Trust and Network Formation

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Abstract

We study whether trust towards strangers is a determinant of social networks among an incoming cohort of first-year undergraduate students. We employ an experiment and survey questions to measure students' trust before they have substantial chances to meet and socialize. After four months, during which the students have many opportunities to interact, we elicit five networks capturing different relationships between them. The students' initial levels of trust do not significantly predict the relationships they formed after four months. In contrast, time of exposure, similarity in socioeconomic status, and hometown are relevant determinants of relationship formation.

Keywords: trust, prosocial beliefs, network formation, social capital.
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Social networks are a fundamental aspect of human life and affect many economic situations, such as peer effects, information transmission, and job search (Jackson et al. (2017) and Bailey et al. (2018)). Understanding how we form social connections can shed light on the economic consequences of networks. Several studies in the network formation literature show that we are more likely to befriend individuals who are similar to us along a range of characteristics (homophily) and people we are exposed to by chance (McPherson et al. (2001), Marmaros and Sacerdote (2006), and Currarini et al. (2009)).

Despite significant advances in understanding how relationships form, little is known about how personality traits interact with the creation of social connections. A key personality characteristic, and one that could play an important role in relationship formation is prosociality. This trait encapsulates a person's tendency to be altruistic, reciprocal, and cooperative and affects a wide range of economic outcomes (Kosse and Tincani (2020) and Falk et al. (2018)). Among the components of prosociality, trust towards strangers is of particular interest to relationship formation. Trust describes how strongly a person believes in the goodwill and cooperativeness of strangers. Since high-trust individuals hold more positive beliefs about strangers, they should expect higher utility from interacting with unknown people. Thus, trust could act as a social icebreaker, increasing people's likelihood of making the first move to start cooperating with others. If part of these attempts get reciprocated, eventually breaking into cooperative relationships, high-trust individuals should be more likely to form relationships, other things being equal.

In this paper, we ask the following question: are people's prosocial beliefs, and willingness to trust in particular, drivers of the relationships they form, or is network formation more a matter of exposure and demographic traits? Specifically, we study whether trust is a determinant of social networks formation among an incoming cohort of first-year undergraduate students at a university in Bogotá, Colombia. This is an important population due to the very large number of young people that take part in higher education throughout the world, and the fact that they do so at a critical time of their lives during which friendships are often a fundamental source of support. Moreover, universities may play an important role in enabling social mobility in parts of the world, such as Colombia, in which it is quite limited.

Our findings suggest that trust plays a negligible role in the construction of social connections among our subjects. We fail to reject the null hypothesis that trust predicts link formation probabilities, and we retain sizeable power when doing so conditional on the hypothesis that the true effect of trust is comparable in size to other significant determinants of the social networks. On the other hand, time of exposure (as measured by the number of credits any two students share with each other) is a critical determinant of network formation.

We find that, for example, a one standard deviation increase in the number of course credits that two students share because of this assignment is associated with a 5% increase in the probability that one student befriends the other. Students whose hometown is Bogotá are generally less likely to form relationships during the first semester, possibly because they already have a network of relationships in town. Moreover, the subjects' networks exhibit segregation along socioeconomic status and hometown, attesting to the importance of homophily along demographic traits. Overall, our results point to a picture where relationships are more the outcome of chance and demographics rather than the result of people's confidence in others' cooperativeness. These results provide insights on improving integration between people starting higher education in the presence of segregation and socioeconomic differences.

We collected data from an entire incoming cohort of first-year economics undergraduate students at a university in Bogotá. We put together the data in two stages. In the first stage, we asked each of the 81 students comprising the entire cohort to participate in activities to measure their trust towards strangers before they had significant chances to get to know each other and socialize. This feature of the data collection strategy allows us to avoid the possibility of reverse causality from relationships to trust.[1] Specifically, we conducted our measurements of trust on the university welcome day, which is the first day in which students formally attend the university campus.[2] Out of the 81 students comprising the entire cohort, 72 took part in the activities we conducted to measure trust. These activities comprised (1) a trust experiment, taken from Berg et al. (1995), and (2) two survey questions adapted from Glaeser et al. (2000).[3] Out of the different facets of prosociality, which also include altruism and other-regarding behavior (Kosse et al. (2020)), we focus on trust because it captures a person's *beliefs* about others' cooperativeness. As such, this trait perfectly encapsulates a person's unconditional willingness to take the first step to cooperate with others, when he or she doesn't know whether others are going to reciprocate or not. In the second stage of the data collection process, which was conducted at the end of the first academic semester (i.e., four months after the measurement of trust), we administered a survey to elicit five social networks among the subjects representing different relationships (greeting, having lunch together, studying together, confiding in, and friendship). Out of the 72 subjects for whom we collected trust measures, 58 completed the network elicitation survey. Our timing for conducting the second stage of the data collection is consistent with the evidence that the formation of close relationships in late adolescents requires three to four months (van Duijn et al. (2003) and Saramäki et al. (2014)).

Our sample choice aimed at three goals. First, we chose a group of people for whom we could accurately measure trust before they had significant opportunities to socialize.

[1] For example, friendships with prosocial people is associated with increases in one's prosocial behavior (Barry and Wentzel (2006), Berger and Rodkin (2012), and Logis et al. (2013)). Thus, if we measured the students' trust after relationships between them were established, we could not have ruled out the possibility that those particular relationships helped shaping their trust towards strangers.

[2] In the second stage of the data collection, we asked each subject to name each of the other participants that he or she knew from before starting university. Hence, we can control for whether subjects knew each other from before the university welcome day.

[3] Albeit our survey questions have been experimentally validated (Fehr et al. (2002)), we measured trust using both a lab experiment and survey questions because the use of different data collection methods reduces measurement error.

Second, we wanted our subjects to have many chances to get to know each other over an extended period of time after the measurement of trust. Finally, we selected people for whom we could collect detailed information on many characteristics, at both the individual and the relationship level. This objective is essential to isolate the role of trust in the creation of social links since network formation is affected by many variables, and these variables could be correlated with trust. While our sample is not large nor representative of the entire population, our strategy allows us to obtain precise measures for the variables of interests and information on many other characteristics in a controlled setting. Importantly, in this setting, all the subjects come together in a new and circumscribed social environment where they have substantial chances of getting exposed to each other (Girard et al. (2015)).[4]

We estimate linear probability models (LPMs) to identify how trust, demographic characteristics, and exogenous variation in exposure predict link formation probability in the networks elicited.[5] The estimates of trust on link formation probabilities are negative and statistically insignificant. Moreover, we can safely assert that trust does not have an impact on link formation probability as quantitatively meaningful as other characteristics, such as time of exposure, knowing in each other from before, and hometown. For example, conditional on the hypothesis that the true effect of i's trust on the probability that a link from i to j forms has the same size of the effect of i's hometown (whether i is from Bogotá), we retain approximately 90% power when failing to reject the null that i's trust does not affect the likelihood that a relationship from i to j forms.

The empirical evidence we provide does not support our initial hypothesis that high-trust individuals are generally more likely to form relationships. However, it could be the case that trust plays an important role for certain individuals or in the formation of

[4]Our intended sample corresponds to the entire cohort of undergraduate economics students who started university in the first academic semester of 2017.

[5]We use dyadic-robust standard errors (Fafchamps and Gubert (2007)) and the quadratic assignment procedure (QAP) to account for possible correlation between unobservables affecting link formation. See Birke and Swann (2010), Giné et al. (2010), Santos and Barrett (2010), Santos and Barrett (2011), and Giné and Mansuri (2018) for applications of QAP in economics.

links between particular pairs of individuals. For example, students from Bogotá might have less of a need to form new relationships because they already have a network of friends in place. Thus, trust could play a relatively more important role in relationship formation for people who are not from Bogotá. Alternatively, the effect of trust on link formation probability could be more important when two students have very different socioeconomic status. We test for these (and other) ways in which trust could affect relationship formation for particular people or pairs of people. To do so, we regress the probability of a link from i to j on the interaction of i's trust with variables such as i's hometown, the time of exposure between i and j, the similarity in i and j's socioeconomic status, and whether i and j knew each other from before entering university. We do not find that trust plays a comparatively more important role in relationship formation in any of the possibilities we consider.

Related literature

This paper focuses on the relationships between social connections and personality characteristics, concentrating on prosocial traits. Several researchers have begun to shed light on the interconnections between networks and prosocial traits such as altruism (Kim et al. (2015)) and cooperation in social dilemmas (Cuesta et al. (2015) and Gross and De Dreu (2019)). We contribute to this endeavor by studying the role of trust as a determinant of social connections. Focusing on trust is compelling because it measures how strongly a person believes that interacting with strangers will be beneficial to him or her, or create mutual gains. Hence, it is natural to suppose that more trusting individuals should be more willing to engage in social interactions with unknown people. Indeed, researchers in sociology and psychology argue that trust encourages individuals to approach strangers to form relationships (Yamagishi et al. (1998) and Igarashi et al. (2008)). Moreover, evidence from neuroscience and neuroeconomics suggests that trusting behavior in the laboratory might be associated with factors contributing to prosocial behavior in mammals. Specifically, Fehr et al. (2005), Kosfeld et al. (2005), and Baumgartner et al. (2008) show that administration of oxytocin (a neuropeptide playing an important role in social attachment and affiliation in mammals) causes a substantial increase in trust among human subjects in a trust experiment.[6]

