Social Capital in Social Networks*

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Abstract

We define and measure social capital within a large social network where agents take actions which have externalities on other agents. Our concept of social capital measures the extent to which agents are able to internalize these externalities. We distinguish between preference-based social capital (directed altruism) and cooperative social capital based on repeated interaction between pairs or groups of agents. We find that preference-based social capital increases an agent's weight on a friend's utility by about 15 percent and cooperative social capital adds another 5 percent.

1 Introduction

Social capital helps to internalize externalities for which there is no market and where transactions costs are too high to write complete contracts. Informal credit arrangements, financial and in-kind assistance to neighbors and friends or investments in public goods are just one of the many examples of social capital.

In this paper we provide a simple definition of social capital with a community or social network and measure social capital in a real-world social network using a series of experiments by building on the work of Andreoni and Miller (2002).

Our methodology distinguishes between two sources of social capital: preference-based and cooperative social capital. Preference-based social capital is based on simple altruism - agents can obviously internalize externalities if they take each

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other's utility into account. However, we expect the strength of altruism to vary systematically with the relative position of agents within the social structure which makes the empirical calibration of such a model interesting. How strongly do agents care about the utility of their friends, cliques or people who live close to them?

Cooperative social capital arises from repeated interactions between pairs or groups of agents. This makes agents appear to act like altruists even if they have perfectly selfish preferences. Due to the multiplicity of equilibria in repeated games the empirical calibration of our model provides interesting insights into the extent and relative important of cooperative social capital.

We find evidence of both cooperative and preference-based social capital. While there is considerable heterogeneity in the base level of altruism amongst agents we find that preference-based social capital increases the weight on a friend's utility by about 15 percent while cooperative social capital adds another 5 percent.

Our approach to social capital is quite different from other experimental work which mostly builds on the trust game (Berg, Dickhaut, and McCabe 1995). The trust game is typically played in a computer lab with anonymous players (Glaeser, Laibson, Scheinkman, and Soutter (1999) is an important exception). In this setting we expect that both preference-based and cooperative social capital are weaker than within a non-anonymous social network setting. In this paper we study social capital within a well-defined community. Moreover, the anonymous interaction setting lacks the rich structure of the social network which makes it more difficult to test micro models of social capital.

The balance of the paper is as follows. In sections 2 and 3 we develop a simple theory framework and define what we mean with social capital. Section 4 discusses the design of the experiment. Results are presented in section 5.

2 Theory Framework

2.1 Social Network

The social network consists of n agents who are either directly or indirectly connected with each other. We define the network distance between two agents i and j as the shortest chain which connects two agents. *Friends* are agent who live a distance 1 away. *Indirect Friends* live a distance of 2 away.

2.2 Actions

Time is continuous and all agents share a common discount factor δ. At rate 1 an agent faces a decision problem of type $q \in [0, \overline{q}]$ with $\overline{q} > 1$. The type is distributed over $[0, \overline{q}]$ according to some distribution $f(q)$. Agent i can take an action $a_i \in [0, 1]$ which will impact both him and some other agent j. We assume that the probability that agent i is matched to j is p_{ij} and that $p_{ij} = p_{ji}$.

If agent i takes action a_i he generates the following outcomes x_i and x_j for himself and player j:

$$\begin{aligned} x_i &= a_i \\ x_j &= q(1 - a_i) \end{aligned} \tag{1}$$

Intuitively, player i is dividing a pie of size 1 between himself and the other player where the price of a share of pie to the other player is q.

Note, that this setup implies that each agent j consumes on average at rate 2 - at rate 1 he enjoys utility from his own decisions and at the same rate he is subject to decisions made by another player.

This setup is meant to capture the fact that our actions often affect our social neighbors. An agent, who receives some cash, for example, might decide to consume it herself or lend some of it to a friend who might have better use for the money.

2.3 Utility

Agents derive 'selfish' instantaneous utility $u_i = v(x_i)$ from consuming x_i where v is a standard concave and increasing function such that $v(0) = 0$.

Agents are also altruistic when taking an action and they face the following altruistic utility function which is a weighted average of their own selfish utility and the utility of the other agent:

$$u_i = s_{ij} v(x_i) + (1 - s_{ij}) v(x_j) \tag{2}$$

We say that agent i is perfectly selfish towards agent j if $s_{ij} = 0$ and that he is perfectly altruistic if $s_{ij} = \frac{1}{2}$.

