measure. Increasing similarity in prosociality between two students by 1 standard deviation (SD) is associated with a 2 percentage points (p.p) higher probability of being friends. Similarity in risk tolerance, depth of reasoning, and competitiveness boost friendship chances by respectively 1 p.p, 0.7 p.p, and 0.5 p.p. Importantly, the degree of homophily is further amplified by similarity in demographic characteristics, such as gender. For example, when students share the same gender, similarity in students' prosociality is associated with a 2.5 p.p. higher friendship chance, but this effect drops to 0.8 p.p. for opposite-gender students.

We also find that high school students exhibit large homophily based on demographic characteristics such as gender, ethnicity, shared postcode, socio-economic status (SES), and attendance of the same middle school. We then show that homophily based on behavioral traits comes on top of this. Despite large gender and social differences in behavioral traits—girls are more prosocial, less competitive, and more risk averse; low-SES students are less prosocial and less competitive— these differences explain only marginally the degree of homophily based on gender and other demographic characteristics. For instance, while similarity in gender is associated with a 7.2 p.p. higher chance of being friends, controlling for all behavioral traits only reduces this probability by 0.1 p.p. We further show that similarity in each behavioral trait is individually and independently associated with higher friendship chances, so that students who are similar in multiple traits see their friendship chances increase cumulatively with the number of shared traits.

Our second main contribution is to identify peer effects on behavioral traits. There are two different reasons why students who share similar behavioral traits are more likely to be friends. Either they became friends because of their similarity in behavioral traits (selection effect). Or, once friends, students influenced each other so that their traits ended up converging (peer

[1] The latter is the only trait that we do not measure using incentivized experiments, but by asking students to report the level of education they expect to attain.

effect). The fact that homophily can stem from peer effects is specific to the study of behavioral traits that are malleable. In contrast, homophily by gender or ethnicity, two traits that are fixed, can only originate from girls befriending other girls or minority students befriending other minority students. Peer effects play no role in homophily by fixed demographic characteristics. Yet, it is important to tease out the selection effect from the peer effect in behavioral traits because the two alternative explanations have vastly different policy implications.

The identification of peer effects poses three well-known issues: (i) Manski's reflection problem (Manski, 1993)—Do I influence my friends or do my friends influence me?— (ii) endogenous friendship formation—friendships are not formed at random—, and (iii) correlated effects—peers share similar environments, typically teachers in our case, that can affect their behavioral traits. To address the reflection problem, we use the method developed by Case and Katz (1991) and Bramoullé et al. (2009), which consists of instrumenting the behavioral traits of the friends with the exogenous component of demographic characteristics (gender, ethnicity, nationality, etc.) of the friends, friends of friends, and friends of friends of friends. To address endogenous friendship formation, we use a solution introduced by König et al. (2019) and Gagete-Miranda (2020). Namely, we predict the network based on students' shared predetermined demographic characteristics on which they exhibit homophily (instead of using the endogenous friendship network that students report). Finally, to address the correlated effects problem, we include classroom fixed effects in our regressions.

Our findings on peer effects can be summarized with two facts. First, we identify significant peer effects for almost all traits. For prosociality, risk tolerance, depth of reasoning, and educational aspirations, we see positive peer effects, for competitiveness negative peer effects. A one-standard deviation increase in one's peers' prosociality (resp. risk tolerance and depth of reasoning) leads to an increase in a student's own prosociality by 0.54 SD (resp. 0.48 SD and 0.46 SD). In contrast, a one-standard deviation increase in one's peers' competitiveness leads to a reduction in a student's own competitiveness by 0.58 SD. Second, we show that peer effects are larger in groups that are more homogeneous in terms of demographics. For example, increasing prosociality by one SD in a network of same-gender friends leads to a 0.76 SD jump in a student's own prosociality. This peer effect moves down to a non-significant 0.24 SD when friends are of different gender.

This paper contributes to four broad strands of literature. First, we contribute to a rich literature that has documented homophily based on demographic characteristics such as gender, race, age, religion, education, and social background (McPherson et al., 2001; Jackson, 2010). Yet, while homophily based on demographic characteristics is now well documented, evidence that homophily also exists based on malleable traits is scant. Girard et al. (2015) study homophily in student networks based on risk and time preferences and cooperativeness. Compared to their paper, we examine a much broader set of behavioral traits and show a direction of causality in the relationship from social networks to behavioral traits by also studying peer effects.

A recent paper by Jackson et al. (2022) studies friendship dynamics of university students. While homophily on socio-demographics (like gender and ethnicity) persists over several years, they also find evidence of weaker homophily on behavioral traits such as risk preferences, altruism, or study habits. The paper by Jackson et al. (2022) and ours have been developed independently at the same time. They complement each other in several ways. First, the overlap in the sets of behavioral traits studied in both papers is fairly small as it only covers risk preferences and generosity. Our paper provides novel evidence on homophily with respect to many different traits that have not been studied before. Moreover, while Jackson et al. (2022) documents homophily among a cohort of students attending an elite university (Caltech), we consider a large sample of French high school students representative of the population in terms of gender and social background. Finally, the most important difference is arguably the younger age of the students in our sample. The behavioral traits that we study have been shown to be fairly malleable in childhood and adolescence, usually more so than in adulthood (Sutter et al., 2019), so we might expect larger peer effects among adolescents than among adults.[2] Understanding how these traits are formed at younger age is important as they often have life-long consequences.

Therefore, we contribute, second, to the literature on the determinants of behavioral traits. There is a substantial body of evidence that behavioral traits at an early age impact the socio-economic outcomes of adolescents and adults (Cunha and Heckman, 2007b, 2008; Caliendo et al., 2010, 2014; Dohmen et al., 2012; Sutter et al., 2013; Golsteyn et al., 2014; Algan et al., 2022). However, the literature so far has placed particular emphasis on the transmission and cultivation of these traits from parents (Almås et al., 2016; Falk et al., 2021; Chowdhury et al., 2022) and whether interventions in childhood can causally influence these traits (Cappelen et al., 2020; Kosse et al., 2020). Less is known about the role played by peers, with a few recent exceptions. Rao (2019) and Alan et al. (2021) have shown that the diversity of a peer group increases pro-sociality among students in primary schools. Zárate (2023) shows that peer centrality and achievement affect academic outcomes as well as several social outcomes. Charroin et al. (2022) have identified in a laboratory experiment the extent of peer effects in dishonesty, and Beugnot et al. (2019) have shown in laboratory experiments that there are gender differences in peer effects. In a recent study, ran independently from ours at the same time, Shan and Zölitz (2022) find that the personality of peers in (randomly assigned) study groups influences the development of Big-5 personality traits among college students. They find that more conscientious and open-minded peers improve a student's conscientiousness and open-mindedness. We make three main contributions to this literature on the development of behavioral traits. First, we examine an unusually large set of behavioral traits with a focus on economic prefer-

[2] Jackson et al. (2022) report fairly stable traits and low assimilation in their adult sample.

ences that have been shown to be important for life outcomes (Heckman et al., 2021). As such, we have a broader set of outcomes than Rao (2019) or Alan et al. (2021), and we complement the focus on personality traits by Shan and Zölitz (2022). Considering behavioral traits along with personality traits is particularly important given the weak relationship that exits between both (Almlund et al., 2011; Becker et al., 2012).[3] Second, in contrast to Shan and Zölitz (2022), we elicit students' behavioral traits with incentives, which limits measurement error, reference biases, and social desirability biases in the measure of our outcomes (Dohmen and Jagelka, 2022). Finally, while Shan and Zölitz (2022) identify peer effects among undergraduate students attending the University of Zurich, we collect data on a large and diverse sample of over 2,500 French high school students. Diversity of age, gender, and social background is important as these characteristics affect how malleable behavioral traits are (Cunha and Heckman, 2007a).

Third, our paper contributes to the fast-growing literature on peer effects in educational institutions. A large body of work at the school-level has sought to study peer effects on educational outcomes, primarily on test scores (see surveys in Epple and Romano (2011) and Sacerdote (2014)). Other studies have focused on peer effects in students' attitudes and behaviors, such as disruptive classroom behavior, substance abuse, school dropout rates, and criminal activity (Case and Katz, 1991; Gaviria and Raphael, 2001; Santavirta and Sarzosa, 2019). However, peer effects in exogenously-formed groups might differ quite substantially from peer effects in endogenously-formed groups (Carrell et al., 2013). For that reason, documenting peer effects in both exogenous and endogenous contexts is important. Yet there are only a few papers on endogenous peer effects, and they examine risky behaviors, such as smoking, drinking or substance abuse (Patacchini and Zenou, 2012). Our paper instead relies on incentivized measures of a broad set of behavioral traits that are also important for subsequent life outcomes.

Finally, we contribute to an emerging literature that stresses the importance of analysing economic preferences jointly rather than separately. Studies that have collected data on a large range of economic preferences are rare (Falk et al., 2018; Dean and Ortoleva, 2019; Chowdhury et al., 2022; Stango and Zinman, 2022). As stressed by Chapman et al. (2023), measuring all behaviors simultaneously in a representative sample ensures that the patterns we identify are not due to shifting participant populations between studies. In our context, considering several traits is all the more important as these traits are not all equally malleable and their correlation with both students' demographic characteristics (such as gender or SES) and longer-term outcomes (such as labor market success or health) differs (Heckman et al., 2021).[4]

[3] A notable exception is the recent paper by Jagelka (2024) which finds that three of the Big Five personality traits (extraversion, conscientiousness, and emotional stability) explain individuals' risk and time preferences. No evidence exists on the relationship between prosocial behaviors (studied in our paper) and personality traits.

[4] See Golsteyn and Schildberg-Hörisch (2017) on the stability of preferences and personality and Chapman et al. (2023) on the correlation between traits, cognitive abilities, and demographics.

The rest of the paper is structured as follows. In the next section we describe our data. Section 3 presents the methodology and results on homophily. Section 4 outlines first the econometric methodology we use to identify peer effects in endogenous networks, and then presents our findings. Section 5 concludes the paper.

2 Sample Description and Data

In October 2019, we partnered with 67 high schools in three French regions (Nantes, Montpellier, and Créteil) to collect data on behavioral traits and friendship networks. We got IRB approval from the Toulouse School of Economics. A total of 2,565 students, aged 15 to 18 (with an average age of 15.8 years), participated in our study.[5] The study was conducted during regular school hours, thus reducing self-selection concerns. We set up a novel online platform for data collection using oTree (Chen et al., 2016). First subjects played a series of incentivized games or allocation tasks, after which we elicited their friendship networks. We start with a brief description of all behavioral traits that we elicited.[6]

1. **Risk tolerance**. Students had to choose how many out of ten boxes to open (Crosetto and Filipin, 2013). Nine boxes contained one credit (our experimental currency unit) each, but one box contained a shark. After having decided on how many boxes to open, they could choose which ones. If one of the opened boxes contained the shark, they earned nothing in this game, otherwise they received all the credits from the opened boxes. The number of boxes opened by a student is our measure of risk tolerance. See Figure D1 in the appendix for an illustration.
2. **Competitiveness**. We asked students to place 48 sliders in the middle of a [0,1] axis. Students had two minutes to perform the task, and had to choose between two payment options (Niederle and Vesterlund, 2007): (i) playing alone and gaining 0.2 credits for each slider correctly positioned, or (ii) competing with another player. In the latter option they would earn 0.5 credits for each correctly positioned slider, if students performed better than their competitor, else they would earn nothing. We take the choice of the second payment option as our measure of competitiveness. See Figure D2 for an illustration.
3. **Trust**. Each student made a choice to send between 0 and 5 credits to a partner. The quantity sent was tripled and the second student subsequently chose what amount of this

[5] Our recruitment of survey participants took place in several steps. First, we obtained support from the superintendents of three French regions—Nantes, Montpellier, and Créteil. These superintendents informed school principals about our research project. Interested principals invited their teachers to use one of their class hours for their students to take the survey. Although participation was on a voluntary basis, we show below that our sample is reasonably representative in terms of gender and social composition.

[6] We elicited time preference, but the data were not recorded correctly for most participants, so we do not report results on time preferences.

tripled quantity they wanted to send back to the first student (Berg et al., 1995). Our trust measure is the amount the first mover transfers to a second mover.[7] See Figure D3 for an illustration.

4. **Cooperation**. Here, students were paired with another student for four rounds.[8] In each round, they were endowed with one credit. Then they had to choose simultaneously how much they wanted to transfer to the other player (in steps of 0.1 credits). The amount transferred was then doubled (Angerer et al., 2016). A student's final payoff was therefore equal to $1 - \mathbf{x} + 2\mathbf{y}$, where $\mathbf{x}$ is the own amount transferred and $\mathbf{y}$ is the amount transferred by the partner. Our measure of cooperation is the average amount of credits transferred over the four rounds. See Figure D4 for an illustration.

5. **Coordination**. In this game, students played for four rounds with the same partner. They had to simultaneously choose between options A and B, like in a stag hunt game (Cooper et al., 1990). Choosing A gave a student 3 credits irrespective of the other player's decision, while choosing B gave 5 credits if and only if the second player made the same choice, but zero otherwise. Our measure of coordination is the average number of times a student chose option B. See Figure D5 for an illustration.

6. **Altruism:** Students were allotted 10 credits in a dictator game (Forsythe et al., 1994) and were told that another student didn't receive any credits. They had to make a choice of transferring any amounts of credits (in steps of 1) to the other student. This constitues our measure of altruism.[9] See Figure D6 for an illustration.

7. **Morality**. Students had to decide between receiving x credits from the research team versus letting the researchers donate 10 credits to a vaccination campaign (against measles) run by UNICEF (Kirchler et al., 2016). The amount x increased progressively and took on the values 2, 4, 6, 8, and 10. Our measure of morality is the frequency with which subjects donate the 10 credits to UNICEF rather than keeping the credits for themselves. See Figure D7 for an illustration.

8. **Tolerance for inequality**. A student was first informed that two other students had performed a task and the better performing of those had received an initial amount of 9 credits, and the other one of 1 credit. Then the student had the option to re-allocate the sum of 10 credits in any preferred way between the two students (Cappelen et al., 2007). Our measure of a tolerance of inequality is the absolute difference between the amounts allocated to both students. A difference of zero (10) indicates the strongest preference

[7] Students also played the role of a second mover. Yet, due to a software bug the data collected for the second mover was incorrect, which prevents us from including trustworthiness as a behavioral trait.

[8] Students played this game with either the same person or a randomly selected student who changed every round. Students were informed which condition applied.

[9] Due to a recording error, we were only able to use the information on a limited subsample of the students.

for equality (inequality). See Figure D8 for an illustration.

9. **Depth of reasoning**. We randomly matched each student with 3 other players in a so-called beauty contest or guessing game (Nagel, 1995). Each player had to submit a number between 0 and 100. We defined a target number as the average of the four proposed numbers multiplied by a certain factor (which was either 1/3, 1/2, or 2/3). The student who proposed the number closest to the target number earned 6 credits. Students played this game for four rounds. Our measure of depth of reasoning is a student's mean of the numbers chosen over all rounds (i.e. higher values imply a lower level of depth of reasoning). See Figure D9 for an illustration.

10. **Generosity**. At the end of a session, we gave students the option to donate a share of their total payoff (from all games) to a charitable organization. Our measure of generosity is the share of each student's total payoff that they decided to donate.

11. **Educational aspirations**. As the only non-incentivized task, we asked subjects to report the highest level of educational qualification they wished to obtain (with 1 corresponding to finishing high school, 2 obtaining an undergraduate degree, 3 a graduate degree, and 4 a PhD). This is our measure for educational aspirations.

To ensure that the duration of the survey would fit in a one hour class, and to limit survey fatigue and students disengaging midway through the incentivized games, we set a limit on the number of games that each student would play by randomizing some of the games that a student would play. This implies that not all students played all games, but (except for altruism) we have more than 2,000 observations for each behavioral trait (see Table 1). With regards to incentives, we informed students that we would randomly draw 300 of them who would receive their credits converted in gift vouchers.[10,11]

To reduce the number of traits to be presented in the results section, and to account for potential measurement error in behavioral traits, we follow the approach in Terrier et al. (2021) and apply a principal components analysis (PCA) to get a compound measure of prosociality. To construct this measure, we include the traits altruism, tolerance for inequality, morality, trust, generosity and cooperation.[12] We present results based on the PCA-measure of prosociality in

[10] The Créteil region did not want to incentivize students with money. We did not convert credits in gift vouchers there. We account for that by controlling for students' region in the analysis.

[11] Four of the games were interactive (the trust, cooperation, coordination, and competition games). Students played these games with another student. We randomly chose whether the student would play with someone (i) from their class, (ii) from their school, (iii) from their region. A fourth group of students were told the other player's first name (but without the above information). Finally, a last group was not given any information on their partner. The other student's identity in the dictator game also followed the 4 treatments mentioned above. Our analysis does not exploit these different treatments, but we control for this treatment variation in all regressions.

[12] We used all variables when they were available, but recall that not all participants played all games. So, when one was missing, we adopted a quasi-iterative process, i.e. we only used the available variables (up to a minimum of two). We computed the PCA on prosociality traits only (excluding, e.g., risk tolerance or competitiveness) because prosociality traits tend to be more correlated than prosociality with the other traits.

the paper and we show results for each trait separately in the Appendix.

Student friendship network. We measured friendship networks by asking students to report the five closest friends they have in their classroom. We asked them about friends in their class rather than in their school because the latter question would have left us unable to measure the behavioral traits of the friends in classes of teachers who did not participate in our study.[13] The friends question came after students played the games to make sure that it did not influence their decisions.

Student demographic characteristics. Finally, we merge the data we collected with administrative data from the French ministry of education which contains information on student gender, age, nationality, parents' occupation, number of siblings, place of residence, and middle school attended. We use parents' profession to capture a student's socio-economic status (SES).[14] We use student names to determine their ethnicity. It is forbidden to collect data on ethnicity in France, so we relied on the python package *ethnicolr* to predict student ethnicity based on their full name.[15]

Table 1 provides summary statistics of our data; in panel A on the number of friends, in panel B on their behavioral traits, and in panel C on the demographic characteristics based on administrative data. 55.7% of the students are female (versus 54.3% at the national level in 2021), 41.9% are low SES, which is slightly lower than the 46.4% national average (see Table A.1), and slightly higher than the share of low-income children in the U.S (35%) in 2021 (U.S. Census Bureau, 2024). Students in our sample are 15.8 years old on average, and 79.2% are white. They reported 4.6 friends on average.

[13] Participation in our project was voluntary and the decision to participate was made by teachers (not students). As a result, we either enrolled all the students of a class (when the teacher was in) or no students (when the teacher did not want to participate). In most schools, only a few teachers would participate, so asking students to identify friends in different classes meant that we would not have been able to collect data on behavioral traits for these friends.

[14] Following the guidelines from the French Statistical Office (INSEE), we define a student as having low SES if the occupation of the parent who is the head of household is either a manual worker ("ouvrier" in French), a non-manual worker ("employé"), an agricultural worker, a retired person, or out of market. Non-manual workers include, e.g., professions like postman, ambulance driver, caregiver, cashier, shop seller, police officer, security agent, or secretary. Manual workers include, e.g., professions like electrician, carpenter, painter, taxi driver, gardener, or builder. Appendix Table A.1 contains the list of professional classifications by INSEE, their relative frequency, the mean wage, and the fraction of workers with a high-school degree in each profession (referring to the whole French working population).

[15] The Pearson correlation coefficient between the broad categorization between white / non-white and the confidence score generated by *ethnicolr* predictor is 0.9.

Table 1: Summary Statistics

	Mean	Std. Dev.	Min.	Max.	N
Panel A: Friendship Information					
No. of friends reported	4.640	0.856	1	5	2565
No. of friends matched	3.395	1.298	1	5	2565
No. of times reported as a friend	2.287	1.681	0	10	2565
Panel B: Behavioral Traits					
Altruism	3.172	2.597	0	10	610
Tolerance for inequality	1.629	2.672	0	8	2332
Morality	7.550	3.028	0	10	2450
Trust	2.433	1.619	0	5	2332
Generosity	0.452	0.404	0	1	2061
Cooperation	0.488	0.278	0	1	2332
Coordination	0.479	0.310	0	1	2332
Risk Tolerance	5.712	2.750	0	10	2565
Competitiveness	0.477	0.500	0	1	2332
Depth of reasoning	33.496	14.198	0	100	2332
Educational aspirations	2.852	0.816	1	4	2565
Prosociality PCA	0.042	1.274	-4	4	2426
Panel C: Demographic characteristics					
Female	0.557	0.497	0	1	2565
French	0.961	0.193	0	1	2565
White	0.792	0.406	0	1	2565
Arab	0.053	0.223	0	1	2565
Hispanic	0.062	0.242	0	1	2565
Black	0.061	0.239	0	1	2565
Asian	0.032	0.177	0	1	2565
Primary parent occupation: low skill	0.419	0.493	0	1	2565
No. of siblings from primary parent	1.073	1.047	0	11	2565
Single Child	0.329	0.470	0	1	2565
Born in France	0.950	0.218	0	1	2565
Age (in years)	15.766	0.942	13	19	2565
From Créteil	0.170	0.376	0	1	2565
From Montpellier	0.306	0.461	0	1	2565
From Nantes	0.524	0.500	0	1	2565
Grade 10	0.498	0.500	0	1	2565
Grade 11	0.274	0.446	0	1	2565
Grade 12	0.228	0.420	0	1	2565

Note: This table presents descriptive statistics for the sample of 2565 students who (i) participated in our study, (ii) were successfully matched to the administrative data and (iii) had at least one reported friend participating in the survey. See section 2 for a detailed description of the games used to measure behavioral traits. The prosociality PCA-measure uses the variables altruism, tolerance of inequality, morality, trust, generosity, and cooperation.

3 Homophily on Behavioral Traits

3.1 Method

To document homophily on behavioral traits among high school students, we investigate how the probability of two students being friends depends on their similarity in behavioral traits. We use the following specification:

$$d_{ij} = \beta_0 + \beta_1 \left(-|y_i - y_j|\right) + \beta_2 \mathbf{1}[\mathbf{x}_i = \mathbf{x}_j] + \zeta_i + \psi_j + \nu_{ij} \tag{1}$$

where d_{ij} is a potential friendship pair, i.e., $d_{ij} = 1$ if student i nominates student j as their friend and 0 otherwise. Friendship links are directed, meaning that $d_{ij} = 1$ does not necessarily imply $d_{ji} = 1$.[16] Potential links are also restricted to students within the same classroom. y_i captures student i's behavioral traits, so that $\left(-|y_i - y_j|\right)$ captures how close two students are in terms of these traits. $\mathbf{x}_i$ captures student demographic characteristics such as their age, ethnicity, nationality, country of birth, parental occupation, number of siblings, postal code of residence, and the middle school attended. For all these variables, except for age and number of siblings, $\mathbf{1}[x_i = x_j] = 1$ if student i and j share the same demographic characteristic and 0 otherwise.[17] For the sake of comparison, all measures of similarity in the regressions are standardized.[18] We also control for a set of *sender* and *receiver* fixed effects (ζ_i and ψ_j), i.e., a fixed effect for each student nominating a friend (the sender) and each student being nominated as a friend (the receiver). These fixed effects account for student idiosyncratic characteristics which may increase a student's likelihood of nominating or being nominated as a friend, such as popularity, charisma, amicability, etc. We cluster standard errors at the classroom level.