There is evidence of correlations between measures of trust and different characteristics of people's social environments (Carpenter et al. (2004) and Carpiano and Fitterer (2014)). These correlations may suggest trust is a determinant of social networks, as higher trust could help people to approach others to form social connections. However, it could also be that having more bountiful social surroundings, or being embedded in social networks with certain structural properties encourages people to trust more. Indeed, there is evidence suggesting that the latter hypothesis holds: Glanville and Paxton (2007) shows that people develop trust based on their experiences with others and Kosse et al. (2020) provides causal evidence on the positive effect of enriching a person's social environment on his or her trust. Buskens (1998) studies the network-structural determinants of trust in a game theoretic framework and shows that higher density and outdegree give rise to more trust. A related laboratory experiment where the possible causal effects between trust and network formation are tested is Di Cagno and Sciubba (2010). They invited 108 undergraduate economics students in Rome who could start a possible network connection which was realized when both players agreed, and if made, players could benefit financially from such links. They also played the canonical version of the Trust Game, and by randomizing the sequence between the trust game and the network formation game, the authors study possible effects of one on the other. Their results suggest that a prior network formation game decreases trust, but trust increases when the network formation follows the trust game due to the repetition of interactions. Di Cagno and Sciubba, however, acknowledge that their laboratory controlled networks

[6] However, this evidence is not robust, as it has failed to be replicated (Declerck et al. (2020)). See also Nave et al. (2015) for a review of the literature on the associations between oxytocin and trust in humans.

are less realistic than naturally occuring ones, and in contrast with our own study where we explore not only natural networks among the students but also months after the trust game is played. In our study, we disentangle the effect of trust on network formation by measuring the subjects' trust before they have significant chances to get to know each other and socialize. While we cannot claim that our estimates correspond to the causal impact of trust on network formation, we deal with possible measurement error by using both lab and survey methods to measure trust and tackle omitted variable concerns by collecting information on a vast array of individual and pairwise characteristics. Finally, our study is cast in the context of an incoming cohort of first-year undergraduate students. This setting is an ideal one to study relationship formation because our subjects are jointly facing a new and self-contained environment, in which they face significant exposure between themselves and relatively little exposure with other groups of people.

This paper also speaks to the social capital literature, which frequently relates trust and social networks. Trust has often been bundled into the very definition of social capital.[7] Other times, measures of trust have been used as proxies for social capital (Kawachi (2010)). While trust and networks might both play a role in determining social capital, we contribute to this literature by shedding light on the interconnection between trust and network formation.[8]

This work also relates to research connecting laboratory experiments with social networks. Many papers in this line of research try to understand how a given network structure influences play in an experimental setting (e.g., Leider et al. (2009) and Goeree et al. (2010)). Conversely, our paper studies how certain behaviors elicited in the

[7]For example, Inglehart (1997) defines social capital as "a culture of trust and tolerance, in which extensive networks of voluntary associations emerge." Putnam (1995) defines it as "features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit." Woolcock (1998) defines it as "the information, trust, and norms of reciprocity inhering in one's social networks."

[8]According to Carpenter et al. (2004), the term "social capital" is poorly defined because it means the propensities of individuals to trust others to some researchers, and the networks among individuals to other scholars. The authors refer to the first definition as behavioral social capital and the second as associational social capital. From this perspective, our paper studies whether behavioral social capital influences associations social capital.

laboratory predict link formation, as in Girard et al. (2015), which also focuses on network formation among students in their naturally occurring college life environment.

1 Design and protocols

We collected data from incoming first-year undergraduate students choosing economics as their major at a university in Bogotá. Our design consisted of two stages. We conducted the first stage on August 4, 2017, and its main goal was to measure the students' trust. Crucially, we carried out this stage on the university welcome day, which is the very first day in which incoming students formally attend the university campus. The rationale behind this choice was to measure the students' trust before they had significant opportunities to socialize, to avoid the possibility of reverse causality from relationships to trust. We conducted the second stage online between December 7, 2017, and January 5, 2018, at the end of the first academic semester, and its main aim was to elicit social networks among the students. In what follows, we describe the design of the two stages in detail.

First stage. We directed the first stage to the 81 students comprising the entire incoming undergraduate economics cohort of the first semester of 2017, and its main goal was to measure their trust. We conducted this stage in a single session on the university welcome day, right after lunchtime. The session lasted 90 minutes. Out of the 81 intended subjects, 72 were present on the welcome day. All of these 72 students agreed to participate in the experiment. We gave each student four paper handouts labeled A, B, C, and D. The Online Appendix contains an English translation of the handouts. Handout A is a general description of the activity and an informed consent form that we required the students to complete for participating in the session. Handout B is a detailed description of the trust experiment. Handout C is a form for recording the students' strategies in the experiment. Finally, handout D is a questionnaire with two questions (4(a) and 4(b)) on generalized trust, six (5(a)-5(e)) questions on particularized trust towards friends and neighbors,[9] and six (1-3 and 6-8) questions on individual characteristics.[10]

In the trust experiment, we endowed every participant with $e = 20,000$ Colombian Pesos ($\$COP$) (about $USD\$7$). In every anonymously created sender-receiver pair, each sender had to decide how much money s to transfer to the receiver in a range from 0 to e in $\Delta := COP\$2,000$ increments. For each possible s chosen by the sender, the receiver would receive $3s := r(s)$; i.e., three times the money sent to him or her by the sender. The receiver had to decide how much money to send back to the receiver $f(r(s))$, for each possible s he or she could have received, following the convention of the strategy method in the trust game. For each s, the sender could send back any amount in a range from 0 to $r(s)$ in Δ increments. The monetary payoffs at the end of the game for a sender-receiver pair in which the sender uses strategy s and the receiver uses strategy $f(r(s))$ are $e - s + f(3s)$ to the sender and $e + 3s - f(3s)$ to the receiver. We described the two roles in the trust experiment to all participants. We informed them that each had to report how they would behave both as a sender and as a receiver, as we would then assign these roles randomly[11] and randomly match senders and receivers, to implement their reported strategies and realize monetary payoffs.[12] Handout B included instructions for the strategies available to the sender and the receiver, the functions

[9] The psychology literature refers to trust towards strangers as generalized trust and distinguishes it from particularized trust, which is trust directed towards particular groups of people. Unless otherwise noted, we refer to trust towards strangers simply as trust, as it is customary in the economics literature.

[10] These were sex, age, number of siblings, number of friends outside the university, number of people in the incoming cohort of first-year economics undergraduate students knew from before the first day of university, and self-assessed happiness on a 0–3 scale.

[11] After we collected the subjects' choices, we randomly assigned half of the subjects to the role of sender and the other half to the role of receiver. In case of an odd number of participants (this was not the case) we planned to include an extra artificial player relying on a pair of strategies (one for each role) randomly chosen from the set of strategy pairs submitted by the subjects.

[12] We chose to have every participant assume both roles to record the behavior of as many senders as possible. No student knew during or was revealed after the experiment to whom he or she was paired with. To avoid the possibility that the monetary payoffs realized in the experiment could contaminate the formation of relationships between the subjects, we only informed them about the payoffs realized and made the payments four months after the experiment.

used to calculate the monetary payoffs, and a detailed example. We read out loud the instructions and the example and conducted a question-and-answer session right afterward. We then instructed the students to fill out handout C, which contained the strategy sets for the sender and the receiver. Specifying the strategy for the role of sender entailed stating one among 11 (0-10) transfer options in Δ units. Specifying the strategy for the role of receiver entailed stating 11 *contingent* transfers, one for each of the 11 possible amounts received from the sender. For each possible amount that he or she might receive, the receiver could choose to send back to the sender an amount ranging from 0 to the entire amount in Δ units.

After the experiment, the students filled out a survey contained in handout D. First, the survey contained 8 questions aimed to measure generalized trust, particularized trust towards friends and neighbors, and particularized trustworthiness towards friends and neighbors. We report the questions below.

4. To what extent do you agree with the following statements (on a 1–5 scale, where 1 denotes total disagreement and 5 total agreement):

a. One cannot trust strangers.

b. When dealing with strangers it is important to be careful and not to readily trust them.

5.a. How many among your 10 closest friends have you lent money to?

5.b. How many among your 10 closest friends have lent money to you?

5.c. To how many among your 10 closest friends have you lent your belongings (e.g., books, CDs, clothing, bicycle)?

5.d. How many among your 10 closest friends have lent their belongings (e.g., books, CDs, clothing, bicycle) to you?

5.e. How many among your 10 closest neighbors would you trust with your house keys?

5.f. How many among your 10 closest neighbors would trust you with their house keys?

Questions 4.a and 4.b measure generalized trust, questions 5.a and 5.c measure particularized trust towards friends, question 5.e measures particularized trust towards neighbors, questions 5.b and 5.d measure particularized trustworthiness towards friends, and question 5.f measures particularized trustworthiness towards neighbors. We adapted all the questions aimed to measure generalized and particularized trust from Glaeser et al. (2000). However, notice that what we refer to as questions to measure particularized trust (questions 5.a, 5.c, and 5.e), Glaeser et al. (2000) refers to as questions to measure past trusting behavior. We think of these questions as aimed to measure particularized trust because they explicitly refer to particular groups of people (i.e., friends and neighbors) to which trust is directed, instead of unknown individuals (i.e., strangers). Our aim in collecting this information was to have additional (non-experimental) measures of trust that we could use in combination with our main trust measure to reduce possible measurement error concerns.[13] The survey also included five questions on demographic characteristics (sex, age, number of siblings, number of friends outside the university, number of people in the cohort that the person knew from before starting university) and one question on self-assessed happiness.

Second stage. We conducted the second stage of the data collection process four months after the first stage (i.e., at the end of the first academic semester), and its goal was to elicit some of the networks of relationships among the 81 students comprising the entire incoming cohort of 2017. Additionally, we asked the participants questions on individual characteristics. We sent emails to 113 students asking them to complete an incentivized survey.[14] The set of 113 students consisted of the 81 students comprising

[13]While our research question is primarily concerned with the impact of trust on social networks, we decided to collect survey question on trustworthiness too. The rationale was to be able to compare laboratory and survey measures of trustworthiness, which mirrors our interest in the comparison of laboratory and survey measures of trust.

