Laboratory on the Social Network : Homophily and Peer Influence for Economic Preferences

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Abstract

We provide evidence for two separate mechanisms (homophily and influence) that can be the source of the frequently observed contemporaneous correlation between an individual's behavior or preferences and their social network's behavior and preferences. We demonstrate these effects for the subtle (but broadly important) underlying economic preferences, rather than the observable but potentially domain-specific behaviors previously studied. To do so, we use a longitudinal design, in which we follow incoming freshman through their first academic year at the university, to test for two mechanisms: the impact of one's social network on economic preferences, and the impact of economic preferences on the changes in one's social network. The first mechanism captures a dynamic process of preference change, while the latter reflects selection and homophily in the network dynamics. Subjects participate in three waves of an online experiment where we elicit their social network using an incentive compatible mechanism and then measure participants' levels of altruism, willingness to take risks, and willingness to delay rewards using diagnostic tasks. We find that subjects' risk and time preferences are significantly positively correlated with the preferences of their friends, consistent with peer influence on preferences. Additionally, we find that changes in subject's social networks are significantly influenced by social preferences. Subjects are more likely to add someone as a friend, and less likely to drop as a friend, the more similar their social preferences are.

Introduction

Ample cross-sectional data finds that the behaviors of individuals in one's social network are positively correlated with one's own behavior. This correlation is observed for behaviors such as academic performance (Burke and Sass, 2013; Calvo-Armengol et al., 2009; Sacerdote, 2001), technology uptake (Conley and Udry, 2001), health outcomes (Stevens and Prinstein, 2005; Christakis and Fowler, 2007, 2009), labor market participation (Calvo-Armengol and Jackson, 2004; Topa, 2001), crime participation (Glaeser et al.; 1999), new product diffusion (Aral and Walker, 2011a, b) and the exchange of goods and information (Granovetter, 2005; Bramoulle and Kranton, 2007). For example, Sacerdote (2001) studies peer effects on academic outcomes. To do so he contrasts peers at the dorm level and at the classroom level by exploiting the random assignment of roommates at Dartmouth. He finds that roommates influence each other's GPA and decisions to join social groups (such as fraternities) while peer effects are absent in other major life decisions such as choice of college major. Mayer (2013) finds that students who are Facebook friends are four times more likely to end up at the same company after graduating college – lending further support to the strong intuition that the social network matters both for proximate success (a high grade in a class) but also for ultimate goals (employment upon graduation). Looking at high school boys and girls, Frank et al. (2008) find that when high achieving students were co-enrolled in math courses, then students (and girls in particular) were more likely to advance to a higher level of math. However, we know less about how the behavior and attitudes of individuals in one's social network affects *changes in our behavior and preferences over time* or how these behaviors *affect the dynamics of network formation* (eg. which ties are added or dropped in the network).

Several cross-sectional studies have focused on behavior and diagnostic tasks that are more closely tied to fundamental economic preferences.[1] Andreoni and Scholz (1998) use household data on charitable giving, and demonstrate that a 10% increase in the level of giving by an individual's "social reference space" would lead to an increase in charitable giving of 2-3%. Leider et al. (2009) measure the allocations in dictator-like games of individuals and their friends, and find that individuals in the top quintile of generosity have friends that are 15-25% more generous than the average. Dohmen et al. (2012) find that an individual's risk preference and levels of trust are positively correlated both with their parents' preferences, and with the average preferences of their region (c.f. Fehr et al. 2013). Bettinger and Slonim (2006, 2007), by contrast, find no correlation between the altruism or patience of a parent and a child.

However, these cross-sectional studies have only looked at the correlation at a particular point in time, and are not able to observe the process of preference change that peer influence could imply (as Meyer and Waller, 2001 and Christakis and Fowler, 2007, for example, show with health attitudes and behavior). The one exception that we are aware of is Ahern et al. (2013); they look at how the average preferences in an MBA student's randomly assigned class section affects an individual's own preferences relative to their initial preferences before enrollment. The authors find a positive peer effect for risk attitudes, and a negative peer effect of altruism. By using the pre- and post-enrollment measures of preferences, the authors are able to provide causal evidence for peer influence on preferences. Random assignment to class section eliminates the confound that arises when students can pick who is in or out of their network. It remains to be determined how much of the contemporaneous correlations observed in networks stem from dynamic preference socialization and from homophily.

We know that social networks develop and change over time, and what changes occur depend on both the characteristics of the individuals and the broader context. For example, for college students becoming friends is strongly determined by geographic proximity such as living in the same neighborhood, having the same dorm location or being co-enrolled in the same classroom (Marmaros and Sacerdote, 2006; Kossinets and Watts, 2006; Durlauf, 2004; Meyer and Waller, 2001). Yet other work directly estimates how the structure of the network (and one's place in it) interacts with how the network will change, and how much that network will influence behavior (Backstrom et al., 2006; Marlow et al., 2006; Calvo-Armengol et al. 2009). Studying high school students, Frank et al. (2013) find

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[1] The preferences we focus on are time, risk and altruism. Understanding individual decision-making under risk and over time, as well as an individual's inclination to exhibit generosity toward others, are three foundations of economic analysis and are correlated with important behaviors. For example, risk preferences describe an individual's willingness to accept more or less risky choices and are correlated with decisions such as whether to enter competitive environments such as high stakes testing or entrance exams to competitive schools (Ors et al. 2013). Time preferences characterize how an individual is willing to trade off amongst costs and benefits that occur at different times and have been shown to predict cumulative GPA of college graduates and whether or not they complete college within four years (Burks et al. 2015). Altruism preferences describe a person's concern for the welfare of others and are correlated with college students' willingness to donate to a charitable fund offering low interest loans to financially challenged students (Benz and Meier 2008).

that friendship nominations are much higher (1.77 times greater) when students take courses together and, in earlier work, Frank et al. (2008) show that co-enrolled high achieving math students influence their peers to achieve more.

The detection and measurement of network effects that produce the observed behavior and preference correlations is a difficult exercise but a critical one for understanding how institutions and social contexts shape behavior (Aral and Walker, 2011b, Fehr and Hoff, 2011; Fehr et al. 2013; Frank et al. 2011). This correlation can occur because we tend to select friends because they are similar to us, *homophily* or *selection based on similar behavior or similar preferences* (Kandel, 1978; Fisher and Bauman, 1988; Bauman and Ennett, 1996; McPherson et al., 2001; Golub and Jackson, 2012; Currarini et al., 2010), or because we become more similar to our friends over time, *dynamic preference formation* (Bauman and Ennett, 1996; Meyer and Waller, 2001; Fehr and Hoff, 2011). However, most of these studies either explicitly use exogenous social network assignment (in the case of Ahern et al. 2013 and Falk et al., 2013) or implicitly use it (as is the case when the researcher relies on where focal subjects were born to get exogenous variation (cf. Dohmen et al., 2012 or Henrich et al., 2010 & 2001 or Hermann et al., 2008) to identify the influence of the social and institutional environment on preferences. Distinguishing dynamic preference formation from homophily (while eliminating confounds) requires dynamic, longitudinal network information about the emergence of ties between people in a network and also *separate* measures of behaviors, aspirations and preferences of the individuals in the network (i.e., repeated measures on preference constructs, on behaviors such as academic course selection or study group attendance and on attitudes such as aspirations as major or graduate).

In this paper we test for the effects of friend behavior on dynamic social network formation as well as behavior and economic preference change in the context of newly arriving undergraduate students. When college students arrive on campus for the first time, they are also arriving to a whole new social environment from which they will build new friendship, mentoring, studying, and employment networks. During their first year away from home, they will develop new work and personal habits and they will make choices about college courses and majors that will impact them for years to come. The newly formed social networks, and associated social capital (Coleman, 1988), can have profound effects on their experiences at college - from which major they choose to where they get a job on campus, to whether they experience mental health issues during their college years.

We focus on testing the effect of social networks on risk, time and generosity preferences as well as testing the dynamics of adding and dropping friendship ties. To do this we create a *laboratory on the social network* in which we measure the emerging social network of 399 incoming freshman at the University of Michigan. Our data collection strategy consists of (1) recruiting voluntary participants, (2) mapping students' social network intensely in their first year and (3) using surveys and economic experiments to measure key variables of interest during the course of their first year. Unlike other studies that provided only cross-sectional evidence, or looked only at one mechanism (influence or homophily), our design allows us to observe and distinguish between two mechanisms for correlated behavior on a network: network dynamics and peer influences. Additionally, we can provide direct evidence for homophily based on behavioral measures of economic preferences (rather than behaviors correlated with economic preferences), and evidence for influence of social peers on preferences (rather than an influence of family members such as parents on preferences).

