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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. Behavioral traits are important determinants of life outcomes. While recent work has focused on how these traits are influenced by the family environment, or how they can be affected by childhood interventions, little is known about how these traits are related to social networks. Based on unique data collected using incentivized experiments on more than 2,500 French high-school students, we find high levels of homophily across all ten behavioral traits that we study. Notably, the extent of homophily depends on similarities in demographic characteristics, in particular with respect to gender. Furthermore, the larger the number of behavioral traits that students share, the higher the overall homophily. 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, have longer periods of friendship, or are friends with more popular individuals.

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

Keywords: Homophily, social networks, behavioral traits, peer effects, experiments

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1 Introduction

An individual's social network is a key factor of success in life. People depend on friends, relatives, and peers for information, opportunities, and norms of behavior (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 through referrals (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 (Sacerdote, 2014; Epple and Romano, 2011; Golsteyn et al., 2021), educational aspirations (Gagete-Miranda, 2020; Norris, 2020), disruptive classroom behavior, substance abuse, school dropout rates (Santavirta and Sarzosa, 2019; Case and Katz, 1991; Gaviria and Raphael, 2001; Lee et al., 2020), and prosocial behavior (Rao, 2019; Alan et al., 2021), which has been shown to influence labor market success during one's professional life (Kosse and Tincani, 2020).

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 the observation that people associate 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 (Chetty et al., 2022b; Currarini et al., 2009; McPherson et al., 2001). 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). Homophily starts early on. Using data on the social networks of 70.3 million Facebook users, Chetty et al. (2022b) document large homophily by parental SES among high school friends. Overall, 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, including trust, generosity, and the ability to cooperate with others, 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 as a means to escape poverty traps (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, if such homophily exists, do the behavioral traits of friends affect one's own behavioral traits (instead of only self-selecting into friendship networks where peers have similar 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 high school students in France. Students are on average 15.8 years old.

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: risk tolerance, trust, cooperation, coordination, depth of reasoning, competitiveness, generosity, morality, preferences for redistribution, 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 on homophily in a very broad set of behavioral traits by documenting the extent to which friendships are associated with similarity not only in demographic characteristics, but also in behavioral traits. We first confirm a well-established conclusion in the literature: 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. For instance, two students who have the same gender are 15.4 percentage points more likely to be friends than two student of opposite gender. Since behavioral traits themselves differ by gender and social-economic characteristics, the degree to which homophily is based on demographic characteristics or behavioral traits is, a priori, unclear.

This leads to our main finding with respect to homophily: high school students exhibit a large degree of homophily based on behavioral traits, which comes on top of the well-documented homophily on demographic characteristics. Similarity in morality, depth of reasoning, cooperation, or generosity is respectively associated with a 6.3 percentage points higher friendship likelihood (respectively 5.8, 5.6, and 4.9 percentage points). Remarkably, homophily arises based on each of the ten behavioral traits we measure. Furthermore, similarity in demographic characteristics, such as gender, strongly amplifies homophily in behavioral traits. For example, two girls or two boys who share the same level of cooperativeness are 9.4% more likely to be friends, but this effect goes down to 1.5% for opposite-gender students. In a nutshell, for most behavioral traits, homophily only exists if students have initially formed friendships based on more observable demographic characteristics such as gender. Finally, we 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 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

[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.

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 (which we discuss in the conclusion).

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 Bramoullé et al. (2009) and Case and Katz (1991), which consists of instrumenting the behavioral traits of the friends with the exogenous 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).[2] 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 five out of ten behavioral traits. Specifically, a student's risk tolerance, depth of reasoning, cooperativeness, coordination behavior, and competitiveness are all affected by their peers. While the first four traits are positively influenced by peers, the last one, competitiveness, is negatively influenced. Second, the magnitude of peer effects is accentuated with the longevity of social networks, the popularity of one's peers, and shared demographic characteristics.

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 (Jackson, 2010; McPherson et al., 2001), notably among school-age students (Chetty et al., 2022a,b; Currarini et al., 2009; Baerveldt et al., 2004). Yet, if 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 this 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 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 (in a dictator game in Jackson et al. (2022)). Our paper provides novel evidence

[2] The main source of variation in the first stage of our IV methodology comes from variation in the shared demographic characteristics of a network of predicted friends.

on homophily with respect to eight 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). We might therefore expect larger peer effects among adolescents than among adults.[3] Understanding how these traits are formed at younger age is particularly 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 preschool or in childhood and adolescence can causally influence these traits (Cappelen et al., 2020; Kosse et al., 2020). Less is known about the role played by peer groups, 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 (2020) shows that peer popularity and achievement affect student academic outcomes as well as several social outcomes, and Charroin et al. (2022) have identified in a laboratory experiment the extent of peer effects in dishonesty. 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.[4]

We make three main contributions to this emerging literature on the transmission of behavioral traits in networks. First, we examine an unusually large set of behavioral traits with a focus on economic preferences 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).[5,6] Second, in contrast to Shan and Zölitz (2022), we elicit student behavioral traits with incentives, which limits measurement error, reference biases, and social desirability biases in the measure of our outcomes (Dohmen and

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

[4] Wu et al. (2023) also document peer effects in extraversion and agreeableness among students. In addition to focusing on Big-5 personality traits, Shan and Zölitz (2022) also find positive peer effects in competitiveness.

[5] A notable exception is the recent paper by Jagelka (2020) 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.

[6] As summarized by Heckman et al. (2021) in a recent survey of the literature, Becker et al. (2012) find that while both preferences and personality skills predict behavior such as labor market success, health, and life satisfaction, they are only weakly related and thus likely capture separate underlying constructs.

Jagelka, 2022).[7] 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 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 controlled and incentivized measures of a broad set of behavioral traits that are also important antecedents to subsequent life outcomes.[8]

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; 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, ability, social background) and longer-term outcomes (such as educational attainment, labor market success, health, and criminality) differs (Heckman et al., 2021).[9]

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

[7] For more on attenuation bias resulting from measurement error in economic preferences/behavioral traits, see for example Cunha et al. (2010); Cunha and Heckman (2009).

[8] Note that behavioral traits measured through incentivized games might capture an individual's characteristics which may be different from the social behaviors they exhibit. For example, an individual, despite being intrinsically risk averse, can engage in socially risky habits such as drug and alcohol consumption. The latter might be driven by emulation of peers without internalizing the costs of the action. The former (behavioral traits in our case) may speak to a more fundamental personality trait.

[9] See Golsteyn and Schildberg-Hörisch (2017) for a recent summary of the literature on the stability of preferences and personality and Chapman et al. (2023) for evidence on the correlation between traits, cognitive abilities, and demographics.

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. The study was conducted during regular school hours, thus reducing self-selection concerns. We set up a novel online platform for data collection. 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.[10]

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 for an illustration.
2. **Competitiveness**. We asked students to place 48 sliders in the middle of a [0,1] axis as quickly as possible. Students had two minutes to perform the task, and had to choose between two payment options (Niederle and Vesterlund, 2007): (i) they could play alone and gain 0.2 credits for each slider correctly positioned, or (ii) they could choose to compete with another player. In the latter option, if a student performed better than their competitor, they would earn 0.5 credits for each correctly positioned slider. If they performed worse, 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 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.[11] See Figure D3 for an illustration.
4. **Cooperation**. Here, students were paired with another student for four rounds.[12] 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 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

[10] We had one additional trait by eliciting time preferences. Unfortunately, the data were not recorded correctly for most participants, due to which we don't report on time preferences.

[11] 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.

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

zero otherwise. Our measure of coordination is the average number of times a student chose option B. See Figure D5 for an illustration.

6. **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 D6 for an illustration.

7. **Tolerance for inequality**. Here, 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 indicates the strongest preference for equality, while a difference of 10 represents the strongest form of inequality tolerance. See Figure D7 for an illustration.

8. **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 varied as 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 the four rounds (i.e. a higher value of the measure would imply a lower level of depth of reasoning). See Figure D8 for an illustration.

9. **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.

10. **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 to obtaining an undergraduate degree, 3 a graduate degree, and 4 a PhD). We use this as our measure for educational aspirations.

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 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

Table 1: Descriptive Statistics

	Mean	Std. Dev.	Min.	Max.	N
Panel A: Friendship Information					
No. of friends reported	4.640	0.856	1	5	2565
No. of times reported as a friend	2.287	1.681	0	10	2565
Panel B: Behavioral Traits					
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
Panel C: Demographic characteristics					
Female	0.557	0.497	0	1	2565
Age (in years)	15.766	0.942	13	19	2565
French	0.961	0.193	0	1	2565
Born in France	0.950	0.218	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
Low Socio-Economic Status (SES)	0.419	0.493	0	1	2565
No. of siblings	1.073	1.047	0	11	2565
Only Child	0.329	0.470	0	1	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. Lower value of the measure of depth of reasoning implies a higher level of depth of reasoning.

converted in gift vouchers.[13,14]

[13] The superintendent in Créteil did not want to incentivize students with money. We therefore did not convert credits in gift vouchers in these schools. We account for that difference by systematically controlling for students' region in the analysis.

[14] Four of the games were interactive (the trust, cooperation, coordination, and competition games). Students played

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.[15] 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 parent profession to capture a student's socio-economic status (SES).[16] We used 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.[17]

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). Students in our sample are 15.7 years old on average, and 79.2% are white. With a maximum of five permitted, students reported 4.6 friends on average.

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

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 name (but without the above information). Finally, a last group was not given any information on their partner. Our analysis does not exploit these different treatments, which can be the subject of future research. In all our regressions, we control for this treatment variation.

[15]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.

[16]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, among others, professions like postman, ambulance driver, caregiver, cashier, shop seller, police officer, security agent, or secretary. Manual workers include, for instance, 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).

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

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 $d_{ji} = 1$.[18] 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. For the sake of comparison, all measures in the regressions are scaled down to lie between 0 and 1. $\mathbf{x}_i$ 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.[19] 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 who nominates other students as friends (the sender) and each student who is 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.*

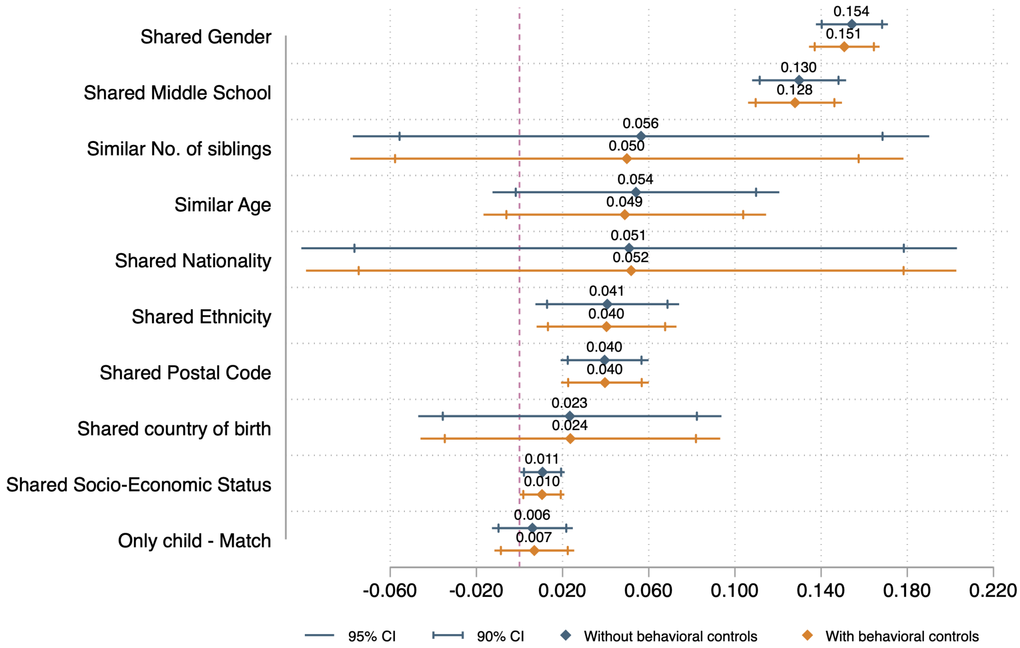
Sharing a demographic characteristic such as gender, ethnicity, or attendance of the same middle school strongly predicts friendship formation. Figure 1 reports homophily coefficients on demographic characteristics. In blue, we present the estimations without controls for behavioral traits. Two students who have the same gender are 15.4 percentage points more likely to be friends than two students of opposite gender. Similarly, having attended the same middle school increases friendship chances by 13 percentage points, as does having the same ethnicity (+4.1 pp.), living in the same geographical area (+4.0 pp.), and having the same socio-economic status (+1.1 pp.). In contrast, our results suggest that similarity in age, nationality, country of birth, or number of siblings does not increase friendship chances. This is partly due to the limited variation in these characteristics within the sample, let alone within a class.[20]

The large homophily based on demographic characteristics we document among high school

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

[19] 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

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 yellow coefficient corresponds to a regression that controls for the following shared behavioral traits: tolerance to inequality, trust, generosity, morality, cooperation, coordination, risk tolerance, competitiveness, depth of reasoning and educational aspirations. Standard errors are clustered at the classroom level.

students raises the question: How much of this homophily is explained by similarity in behavioral traits? In fact, we find an association between demographic characteristics and behavioral traits. For example, Figure 2 shows that girls are more moral, generous, and risk averse than boys, but less competitive and tolerant of inequalities. Low-SES students are also less generous, trusting, and competitive than high-SES students.