[14]We offered each respondent a $COP\$20,000$ (about $USD\$7$) voucher for a fast food restaurant on the university campus. The Online Appendix includes an English translation of the survey, which was

the incoming cohort plus 32 other students who, due to their course schedules, were in frequent contact with the 81 intended subjects throughout the semester.[15] We elicited social networks as follows. First, we presented each student with the list of names of the other 112 students invited to complete the survey (in random order), and we asked him or her to indicate the students who he or she greeted (henceforth, hello partners). Specifically, for each student on the list, we asked him or her to tick a box if they would say hi to that student upon encountering him or her. Secondly, we presented each student with his or her list of hello partners and, for each of them, we asked the student to check one or more of six boxes acknowledging the following relationships: (1) "I met this person before starting university," (2) "I frequently have lunch with this person," (3) "I frequently study or work together with this person," (4) "I share my personal feelings with this person," (5) "I believe this person is a friend of mine," and (6) "None of the previous options apply to my relationship with this person."[16] Thanks to box (1) we can control for whether relationships formed before our intended socialization period (the first academic semester), and so we end up with five possible relationships (greeting, having lunch together, studying together, confiding in, and friendship). Out of the 113 students that were invited to complete the survey, 95 filled out the questionnaire. Out of the 72 students that participated in the trust experiment in the first stage, 62 completed the survey.

Besides questions to elicit networks, the survey included questions on many individual characteristics that we suspect to play a role in relationship formation. The rationale

conducted using Qualtrics.

[15]The intended subjects had to take 6 courses. The 32 remaining students were students from other semesters who also took the course "Pensando Problemas" (one of the mandatory courses) that same semester together with the 81 intended subjects. The 32 remaining students were individuals who decided to declare themselves as students of the economics program later in their university careers or who failed and had to retake the "Pensando Problemas" course. Although our focus was on the 81 students that made up the entire incoming cohort, we decided to include the other 32 students to have a more complete picture of the self-contained social environment the intended subjects were facing.

[16]We decided to ask the students to check these boxes only for their hello partners to avoid overwhelming them with questions, which could have increased the possibility that subjects make mistakes or do not the survey.

behind this design is that isolating the impact of trust in network formation requires controlling for variables that might affect the creation of social links and correlate with trust. In particular, we collected information on the number of siblings, the number of friends enrolled in the same university met before starting university, the number of friends enrolled in the same university met after starting university, the number of friends not enrolled in the same university, weekly hours spent socializing with friends enrolled in the same university, weekly hours spent socializing with friends not enrolled in the same university, weekly hours spent doing physical activities, hobbies, age, eye color, hair color, height, weight, whether wearing glasses, whether wearing tattoos, whether wearing piercings, whether smoking, whether attending parties, whether their hometown is Bogotá, and four personality questions. In the latter questions, we asked the students to rate on a scale from 1 to 5 how much they perceived themselves as realistic, introverted, inhibited, and shy. Finally, we asked the students to rate on a scale from 1 to 5 how much they agreed with the following statements: "I am very sociable," "I am satisfied with my social life," "making friends at university is easier than I thought," and "I am satisfied with the number of friends I have." In addition to the data collected with our survey questions, our empirical analysis uses administrative data from the university on several student characteristics, such as the scores obtained at the high school exit examination, their GPAs at the end of the first academic semester, and their socioeconomic status. Moreover, we use the administrative data to obtain information on the time that each pair of students are exposed to each other because assigned to the same classrooms during the first semester. See Subsection 2.2.1 for a more detailed discussion.

Out of the 81 students comprising the entire cohort, 72 participated in the activities to measure their trust. Out of these 72 students, 58 participated in the activities to measure their networks. We could obtain administrative information for 52 students out of the latter 58. Hence, we end up with a sample of 52 students for whom we have all the information needed to conduct our empirical analysis.

2 Empirical analysis

Here we present our empirical analysis of the effect of trust on link formation probability. Overall, our results suggest that trust does not play a relevant role in relationship formation among our subjects, while time of exposure, knowing each other from before, and different demographic traits are important determinants of social links. We begin in Subsection 2.1 by describing the subjects' characteristics, behavior in the trust experiment, and networks. In Subsection 2.2 we present our baseline specification. We provide a detailed description of the controls we used in the regressions and show that our results do not change when employing alternative trust measures. In Subsection 2.3, we present robustness checks, which confirm that trust does not play an important role in predicting link formation probability, and discuss possible mechanisms. In Subsection 2.4 we interpret our results.

2.1 Students' characteristics, behavior, and networks

Students' characteristics. Table 1 contains summary statistics for the main individual variables used in the empirical analysis and some demographics. The statistics reported refer to the sample of 52 students (1) who participated in the first stage, (2) who accessed the online survey we administered in the second stage, and (3) for whom we could obtain administrative data. Besides the demographic characteristics, in Table 1, we present summary statistics for the students' socioeconomic status, the score they obtained at the high school exit examination, whether their hometown is Bogotá, whether they attend parties, and how many hours per week they spend doing physical activity. We proxy socioeconomic status with an administrative classification referred to as "estratificación socioeconómica" (socioeconomic stratification), which classifies residential real estates into six categories, ranging from 1 (corresponding to the poorest socioeconomic status) to 6 (corresponding to the richest one). The high school exit examination,

Table 1: Summary statistics for the individual characteristics

Variable	Avg.	S.d.
Socioeconomic status (1—6)	5.06	0.96
Sex (1 = male)	0.69	0.47
Exit exams	399.56	23.53
Hometown (1 = Bogotá)	0.77	0.43
Weight (kg)	65.50	10.14
Height (cm)	173.69	8.78
Number of siblings	1.27	0.79
Wearing glasses (1 = yes)	0.31	0.47
Wearing piercings (1 = yes)	0.21	0.41
Attending parties[a]	1.44	0.54
Smoker (1 = yes)	0.29	0.46
Weekly hours of physical activity	4.56	4.72

Notes: Sample of 52 students who participated in both stages of the data collection process and for whom we could obtain administrative data.
[a] (0 = never, 1 = once in a while, 2 = frequently)

officially referred to as the ICFES examination, is a standardized test administered for every graduating high school cohort in Colombia. This examination is similar to the SAT and ACT examinations in the United States, and its score ranges from 0 to 500. In our sample, most of the students come from rich families in Bogotá, and the average socioeconomic status is 5 out of 6. The average score obtained at the high school exit examination is about 400, which usually falls in the top percentiles of the country-level score distribution.

Table 2 presents a balance test showing that the observable characteristics of the 52 students who participated in both stages of the data collection process and for whom we could obtain administrative data are similar on average to characteristics of the students who we could not retain for the empirical analysis because they did not participate to the second stage of the data collection process.

Table 2: Descriptive statistics and balance

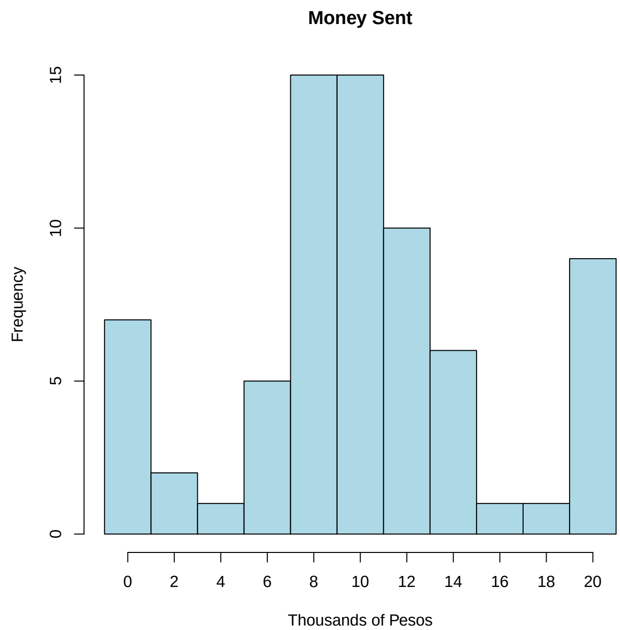
	Analysis sample			Excluded participants			
	n	Avg.	S.d.	n	Avg.	S.d.	Diff.
Money Sent	52	4.92	2.65	13	5	3	-0.077
Socioeconomic background[a]	52	5.06	0.96	10	4.8	0.92	0.26
Gender	52	0.69	0.47	13	0.77	0.44	-0.077
GPA	52	4.06	0.41	13	3.81	0.77	0.25
High-school exit exam	52	399.6	23.53	10	389.1	21.2	10.46

Notes: Comparison of the average observable characteristics between the set of students we use in the empirical analysis and the set of students who participated in the first stage but failed to to participate in the second stage of the data collection process for whom we have administrative data.

[a] Socioeconomic background (estrato)

Students' behavior in the trust experiment. In the trust experiment, on average, the sender sent about half of his or her endowment of $COP\$20,000$ (standard deviation is $COP\$5,251.58$). Figure 1 shows the distribution of the amount sent by senders. Overall, our subjects' behavior in the laboratory squares well with the literature. In a meta-study of 162 trust experiments, Johnson and Mislin (2011) find that senders send half of their endowment, on average. We find that receivers return 35% of the amount received, on average. According to Johnson and Mislin (2011), on average, receivers return 37% of the amount received.