To measure students' social networks we use an incentivized elicitation method taken from Leider et al. (2009). In each of three phases (October, January and April), participating students are asked to name ten other freshman as friends. Students receive a monetary lottery payment for each named student that names them back. For each phase, after the friendship elicitation stage, subjects are invited to also complete an incentivized preference elicitation survey. Because we want to have a measure of fundamental economics preferences, we use diagnostic tasks that are closely tied to our preferences of interest (risk tolerance, patience and altruism). We use multiple price lists between safe and risky outcomes to measure risk attitudes, multiple price lists between sooner and distant payments to measure patience, and dictator allocation decisions to measure altruism. We also ask subjects to self-report their tolerance for risk and their patience. Using this data we can ask two broad sets of questions: (1) are changes in a student's network (e.g. adding or dropping a friendship link) between phases driven by the similarity between the two students on some economic preference? (2) Are a student's economic preferences influenced by the corresponding preferences of the student's current and/or past social ties?

We find in the affirmative for both questions. First, we find that an individual is significantly more likely to add a friendship tie with another student, and significantly less likely to drop an existing friendship tie, if that student has similar level of generosity to the focal student. The magnitude of homophily is substantial – a one standard deviation increase in similarity changes the likelihood of adding or dropping by an amount equal to 20-50% of the base rate. It is also large compared to other factors that one would expect might drive network changes – a one SD change in altruism similarity has an effect half as large as participating in the same activity, and is ~2.5 times as large as a one SD increase in the network centrality of the other student.

Additionally, we find evidence for peer influence on risk preferences, as well as some evidence for peer influence on time preferences. We find that an individual's self-reported tolerance for risk is significantly correlated with the average rating for both the individual's friends, and their broader network community. The correlation is also robust to looking at both the average behavior of others in the same phase as well as the lagged behavior from previous phases. A one standard deviation increase in the average choices of an individual's friends or social community is associated with an increase of 1/8th to 1/10th of a SD for that individual. Similarly, we find that an individual's incentivized patience choices are correlated with their friends and community. A one SD increase in friends' or community's patience increases the patience of the focal individual by 1/7th to 1/12th of a SD. The results for risk preferences, but not time preferences, are robust to the inclusion of lagged dependent variables, although with our short panel (and the incomplete participation of some subjects) this substantially reduces our sample size.

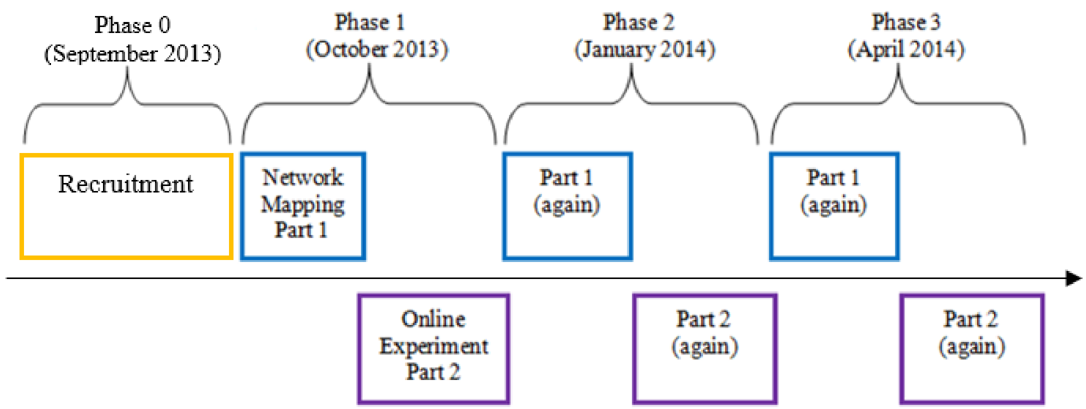
We additionally find robust evidence for a negative peer influence effect on generosity. That is, individuals become significantly *less* generous when they have friends or a social community that are particularly altruistic. This result is consistent with free-riding behavior, and aligns with recent evidence from a related study by Ahern et al. (2013) on peer influence among MBA students.

Our contribution is to provide evidence for two separate mechanisms (homophily and influence) that can be the source of the often observed contemporaneous correlation between an individual's behavior or preferences and their social network's behavior and social preferences. Additionally, we demonstrate these effects for the subtle (but broadly important) underlying economic preferences, rather than the observable but potentially domain-specific behaviors previously studied. Further this work advances both the understanding of how a student's social network and preferences evolve upon entering college, and how a student's social network affects one's economic preferences.

Research Design

Figure 1 shows an overview of the experimental timeframe. Our target population were the incoming freshman at the University of Michigan. To this end, we needed to create our own freshman subject pool from which to recruit subjects into our experiment. Thus, in Phase 0 we recruited freshman using (the traditional method of) flyers and we also developed a Facebook application. We created the Facebook application as both a method of gathering general personal data (including friend lists) and a recruitment tool for the next phases of the research. All students who were eligible to participate had to provide a valid university email address when enabling the application; this allowed us to verify that they were in fact incoming University of Michigan freshman (this was crossed checked with a database of freshman email addresses which we obtained in cooperation with the Registrar).[2] We concluded recruiting by late September of 2013; all subjects who had consented during the month of September were eligible for receiving emails which invited them to participate in our online experiments in Phase 1 – 3.

Figure 1: Research Structure and Data Collection Timeline



Having concluded recruiting, we moved on to *Network Mapping* stage of Phase 1. Consented freshman were contacted via email and invited to participate in an online survey. Subjects were told that the online study would consist of two parts and that they would be paid for their participation after completing both parts. In part one we mapped subjects' social network. Subjects were sent a link to part one and told that they could complete part one (and subsequently part two) within a 3 day window. However, once they opened the link to part one, they would be required to finish part one before receiving a separate link to part two. They were told that they had 30 minutes to complete part one[3], once they had moved to the next screen they would not be able to return to the previous question to change their answers and that they would not able to come back to Part 1 of the study once they logged out of Part 1 or once the 30 minutes are up.

To elicit the network we used a protocol developed by Leider et al. (2009).[4] The protocol asks a participant to list their 10 best friends on campus and pays subjects a bonus for any friend who also participated and listed them as well. If the subject listed a friend who also completed the survey and

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[2] We designed the Facebook application to pilot a mechanism for reaching and identifying densely connected subsets of students. However, for this study we ended up using everyone who agreed to participate.

[3] We timed how long it would take and determined that for most it would take about 10 minutes to answer all of the questions.

[4] There are multiple ways to collect social network data. Advantages and disadvantages of those methods are discussed in Carrington et al. (2005), Prell (2011) and Branas-Garza et al. (2013).

listed her as well, she received a 50 percent chance of getting a prize of $0.50. Otherwise, she was be paid nothing. If both also agreed on the amount of time spent together each week the winning probability was increased to 75 percent. However, if the subjects names a person who does not name them, then they will received nothing. Thus, subjects had ten independent chances to win $0.50 because they could name up to ten friends. Following Leider et al. (2009) we use a lottery-based incentive so that subjects could not definitively know if the person they named had also named them. This avoids the problem that a subject may choose not to list someone because they don't want to know if the person listed them back, or that a subject would feel obliged to list someone to avoid giving offense.

Figure A1 in the Appendix shows how a subject reports a freshman friend. She first selects the last initial of the friend in the first drop down menu. Then the system automatically filters the second drop down menu so that all the last names in the drop down menu start with the chosen last initial. Then the system again filters the third drop down menu so that it only contains the names of freshmen with the chosen last name. After a subject chooses the first name, the fourth drop down menu displays the university email address of this selected friend for confirmation.

After selecting a friend, a subject also indicated how much time they spent with the friend (the scale ranged from "0-30 minutes" to "more than 8 hours" per week) and also whether the person was a roommate or not.[5] We also incentive truthful time reporting by telling a subject that she can increase the probability to win the $0.50 prize from 50 percent to 75 percent for each friend who lists her and also agrees on the amount of time spent. Thus, when subjects completed part one, we obtained a list of whom they consider to be their ten best friends (as well as a description of how much they interact with each friend). When a subject's friend completed the survey, we also see whether the friend lists her.

Once subjects completed part one, they were sent a link to part two of the study, *the online experiment*. In this part of the study they were asked to make a series of financial decisions; they had 30 minutes to complete the study. The online experiment included questions to elicit the subject's level of altruism (using a dictator game), risk aversion, and time preferences. We use diagnostic tasks to elicit risk, time and social preferences, as well as subjects' guesses about the behaviors of the ten friends from the friendship elicitation survey. For each preference we use a diagnostic choice task that is well established in the literature to identify and measure preferences along each of our dimensions. All the games and guesses are incentivized.

To elicit risk attitudes, we employ a 15 question multiple price list, where subjects make choices between a 50-50 lottery with prizes of $200 or $0, and a fixed payoff that ranges from $0 to $140. For time preferences, subjects make choices between an $80 payment in three months, or a payment in two weeks that ranges from $5 to $75. See Figures A2 and A3 for a picture of the two tasks.

For the social preference elicitation task (shown in Figure A4), subjects make a "dictator allocation", where they divide 100 tokens between themselves and another randomly selected anonymous participant. Tokens are worth $0.75 to the person making the decision about how to divide the tokens, and $1.50 for the anonymous recipient.