3.2 Results on homophily

Five main facts stand out from our analysis of homophily. We start by confirming a well-established finding in the literature:

Fact 1: *High school students exhibit a large degree of homophily based on demographic characteristics.*

[16] We allow networks to be undirected in our robustness checks.

[17] Age is measured in months and for any two students i and j, $|\text{Age}_i - \text{Age}_j| / \max_{xy} |\text{Age}_x - \text{Age}_y|$ captures how close two students are in age relative to the maximum age distance between all pairs of students. Similarly, $|\#\ \text{Siblings}_i - \#\ \text{Siblings}_j| / \max_{xy} |\#\ \text{Siblings}_x - \#\ \text{Siblings}_y|$ captures the similarity in the number of siblings between student i and j. We abuse notation by denoting the variables capturing similarity in age and number of siblings by $\mathbf{1}[x_i = x_j]$.

[18] In the Appendix A, we also report results where we scale the measures to take a value between 0 and 1 where 0 implies completely dissimilar w.r.t the trait in consideration and 1 implies completely similar.

Figure 1 reports homophily coefficients on demographic characteristics. In blue, we present the estimations without controls for behavioral traits. To facilitate the comparison of homophily based on demographic characteristics and homophily based on behavioral traits, we standardize all demographic and behavioral variables to have a standard deviation of 1.

Two students who have the same gender are 15.4 percentage points more likely to be friends than two students of opposite gender. Expressed in standardized terms, increasing gender similarity between two students by 1 SD is associated with a 7.2 percentage point higher chance of being friends. Similarly, having attended the same middle school increases friendship chances by 13 percentage points, as does having the same ethnicity (+4.1 p.p.), living in the same geographical area (+4.0 p.p.), and having the same socio-economic status (+1.1 p.p.). The coefficients reported in Figure 1 use the standardized value of the student characteristics. Increasing by 1 SD the similarity in attendance of the same middle school increases friendship chances by 4.7 percentage points, as does having the same ethnicity (+1.6 p.p.), living in the same geographical area (+1.5 p.p.), and having the same socio-economic status (+0.4 p.p.). In contrast to these demographic variables, our results suggest that similarity in nationality, country of birth, or number of siblings does not increase friendship chances.[19]

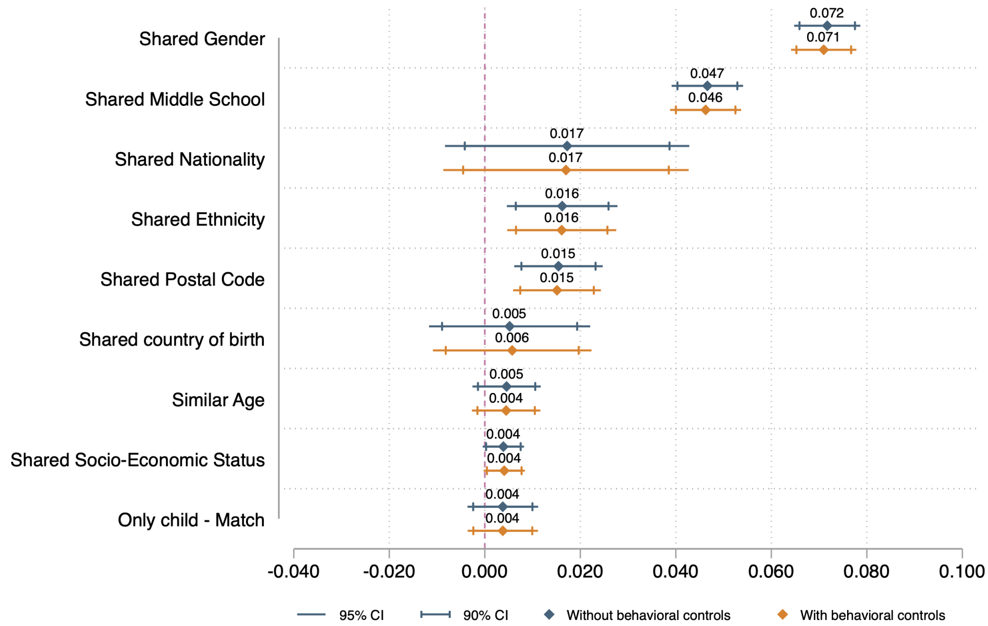
The large homophily based on demographic characteristics we document among high school students raises the question: How much of this homophily is explained by similarity in behavioral traits? A rich body of literature has documented differences in behavioral traits by gender, social background, and race (Niederle and Vesterlund, 2007; Croson and Gneezy, 2009; Buser et al., 2014; Almås et al., 2016). Our data confirms these associations. Figure 2 plots gender, social, and ethnic differences in behavioral traits. We find that girls have a 0.26 SD higher prosociality index. Girls also have higher levels of depths of reasoning (+0.14 SD). Yet, they are also significantly less competitive (-0.27 SD), less likely to coordinate on the efficient outcome (-0.10 SD), and less risk tolerant (i.e., 1.10 SD more risk averse).

A student's social background is also associated with behavioral traits. Students with higher socio-economic status are more prosocial (+0.09 SD), have higher educational aspirations (+0.24 SD), are more competitive (+0.06 SD) and they more frequently coordinate on the efficient outcome in a coordination game (+0.12 SD). Regarding ethnicity, we find that whites are more prosocial (+0.08 SD), but they have lower educational aspirations than non-whites (-0.11 SD), which might be driven by Asian students being classified as non-whites.

Next, we tease out homophily based on demographic characteristics from homophily based on behavioral traits using the combined administrative and experimental data. More specifically, we test how much the homophily coefficients change when we control for students' behavioral traits. The results are reported in orange in Figure 1 (compared to the blue coefficients without controls for behavioral traits).

[19]96.5% of students are French, and 95% were born in France, so there is very little variation.

Figure 1: Hompohily based on demographic characteristics **(Facts 1 and 2)**



Note: This figure plots coefficients for homophily based on demographic characteristics. Each coefficient corresponds to a separate regression. The dependent variable is an indicator variable which takes the value 1 if individual i sends a link to individual j and 0 otherwise. Each regression controls for sender and receiver fixed effects. For each behavioral trait, the top blue coefficient corresponds to a regression that does not control for shared behavioral traits. The bottom orange coefficient corresponds to a regression that controls for shared behavioral traits. Standard errors are clustered at the classroom level. All variables are standardized to facilitate comparisons.

Fact 2: *Homophily on behavioral traits does not explain homophily based on demographic characteristics.*

Despite large gender and social differences in behavioral traits, these differences explain only marginally the degree of homophily based on demographic characteristics. For instance, we previously showed that increasing gender similarity between two students by 1 SD is associated with a 7.2 percentage point higher chance of being friends. Controlling for all behavioral traits only reduces this probability by 0.1 percentage points. Comparing the homophily coefficients across both specifications in Figure 1 yields similar conclusions for homophily based on ethnicity, middle school, socio-economic status and shared postal code. It is hardly driven by similarity in behavioral traits. We show next that a large amount of homophily also exists based on students' behavioral traits.

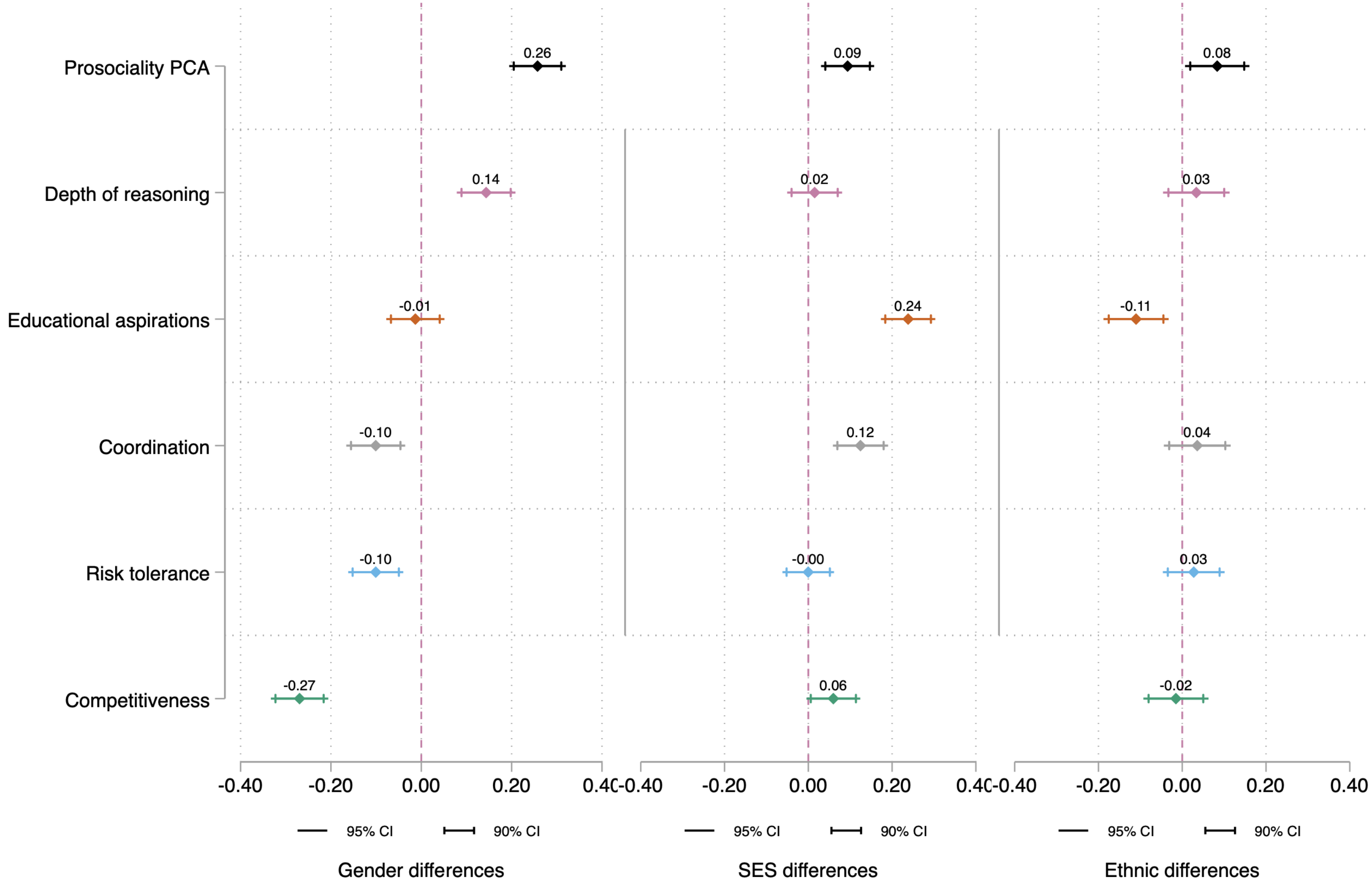
Fact 3: *High school students exhibit a large degree of homophily based on behavioral traits,* *above and beyond the well-documented homophily on demographic characteristics.*

In Figure 3 we present our results (see also column 4 in Table 2). We show coefficients from a regression of friendship on similarity in behavioral traits, based on eq. 1. We control for students' demographic characteristics, meaning that the homophily by behavioral traits comes on top of the homophily by demographic characteristics.

Our results reveal that similarity in behavioral traits is independently and significantly associated with the likelihood of being friends. All homophily estimates are positive and significant, with the larger effects observed for prosociality, educational aspirations, and risk aversion. Increasing similarity in prosociality between two students by 1 SD is associated with a 2 percentage points higher probability of being friends. Figure A.1 decomposes this effect into the sub-components of prosociality and shows that similarity in generosity is strongly associated with friendships (+4.9 percentage points). Similarly, increasing similarity in educational aspirations, risk tolerance, and depth of reasoning by 1 SD is associated with a 1.3 percentage points (respectively 1 p.p. and 0.7 p.p.) higher probability of being friends. To better grasp the relative impact of homophily in behavioral traits compared to demographic factors, consider the following: an increase in gender similarity by one standard deviation (SD) corresponds to a 7.2 p.p. increase in the likelihood of forming a friendship, while the same increase in ethnic similarity leads to a 1.6 p.p. increase. This suggests that the influence of homophily based on behavioral traits is comparable to that of various demographic characteristics. For a more detailed comparison, refer to Figure A.2, which presents the normalized values of trait similarity, ranging from 0 (indicating no similarity) to 1 (indicating complete similarity). This figure also breaks down the prosociality index into its individual components.

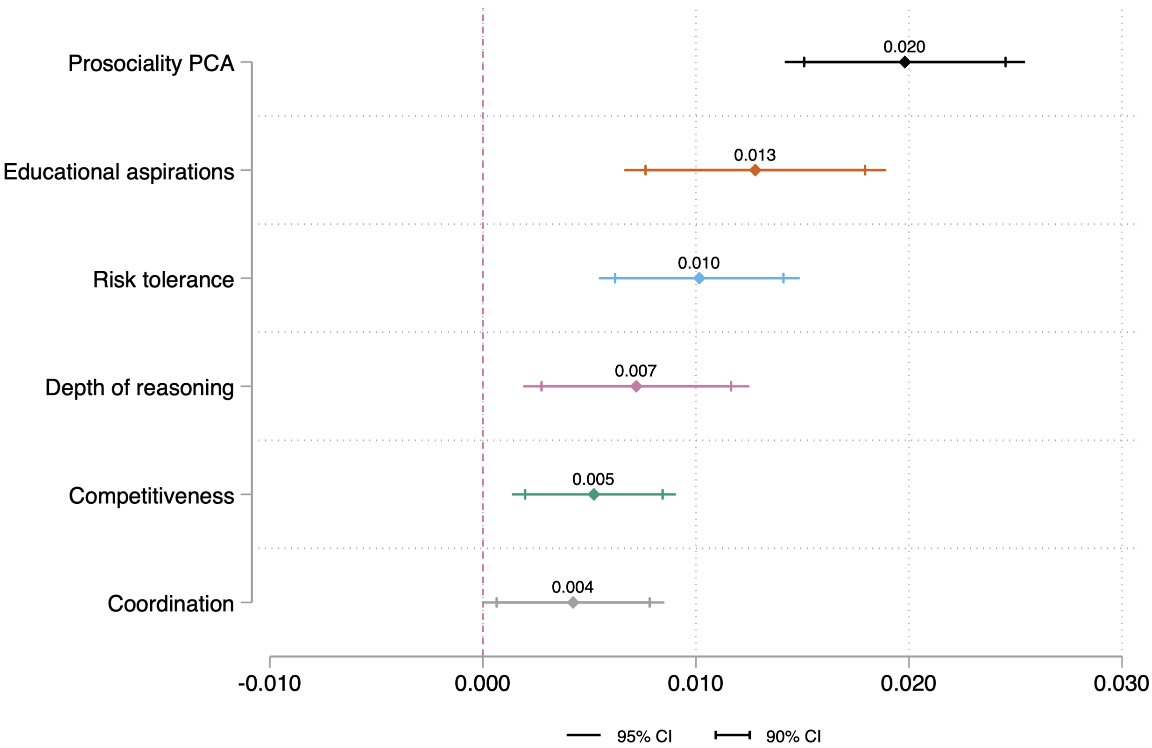
Our results on homophily in behavioral traits persist across a range of robustness checks we carry out. Columns 1, 2, and 3 of Table 2 report results from different specifications in which we (i) replace the sender and receiver fixed effects by variables that control for sender and receiver demographic characteristics (Column 3), (ii) omit the sender and receiver demographic characteristics (Column 2), and (iii) further omit variables that control for students' shared demographic characteristics (Column 1). Table 2 confirms that our homophily results hold across these alternative specifications, suggesting that student friendships are far from being randomly formed. They depend not only on similarity in demographic characteristics, but also to a large extent on similarity in behavioral traits.

Figure 2: Gender, social, and ethnic differences in behavioral traits



Note: This figure plots gender, social, and ethnic differences in behavioral traits. The reported coefficients come from separate OLS regressions. The dependent variable is a behavioral trait (standardized). Each regression controls for gender, low-SES, ethnicity, and age. The gender variable takes the value 1 if the student is female and 0 otherwise. The SES variable takes the value 1 if the student's parents are from a high SES and 0 otherwise. The ethnicity variable takes the value 1 if the individual is white and 0 otherwise.

Figure 3: Homophily based on behavioral traits **(Fact 3)**



Note: This figure plots coefficients for homophily based on behavioral traits. Each coefficient corresponds to a separate regression based on eq. 1. The dependent variable is an indicator variable which takes the value 1 if individual i sends a link to individual j and 0 otherwise. On the right-hand-side, $|y_i - y_j|$, whose coefficient is reported in this figure, captures how close two students are in terms of behavioral traits. For the sake of comparison, all measures of similarity in behavioral traits in the regressions are standardized. We control for shared demographic characteristics such as gender, ethnicity, nationality, place of residence, SES, number of siblings, age (in months), a dummy to indicate whether the individual is an only child or not, and a dummy to indicate if the individual was born in France. We also control for sender and receiver fixed effects. Standard errors are clustered at the classroom level.

Next we test if homophily by behavioral traits is more prevalent among students who are more alike in terms of demographic characteristics. We investigate this by running our baseline specification (eq. 1) separately on pairs of same-gender (vs. different gender), same middle school, same ethnicity, and same SES. Figure A.3 shows the coefficients we obtain for these different samples, and Figure A.1 decomposes the prosociality effect into the sub-components. The results for gender suggest that similarity in demographics matters for the degree of homophily in behavioral traits.

Fact 4: *Similarity in demographic characteristics, particularly with respect to gender, amplifies homophily based on behavioral traits.*

Table 2: Homophily coefficients for behavioral traits

	(1)	(2)	(3)	(4)
Prosociality PCA	0.013***	0.010***	0.012***	0.020***
	(0.002)	(0.002)	(0.002)	(0.003)
Coordination	0.004**	0.004**	0.004***	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Risk tolerance	0.007***	0.006***	0.007***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
Competitiveness	0.006***	0.004**	0.004**	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
Rationality	0.005***	0.004**	0.004**	0.007***
	(0.002)	(0.002)	(0.002)	(0.003)
Educational aspiration	0.009***	0.007***	0.007***	0.013***
	(0.002)	(0.002)	(0.002)	(0.003)
Shared demographic characteristics	N	Y	Y	Y
Sender and receiver characteristics	N	N	Y	N
Sender and receiver fixed effects	N	N	N	Y

Note: This table reports coefficients for homophily based on behavioral traits. Each coefficient corresponds to a separate regression based on Eq. 1. The dependent variable is an indicator variable which takes the value 1 if individual i sends a link to individual j and 0 otherwise. On the right-hand-side, $|y_i - y_j|$, whose coefficient is reported above, captures how close two students are in terms of behavioral traits. For the sake of comparison, all measures of similarity in behavioral traits are standardized. "Sender and receiver characteristics" as well as "shared demographic characteristics" include gender, ethnicity, nationality, commune of residence, low SES, number of siblings, age (in months), dummy to indicate whether the individual is an only child or not and a dummy to indicate if the individual was born in France. Standard errors are clustered at the classroom level. *** p<0.01, ** p<0.05, * p<0.1, + p<0.15

The estimates for homophily based on behavioral traits are always higher when students share the same gender than when considering pairs of boys and girls. Figure 4 shows that homophily based on behavioral traits is often close to zero and statistically insignificant when students are of different gender. For most behavioral traits, homophily only exists if students have initially sorted themselves based on gender. For example, increasing similarity in students' prosociality by 1 SD is associated with a 2.5 p.p. higher friendship chance when students share the same gender, but it only raises friendship chances by 0.8 p.p. for opposite-gender students. We find similar differences for homophily based on educational aspirations (+1.7 p.p. for same-gender students versus +1.0 p.p. for opposite-gender), risk tolerance (+1.6 p.p. versus non-significant +0.2 p.p.), depth of reasoning (+1.0 p.p. versus non-significant +0.1 p.p.), competitiveness (+0.9 p.p. versus non-significant +0.1 p.p.), and coordination (+0.7 p.p. versus non-significant +0.1 p.p.). These patterns are mirrored when prosociality is broken down into its components in Appendix Figure A.3 and A.4.[20] We find weaker evidence that shared middle school, shared ethnicity, and shared SES increase the level of homophily based on behavioral traits.

Finally, we show that similarity in one behavioral trait does not substitute well for similarity in another trait when it comes to network formation. We run a kitchen sink regression in which we regress potential friendship links on similarity across all behavioral traits, while controlling for demographic characteristics and sender and receiver fixed effects.[21]

Fact 5: *The larger the number of behavioral traits that students share, the higher the overall homophily. In other words, similarity in one behavioral trait does not substitute well for similarity in another one when it comes to determining friendships.*

The results we obtain (reported in Figure 5) do not substantially differ from the results discussed above (in Figure 3).[22] In other words, similarity in each behavioral trait is individually and independently associated with higher friendship chances. This notable result implies that students who are similar in several behavioral traits (rather than only one) see their friendship chances increased by the number of similar traits.