Figure 1: Money sent by senders in the trust experiment



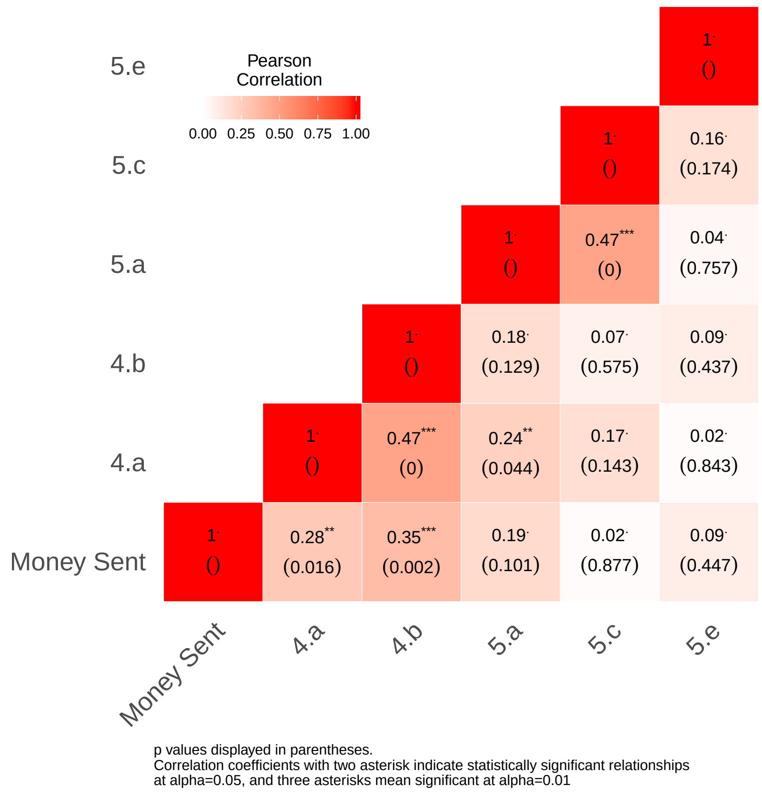
During the first stage of the data collection process (right after the trust experiment took place), we also asked survey questions aimed to measure generalized (4.a and 4.b), and particularized trust towards friends (5.a and 5.c) and neighbors (5.e).[17] Figure 2 shows correlations between the amounts of money sent by senders in the experiment (behavioral trust) and the answers to survey questions 4.a, 4.b, 5.a, 5.c, and 5.e (attitudinal trust), as well as the correlations between the answers to the questions. Behavioral trust significantly correlates with (attitudinal) generalized trust but not with particularized trust. Glaeser et al. (2000) finds that the answers to two questions on generalized trust (similar to questions 4.a and 4.b), and the answers to the questions on particularized trust (what they refer as 'past trusting behavior') are all correlated with money sent in a trust experiment. Our results confirm Glaeser et al. (2000)'s finding that generalized trust significantly predicts trusting behavior in the laboratory.[18] However, contrary to

[17]We distribute the surveys only after the experiment was finished to avoid biasing subjects.
[18]This evidence supports Glaeser et al. (2000)'s conclusion that questions on generalized trust are

Glaeser et al. (2000), we find that particularized trust does not significantly correlate with money sent in the experiment. We believe that this discrepancy stems from a difference in Glaeser et al. (2000)'s experimental design, as their subjects knew each other's identities while playing the trust game. Moreover, in their study, people who arrived together at the experiment were allowed to play with each other. As a result, subjects who are friends are more likely to play together, and so particularized trust towards friends likely plays a crucial role in their behavior. The fact that our experiment is anonymized likely explains why past trusting behavior towards particular groups of people (i.e., friends and neighbors) does not play a significant role in predicting our subjects' behavior in the experiment.

"more precise and meaningful than completely general, nonspecific questions regarding trust," such as the one asked in the General Social Survey.

Figure 2: Correlations between the amounts of money sent by senders in the experiment (behavioral trust) and the answers to survey questions 4.a, 4.b, 5.a, 5.c, and 5.e (attitudinal trust)



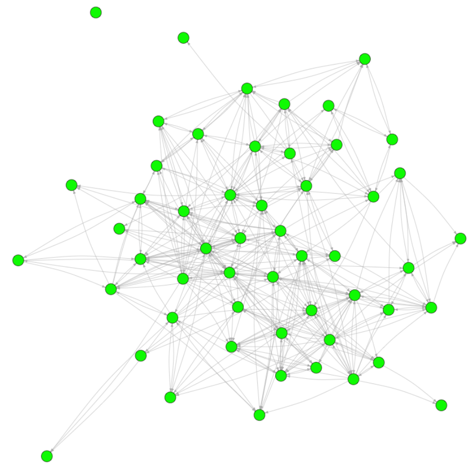
Students' networks. Figure 3 displays the directed friendship network for the sample of 52 students who participated in both stages of the data collection process and for whom we could obtain administrative data.[19] We draw a thin (light grey) arrow from subject i to subject j when i states to believe that j is a friend of his or her in the network elicitation survey.[20] Table 3 displays some summary statistics for the social networks. Average in- and out-degrees in the friendship network are 6.85, average local clustering in 0.44, global clustering is 0.38, and the average path length is 2.16.[21] The charac-

[19]Figures displaying the other networks are presented in the Online Appendix.

[20]For comparability, the nodes in all networks reported in the Online Appendix are displayed using a Fruchterman-Reingold layout of the friendship network.

[21]The in- out-degrees of an individual i are the number of links (edges) to i and the number of links from i. A person's neighbors are all the individuals to whom i links or that link to i. To calculate an individual's local clustering, we divide the number of edges between his or her neighbors by the number

Figure 3: Friendship network



Notes: Sample of 52 students who participated in both stages of the data collection process and for whom we could obtain administrative data. An arrow from student i to student j is drawn when i states to believe that j is a friend of his or her in the network elicitation survey.

teristics of the networks we retrieve square well with the literature (Jackson (2010)). In particular, they all exhibit high degrees of clustering and low average path lengths. The greeting network is denser than the other networks, the having lunch together and confiding in networks are the sparser, and the studying together and friendship networks sit in between the two opposites. In all networks there is one giant component, and the greeting network is connected.

of links that could exist between them. Let a triplet be three individuals that are connected by either two or three undirected links. Say that a triplet is closed if three undirected edges are connecting these individuals. The global clustering of a network is the share of closed triplets among all triplets. A path from i to j is the smallest number of links that need to be crossed to go from i to j.

Table 3: Summary statistics for the networks

Network	Variable	Avg.	S.d.
Greeting	Degree (in)	13.5	6.29
	Degree (out)	13.5	7.19
	Clustering (local)	0.52	0.12
	Clustering (global)	0.49	0.00
	Path length	1.70	0.50
Having lunch together	Degree (in)	2.58	2.05
	Degree (out)	2.58	2.32
	Clustering (local)	0.40	0.30
	Clustering (global)	0.38	0.00
	Path length	4.00	2.04
Studying together	Degree (in)	5.77	3.18
	Degree (out)	5.77	4.91
	Clustering (local)	0.44	0.20
	Clustering (global)	0.33	0.00
	Path length	2.13	0.69
Confiding in	Degree (in)	2.98	2.12
	Degree (out)	2.98	2.53
	Clustering (local)	0.35	0.28
	Clustering (global)	0.31	0.00
	Path length	2.89	1.09
Friendship	Degree (in)	6.85	3.60
	Degree (out)	6.85	4.81
	Clustering (local)	0.44	0.21
	Clustering (global)	0.38	0.00
	Path length	2.16	0.75

2.2 Baseline specification

We hypothesize that subjects with higher trust are more likely to establish new relationships, other things being equal. Consider this possible conceptual framework. Suppose a student i has to decide whether to engage in social interaction with an unknown student j.[22] Normalize i's expected utility from not interacting with j to zero.

[22] For example, i must decide whether to start talking to a deskmate during the first lecture of the first course. Alternatively, i must choose whether to accept an invitation to lunch with a deskmate just met.

A relationship with student j can be beneficial or unfruitful. Student i's utility from a beneficial relationship with j is $a > 0$ (e.g., in each interaction with j, i enjoys a flow of knowledge and favors). On the other hand, if i starts engaging with j but an unfruitful relationship eventually forms, his or her utility is $b < 0$ (e.g., i wastes time and other resources in initial interactions with j but cannot enjoy the benefit of an advantageous relationship). When starting to engage in social interaction with an unknown j, i does not know whether a relationship with j will be beneficial or unfruitful. Let τ_i be i's prior belief over the event that a relationship with j will turn out to be beneficial (hence, $1-\tau_i$ is i's prior belief that a relationship with j will be unfruitful). We conceptualize τ_i as i's trust. Finally, suppose that if i engages in social interaction with j, he or she experiences some relation-specific cost η_{ij} (which encompasses, for example, the time required to maintain the relationship) and can be influenced by personal characteristics of the pair. Then, i's expected utility from engaging in social interaction with an unknown j is

$$\mathbb{E}u_{ij} = \tau_i a + (1 - \tau_i)\, b - \eta_{ij}.$$

Hence, the probability that i starts engaging in social interaction with j is

$$\Pr\left(\mathbb{E}u_{ij} > 0\right) = \Pr\left(\eta_{ij} < \tau_i a + (1 - \tau_i)\, b\right).$$

This probability is increasing in τ_i. Since engaging in social interactions with unknown people is a prerequisite for relationships to form, and more trusting individuals are more likely to start engaging in social interactions with strangers, they are more likely to establish relationships with unknown people.