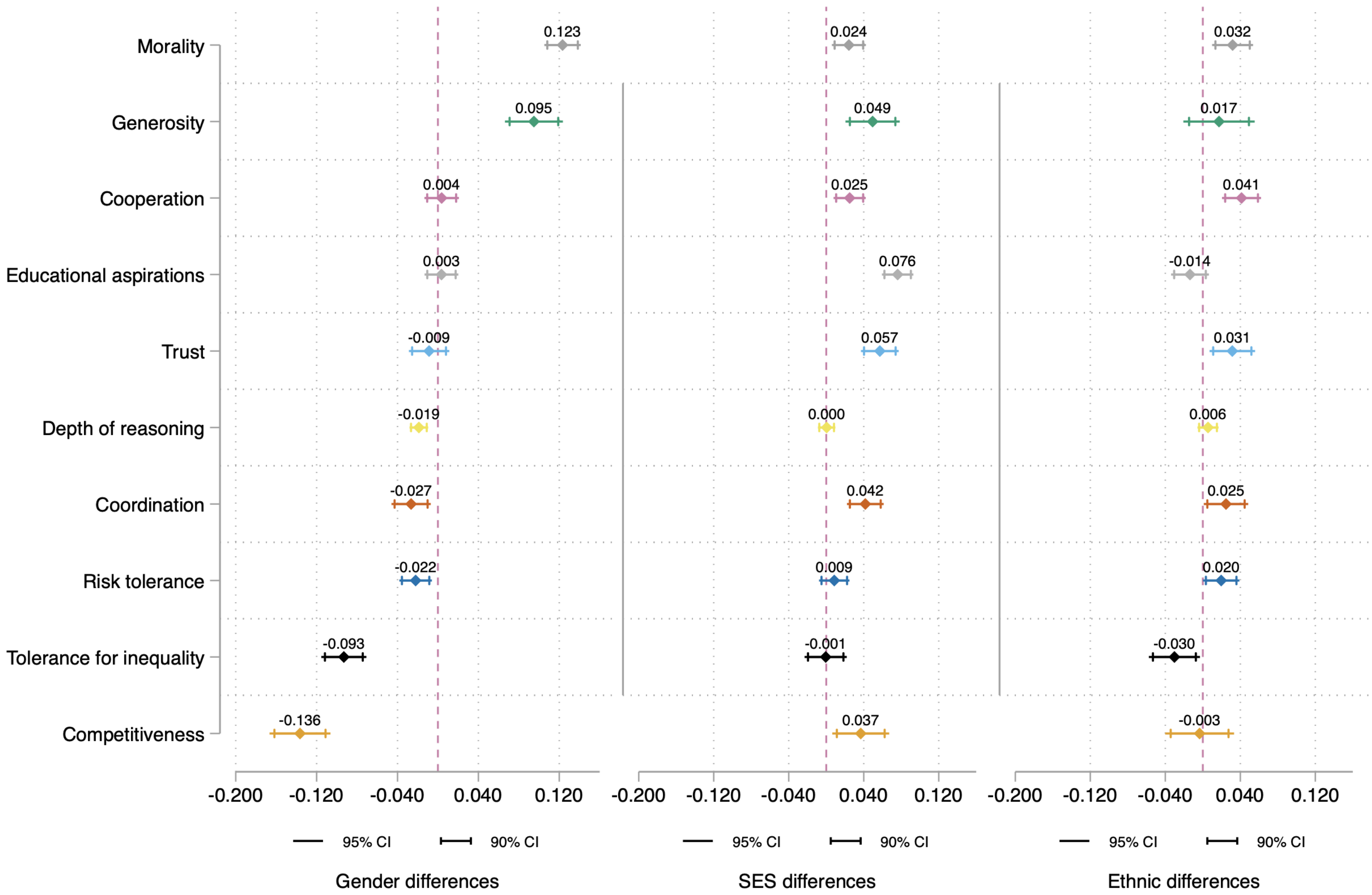
We tease out homophily based on demographic characteristics from homophily based on behavioral traits using the combined administrative and experimental data. More specifically, we test how much the homophily coefficients change when we control for students' behavioral traits. The results are reported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

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

$\mathbf{1}[x_i = x_j]$.

[20]96.5% of high school students are French. 95% were born in France, and age only varies in months within a class.

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. 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. Lower value of the measure of depth of reasoning implies a higher level of depth of reasoning.

Despite large gender and social differences in behavioral traits[21], these differences explain only marginally the degree of homophily based on gender and other demographic characteristics. For instance, we previously showed that two students who have the same gender are 15.4% percentage points more likely to be friends than two students of opposite gender. Controlling for all behavioral traits only reduces this probability by 0.3 percentage points. Comparing the homophily coefficients across both specifications in Figure 1 brings 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. After having confirmed the well-established homophily based on demographic characteristics, 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 students' behavioral traits comes on top of the homophily by demographic characteristics.

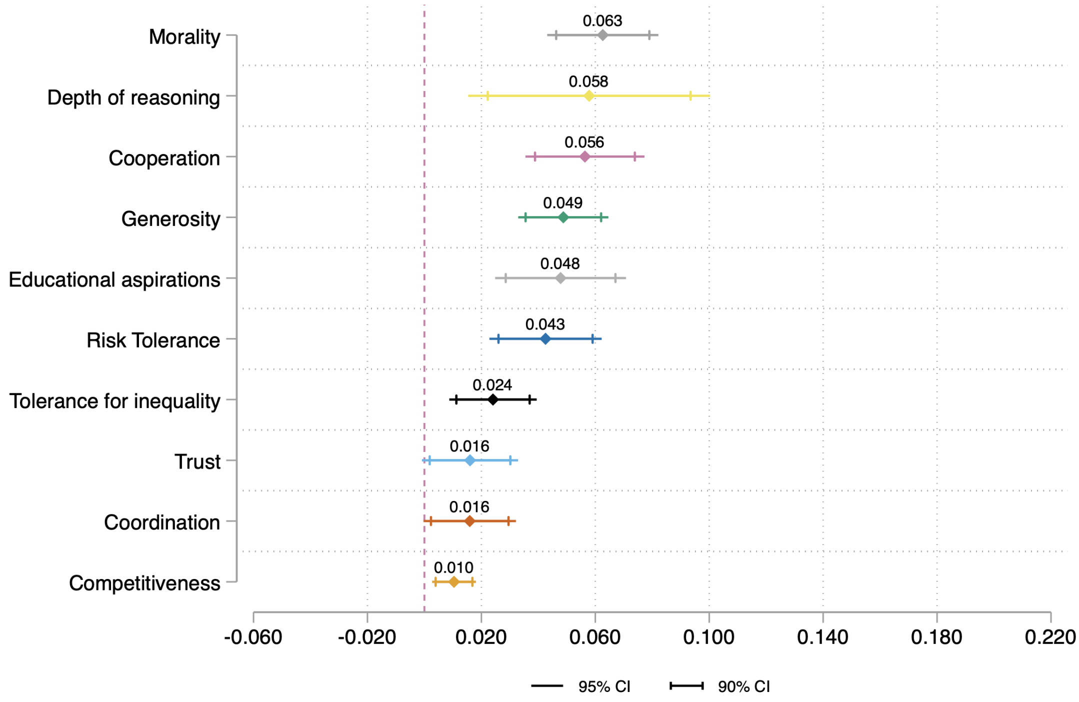
Our results reveal that similarity in behavioral traits is independently and significantly associated with the likelihood of being friends. This holds for all ten behavioral traits. Moving from the minimum to the maximum value – which one can interpret as a move from totally dissimilar traits to identical traits – increases the friendship likelihood between 1 percentage point (for competitiveness) and 6.3 percentage points (for morality). Next to morality, we observe the strongest degree of homophily for depth of reasoning, cooperation, generosity and educational aspirations.

These results 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, yielding the conclusion 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.

Next we test if homophily by behavioral traits is more prevalent among students who are more alike in terms of demographic characteristics such as gender, ethnicity, or social background. We investigate this by running our baseline specification (eq. 1) separately on pairs of same-gender (resp. same-SES / same-ethnicity) students and different-gender students (resp. different-SES /

[21]Girls tend to be more risk averse, i.e., less risk tolerant (Croson and Gneezy, 2009), more prosocial, and less competitive than boys (Niederle and Vesterlund, 2007; Buser et al., 2014; Almås et al., 2016; Sutter and Glätzle-Rützler, 2015). Similarly, children from poorer and less educated families have been found to be significantly less altruistic, more selfish, less cooperative, and less trusting (Falk et al., 2021; Sutter and Untertrifaller, 2020; Chowdhury et al., 2022).

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 above, captures how close two students are in terms of behavioral traits. For the sake of comparison, all measures of behavioral traits in the regressions are scaled down to lie between 0 and 1. We control for shared demographic characteristics such as gender, ethnicity, nationality, place of residence, low 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.

different-ethnicity). Figure 4 shows the coefficients we obtain for these two samples. A clear difference emerges, which leads to our next fact.

Fact 4: *Similarity in demographic characteristics (in particular with respect to gender, but also concerning attendance of the same middle school) strongly amplifies homophily based on behavioral traits.*

Homophily based on behavioral traits is significantly higher when students share the same gender than when considering pairs of boys and girls. For example, we previously found that increasing similarity in students' cooperativeness from 0 to 1 was associated with a 5.6 p.p. higher friendship chance. This effect goes up to 9.4 p.p. when students share the same gender, while it goes down to 1.5 p.p. for opposite-gender students. This last coefficient is not even statistically significant. We find similarly large differences for homophily by morality (+9.3 p.p. for

Table 2: Homophily based on behavioral traits

	(1)	(2)	(3)	(4)
Tolerance for inequality	0.022***	0.015***	0.019***	0.024***
	(0.006)	(0.006)	(0.005)	(0.008)
Morality	0.043***	0.029***	0.035***	0.063***
	(0.007)	(0.006)	(0.006)	(0.010)
Trust	0.021***	0.017**	0.020***	0.016*
	(0.007)	(0.007)	(0.007)	(0.009)
Generosity	0.052***	0.044***	0.044***	0.049***
	(0.007)	(0.007)	(0.007)	(0.008)
Cooperation	0.045***	0.040***	0.043***	0.056***
	(0.008)	(0.008)	(0.008)	(0.011)
Coordination	0.015**	0.015**	0.016**	0.016*
	(0.006)	(0.006)	(0.006)	(0.008)
Risk tolerance	0.029***	0.027***	0.028***	0.043***
	(0.008)	(0.008)	(0.008)	(0.010)
Competitiveness	0.012***	0.008**	0.008**	0.010***
	(0.004)	(0.004)	(0.004)	(0.004)
Rationality	0.044***	0.031**	0.035**	0.058***
	(0.015)	(0.015)	(0.015)	(0.022)
Educational aspiration	0.035***	0.024***	0.025***	0.048***
	(0.007)	(0.008)	(0.008)	(0.012)
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 behavioral traits in the regressions are scaled down to lie between 0 and 1. "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

same-gender students versus non-significant +1.8 p.p. for opposite-gender), generosity (+6.4 p.p. versus +2 p.p.), depth of reasoning (+8.1 p.p. versus non-significant +0.5 p.p.), risk tolerance (+6.6 p.p. versus non-significant +0.9 p.p.), and tolerance for inequality (+3.7 p.p. versus non-significant +0.3 p.p.). Figure 4 clearly shows that homophily based on behavioral traits is often close to zero and statistically insignificant when students are of different gender. In a nutshell, for most behavioral traits, homophily only exists if students have initially sorted themselves based on more observable demographic characteristics such as gender. A similar magnification of homophily is observed when students attended the same middle school, which proxies the longevity of friendships. Students from the same middle school show considerably more homophily than those who entered high school from different middle schools (see the second column in Figure

4). Homophily is less saliently different along the dimension of ethnicity and SES of parents. Students who share ethnicity (parental SES) do not show considerably more homophily than those who differ in ethnicity (parental SES) (see the two last columns in Figure 4).