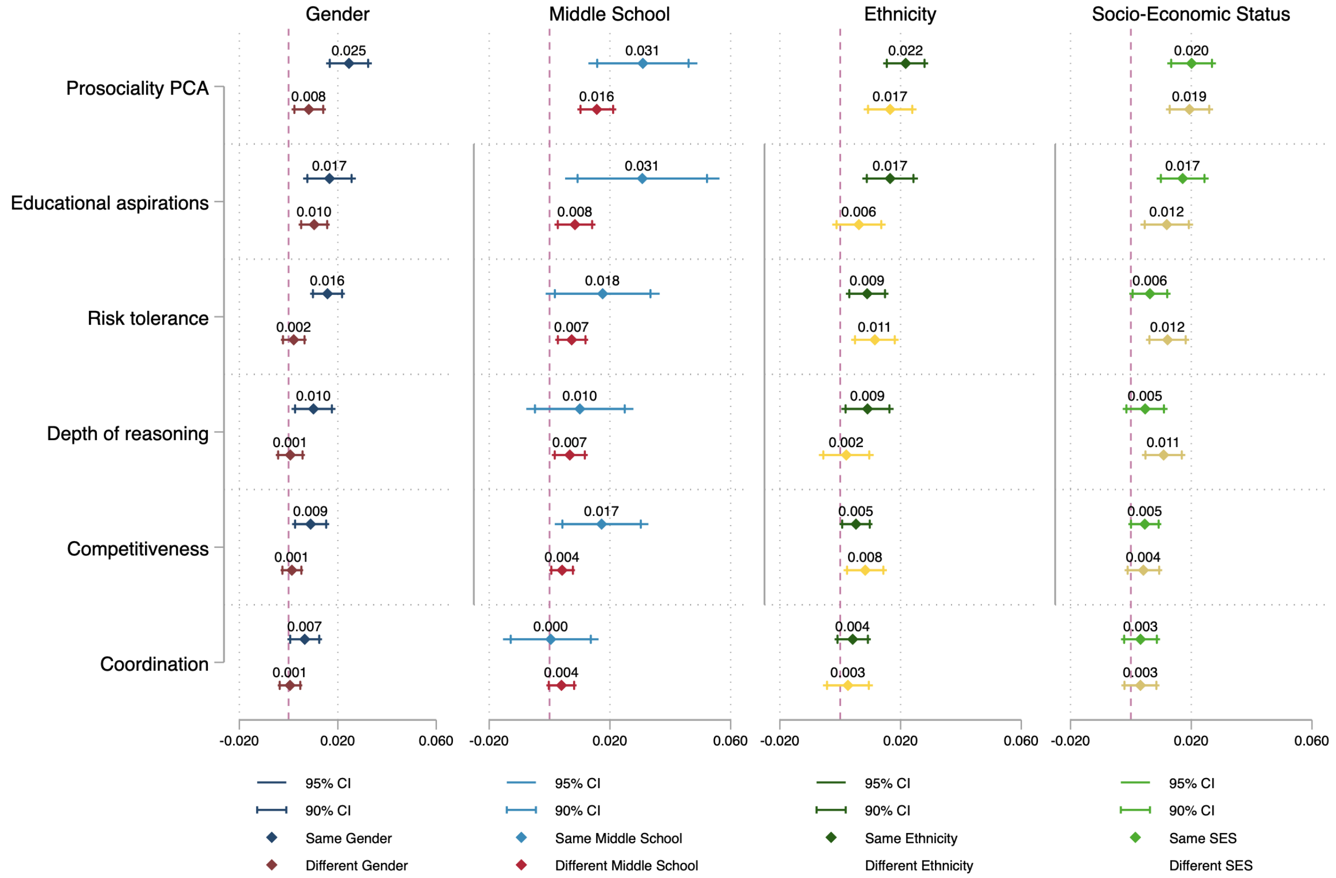
Robustness check: Weighted and directed networks. As a robustness check, we discuss the effects of considering different structures of the underlying network. Imposing an upper bound on the number of friends an individual can report in network data can introduce censorship bias and can attenuate the homophily results (Griffith, 2022). In order to address any potential attenuation bias, we consider two different modifications. First, we consider friendship networks to be weighted. Even though we did not ask students to report their friends in the order of strength of their friendship, we assume that the order in which they typed in their friend's name (which we observe) reflects the strength of their friendship. Out of the individuals within our sample who report at least two friends, the order in which friends are reported follows a strict alphabetical ordering (by either first or last name) only for 5% of the sample. The drop down menu available for the friendship question on the other hand was arranged alphabetically. This bolsters our belief that the friendship reporting order reflects the relative strength of friendship links. Friends then receive weights in a decreasing order based on the intensity of friendship.

[20]Figure A.3 reports coefficients in which measures of similarity in behavioral traits are standardized with a mean of 0 and an SD of 1, while A.4 reports coefficients in which measures of similarity are normalized to take values between 0 and 1. This normalization makes it easier to see what is the effect of having identical versus completely different behavioral traits.

[21]The number of observations in this regression can be lower as some students did not play all the games.

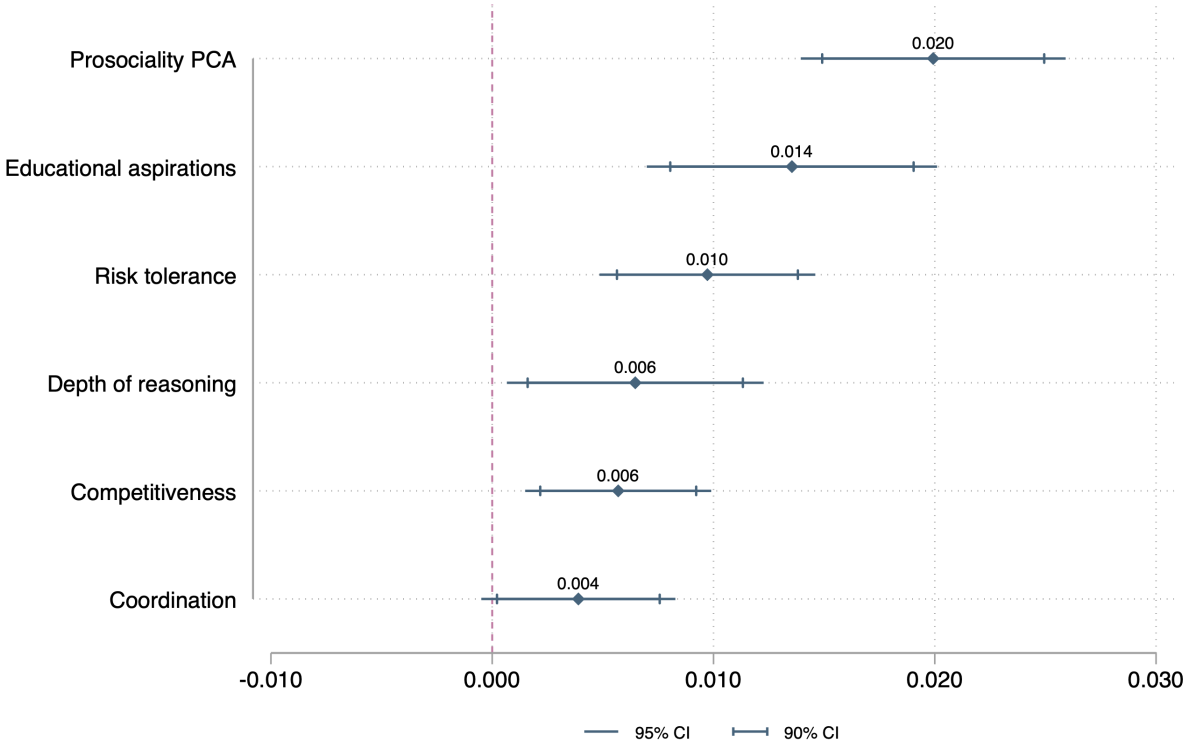
[22]Statistical significance for the coordination coefficient drops to 10%. The remaining coefficients remain statistically significant at the 5% level.

Figure 4: Homophily based on behavioral traits for students who share the same demographic characteristics **(Fact 4)**



Note: This figure plots coefficients for homophily based on behavioral traits. Coefficients in the first sub-panel correspond to sub-samples where individuals either share the same gender or have different gender. Coefficients from the second, third, and fourth sub-panels analogously correspond to sub-samples where individuals either share the same middle school, ethnicity, or SES or have different middle school, ethnicity, SES respectively. Each coefficient corresponds to a separate regression based on eq. 1. We run regressions separately for each sub-group (same gender v.s. different gender, same SES v.s. different SES, and so on). The dependent variable is an indicator variable, which takes the value 1 if individual i sends a friendship link to individual j and 0 otherwise. On the right-hand-side, $|y_i - y_j|$, whose coefficient is reported in the figure, captures how close two students are in terms of behavioral traits. For the sake of comparison, all measures of similarity in behavioral traits in the regressions are standardized. We control for shared demographic characteristics such as gender, ethnicity, nationality, place of residence, SES, number of siblings, age (in months), a dummy to indicate whether the individual is an only child or not, and a dummy to indicate if the individual was born in France. We also control for sender and receiver fixed effects. Standard errors are clustered at the classroom level.

Figure 5: Homophily based on behavioral traits (with control for similarity in each trait) **(Fact 5)**



Note: This figure plots coefficients for homophily based on behavioral traits. The coefficients come from a single regression that includes all the shared behavioral traits on the right-hand side. The dependent variable is an indicator variable which takes the value 1 if individual i sends a link to individual j and 0 otherwise. On the right-hand side, $|y_i - y_j|$, whose coefficient is reported in the figure, captures how close two students are in terms of behavioral traits. All measures of similarity in behavioral traits in the regressions are standardized. We control for shared demographic characteristics such as gender, ethnicity, nationality, place of residence, SES, number of siblings, age (in months), a dummy to indicate whether the individual is a single child or not, and a dummy to indicate if the individual was born in France. We also control for sender and receiver fixed effects. Standard errors are clustered at the classroom level.

We assign the first friend a weight of 1, the second friend a weight of 0.5, the third friend a weight of 0.25 and so on. The averages for friends' predetermined characteristics and behavioral traits are also weighted accordingly. Any bias that might be present due to unreported friends would thus be minimized.

As a second check, we also consider undirected networks, in which a friendship link from student i to j always implies also one from student j to i. This specification therefore includes the additional friendship links, their predetermined characteristics and behavioral traits, that we may obtain by considering a larger undirected network. Considering undirected friendships minimizes the chances of missing out on a friend or a close social acquaintance.

Fig A.5 in the appendix compares the results from our original specification (using a directed and unweighted network in panel A) with those using a weighted network (panel B) or an undirected one (panel C). The overall pattern shows a similar set of coefficients across different network specifications, suggesting at best a minimal censorship bias in the number of reported friends.

4 Peer Effects in Behavioral Traits

Our results so far uncover large homophily in behavioral traits, which raises a natural follow-up question: Does this homophily stem from similar individuals befriending each other—the selection channel— or does homophily stem from behavioral traits transmitting over peer networks—the peer effect channel? When studying homophily in behavioral traits, teasing out the selection effect from the peer effect is important because these two alternative explanations have different implications in terms of mechanisms to influence behavioral traits among children and adolescents. We therefore turn now to the analysis of peer effects in behavioral traits.

4.1 Empirical Strategy

We use a standard equation to identify peer effects[23]:

$$y_{li} = \beta \frac{\sum_{j \in P_{li}} y_{lj}}{n_{li}} + \gamma \mathbf{x}_{li} + \delta \frac{\sum_{j \in P_{li}} \mathbf{x}_{lj}}{n_{li}} + \eta_l + \epsilon_{li} \tag{2}$$

where y_{li} is the behavioral trait of student i in class l, P_{li} is student i's reference group (self reported friends in class l), n_{li} is the number of friends student i has in the class l, y_{lj} is the behavioral trait of the friend j of student i, $\mathbf{x}_{li}$ captures demographic characteristics of student i (such as gender, race, nationality), $\mathbf{x}_{lj}$ captures demographic characteristics of the friend j of student i and η_l captures classroom fixed effect. The coefficient of interest β captures the effect of peer traits on a student's traits. Using the row normalized interaction (adjacency) matrix $\mathbf{G}$ (where $G_{ij} = \dfrac{1}{n_{li}}$ if j nominates i as a friend and 0 otherwise), we can rewrite eq. 2 in the

[23]This equation can be rationalized as a best response function of a social cohesion game where individuals incur disutility by either not conforming or conforming to the social norm of the group (based on their preferences and the behavioral trait in consideration). See section B of the appendix.

matrix form:[24,25]

$$\mathbf{y} = \beta\mathbf{G}\mathbf{y} + \gamma\mathbf{x} + \delta\mathbf{G}\mathbf{x} + \eta + \epsilon \tag{3}$$

The identification of endogenous peer effects poses three well-known issues: (i) Manski's reflection problem (Manski, 1993), (ii) endogenous friendship formation, and (iii) correlated effects. We address the latter—according to which peers share similar environments, typically teachers, that can affect their behavioral traits—by including classroom fixed effects in eq. 2. We explain the way we address the reflection problem and the endogenous friendship formation in the following paragraphs.

To understand our estimation, consider the following example. Assume that in a given classroom, individuals are lined up in a row and every single individual has only 1 friend who stands on their right. Further, assume that these friendships are assigned exogenously (we will lift this assumption later). That is, none of the individuals get to decide who their friend is. Using the serially ordered structure of the classroom and the notation $i-1$ for the friend who stands on the right of student i, eq. 2 can be rewritten as:

$$y_{li} = \beta y_{li-1} + \gamma\mathbf{x}_{li} + \delta\mathbf{x}_{li-1} + \eta_l + \epsilon_{li} \tag{4}$$

Given the assumed exogeneity of the friendship assignment and the fact that classroom fixed effects capture common unobservables, the key problem to be solved is Manski's reflection problem.

Addressing the reflection problem. To address the reflection problem, we can iteratively write eq. 4 in the following form:

$$\begin{aligned} y_{li} &= \beta y_{li-1} + \gamma\mathbf{x}_{li} + \delta\mathbf{x}_{li-1} + \eta_l + \epsilon_{li} \\ y_{li-1} &= \beta y_{li-2} + \gamma\mathbf{x}_{li-1} + \delta\mathbf{x}_{li-2} + \eta_l + \epsilon_{li} \\ y_{li-2} &= \beta y_{li-3} + \gamma\mathbf{x}_{li-2} + \delta\mathbf{x}_{li-3} + \eta_l + \epsilon_{li} \\ &\dots \end{aligned}$$

Similar to an Arellano-Bond structure, y_{li-1} can be instrumented by $\mathbf{x}_{li-1}$, $\mathbf{x}_{li-2}$ and $\mathbf{x}_{li-3}$. Generalizing this to our framework implies instrumenting the behavioral traits of the friends

[24] See Lee et al. (2020) and Patacchini et al. (2017) for additional references on this row normalization.

[25] We also report results using an alternate specification in which we drop the peers' characteristics, i.e. $\frac{\sum_{j \in P_{li}} \mathbf{x}_{lj}}{n_{li}}$ $(\mathbf{G}\mathbf{x})$.

($\mathbf{Gy}$) with the predetermined demographic characteristics (gender, ethnicity, nationality, etc.) of the friends ($\mathbf{Gx}$), friends of friends ($\mathbf{G^2x}$) and friends of friends of friends ($\mathbf{G^3x}$).[26] The intuition behind these instruments, introduced by Case and Katz (1991) and Bramoullé et al. (2009), is simple. The friends of a student i might be more risk averse, for example, if the friends' own network is composed of a larger share of girls (see Figure 2 for evidence of this gender difference in our sample).

Assuming for now that friendships are formed exogenously—an assumption that we lift below— this IV strategy relies on the following exclusion restriction: the only reason why the predetermined characteristics of second degree friends ($\mathbf{G^2x}$) or third degree friends ($\mathbf{G^3x}$) impact the behavioral traits of the individual ($\mathbf{y}$) is through their impact on the behavioral traits of their direct friends ($\mathbf{Gy}$). For instance, the only reason why the gender composition of my friends' networks ($\mathbf{G^2x}$) affects my level of risk aversion ($\mathbf{y}$) is because it affects my friends' risk aversion ($\mathbf{Gy}$). Said differently, the fact that my friends' network is composed of many girls has no direct effect on the unobservable characteristics (ϵ) that affect my level of risk aversion.[27] The plausibility of this assumption depends on the exogeneity of the network.

In our environment, friendships are not assigned exogenously. They are formed endogenously. They can be shaped by shared experiences and similarity in behavioral traits. As a result, the friendship matrix $\mathbf{G}$ can be correlated with the unobservable characteristics of the student i or similarity in behavioral traits may influence friendship formation. If a student chooses their friend based on the similarity of behavioral traits, then the β coefficient in our regression could pick up both peer effects and a selection effect. To address the endogenous formation of networks, we now turn to the second central element of our identification strategy.

Addressing endogenous friendship formation. Instead of using the endogenous friendship network of students within our instruments, we use the predicted friendship network, where the prediction is based on students' shared predetermined demographic characteristics, a solution introduced by König et al. (2019) and Gagete-Miranda (2020). [28]

[26] When eq. 3 includes contextual variables (i.e., $\mathbf{Gx}$), the demographic characteristics of the direct friends ($\mathbf{Gx}$) are no longer excluded instruments for the behavioral traits of the direct friends ($\mathbf{Gy}$).

[27] I.e. the Bramoullé et al. (2009) instruments are essentially auto-spatial regressive Arellano-Bond instruments.

[28] Other papers have dealt with endogenous network formation by using randomization (Comola and Prina, 2021) or through the joint estimation of the network-formation process and actions (Goldsmith-Pinkham and Imbens, 2013; Johnsson and Moon, 2021; Hsieh et al., 2020; Griffith, 2024). The latter solution is not well-suited to our setting for several reasons. First, some of the functional form assumptions required to ensure uniqueness of the equilibrium are not plausible enough in our setting. For instance, pairwise stable graphs with optimal actions should take the form of nested split graphs or overlapping cliques (Golub and Sadler, 2021), a network structure that is unlikely to be observed when measuring peer effects over a host of outcomes because effort and actions are multidimensional. Second, most methods that jointly estimate network formation and actions are computationally intensive and shy away from the inclusion of fixed effects which are important in our case (especially classroom fixed effects). Finally, our method of partialling out the effect of homophily in behavior and only relying on similarity in demographic characteristics in our instruments comes close to a partial equilibrium analysis with minimal structural assumptions. Our work therefore closely follows Lee et al. (2020), Patacchini and Zenou

Our instruments only retain the variation in friendship links that stem from sharing predetermined demographic characteristics with friends. Controlling for an individuals' own demographic characteristics, their friends' demographic characteristics and classroom level fixed effects, the variation in our instruments relies on the fact that shared demographic characteristics induce exogenous variation in the probability of friendship formation (independent of shared behavioral traits). This solution originates from evidence documented earlier in the paper that friendships are subject to a large degree of homophily among individuals who share the same demographic characteristics (such as gender, ethnicity, social background, or postal code). In essence, to tackle the endogenous friendship network, we replace the reported network $\mathbf{G}$ in our instruments by the first, second, and third degree predicted networks $\hat{\mathbf{G}}$.

Identifying assumption. Our method generates a set of predicted n^{th}-order friends. Our source of identifying variation—the predetermined demographic characteristics of the n^{th}-order predicted friends—is valid so long as the characteristics of these predicted 2^{nd} or 3^{rd}friends (i) affect the behavioral traits of the friends—first stage—but (ii) do not directly impact a student's traits beyond the average effect of these characteristics at the class level. In essence, our identification assumption can be summarized in the following sequential steps:

1. *Assume exogenous friendship formation.* Under this assumption, rely on the fact that controlling for an individual's, their friends' demographic characteristics and classroom level fixed effects, the friends' behavioral traits are as-good-as-random, i.e., uncorrelated with a student's unobservable characteristics (the error term). Moreover, the demographic characteristics of non-friends (second and third order friends) can only impact an individual's behavioral trait through the behavioral trait of their friends. Then the demographic characteristics of second and third order friends provide valid instruments for the behavioral traits of friends.

2. *Lift the exogenous friendship assumption.* Within instruments, we use the exogenous variation in friendships driven by shared pre-determined demographic variables that cannot be endogenously altered by students. Variation in the demographic characteristics of second and third order *predicted* friends provide valid instruments for the behavioral traits of friends.

In summary, for our identification to be valid, we need the correlation between the traits of individuals and their friends to be independent of unobserved factors beyond classroom fixed effects and the demographic characteristics we control for. Despite being strong, we believe our assumption is reasonably plausible for two reasons. First, classroom fixed effects control

(2012) and special models laid down in Goldsmith-Pinkham and Imbens (2013).

for a large set of factors in an individual and their friends' environment. Second, a strength of our analysis is the very rich set of demographic characteristics we are able to control for, both for the students and their friends (such as gender, race, socio-economic status, nationality, residential postal code, parental occupation, age (in months), number of siblings, and birth location). With these controls, we capture a large set of plausible determinants of behavioral traits documented in the economics and sociology literature.

Friendship prediction. We use the following logit model to predict the friendship probabilities:

$$\mathbb{P}(d_{ij} = 1|\mathbf{M}'_{ij}, \mathbf{x}_i, \mathbf{x}_j) = \frac{\exp(\mathbf{M}'_{ij}\psi + \theta_i\mathbf{x}_i + \theta_j\mathbf{x}_j + \gamma_l + \nu_{ij})}{1 + \exp(\mathbf{M}'_{ij}\psi + \theta_i\mathbf{x}_i + \theta_j\mathbf{x}_j + \gamma_l + \nu_{ij})} \quad (5)$$

where $d_{ij} = 1$ if student i nominates student j as a friend and $d_{ij} = 0$ otherwise. In our analysis, friendship pairs only exist within a class. $\mathbf{M}'_{ij}$ captures the vector of *shared* predetermined demographic characteristics based on which networks can exhibit homophily. This vector contains dummies for shared gender, ethnicity, nationality, middle school, residential postal code, SES, single child status, country of birth, as well as continuous variables that capture differences in age (in months) and the number of siblings. $\mathbf{x}_i$ and $\mathbf{x}_j$ are vectors of sender and receiver demographic characteristics, including gender, nationality, ethnicity, parental occupation, age (in months), and number of siblings. When estimating the model, we also include a set of interaction terms between the demographic characteristics of student i (sender) and student j (receiver). γ_l is a class fixed effect and ν_{ij} is an error term.

Using eq. 5, we compute $\hat{d}_{ij}$, the predicted probability of individual i sending a friendship link to individual j in their class. Then, using $\hat{d}_{ij}$, we construct $\hat{\mathbf{G}}$ which contains the predicted (row normalized) friendship probabilities within a class with $\hat{g}_{ij} = \frac{\hat{d}_{ij}}{\sum_j \hat{d}_{ij}}$.[29]

2SLS estimation. After having predicted the friendship network, we use a standard 2SLS estimation approach. We regress friends' behavioral traits on a set of predetermined demographic characteristics of predicted n-degree friends $Z = [\hat{\mathbf{G}}\mathbf{x}, \hat{\mathbf{G}}^{\mathbf{2}}\mathbf{x}, \hat{\mathbf{G}}^{\mathbf{3}}\mathbf{x}]$ in order to predict $\widehat{\mathbf{Gy}}$. Said differently, we use the demographic characteristics of the predicted friends, friends of friends and friends of friends of friends to predict the behavioral trait of the predicted friends $\widehat{\mathbf{Gy}}$. This gives us a single instrumental variable for the observed behavioral trait of the friends $\mathbf{Gy}$.