Note, that we make the important assumption that an agent only derives utility from altruism when making a decision herself. In particular, we assume implicitly that she derives no utility from the actions of another agent who makes a decision impacting a third agent. This keeps the setup particularly simple.

3 Preference-based and Cooperative Social Capital

Our framework allows us to define two types of social capital - *preference-based* and *cooperative* social capital. We define both types of social capital with respect to the benchmark of a social planner who has a utilitarian social welfare function with equal weights on the utilities of each agent. This social planner always chooses an agent which assumes equal weight $s_{ij} = \frac{1}{2}$ on both agent i's and j's utility.

3.1 Preference-based Social Capital

The closer social welfare in the decentralized equilibrium is to social welfare in social planner's equilibrium the greater we say is social capital. We can capture this notion formally by defining *social capital* as a matrix (s_{ij}). If all agents value the utility of the other agent as much as their own utility then the decentralized equilibrium will be identical to the social planner's solution.

However, we do not expect that altruistic preferences alone are strong enough to bring about this solution. First of all, we expect that agents value their own utility more than the utility of other agents such that $s_{ij} \geq \frac{1}{2}$. Second, we expect that altruistic preferences decline with social distance.

We call the social capital defined by the matrix (s_{ij}) *preference-based social capital*. In contrast to cooperative social capital which we defined in the next section preference-based social capital does not require agents to be forward-looking.

3.2 Cooperative Social Capital

If agents are forward-looking they can partially or fully internalize the action externalities in our framework by cooperating through repeated game.

The simplest type of repeated game is bilateral cooperation played between independent pairs of players i and j. We focus on the equilibrium which gives both players the highest utility. We also assume for simplicity that there is only a single decision problems of type q^*.

Since our setup is symmetric and $p_{ij} = p_{ji}$ we can focus on symmetric trigger-strategy equilibria where both players take action a^*. This gives them discounted utility U:

$$U = \frac{1}{1 - \delta p_{ij}} [\underbrace{(s_{ij} v(a^*) + (1 - s_{ij}) v(q(1 - a^*)))}_{\text{altruistic utility from own actions}} + \underbrace{\delta p_{ij} v(q(1 - a^*)}_{\text{utility derived from actions of other player}}] \tag{3}$$

The equilibrium which gives both players the highest utility achievable through bilateral cooperation is described by the action a^* which maximizes this expression. It is easy to see that this equilibrium essentially implements the same action as a decision maker with some $\hat{s}_{ij}(s_{ij}, p_{ij}) < s_{ij}$. The higher the frequency p_{ij} of interaction the less selfish the agent will act.

We call (s_{ij}) the preference-based component of social capital and $(\hat{s}_{ij} - s_{ij})$ the cooperative component of social capital. The sum of both components describes total social capital.

Cooperative social capital increases if cooperation is not just bilateral but involves groups of cooperating agents. The highest degree of cooperation can be achieved if the entire community forms one large group. In this case each individual cooperates with the group at rate 1 rather than rate p_{ij} which implies an increase in cooperative social capital.

3.3 Discussion

Our definition of preference-based and cooperative social capital allows us to compare social capital across communities by comparing the social capital vectors. This ordering is a partial ordering.

4 Design

Our experiment has two parts. First, we measure the social network through a network elicitation game which is essentially a coordination game. This provides us with measures of social distance between agents as well as measures for the *strength* of links. we will use Granovetter's concept of weak and strong links (Granovetter 1973) according to which link strength increases with the number of common friends.

In the second phase of the experiment we select pairs of subjects randomly to play an allocation where player 1 (allocator) divides 0 tokens between himself and player 2 (recipient). Each of these decision problems is presented in two possible situations - in one situation the recipient is told about the action choices of player 1 and in the second situation the recipient is not old about the action choices.

This allows us to separately measure both s_{ij} (when the recipien is not told about the choices of the other agent) and $\hat{s}_{ij}$ (when the recipient is told about the allocator's choices).