After subjects completed these parts, they were also asked to guess about the average choices (among participants) of the ten friends from the friendship elicitation survey. They were asked to guess if the average choices of their friends are similar to their own choice (within +/- 1 for risk and time, +/- 10 for

[5] We asked them to report the number of hours with the friend but not to include class time.

social preferences), or are above or below their own choice. Subjects could also answer that they are not sure. Subjects were rewarded $1.00 for correct guesses (and receive $0.50 if they say they are not sure).

Finally, subjects made un-incentivized self-reports about risk tolerance and patience (shown in Figures A5 and A6). Subjects rated themselves on a 10 point scale. The risk scale ranges from "risk averse" to "fully prepared to take risks", while the patience scale ranges from "very impatient" to "very patient. Finally, subjects also reported how frequently they engage in various activities (such as volunteering, attending religious activities, eating out and so on).

For payment of the online experiment, one out of every seven subjects were randomly selected for payment. For selected subjects, we randomly selected one incentivized task, and then for the risk and time preference tasks randomly selected one choice to implemented for payment. All subjects were informed of this payment mechanism. Subjects could choose to be paid via electronic or physical gift card, or check.

The two parts of Phase 1 were repeated three times in total (in Phase 1, 2 and 3). All phases were identical to the procedures described above for Phase 1.

This design generates a panel dataset where for each subject (conditional on participation) we observe their friendship linkages, and their preferences, at three points in time. If they have friends who also participate we can also observe the preference of their friends. This allows us to observe the two main dynamics of interest: changes in the social network over time, and changes in preferences over time. We can then test for our two mechanisms of interest: homophily based on economic preferences, and peer influence on economic preferences. The results section below describes our analysis strategy and predictions.

Results

Participation and Network Information

A total of 399 freshman participated in our experiment. However, subjects are most useful to use when they participate in both the friendship elicitation and behavioral measurement survey. Furthermore, to answer many of our questions we need subjects to participate in multiple phases of the experiment. Table 1 reports the number of students participating in each survey of each wave. We have approximately 200 students who participated fully in at least two waves. Finally, for many of our research questions we need to have the friend of a subject also participate. In total we have 199 subjects who fully participated in, and had a friend also participate in, at least one phase.

Table 1: Student Participation

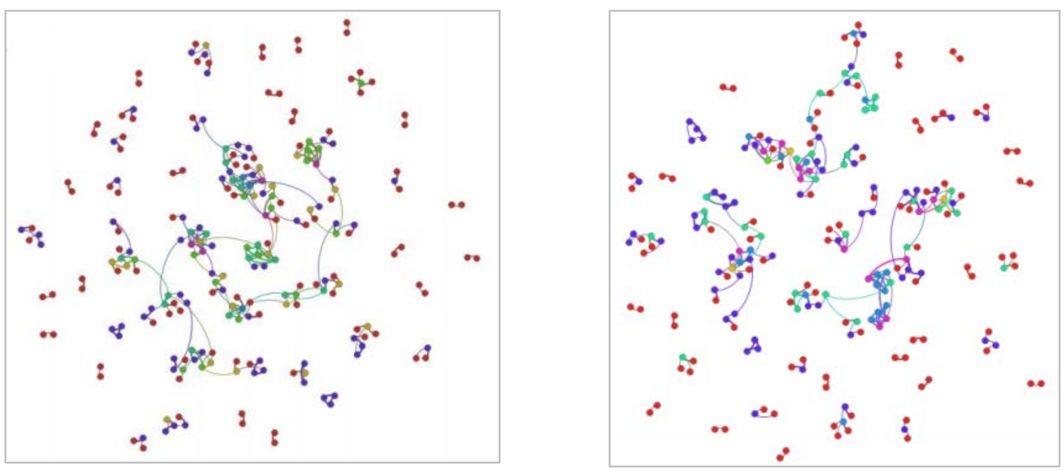
Phase	Friendship	Behavior	Both
Phase 1	399	287	287
Phase 2	198	189	177
Phase 3	298	211	202

On average subjects had 1.2-1.5 friends who also participated (depending on the phase), and for those friends the average amount of reported time spent together was "2 to 4 hours per week". Housing arrangements played an important role in friendships. In Phase 1 every student listed their roommate as a friend, while in Phase 3 80% of students listed their roommate. Similarly, 64% of friends in Phase 1, and 68% of friends in Phase 3, were from the same dorm. Shared academics and activities were also relevant, with approximately 20% of friends having the same major and approximately 50% of friends participating in the same club.

Figure 1 shows the measured social network from Phase 1 and 3. In Phase 1 there was one large connected component of 242 students, and then a number of smaller components. The average clustering coefficient was 0.181, while the average eigenvector centrality was 0.141. Phase 3 had a somewhat more fracture network – the largest component had 49 students, however there were three other moderately large components. The average clustering coefficient decreased slightly to 0.154, while the average eigenvector centrality decreased to 0.123.

Figure 1: Friendship Networks

Phase 1 **Phase 3**



Behavioral Measurements

We next turn to the preferences and choices elicited by our behavioral survey. Table 2 reports the average choices in our incentivized choice tasks, as well as the self-reported measures. For both Risk and Time preferences almost every participant made monotonic choices. Subjects were on average moderately risk averse, with the average indifference point being \$75 (compared to the lottery with an expected value of \$100). As expected, the incentivized behavioral measure is correlated with the self-reported measure of risk tolerance – subjects who rated themselves higher on willingness to take risks chose the safe option fewer times (β = -.307, s.e. = .081). Subjects were also moderately impatient, with the average indifference point being a sooner payment of \$64 (compared to a delayed payment of \$80). The self-reported measure for patience is also correlated with the behavioral measure – subjects who rated themselves as more patient chose the sooner payment less often (β = .260, s.e. = . 087). Allocations from our social preference task indicates a moderate level of altruism, with the average allocation being \$45 for the decision-maker and \$60 for the recipient.

While we are interested in how a student's social context influences their preferences, and hence we expect some amount of change in the observed preferences, we do want to make sure that our behavioral measures are capturing true fundamental preferences. Therefore, we should expect that the observed measures have in general a fair amount of stability. Fortunately, all of our behavioral measures do appear to be fairly stable. Each measure is quite highly correlated with itself in each pair of phases.[6]

Table 2: Behavioral Measures Summary Statistics

	Behavioral Measures			Self-Reported Measures	
	Risk	**Time**	**Social**	**Risk**	**Time**
Phase 1	8.53	3.21	59.50	5.76	5.88
Phase 2	8.58	3.21	59.86	5.79	6.16
Phase 3	8.17	3.51	60.00	5.83	6.04
Correlation (1 to 2)	0.532	0.549	0.528	0.614	0.601
Correlation (2 to 3)	0.637	0.609	0.603	0.775	0.522
Correlation (1 to 3)	0.534	0.616	0.475	0.633	0.524

The Risk behavioral measure reports the average number of safer choices. The Time behavioral measure reports the average number of sooner choices. The Social behavioral measure reports the average allocation to the other recipient. The self-reported measures are 10-point scales with larger values denoting a greater willingness to take risks/be patient.

Network Dynamics

We now examine in greater detail how the social network changed over the course of the year. We can first observe that there is a fair amount of turnover among our subjects' friendships. Between Phase 1 and Phase 2 subjects kept on average 6.3 friends, and changed 3.7 friends. Between Phase 1 and Phase 3 subjects kept 5.5 friends and changed 4.5 friends. Our primary question, then, is what factors affect an individual's decision to add or drop friends. Specifically, are individuals more like to add friendships with individuals who are similar to themselves on certain dimensions and/or more likely to drop friendships with those who are dissimilar. Specifically, for each characteristic X, we want to see whether the absolute difference $\Delta_X = \left|X_i - X_j\right|$ in that characteristic between an individual i and a (potential) friend j is predictive of a change in their friendship. We will use a probit specification as follows:

$$\text{Prob}\left(Change_{ij}\right) = \Phi(\alpha + \beta\Delta_X + \varepsilon)$$

[6] In order to make sure that there is no selection bias between those freshmen who agree to participate in our survey and those who do not, in February 2016 we conduct the surveys again to compare a sample of subjects recruited through these methods with subjects from the standard lab pool. To do so, we send out the network survey to all current freshman 2016 cohort. Among those finish the network elicitation survey, we invite 80 of them to take the behavior survey. Then we also contacted 80 randomly selected freshman students and invite them to the same behavior survey as well. Both groups have the same behavior survey completion rate (44/80). We see no significant differences in survey responses between these two groups except the self-reported trust when the stake is large. The network survey participants have more trust. Using an ordered logit specification, the difference is significant at the 90% level (beta = 0.66, p = 0.083). See Appendix B for more details.

If students expressed homophily along a particular behavioral dimension we would expect a negative β for additions (decreased likelihood of forming friendships with dissimilar others) and a positive β for drops (increased likelihood of ending friendships with dissimilar others).

In analyzing added friendships we need to identify a pool of possible new friends. One natural set of potential new friends is the other students from the same dorm. For another measure, we use Clauset et al. (2004)'s community detection algorithm to identify the close social environment of the student. The community detection algorithm partitions the social network so that the number of links within communities is as large as possible, and the number of links between communities is as small as possible. We can then use anyone in the student's community that is not currently their friend as a socially individual who is a candidate to be a new friend. Similarly, we can look at changes in the network such that an individual is no longer a friend, or no longer in the same community.