Specifically, we estimate:

$$\mathbf{Gy} = \zeta_1\hat{\mathbf{G}}\mathbf{x} + \zeta_2\hat{\mathbf{G}}^{\mathbf{2}}\mathbf{x} + \zeta_3\hat{\mathbf{G}}^{\mathbf{3}}\mathbf{x} + \zeta_4\mathbf{x} + \zeta_5\mathbf{G}\mathbf{x} + \eta + \epsilon \quad (6)$$

[29]If individual i and j do not belong to the same classroom then $\hat{g}_{ij} = 0$.

where $\mathbf{Gy}$ captures the behavioral traits of the friends. $\hat{\mathbf{G}}\mathbf{x}$, $\hat{\mathbf{G}}^{\mathbf{2}}\mathbf{x}$, and $\hat{\mathbf{G}}^{\mathbf{3}}\mathbf{x}$, respectively, correspond to the demographic characteristics of the predicted first-, second-, and third-degree friends—i.e., their gender, ethnicity, SES, nationality, residential postal code, parental occupation, age (in months), number of siblings, a single child dummy, and location of birth. $\mathbf{x}$ captures the same demographic characteristics for student i, and $\mathbf{Gx}$ the observed demographic characteristics of the first degree friends. η is a class fixed effect.[30]

In a second stage, we use the predicted behavioral trait of the predicted friends $\widehat{\mathbf{Gy}}$ as an instrumental variable for the observed behavioral trait of the friends $\mathbf{Gy}$. The **second stage** regression corresponds to eq. 3 in which we use the predicted value $\widehat{\mathbf{Gy}}$ as an instrument for $\mathbf{Gy}$ ((Kuersteiner and Okui, 2010)).

$$\mathbf{y} = \beta\mathbf{Gy} + \gamma\mathbf{x} + \delta\mathbf{Gx} + \eta + \epsilon \tag{7}$$

We use the same vector of demographic characteristics as in the first stage regression. β is our coefficient of interest which captures how much one's friends' behavioral traits affect a student's own traits.

In order to further ensure the validity of our assumptions and test the robustness of our results, we carry out a host of alternate specifications. Firstly, we test how stable the results are to the inclusion or exclusion of the friends' demographic characteristics. While common practice, the inclusion of contextual variables (the demographic characteristics of friends) when the behavioral traits of friends are already accounted for, runs the risk of overfitting the model.[31] Our results are fairly stable to both the inclusion and exclusion of contextual variables.

Secondly, since we asked students to report up to 5 friends, we may run into ceiling bias ((Griffith, 2022)) and this may cause potential threats to identification.[32] However, using a predicted network rather than the observed network in the instruments, by ruling out the possibility of endogenous unobserved friendships, assuages concerns of potential threats to identification that missing links in networks may cause. We also test specifications where we alter the underlying friendship network to be either weighted or undirected. In the weighted network analysis, a friend listed last is given a lower weight, whereas, in an undirected network analysis, we allow a link to appear when someone is listed as a friend. The consistency of results under these robustness checks further assuages the concern of missing links and shows that censorship bias

[30]To estimate eq. 6, we take a global difference by subtracting the class average to each variable.

[31]For example, controlling for the risk tolerance of friends and one's own demographic characteristics, there is no reason to believe why the gender / nationality / ethnicity of an individuals' friends will have an independent impact on an individual's risk tolerance.

[32]Because students can only name 5 friends, we miss information on friends ranked lower than the 5th rank which can hamper the plausibility of the exogeneity of the instruments. For instance, when student A names B as a friend and B and C are friends, but C is ranked 6th among A's friends, then A and C do not name each other in the survey. As a result, when C's characteristics are used as instruments for B's traits, C's characteristics might be directly correlated to A's traits, which makes C's characteristics an invalid set of instruments.

is not a major concern in our setting.

4.2 Results on peer effects in behavioral traits

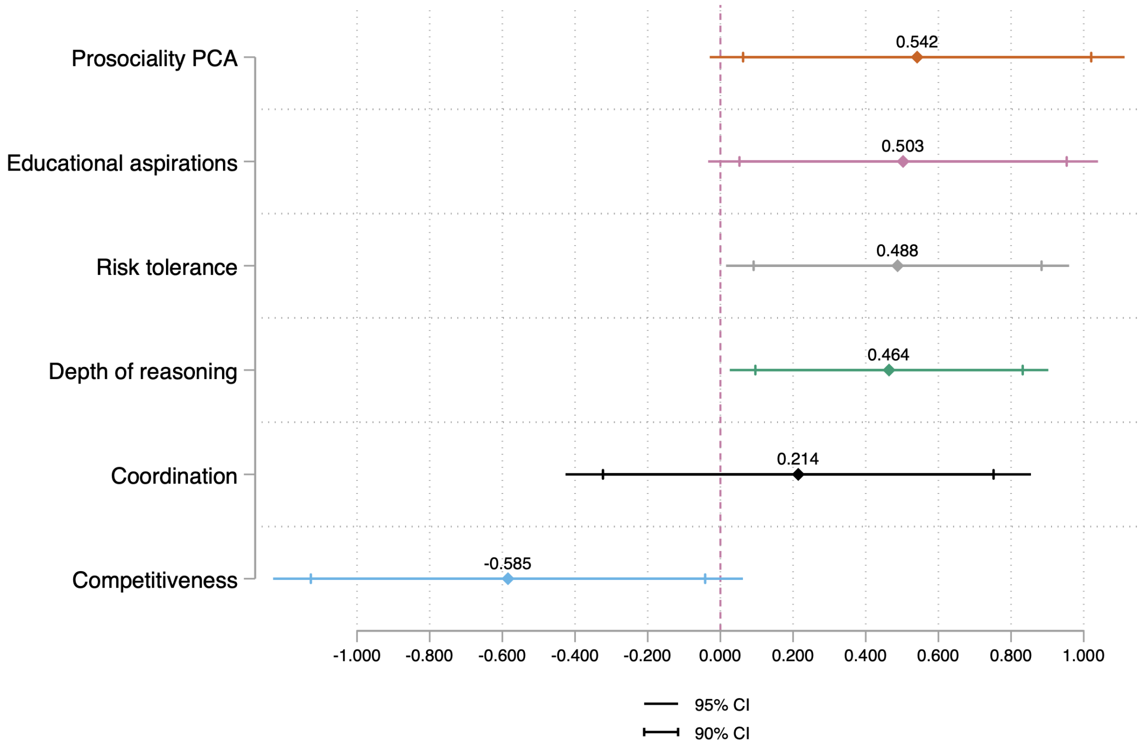
Friendship prediction. Table A.2 in the appendix reports results from the friendship prediction exercise. As seen when discussing homophily, students' predetermined characteristics play a key role in explaining link formation. Shared gender has the highest explanatory power. Shared geographical proximity (postal code), shared ethnicity, shared social background, having attended the same middle school, and similarity in age also substantially explain the probability of link formation.[33] Table 3 reports that Cragg Donald F statistics for the first stage regressions (eq. 6) are all larger than 10.

Peer effects in behavioral traits. Figure 6 shows the results on peer effects in behavioral traits. The corresponding coefficients are reported in Table 3. To ease the interpretation and comparison of the coefficients, we standardized the behavioral traits variables to have a mean of zero and a standard deviation of one. We present the results from the specification that includes contextual variables (i.e., demographic characteristics of friends).[34] Overall, we see fairly large peer effects. For the top four traits shown in Figure 6, a one-standard deviation increase in one's peers' traits leads to an increase in a student's own trait by about 50% of a standard deviations. So, peers' prosociality, educational aspirations, risk tolerance and depth of reasoning have strongly positive effects on a student's own traits. The only insignificant result is found for coordination behavior. Interestingly, we find a (weakly) significantly negative effect for competitiveness. If peers are more competitive by one standard deviation, a student's competitiveness is reduced by about 0.59 standard deviations. Shan and Zölitz (2022) found positive peer effects on competitiveness in their exogenously manipulated networks (of university students). With endogenous networks this looks different, illustrating nicely in our setting the differences between exogenous and endogenous network effects identified by Carrell et al. (2013). In fact, work by Kosse et al. (2022) shows a causally negative effect of competitiveness on prosociality. Given the importance of prosociality, like cooperation or trust, for friendship links, our negative estimates for peer effects on competitiveness may suggest that friendship networks are at risk if all of its members became too competitive. Yet, we will get back to competitiveness below, revealing an interesting interaction with the popularity of peers.

[33] Table A.2 also reports the McFadden pseudo R^2 and adjusted R^2. Note that the pseudo R^2s of the regressions are relatively low and do not increase significantly with the inclusion of interaction terms and classroom fixed effects. This is because shared predetermined characteristics can only explain part of the dimensions on which networks exhibit homophily. However, to ensure the validity of the instruments, any other dimensions, such as behavioral traits or student fixed effects, cannot be used to predict friendship as they would generate an automatic correlation between the network and the error term of the second stage equation of the IV model.

[34] The results from the specification without contextual variables are reported in section 4.3.

Figure 6: Coefficients from peer effects analysis **(Fact 6)**



Note: This figure reports coefficients of peer effects in behavioral traits. Each coefficient corresponds to a separate regression based on eq. 7. The dependent variable is the behavioral trait of a student. The coefficient reported in the figure corresponds to the effect of the friends' average behavioral trait. We standardized the behavioral traits variables to have a mean of zero and a standard deviation of one. For instance, the top coefficient reports the effect of a one standard deviation increase in the average depth of reasoning of friends on an individual's depth of reasoning. We instrument the friends' average behavioral trait using the predicted behavioral trait of the predicted friends $\widehat{\mathbf{Gy}}$. Each regression includes control variables for the following demographic characteristics of the individual and of the friends: gender, ethnicity, nationality, SES, only child status, country of birth, age (in months), and number of siblings. Regressions include classroom fixed effects. Standard errors are clustered at the classroom level.

All in all, our set of results on peer effects shows that students are strongly influenced by the behavioral traits of their peers. These novel results suggest that peer effects contribute to the large homophily based on behavioral traits.

Fact 6: *Students are influenced considerably by the behavioral traits of their peers. These peer effects contribute to the sizeable homophily based on behavioral traits that we documented in Section 3 (Fact 3).*

When familiarity breeds influence: Under which conditions are peer effects particularly strong? We documented in Section 3 that homophily based on behavioral traits is higher

Table 3: Coefficients from peer effects analysis

	Reasoning	Risk	Coord.	Aspiration	Compet.	Prosociality
Friend avg. skill	0.464**	0.488**	0.214	0.503*	-0.585*	0.542*
	(0.224)	(0.241)	(0.327)	(0.274)	(0.330)	(0.291)
Female	-0.166***	-0.053	-0.124**	-0.064	-0.258***	0.117**
	(0.051)	(0.057)	(0.053)	(0.051)	(0.059)	(0.050)
French	-0.369**	-0.007	-0.028	-0.061	0.083	0.206+
	(0.158)	(0.162)	(0.204)	(0.152)	(0.167)	(0.142)
White	-0.027	0.030	-0.006	-0.033	0.062	0.054
	(0.058)	(0.059)	(0.056)	(0.051)	(0.064)	(0.058)
Age	0.002	-0.001	-0.001	-0.011***	0.001	-0.003
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
No. of sib	-0.002	0.009	-0.016	0.035	0.002	-0.048+
	(0.030)	(0.027)	(0.032)	(0.027)	(0.033)	(0.031)
Single child	0.051	-0.024	-0.086	-0.031	-0.056	-0.001
	(0.063)	(0.060)	(0.065)	(0.060)	(0.081)	(0.067)
SES	0.036	0.011	-0.088**	-0.116***	-0.016	-0.088**
	(0.047)	(0.050)	(0.044)	(0.041)	(0.048)	(0.043)
Born in France	0.222*	-0.026	-0.104	0.107	-0.163	-0.217*
	(0.118)	(0.130)	(0.138)	(0.130)	(0.134)	(0.120)
Contextual var.	Y	Y	Y	Y	Y	Y
Adj. R-sq	-0.084	-0.089	-0.022	-0.074	-0.065	-0.025
N	2296	2547	2294	2514	2308	2393
CD F Stat.	41.256	37.486	43.242	29.864	29.982	19.012
MP F Stat.	41.256	37.486	43.242	29.864	29.982	19.012

Note: This table reports coefficients of peer effects in behavioral traits. Each column corresponds to a separate regression based on Eq.7. The dependent variable is the behavioral trait of a student. The coefficient of interest, reported in the first row, corresponds to the effect of the friends average behavioral trait. We standardized the behavioral traits variables to have a mean of zero and a standard deviation of one. We instrument the friends' average behavioral trait using the predicted behavioral trait of the predicted friends $\hat{\mathbf{G}}\mathbf{y}$. Each regression includes control variables for the following demographic characteristics of the individual and of the friends: gender, ethnicity, nationality, SES, only child status, country of birth, age (in months), and number of siblings. Regressions include classroom fixed effects. Standard errors are clustered at the classroom level. The last row reports the Cragg Donald F statistic of the first stage regression (based on Eq 6). *** p<0.01, **p<0.05, * p<0.1, + p<0.15

when students share the same gender than when considering opposite gender pairs (Figure 4). For other demographic characteristics, like attending same middle school, SES or ethnicitiy, we found less clear effects. Next we want to investigate whether similarity in those demographic factors also interacts with the level of peer effects.

To look into this question, we first re-estimated peer effects separately for those male and female students whose network is predominantly composed of male (resp. female) friends. Specifically, we split our sample into two subgroups. The first group corresponds to males (resp. females) whose network is composed of more than 50% of male (resp. female) friends. We refer to this sample as the "Same gender" sample. The second group corresponds to males (resp. females) whose network is composed of less than 50% of male (resp. female) friends. We refer to this sample as "Different gender".

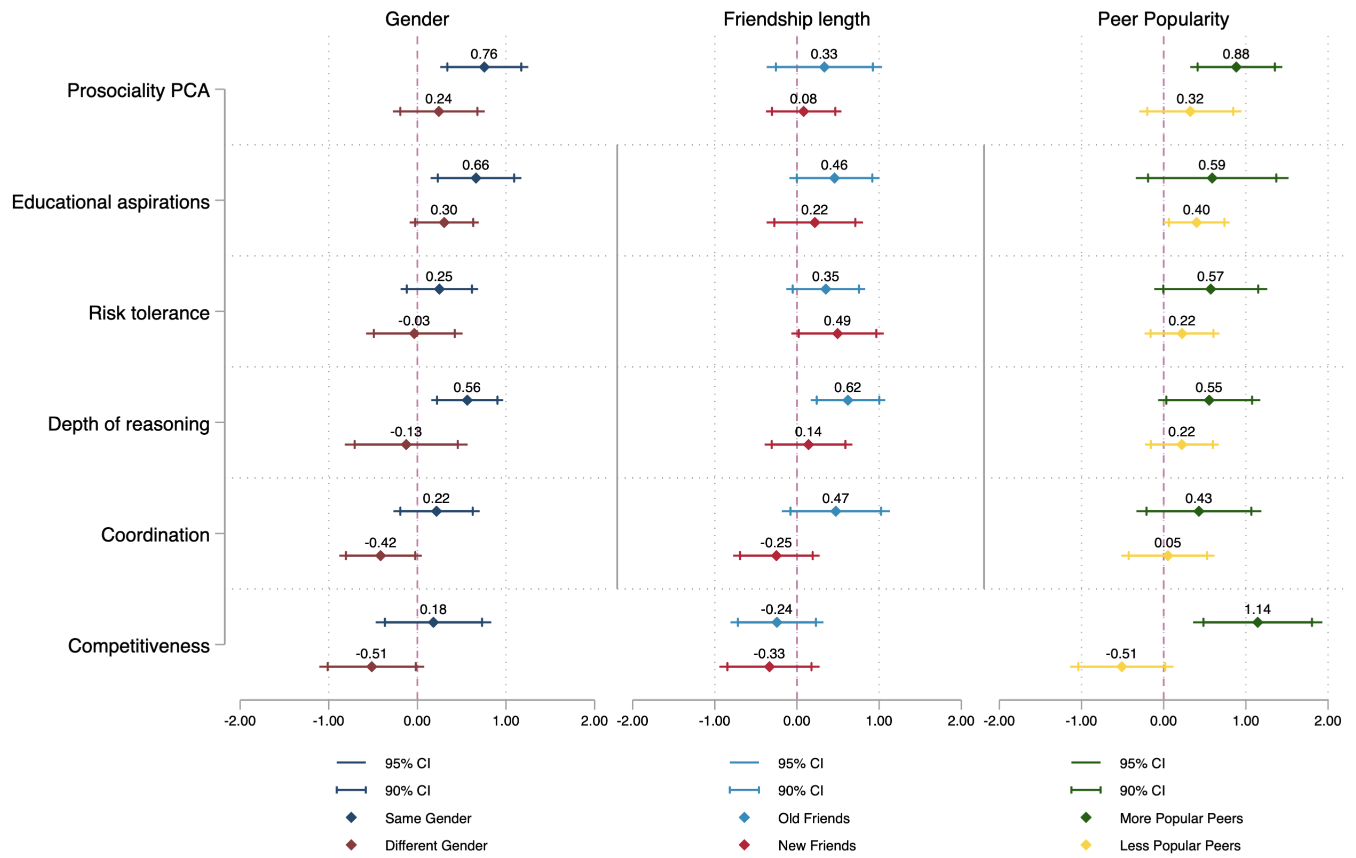
Figure 7 shows that the estimated peer effects are always larger in same-gender friendship networks than if friends are of opposite gender. Increasing prosociality by one SD in a network of same-gender friends leads to a 0.76 SD jump in a student's own prosociality. This peer effect moves down to a non-significant 0.24 SD in case of different-gender friends. We find similar differences for other traits (+0.66 SD versus +0.20 SD for educational aspirations, and +0.56 SD versus -0.13 for depth of reasoning, just to mention two examples). We find some limited evidence that friendship length (middle panel of Figure 7) and peer popularity (right panel) enhances peer effects. Yet, the estimates are generally closer to each other than in the panel for gender.

The last line on competitiveness in the panel on peer popularity is noteworthy, however. To start with, the analysis of peer effects conditional on the popularity of peers is based on the following approach. Our measure of popularity is the number of students within a class who nominate an individual as their friend. The median of the average popularity of an individual's friend is 3. Therefore, we split the sample into subsets of individuals who are friends with more popular peers (average popularity of friends is greater than 3) and individuals who are friends with less popular peers (average popularity of friends is less than or equal to 3). For competitiveness, we see significantly positive peer effects in case of popular peers, but significantly negative peer effects for less popular peers.[35] Overall, these findings seem to suggest that individuals are more strongly influenced by popular peers and hence try to emulate them. In Figure A.6 in the appendix we also present results on whether peer effects differ conditional on friends having similar SES or not. There we find no clear-cut pattern, with peer effects sometimes being stronger, but sometimes also being weaker in case of shared SES.

Fact 7: *Similarity in gender seems to amplify peer effects in behavioral traits. This amplifying effect can explain why similarity in demographic characteristics amplifies homophily based on behavioral traits, as documented in Section 3 (Fact 4).*

[35]This means that for the group of popular peers we observe positive peer effects, just like in Shan and Zölitz (2022), but the direction of peer effects on competitiveness seems to depend on peers' popularity.

Figure 7: Peer effects by similarity in demographic characteristics, friendship length, and peer popularity **(Fact 7)**



Note: This figure reports coefficients of peer effects in behavioral traits. Each coefficient corresponds to a separate regression based on eq. 7. The dependent variable is the behavioral trait of a student. The coefficient reported in the figure corresponds to the effect of the friends' average behavioral trait. Behavioral traits are standardized to have a mean of zero and a standard deviation of one. We instrument the friends' average behavioral trait using the predicted behavioral trait of the predicted friends $\widehat{\mathbf{G}\mathbf{y}}$. Each regression includes classroom fixed effects as well as control variables for the following demographic characteristics of the individual and of the friends: gender, ethnicity, nationality, SES, only child status, country of birth, age (in months), and number of siblings. Standard errors are clustered at the classroom level. The samples in the first panel are split by the gender composition of one's friends. Same gender refers to the group of male (female) students with more than half of their friends also being males (females). Different gender refers to the group of female (male) students with more than half of their friends being of the opposite gender. The second panel splits the sample by individuals who on an average have older (newer) friends in their network. The third panel splits the sample by individuals who have more (less) popular friends.

4.3 Robustness checks

Weighted and directed networks. As a first robustness check, we discuss the effects of considering different structures of the underlying network, namely, directed and weighted networks. Intuitively, the influence that a close friend has on a student might be stronger than the influence of distant friends. Weighting friendship links might therefore affect the results.

Figure A.8 in the appendix compares the results using directed networks (our baseline specification), weighted networks, and undirected (and unweighted) networks. As before, we run separate regressions for our behavioral traits.[36] The coefficients are similar across different network specifications, giving rise to two conclusions. First, for most behavioral traits we consider, accounting for the strength of a relationship has little effect on the estimated peer effects, suggesting that close and distant friends have a similar influence. Second, as noticed in the homophily section, censorship bias in the number of reported friends seems to be a limited concern in our setting.

Controlling for exogenous peer effects. We assess the extent to which our results change if we do not control for the peers' demographic characteristics, a relevant specification if one believes that peers' characteristics do not affect a student's traits above and beyond peers' own traits. The results are reported in Figure A.7 and are broadly similar to what we find in our original analysis. As a matter of fact, when we do not control for peers' demographic characteristics, the peer effects of some traits become slightly more statistically significant. This might be because controlling for peers' demographic characteristics in our original specification runs the risk of overfitting the model by leaving too little room for peers' behavioral traits to influence a student's own behavioral traits when we already account for the influence of peers' demographic characteristics.[37]

Variations on network prediction. Finally, to rule out concerns related to a potential correlation between the demographic characteristics of the predicted friends and the unobserved characteristics of a student, we check whether our results are sensitive to the use of alternative specifications to predict the friendship networks. We test eight different specifications for the network prediction. In Columns 1 and 2 of Table A.3, we only use the sender and receiver shared characteristics to predict friendships. In Columns 3 and 4, we additionally include interaction terms between each demographic characteristic (e.g., *Female*$\times$*French*, *Female*$\times$*White*

[36] In weighted networks, we assign the first friend a weight of 1, the second friend a weight of 0.5, the third friend a weight of 0.25 and so on. The averages for friends' predetermined characteristics and behavioral traits are also weighted accordingly. To predict the network, we resort to a simple OLS design (rather than the logit specification) because the dependent variable is no longer a binary variable.

[37] Excluding peers' demographic characteristics from the peer effect regression has the additional benefit of freeing up this variable as an additional instrumental variable to determine friends' behavioral traits.

and so on). In Columns 5 and 6, we return to the specification with no interaction terms and introduce classroom fixed effects to account for idiosyncrasies in friendship formation that may exist at a classroom level. Finally, in Columns 7 and 8, we incorporate sender and receiver characteristics, interaction terms, and classroom fixed effects to extract as much explanatory power as possible. This last version is the one we use for all results reported earlier.[38] Table A.3 shows that our results are very consistent across alternative specifications.

5 Conclusion

We have explored a unique data set that combines surveys, incentivized experiments, and administrative data from more than 2,500 French high school students. Besides collecting data on their friendship networks and demographic background, we elicited many behavioral traits. This allowed us to, first, examine the extent of homophily in behavioral traits among these students, and, second, to estimate the degree of peer effects in such endogenously evolving networks. Both aspects of our paper provide new insights.