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.[22]

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 or peer effects.*

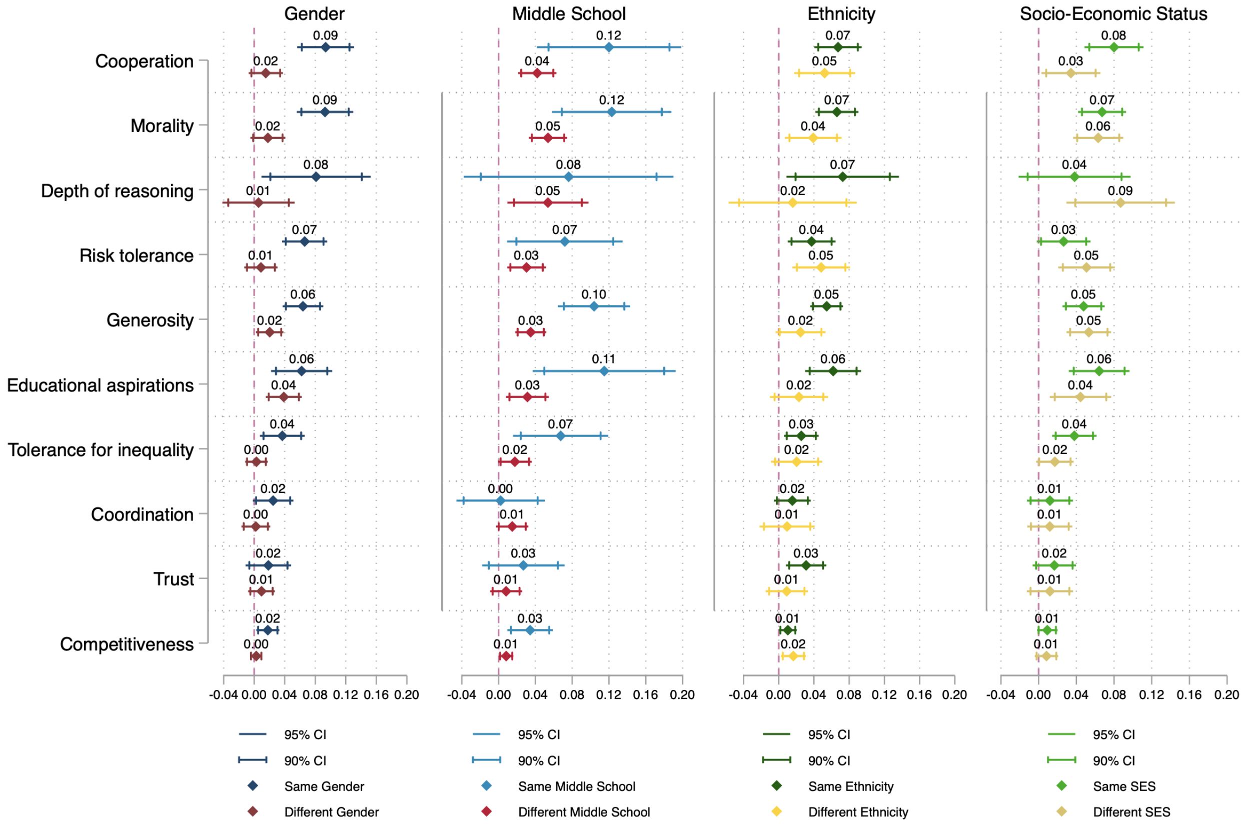
The results we obtain (reported in Figure 5) do not substantially differ from the results discussed above.[23] In other words, similarity in each behavioral trait is individually and independently associated with higher friendship chances. This notable result implies that students who are similar in 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, 2021). 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 friends 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 further 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. 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.

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

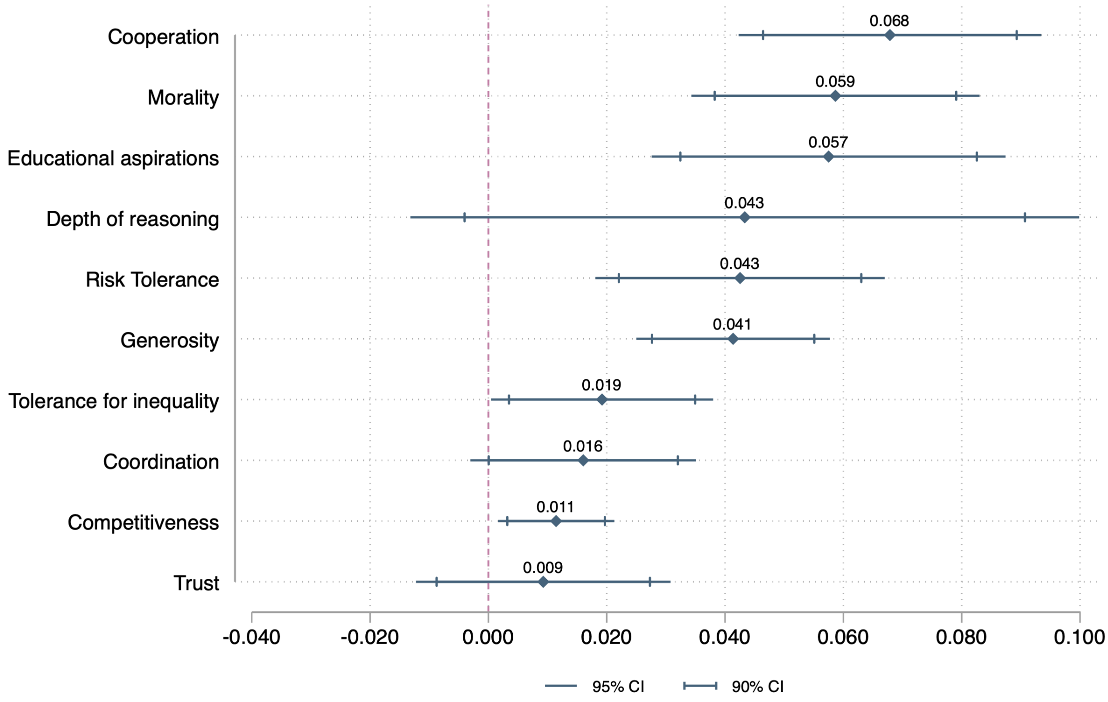
[23] All homophily coefficients remain statistically significant, except for trust and depth of reasoning. Statistical significance for the coordination coefficient drops to 10%. The remaining coefficients remain statistically significant at 5% level.

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 above, captures how close two students are in terms of behavioral traits. For the sake of comparison, all measures of behavioral traits in the regressions are scaled down to lie between 0 and 1. We control for shared demographic characteristics such as gender, ethnicity, nationality, place of residence, low 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 above, captures how close two students are in terms of behavioral traits. All measures of behavioral traits in the regressions are scaled down to lie between 0 and 1. We control for shared demographic characteristics such as gender, ethnicity, nationality, place of residence, low 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.

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.1 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.

On the origins of homophily: Teasing out selection effects from peer effects. 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 Peer Effects in Behavioral Traits

4.1 Empirical Strategy

We use a standard equation to identify peer effects[24]:

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

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, $\mathbf{x}_{li}$ captures demographic characteristics of student i (such as gender, race, nationality), y_{lj} is the behavioral trait of the friend j of student i, $\mathbf{x}_{lj}$ 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 matrix form:[25,26]

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

The identification of 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 discuss in the following how we address the other two challenges.

Addressing the reflection problem. To address the reflection problem, we use the method developed by Bramoullé et al. (2009) and Case and Katz (1991), which consists of instrumenting the behavioral traits of the friends ($\mathbf{Gy}$) with the predetermined demographic characteristics (gender, ethnicity, nationality, etc.) of the friends ($\mathbf{Gx}$), friends of friends ($\mathbf{G^2x}$) and friends of friends

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[24]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). More details can be found in section A of the appendix.

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

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

of friends ($\mathbf{G^3x}$).[27] The intuition behind these instruments is simple. The friends of a student i might be more risk averse, for example, if the friend's own network is composed of a larger share of girls (who are on average more risk averse; see Figure 2 for our data on this relationship).

This IV strategy relies on two identifying assumptions. First—assuming for now that friendships are formed exogenously, an assumption that we lift below—the exclusion restriction states that, beyond common classroom effects, the behavioral traits of the individual ($\mathbf{y}$) are only impacted by their own predetermined characteristics ($\mathbf{x}$), the behavioral traits of their friends ($\mathbf{Gy}$) and the predetermined characteristics of their friends ($\mathbf{Gx}$).[28] In other words, 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 ($\mathbf{Gy}$).

Second, using the demographic characteristics of the friends of friends as instrumental variables respects the IV independence assumption so long as these demographic characteristics are independent from student i's unobservable traits ϵ_{li}. For instance, the only reason why the gender composition of my friends' networks ($\mathbf{Gx}$) affects my level of risk aversion ($\mathbf{y}$) is because it affects my friends' risk aversion ($\mathbf{Gy}$). For instance, 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.[29] As discussed below, these two identification assumptions are less likely to hold when networks are endogenously formed, which motivates the second central element of our identification strategy.

Addressing endogenous friendship formation. In our environment, friendships are formed endogenously. They can be shaped by shared experiences, similarity in behavioral traits, and similarity in demographic characteristics. As a result, the friendship matrix $\mathbf{G}$ can be correlated with the unobservable characteristics of the student i. In other words, who my friends are, but also who the friends of my friends are, could be correlated with unobservable characteristics that determine my behavioral traits. This would violate the identifying assumptions of our IV strategy.

In order to circumvent this issue, we use a solution introduced by König et al. (2019) and Gagete-Miranda (2020). Instead of using the endogenous friendship network that students report, we predict the friendship network based on students' predetermined demographic characteristics. 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. Students who share the same gender, ethnicity, social background, or hometown are more likely to be friends. To tackle the endogenous friendship network, we therefore replace the reported network $\mathbf{G}$ by the first, second, and third degree predicted networks $\hat{\mathbf{G}}$.

[27] When eq. 3 includes contextual variables ($\mathbf{Gx}$), the demographic characteristics of the direct friends ($\mathbf{Gx}$) are no longer excluded instruments for the behavioral traits of the direct friends ($\mathbf{Gy}$). To avoid the risk of transitive triads, we remove classrooms which have a network diameter of less than 3.

[28] The predetermined characteristics of friends do not have a role to play in our alternative specification without contextual effects.

[29] The Bramoullé et al. (2009) instruments have a flavor of auto-spatial regressive Arellano-Bond instruments.