4.1 Network Elicitation Game

In December 2003 Subjects were recruited through posters, flyers and mail invitation and directed to go to a website (in our case www.houseexperiment.org). Subjects provided their email address and were sent a password.[1] After login subjects were asked to specify their own names from a drop-down menu of all students

[1] This allows us to exclude subjects without a valid email address.

in the university.[2] All future earnings from the experiment were then transferred to the electronic cash-card account of that student.[3]

To give subjects an incentive to make truthful reports we frame their choice as a coordination game: subjects receive 50 cents with 50 percent probability if they name each other. We consider the expected payoff of 25 cents to be sufficiently large to give subjects an incentive to report their friends truthfully but not large enough to induce 'gaming'. The randomization helps to avoid disappointment if a subject is not being named by his or her list of friends because there is always the possibility that a small number of matches is the result of bad luck.

The total earnings of subjects in our pilot consisted of a baseline compensation for completing the full online survey (network elicitation game plus an additional questionnaire collecting socio-economic data from subjects) and the earnings from the network game. Subjects also entered a raffle where they could win valuable prizes nine months later provided they completed the initial surveys plus all follow-up treatments.

The network elicitation game can be easily modified to provide further information on friendship links. For example, we also wanted to know how much time friends spent on average per week together (in half hour increments) as a measure of link strength. If subjects agreed on this dimension of their friendship the winning probability increased from 50 percent to 75 percent. It is equally simple to add further dimensions, such as length of friendship, whether friends met in their dorm, in class or at some social event etc.

Our coordination game worked very well and provided high-quality social network data that is comparable to data obtained with traditional (and very expensive) survey techniques. Our pilot focused on two dorms with 806 students of whom 569 signed up. The survey netted 5690 one-way links. Of those, 2086 links were symmetric links were both agents had named each other. Most participants spent less than half an hour with their 10th friend which indicated that a rooster of 10 friends is sufficient to measure the network or 'real' friends. Across symmetric links subjects agreed in 80 percent of the cases on the time they spend together in a typical week ($\pm$ half an hour). The average cluster coefficient was 0.58 - it measures the average probability that a friend's friend is also my friend. The network defined by symmetric links is mostly connected - there is a 'giant connected cluster' that indirectly linked all but 34 agents to each other. This is a typical

[2] The registrar provided us with a complete list of upper-class students from the university including full campus address and room number but without email. Emails had to be provided by students themselves. Subjects could select their name by choosing first their dorm and class year which narrowed down the selection to about 100 names. To protect subjects' privacy we only provided the first name and the initial of the second name.

[3] Most universities provide such cards to purchase food and beverages and these cards are ideally suited to make multiple small transfers on a large scale.

feature of social networks (Watts and Strogatz 1998).

4.2 Treatment Phase

In May 2004 we ran various treatments to measure social preferences of students in our sample. Within each house we randomly selected an equal number of player 1's and player 2's. Player 1's were allocators in a modified dictator game. During the course of the experiment they were matched with 5 potential player 2's:

- one direct friend
- one indirect friend
- one friend of an indirect friend
- a student in the same staircase/floor who is at least a distance 4 removed from the student
- a randomly selected student from the house who falls into none of the above categories

Each of these pairs was played twice - in the first situation player 2 would find out about player 1's action and in the second situation she would not find out.

For each pair and each situation player 1 had to make three allocation decisions. In each decision he had to allocate 50 tokens between himself and the other player.

- In the first decision the token was worth 1 point to him and 3 points to the other player. This corresponds to a decision of type $q = 3$ in our model (i.e. the relative value of a token is 3 to the other player).
- In the second decision the tokens were worth 2 points to both players ($q = 1$).
- The the third decision the tokens were worth 3 points to player 1 and 1 point to the other player ($q = \frac{1}{3}$).

One point equalled 10 cents. The maximum winnings of a player and one match were $15.

All these decisions, situations and pairs were randomly presented to each player. Because they had to take so many decisions we asked them to login twice on two different days. On each day one of their decisions for one pair was randomly selected and implemented. Our algorithm ensured that each recipient was matched up with exactly two allocators eventually.

5 Results

We start our analysis with simple regressions of tokens held by allocators (HOLD) on characteristics of the network relationship between allocator and recipient. We focus on two dimensions of this relationship: network distance and link strength. Network distance can take the values 0 (stranger), 1 (direct friend), 2 (indirect friend), 3 (friend of indirect friend). We form three indicator variables called DIST1 (which is 1 if distance is 1), DIST2 and DIST3. We also have a variable called SAMESTAIR which is 1 if player 1 and player 2 live in the same staircase. This variable is never significant and hence dropped from the regressions.