Table 3 reports the results of regressing the likelihood of adding a friend from the dorm or network community and dropping a friendship or shared community, on the absolute difference in risk measures. Panel A uses the incentivized behavioral measure of risk, while Panel B uses the self-reported measure.

Table 3: Network Dynamics for Risk Measures

Panel A: Behavioral Measures

	Add Friend				Drop Relationship			
	From Dorm		From Community		Friend		Community	
	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_{Risk}	-0.0306	-0.000399	0.0250	0.00119	0.0330	0.0121	-0.0308**	-0.0117**
	(0.0198)	(0.000250)	(0.0210)	(0.000991)	(0.0412)	(0.0150)	(0.0141)	(0.00537)
Constant	-2.515***		-2.144***		-0.535***		0.427***	
	(0.0714)		(0.105)		(0.191)		(0.0831)	
# Obs	11,854		1,957		180		1,374	

Panel B: Self-Reported Measures

	Add Friend				Drop Relationship			
	From Dorm		From Community		Friend		Community	
	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_{Risk}	-0.0333	-0.000438	-0.0103	-0.000497	0.0482	0.0176	0.0176	0.00667
	(0.0319)	(0.000419)	(0.0382)	(0.00185)	(0.0625)	(0.0229)	(0.0250)	(0.00950)
Constant	-2.538***		-2.032***		-0.518***		0.278***	
	(0.0830)		(0.116)		(0.155)		(0.0847)	
# Obs	11,854		1,957		180		1,374	

All specifications are probit regressions with standard errors clustered at the subject level. Odd numbered columns report coefficients, while even numbered columns report marginal effects. Dependent variables are: adding a friendship (columns 1-4), dropping a friendship (columns 5-6), or ceasing to be in the same network community (columns 7-8). For columns 1-2 the sample includes all subjects who are in the same dorm (but not currently a friend). For columns 3-4 the sample includes all subjects who are in the same network community (but not currently a friend). For Panel A the independent variable is the absolute difference in the number of sure choices, while for Panel B it is the absolute difference in the self-reported measure of risk tolerance.

Overall we find relatively little evidence that risk attitudes matter for the dynamics of our subjects' social network. There is no effect of a pair's similarity in either our incentivized risk measure or the self-reported on the likelihood of adding or dropping direct friendship linkages. We do see a significant effect for the likelihood of no longer being in the same social community – however the sign of the effect is the opposite of what one would expect from a homophily dynamic. Our results suggest that a pair of individuals who have more dissimilar risk attitudes are less likely to change social communities.

Table 4 presents the same regression specifications for the absolute difference in patience. In line with our results for risk attitudes, we find no effect of the difference in any measure of time preference on any measure of network dynamics.

Table 4: Network Dynamics for Time Preference Measures

Panel A: Behavioral Measures

	Add Friend				Drop Relationship			
	From Dorm		From Community		Friend		Community	
	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_{Time}	-0.0112	-0.000149	0.00723	0.000349	0.0396	0.0145	-0.0179	-0.00681
	(0.0181)	(0.000240)	(0.0239)	(0.00114)	(0.0386)	(0.0141)	(0.0152)	(0.00579)
Constant	-2.570***		-2.083***		-0.534***		0.383***	
	(0.0795)		(0.123)		(0.152)		(0.0806)	
# Obs	11,854		1,957		180		1,374	

Panel B: Self-Reported Measures

	Add Friend				Drop Relationship			
	From Dorm		From Community		Friend		Community	
	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_{Time}	-0.0346	-0.000454	-0.0407	-0.00190	-0.0362	-0.0131	0.00929	0.00351
	(0.0287)	(0.000379)	(0.0436)	(0.00207)	(0.0557)	(0.0201)	(0.0208)	(0.00788)
Constant	-2.522***		-1.960***		-0.341**		0.301***	
	(0.0898)		(0.141)		(0.157)		(0.0868)	
# Obs	10,974		1,744		172		1,302	

All specifications are probit regressions with standard errors clustered at the subject level. Odd numbered columns report coefficients, while even numbered columns report marginal effects. Dependent variables are: adding a friendship (columns 1-4), dropping a friendship (columns 5-6), or ceasing to be in the same network community (columns 7-8). For columns 1-2 the sample includes all subjects who are in the same dorm (but not currently a friend). For columns 3-4 the sample includes all subjects who are in the same network community (but not currently a friend). For Panel A the independent variable is the absolute difference in the number of sooner choices, while for Panel B it is the absolute difference in the self-reported measure of patience.

By contrast, we find evidence for differences in generosity influencing several dimensions of change within the social network. Table 5 reports the results of regressing relationship changes on the absolute difference in the number of tokens kept in the allocation game. We find that an individual is significantly less likely to add a potential friend (either from the set of students in the same dorm, or in the same social community) the more dissimilar they are in generosity. Specifically, a one SD increase in the difference in tokens kept would lead to a 0.19 percentage point decrease in the likelihood of adding someone in the same dorm as a friend, approximately half the base rate probability of 0.38% of adding them as a friend. We also find that greater dissimilarity increases the likelihood of dropping a friendship with someone. A one SD increase the dissimilarity would increase the likelihood of dropping someone as a friend by 7.3 percentage points, one fifth of the base rate probability of 33.9%. These results are consistent with students exhibiting homophily with respect to generosity. Our subjects prefer to form friendships with those who are similarly generous, and drop friendships with those who are differently generous.

Table 5: Network Dynamics for Generosity

	Add Friend				Drop Relationship			
	From Dorm		From Community		Friend		Community	
	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_{Kept}	-0.0108***	-0.000126***	-0.0110***	-0.000487***	0.0107**	0.00392**	0.00212	0.000803
	(0.00317)	(3.29e-05)	(0.00422)	(0.000170)	(0.00507)	(0.00186)	(0.00231)	(0.000877)
Constant	-2.429***		-1.886***		-0.655***		0.277***	
	(0.0639)		(0.0835)		(0.147)		(0.0836)	
# Obs	11,854		1,957		180		1,374	

All specifications are probit regressions with standard errors clustered at the subject level. Odd numbered columns report coefficients, while even numbered columns report marginal effects. Dependent variables are: adding a friendship (columns 1-4), dropping a friendship (columns 5-6), or ceasing to be in the same network community (columns 7-8). For columns 1-2 the sample includes all subjects who are in the same dorm (but not currently a friend). For columns 3-4 the sample includes all subjects who are in the same network community (but not currently a friend). The independent variable is the absolute difference in the number of tokens kept in the allocation decision.

Risk, time and social preferences are potentially subtle and hard to observe aspects of an individual's behavior. While the effects of differences in generosity seem to be large compared to the base rates for relationship changes, it is difficult to say whether the effect is as large as one might expect. In order to provide an alternative benchmark, we can also examine the effect on friendships of two clear markers of shared interests: sharing the same academic major, and participating in the same extracurricular club. Intuition suggests that these traits should have a strong effect on friendship formation and maintenance. For each pair of subjects we construct an indicator variable I_X that equals 1 if the two subjects share the same major, or participate in the same club (respectively). We then estimate the previous regressions using the indicator variable in place of the absolute difference measures:

$$\text{Prob}\left(Change_{ij}\right) = \Phi(\alpha + \beta I_X + \varepsilon)$$

In these regressions homophily would predict a positive β for additions and a negative β for drops. The results are reported in Table 6.

For shared major we find significant effects for reducing the likelihood of dropping a friendship, but no effect for adding a friendship. By contrast, we find a significant effect of shared clubs for both adding and dropping friendships. If we compare these effects to the previously estimated effect of differences in generosity, we see that the effect of shared activities is about twice the magnitude of a one SD difference in generosity. This provides an alternative demonstration that homophily with respect to generosity plays a substantial role in the changes in the social network.

Table 6: Network Dynamics for Shared Interests and Activities

Panel A: Same Major

	Add Friend				Drop Relationship			
	From Dorm		From Community		Friend		Community	
	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I_{SameMajor}$	0.0957	0.00119	-0.0152	-0.000436	-0.507*	-0.171**	-0.280**	-0.109**
	(0.0949)	(0.00129)	(0.0689)	(0.00196)	(0.270)	(0.0825)	(0.135)	(0.0531)
Constant	-2.681***		-2.287***		-0.316***		0.362***	
	(0.0393)		(0.0349)		(0.115)		(0.0685)	
# Obs	23,684		21,176		180		1,374	

Panel B: Same Club

	Add Friend				Drop Relationship			
	From Dorm		From Community		Friend		Community	
	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I_{SameClub}$	0.288***	0.00417***	0.392***	0.0172***	-0.388*	-0.144*	-0.285***	-0.109***
	(0.0796)	(0.00145)	(0.107)	(0.00662)	(0.208)	(0.0779)	(0.0890)	(0.0341)
Constant	-2.727***		-2.308***		-0.174		0.433***	
	(0.0420)		(0.0329)		(0.164)		(0.0741)	
# Obs	23,684		21,176		180		1,374	

All specifications are probit regressions with standard errors clustered at the subject level. Odd numbered columns report coefficients, while even numbered columns report marginal effects. Dependent variables are: adding a friendship (columns 1-4), dropping a friendship (columns 5-6), or ceasing to be in the same network community (columns 7-8). For columns 1-2 the sample includes all subjects who are in the same dorm (but not currently a friend). For columns 3-4 the sample includes all subjects who are in the same network community (but not currently a friend). For Panel A the independent variable is an indicator variable that equals one if the two students share the same major, while for Panel B it is an indicator variable that equals one if the two students participate in the same club.