Homophily in behavioral traits prevails in each single trait. The breadth of this set, and the fact that these traits (except for the educational aspirations) were elicited with incentives, distinguishes our paper from previous work. While our focus has been on behavioral traits, our paper confirms earlier findings that have found large degrees of homophily in demographic characteristics (such as gender, SES, and geographic proximity; McPherson et al. (2001)). We add to this the insight that similarity in demographic characteristics facilitates homophily in behavioral traits. We find across the board that individuals who share demographic characteristics exhibit homophily on behavioral traits more often than individuals who do not.

Using network econometric techniques, we then explore to what extent this homophily exists because of transmission of behavioral traits over social networks. To estimate the effect of friends' behavioral traits on an individual's traits, we instrument the behavioral traits of friends with the demographic characteristics of the predicted friends, friends of friends, and friends of friends of friends. We find significant peer effects for all behavioral traits except for coordination. For instance, a one SD increase in friends' prosociality, risk tolerance, aspirations, and depth of reasoning increases a student's own level of that trait by about 0.5 SD for each trait. Peer effects are stronger in more homogenous groups, typically when friends have the same gender. We conclude that the observed homophily in behavioral traits is not only due to self-selection, but is also driven by the transmission of these traits in social networks.

Overall, the findings of this study can be of substantive policy importance. Behavioral traits have been shown to be important for life outcomes (Cunha and Heckman, 2007b, 2008; Kosse

[38]For each behavioral trait, Table A.3 reports 8 coefficients (4 network predictions $\times$ 2 specification to include / exclude contextual variables.)

and Tincani, 2020; Algan et al., 2022). We provide novel evidence on the influence of social networks on the formation of these traits. While recent work has looked into the effects of the family (Falk et al., 2021; Chowdhury et al., 2022) or educational interventions on behavioral traits (Cappelen et al., 2020; Kosse et al., 2020), social networks represent another major factor of influence. Previous work has shown that demographic factors are often a source of segregation of networks. People are more likely to befriend those similar to them, for example, in gender, SES, or geographic location. We show that homophily also prevails with respect to a broad set of behavioral traits. So this may also contribute to some segregation of social networks and may thus amplify the segregation due to demographic characteristics. Because behavioral traits are partly malleable, finding homophily in them means that interventions that affect behavioral traits will not only have a direct effect on students' outcomes, as documented by Kautz et al. (2014), Alan et al. (2021), or Sorrenti et al. (2020)), but also an indirect effect through a potential change of peers and their behavioral traits.

References

Alan, Sule, Ceren Baysan, Mert Gumren, and Elif Kubilay, "Building social cohesion in ethnically mixed schools: An intervention on perspective taking," *Quarterly Journal of Economics*, 2021, *136* (4), 2147–2194.

__ **, Teodora Boneva, and Seda Ertac**, "Ever failed, try again, succeed better: Results from a randomized educational intervention on grit," *Quarterly Journal of Economics*, 2019, *134* (3), 1121–1162.

Algan, Yann, Elizabeth Beasley, Sylvana Côté, Jungwee Park, Richard E Tremblay, and Frank Vitaro, "The impact of childhood social skills and self-control training on economic and noneconomic outcomes: Evidence from a randomized experiment using administrative data," *American Economic Review*, 2022, *112* (8), 2553–79.

Almås, Ingvild, Alexander W Cappelen, Kjell G Salvanes, Erik Ø Sørensen, and Bertil Tungodden, "Willingness to compete: Family matters," *Management Science*, 2016, *62* (8), 2149–2162.

Almlund, Mathilde, Angela Lee Duckworth, James Heckman, and Tim Kautz, "Personality psychology and economics," in "Handbook of the Economics of Education," Vol. 4, Elsevier, 2011, pp. 1–181.

Angerer, Silvia, Philipp Lergetporer, Daniela Glätzle-Rützler, and Matthias Sutter, "Cooperation and discrimination within and across language borders: Evidence from children in a bilingual city," *European Economic Review*, 2016, *90*, 254–264.

Ballester, Coralio, Antoni Calvó-Armengol, and Yves Zenou, "Who's who in networks. wanted: The key player," *Econometrica*, 2006, *74* (5), 1403–1417.

Banerjee, Abhijit, Arun G Chandrasekhar, Esther Duflo, and Matthew O Jackson, "Using gossips to spread information: Theory and evidence from two randomized controlled trials," *Review of Economic Studies*, 2019, *86* (6), 2453–2490.

Becker, Anke, Thomas Deckers, Thomas Dohmen, Armin Falk, and Fabian Kosse, "The relationship between economic preferences and psychological personality measures," *Annual Review of Economics*, 2012, *4* (1), 453–478.

Berg, Joyce, John Dickhaut, and Kevin McCabe, "Trust, reciprocity, and social history," *Games and Economic Behavior*, 1995, *10*, 121–142.

Beugnot, Julie, Bernard Fortin, Guy Lacroix, and Marie Claire Villeval, "Gender and peer effects on performance in social networks," *European Economic Review*, 2019, *113*, 207–224.

Borghans, Lex, Bart HH Golsteyn, James Heckman, and John Eric Humphries, "Identification problems in personality psychology," *Personality and Individual Differences*, 2011, *51* (3), 315–320.

Bramoullé, Yann, Habiba Djebbari, and Bernard Fortin, "Identification of peer effects through social networks," *Journal of Econometrics*, 2009, *150* (1), 41–55.

Buser, Thomas, Muriel Niederle, and Hessel Oosterbeek, "Gender, competitiveness, and career choices," *Quarterly Journal of Economics*, 2014, *129* (3), 1409–1447.

Cadena, Brian C and Benjamin J Keys, "Human capital and the lifetime costs of impatience," *American Economic Journal: Economic Policy*, 2015, *7* (3), 126–53.

Caliendo, Marco, Frank Fossen, and Alexander Kritikos, "The impact of risk attitudes on entrepreneurial survival," *Journal of Economic Behavior & Organization*, 2010, *76(1)*, 45–63.

_ , _ , and _ , "Personality characteristics and the decisions to become and stay self-employed," *Small Business Economics*, 2014, *42(4)*, 787–814.

Cappelen, Alexander, John List, Anya Samek, and Bertil Tungodden, "The effect of early-childhood education on social preferences," *Journal of Political Economy*, 2020, *128* (7), 2739–2758.

Cappelen, Alexander W., Astri Drange Hole, Erik Ø Sørensen, and Bertil Tungodden, "The pluralism of fairness ideals: An experimental approach," *American Economic Review*, 2007, *97* (3), 818–827.

Carrell, Scott E., Bruce I. Sacerdote, and James E. West, "From natural variation to optimal policy? The importance of endogenous peer group formation," *Econometrica*, 2013, *81* (3), 855–882.

Case, Anne C. and Lawrence F. Katz, "The company you keep: The effects of family and neighborhood on disadvantaged youths," *Technical Report, National Bureau of Economic Research*, 1991.

Castillo, Marco, Jeffrey L. Jordan, and Ragan Petrie, "Children's rationality, risk attitudes and field behavior," *European Economic Review*, 2018, *102(C)*, 62–81.

_ , Paul J Ferraro, Jeffrey L Jordan, and Ragan Petrie, "The today and tomorrow of kids: Time preferences and educational outcomes of children," *Journal of Public Economics*, 2011, *95* (11-12), 1377–1385.

Chapman, Jonathan, Mark Dean, Ortoleva Pietro, Erik Snowberg, and Camerer Colin, "Econographics," *Journal of Political Economy: Microeconomics*, 2023, *1* (1), 115–161.

Charroin, Liza, Bernard Fortin, and Marie Claire Villeval, "Peer effects, self-selection and dishonesty," *Journal of Economic Behavior & Organization*, 2022, *200*, 618–637.

Chen, Daniel L, Martin Schonger, and Chris Wickens, "oTree—An open-source platform for laboratory, online, and field experiments," *Journal of Behavioral and Experimental Finance*, 2016, *9*, 88–97.

Chetty, Raj, Matthew O. Jackson, Theresa Kuchler, Johannes Stroebel, Nathaniel Hendren, Robert B. Fluegge, Sara Gong, Federico Gonzalez, Armelle Grondin, Matthew Jacob, Drew Johnston, Martin Koenen, Eduardo Laguna-Muggenburg, Florian Mudekereza, Tom Rutter, Nicolaj Thor, Wilbur Townsend, Ruby Zhang, Mike Bailey, Pablo Barberá, Monica Bhole, and Nils Wernerfelt, "Social capital II: determinants of economic connectedness," *Nature*, 2022, *608* (7921), 122–134.

Chowdhury, Shyamal, Matthias Sutter, and Klaus F Zimmermann, "Economic preferences across generations and family clusters: A large-scale experiment in a developing country," *Journal of Political Economy*, 2022, *130* (9), 2361–2410.

Comola, Margherita and Silvia Prina, "Treatment effect accounting for network changes," *Review of Economics and Statistics*, 2021, *103* (3), 597–604.

Cooper, Russell, Douglas DeJong, Robert Forsythe, and Thomas Ross, "Selection criteria in coordination games: Some experimental results," *American Economic Review*, 1990, *80* (1), 218–233.

Cox, Daniel A, Ryan Streeter, Samuel J Abrams, and Jacqueline Clemence, "Socially distant: How our divided social networks explain our politics," *American Enterprise Institute, National Social Network Survey*, 2020.

Crosetto, Paolo and Antonio Filipin, "The bomb risk elicitation task," *Journal of Risk and Uncertainty*, 2013, *147*, 31–65.

Croson, Rachel and Uri Gneezy, "Gender differences in preferences," *Journal of Economic Literature*, 2009, *47* (2), 448–74.

Cunha, Flavio and James Heckman, "The technology of skill formation," *American economic review*, 2007, *97* (2), 31–47.

_ and James J Heckman, "The technology of skill formation," *American Economic Review*, May 2007, *97* (2), 31–47.

_ and _ , "Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation," *Journal of Human Resources*, 2008, *43* (4), 738–782.

Currarini, Sergio, Matthew O. Jackson, and Paolo Pin, "An economic model of friendship: Homophily, minorities, and segregation," *Econometrica*, July 2009, *77* (4), 1003–1045.

Dalton, Patricio S., Sayantan Ghosal, and Anandi Mani, "Poverty and Aspirations Failure," *Economic Journal*, 2016, *126* (590), 165–188.

Dean, Mark and Pietro Ortoleva, "The empirical relationship between nonstandard economic behaviors," *Proceedings of the National Academy of Sciences*, 2019, *116* (33), 16262–16267.

Deming, David J, "The growing importance of social skills in the labor market," *Quarterly Journal of Economics*, 2017, *132* (4), 1593–1640.

Dohmen, Thomas and Tomas Jagelka, "Individual-Specific Reliability of Self-Assessed Measures of Economic Preferences and Personality Traits," 2022.

_ , Armin Falk, David Huffman, and Uwe Sunde, "The intergenerational transmission of risk and trust attitudes," *Review of Economic Studies*, 2012, *79* (2), 645–677.

_ , _ , _ , _ , Jürgen Schupp, and Gert G Wagner, "Individual risk attitudes: Measurement, determinants, and behavioral consequences," *Journal of the European Economic Association*, 2011, *9* (3), 522–550.

Epple, Dennis and Richard E. Romano, "Peer effects in education: A survey of the theory and evidence," *Handbook of Social Economics*, 2011, *1*, 1053–1153.

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde, "Global evidence on economic preferences," *Quarterly Journal of Economics*, 2018, *133* (4), 1645–1692.

_ , Fabian Kosse, Pia Pinger, Hannah Schildberg-Hörisch, and Thomas Deckers, "Socioeconomic status and inequalities in children's IQ and economic preferences," *Journal of Political Economy*, 2021, *129* (9), 2504–2545.

Flory, Jeffrey A, Andreas Leibbrandt, and John A List, "Do competitive workplaces deter female workers? A large-scale natural field experiment on job entry decisions," *Review of Economic Studies*, 2015, *82* (1), 122–155.

Forsythe, Robert, Joel L Horowitz, Nathan E Savin, and Martin Sefton, "Fairness in simple bargaining experiments," *Games and Economic behavior*, 1994, *6* (3), 347–369.

Gagete-Miranda, Jessica, "An aspiring friend is a friend indeed: school peers and college aspirations in Brazil," *WP*, 2020.

Gaviria, Alejandro and Steven Raphael, "School-based peer effects and juvenile behaviour," *Review of Economics and Statistics*, 2001, *83(2)*, 257–268.

Genicot, Garance and Debraj Ray, "Aspirations and inequality," *Econometrica*, 2017, *85* (2), 489–519.

Girard, Yann, Florian Hett, and Daniel Schunk, "How individual characteristics shape the structure of social networks," *Journal of Economic Behavior & Organization*, 2015, *115(C)*, 197–216.

Goldsmith-Pinkham, Paul and Guido W Imbens, "Social networks and the identification of peer effects," *Journal of Business & Economic Statistics*, 2013, *31* (3), 253–264.

Golsteyn, Bart and Hannah Schildberg-Hörisch, "Challenges in research on preferences and personality traits: Measurement, stability, and inference," *Journal of Economic Psychology*, 2017, *60*, 1–6.

Golsteyn, Bart HH, Arjan Non, and Ulf Zölitz, "The impact of peer personality on academic achievement," *Journal of Political Economy*, 2021, *129* (4), 1052–1099.

_ , Hans Grönqvist, and Lena Lindahl, "Adolescent time preferences predict lifetime outcomes," *Economic Journal*, 2014, *124* (580), F739–F761.

Golub, Benjamin and Evan Sadler, "Games on Endogenous Networks," Papers 2102.01587, arXiv.org February 2021.

Griffith, Alan, "Name your friends, but only five? The importance of censoring in peer effects estimates using social network data," *Journal of Labor Economics*, 2022, *40* (4), 779–805.

_ , "Random Assignment with Nonrandom Peers: A Structural Approach to Counterfactual Treatment Assessment," *Review of Economics and Statistics*, 2024, *106* (3), 859–871.

Heckman, James J, Tomáš Jagelka, and Tim Kautz, *Some contributions of economics to the study of personality.*, The Guilford Press, 2021.

Hsieh, Chih-Sheng, Lung-Fei Lee, and Vincent Boucher, "Specification and estimation of network formation and network interaction models with the exponential probability distribution," *Quantitative economics*, 2020, *11* (4), 1349–1390.

Jackson, Matthew O, *Social and Economic Networks*, Princeton University Press, 2010.

Jackson, Matthew O., "Inequality's economic and social roots: The role of social networks and homophily," *Working Paper*, 2021.

_ , Stephen Nei, Erik Snowberg, and Leeat Yariv, "The dynamics of networks and homophily," *WP*, 2022.

Jagelka, Tomas, "Are Economists' Preferences Psychologists' Personality Traits? A Structural Approach," *Journal of Political Economy*, 2024, *132*, 910–970.

Johnsson, Ida and Hyungsik Roger Moon, "Estimation of peer effects in endogenous social networks: Control function approach," *Review of Economics and Statistics*, 2021, *103* (2), 328–345.

Kautz, Tim, James J Heckman, Ron Diris, Bas Ter Weel, and Lex Borghans, "Fostering and measuring skills: Improving cognitive and non-cognitive skills to promote lifetime success," *OECD Education Working Papers*, 2014, *110.*

Kearney, Melissa S. and Phillip B. Levine, "Media influences on social outcomes: The impact of MTV's 16 and pregnant on teen childbearing," *American Economic Review*, 2015, *105* (12), 3597–3632.

Kirchler, Michael, Juergen Huber, Matthias Stefan, and Matthias Sutter, "Market design and moral behavior," *Management Science*, 2016, *62* (9), 2615–2625.

Kosse, Fabian and Michaela M. Tincani, "Prosociality predicts labor market success around the world," *Nature Communications*, 2020, *11* (5298).

_ , Ranjita Rajan, and Michela Tincani, "Prosociality and competition: Evidence from a long-run field experiment," 2022.

_ , Thomas Deckers, Pia Pinger, Hannah Schildberg-Hörisch, and Armin Falk, "The Formation of Prosociality: Causal Evidence on the Role of Social Environment," *Journal of Political Economy*, 2020, *128* (2), 434–467.

Kuersteiner, Guido and Ryo Okui, "Constructing optimal instruments by first-stage prediction averaging," *Econometrica*, 2010, *78* (2), 697–718.

König, Michael D, Xiaodong Liu, and Yves Zenou, "R&D networks: Theory, empirics, and policy implications," *Review of Economics and Statistics*, 2019, *101* (3), 476–491.

Lazarsfeld, Paul F, Robert K Merton et al., "Friendship as a social process: A substantive and methodological analysis," *Freedom and control in modern society*, 1954, *18* (1), 18–66.

Lee, Lung-Fei, Xiaodong Liu, Eleonora Patacchini, and Yves Zenou, "Who is the Key Player? A Network Analysis of Juvenile Delinquency," *Journal of Business & Economic Statistics*, 2020, *39* (3), 849–857.

Manski, Charles, "Identification of Endogenous Social Effects: The Reflection Problem," *The Review of Economic Studies*, 1993, *60* (3), 531–542.

McPherson, Miller, Lynn Smith-Lovin, and James M Cook, "Birds of a feather: Homophily in social networks," *Annual Review of Sociology*, 2001, *27*, 415–444.

Meier, Stephan and Charles D Sprenger, "Present-biased preferences and credit card borrowing," *American Economic Journal: Applied Economics*, 2010, *2* (1), 193–210.

_ **and** _ , "Time discounting predicts creditworthiness," *Psychological science*, 2012, *23* (1), 56–58.

Nagel, Rosemarie, "Unravelling in guessing games: An experimental study," *American Economic Review*, 1995, *85*, 1313–1326.

Niederle, Muriel and Lise Vesterlund, "Do women shy away from competition? Do men compete too much?," *Quarterly Journal of Economics*, 2007, *122* (3), 1067–1101.

Norris, Jonathan, "Peers, parents, and attitudes about school," *Journal of Human Capital*, 2020, *14* (2), 290–342.

Patacchini, Eleonora and Yves Zenou, "Juvenile delinquency and conformism," *Journal of Law, Economics, & Organization*, 2012, *28* (1), 1–31.

_ **, Edoardo Rainone, and Yves Zenou**, "Heterogeneous peer effects in education," *Journal of Economic Behavior and Organization*, 2017, *134*, 190–227.

Paulhus, D. L., "Two-component models of socially desirable responding," *Journal of Personality and Social Psychology*, 1984, *46* (3), 598–609.

Rao, Gautam, "Familiarity does not breed contempt: Generosity, discrimination, and diversity in Delhi schools," *American Economic Review*, 2019, *109* (3), 774–809.

Rubineau, Brian and Roberto M Fernandez, "Missing links: Referrer behavior and job segregation," *Management Science*, 2013, *59* (11), 2470–2489.

Sacerdote, Bruce, "Experimental and quasi-experimental analysis of peer effects: two steps forward?," *Annual Review of Economics*, 2014, *6*, 253–272.

Santavirta, Torsten and Miguel Sarzosa, "Effects of disruptive peers in endogenous social networks," *WP*, 2019.

Shan, Xiaoque and Ulf Zölitz, "Peers affect personality development," *CEPR Discussion Paper*, 2022.

Sorrenti, Giuseppe, Ulf Zölitz, Denis Ribeaud, and Manuel Eisner, "The causal impact of socio-emotional skills training on educational success," CEPR Discussion Papers 14523 2020.

Stango, Victor and Jonathan Zinman, "We Are All Behavioural, More, or Less: A Taxonomy of Consumer Decision-Making," *Review of Economic Studies*, 08 2022.

Sutter, Matthias, Claudia Zoller, and Daniela Glaetzle-Ruetzler, "Economic behavior of children and adolescents – A first survey of experimental economics results," *European Economic Review*, 2019, *111*, 98–121.

_ **, Martin G Kocher, Daniela Glätzle-Rützler, and Stefan T Trautmann**, "Impatience and uncertainty: Experimental decisions predict adolescents' field behavior," *American Economic Review*, 2013, *103* (1), 510–31.

Terrier, Camille, Daniel L Chen, and Matthias Sutter, "COVID-19 within families amplifies the prosociality gap between adolescents of high and low socioeconomic status," *Proceedings of the National Academy of Sciences*, 2021, *118* (46), e2110891118.

U.S. Census Bureau, "Current Population Survey, 2024 Annual Social and Economic Supplement (CPS ASEC)," 2024.

Zárate, Román Andrés, "Uncovering peer effects in social and academic skills," *American Economic Journal: Applied Economics*, 2023, *15* (3), 35–79.

Zeltzer, Dan, "Gender homophily in referral networks: Consequences for the Medicare physician earnings gap," *American Economic Journal: Applied Economics*, April 2020, *12* (2), 169–97.