To test this hypothesis, we use linear probability models to estimate the impact of trust on link formation probability in the networks elicited. In the following, we use capital letters for random variables, small letters for possible realizations, and bold letters for vectors. Suppose that, for each ordered pair of subjects i, j,[23] the probability that a link from i to j forms is

$$\Pr\left(Y_{ij} = 1 \mid \boldsymbol{X}_i, \boldsymbol{X}_j, \boldsymbol{Z}_{ij}\right) = F\left(\beta^0 + \boldsymbol{\beta}^1 \boldsymbol{X}_i + \boldsymbol{\beta}^2 \boldsymbol{X}_j + \boldsymbol{\beta}^3 \boldsymbol{Z}_{ij}\right),$$

where $Y_{ij} = 1$ indicates that i states to have a certain relationship with j in the network elicitation survey (e.g., i indicates j as a friend of his or her), $\boldsymbol{X}_i$ and $\boldsymbol{X}_j$ are vectors of individual characteristics, and $\boldsymbol{Z}_{ij}$ is a vector of link characteristics. Examples of individual characteristics include the students' trust, sex, height, and socioeconomic status. Examples of link characteristics are similarity in physical traits (such as height and weight) and demographic characteristics (such as sex and socioeconomic status), and whether the subjects knew each other from before the intended socialization period (the first academic semester). Subsection 2.2.1 presents a description of all the explanatory variables we introduce in the regressions and the way we construct them. For LPMs, we assume that F is the identity function.[24] Thus, the regression equation for an LPM is

$$Y_{ij} = \beta^0 + \boldsymbol{\beta}^1 \boldsymbol{X}_i + \boldsymbol{\beta}^2 \boldsymbol{X}_j + \boldsymbol{\beta}^3 \boldsymbol{Z}_{ij} + \varepsilon_{ij}. \tag{1}$$

In terms of the conceptual framework outlined above, a LPM for the probability that i has a relationship with j follows if η_{ij} is a linear combination of the explanatory variables other than i's trust plus a random utility component drawn from a uniform distribution.[25]

[23] Our baseline specification uses directed networks as outcome variables: for each relationship elicited, we draw a link from i to j if i nominates j in the network elicitation survey. In this way, we can account for the fact that non-sampling errors in the network elicitation survey might not be symmetric across pairs of individuals. All the results we present here are virtually unchanged when we use undirected networks as outcome variables. In constructing the undirected networks, we consider both the union network (we draw a relationship between i and j if either i nominates j or j nominates i) and the intersection network (we draw a relationship between i and j if both i nominates j and j nominates i).

[24] If we wanted to run a logit regression instead, we would take F to be the standard logistic function.

[25] For logit regressions, assume there is a (continuous) latent variable Y^*_{ij} such that

$$Y^*_{ij} = \beta^0 + \boldsymbol{\beta}^1 \boldsymbol{X}_i + \boldsymbol{\beta}^2 \boldsymbol{X}_j + \boldsymbol{\beta}^3 \boldsymbol{Z}_{ij} + \varepsilon_{ij}, \tag{2}$$

If we were to assume that ε_{ij} is independent of $\varepsilon_{k\ell}$, for each $ij \neq k\ell$, then we could estimate Equation (1) with a standard OLS regression. However, when the observations $(Y_{ij})_{i,j=1,\ldots,N,i\neq j}$ correspond to the presence of links between N individuals it is not generally safe to assume that errors are independent across ordered pairs of individuals. For example, suppose subject i gives consistently low friendship ratings. In this case, i's residuals (i.e., all of the $2(N-1)$ error terms $\varepsilon_{k\ell}$ such that $k = i$ and $\ell \neq i$) in the friendship network will tend to be low, making conditional independence break between all observations k, ℓ such that $k = i$ and $\ell \neq i$. Given this autocorrelation, standard OLS regressions produce consistent point estimates but underestimate p-values (Birke and Swann (2010)).[26] We could hope to account for much of this autocorrelation by controlling for observed characteristics. A more conservative approach would instead assume that, in practice, there is always some degree of correlation between the error terms from the same row and the same column in the adjacency matrix corresponding to the network.

In this paper, we take the more conservative approach. To address the autocorrelation issue, we do two things. First, we use the dyadic-robust variance estimator (Fafchamps and Gubert (2007) and Tabord-Meehan (2019)) to correct standard errors. This correction takes into account possible correlation between dyads that share a node in the networks. Second, we use the Quadratic Assignment Procedure (henceforth, QAP) to obtain amended p-values. This procedure starts with a standard OLS regression of the observations of the dependent variable on the matrix of explanatory variables. Instead

where is distributed according to the standard logistic distribution. We interpret Y^*_{ij} as i's relationship rating with j; i.e., how strong i's relationship (e.g., friendship) with j is in i's view. Given Equation (2), we assume that

$$Y_{ij} = \begin{cases} 1 & \text{if } Y^*_{ij} > 0 \\ 0 & \text{if } Y^*_{ij} \leq 0 \end{cases}.$$

In terms of the conceptual framework outlined above, a logit regression follows if η_{ij} is a linear combination of the explanatory variables other than i's trust plus a random utility component drawn from the standard logistic distribution.

[26]Hence, p-values would too easily lead to rejecting the null hypothesis that an explanatory variable is uncorrelated to the probability that a link forms.

of relying on the underestimated OLS standard errors to determine the p-values, the QAP runs many more regressions by first randomly permuting the rows and columns of the adjacency matrix corresponding to the observed network. By regressing many randomly permuted networks on the (fixed) explanatory variables, the QAP allows us to recover a sampling distribution of the estimator under the null hypothesis that $\boldsymbol{\beta} = \left(\beta^0, \boldsymbol{\beta}^1, \boldsymbol{\beta}^2, \boldsymbol{\beta}^3\right) = \mathbf{0}$, where $\boldsymbol{\beta}$ is the vector of parameters to be estimated. To determine the significance of the coefficient of an explanatory variable, say β^{1m}, where β^{1m} denotes the m-th component of $\boldsymbol{\beta}^1$, the QAP compares the estimate in the initial regression (i.e., the OLS estimate) $\widehat{\beta}^{1m}$ to the sampling distribution of the estimator of β^{1m} under the null. If, for example, $\widehat{\beta}^{1m}$ falls within the 90% confidence interval of that distribution, the QAP says that it is insignificant at the 10% level. More generally, we compute the QAP p-value of $\widehat{\beta}^{1m}$ by looking at the observations in the sampling distribution of the estimator of β^{1m} under the null and then computing the fraction of these observations that are higher than β^{1m} in absolute value.

2.2.1 Explanatory variables

In the baseline specification, we take i and j's trust to be the amount of money sent by senders in the experiment. We prefer the behavioral measure of trust because it directly relates to making the first move to start cooperating with unknown others, coming very close to our hypothesis of how trust helps people engage in social interaction with strangers. Moreover, some researchers consider survey questions on trust vague and hard to interpret (Glaeser et al. (2000) and Naef and Schupp (2009)).[27] For each ordered pair i, j, the variables called "Trust i" and "Trust j" are the amounts of money sent by individuals i and j as senders in the trust experiment. These amounts are measured in

[27]While we do not think that attitudinal measures of trust are necessarily noisier than behavioral measures, we believe that behavior in the trust experiment is more related to our hypothesis on the role of trust in network formation. In Subsection 2.3.1, we re-perform our baseline specification taking the answers to the survey questions on generalized trust as the measure of trust. The results confirm that trust is unlikely to have a significant and positive role in relationship formation.

$COP\$2,000$ units (from 0 to 10). Our subjects might select friends based on similar prosociality (Logis et al. (2013)). To control for the possibility of homophily in trust, we include a variable called "Trust Δ," which we define as the absolute value of the difference between "Trust i" and "Trust j."

To reduce omitted variable bias, we gather information on several individual and pairwise characteristics that may affect network formation and might correlate with trust, which we can use as controls. As for individual characteristics, we have information on sex, age, eye color, hair color, height, weight, whether wearing glasses, whether wearing tattoos, whether wearing piercings, number of siblings, number of friends enrolled in the university met before starting university, average weekly hours spent doing physical activity, whether attending parties, score obtained at the high school exit examination, GPA at the end of the first academic semester, self-assessed personality type (shy, inhibited, introverted, realistic), socioeconomic status, and whether their hometown is Bogotá. As for pairwise characteristics, we have information on whether the students reported knowing each other from before our intended socialization period, and the amount of time they spent together in the same classrooms during the first semester, as measured by the number of university credits that the students share.[28] Moreover, for each individual characteristic, we wish to control for the possibility of homophily in that characteristic. For example, students who have a relatively similar socioeconomic status might be more likely to form a relationship. To do so, for each pair of individual characteristics X_i and X_j we build a pairwise variable $X\Delta$ that is defined as follows. When X_i and X_j are non-binary individual characteristics (e.g., i and j's socioeconomic status), $X\Delta$ is the absolute value of the difference between X_i and X_j. When X_i and

[28]All of our subjects take the same six courses in the first semester but are allocated to different classrooms, corresponding to different time schedules. Selection is likely not an issue in this context. While students can express preferences for different classrooms, they can only do so before the first semester starts, and these preferences are not necessarily reflected in the final allocation of students to classrooms. The majority of students do not know each from before; hence, it is unlikely that the variation in time of exposure arises from students purposefully choosing to attend the same classrooms. Even if that were the case, in our regressions we control for whether students knew each other from before whenever we introduce time of exposure as an explanatory variable.

X_j are binary characteristics (e.g., i and j's sexes), $X\Delta$ is a binary variable that equals zero as long as i and j share the same trait. Abusing terminology, we refer to $X\Delta$ as similarity in X. In terms of Equation (1), these $X\Delta$ variables are contained in the vector of link characteristics $\boldsymbol{Z}_{ij}$.

To ease the comparison of the effect of different covariates, we standardize each non-binary variable by subtracting its average from the variable and dividing the result by the standard deviation of the variable.[29] Thus, we can interpret the marginal effects in the regressions below as one standard deviation increases in the original variables.