One potential reason why behavioral and preference differences don't play a larger role in friendship dynamics is that subjects had quite inaccurate beliefs about their friends' behavior. Subjects accurately predicted the average choices of their friends 39% of the time for lottery choices, 43% of the time for time preference choices, and 46% of the time for token allocations. Inaccurate beliefs were primarily driven by subjects overestimating how similar their choices were to their friends. The bias was largest for risk preferences, where 70% of subjects guessed that they made the same lottery choices as their friends, while only 27% of them did. Similarly, 74% of subjects guessed that they made the same payment timing choices as their friends, compared to 37% that actually did so. In both cases belief accuracy was significantly lower for those who guessed their friends were the same ($p < 0.01$ in both cases). Subjects also believed they made similar generosity choices as their friends, but they were more correct in doing so: 74% guessed they made the same choices, compared to 62% who actually did so.

This may suggest that the observed homophily for social preferences is primarily an unconscious behavior. Subjects believe that their friends are similar on all three preference dimensions, and don't recognize the differences with their friends for risk tolerance and patience. Explicitly sorting based on preferences would require individuals to be able to accurately infer the preferences of others, which our data suggests they cannot do very well. We note that Leider et al (2010) also found that subjects had somewhat inaccurate beliefs about their friends. They found that although subjects were approximately accurate in predicting how much more their friends would allocate to them in a dictator game, they were completely unable to identify which friends would be relatively more or less generous.

However, we can show that the sorting behavior we observe for generosity is not simply a side effect of sharing the same major or extracurricular activity. Table 7 reports the results from regressing network changes on differences in generosity while also controlling for shared major or club. Our results are largely unchanged, which suggests that other factors, such as direct interpersonal kindness, must be the driver of sorting on generosity.

Table 7: Network Dynamics for Generosity controlling for Major/Club

Panel A: Same Major

	Add Friend				Drop Relationship			
	From Dorm		From Community		Friend		Community	
	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_{Kept}	-0.0117***	-0.000128***	-0.0119***	-0.000507***	0.0132**	0.00477**	0.00357	0.000975
	(0.00313)	(3.22e-05)	(0.00420)	(0.000168)	(0.00507)	(0.00184)	(0.00235)	(0.000893)
$I_{SameMajor}$	0.362***		0.369***		-0.605**		-0.291**	
	(0.108)		(0.149)		(0.294)		(0.135)	
Constant	-2.480***		-1.934***		-0.591***		0.315***	
	(0.0731)		(0.0940)		(0.153)		(0.0842)	
# Obs	11,854		1,957		180		1,374	

Panel B: Same Club

	Add Friend				Drop Relationship			
	From Dorm		From Community		Friend		Community	
	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ_{Kept}	-0.0112***	-0.000123***	-0.0114***	-0.000489***	0.0121**	0.00440**	0.00229	0.000867
	(0.00322)	(3.06e-05)	(0.00418)	(0.000164)	(0.00516)	(0.00188)	(0.00232)	(0.000880)
$I_{SameClub}$	0.298***		0.239*		-0.438**		-0.287***	
	(0.0945)		(0.131)		(0.211)		(0.0889)	
Constant	-2.537***		-1.967***		-0.412**		0.391***	
	(0.0741)		(0.0986)		(0.186)		(0.0878)	
# Obs	11,854		1,957		180		1,374	

All specifications are probit regressions with standard errors clustered at the subject level. Odd numbered columns report coefficients, while even numbered columns report marginal effects. Dependent variables are: adding a friendship (columns 1-4), dropping a friendship (columns 5-6), or ceasing to be in the same network community (columns 7-8). For columns 1-2 the sample includes all subjects who are in the same dorm (but not currently a friend). For columns 3-4 the sample includes all subjects who are in the same network community (but not currently a friend). The first independent variable is the absolute difference in the number of tokens kept in the allocation decision. For Panel A the second independent variable is an indicator variable that equals one if the two students share the same major, while for Panel B it is an indicator variable that equals one if the two students participate in the same club.

Network centrality is another natural characteristic to explain the changes in the observed social network throughout the study. The network formation literature (see de Solla Price (1976) and Barabási and Albert (1999)) suggests that if individuals choose whether to form and maintain friendships based on the instrumentality of the relationship then nodes that are *central* in the network will be particularly desirable.[7] We examine two measures of network centrality. Eigenvector centrality (C_{Eigen}) uses the eigenvector for the principle eigenvalue of the adjacency matrix as the measure of centrality. With this measure, an individual is assigned more centrality if they are connected to others who are themselves highly central. Betweenness centrality ($C_{Between}$) counts the number of shortest paths that pass through the individual. For betweenness centrality, an individual is assigned more centrality if they help connect many other people together.

We use the observed social network in Period 1, calculate the centrality for each individual, and then examine whether the changes in the network between Period 1 and Period 3 are driven by the centrality of the individuals. We estimate the previous relationship change regressions using the centrality measures as the independent variables:

$$\text{Prob}\left(Change_{ij}\right) = \Phi(\alpha + \beta C_X + \varepsilon)$$

In these regressions, if individuals prefer to form and maintain friendships with highly central individuals, we would expect a positive β for additions and a negative β for drops. The results are reported in Table 8.

Table 8: Network Dynamics for Network Centrality
Panel A: Eigenvector Centrality

	Add Friend				Drop Relationship			
	From Dorm		From Community		Friend		Community	
	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C_{Eigen}	0.203	0.00178	1.578***	0.00605***	-3.782***	-1.470***	-3.786***	-0.679***
	(0.499)	(0.00437)	(0.480)	(0.00193)	(1.002)	(0.389)	(0.446)	(0.0841)
Constant	-2.767***		-3.054***		0.252***		1.280***	
	(0.0371)		(0.0308)		(0.0376)		(0.0162)	
# Obs	31,887		200,168		3,975		201,610	

[7] de Solla Price (1976) proposed this mechanism as *cumulative advantage*, known today more commonly as *preferential attachment* (a term introduced by Barabási and Albert (1999)). The preferential attachment mechanism assumes that a new node prefers to connect to existing nodes with more links (a larger degree). This generates a “rich-get-richer” effect as existing nodes with high degrees gain more links faster than nodes with low degrees. The advantage of the preferential attachment model is that it can reproduce networks with commonly observed power-law degree distributions.

Panel B: Betweenness Centrality

	Add Friend				Drop Relationship			
	From Dorm		From Community		Friend		Community	
	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.	Coeff.	Marg. Eff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$C_{Between}$	4.244	0.0370	11.68***	0.0444***	-3.976	-1.545	-21.13***	-3.780***
	(5.142)	(0.0446)	(2.856)	(0.0111)	(3.664)	(1.423)	(0.792)	(0.187)
Constant	-2.810***		-3.080***		0.241***		1.319***	
	(0.0693)		(0.0327)		(0.0399)		(0.0159)	
# Obs	31,887		200,168		3,975		201,610	

All specifications are probit regressions with standard errors clustered at the subject level. Odd numbered columns report coefficients, while even numbered columns report marginal effects. Dependent variables are: adding a friendship (columns 1-4), dropping a friendship (columns 5-6), or ceasing to be in the same network community (columns 7-8). For columns 1-2 the sample includes all subjects who are in the same dorm (but not currently a friend). For columns 3-4 the sample includes all subjects who are in the same network community (but not currently a friend). For Panel A the independent variable is the eigenvector centrality of the (potential) friend, while for Panel B it is the betweenness centrality.

Our results are broadly consistent with a preference to form and maintain relationships with central individual, with similar results for both measures. In particular, the preference for centrality seems to be more important for maintaining relationships than in forming new ones. This difference could be because it is hard to know the network position of people you are not already socially close with. Difficulty knowing the network position of potential friends could help explain why we find an effect for adding from the community compared to adding from the dorm. Subjects may be more likely to know the network position of people who are already in their social environment.

The effect of network centrality on friendship dynamics appears to be somewhat smaller than the effect of homophily. A one SD increase in the network centrality of a potential friend from the network community increases the likelihood of forming a friendship by .014 percentage points (approximately one-tenth of the baserate) for eigenvector centrality, and .024 percentage points (approximately one-fifth of the baserate) for betweenness centrality. Recall that the effect of decreased similarity in generosity was about half the baserate. Similarly, a one SD increase in eigenvector centrality decreases the likelihood of dropping a friendship by 5 percentage points (approximately one-twelfth the baserate), and a one SD increase in betweenness centrality decreases the likelihood by 0.9 percentage points (1.5% of the baserate). By contrast, the effect of decreasing similarity was one-fifth the baserate.