Online Appendix

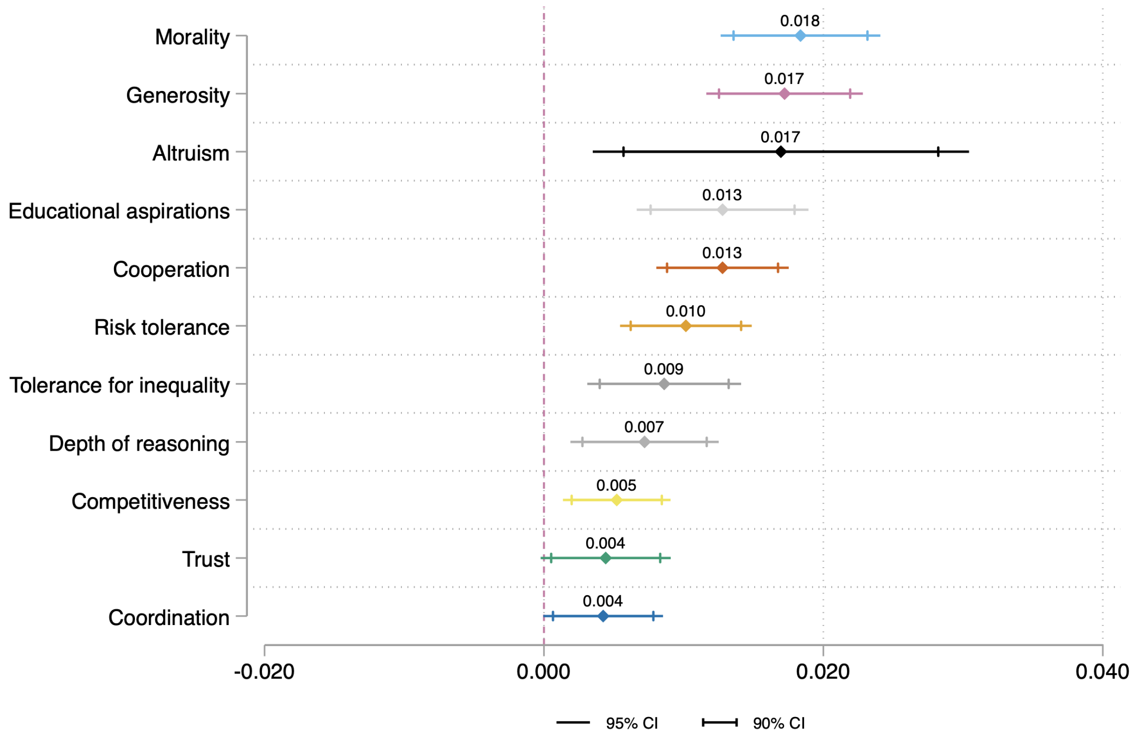
A Additional Tables and Figures

Table A.1: Profession classifications of the French statistical agency (INSEE)

	Share of pop in 2020 (1)	Wage (mean) in euros (2)	% graduated from high school (or more) (3)
Farmers	1.4	1210	41
Craftsmen, small business owners, and CEOs	6.8	2580	48
Managers and intellectual professions	20.4	4060	93
Intermediate professions	26.0	2241	78
Non-manual workers (Employees)	25.8	1590	46
Manual workers	19.2	1681	23
Undefined	0.4	-	-
All	100.0	2238	57

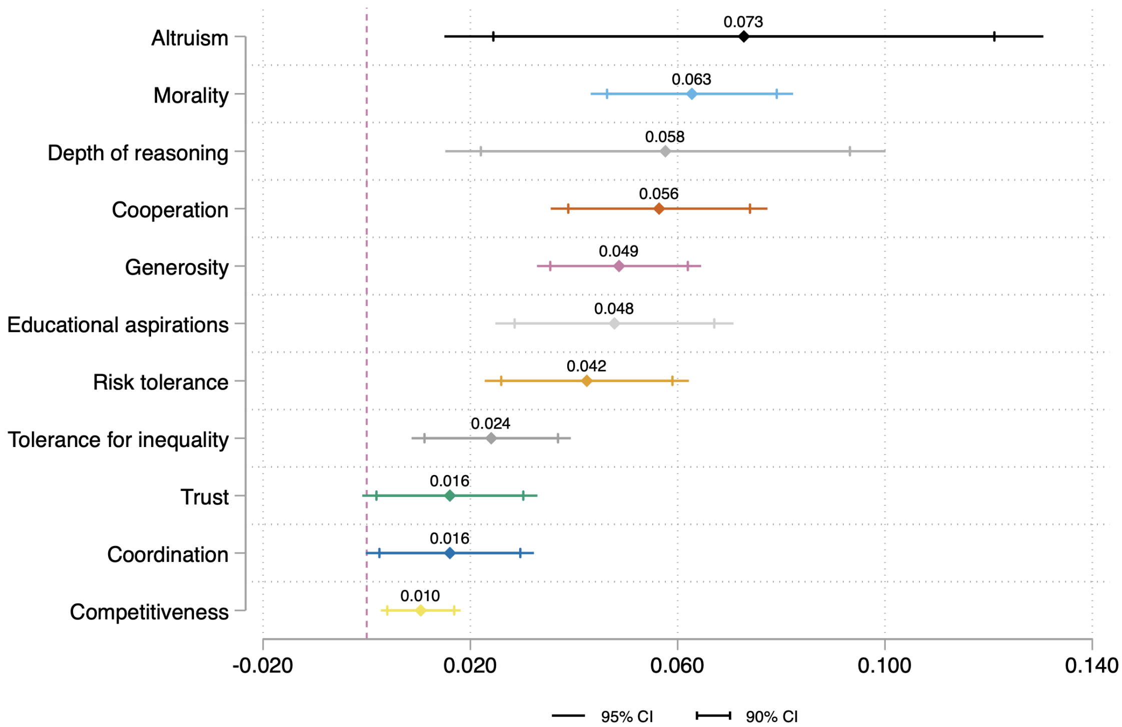
Note: This table presents the six occupation categories of the French Statistical Office (INSEE), the share of the employed population that belongs to each category (Column 1), the average wage of the category (Column 2) and the share of the employed population that graduated with a high school degree or a higher degree (Column 3).

Figure A.1: Homophily based on behavioral traits - Disaggregated **(Fact 3)**



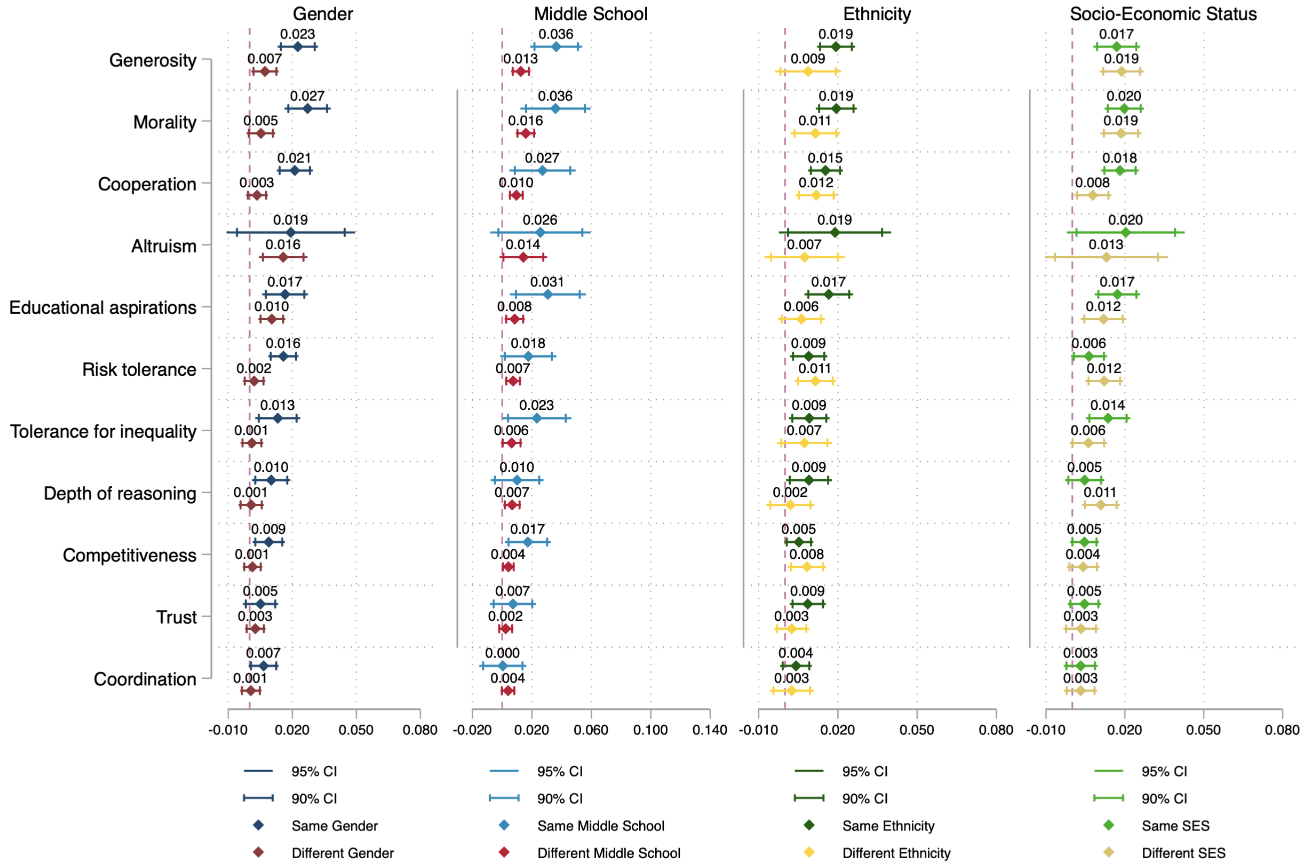
Note: This figure plots coefficients for homophily based on behavioral traits. Each coefficient corresponds to a separate regression based on eq. 1. The dependent variable is an indicator variable which takes the value 1 if individual i sends a link to individual j and 0 otherwise. On the right-hand-side, $|y_i - y_j|$, whose coefficient is reported above, captures how close two students are in terms of behavioral traits. For the sake of comparison, all measures of similarity in behavioral traits in the regressions are standardized. We control for shared demographic characteristics such as gender, ethnicity, nationality, place of residence, SES, number of siblings, age (in months), a dummy to indicate whether the individual is an only child or not, and a dummy to indicate if the individual was born in France. We also control for sender and receiver fixed effects. Standard errors are clustered at the classroom level.

Figure A.2: Homophily based on behavioral traits - Disaggregated and Scaled **(Fact 3)**



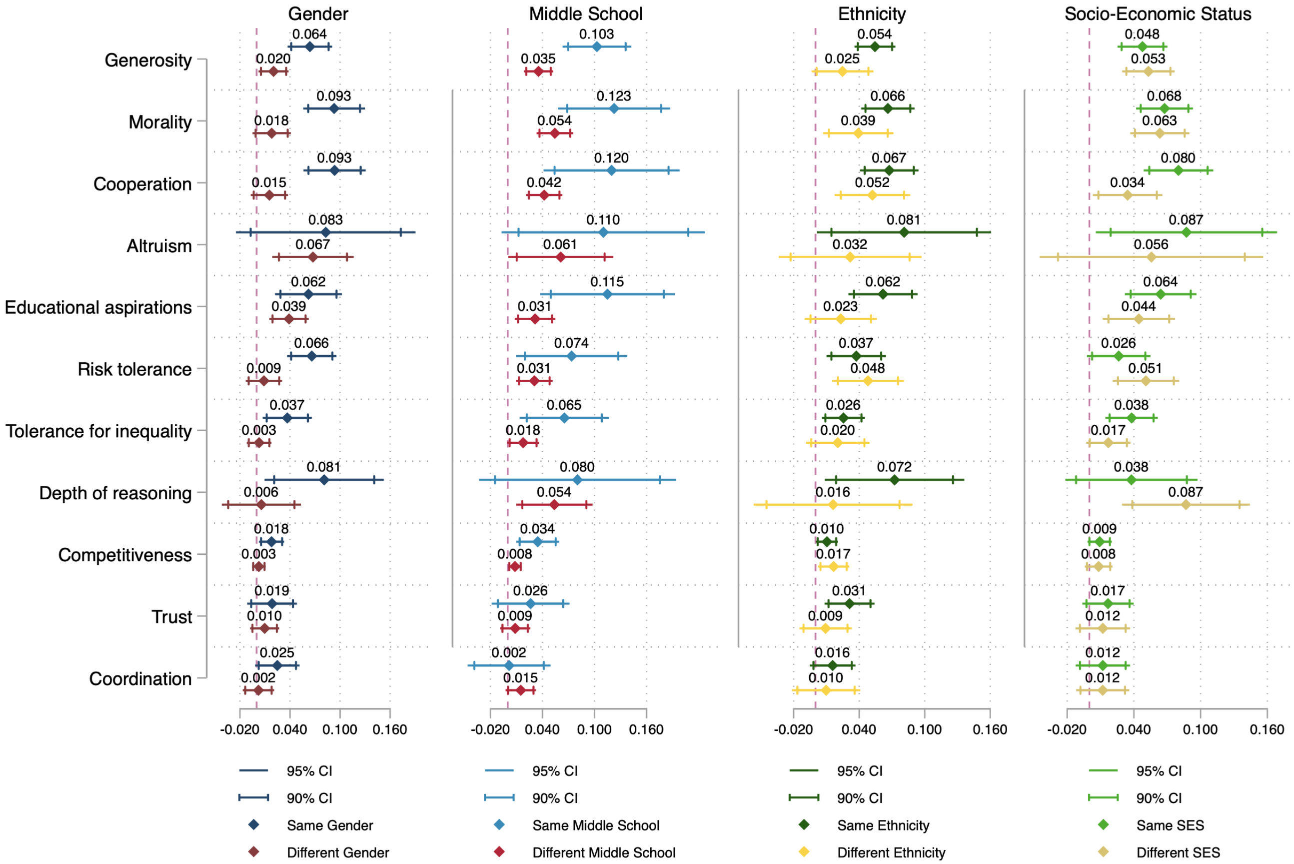
Note: This figure plots coefficients for homophily based on behavioral traits. Each coefficient corresponds to a separate regression based on eq. 1. The dependent variable is an indicator variable which takes the value 1 if individual i sends a link to individual j and 0 otherwise. On the right-hand-side, $|y_i - y_j|$, whose coefficient is reported in the figure, captures how close two students are in terms of behavioral traits. For the sake of comparison, all measures of similarity in behavioral traits in the regressions are normalized to take a value between 0 and 1. We control for shared demographic characteristics such as gender, ethnicity, nationality, place of residence, SES, number of siblings, age (in months), a dummy to indicate whether the individual is an only child or not, and a dummy to indicate if the individual was born in France. We also control for sender and receiver fixed effects. Standard errors are clustered at the classroom level.

Figure A.3: Homophily based on behavioral traits for students who share the same demographic characteristics - Disaggregated **(Fact 4)**



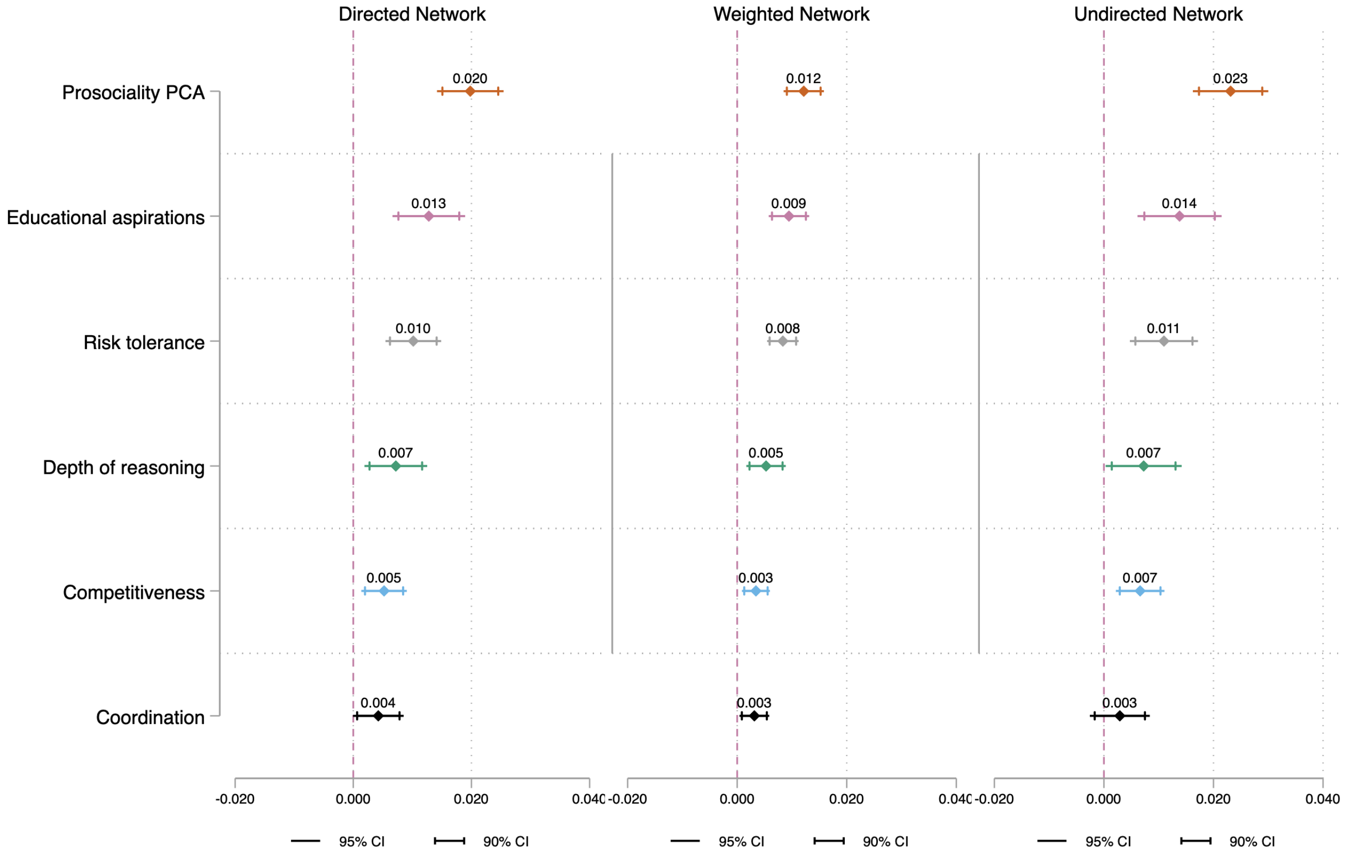
Note: This figure plots coefficients for homophily based on behavioral traits. Coefficients in the first sub-panel correspond to sub-samples where individuals either share the same gender or have different gender. Coefficients from the second, third, and fourth sub-panels analogously correspond to sub-samples where individuals either share the same middle school, ethnicity, or SES or have different middle school, ethnicity, SES respectively. Each coefficient corresponds to a separate regression based on eq. 1. We run regressions separately for each sub-group (same gender v.s. different gender, same SES v.s. different SES, and so on). The dependent variable is an indicator variable, which takes the value 1 if individual i sends a friendship link to individual j and 0 otherwise. On the right-hand-side, $|y_i - y_j|$, whose coefficient is reported in the figure, captures how close two students are in terms of behavioral traits. For the sake of comparison, all measures of similarity in behavioral traits in the regressions are standardized (with a mean of 0 and SD of 1). We control for shared demographic characteristics such as gender, ethnicity, nationality, place of residence, SES, number of siblings, age (in months), a dummy to indicate whether the individual is an only child or not, and a dummy to indicate if the individual was born in France. We also control for sender and receiver fixed effects. Standard errors are clustered at the classroom level.

Figure A.4: Homophily based on behavioral traits for students who share the same demographic characteristics - Disaggregated and Scaled (**Fact 4)**



Note: This figure plots coefficients for homophily based on behavioral traits. Coefficients in the first sub-panel correspond to sub-samples where individuals either share the same gender or have different gender. Coefficients from the second, third, and fourth sub-panels analogously correspond to sub-samples where individuals either share the same middle school, ethnicity, or SES or have different middle school, ethnicity, SES respectively. Each coefficient corresponds to a separate regression based on eq. 1. We run regressions separately for each sub-group (same gender v.s. different gender, same SES v.s. different SES, and so on). The dependent variable is an indicator variable, which takes the value 1 if individual i sends a friendship link to individual j and 0 otherwise. On the right-hand-side, $|y_i - y_j|$, whose coefficient is reported in the figure, captures how close two students are in terms of behavioral traits. For the sake of comparison, all measures of similarity in behavioral traits in the regressions are normalized to take a value between 0 and 1. We control for shared demographic characteristics such as gender, ethnicity, nationality, place of residence, SES, number of siblings, age (in months), a dummy to indicate whether the individual is an only child or not, and a dummy to indicate if the individual was born in France. We also control for sender and receiver fixed effects. Standard errors are clustered at the classroom level.

Figure A.5: Homophily based on behavioral traits - Alternative network specifications



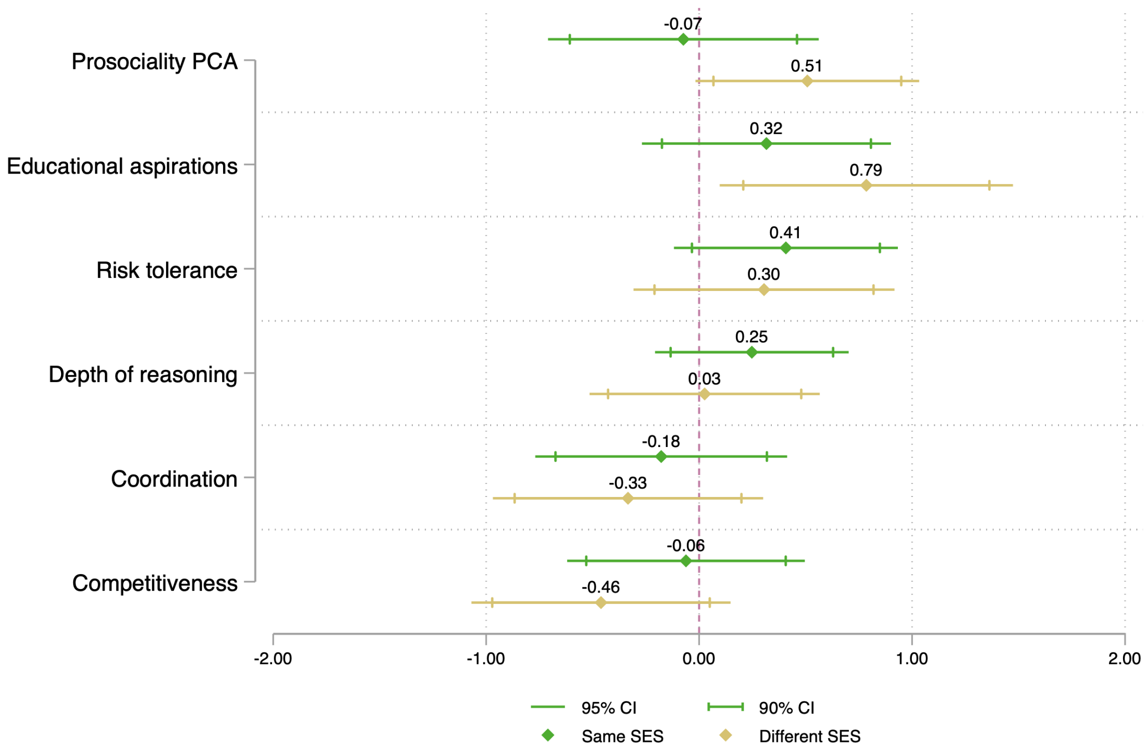
Note: This figure plots coefficients for homophily based on behavioral traits. Each coefficient corresponds to a separate regression based on eq. 1. In directed networks, the dependent variable is an indicator variable which takes the value 1 if individual i sends a link to individual j and 0 otherwise. In undirected networks, the indicator variable takes the value 1 if either individual i or individual j sends a friendship link to the other and 0 otherwise. For weighted networks, we weight the friendship links by the order in which friends are reported. $d_{ij} \in \{0.0675, 0.125, 0.25, 0.5, 1\}$ depending on the order in which individual j is reported as a friend by individual i and 0 otherwise. The first reported friend takes the highest weight. On the right-hand-side, $|y_i - y_j|$, whose coefficient is reported in the figure, captures how close two students are in terms of behavioral traits. All measures of similarity in behavioral traits in the regressions are standardized. We control for shared demographic characteristics such as gender, ethnicity, nationality, commune of residence, SES, number of siblings, age (in months), a dummy to indicate whether the individual is an only child or not, and a dummy to indicate if the individual was born in France. We also control for sender and receiver fixed effects. Standard errors are clustered at the classroom level.