Some of the variables described above may be "bad controls." For example, a more trusting student may be more willing to attend parties, which in turn affects his or her chances of forming relationships. To tackle this problem, we run hourse-race regressions for different specifications of the baseline strategy, some of which include only controls that are predetermined relative to the measurement of our subjects' trust.

Table 4 reports summary statistics for the main (non-standardized) pairwise variables used in the empirical analysis.

2.2.2 Results

To save space, we only report the results of the baseline specification running linear probability models with the friendship network as the dependent variable: the outcomes of applying the baseline strategy to the other relationships (greeting, having lunch together, studying together, and confiding in) are virtually identical (see Subsection 2.3.2). Table 5 reports the results of our baseline strategy. We show three specifications of the linear probability model for the friendship network, each one having a different set of controls. For each specification, we present the estimated coefficients on the left (dyadic-robust standard errors are in parenthesis below) and the QAP p-values on the right. First, we run a version of regression (2) that only includes the subjects' trust levels and similarity

[29] Notice that when $X\Delta$ is a non-binary variable, we standardize it after having computed the difference.

Table 4: Summary statistics for the pairwise characteristics

Variable	Avg.	S.d.
Knew each other from before	0.03	0.18
Time of exposure	5.61	3.63
Socioeconomic status Δ	1.04	0.87
Sex Δ	0.43	0.50
Exit exam Δ	25.28	21.64
Hometown Δ	0.36	0.48
Weight Δ	11.34	8.78
Eye color Δ	0.57	0.50
Hair color Δ	0.55	0.50
Number of siblings Δ	0.86	0.73
Wearing glasses Δ	0.43	0.50
Height Δ	10.12	7.20
Wearing piercing Δ	0.34	0.47
Attending parties Δ	0.55	0.53
Smoker Δ	0.42	0.49
Weekly hours of physical activity Δ	4.74	4.69

Notes: Sample of all the 2652 possible directed links between the 52 students.

in trust as explanatory variables.

The first two columns of Table 5 show the results of an LPM that regresses the friendship network on i and j's trust, and similarity in i and j's trust. The first column reports point estimates and dyadic-robust standard errors (in parenthesis, below the point estimates). The second column reports the QAP p-values associated with the coefficients. While their coefficients are virtually zero, the trust variables are highly insignificant predictors of whether i nominates j as a friend of his or her. Next, we introduce in the regression some controls that we suspect to play a role in network formation (henceforth, base controls). These are whether the students knew each other from before, their time of exposure in class, socioeconomic status, sex, score at the high school exit examination, and whether their hometown is Bogotá (hometown).[30] For each individual characteristics, we also control for similarity in that characteristic (see Subsection 2.2.1 for a more

[30] We do not include age in the list of base controls because there is little variation in age among our subjects.

detailed discussion). An advantage of limiting the set of variables introduced to the base controls is that these variables are predetermined relative to the measurement of our subjects' trust, which limits the possibility of bad control problems.

Table 5: Friendship network — linear probability models

	(i)		(ii)		(iii)	
	β	QAP	β	QAP	β	QAP
	(s.e.)	p-value	(s.e.)	p-value	(s.e.)	p-value
Constant	0.135	0	0.135	< 0.01	0.135	< 0.01
	(0.018)		(0.018)		(0.016)	
Trust i	< 0.001	> 0.99	-0.005	0.75	-0.001	0.91
	(0.011)		(0.013)		(0.017)	
Trust j	-0.008	0.39	-0.012	0.26	-0.010	0.43
	(0.009)		(0.008)		(0.012)	
Trust Δ	0.009	0.54	0.005	0.75	0.002	0.85
	(0.016)		(0.015)		(0.014)	
Knew each other			0.088	< 0.01	0.089	< 0.01
from before			(0.016)		(0.017)	
Time of exposure			0.037	< 0.01	0.049	< 0.01
			(0.011)		(0.014)	
Socio-economic			-0.003	0.81	-0.008	0.74
background i			(0.016)		(0.016)	
Socio-economic			-0.012	0.34	-0.012	0.28
background j			(0.014)		(0.014)	
Socio-economic			-0.020	< 0.01	-0.027	0.01
background Δ			(0.013)		(0.015)	
Sex i			-0.003	0.75	-0.014	0.60
			(0.015)		(0.018)	

Sex j			-0.022	0.03	-0.025	0.22
			(0.012)		(0.014)	
Sex Δ			-0.015	0.13	-0.005	0.67
			(0.012)		(0.014)	
Exit exams i			0.003	0.94	-0.010	0.63
			(0.011)		(0.012)	
Exit exams j			-0.013	0.26	-0.027	0.07
			(0.008)		(0.010)	
Exit exams Δ			0.001	0.90	-0.003	0.81
			(0.012)		(0.013)	
Hometown i			-0.043	< 0.01	-0.048	0.02
			(0.018)		(0.017)	
Hometown j			-0.042	0.01	-0.049	< 0.01
			(0.017)		(0.018)	
Hometown Δ			-0.047	< 0.01	-0.047	< 0.01
			(0.021)		(0.021)	
Other controls	No		No		Yes	
Observations: 2652						

This table reports three specifications of the linear probability model for the friendship network. For each specification, the estimated coefficients are on the left, dyadic-robust standard errors are in parenthesis below, and QAP p-values are on the right.

The middle two columns show the results of an LPM that adds the base controls to the trust measures. Introducing these controls does not change the evidence that the effect of the trust measures is small and highly insignificant. As for the base controls, we find that knowing each other from before has a significant and sizeable effect on relationship formation. On average, if i indicates that he or she knew j from before starting university, the chance that i declares j to be a friend of him of her at the end of the first academic semester increases by 0.09. This effect is not surprising and shows that friendship relationships tend to be persistent or that it is easier to befriend a person that was already acquainted. When i and j spend more time together because assigned to the same classrooms, i is significantly more likely to consider j a friend of his or her. A one standard deviation increase in time spent together because assigned to the same classrooms increases the probability that a student befriends another by 0.04. These results square well with the evidence presented in Marmaros and Sacerdote (2006), which finds that first-year students interact with peers that are more easily approachable and form long-term friendships with a subset of these people. Moreover, the significant positive effect of time of exposure on link formation probability supports Girard et al. (2015)'s result that students who belong to the same groups tend to form friendships among themselves. Homophily in socioeconomic status is significant: on average, a one standard deviation increase in the difference between i and j's socioeconomic statuses decreases the probability that i nominates j as a friend of his or her by 0.02. Homophily in hometown is also significant: on average, if i and j both come from Bogotá or both come from outside Bogotá, i has a 0.05 higher chance that i nominates j as a friend of his or her. These findings are consistent with a large body of empirical evidence (McPherson et al. (2001)). Also, student i is less likely to consider j to be a friend when he or she comes from Bogotá or if j comes from Bogotá. These results are intuitive since students that come from Bogotá probably already have a network of friends in town, and hence they might have less of a need to form new friendships relative to outsiders. We also find that i is significantly less likely to nominate j as a friend of his or her if j is a male. This finding is harder to interpret and likely due to omitted variables, as discussed below.

Finally, we consider an LPM that adds additional variables that we can control for (other controls) to the trust measures and the base controls. The idea is to reduce the possibility of omitted variable bias even more. In the results reported here, we do not control for all the variables described in Section 2.2.1 because some of them are likely to be "bad controls." In particular, we exclude the variables that we suspect to be endogenous to the observed network structure (e.g., GPA at the end of the first semester) or mediators of the effect of trust (e.g., shyness).[31] The final two columns of Table 5 show the results of an LPM that adds the other controls to the trust measures and the base controls. We omit the coefficients associated with the other controls for readability.[32] The results confirm the intuition from previous specifications; i.e., trust does not predict friendship link formation. Once we introduce the other controls, the significance of j's sex on the probability that i forms a friendship with j disappears. This result strengthens our belief that to the the effect of j's sex on link formation probability found in previous specification is due to omitted variables. Finally, this specification confirms that knowing each other from before, time of exposure, similarity in socioeconomic status, and hometown are important determinants of network formation.

Does the insignificance of trust follow from the effect of this variable being small or by high standard errors? To answer this question, we analyze the power of our test. Suppose that, in reality, $\beta^1_{\text{Trust}} = 0.09$, where β^1_{Trust} is the true effect of i's trust on the probability that there is a friendship from i to j. If this were the case, the true effect of trust on link formation probability would be the same magnitude as the estimated effect of knowing each other from before. In this case, given our sample size and the dyadic-robust standard errors of the estimated β^1_{Trust}, the probability of failing to reject the null that $\beta^1_{\text{Trust}} = 0$ is less than 1%. More generally, given our sample size and standard errors, the minimum detectable effect of trust on link formation probability with 80% power is roughly 0.0364, which is slightly less than the effect of time of exposure. Hence, we can safely assert that if the true effect of i's trust on link formation probability is

[31]The complete list of the other controls is: number of siblings, weekly hours spent doing physical activity, age, eye color, hair color, height, weight, whether wearing glasses, whether wearing piercings, whether smoking. For completeness, we also try a specification of the LPM which includes all the variables we can control for. The results are virtually identical.

[32]Section 1 of the Online Appendix reports the table including the coefficients associated with all the controls in the regression.

positive, this effect is very likely to be smaller than the impact of variables such as knowing each other from before and hometown.