Influence Effects on Preferences

We now turn to our second research question – are an individual's economic preferences influenced by the social context the individual experiences? Specifically, is an individual's risk, time or social preferences correlated with the average preferences of his or her friends (or broader social community). To measure this effect, we use the following specification:

$$Preference_{i,t} = \alpha + \beta * Preference_{-i,t-\Delta t} + \varepsilon$$

$Preference_{i,t}$ denotes the choice in the preference elicitation task (or the self-reported preference measure) for individual i in Phase t. $Preference_{-i,t-\Delta t}$ is the average choice (or self-report) for the individuals friends (or network community) in Phase t-Δt. The error term ε is clustered at the subject level, allowing for arbitrary correlations in the choices/reports of the focal individual. As before we also look at the network community as a broader measure of the individual's social context. The network community specifications also have a somewhat larger sample size, as some subjects did not have direct friends who also took the behavioral survey.

We look at both the contemporaneous correlation (Δt = 0; e.g. April preferences as a function of April friends' preferences), as well as the correlation with the individual's friends from earlier in the year (Δt = 1 or 2; e.g. April preferences as a function of January or October friends' preferences). We are interested in looking at the effect of friends at various different time lags for several reasons. First, if we focused on the contemporaneous correlation we might worry that it was due simply to common shocks or contextual factors. However, it is unlikely that I would experience the same shock today that my friends experienced three months ago. Second, it is not immediately clear over what time scale we should expect to see influence effects. An individual's current social context may be the most prominent, on the other hand it may take an extended amount of time and/or sustained exposure for influence to occur. On the other hand, the shared experiences with friends from too long ago may have faded in memory or influence. Third, seeing effects at multiple lags would actually be the most encouraging result – as it would be the clearest and most robust evidence for influence. Seeing a significant effect only with a one period lag, for example, could represent real influence that is highly time sensitive, or it could be a spurious correlation. Consistent correlations across multiple time periods are less likely to be spurious.

As an additional robustness check, we also consider specifications using the focal individual's previous choices/reports:

$$Preference_{i,t} = \alpha + \beta * Preference_{-i,t-\Delta t} + \gamma * Preference_{i,t-1} + \varepsilon$$

$$Preference_{i,t} = \alpha + \beta * Preference_{-i,t-\Delta t} + \gamma * Preference_{i,t-2} + \varepsilon$$

This provides a more direct control of the individual's "initial" preference than just the clustered standard errors. However, the structure of our data does give us a smaller sample size for many specifications.

One caveat to keep in mind is that we are using the individual's measured social network in the reference period – this means that in the contemporaneous influence specification, for example, the set of friends that make up $Preference_{-i}$ is changing over the course of the experiment. If there are strong homophily effects in the social network dynamics this could drive positive correlation in later periods. We have several ways of addressing this problem. First, we cluster the errors at the subject level, so if the subject's preferences are primarily fixed (or evolving for non-influence reasons) the repeated measures should help account for this. Additionally, for risk and time preferences the changing social network is unlikely to be a problem in this respect, as we have already demonstrated that there is no significant homophily on these dimensions. For generosity this could be a problem for Δt = 0 or 1. However, this is unlikely to be driving results for Δt = 2, which uses the friends from the social network measured in October to predict behavior in April. At this point there has been very little time for homophily to shape the social network, so a homophily-driven correlation is unlikely. Finally, if the observed correlation is primarily driven by homophily changing the network, we would expect the correlation to strengthen as the lag shrinks from 2 to 0 and there is more time for homophily to shape the network.

Table 9 reports the results of regressing our measures of risk preferences on the average measure for friends and social communities. We find essentially zero correlation for the incentivized elicitation task, however we do find a significant positive correlation for five of the six specifications using the self-reported measure (and a positive but insignificant result for the sixth). Additionally, we do not find that the magnitude of the effect is systematically growing as we go from Δt = 2 to Δt = 0, suggesting that this is not simply a reflection of underlying homophily. As a demonstration of the magnitude of the influence effect, a one SD increase in the average self-reported risk measure for an individual's friends is predicted to increase that individual's self report in the same time period by 0.25 categories (1/8th of a SD). We find similar sized effects for the influence of the broader social community, with a one SD increase the average self-report for an individual's community corresponding to increase in the individual's report of 0.21 categories (1/10th of a SD). This suggests that both an individual's immediate friends and the larger social context can have a significant influence on risk attitudes.

Table 9: Influence Effects for Risk Measures

Panel A: Behavioral Measures

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Risk_{-i,t-\Delta t}$	0.00832	-0.0506	0.0298	-0.0853	0.110	0.0403
	(0.0668)	(0.115)	(0.123)	(0.0880)	(0.122)	(0.198)
Constant	8.381***	8.794***	7.925***	9.195***	7.503***	7.860***
	(0.629)	(1.081)	(1.099)	(0.768)	(1.084)	(1.736)
# Obs	380	139	97	648	306	197

Panel B: Self-Reported Measures

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Risk_{-i,t-\Delta t}$	0.148**	0.322***	0.151	0.202**	0.212*	0.298**
	(0.0672)	(0.113)	(0.125)	(0.0869)	(0.124)	(0.133)
Constant	4.874***	4.123***	4.918***	4.592***	4.499***	4.096***
	(0.431)	(0.745)	(0.780)	(0.531)	(0.773)	(0.807)
# Obs	380	139	97	648	306	197

All specifications are OLS regressions with standard errors clustered at the subject level. The dependent measure is the number of safe choices (Panel A) or self-reported risk measure (Panel B) of the focal individual. The independent measure is the average choice/report of the focal individual's friends (columns 1-3) or network community (columns 4-6). Columns 1 and 4 report the contemporaneous correlation (Δt = 0), columns 2 and 5 use the one-period lagged friend/community average (Δt = 1), while Columns 3 and 6 use the two-period lagged average (Δt = 2).

Table 10 reports the corresponding specifications with once- and twice-lagged dependent variables included as additional controls. We find results that are largely consistent with our main specification, albeit with a reduction in power, likely due to a smaller sample size. All of the estimated coefficients for the self-reported measure are positive, with many of them remaining statistically significant.

Table 10: Influence Effects for Risk Measures with Lagged Choices

Panel A: Behavioral Measures, Once-Lagged Choices

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Risk_{-i,t-\Delta t}$	0.0252	-0.0206	0.182	-0.0290	0.0985	0.285*
	(0.0921)	(0.0846)	(0.181)	(0.0982)	(0.0945)	(0.163)
$Risk_{i,t-1}$	0.485***	0.484***	0.588***	0.588***	0.587***	0.633***
	(0.111)	(0.112)	(0.151)	(0.0634)	(0.0631)	(0.0683)
Constant	3.969***	4.371***	1.423	3.551***	2.465**	0.371
	(1.427)	(1.340)	(2.093)	(1.117)	(0.978)	(1.651)
# Obs	139	139	55	306	306	141

Panel B: Behavioral Measures, Twice-Lagged Choices

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Risk_{-i,t-\Delta t}$	-0.186	0.257	0.0105	-0.324***	0.252**	0.148
	(0.125)	(0.163)	(0.101)	(0.110)	(0.121)	(0.176)
$Risk_{i,t-2}$	0.385***	0.388***	0.388***	0.470***	0.534***	0.489***
	(0.121)	(0.143)	(0.122)	(0.0770)	(0.0864)	(0.0770)
Constant	6.429***	2.421	4.754***	6.795***	1.406	2.691
	(1.729)	(1.683)	(1.455)	(1.189)	(1.227)	(1.669)
# Obs	97	55	97	197	141	197

Panel C: Self-Reported Measures, Once-Lagged Choices

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Risk_{-i,t-\Delta t}$	0.0710	0.213**	0.128	0.0412	0.0890	0.374***
	(0.0972)	(0.0823)	(0.178)	(0.101)	(0.0949)	(0.133)
$Risk_{i,t-1}$	0.673***	0.658***	0.638***	0.665***	0.663***	0.698***
	(0.0843)	(0.0797)	(0.109)	(0.0548)	(0.0543)	(0.0570)
Constant	1.596**	0.874	1.177	1.688**	1.425**	-0.467
	(0.719)	(0.661)	(1.425)	(0.671)	(0.673)	(0.747)
# Obs	139	139	55	306	306	141

Panel D: Self-Reported Measures, Twice-Lagged Choices

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Risk_{-i,t-\Delta t}$	0.198**	0.252*	0.0290	0.209**	0.163	0.0850
	(0.0978)	(0.144)	(0.106)	(0.103)	(0.131)	(0.111)
$Risk_{i,t-2}$	0.553***	0.557***	0.557***	0.617***	0.701***	0.613***
	(0.0829)	(0.149)	(0.0904)	(0.0594)	(0.0712)	(0.0621)
Constant	1.407*	1.211	2.397***	1.045*	0.807	1.790**
	(0.774)	(0.962)	(0.785)	(0.586)	(0.822)	(0.688)
# Obs	97	55	97	197	141	197

All specifications are OLS regressions with standard errors clustered at the subject level. The dependent measure is the number of safe choices (Panels A and B) or self-reported risk measure (Panels C and D) of the focal individual. The first independent measure is the average choice/report of the focal individual's friends (columns 1-3) or network community (columns 4-6). Columns 1 and 4 report the contemporaneous correlation (Δt = 0), columns 2 and 5 use the one-period lagged friend/community average (Δt = 1), while Columns 3 and 6 use the two-period lagged average (Δt = 2). Panels A and C also include the focal individuals' choice/report from the previous period, while Panels B and D include the focal individuals' choice/report from two periods ago.