Network strength measures how many common friends the allocator i and the recipient j share. Formally, our variable STRENGTH takes values between 0 and 1 and is defined as follows:

1. Take the set of 10 friends named by player 1 and intersect it with the set of 10 people named by player 2.

2. The intersection varies between 0 and 10. Divide this number by 10. This is our index of network strength.

A *strong link* exists between two agents who share many common friends. A *weak link* exists between a pair of agents who have few common friends. If STRENGTH is 0 then the two subjects have no friends in common at all. This distinction of weak and strong links was first introduced by Granovetter (1973).

Note that our network strength measure is defined even if the allocator i and recipient j are not direct friends and did not name each other. Generally, however, we would expect that STRENGTH decreases with social distance which is indeed the case.

We run all our regressions using fixed effects on allocators. This is important because of considerable heterogeneity amongst allocators.

5.1 Averages

The average number of tokens held by player 1 in situations where player 2 does not find out about the allocator's choices range from 34 ($q = 3$) to 40 ($q = 1$) and 43 ($q = \frac{1}{3}$).

In situations where the recipient does find out the allocator's choices the allocator holds fewer tokens for each of the three decision types ranging from 29 tokens ($q = 3$) to 35 ($q = 1$) and 40 tokens ($q = \frac{1}{3}$).

5.2 Basic Regressions

Our first regression only includes network distance:

$$y_{ij} = \alpha_1 * DIST1_{ij} + \alpha_2 * DIST2_{ij} + \alpha_3 * DIST3_{ij} + \eta_i + \epsilon_{ij} \tag{4}$$

where

$$\begin{aligned} y_{ij} &= \text{Tokens held by player } i \text{ when playing with player } j \\ \eta_i &= \text{player 1 fixed effect} \\ DIST1_{ij} &= \text{DIST1 between } i \text{ and } j \\ DIST2_{ij} &= \text{DIST2 between } i \text{ and } j \\ DIST3_{ij} &= \text{DIST3 between } i \text{ and } j \\ \epsilon_{ij} &= \text{an error term which is conditionally independent i.i.d. draw from some error distribution given } (\eta_i, DISTANCE) \end{aligned} \tag{5}$$

We run this regression separately for each of the three decisions and each of the two situations using fixed effects. The results are in table 2 for the case where the recipient does not find out about the allocator's actions and in table 1 for the case of non-anonymous interaction.

We find that for non-anonymous interaction about 20 percent more tokens are passed to direct friends and about 8 percent more to indirect friends. For anonymous interaction about 15 percent more tokens are passed to direct friends.

5.3 Gender Effects

We next estimate equation 4 separately for men and women. The results are reported in tables 3 and 4.

We find that women are consistently less generous than men (looking at intercept) and hold more tokens back on average. However, social distance effects are very similar *except* for decision 3 where social network does not matter for men but it does matter for women.

5.4 Social Network Strength

In the next specfication we include the network strength variable. Results are reported in tables 4 and 5.

We find that strength is very significant and of similar magnitude as the coefficients on DIST1. In fact, the strength variable sweeps away DIST2 and DIST3 effects in the case of non-anonymous interaction. We include interaction term between DIST1 and network strength to make sure that DIST1 coefficient measures social closeness. It seems indeed the case that social distance and network strength effects are different.

5.5 Unified Regressions

To distinguish between network distance and strength effects between the anonymous and non-anonymous treatments we also run the following specification which includes a single allocator fixed effect across both the anonymous and non-anonymous treatments (see table 6):

$$\begin{aligned} y_{ij} &= \alpha_1 * DIST1_{ij} * (1 - A_{ij}) + \tilde{\alpha}_1 * DIST1_{ij} * A_{ij} + \alpha_2 * DIST2_{ij} * (1 - A_{ij}) + \\ &+ \tilde{\alpha}_2 * DIST2_{ij} * A_{ij} + \alpha_3 * DIST3_{ij} * (1 - A_{ij}) + \tilde{\alpha}_3 * DIST3_{ij} * A_{ij} + \\ &+ \beta * STRENGTH_{ij} * (1 - A_{ij}) + \tilde{\beta} * STRENGTH_{ij} * A_{ij} + A_{ij} + \eta_i + \epsilon_{ij} \end{aligned} \quad (6)$$

We find that distance effects are concentrated on direct friends and we cannot reject that they are equal in both treatments. Anonymity leads to less giving across all friends and treatments. In decision $T = 1$ strength matters only in the non-anonymous treatment.