We use the following simple logit model to predict the friendship probabilities:

$$\mathbb{P}(d_{ij} = 1|\mathbf{M}'_{ij}, \mathbf{x}_i, \mathbf{x}_j) = \frac{\exp(\mathbf{M}'_{ij}\psi + \theta_i\mathbf{x}_i + \theta_j\mathbf{x}_j + \gamma_l + \nu_{ij})}{1 + \exp(\mathbf{M}'_{ij}\psi + \theta_i\mathbf{x}_i + \theta_j\mathbf{x}_j + \gamma_l + \nu_{ij})} \tag{4}$$

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, low 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. 4, 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 $\hat{g}_{ij} = \frac{\hat{d}_{ij}}{\sum_j \hat{d}_{ij}}$.[30]

2SLS estimation. After having predicted the friendship network, we use a standard 2SLS estimation approach.[31] In the **first stage**, we regress friends' behavioral traits on the set of instruments $Z = [\hat{\mathbf{G}}\mathbf{x}, \hat{\mathbf{G}}^2\mathbf{x}, \hat{\mathbf{G}}^3\mathbf{x}]$ in order to predict $\widehat{\mathbf{Gy}}$. Specifically, the first stage regression corresponds to:

$$\mathbf{Gy} = \zeta_1\hat{\mathbf{G}}\mathbf{x} + \zeta_2\hat{\mathbf{G}}^2\mathbf{x} + \zeta_3\hat{\mathbf{G}}^3\mathbf{x} + \zeta_4\mathbf{x} + \zeta_5\mathbf{Gx} + \eta + \epsilon \tag{5}$$

where $\mathbf{Gy}$ captures the behavioral traits of the friends. $\hat{\mathbf{G}}\mathbf{x}$, $\hat{\mathbf{G}}^2\mathbf{x}$, and $\hat{\mathbf{G}}^3\mathbf{x}$, respectively, correspond to the demographic characteristics of the predicted first-, second-, and third-degree friends—i.e., their gender, ethnicity, 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.[32]

The **second stage** regression corresponds to eq. 3 in which we use the predicted value $\widehat{\mathbf{Gy}}$ instead of $\mathbf{Gy}$:

$$\mathbf{y} = \beta\widehat{\mathbf{Gy}} + \gamma\mathbf{x} + \delta\mathbf{Gx} + \eta + \epsilon \tag{6}$$

We use the same vector of demographic characteristics as in the first stage regression. β is our

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

[31]Using the predicted network rather than the observed network as instrumental variables raises the risk of having weak instruments if the demographic characteristics (such as race, gender, etc.) have a low predictive power for network links. We discuss this in Section 4.3 on robustness checks

[32]In practice, to estimate eq. 5, we take a global difference by subtracting the class average to each variable.

coefficient of interest which captures how much friends' behavioral traits affect a student's own traits.

Identifying assumption. Ultimately, our method generates a set of predicted friends and non-friends in a class. Our instruments—the predetermined demographic characteristics of the predicted friends—are valid so long as the characteristics of the non-friends do not impact a student's traits beyond the average effect of these characteristics at the class level. Put differently, shared demographic characteristics are used to predict friendship links through which we identify the causal impact of the friendship link. We control for classroom fixed effects and, in robustness checks, assess the stability of our results to the inclusion or exclusion of contextual variables, such as the demographic characteristics of the friends.

Finally, we would like to note that using a predicted network rather than the observed network largely addresses concerns of missing links in networks and the potential threats to identification they cause. 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.[33] Using a predicted network rather than the observed network rules out the possibility of this endogenous unobserved link. We also find that homophily estimates are consistent with undirected and weighted networks. These different network specifications further assuage the concern of missing links because, 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. Because we allow these links to become undirected or weighted and the results are robust, censorship bias is not a major concern in our setting.

4.2 Results on peer effects in behavioral traits

Friendship prediction. Table A.2 reports the 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 (shared 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.[34]

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

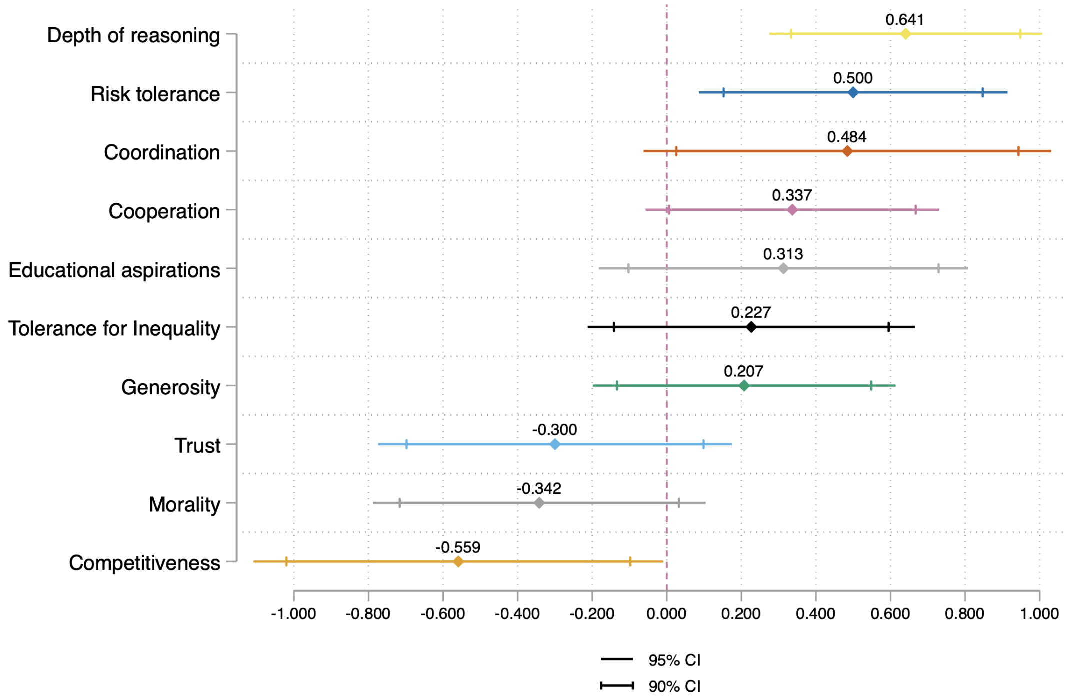
[33] For instance, when student A names B as a friend and B and C are friends, but C is ranked 6th among A's friends, then A and C do not name each other in the survey. As a result, when C's characteristics are used as instruments for B's traits, C's characteristics might be directly correlated to A's traits, which makes C's characteristics an invalid set of instruments.

[34] 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.

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 (demographic characteristics of friends).[35] We see fairly large peer effects in five out of the ten behavioral traits measured in our experiment. The strongest estimate is found for depth of reasoning where a one-standard deviation increase in peers' depth of reasoning leads to an increase in a student's depth of reasoning by 0.64 standard deviations. Risk tolerance and the willingness to coordinate on an efficient outcome have similarly large estimates on peer effects (around 0.5 standard deviations per one standard deviation change in friends' risk tolerance or coordination behavior). Like coordination, the estimate for cooperation of 0.37 standard deviations is weakly significant at the 10%-level. Besides those four behavioral traits with positive peer effects, we find a significantly negative effect for competitiveness. If peers are more competitive by one standard deviation, a student's competitiveness is reduced by about 0.55 standard deviations. The negative peer effects on competitiveness in endogenous networks may be due because competitiveness can potentially hinder social interactions, and therefore may endanger friendship links.

[35]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. 6. 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 with the demographic characteristics of the predicted friends $\hat{\mathbf{G}}\mathbf{x}$, friends of friends $\hat{\mathbf{G}}^{\mathbf{2}}\mathbf{x}$, and friends of friends of friends $\hat{\mathbf{G}}^{\mathbf{3}}\mathbf{x}$. Each regression includes control variables for the following demographic characteristics of the individual and of the friends: gender, ethnicity, nationality, low 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.

Table 3: Coefficients from peer effects analysis

	Reasoning (1)	Risk (2)	Coord. (3)	Coop. (4)	Aspiration (5)	Inequality (6)	Generosity (7)	Trust (8)	Morality (9)	Compet. (10)
Friend avg. skill	0.641***	0.500**	0.484*	0.337*	0.313	0.227	0.207	-0.300	-0.342+	-0.559**
	(0.187)	(0.211)	(0.279)	(0.201)	(0.253)	(0.224)	(0.207)	(0.242)	(0.228)	(0.280)
Female	-0.165***	-0.043	-0.160***	-0.037	-0.019	-0.268***	0.049	-0.116**	0.319***	-0.332***
	(0.047)	(0.054)	(0.047)	(0.047)	(0.049)	(0.050)	(0.056)	(0.049)	(0.048)	(0.050)
French	-0.389***	-0.067	-0.118	0.239*	-0.079	0.000	0.375**	0.183	0.095	0.115
	(0.146)	(0.153)	(0.181)	(0.124)	(0.130)	(0.132)	(0.162)	(0.141)	(0.142)	(0.148)
White	-0.025	-0.007	0.010	0.043	-0.011	-0.162***	-0.003	-0.010	0.019	0.082
	(0.054)	(0.055)	(0.051)	(0.057)	(0.046)	(0.050)	(0.056)	(0.053)	(0.055)	(0.058)
Age	0.002	0.002	-0.000	0.001	-0.011***	0.001	-0.012***	-0.005+	-0.001	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
No. of sib	0.012	0.005	-0.021	-0.041+	0.029	0.063**	-0.014	-0.029	-0.076**	-0.010
	(0.027)	(0.026)	(0.031)	(0.028)	(0.025)	(0.026)	(0.034)	(0.028)	(0.031)	(0.029)
Only child	0.083	-0.059	-0.091+	-0.025	-0.077	0.060	-0.010	0.046	-0.116*	-0.086
	(0.058)	(0.057)	(0.063)	(0.060)	(0.057)	(0.060)	(0.072)	(0.062)	(0.065)	(0.067)
Low SES	0.032	0.007	-0.093**	-0.020	-0.105***	-0.056	-0.052	-0.110***	-0.088*	-0.017
	(0.043)	(0.049)	(0.041)	(0.041)	(0.038)	(0.041)	(0.048)	(0.042)	(0.048)	(0.045)
Born in France	0.172+	-0.042	-0.110	-0.408***	0.088	0.100	-0.114	-0.257**	0.112	-0.191+
	(0.109)	(0.123)	(0.130)	(0.117)	(0.113)	(0.104)	(0.127)	(0.122)	(0.119)	(0.126)
Contextual variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R-sq	-0.163	-0.094	-0.093	-0.030	-0.022	-0.005	0.018	-0.001	-0.000	-0.059
N	2296	2547	2294	2299	2514	2293	2003	2292	2419	2308
F Stat.	2.487	2.479	3.093	2.188	1.849	2.863	1.648	2.045	1.384	4.248

Note: This Table reports coefficients of peer effects in behavioral traits. Each column corresponds to a separate regression based on Eq.6. 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 with the demographic characteristics of the predicted friends $\hat{\mathbf{G}}\mathbf{x}$, friends of friends $\hat{\mathbf{G}}^{\mathbf{2}}\mathbf{x}$, and friends of friends of friends $\hat{\mathbf{G}}^{\mathbf{3}}\mathbf{x}$]. Each regression includes control variables for the following demographic characteristics of the individual and of the friends: gender, ethnicity, nationality, low 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 5). *** $p<0.01$, ** $p<0.05$, * $p<0.1$, + $p<0.15$

Recall that 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 cooperativeness or the quest for efficient coordination of actions, 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.

All in all, this set of results shows that students are influenced by the behavioral traits of their peers. These novel results provide an answer to the question we raised after showing substantial homophily in behavioral traits: Does this homophily stem from similar individuals befriending each other—selection channel—or does homophily stem from behavioral traits transmitting over peer networks—peer effect channel? Our results suggest that peer effects contribute to the large homophily based on behavioral traits.[36]

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 significantly higher when students share the same gender than when considering opposite gender pairs (Figure 4). Similarly, we found much higher levels of homophily among students who went to the same middle school (one to three years before we measured homophily) than among students who went to different middle schools. Next we want to investigate whether these patterns can be explained by peer effects becoming stronger when friends share some demographic characteristics.

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 friends (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 reveals large differences in peer effects between these two subgroups. While peer effects are almost always positive (and in five cases significantly so) for same-gender friends across the ten behavioral traits we consider, peer effects turn mostly to zero (and sometimes even negative) in the different gender sample. To illustrate the magnitude of the differences, increasing the depth of reasoning by one SD in a network of same-gender friends leads to a 0.77 SD jump in a

[36]Peer effects and selection effects might both play a role, although our paper does not shed light on the second channel.