Table 11 reports the results of the time preference regressions. For this measure we find similar, albeit slightly weaker evidence, for social influence using the incentivized behavioral measure. We find a strongly significant result for the contemporaneous friends regression, and similar magnitudes but weaker significance for the lagged regressions. For the community regressions we see marginal significantly only in the contemporaneous regression, and no significance for the lagged regressions. The magnitude of the contemporaneous effect is similar to the risk preference effect: a one SD increase in the average number of sooner choice by an individual's friends increases the average number of the individual's sooner choices by 0.48 (an increase in the indifference point of $2.39, equal to 1/7th a SD). A one SD increase in the community average would increase the number of sooner choices by 0.27 (a $1.34 increase in the indifference point, equal to 1/12th a SD). We find no corresponding influence effect for the self-reported measure of patience.

Table 11: Influence Effects for Patience Measures

Panel A: Behavioral Measures

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Time_{-i,t-\Delta t}$	0.168***	0.242*	0.202*	0.159*	0.0352	0.0887
	(0.0615)	(0.125)	(0.105)	(0.0841)	(0.113)	(0.126)
Constant	2.623***	2.758***	2.495***	2.733***	2.954***	3.161***
	(0.281)	(0.499)	(0.437)	(0.313)	(0.401)	(0.456)
# Obs	380	139	97	648	306	197

Panel B: Self-Reported Measures

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Time_{-i,t-\Delta t}$	0.0993	0.127	0.116	-0.163**	0.147	-0.0479
	(0.0645)	(0.108)	(0.126)	(0.0806)	(0.134)	(0.166)
Constant	5.406***	5.359***	5.365***	6.972***	5.220***	6.332***
	(0.414)	(0.708)	(0.767)	(0.489)	(0.797)	(0.996)
# Obs	362	137	95	631	306	197

All specifications are OLS regressions with standard errors clustered at the subject level. The dependent measure is the number of sooner choices (Panel A) or self-reported patience measure (Panel B) of the focal individual. The independent measure is the average choice/report of the focal individual's friends (columns 1-3) or network community (columns 4-6). Columns 1 and 4 report the contemporaneous correlation (Δt = 0), columns 2 and 5 use the one-period lagged friend/community average (Δt = 1), while Columns 3 and 6 use the two-period lagged average (Δt = 2).

As before, we also consider specifications with lagged dependent variables as a robustness check. These results are reported in Table 12. Our previous results for patience appear to be less robust to this alternate specification than the results for risk tolerance. None of the coefficients for the self-reported measure remain significant, and many of them are smaller in magnitude. However, we again note that this robustness check comes with a significant reduction in our sample size.

Table 12: Influence Effects for Patience Measures with Lagged Choices

Panel A: Behavioral Measures, Once-Lagged Choices

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Time_{-i,t-\Delta t}$	0.0929	0.127	0.130	0.0481	-0.0608	0.0864
	(0.121)	(0.131)	(0.126)	(0.0877)	(0.0843)	(0.115)
$Time_{i,t-1}$	0.481***	0.470***	0.519***	0.528***	0.533***	0.626***
	(0.105)	(0.110)	(0.129)	(0.0695)	(0.0698)	(0.0788)
Constant	1.680***	1.636***	0.958	1.347***	1.678***	0.881*
	(0.456)	(0.419)	(0.745)	(0.347)	(0.310)	(0.461)
# Obs	139	139	55	306	306	141

Panel B: Behavioral Measures, Twice-Lagged Choices

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Time_{-i,t-\Delta t}$	0.101	0.0178	0.0644	-0.0311	-0.00995	-0.101
	(0.0907)	(0.180)	(0.106)	(0.109)	(0.129)	(0.0911)
$Time_{i,t-2}$	0.467***	0.441***	0.459***	0.609***	0.570***	0.614***
	(0.106)	(0.147)	(0.114)	(0.0711)	(0.0851)	(0.0700)
Constant	1.454***	1.808**	1.629***	1.692***	1.529***	1.895***
	(0.514)	(0.716)	(0.452)	(0.436)	(0.488)	(0.404)
# Obs	97	55	97	197	141	197

Panel C: Self-Reported Measures, Once-Lagged Choices

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Time_{-i,t-\Delta t}$	0.000239	-0.0294	0.144	-0.125	0.258**	-0.109
	(0.0702)	(0.0799)	(0.117)	(0.102)	(0.115)	(0.181)
$Time_{i,t-1}$	0.647***	0.653***	0.594***	0.535***	0.554***	0.518***
	(0.0686)	(0.0670)	(0.120)	(0.0652)	(0.0605)	(0.0790)
Constant	2.249***	2.415***	1.653	3.671***	1.246*	3.552***
	(0.615)	(0.689)	(0.993)	(0.865)	(0.645)	(1.148)
# Obs	137	135	54	303	303	141

Panel D: Self-Reported Measures, Twice-Lagged Choices

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$Time_{-i,t-\Delta t}$	0.0132	0.120	0.0144	-0.0724	0.158	0.00307
	(0.0925)	(0.147)	(0.125)	(0.128)	(0.107)	(0.135)
$Time_{i,t-2}$	0.406***	0.377**	0.408***	0.483***	0.524***	0.484***
	(0.0997)	(0.147)	(0.102)	(0.0670)	(0.0746)	(0.0669)
Constant	3.628***	3.132**	3.648***	3.603***	2.032**	3.139***
	(0.797)	(1.229)	(0.879)	(0.892)	(0.867)	(0.859)
# Obs	95	55	93	191	139	191

All specifications are OLS regressions with standard errors clustered at the subject level. The dependent measure is the number of sooner choices (Panels A and B) or self-reported patience measure (Panels C and D) of the focal individual. The first independent measure is the average choice/report of the focal individual's friends (columns 1-3) or network community (columns 4-6). Columns 1 and 4 report the contemporaneous correlation (Δt = 0), columns 2 and 5 use the one-period lagged friend/community average (Δt = 1), while Columns 3 and 6 use the two-period lagged average (Δt = 2). Panels A and C also include the focal individuals' choice/report from the previous period, while Panels B and D include the focal individuals' choice/report from two periods ago.

We report the results for generosity in Table 13. Here we actually see a negative influence effect, with individuals that are part of generous social communities becoming significantly more selfish. Specifically, if the average generosity of an individual's social community increases by one SD, the results predict the individual's own generosity to decrease by 1.9 tokens (or $2.85 for the recipient, equal to 1/11 a SD). The results for friends also have a negative sign, however the effect size is small and the coefficients are not close to significance. While we did not anticipate this reverse-influence effect, we do note that Ahern et al. (2013) also found negative peer effects for generosity. It is possible that this is a form of free-riding, where individuals attempt to benefit from the generosity of their social context. We also note that this free-riding has limits, since if an individual becomes too dissimilar from their friends and social community the previously demonstrated homophily effect will increase the chances that they are cut off from the network.

Table 13: Influence Effects for Generosity Measure

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$\#Kept_{-i,t-\Delta t}$	-0.0553	-0.0295	-0.0497	-0.172**	-0.0611	-0.463**
	(0.0617)	(0.103)	(0.121)	(0.0794)	(0.149)	(0.222)
Constant	63.41***	62.63***	63.53***	69.92***	63.92***	87.10***
	(3.854)	(6.100)	(7.708)	(4.644)	(9.032)	(13.47)
# Obs	380	139	97	648	306	197

All specifications are OLS regressions with standard errors clustered at the subject level. The dependent measure is the number of tokens kept by the focal individual. The independent measure is the average choice of the focal individual's friends (columns 1-3) or network community (columns 4-6). Columns 1 and 4 report the contemporaneous correlation (Δt = 0), columns 2 and 5 use the one-period lagged friend/community average (Δt = 1), while Columns 3 and 6 use the two-period lagged average (Δt = 2).

We report the robustness specifications with lagged choices in Table 14. For both alternate specifications we again find evidence for the negative influence effect of an individual's community, with similar magnitudes and levels of significance. We also now find some significant negative effects for the regressions using friends' choices. While we had not anticipated finding this free-riding result, the effect appears to be quite robust.