Table A.2: Coefficients from first stage regression for predicted links (Comparisons)

	(1)	(2)	(3)	(4)
Shared postal code	0.145***	0.140***	0.191***	0.191***
	(0.037)	(0.037)	(0.046)	(0.047)
Shared middle school	0.546***	0.554***	0.671***	0.675***
	(0.045)	(0.045)	(0.046)	(0.046)
Shared gender	1.155***	1.158***	1.174***	1.180***
	(0.053)	(0.053)	(0.055)	(0.054)
Shared nationality	0.496*	0.438+	0.465+	0.432+
	(0.263)	(0.267)	(0.284)	(0.282)
Shared ethnicity	0.189***	0.187***	0.172**	0.169**
	(0.072)	(0.070)	(0.070)	(0.070)
Similar age (in months)	0.010***	0.010***	0.012***	0.010***
	(0.003)	(0.003)	(0.004)	(0.004)
Similar no. of siblings	0.012	0.011	0.014	0.011
	(0.028)	(0.031)	(0.028)	(0.032)
Shared single child status	0.049	0.049	0.061	0.062
	(0.048)	(0.049)	(0.047)	(0.051)
Shared primary parent occu. cat.	0.070**	0.071**	0.064**	0.068**
	(0.030)	(0.029)	(0.031)	(0.030)
Shared country of birth	-0.008	0.034	0.004	0.040
	(0.161)	(0.161)	(0.166)	(0.167)
Sender and Receiver Characteristics	Y	Y	Y	Y
Interaction terms	N	Y	N	Y
Classroom Fixed Effects	N	N	Y	Y
Mc. Fadden R-sq	0.055	0.057	0.072	0.074
Mc. Fadden Adj. R-sq	0.054	0.054	0.071	0.070
N	61736	61736	61618	61618

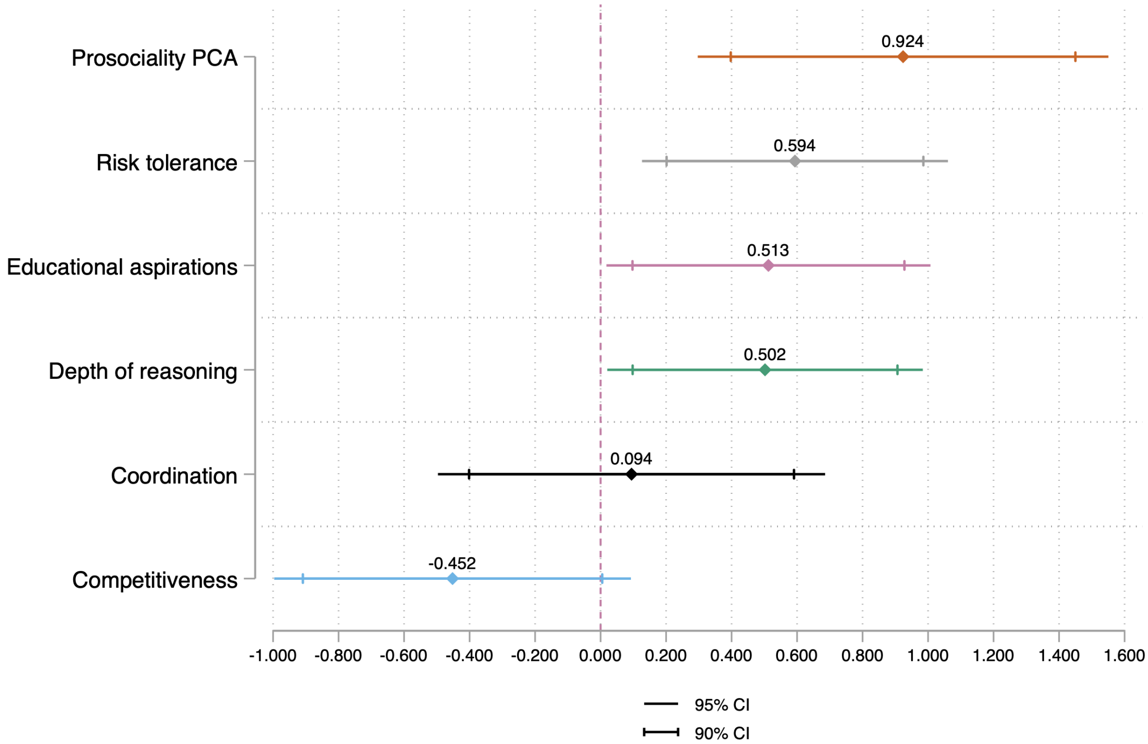
Note: This table reports coefficients from the friendship prediction based on Eq. 5. The dependent variable is a potential friendship link which takes the value 1 if student i nominates student j as a friend and 0 otherwise. All regressions are based on a Logit specification. The vector of shared predetermined demographic characteristics contains dummies for shared gender, ethnicity, nationality, middle school, residential postal code, low SES, single child status, country of birth as well as continuous variables that capture differences in age (in months) and differences in the number of siblings. Vectors of sender and receiver demographic characteristics include gender, nationality, ethnicity, low SES, age (in months), and number of siblings. In columns 2 and 4, we also include a set of interaction terms between the demographic characteristics of student i (sender) and those of student j (receiver). Columns 3 and 4 include class fixed effects. Standard errors are clustered at classroom level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$, + $p<0.15$

Figure A.6: Peer effects by similarity in socio-economics status **(Fact 7)**



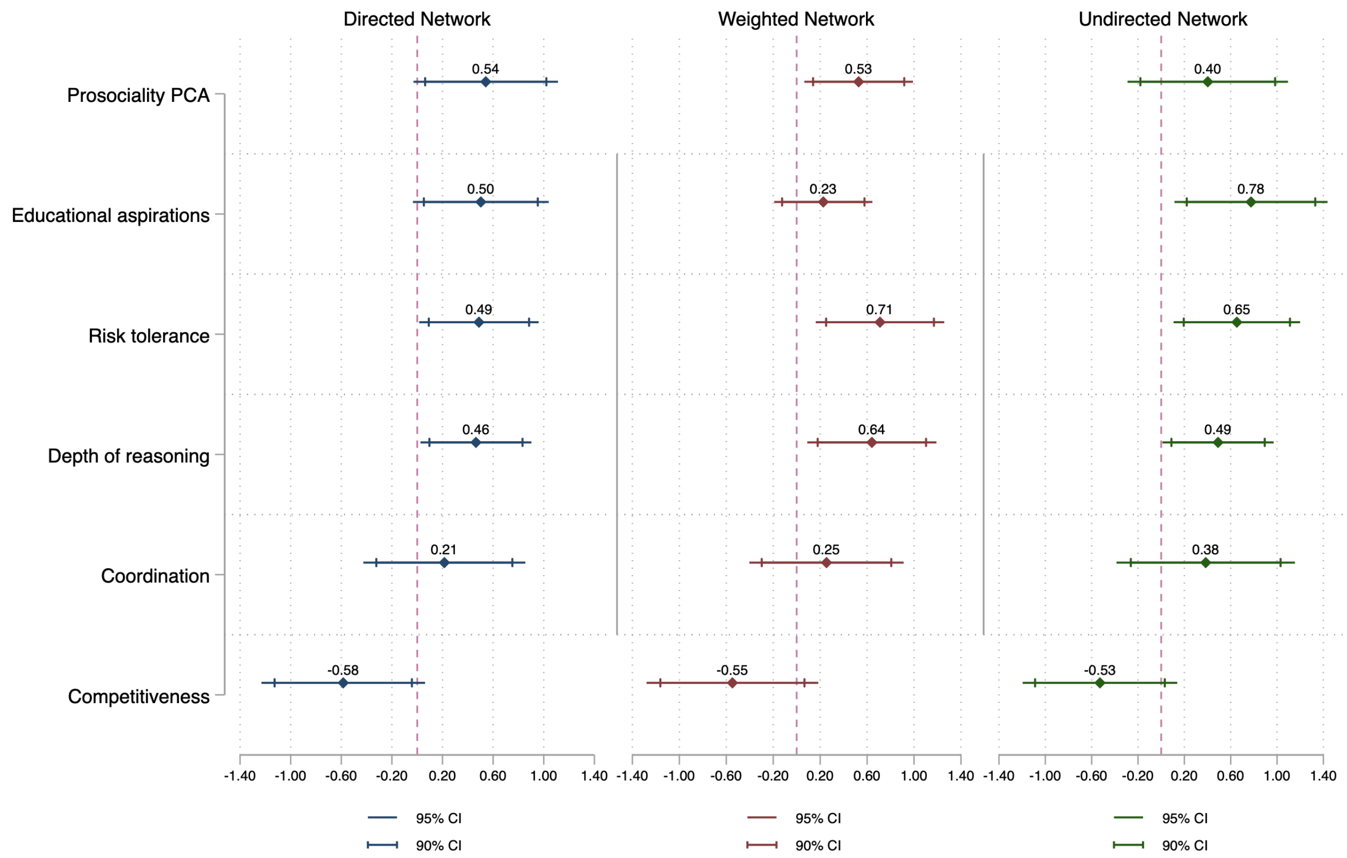
Note: This figure reports coefficients of peer effects in behavioral traits. Each coefficient corresponds to a separate regression based on eq. 7. The dependent variable is the behavioral trait of a student. The coefficient reported in the figure corresponds to the effect of the friends' average behavioral trait. Behavioral traits are standardized to have a mean of zero and a standard deviation of one. We instrument the friends' average behavioral trait using the predicted behavioral trait of the predicted friends. Each regression includes classroom fixed effects as well as control variables for the following demographic characteristics of the individual and of the friends: gender, ethnicity, nationality, SES, only child status, country of birth, age (in months), and number of siblings. Standard errors are clustered at the classroom level. The samples are split by the similarity of an individual's SES group and the SES composition of their friend group. Same SES refers to the group of high SES (low SES) students with more than half of their friend group also being high SES (low SES). Different SES refers to the group of high SES (low SES) students with more than half of their friend group being of the opposite SES group.

Figure A.7: Coefficients from peer effects analysis (without contextual variables)



Note: This figure reports coefficients of peer effects in behavioral traits. Each coefficient corresponds to a separate regression based on eq. 7. The dependent variable is the behavioral trait of a student. The coefficient reported in the figure corresponds to the effect of the friends' average behavioral trait. We standardized the behavioral traits variables to have a mean of zero and a standard deviation of one. For instance, the top coefficient reports the effect of a standard deviation increase in the average depth of reasoning of friends on an individual's depth of reasoning. We instrument the friends' average behavioral trait using the predicted behavioral trait of the predicted friends. Each regression includes control variables for the following demographic characteristics of the individual: gender, ethnicity, nationality, SES, only child status, country of birth, age (in months), and number of siblings. Regressions include classroom fixed effects. Standard errors are clustered at the classroom level.

Figure A.8: Coefficients from peer effects analysis - Alternative network specifications



Note: This figure reports coefficients of peer effects in behavioral traits. Each coefficient corresponds to a separate regression based on eq. 7. The dependent variable is the behavioral trait of a student. The coefficient reported in the figure corresponds to the effect of the friends' average behavioral trait. We standardized the behavioral traits variables to have a mean of zero and a standard deviation of one. For instance, the top coefficient reports the effect of a one standard deviation increase in the average depth of reasoning of friends on an individual's depth of reasoning. We instrument the friends' average behavioral trait using the predicted behavioral trait of the predicted friends. Each regression includes control variables for the following demographic characteristics of the individual and of the friends: gender, ethnicity, nationality, SES, only child status, country of birth, age (in months), and number of siblings. Regressions include classroom fixed effects. Standard errors are clustered at the classroom level. In directed networks, the friendship network takes the value 1 if individual i sends a link to individual j and 0 otherwise. In undirected networks, the friendship network takes the value 1 if either individual i or individual j sends a friendship link to the other and 0 otherwise. For weighted networks, we weight the friendship links by the order in which friends are reported. $d_{ij} \in \{0.0675, 0.125, 0.25, 0.5, 1\}$ depending on the order in which individual j is reported as a friend by individual i and 0 otherwise. The first reported friend takes the highest weight.

Table A.3: Robustness checks for peer effect estimates

	Dem Char		Dem Char + Int		Dem Char + FE		Dem Char + Int + FE	
Cont. var.	Coeff. (1)	F stat. (2)	Coeff. (3)	F stat. (4)	Coeff. (5)	F stat. (6)	Coeff. (7)	F stat (8)
Outcome: Prosociality PCA								
Y	0.613**	20.216	0.621**	21.651	0.516*	18.922	0.542*	19.012
	(0.299)		(0.298)		(0.290)		(0.291)	
N	1.012***	17.050	0.999***	18.126	0.906***	17.345	0.924***	17.566
	(0.324)		(0.315)		(0.323)		(0.320)	
Outcome: Educational aspirations								
Y	0.420*	34.877	0.416*	34.434	0.498*	31.350	0.503*	29.864
	(0.246)		(0.250)		(0.265)		(0.274)	
N	0.429*	39.121	0.428*	39.186	0.507**	35.019	0.513**	34.149
	(0.230)		(0.232)		(0.247)		(0.252)	
Outcome: Risk tolerance								
Y	0.520**	36.757	0.516**	35.681	0.510**	37.296	0.488**	37.486
	(0.242)		(0.244)		(0.243)		(0.241)	
N	0.620***	40.710	0.621***	39.057	0.612***	41.872	0.594**	41.841
	(0.238)		(0.240)		(0.240)		(0.238)	
Outcome: Depth of reasoning								
Y	0.376+	39.599	0.388*	41.386	0.448**	40.742	0.464**	41.256
	(0.230)		(0.230)		(0.223)		(0.224)	
N	0.408+	40.256	0.419*	42.028	0.487**	41.345	0.502**	42.132
	(0.253)		(0.254)		(0.245)		(0.246)	
Outcome: Coordination								
Y	0.144	44.170	0.149	40.459	0.198	45.721	0.214	43.242
	(0.330)		(0.331)		(0.327)		(0.327)	
N	0.033	48.670	0.031	44.633	0.084	48.356	0.094	45.676
	(0.294)		(0.294)		(0.300)		(0.302)	
Outcome: Competitiveness								
Y	-0.738**	26.950	-0.566*	30.149	-0.708**	27.425	-0.585*	29.982
	(0.337)		(0.329)		(0.341)		(0.330)	
N	-0.570**	33.414	-0.424+	37.551	-0.566**	33.282	-0.452+	37.038
	(0.282)		(0.277)		(0.286)		(0.278)	

Note: This table reports coefficients of peer effects in non-cognitive skills. Each coefficient corresponds to a separate regression based on Eq.7. The dependent variable is the non-cognitive skill of a student. The coefficient of interest, reported in the first row, corresponds to the effect of the friends average non-cognitive skill. We standardized the non-cognitive skills variables to have a mean of zero and a standard deviation of one. We instrument the friends' average behavioral trait using the predicted behavioral trait of the predicted friends. Each regression includes control variables for the following demographic characteristics of the individual: gender, ethnicity, nationality, low SES, single child status, country of birth, age (in months), and number of siblings. For each non-cognitive skill, the top row reports the coefficient of a specification that controls for friends demographic characteristics (Cont. var. = Y in the first column)—using the same set of characteristics as described above—, and the bottom row reports the coefficient of a specification that does not control for friends demographic characteristics (Cont. var. = N in the first column). All regressions include classroom fixed effects. Standard errors are clustered at the classroom level. Columns 2, 4, 6, and 8 report the Cragg Donald F statistic of the first stage regression (based on Eq 6). *** p<0.01, **p<0.05, * p<0.1, + p<0.15

The Table reports results from four different specifications for the network prediction. In columns 1 and 2 (labelled Dem Char), we only use the sender and receiver shared characteristics to predict friendships. In column 3 and 4 (labelled Dem Char + Int), we enrich the set of sender and the receiver characteristics by including interaction terms between each demographic characteristics (for instance *Female*$\times$*French*, *Female*$\times$*White* and so on). In column 5 and 6 (labelled Dem Char + FE), we return to the specification with no interaction terms and introduce classroom fixed effects. Finally, in column 7 and 8 (labelled Dem Char + Int + FE), we incorporate sender and receiver characteristics, interaction terms, and classroom fixed effects. This last version is the one we use for all results reported in the paper.

B Microfoundation of the peer effects model

Consider a finite set of players $\mathcal{N} = \{1, 2, ..., N\}$ embedded in a social network $\mathcal{S}$. Let $\mathcal{B}$ be the set of behavioral traits: $\mathcal{B} = \{\text{Risk aversion, Cooperation, Trust, ..., Tolerance for inequality}\}$. Additionally, assume that each trait can be measured on a continuous scale of $[-1, 1]$. For example, for cooperation, a value of -1 (1) would indicate that the player is never (always) cooperating.

Player $i \in \mathcal{N}$ has a type $\mathbf{a}_i$ which captures the level of his intrinsic behavioral trait. $\mathbf{a}_i$ is an $M \times 1$ vector where M is the cardinality of the set of traits $\mathcal{B}$. Players form directed links based on predetermined characteristics of homophily[39] and factors such as reciprocity[40], similarity of behavioral traits and other characteristics unobservable to the econometrician. We keep track of the social connections with the matrix $S = [s_{ij}]$, where $s_{ij} = 1$ if player i sends a friendship link to player j and 0 otherwise. Let P_i be the reference group for player i, i.e. $P_i = \{j | s_{ij} = 1\}$. Let n_i capture the number of friends for player i.

Given the network structure, players adjust the level of their revealed behavior[41] ($\mathbf{y}_i$) according to a social cohesion game. The payoff for agent i is given by:

$$u_i(\mathbf{y}_i, \mathbf{a}_i, P_i) = -\sum_{m=1}^{M} \left(\underbrace{\left(a_{im} - y_{im} \right)^2}_{\text{Behavior adjustment cost}} + \underbrace{\tilde{\zeta}_m \left(\frac{\sum_{j \in P_i} y_{jm}}{n_i} - y_{im} \right)^2}_{\text{Cost for deviating from social norm}} \right) \tag{8}$$

i.e., the player tries to match the average revealed behavior in his reference group on each dimension. The two contrasting choices that the player has is to choose his social network and adjust his behavior to the resulting network. If an individual's social network impacts his revealed behavior, then the adjustment process would be of primary interest. Therefore, for the purpose of the peer effects analysis, we are solely interested in the adjustment process that the player undertakes while keeping his choice of social networks fixed. Any deviation from the group average gives him a quadratic disutility. However, changing his intrinsic behavior also entails a quadratic adjustment cost. $\tilde{\zeta}_m$ captures the relative weight imposed on the social deviation cost. This weight can be negative if the individual prefers to form heterophilous links or tries to distinguish himself from the crowd.[42] It can also be 0 if there is no cost of deviation on that dimension. The level of intrinsic behavioral trait a_{im}, that the player would adhere to

[39] Shared gender, shared ethnicity, shared nationality etc.

[40] I am more likely to call you my friend if you call me your friend.

[41] $\mathbf{y}_i$ is also an $M \times 1$ vector.

[42] For example, highly competitive friends may demotivate me and reduce my competitive spirit.

in the absence of adjustment costs, can be decomposed into his demographic characteristics $\mathbf{x}_i$, the social contextual effects $\frac{\sum_{j \in P_i} \mathbf{x}_j}{n_i}$ (Manski, 1993) and an error term. I.e.,

$$a_{im} = \tilde{\gamma}_m \mathbf{x}_i + \tilde{\delta}_m \frac{\sum_{j \in P_i} \mathbf{x}_j}{n_i} + \tilde{\epsilon}_{im} \tag{9}$$

Given the fact that the behavioral traits captured by our incentivized games are different from risky social actions and social behaviors (documented in the literature so far), there is no inherent reason for a_{im} to be a function of social contextual effects. As a result, within our empirical strategy, we reported results with and without the demographic characteristics of friends. That is, we consider both versions of the model where $a_{im} = \tilde{\gamma}_m \mathbf{x}_i + \tilde{\delta}_m \frac{\sum_{j \in P_i} \mathbf{x}_j}{n_i} + \tilde{\epsilon}_{im}$ or $a_{im} = \tilde{\gamma}_m \mathbf{x}_i + \tilde{\epsilon}_{im}$.[43] Since the player tries to maximise his utility (minimise the total cost), for each $m \in \mathcal{B}$, the level of his revealed behavioral trait will be given by the first order condition:

$$y^*_{im} = \frac{1}{1+\tilde{\zeta}_m} a_{im} + \frac{\tilde{\zeta}_m}{1+\tilde{\zeta}_m} \frac{\sum_{j \in P_i} y^*_{jm}}{n_i} \tag{10}$$

i.e. the level of revealed behavioral trait of player i, in equilibrium, is a weighted average of the level of his intrinsic trait and the average level of the trait observed in his reference group. If we assume, $\beta_m = \frac{\tilde{\zeta}_m}{1+\tilde{\zeta}_m}$, $\gamma_m = \frac{\tilde{\gamma}_m}{1+\tilde{\zeta}_m}$, $\delta_m = \frac{\tilde{\delta}_m}{1+\tilde{\zeta}_m}$ and $\epsilon_{im} = \frac{\tilde{\epsilon}_{im}}{1+\tilde{\zeta}_m}$, we obtain the basic equation we need to identify peer effects:

$$y_{im} = \beta_m \frac{\sum_{j \in P_i} y_{jm}}{n_i} + \gamma_m \mathbf{x}_i + \delta_m \frac{\sum_{j \in P_i} \mathbf{x}_j}{n_l} + \epsilon_{im} \tag{11}$$

Here our parameter of interest is β_m.

Additionally, we can characterize the Nash equilibrium of our social cohesion game further. Let $\mathbf{G}$ represent the row normalised interaction (adjacency) matrix, i.e., $G_{ij} = \frac{1}{n_{li}}$ if j is a friend of i and 0 otherwise. Let $\lambda_1(\mathbf{G})$ represent the spectral radius[44] of $\mathbf{G}$. Additionally, assume $\mu_m = \frac{1}{1+\tilde{\zeta}_m}$, $\mathbf{a}_m = \begin{bmatrix} a_{1m} \\ \vdots \\ a_{Nm} \end{bmatrix}$ and $\mathbf{y}_m = \begin{bmatrix} y_{1m} \\ \vdots \\ y_{Nm} \end{bmatrix}$

Proposition 1. *If $\lambda_1(\mathbf{G}) < \frac{1}{\beta_m}$ for all $m \in \mathcal{B}$, then the social cohesion game, characterised by the payoff function given in eq. 8, has a unique Nash equilibrium. Further, the level of revealed*

[43] For this model, we stick to the specification with social contextual effects. The math doesn't change at all if we remove social contextual effects.