2.3 Robustness checks

2.3.1 Survey measures of trust

The measure of trust we use in the baseline specification (i.e., the amount of money sent by senders in the experiment) may be subject to measurement error or confounded by other factors, such as strategic sophistication (Murtin et al. (2018)). It might also be the case that the type of trust measured by the trust experiment (how much money a subject would endow another with, in the absence of commitment or punishment technologies) is not the type of trust that matters for approaching and interacting with strangers. To address this issue, we modify our baseline strategy by using the answers to the survey questions on generalized trust as trust measures. These questions ask, on a 1-5 scale, to what extent the subjects agree with the following statements: (4.a.) one cannot trust strangers, and (4.b.) when dealing with strangers, one should be careful and not readily trust them. These measures are less context-specific than the measure we build from the trust experiment, and could thus be argued to capture a more comprehensive dimension of trust. In building the trust measures out of the survey questions, we reverse the scale of the answers such that a higher score indicates more trust in strangers.[33]

Table 6: Friendship network on survey measures of trust — LPMs

Question 4.a.	β (s.e.)	QAP p-value	β (s.e.)	QAP p-value
Trust i	-0.010	0.51	-0.009	0.58

[33] Albeit less related to behavioral trust, we also check whether the answers to the survey questions on particularized trust predict link formation probabilities. The idea behind this test is that, in the social environment we consider, it might be trust towards particular groups of people (such as friends) that is relevant for engaging in interactions with unknown individuals. Also in this case, we find that trust plays a negligible role in link formation probability.

	(0.012)		(0.016)	
Trust j	< 0.001	0.98	0.004	0.69
	(0.008)		(0.013)	
Trust Δ	0.014	0.17	0.013	0.29
	(0.009)		(0.009)	
Question 4.b.				
Trust i	-0.022	0.12	-0.029	0.13
	(0.01)		(0.014)	
Trust j	-0.010	0.31	-0.017	0.19
	(0.008)		(0.01)	
Trust Δ	0.001	0.91	0.007	0.43
	(0.011)		(0.012)	
Base controls	Yes		Yes	
Other controls	No		Yes	
Observations: 2652.				

This table reports linear probability models regressing the friendship network on two survey measures of trust and the controls. For each measure, two specifications are reported. For each specification, the estimated coefficients are on the left, dyadic-robust standard errors are in parenthesis below, and QAP p-values are on the right.

Table 6 shows the results of LPMs that regress the friendship network on the survey measures of trust and the controls. We do not report the coefficients, standard errors, and p-values for these controls for readability. The first two columns refer to an LPM that only incorporates the base controls; the second two columns refer to an LPM in which we include base controls and other controls (i.e, all the controls we do not suspect to be "bad controls"). The effect of trust on friendship formation is small and never significant at the 10% level, confirming the results obtained with our baseline specification.[34] Finally, as for the base controls, the results are very close to those in Table 5.[35] In particular, knowing each other from before, time of exposure, similarity in socioeconomic status, and hometown always have a significant and sizeable effect on friendship formation.

2.3.2 Other networks

Another potential source of measurement error comes from collecting information on formed friendships. To be precise, friendship is an abstract concept that each individual may define differently. For example, suppose that trusting individuals tend to hold a more restrictive definition of friendship. Then, we may find no relation between behavior in the trust experiment and reported friendships, even if trust plays a role in encouraging people to interact with strangers. To address this problem, we use networks based on actual interactions between students as outcome variables: having lunch together, studying together, and confiding in each other (sharing personal matters). We chose the having lunch together and studying together networks as representing weaker and more casual relationships, whereas the confiding in network represents deeper and stronger ties.

Table 7: Other networks — linear probability models

	Studying		**Lunch**		**Confiding in**	
	β (s.e.)	QAP p-value	β (s.e.)	QAP p-value	β (s.e.)	QAP p-value
Constant	0.113	< 0.01	0.051	> 0.99	0.059	0.91
	(0.016)		(0.007)		(0.008)	
Trust i	-0.010	0.67	-0.010	0.25	-0.006	0.58

[34] We also build a trust index by performing a principal component analysis of the amount of money sent by senders in the experiment, and the answers to the survey questions on generalized trust. Then, modify our baseline strategy by using this index as the trust measure. The results are virtually identical.

[35] Subsection 1.1 of the Online Appendix reports the table including the coefficients associated with the base controls in the regression.

	(0.015)		(0.007)		(0.009)	
Trust j	−0.010	0.45	−0.010	0.10	−0.002	0.79
	(0.010)		(0.005)		(0.007)	
Trust Δ	0.003	0.84	0.002	0.73	0.010	0.26
	(0.012)		(0.008)		(0.008)	
Knew each other	0.058	< 0.01	0.031	< 0.01	0.051	< 0.01
from before	(0.015)		(0.009)		(0.014)	
Time of exposure	0.059	< 0.01	0.034	< 0.01	0.034	< 0.01
	(0.013)		(0.011)		(0.012)	
Socio-economic	0.001	0.99	−0.010	0.26	−0.018	0.02
background i	(0.017)		(0.010)		(0.009)	
Socio-economic	−0.015	0.27	−0.012	0.05	−0.009	0.34
background j	(0.015)		(0.008)		(0.009)	
Socio-economic	−0.038	< 0.01	−0.015	< 0.01	−0.013	0.10
background Δ	(0.014)		(0.010)		(0.009)	
Sex i	−0.030	0.43	−0.010	0.54	−0.032	< 0.01
	(0.020)		(0.011)		(0.016)	
Sex j	−0.023	0.26	−0.028	< 0.01	−0.036	< 0.01
	(0.016)		(0.009)		(0.012)	
Sex Δ	−0.018	0.05	−0.015	0.04	−0.027	< 0.01
	(0.009)		(0.011)		(0.012)	
Exit exams i	−0.003	0.89	−0.008	0.46	0.001	0.87
	(0.013)		(0.007)		(0.007)	
Exit exams j	−0.012	0.42	−0.008	0.31	−0.011	0.20
	(0.010)		(0.006)		(0.007)	
Exit exams Δ	0.001	0.95	0.006	0.49	0.005	0.46
	(0.011)		(0.008)		(0.009)	

Hometown i	0.001	0.95	-0.016	0.24	$-0.02-$	0.15
	(0.022)		(0.012)		(0.013)	
Hometown j	-0.034	0.02	-0.024	0.02	-0.037	0.01
	(0.015)		(0.012)		(0.012)	
Hometown Δ	-0.019	0.09	-0.022	< 0.01	-0.028	< 0.01
	(0.011)		(0.015)		(0.014)	
Base controls	Yes		Yes		Yes	
Other controls	Yes		Yes		Yes	
Observations: 2652						

This table reports linear probability model for three networks. For each network, the estimated coefficients are on the left, dyadic-robust standard errors are in parenthesis below, and QAP p-values are on the right.

Table 7 shows the results of LPMs that regress the other networks on the behavioral trust measures and the controls.[36] The LPMs incorporate base controls and other controls (i.e, all the controls we do not suspect to be "bad controls"). The effect of trust on the formation of the other relationships is small never significant at the 10% level, except for j's trust in the having lunch together network. However, notice that the effect of j's trust on the probability that this relationship forms is *negative*: a one standard deviation increase in j's trust predicts that i has a 0.013 smaller chance to have lunch together with j. See Subsection 2.4 for a discussion on the interpretation of this evidence. The results for the other controls are consistent with those reported for the friendship network: we confirm that time of exposure, homophily in socioeconomic status, and hometown are important predictors of relationship formation probability. Homophily in sex is relevant

[36]We also regressed the greeting network on behavioral trust and the controls. The results we obtain using this network as outcome variable are very similar to the ones shown in Table 7, but we do not report them for readability. More importantly, we do not believe the greeting relationship to be particularly relevant. The reason why we have information on this relationship comes from the design of the network elicitation survey, which asked each individual to select the subset of students he or she greeted before retrieving the other relationships for this subset of students (see Section 1).

for some, but not all networks.

2.3.3 Other robustness checks

Our hypothesis about the mechanism through which trust mediates friendships works through social engagement: people having higher trust towards strangers are more likely to make the first move to start interacting with others and, as a result, form more relationships. The evidence runs against this hypothesis. There are at least two ways to rationalize this result besides concluding the trust does not matter for network formation among our subjects. First, it could be the case that trust does help students making the first move to start interacting with unknown others, but those initial interactions do not consolidate into relationships.[37] Second, while we do not find evidence that trust predicts link formation probability in general, holding more positive beliefs towards strangers might play a role for particular students or pairs of students. For example, it might be the case that trusting unknown others is more important for students who are not from Bogotá, as these individuals are less likely to have a network of relationships already in place.

To address the second possibility, we regress the probability of a link from i to j on the interaction of i's trust with other (individual or pairwise) variables. We consider the interactions between i's trust and i's hometown, the time of exposure between i and j, the difference between i and j's socioeconomic status, whether i and j knew each other from before entering university, and whether i and j are both from Bogotá or both from a different town. The interaction term between i's trust and his or her hometown is

[37] The data we present in this paper does not allow us to rule out this possibility, since we have a unique snapshot of the students' networks at the end of their first academic semester. However, we consider this hypothesis and conduct some exploratory analyses using different data. In particular, we collected information on the exact time each student ever entered and exited the university in his or her first year. We could collect this information because students at this university are required to scan their student ID card to pass through turnstiles when entering and exiting the university building. Thanks to this information, we construct many networks measuring how often two students were entering or exiting the university together. We check whether our subjects' trust levels predict more interactions, i.e., entering and exiting the building with other people, at different points in time. In early analysis we do not find evidence that trust has a significant effect on the students' interactions.

meant to test whether trust is relatively more important for "outsiders." The interaction term between i's trust and the time of exposure between i and j is meant to test whether the effect of trust only shows up when two individuals are not exposed to each other through other means (in this case, spending time together in class). The interaction term between i's trust and the difference between i and j's socioeconomic status is meant to test whether trust might help students to form relationships with individuals that are not similar to them in terms of socioeconomic traits. The interaction between i's trust and whether i and j knew each other from before entering university is meant to test whether trust might play a more important role for forming relationships with people with whom one has no previous acquaintance. Finally, the interaction between i's trust and whether i and j are both from Bogotá or both from a different town is meant to test whether trust plays a role in forming relationships between insiders and outsiders.