Table 14: Influence Effects for Generosity Measure, with Lagged Choices

Panel A: Once-Lagged Choices

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$\#Kept_{-i,t-\Delta t}$	-0.253***	-0.0562	-0.173	-0.182**	-0.0625	-0.499**
	(0.0942)	(0.101)	(0.137)	(0.0799)	(0.112)	(0.193)
$\#Kept_{i,t-1}$	0.480***	0.469***	0.541***	0.604***	0.613***	0.654***
	(0.114)	(0.118)	(0.165)	(0.0807)	(0.0821)	(0.111)
Constant	45.94***	35.61***	41.07***	35.02***	27.39***	50.90***
	(9.939)	(10.25)	(14.09)	(7.336)	(9.141)	(14.57)
# Obs	139	139	55	306	306	141

Panel B: Twice-Lagged Choices

	-i = Avg of Friends			-i = Avg of Community		
	Δt = 0	Δt = 1	Δt = 2	Δt = 0	Δt = 1	Δt = 2
	(1)	(2)	(3)	(4)	(5)	(6)
$\#Kept_{-i,t-\Delta t}$	-0.0673	-0.367*	-0.0243	-0.256**	-0.148	-0.438**
	(0.120)	(0.200)	(0.133)	(0.117)	(0.165)	(0.203)
$\#Kept_{i,t-2}$	0.432***	0.373**	0.437***	0.513***	0.582***	0.517***
	(0.139)	(0.142)	(0.140)	(0.0949)	(0.109)	(0.0978)
Constant	38.92***	64.36***	36.09**	45.25***	35.70***	55.77***
	(13.06)	(15.95)	(14.37)	(9.945)	(13.56)	(13.83)
# Obs	97	55	97	197	141	197

All specifications are OLS regressions with standard errors clustered at the subject level. The dependent measure is the number of tokens kept by the focal individual. The independent measure is the average choice of the focal individual's friends (columns 1-3) or network community (columns 4-6). Columns 1 and 4 report the contemporaneous correlation (Δt = 0), columns 2 and 5 use the one-period lagged friend/community average (Δt = 1), while Columns 3 and 6 use the two-period lagged average (Δt = 2). Panel A also includes the focal individuals' choice from the previous period, while Panels B includes the focal individuals' choice from two periods ago.

Conclusion

There is extensive evidence that on a number of dimensions the behavior of individuals is positively correlated with the behavior of others in the individual's social network (Christakis and Fowler, 2007, 2009; Backstrom et al. 2006; Marlow et al. 2006; Conley and Udry 2001). This can happen because we tend to select friends because they are similar to us, *selection based on preferences* (*homophily*), or because we become more similar to our friends over time, *dynamic preference formation* (*peer influence on preferences*) (Kandel 1978; Golub and Jackson 2008; Currarini et al. 2010). Several recent studies have tried to assess the underlying mechanism that generates this correlation by looking at changes in individual and social network behavior over time (Acitelli et al. 2001; Burleson and Denton 1992; Kenny & Kashy 1994). These studies have shown that there is convergence in behavior. Further, a handful of studies have also examined how underlying preferences (rather than just the behaviors we observe) between an individual and their social network are correlated; these studies have looked at generosity (Leider et al. 2009, Goeree et al. 2010), risk sharing and loan behaviors (Fafchamps and Lund 2003; De Weedt 2004).

Using a longitudinal design to follow freshman during their first year at university, we test for and demonstrate selection based on preferences and dynamic preference formation for three key and fundamental economic preferences: social risk and time preferences. These fundamental preferences are important to study because they give rise to behaviors that have long term economic social consequences in many domains of life. As an example, social preferences have been linked to macro economic phenomena such as cross county variation in Gross Domestic Product, and poverty disparities (Knack and Keefer,1997; Karlan et al. 2009). Risk preferences have been correlated with investment, retirement health related behavior and career choices, and time preferences have been linked to smoking, obesity, educational and savings behavior (Cardenas & Carpenter, 2008).

We find evidence for each mechanism on at least one important preference. We show that changes in subject's social networks are significantly influenced the similarity or dissimilarity in generosity (as measured by a standard lab-style dictator task). Students who are similarly generous are more likely to become friends, and less likely to end a pre-existing friendship. The effects of homophily for altruism are of a similar magnitude to other key predictors of network changes, such as participating in the same activities, or the network centrality of the (potential) friend. Additionally, we find evidence for peer influence for both self-reported tolerance for risk and our incentivized measure of patience. The influence effect is robust to looking at both contemporaneous and lagged behavior in the network, and is of substantial magnitude: a one standard deviation change in the average behavior of others is associated with a $1/7^{th}$ to $1/12^{th}$ SD change in the corresponding behavior of the focal individual. We additionally find surprising evidence for a negative peer effect on generosity, consistent with free-riding behavior.

We focused on studying students during their freshman year, as it is a time of substantial personal and social change. This gave us the best chance to observe homophily and peer influence on preferences. However, one potential concern is that this might represent the high point for these mechanisms. Whether these mechanisms continue to be important later in life is an open question for future research.

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Appendix

Figure A1 – Friends Elicitation

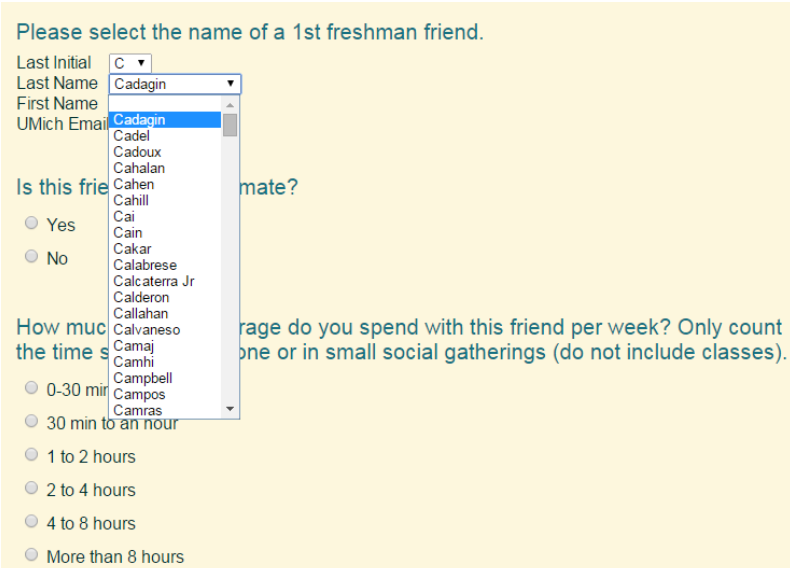

Figure A2 - Risk Preference Elicitation

Figure A3 - Time Preference Elicitation

For each row please indicate whether you prefer the two week column or the future payment.

$75 in two weeks	○	○	$80 in 3 months
$70 in two weeks	○	○	$80 in 3 months
$65 in two weeks	○	○	$80 in 3 months
$60 in two weeks	○	○	$80 in 3 months
$55 in two weeks	○	○	$80 in 3 months
$50 in two weeks	○	○	$80 in 3 months
$45 in two weeks	○	○	$80 in 3 months
$40 in two weeks	○	○	$80 in 3 months
$35 in two weeks	○	○	$80 in 3 months
$30 in two weeks	○	○	$80 in 3 months
$25 in two weeks	○	○	$80 in 3 months
$20 in two weeks	○	○	$80 in 3 months
$15 in two weeks	○	○	$80 in 3 months
$10 in two weeks	○	○	$80 in 3 months
$5 in two weeks	○	○	$80 in 3 months

Figure A4 – Social Preference Elicitation

In this game, you will be randomly and anonymously matched with another student at the University of Michigan who is participating in this survey. You must decide how to divide 100 tokens between yourself and the other person. Each token is worth $0.75 to you, and worth $1.50 to the other person.

Please indicate how many tokens you want to keep to yourself and pass to the other person. The two numbers must add up to 100.

I choose [0] tokens to keep to myself.

I choose [0] tokens to pass to the other person.

Figure A5 – Self-Reported Risk Tolerance

Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?

Please select a value on the scale, where the value **0** means: **"risk averse"** and the value **10** means: **"fully prepared to take risks"**. You can use the values in between to make your estimate.

	risk averse 0	1	2	3	4	5	6	7	8	9	fully prepared to take risks 10
How do you see yourself?	○	○	○	○	○	○	○	○	○	○	○

Figure A6 – Self-Reported Patience

Are you generally an impatient person, or someone who always shows great patience?

Please select a value on the scale, where the value **0** means: **"very impatient"** and the value **10** means: **"very patient"**.

	very impatient 0	1	2	3	4	5	6	7	8	9	very patient 10
How do you see yourself?	○	○	○	○	○	○	○	○	○	○	○

Appendix B

DV:	1(network)	s.e.
sure	0.364	(0.684)
now	-0.114	(0.657)
keep	2.091	(5.223)
risk	-0.0793	(0.377)
patience	0.138	(0.374)
trust_little	0.207	(0.379)
trust_lot	0.659*	(0.380)
student_group	-0.172	(0.379)
sports	0.262	(0.375)
religion	-0.295	(0.384)
volunteer	-0.115	(0.378)
handout	-0.561	(0.383)
lend_money	-0.531	(0.384)
lend_prof	-0.148	(0.380)
helphw	-0.0976	(0.378)
eatout	-0.352	(0.379)

Each line is a logistic regression with the corresponding dependent variable and an indicator for network elicitation survey participants as the independent variable.