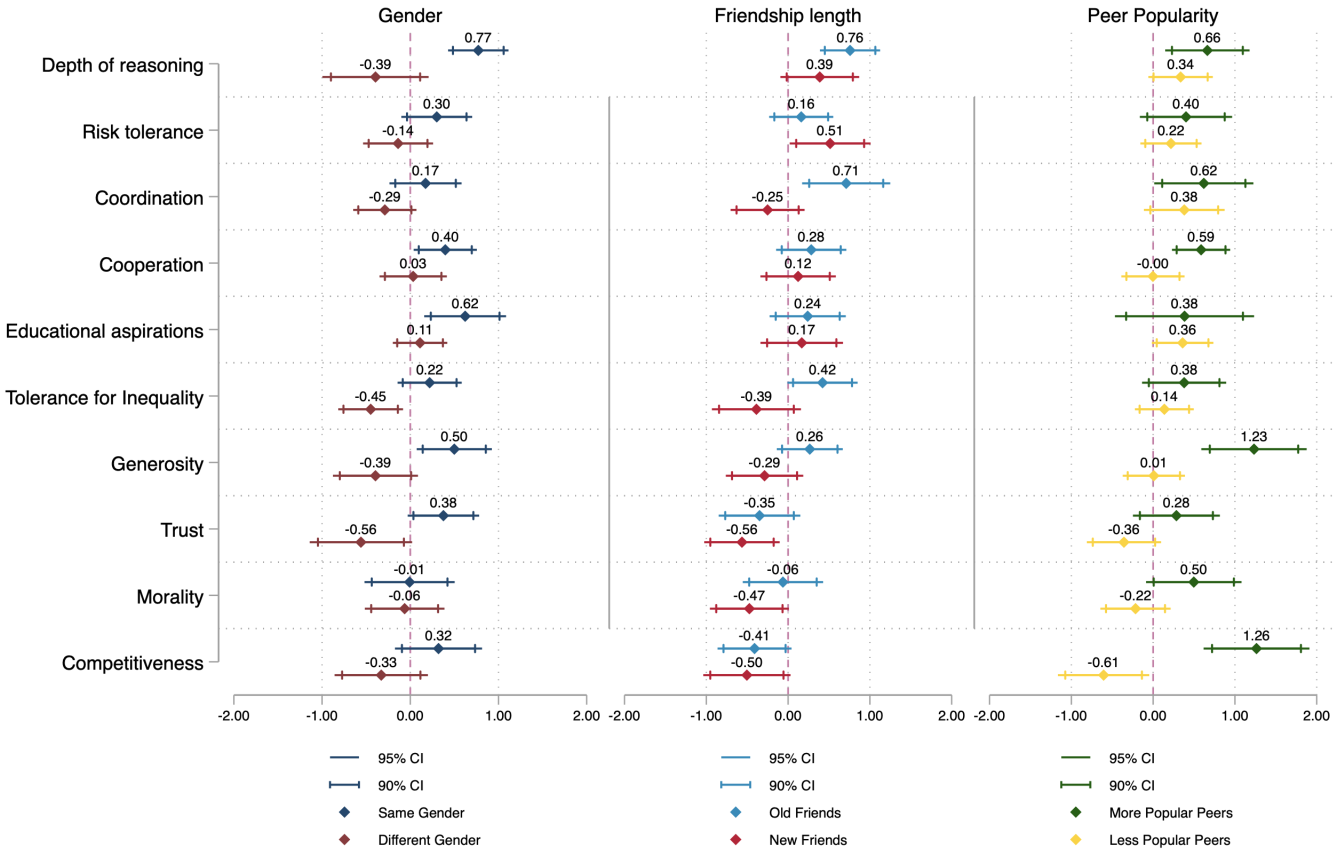
student's own depth of reasoning. This peer effect moves down to a non-significant -0.39 SD in case of different-gender friends. We find similar differences for other traits (+0.3 versus -0.14 SD for risk tolerance, +0.4 versus +0.03 SD for cooperation; +0.62 versus +0.11 SD for educational aspirations; +0.5 versus -0.39 SD for generosity; and +0.38 vs -0.56 SD for trust, just to mention a few examples).

We perform the same analysis for students whose network is predominantly composed of long-term friends (versus short-term friends). To do so, we split our sample into two subgroups. A first group of students who have been, on average, in the same classroom as their friends for three years or more. This is motivated by the fact that the median time that students spend in the same class is three years. We refer to this sample as the "Old friends" sample. The second group of students, the "New friends" sample, has been, on average, in the same classroom as their friends for less than 3 years. Figure 7 shows that peer effects have a slight tendency to be larger when the network of friends is composed of old friends than when it is composed of new friends. It seems that relationships need time to build up and then act as a medium over which behavioral traits may be transmitted.

As a final aspect of heterogeneity in peer effects, we also look in Figure 7 into the effects of whether someone has more or less popular peers as friends. The former might have a stronger influence than the latter on the members of their friendship network. 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 friend group is greater than 3) and individuals who are friends with less popular peers (average popularity of friend group is less than or equal to 3). Figure 7 shows that, for each single behavioral trait, students with more popular peers are more influenced by their peers than students with less popular peers (even though the differences are significant in only a few cases). This difference is particularly pronounced with respect to generosity and competitiveness. For the latter, the sub-sample with more popular peers has, indeed, positive peer effects, like in Shan and Zölitz (2022). Recall that, overall, we had found negative peer effects on competitiveness. The more detailed results conditional on popularity of peers suggests that competitiveness of peers is only attractive—and thus positively transmitted—when these peers are popular (i.e., if many students have them as friends), while if one's own friends are less popular among other students, competitiveness is not an attractive trait to imitate, and instead one observes negative peer effects. Overall, these findings seem to suggest that individuals are more strongly influenced by popular peers and hence try to emulate them. In Figure A.2 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 demographic characteristics (such as gender, middle school attendance) and more popular peers strongly amplify peer effects in behavioral traits. This amplifying effect explains why similarity in demographic characteristics largely amplifies homophily based on behavioral traits, as documented in Section 3 (Fact 4).*

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



Note: This figure reports coefficients of peer effects in behavioral traits. Each coefficient corresponds to a separate regression based on Eq. 6. 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 with the demographic characteristics of the predicted friends $\hat{\mathbf{G}}\mathbf{x}$, friends of friends $\hat{\mathbf{G}}^{\mathbf{2}}\mathbf{x}$, and friends of friends of friends $\hat{\mathbf{G}}^{\mathbf{3}}\mathbf{x}$. 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, low 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 sub-figure are split by the similarity of an individual's gender and the gender composition of their friend group. Same gender refers to the group of male (female) students with more than half of their friend group also being males (females). Different gender refers to the group of female (male) students with more than half of their friend group being of the opposite gender.[37] The second sub graph splits the sample by individuals who on an average have older (newer) friends in their network. The third sub graph 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.4 compares the results using directed networks (our baseline specification), weighted networks, and undirected (and unweighted) networks. As before, we run a separate regression for each behavioral trait.[38] The coefficients are similar across different network specifications, giving rise to two conclusions. First, for most behavioral traits we consider in this study, accounting for strength of a relationship has little effect on the estimated peer effects, suggesting that close and distant friends have a similar influence on a student. 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 whether we control for the peers' demographic characteristics. The results are reported in Figure A.3 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, such as cooperation, generosity and educational aspirations, 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.[39]

Weak IV. Finally, we check whether our results are sensitive to the use of alternative specifications to predict the friendship network. The strength of our instruments rely on the quality of the friendship predictions. If student demographic characteristics (shared ethnicity, gender, etc.) are not predictive enough of friendships, the predicted network can be noisy, and the instruments (the demographic characteristics of the predicted network) can be weak.[40] To alleviate the weak instruments concerns, 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 enrich the set of sender and receiver characteristics by including interaction terms between each demographic characteristic (for instance $Female \times French$, $Female \times White$ 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

[38] 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.

[39] 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.

[40] Moreover, we have 8 predetermined characteristics and we use the characteristics of the predicted friends, friends of friends, and friends of friends of friends as instruments. Our original specification thus contains 24 instruments which can also introduce a weak IV problem emanating from many instrumental variables.

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.[41] Table A.3 shows that our results are very consistent across alternative specifications. The table also contains Cragg Donald F statistics for the first stage regressions (Eq. 5). While the F statistics are often low, the notable consistency of results across alternative specifications provides credence to the results we report in the main text.

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 data, we elicited ten different 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 behavioral trait. Our set of ten such traits is unusually large and covers not only single dimensions of behavioral traits (such as prosociality, for instance), but includes trust, cooperation, coordination behavior, preferences for equality, depth of reasoning in strategic games, generosity, risk tolerance, educational aspirations, morality, and competitiveness. 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. For instance, two girls or two boys who share the same level of cooperativeness are 9.4% more likely to be friends, but this effect goes down to 1.5% for opposite-gender pairs. More generally, we find across the board that individuals who share demographic characteristics exhibit homophily on behavioral traits more 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. Recently, Shan and Zölitz (2022) have identified (in a project that was run simultaneously to ours) peer effects in the development of personality traits, more precisely of the Big-5 dimensions of personality (i.e., openness, conscientiousness, extraversion, agreeableness, and neuroticism). Additionally, they study competitiveness, as we do. While they rely on exogenously formed networks, we study homophily and peer effects in endogenous networks. Moreover, we use incentives and elicit a large set of ten behavioral traits. To obtain our coefficients of interest, i.e., the impact of friends' behavioral traits on an individual's traits, we instrument the behavioral traits of friends with the demographic

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

characteristics of predicted friends, friends of friends, and friends of friends of friends. We find significant peer effects for a number of behavioral traits: depth of reasoning, risk tolerance, cooperativeness, coordination on efficient outcomes, and competitiveness. For example, a one standard deviation increase in friends' risk tolerance increases a student's risk tolerance by about 0.5 standard deviations. For competitiveness, we find a negative peer effect, unlike Shan and Zölitz (2022). The difference might be due to our endogenously formed networks, compared to their randomly assigned networks (which is reminiscent of differences between exogenous and endogenous networks in estimating peer effects (Carrell et al., 2013)).

Notably, we find stronger peer effects in more homogenous groups. More precisely, peer effects on behavioral traits are typically larger when friends share (predominantly) a student's gender or have attended the same middle school (meaning that friendships have existed for longer). When one's friends are more popular, they also seem to have a stronger impact on a student's behavioral traits. All of this provides credence to the fact 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. We can also show that our main findings are robust to the underlying network specification (directed, weighted, or undirected networks), the choice of specification to predict the probability of two individuals in a classroom being friends (which addresses potential weak IV problems), and whether we account for peer effects with respect to students' demographic characteristics on top of peer effects in their behavioral traits.

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 and Tincani, 2020; Algan et al., 2022). We bring 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 (Kosse et al., 2020; Chowdhury et al., 2022) or has examined the role of 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 have found 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), Falk et al. (2018), Alan et al. (2021), and Sorrenti et al. (2020)), but also an indirect effect through a potential change of peers and their behavioral traits.

Our results also help to understand why interventions that foster interactions between women can be so effective. By showing that homophily and peer effects are larger among same-gender friends, our results shed light on one of the key mechanisms behind several existing programs and interventions, such as gender class compositions (Zölitz and Feld, 2021; Hill, 2015), role-models (Carrell et al., 2010; Porter and Serra, 2020; Bettinger and Long, 2005; Beaman et al., 2012), and female mentoring programs (Kofoed and McGovney, 2017; Canaan and Mouganie, 2021). Our findings justify why classroom composition and single-sex education may make a decisive difference in student achievement and in the development of their behavioral traits. Our results also explain why female role-models and mentoring programs, by facilitating positive spillovers of behavioral traits can have such large effects on women's educational and professional decisions. This channel for the development of behavioral traits may provide long-term benefits through the dissemination of behavioral traits in social networks.