Table 8: Friendship network on interaction terms — LPMs

Knowing each other from before	β (s.e)	QAP p-value	β (s.e)	QAP p-value
Trust i × Knew from before	−0.017	0.63	−0.019	0.49
	(0.035)		(0.039)	
Trust i	−0.004	0.75	−0.001	> 0.99
	(0.013)		(0.018)	
Knew each other from before	0.501	< 0.01	0.509	< 0.01
	(0.091)		(0.095)	
Time of exposure				
Trust i × Time of exposure	−0.002	0.75	−0.002	0.71
	(0.011)		(0.012)	
Trust i	−0.005	0.75	−0.001	0.92
	(0.013)		(0.018)	
Time of exposure	0.037	< 0.01	0.049	< 0.01

	(0.011)		(0.016)	
***i*'s Hometown**				
Trust i × Hometown i	−0.040	0.24	−0.050	0.33
	(0.016)		(0.024)	
Trust i	−0.014	0.47	−0.010	0.57
	(0.016)		(0.017)	
Hometown i	−0.106	0.01	−0.131	0.02
	(0.041)		(0.040)	
Hometown Δ				
Trust i × Hometown Δ	0.006	0.70	0.002	0.88
	(0.009)		(0.017)	
Trust i	−0.007	0.67	−0.002	0.94
	(0.014)		(0.017)	
Hometown Δ	−0.098	< 0.01	−0.097	< 0.01
	(0.043)		(0.044)	
Socioeconomic status Δ				
Trust i × Socioeconomic status Δ	−0.001	0.9	−0.002	0.8
	(0.008)		(0.009)	
Trust i	−0.005	0.74	−0.001	0.96
	(0.013)		(0.019)	
Socioeconomic status Δ	−0.02	0.04	−0.027	0.01
	(0.013)		(0.016)	
Base controls	Yes		Yes	
Other controls	No		Yes	
Observations: 2652.				

This table reports the results of linear probability models regressing the friendship network on the behavioral measure of trust, the controls, and interaction terms between i's trust and certain covariates. For each interaction term we consider, two specifications are displayed. For each specification, the estimated coefficients are on the left, dyadic-robust standard errors are in parenthesis below, and QAP p-values are on the right.

Table 8 shows the results of LPMs that regress the friendship network on the behavioral measure of trust and the controls and contain the interaction terms we consider above. We only report the coefficients associated with the interaction terms, i's trust, and the main effect, for readability. All of the signs of the coefficients are in line with our hypothesis, except for the difference between i and j's socioeconomic status. However, all the coefficients are highly insignificant, expect for the interaction between i's trust and his or her hometown, which significant at the 10% level when testing the null hypothesis using the dyadic-robust standard errors (but not when testing it using the QAP p-values). Overall, the results of the table do not suggest that trust is relatively more important for particular individuals or pairs of people, except possibly for people that are not from Bogotá.

One possibility is that we do not find a positive effect of trust on link formation probabilities because uncertainty about others' cooperativeness has already resolved at the end of the first academic semester. That is, the subjects might have learned a good deal about others' trustworthiness by the time in which we collected information on their relationships. In this case, the subjects' initial beliefs about others' cooperativeness (i.e., their trust) might have lost their importance in explaining the students' social links. Hence, we could expect that actual trustworthiness (as opposed to beliefs about others' trustworthiness) is a determinant of link formation probabilities. To test this possibility, we reperform our empirical analysis using trustworthiness measures instead of trust measures to predict link formation probabilities. We use two statistics of trustworthiness from the subjects' behavior in the lab: the average amount of money returned and the average amount returned over the five highest amounts that subjects could receive. We do not find any positive and significant effect of trustworthiness on link formation probability.[38]

Finally, we repeat several of the specifications outlined above using logit regressions instead of linear probability models. In general, the results of the logistic regressions are consistent with those of the LPMs. In particular, the coefficients of the trust measures are non-positive and insignificant.[39]

2.4 Discussion

Our results robustly show that trust, measured through both an experiment and survey questions, does not predict relationship formation among our subjects. Moreover, in the very rare cases in which trust has a significant effect on relationship formation (e.g., j's trust in the having lunch together network), this effect is negative. This evidence stands in opposition to our initial hypothesis that more trusting individuals should have a higher chance of forming relationships. We believe that there are ways in which our results can be rationalized besides concluding that trust does not matter for network formation among our subjects.

One possibility is that more trust is negatively related to some personality trait, e.g., extroversion, that is in turn helpful in establishing new relations. Freitag and Bauer (2016) study how trust is related to Big Five personality traits. They find no evidence of relation between trust and extroversion. Moreover, trust is positively related to openness and agreeableness (traits potentially helpful in establishing relations).[40].

Late adolescents may value traits like dominance, charisma, or nerve when forming relationships with their peers. These traits could, in turn, negatively correlate with trust. This hypothesis stands in line with the literature on social status among adolescents.

[38]Results are available upon request.

[39]Results are available upon request.

[40]See Harris and Vazire (2016) for a literature review on effects of Big Five personality traits on friendship formation

Parkhurst and Hopmeyer (1998) distinguishes between sociometric popularity, representing the in-degree of an individual in a network, and perceived popularity, representing an individual's reputation for being popular. Later studies (Hawke and Rieger (2013) and Franken et al. (2017)) also distinguish between the perception of being popular (popularity) and the perception of being well-liked (likability). The in-degree of adolescents is generally positively correlated with both likability and popularity. However, while likability is mostly related to prosocial behavior and traits, popularity is primarily associated with social dominance (Parkhurst and Hopmeyer (1998)) and correlates with physical aggression, relational aggression, and anti-social behavior (Cillessen and Mayeux (2004), LaFontana and Cillessen (2002), and Hawke and Rieger (2013)). Popular adolescents are also described as manipulative, Machiavellian (Cillessen and Mayeux (2004)) and hard to push around (Parkhurst and Hopmeyer (1998)). We hypothesize that while trust may be positively related to likability, it might have a stronger negative relationship with popularity, as adolescents may perceive trusting individuals as weak or naive. This hypothesis could explain why we find that trust does not generally predict (and sometimes negatively predicts) relationship formation among our subjects. Unfortunately, we have no way to test this hypothesis.

Another possibility is that trust may have a positive impact on network formation in the long but not in the short run. In particular, it is likely that individuals initially form relationships based on similarity in characteristics that can be easily observed, such as hometown and socioeconomic status, because of biases both in people's preferences over others' types and in the chances that people meet individuals of other types (Currarini et al. (2009) and Currarini et al. (2010)). Nevertheless, as time goes by, more trusting individuals might be more successful in maintaining a higher number of their initial relationships because they exhibit more prosociality. If this were the case, our subjects' trust might have no significant effect on relationship formation for the networks we retrieve because we retrieved these networks too early. The data presented here does not allow us to rule out this possibility, since we measure the students' networks only once, at the end of their first academic semester. However, we consider this hypothesis and conduct an exploratory analyses using different data on the students' networks. In particular, we collected information on the exact time each student ever entered and exited the university in his or her first year. We could collect this information because students at this university are required to scan their student ID card to pass through turnstiles when entering and exiting the university building. Thanks to this information, we construct many networks measuring how often two students were entering or exiting the university together. We check whether our subjects' trust levels predict more interactions, i.e., entering and exiting the building with other people, after the end of the first academic semester but do not find a significant effect of trust.

Finally, we also hypothesize that even if trust does not influence the formation of relationships within the study cohort, it can be still relevant for the relationship formation in other contexts. To explore if there is some suggestive evidence pointing to this possibility we study the correlations between the amount of money sent in a trust experiment and several self assessed measures of overall quality of social life; i.e., total number of friends out of the university at the end of the semester, the difference between the total number of friends at the beginning and at the end of the semester, time spent socializing with friends out of the university, satisfaction with social life, and satisfaction with number of friends. The correlations we estimate are weak, do not have consistent signs, and are never significant at 10% level. The results of the analysis are reported in Table 13 in the Online Appendix.

3 Conclusions

We collected experimental and survey data on trust from an incoming cohort of freshman economics students at a university in Bogotá (Colombia) on the first day in which they formally attended the university campus, before they had significant opportunities to get to know each other and socialize. At the end of their first academic semester (i.e., four months after), we collected survey data on five social networks between them. We estimate linear and logistic regressions for each of the networks elicited to identify how the students' initial levels of trust predict link formation probability for the relationships they formed during the first academic semester.

We strongly reject the hypothesis that trust towards strangers positively predicts link formation probability. Moreover, we can confidently assert that if the real effect of trust on relationship formation is positive, its impact is likely to be small relative to several characteristics playing a significant role in relationship formation. Our results suggest that factors like time of exposure, similarity in socioeconomic status, and hometown are much more important than the students' prosocial beliefs for relationship formation during the first academic semester.

This paper contributes to the network formation literature by analyzing prosocial beliefs as determinants of relationship formation. Our empirical strategy allows us to avoid the possibility of reverse causality from relationships to trust. Second, we control for several characteristics that likely play a role in network formation and might correlate with trust. Finally, we use both experimental and survey measures of trust to lessen concerns of measurement error. We also contribute to the literature on social capital by providing a first study of how behavioral social capital (in the form of trust) predicts associational social capital (i.e., social networks). From this point of view, our results could suggest that the positive correlations between measures of behavioral and associational social capital found in the literature might hide a causal relationship going from social networks to trust (as Finseraas et al. (2019) suggests); i.e., having a richer social environment induces people to trust strangers more.

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