The results for payrate $T = 1$ are consistent with the hypothesis that our distance measure picks up directed altruism while the strength measure correlates with effort trust which increases monotonically with the strength of a link.

5.6 Visualizing Types

A disadvantage of the regression analysis so far is that we do not extract the variable of interest, namely the weight s_{ij} on the other agent's utility, from the data.

In order to visualize the distribution of types we estimate the s_{ij} by specifying a CES utility function. In particular we assume that $v(\cdot)$ has the following functional form:

$$v(x) = x^\rho \quad (7)$$

We then estimate ρ_i and s_{ij} from the 15 decisions of each allocator in the anonymous and non-anonymous cases. The distributions of s_{ij} are shown in figures 2 and 3.

It is noteworthy that just as in Andreoni and Miller (2002) we find that about 50 percent of the sample concentrated around perfect altruists ($s = \frac{1}{2}$) and perfectly selfish individuals ($s = 1$).

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Table 1: Basic social network regression for three pay rates (token worth T=1 to T=3 points to allocator) - Player 2 FINDS OUT the identity of player 1

Variable	(T=1)	(T=2)	(T=3)
DIST1	-3.895**	-2.805**	-2.920**
	(0.585)	(0.494)	(0.787)
DIST2	-1.627**	-0.826†	-0.247
	(0.560)	(0.470)	(0.736)
DIST3	-0.880	-0.389	-0.676
	(0.543)	(0.456)	(0.715)
Intercept	22.576**	29.111**	29.523**
	(0.298)	(0.248)	(0.380)
N	670	613	448
R^2	0.081	0.066	0.042

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

The dependent variable is TOKENSHELD; standard errors are shown in paranthesis.

Table 2: Basic social network regression for three pay rates (token worth T=1 to T=3 points to allocator) - Player 2 DOES NOT FIND OUT the identity of player 1

Variable	(T=1)	(T=2)	(T=3)
DIST1	-2.587**	-3.118**	-1.824*
	(0.755)	(0.684)	(0.922)
DIST2	-0.696	-0.400	0.052
	(0.746)	(0.681)	(0.881)
DIST3	0.051	-1.288†	-0.942
	(0.713)	(0.657)	(0.854)
Intercept	22.825**	30.704**	30.875**
	(0.389)	(0.349)	(0.457)
N	530	464	311
R^2	0.033	0.06	0.021

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

The dependent variable is TOKENSHELD; standard errors are shown in paranthesis.

Table 3: Basic social network regression for three pay rates (token worth T=1 to T=3 points to allocator) differentiated by gender (M=player 1 is male,F=player 1 is female)- Player 2 DOES NOT FIND OUT the identity of player 1

Variable	(T=1,M)	(T=1,F)	(T=2,M)	(T=2,F)	(T=3,M)	(T=3,F)
DIST1	-2.861*	-2.311**	-3.861**	-2.374**	0.947	-4.645**
	(1.274)	(0.839)	(1.109)	(0.839)	(1.404)	(1.172)
DIST2	-1.799	0.317	-0.129	-0.623	1.625	-1.296
	(1.297)	(0.806)	(1.142)	(0.809)	(1.453)	(1.046)
DIST3	-0.415	0.467	-1.408	-1.167	-0.838	-1.201
	(1.255)	(0.761)	(1.118)	(0.772)	(1.361)	(1.041)
Intercept	21.109**	24.294**	29.591**	31.597**	28.896**	32.490**
	(0.682)	(0.416)	(0.600)	(0.408)	(0.745)	(0.548)
N	246	284	208	256	135	176
R^2	0.031	0.052	0.08	0.043	0.028	0.112

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

The dependent variable is TOKENSHELD; standard errors are shown in paranthesis.