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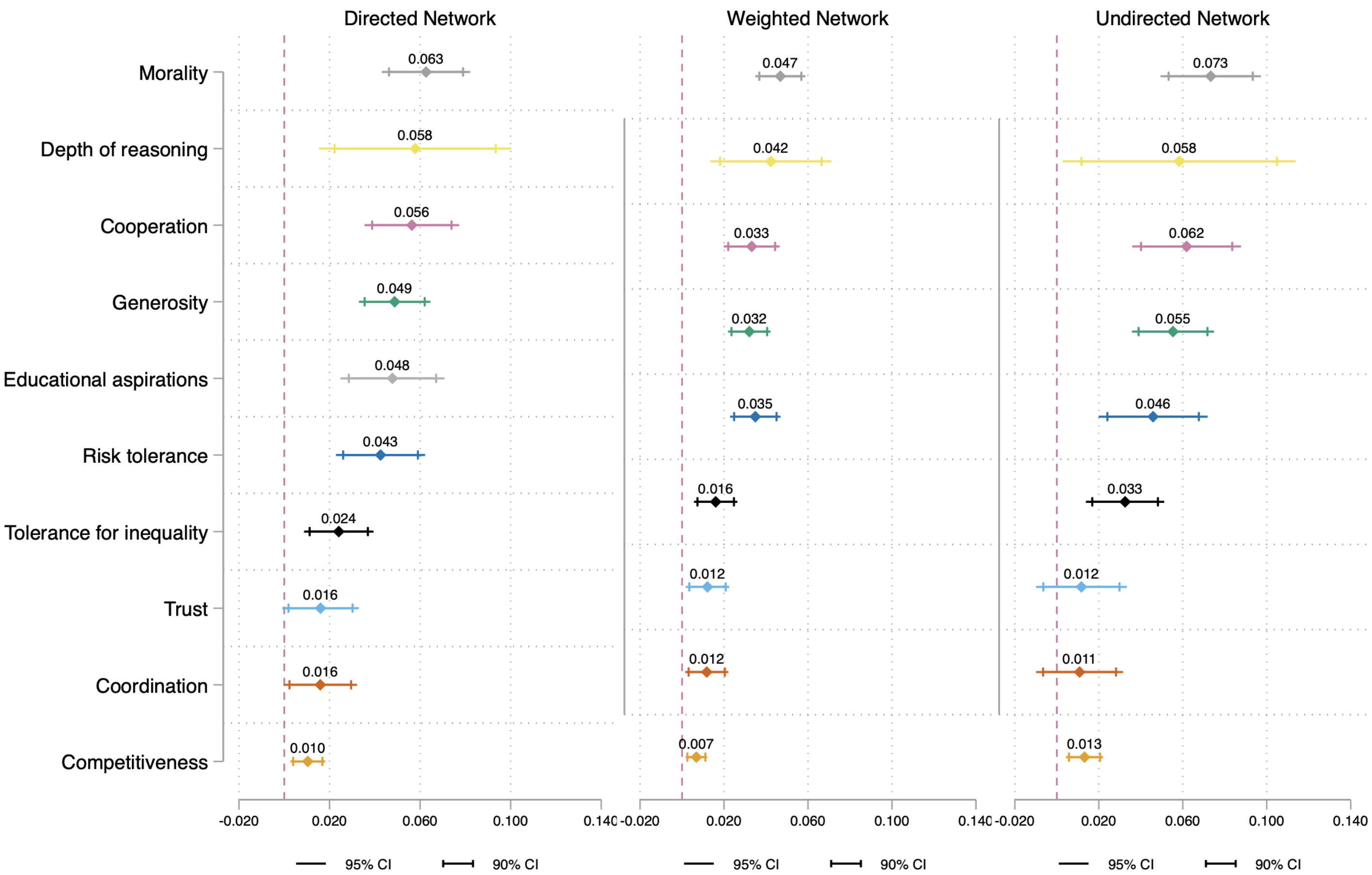
Appendix

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 - Alternative network specifications



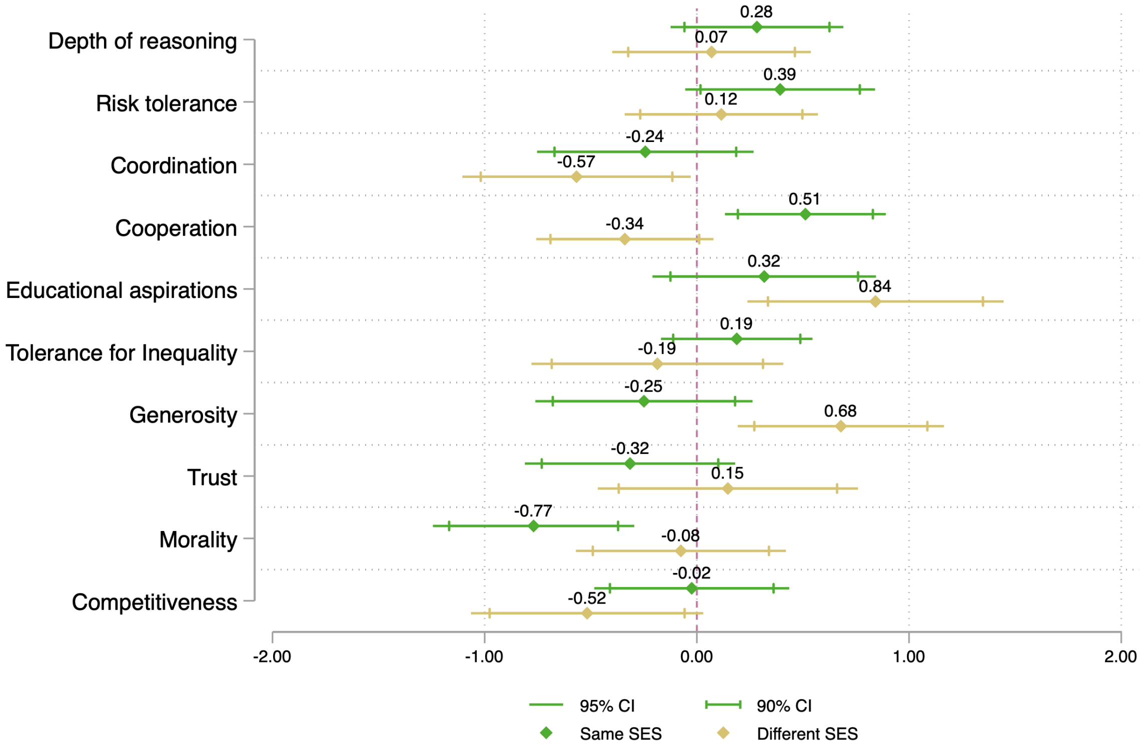
Note: This figure plots coefficients for homophily based on behavioral traits. Each coefficient corresponds to a separate regression based on Eq. 1. In directed networks, the dependent variable is an indicator variable which takes the value 1 if individual i sends a link to individual j and 0 otherwise. 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 above, captures how close two students are in terms of behavioral traits. All measures of behavioral traits in the regressions are scaled down to lie between 0 and 1. We control for shared demographic characteristics such as gender, ethnicity, nationality, commune of residence, low 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: Friendship predictions

	(1)	(2)	(3)	(4)
Shared gender	1.155***	1.158***	1.174***	1.180***
	(0.053)	(0.053)	(0.055)	(0.054)
Shared postal code	0.145***	0.141***	0.190***	0.190***
	(0.037)	(0.037)	(0.046)	(0.047)
Shared middle school	0.547***	0.554***	0.675***	0.679***
	(0.046)	(0.046)	(0.047)	(0.047)
Shared nationality	0.496*	0.437+	0.465+	0.431+
	(0.263)	(0.267)	(0.284)	(0.282)
Shared ethnicity	0.191***	0.189***	0.173**	0.170**
	(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)
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	0.005	0.041
	(0.161)	(0.161)	(0.167)	(0.167)
Only child match	0.049	0.049	0.061	0.062
	(0.048)	(0.049)	(0.047)	(0.051)
Similar no. of siblings	0.012	0.011	0.014	0.012
	(0.028)	(0.031)	(0.028)	(0.032)
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

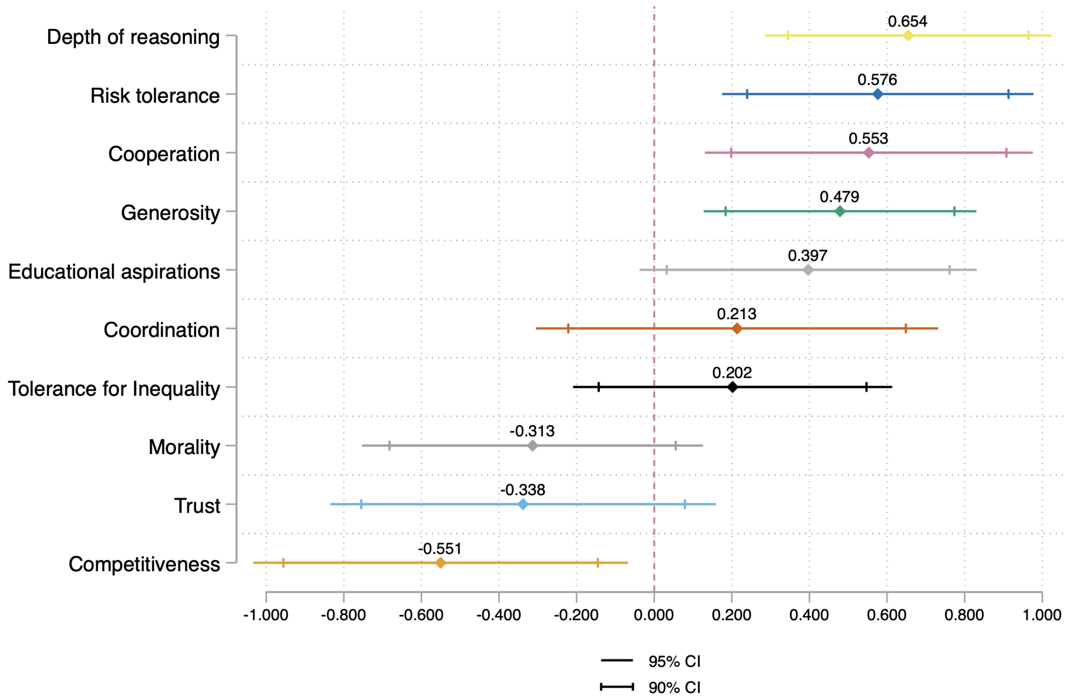
Note: This Table reports coefficients from the friendship prediction based on Eq. 4. The dependent variable is a potential friendship link which takes the value 1 if student i nominates student j as a friend and 0 otherwise. All regressions are based on a Logit specification based . The vector of shared 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.2: Peer effects by similarity in socio-economics status **(Fact 7)**