[44] The largest eigenvalue.

behavioral trait of a player in equilibrium is equal to his weighted Katz-Bonacich centrality with the decay factor, β_m and the weight vector, $\mu_m \mathbf{a}_m$.

Proof. The proof closely follows Theorem 1 of Ballester et al. (2006). Using the row normalised interaction matrix, eq. 10 can be rewritten in a matrix format as follows:

$$\begin{aligned} \mathbf{y}_m^* &= \mu_m \mathbf{a}_m + \beta_m \mathbf{G} \mathbf{y}_m^* \\ \implies (I - \beta_m \mathbf{G}) \mathbf{y}_m^* &= \mu_m \mathbf{a}_m \end{aligned}$$

The condition, $\lambda_1(\mathbf{G}) < \frac{1}{\beta_m}$, guarantees the invertibility of $(I - \beta_m \mathbf{G})$. Therefore, the unique Nash equilibrium for each behavioral trait is given by:

$$\mathbf{y}_m^* = (I - \beta_m \mathbf{G})^{-1} \mu_m \mathbf{a}_m = \mathbf{b}\left(\mathbf{G}, \beta_m, \mu_m \mathbf{a}_m\right)$$

The equivalence relationship between equilibrium revealed trait $\mathbf{y}_m^*$ and the weighted Katz-Bonacich centrality $\mathbf{b}\left(\mathbf{G}, \beta_m, \mu_m \mathbf{a}_m\right)$ directly follows from the definition of the weighted Katz-Bonacich centrality, i.e.

$$\mathbf{b}\left(\mathbf{G}, \beta_m, \mu_m \mathbf{a}_m\right) = \mathbf{M}(\mathbf{G}, \beta_m) \mu_m \mathbf{a}_m$$

where $\mathbf{M}(\mathbf{G}, \beta_m) = (I - \beta_m \mathbf{G})^{-1} = I + \sum_{k \geq 1} \beta_m^k (\mathbf{G})^k$.

□

Using the above framework, we can also tease out the cost of deviation by inverting our β coefficients from the empirical design for each behavioral trait.

C Screenshots of Incentivized Games (Translated in English)

Figure D1: Risk tolerance

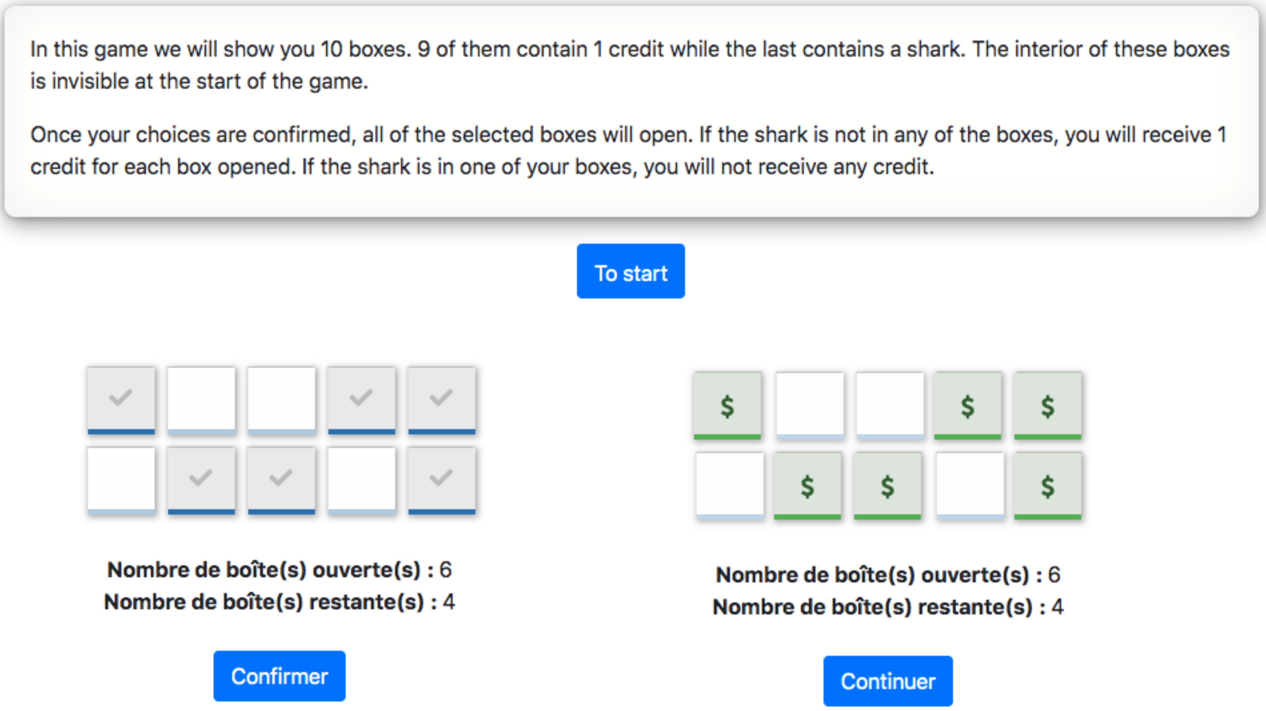


Figure D2: Competitiveness

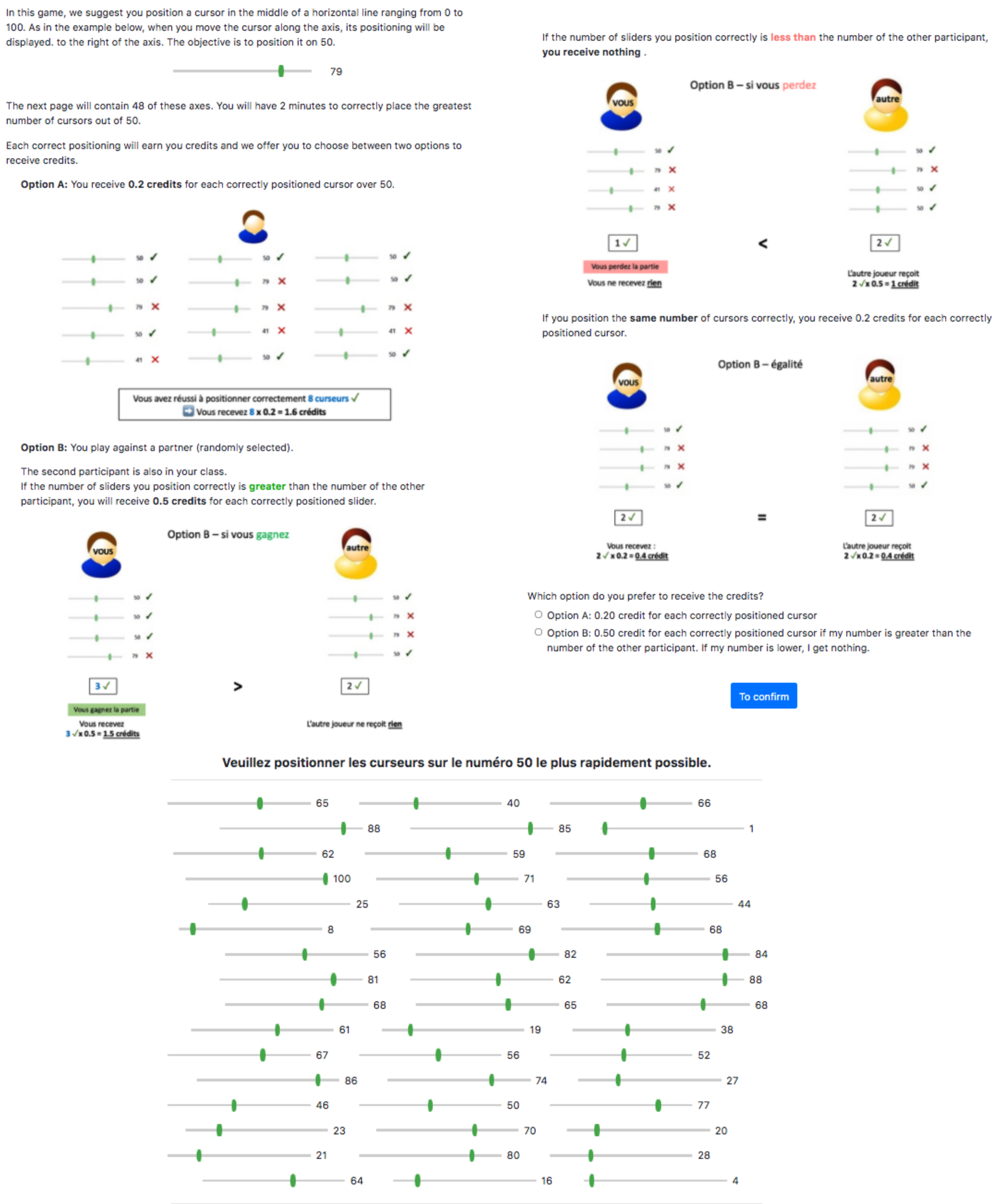


Figure D3: Trust

In this game, we offer you to interact with another participant.

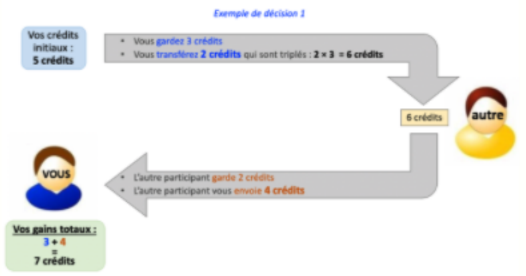
You will each have to make 2 decisions.

Decision 1
We allocate you 5 credits.

1 / You can send between 0 and 5 of these credits to the other participant. The quantity you send will be tripled.

2 / Among this tripled quantity, the other participant must decide how much he wishes to return to you in turn. The quantity returned to you by the other participant is not tripled.

Your final credits are calculated as follows: Your initial 5 credits **minus** your transfer to the other participant **plus** what the other participant returned to you.



Decision 2
Now the other participant receives an endowment of 5 credits.

1 / He chooses the quantity he wishes to send you (between 0 and 5 credits). This quantity is tripled and then sent to you.

2 / You then decide how much you want to return to the other participant. This returned quantity is not tripled.

Your final credits are calculated as follows: credits sent by the other participant tripled **minus** what you returned to the other participant.

When you are ready to start with decision 1, press the start button.

To start

Please indicate how much (between 0 and 5 credits) you wish to transfer to the other participant. Remember that this transferred quantity is tripled and that the other participant can return part of it to you afterwards.

I am transferring:
(Please use multiples of 0.50)

credit (s)

To confirm

Figure D4: Cooperation

We suggest I play with another participant **for 4 rounds** .

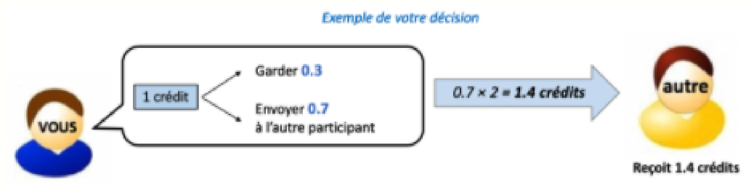
You keep the same partner during the 4 turns.

The second participant is also in your class.

Each turn, you both receive an initial endowment of 1 credit.

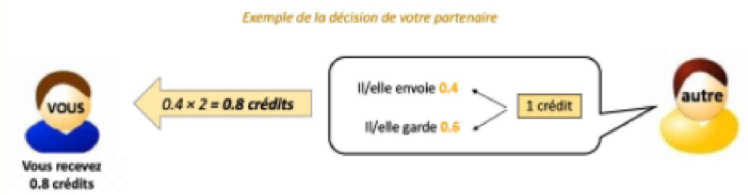
Decision on your part

You must decide how much of this initial endowment you want to transfer to the other participant (between 0 and 1 credit). The transferred quantity will be doubled and the other participant will receive this doubled quantity. What you choose not to transfer remains in your possession but will not however be duplicated.



Decision (simultaneous) from your partner

The other participant simultaneously makes the same decision. He decides how much of his initial endowment he wishes to transfer to you (between 0 and 1 credit). You will receive double the amount transferred.



Your winnings on a round are calculated as the sum of what you keep (from your initial endowment) plus double what the other participant transfers to you.

At the end of each round, you will be able to know the decision made by the other participant and how many credits you have won on that round.

Start round 1

Please choose how much of your initial endowment (between 0 and 1 credit) you wish to transfer to the other participant.

Please use a multiple of 0.1 credit: Credit (s)

To confirm

Figure D5: Coordination

In this game, we offer you to interact with another participant for 4 rounds.

Each turn, each of you has the choice between two options: A and B.

Your earnings are shown in the table below
(your earnings are in blue, your partner's in black)

		L'autre participant	
		Action A	**Action B**
Vous	Action A	3 crédits, 3 crédits	3 crédits, 0 crédits
	Action B	0 crédits, 3 crédits	5 crédits, 5 crédits

If you choose option A , you earn 3 credits, regardless of the choice of the other participant. The other participant also receives 3 credits if he has also chosen option A. Conversely, if he has chosen option B, the other participant receives nothing.

If you choose option B and the other participant also chooses option B, you both receive 5 credits. However, if you choose option B and the other participant chooses option A, you receive nothing while the other participant receives 3 credits

The next page will allow you to make your choices.
Once you have both chosen your option, you will see a summary on the screen showing your choice, the choice of the other participant, and the credits you are entitled to.
The on-screen summary will be displayed for 60 seconds, after which the next round will begin where you can again choose between A and B.

When you are ready, please click on the "Start" button.

To start

Please choose option A or option B by clicking on the corresponding box.

(The gains are recalled in the text below the table.)

		The other participant	
		Action A	**Action B**
You	Action A	3 credits , 3 credits	3 credits , 0 credits
	Action B	0 credits , 3 credits	5 credits , 5 credits

Reminder of earnings

If you choose option A, you earn 3 credits, regardless of the choice of the other participant. The other participant also receives 3 credits if he has also chosen option A. Conversely, if he has chosen option B, the other participant receives nothing.

If you choose option B and the other participant also chooses option B, you both receive 5 credits. However, if you choose option B and the other participant chooses option A, you receive nothing while the other participant receives 3 credits

To confirm

Figure D6: Altruism

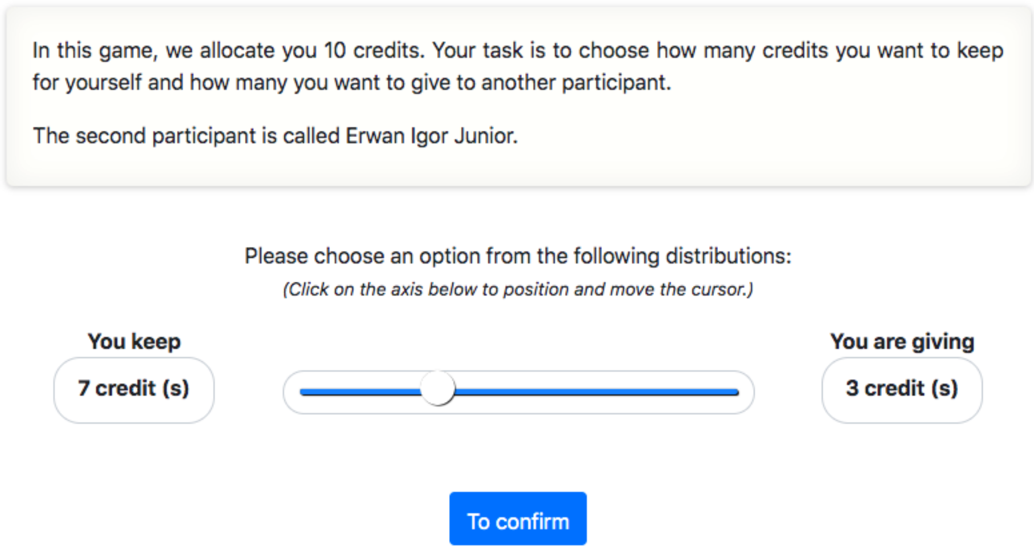


Figure D7: Morality

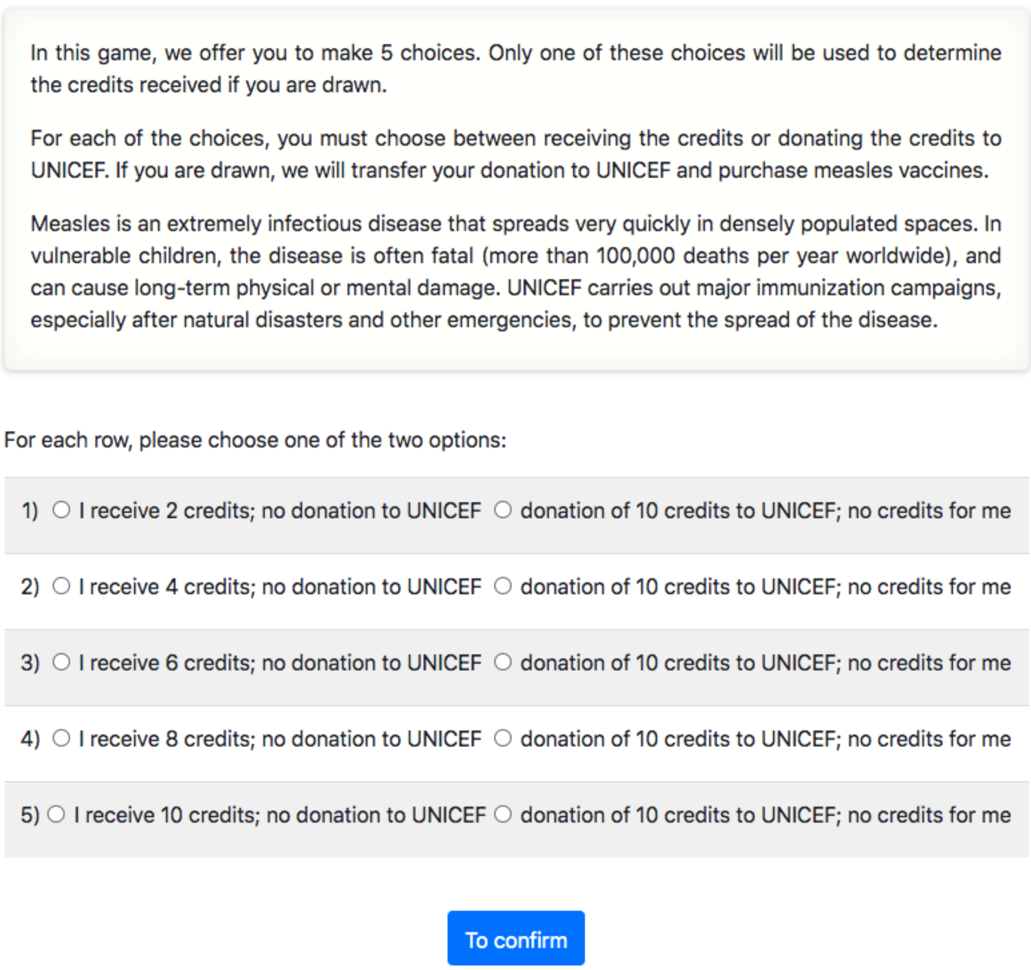


Figure D8: Tolerance for inequality

In this game, we suggest that you determine the credits that will receive two other participants (that we call participant A and participant B).

Participant A is in your class. Participant B is in another school.

Step 1

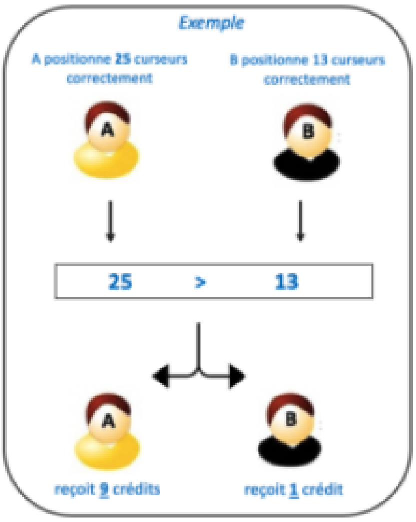
Participants A and B each had the first task of placing cursors in the middle of a row from 0 to 100 (as you did previously). A and B, however, were not playing against each other during this slider game.

2nd step

We randomly match the two participants and we **share 10 credits between them** .

To determine the split, we look at the number of cursors placed correctly by each player.

We allocate 9 credits to the participant who correctly placed the most sliders and 1 credit to the other participant. Between them, the two participants therefore won 10 credits.

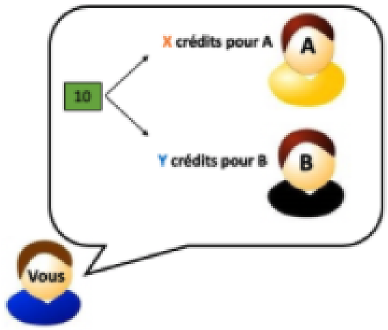


Step 3

Your task is to determine the final allocation of credits between the two participants.

You can leave the current distribution unchanged (9-1), or choose any other final distribution.

Both participants will receive the credits corresponding to the distribution you have chosen.



Which distribution do you want to choose for participants A and B?

(Click on the blue bar below to position and move the cursor.)

Participant A		Participant B
4 credit (s)		6 credit (s)

To confirm

Figure D9: Depth of reasoning

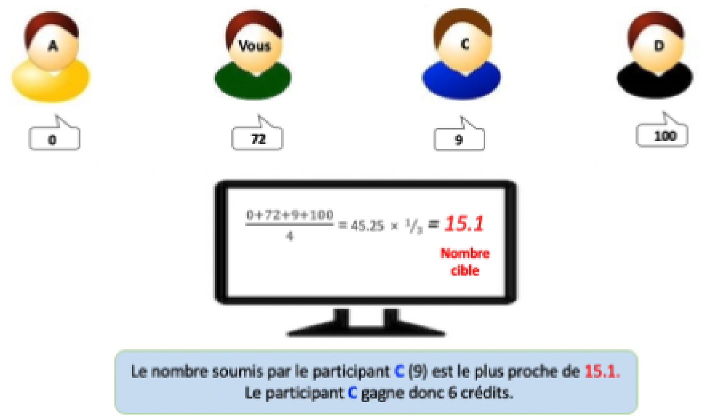
We now suggest you play with **three other participants** .

This game contains **four rounds** .

Each round, each party member submits a number between 0 and 100. Single digit decimal numbers are allowed.

The computer then calculates the average of the 4 proposed numbers, then multiplies this average by a third.

This gives a " target number " as illustrated below.
The group member whose proposed number is closest to the target number earns 6 credits.



At each round, when all the participants have submitted their number, you will see a summary appear on the screen indicating the average of the 4 numbers, the target number and whether or not you have won.

The on-screen summary will display for 60 seconds and then you will start the next round by submitting a new number.

When you are ready, please click on the "Start" button.

To start

Veuillez entrer le nombre que vous avez choisi (entre 0 et 100) :

Confirmer