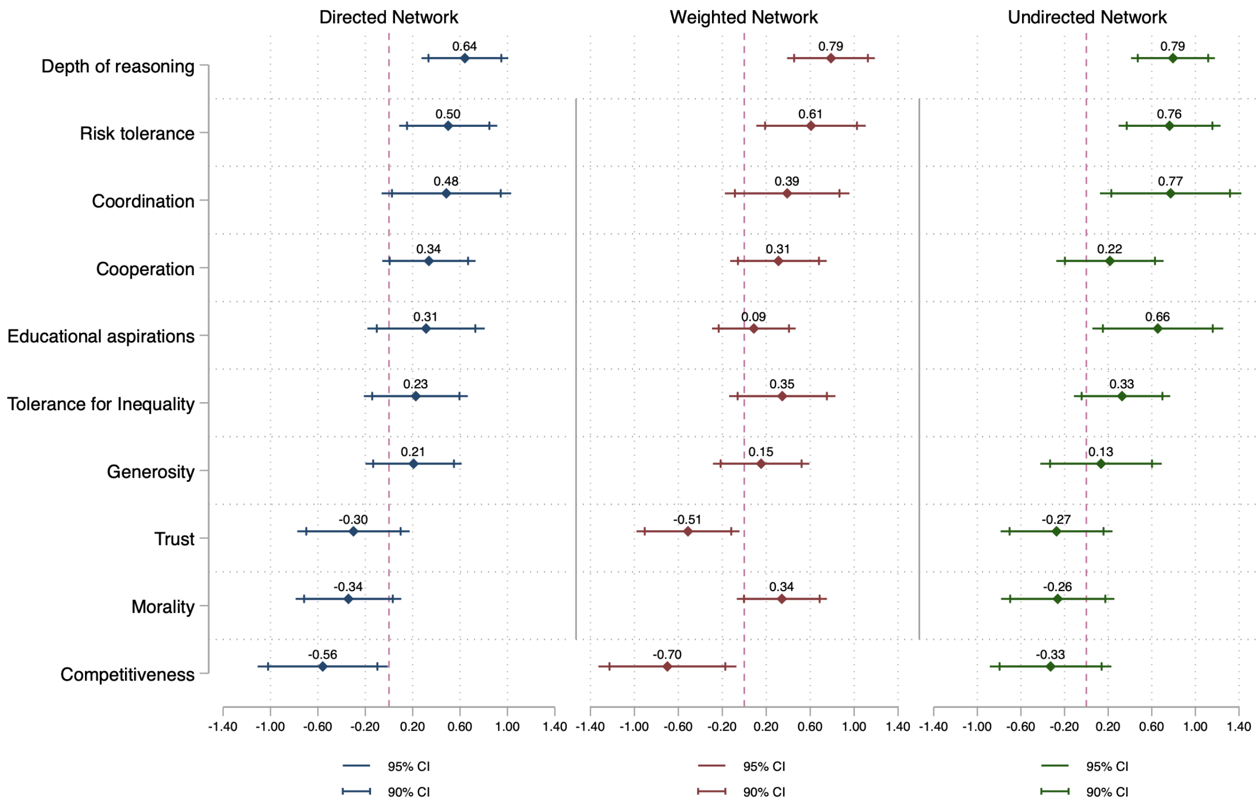
Note: This figure reports coefficients of peer effects in behavioral traits. Each coefficient corresponds to a separate regression based on Eq. 6. The dependent variable is the behavioral trait of a student. The coefficient reported in the figure corresponds to the effect of the friends' average behavioral trait. Behavioral traits are standardized to have a mean of zero and a standard deviation of one. We instrument the friends' average behavioral trait with the demographic characteristics of the predicted friends $\hat{\mathbf{G}}\mathbf{x}$, friends of friends $\hat{\mathbf{G}}^{\mathbf{2}}\mathbf{x}$, and friends of friends of friends $\hat{\mathbf{G}}^{\mathbf{3}}\mathbf{x}$. 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, low 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.3: 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. 6. 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 with the demographic characteristics of the predicted friends $\hat{\mathbf{G}}\mathbf{x}$, friends of friends $\hat{\mathbf{G}}^{\mathbf{2}}\mathbf{x}$, and friends of friends of friends $\hat{\mathbf{G}}^{\mathbf{3}}\mathbf{x}$. Each regression includes control variables for the following demographic characteristics of the individual: gender, ethnicity, nationality, low 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.4: 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. 6. 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 with the demographic characteristics of the predicted friends $\hat{\mathbf{G}}\mathbf{x}$, friends of friends $\hat{\mathbf{G}}^{\mathbf{2}}\mathbf{x}$, and friends of friends of friends $\hat{\mathbf{G}}^{\mathbf{3}}\mathbf{x}$. Each regression includes control variables for the following demographic characteristics of the individual and of the friends: gender, ethnicity, nationality, low 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: Depth of reasoning				
Y	0.549***	2.566	0.557***	2.646	0.631***	2.444	0.641***	2.487
	(0.191)		(0.191)		(0.188)		(0.187)	
N	0.577***	2.464	0.587***	2.550	0.651***	2.263	0.654***	2.332
	(0.192)		(0.193)		(0.189)		(0.188)	
				Outcome: Risk tolerance				
Y	0.566***	2.328	0.552***	2.294	0.541***	2.413	0.500**	2.479
	(0.209)		(0.210)		(0.212)		(0.211)	
N	0.628***	2.743	0.623***	2.642	0.609***	2.853	0.576***	2.939
	(0.203)		(0.203)		(0.205)		(0.205)	
				Outcome: Coordination				
Y	0.359	4.989	0.386	4.311	0.456*	3.378	0.484*	3.093
	(0.289)		(0.293)		(0.276)		(0.279)	
N	0.091	8.070	0.091	6.517	0.198	4.149	0.213	3.788
	(0.266)		(0.268)		(0.261)		(0.264)	
				Outcome: Cooperation				
Y	0.228	2.108	0.274	2.281	0.287+	2.018	0.337*	2.188
	(0.199)		(0.201)		(0.198)		(0.201)	
N	0.423*	1.692	0.465**	1.879	0.500**	1.674	0.553***	1.822
	(0.219)		(0.215)		(0.218)		(0.216)	
				Outcome: Educational aspirations				
Y	0.186	2.017	0.215	2.041	0.264	1.910	0.313	1.849
	(0.224)		(0.227)		(0.245)		(0.253)	
N	0.273	2.210	0.286+	2.228	0.363*	2.101	0.397*	2.045
	(0.194)		(0.196)		(0.218)		(0.222)	
				Outcome: Tolerance for inequality				
Y	0.301	2.929	0.287	2.946	0.250	2.924	0.227	2.863
	(0.225)		(0.226)		(0.225)		(0.224)	
N	0.260	5.580	0.253	5.941	0.219	5.310	0.202	5.366
	(0.208)		(0.209)		(0.211)		(0.210)	
				Outcome: Generosity				
Y	0.152	2.154	0.193	1.940	0.189	1.763	0.207	1.648
	(0.207)		(0.200)		(0.209)		(0.207)	
N	0.417**	2.061	0.437***	1.790	0.463***	1.682	0.479***	1.573
	(0.165)		(0.167)		(0.178)		(0.179)	
				Outcome: Trust				
Y	-0.243	2.024	-0.248	2.020	-0.298	2.151	-0.300	2.045
	(0.246)		(0.246)		(0.239)		(0.242)	
N	-0.280	2.066	-0.307	2.103	-0.315	2.272	-0.338	2.099
	(0.263)		(0.257)		(0.256)		(0.254)	
				Outcome: Morality				
Y	-0.278	1.605	-0.292	1.457	-0.286	1.499	-0.342+	1.384
	(0.218)		(0.222)		(0.225)		(0.228)	

Continued on next page...

... table A.3 continued

Cont. var.	Dem Char Coeff. (1)	Dem Char F stat. (2)	Dem Char + Int Coeff. (3)	Dem Char + Int F stat. (4)	Dem Char + FE Coeff. (5)	Dem Char + FE F stat. (6)	Dem Char + Int + FE Coeff. (7)	Dem Char + Int + FE F stat (8)
N	-0.201	2.344	-0.233	2.145	-0.247	2.146	-0.313	1.973
	(0.213)		(0.217)		(0.218)		(0.224)	
				Outcome: Competitiveness				
Y	-0.785***	4.650	-0.586**	4.767	-0.700***	4.191	-0.559**	4.248
	(0.256)		(0.284)		(0.262)		(0.280)	
N	-0.715***	7.536	-0.612**	8.043	-0.640***	6.495	-0.551**	6.741
	(0.239)		(0.248)		(0.240)		(0.246)	

Note: This Table reports coefficients of peer effects in behavioral traits. Each coefficient corresponds to a separate regression based on Eq.6. 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 with the demographic characteristics of the predicted friends $\hat{\mathbf{G}}\mathbf{x}$, friends of friends $\hat{\mathbf{G}}^2\mathbf{x}$, and friends of friends of friends $\hat{\mathbf{G}}^3\mathbf{x}$]. Each regression includes control variables for the following demographic characteristics of the individual: gender, ethnicity, nationality, low SES, only child status, country of birth, age (in months), and number of siblings. For each behavioral trait, 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 5). *** 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*×*French*, *Female*×*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.

A 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[42] and factors such as reciprocity[43], 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[44] ($\mathbf{y}_i$) according to a social cohesion game. The payoff for agent i is given by:

$$u_i(\mathbf{y}_i, \mathbf{a}_i, P_i) = -\sum_{m=1}^{M} \left(\underbrace{\left(a_{im} - y_{im} \right)^2}_{\text{Behavior adjustment cost}} + \underbrace{\tilde{\zeta}_m \left(\frac{\sum_{j \in P_i} y_{jm}}{n_i} - y_{im} \right)^2}_{\text{Cost for deviating from social norm}} \right) \tag{7}$$

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.[45] It can also be 0 if there is no cost of social deviation on that dimension. The level of intrinsic behavioral trait a_{im}, that the player would adhere to 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. That is

$$a_{im} = \tilde{\gamma}_m \mathbf{x}_i + \tilde{\delta}_m \frac{\sum_{j \in P_i} \mathbf{x}_j}{n_i} + \tilde{\epsilon}_{im} \tag{8}$$

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

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

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

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

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 $a_{im} = \tilde{\gamma}_m \mathbf{x}_i + \tilde{\epsilon}_{im}$.[46] 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:

$$y^*_{im} = \frac{1}{1+\tilde{\zeta}_m} a_{im} + \frac{\tilde{\zeta}_m}{1+\tilde{\zeta}_m} \frac{\sum_{j \in P_i} y^*_{jm}}{n_i} \tag{9}$$

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:

$$y_{im} = \beta_m \frac{\sum_{j \in P_i} y_{jm}}{n_i} + \gamma_m \mathbf{x}_i + \delta_m \frac{\sum_{j \in P_i} \mathbf{x}_j}{n_l} + \epsilon_{im} \tag{10}$$

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.[47] Let $\lambda_1(\mathbf{G})$ represent the spectral radius[48] 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. 7, has a unique Nash equilibrium. Further, the level of revealed 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. 9 can be rewritten in a matrix format as follows:

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

The condition, $\lambda_1(\mathbf{G}) < \frac{1}{\beta_m}$, guarantees the invertibility of $(I - \beta_m \mathbf{G})$. Therefore, the unique

[46] 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.

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

[48] The largest eigenvalue.

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

$\square$

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.

B Screenshots of Incentivized Games (Translated in English)

Figure D1: Risk tolerance

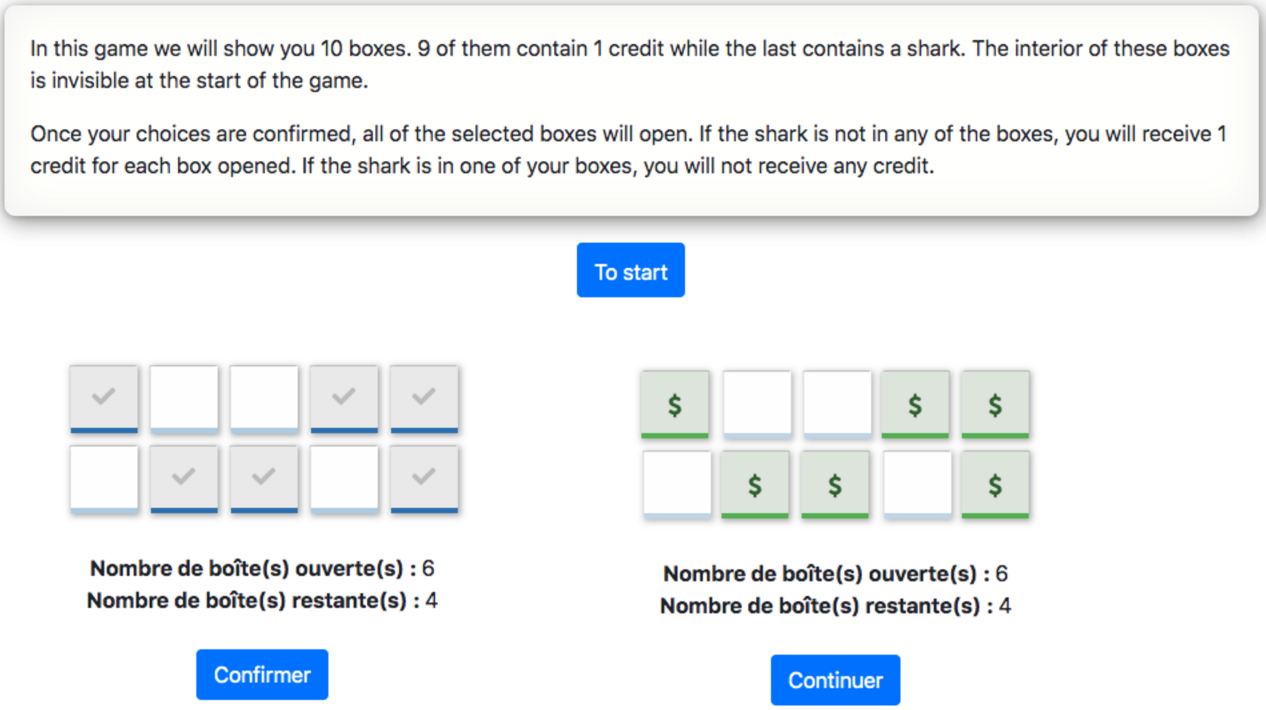


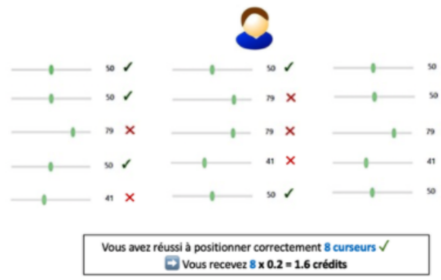
Figure D2: Competitiveness

In this game, we suggest you position a cursor in the middle of a horizontal line ranging from 0 to 100. As in the example below, when you move the cursor along the axis, its positioning will be displayed. to the right of the axis. The objective is to position it on 50.

The next page will contain 48 of these axes. You will have 2 minutes to correctly place the greatest number of cursors out of 50.

Each correct positioning will earn you credits and we offer you to choose between two options to receive credits.

Option A: You receive **0.2 credits** for each correctly positioned cursor over 50.

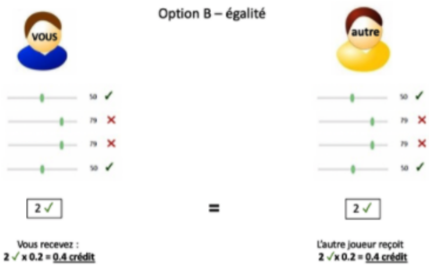


Option B: You play against a partner (randomly selected).

The second participant is also in your class.
If the number of sliders you position correctly is **greater** than the number of the other participant, you will receive **0.5 credits** for each correctly positioned slider.

If the number of sliders you position correctly is less than the number of the other participant, **you receive nothing** .

If you position the **same number** of cursors correctly, you receive 0.2 credits for each correctly positioned cursor.



Which option do you prefer to receive the credits?

- ○ Option A: 0.20 credit for each correctly positioned cursor
- ○ Option B: 0.50 credit for each correctly positioned cursor if my number is greater than the number of the other participant. If my number is lower, I get nothing.

To confirm

Veuillez positionner les curseurs sur le numéro 50 le plus rapidement possible.

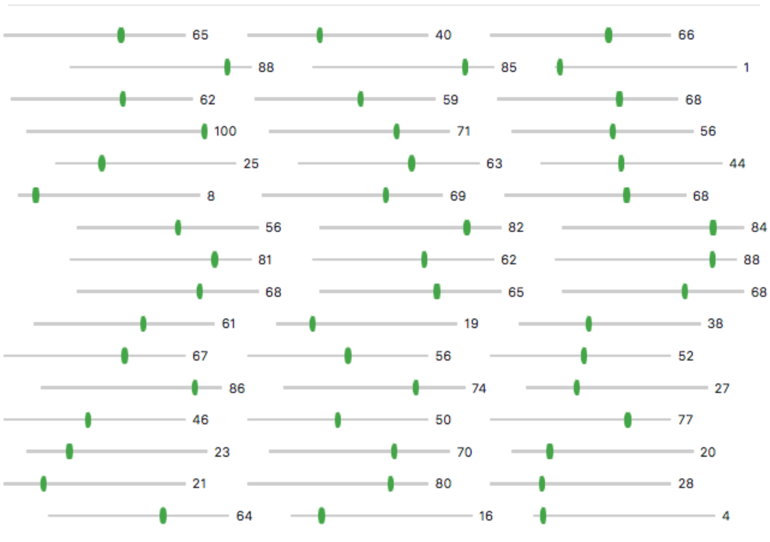


Figure D3: Trust

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

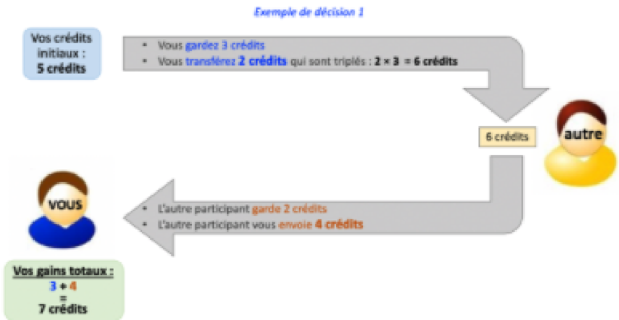
You will each have to make 2 decisions.

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** .

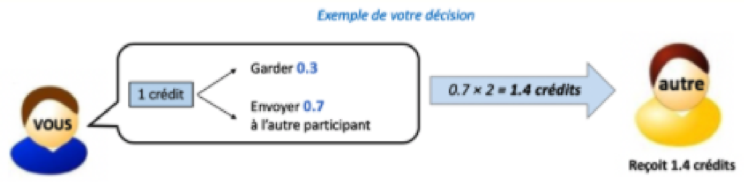
You keep the same partner during the 4 turns.

The second participant is also in your class.

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

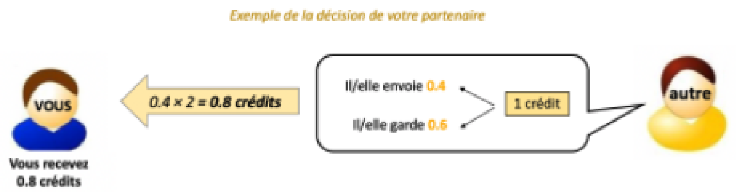
Decision on your part

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

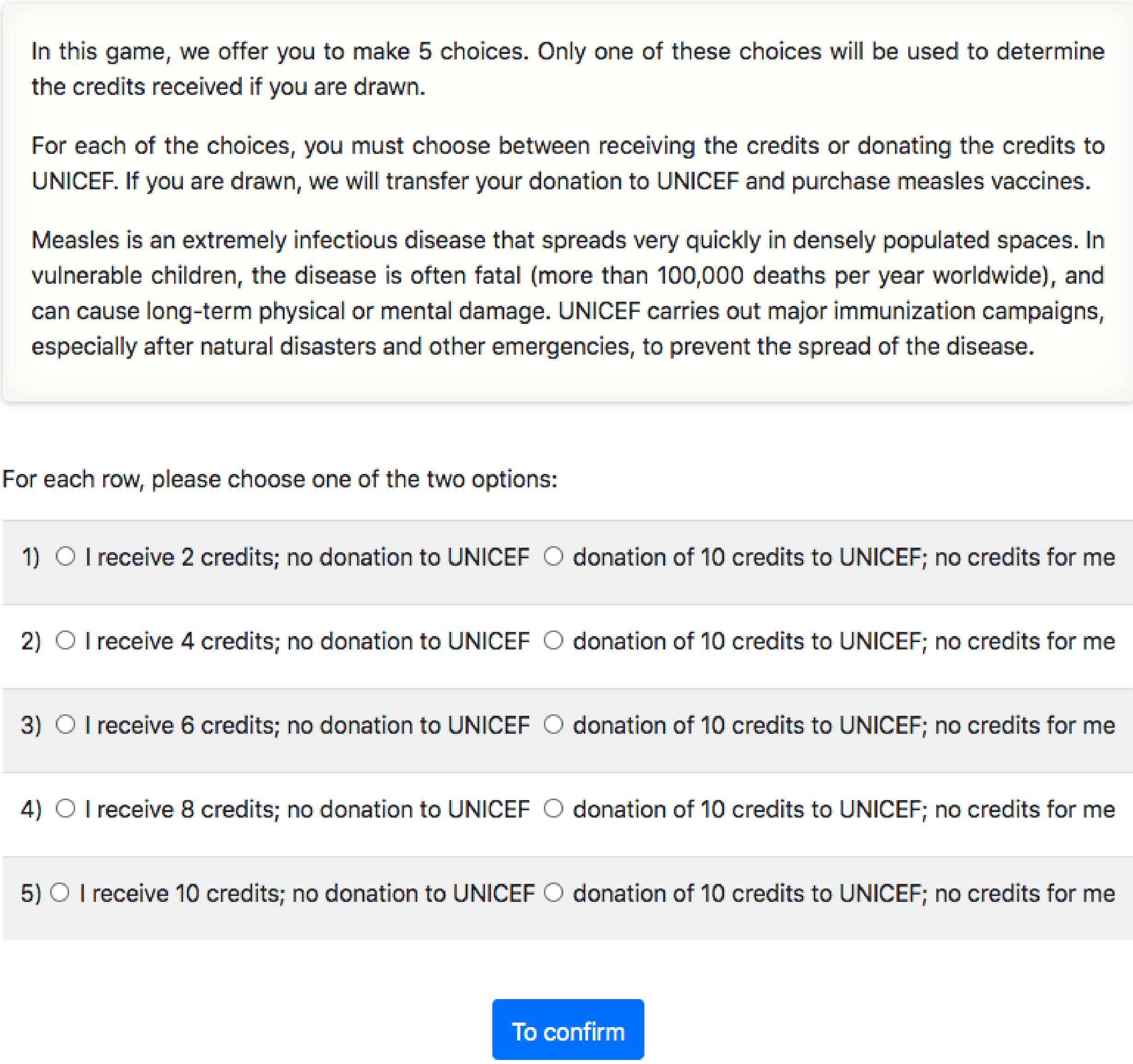
Reminder of earnings

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: Morality



In this game, we offer you to make 5 choices. Only one of these choices will be used to determine the credits received if you are drawn.

For each of the choices, you must choose between receiving the credits or donating the credits to UNICEF. If you are drawn, we will transfer your donation to UNICEF and purchase measles vaccines.

Measles is an extremely infectious disease that spreads very quickly in densely populated spaces. In vulnerable children, the disease is often fatal (more than 100,000 deaths per year worldwide), and can cause long-term physical or mental damage. UNICEF carries out major immunization campaigns, especially after natural disasters and other emergencies, to prevent the spread of the disease.

For each row, please choose one of the two options:

1)	○ I receive 2 credits; no donation to UNICEF	○ donation of 10 credits to UNICEF; no credits for me
2)	○ I receive 4 credits; no donation to UNICEF	○ donation of 10 credits to UNICEF; no credits for me
3)	○ I receive 6 credits; no donation to UNICEF	○ donation of 10 credits to UNICEF; no credits for me
4)	○ I receive 8 credits; no donation to UNICEF	○ donation of 10 credits to UNICEF; no credits for me
5)	○ I receive 10 credits; no donation to UNICEF	○ donation of 10 credits to UNICEF; no credits for me

To confirm

Figure D7: 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

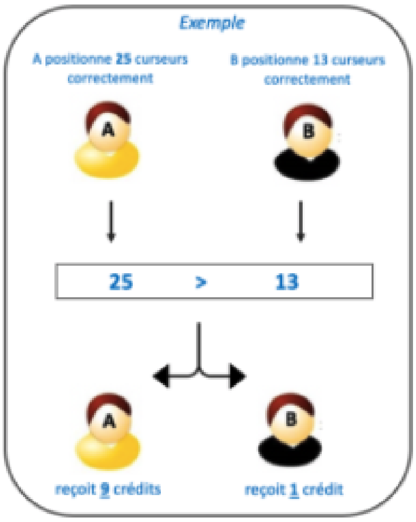
Participants A and B each had the first task of placing cursors in the middle of a row from 0 to 100 (as you did previously). A and B, however, were not playing against each other during this slider game.

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.

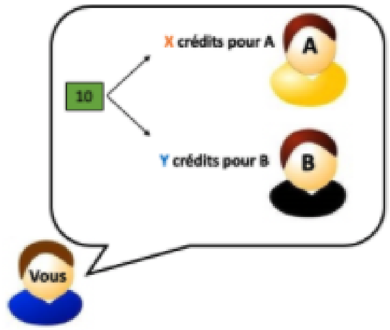


Step 3

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 D8: Depth of reasoning

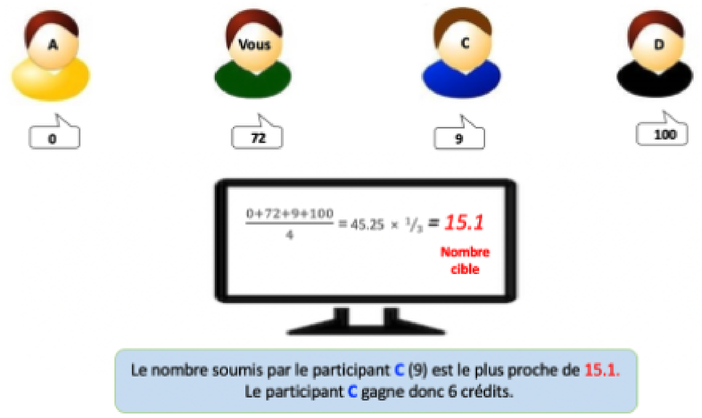
We now suggest you play with **three other participants** .

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