Figure 1: Distribution of STRENGTH variable

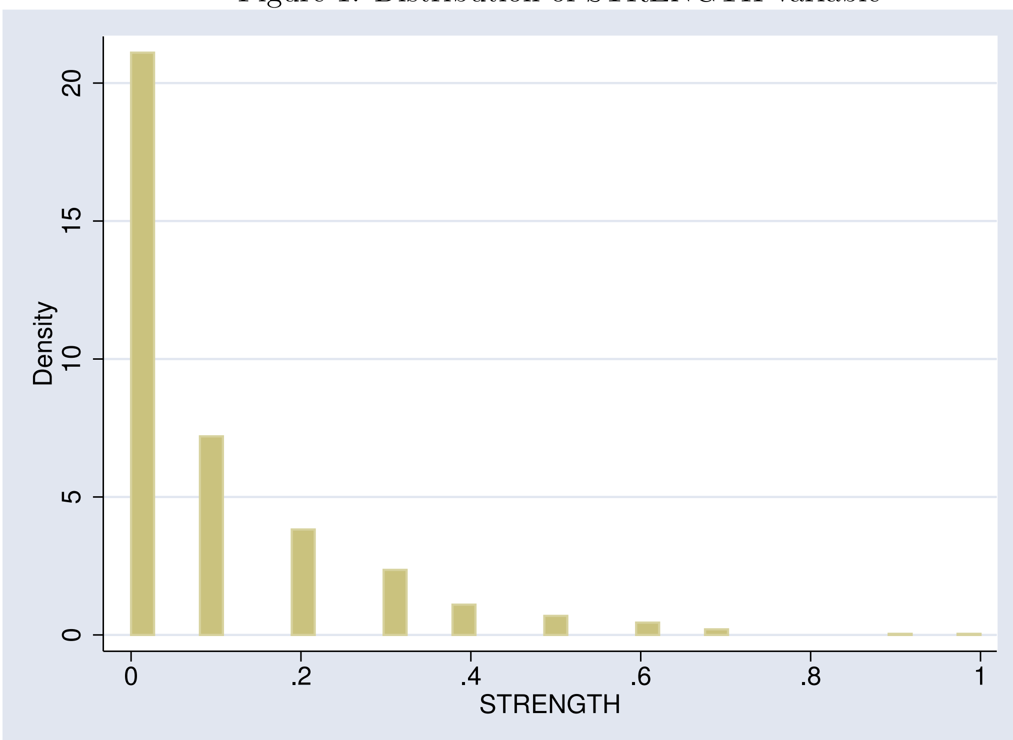

Table 4: Basic social network regression for three pay rates (token worth T=1 to T=3 points to allocator) including network strength - Player 2 FINDS OUT the identity of player 1

Variable	(T=1)	(T=2)	(T=3)
DIST1	-3.329**	-2.164**	-1.528
	(0.864)	(0.740)	(1.168)
DIST1*STRENGTH	2.900	-0.384	1.542
	(3.833)	(3.227)	(4.689)
DIST2	-0.305	-0.252	1.541
	(0.778)	(0.652)	(0.991)
DIST3	-0.656	-0.290	-0.384
	(0.548)	(0.462)	(0.716)
STRENGTH	-5.990*	-2.680	-8.101**
	(2.478)	(2.164)	(3.094)
Intercept	22.673**	29.148**	29.646**
	(0.300)	(0.251)	(0.381)
N	670	613	448
R^2	0.093	0.072	0.069

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

The dependent variable is TOKENSHELD; standard errors are shown in paranthesis.

Table 5: Basic social network regression for three pay rates (token worth T=1 to T=3 points to allocator) including network strength - Player 2 DOES NOT FIND OUT the identity of player 1

Variable	(T=1)	(T=2)	(T=3)
DIST1	-2.745*	-2.578**	0.812
	(1.078)	(0.992)	(1.339)
DIST1*STRENGTH	3.222	3.584	-8.832
	(4.981)	(4.440)	(5.527)
DIST2	-0.131	1.010	0.775
	(1.045)	(0.940)	(1.177)
DIST3	0.141	-1.085	-0.834
	(0.724)	(0.660)	(0.851)
STRENGTH	-2.622	-6.513*	-3.203
	(3.349)	(3.046)	(3.488)
Intercept	22.876**	30.830**	30.929**
	(0.395)	(0.353)	(0.457)
N	530	464	311
R^2	0.034	0.074	0.056

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

The dependent variable is TOKENSHELD; standard errors are shown in paranthesis.

Table 6: Basic social network regression for three pay rates (token worth T=1 to T=3 points to allocator) including network strength across anonymous and non-anonymous treatments

Variable	(T=1)	(T=2)	(T=3)
DIST1*NONANONYMOUS	-2.636**	-2.198**	-1.517
	(0.767)	(0.740)	(1.076)
DIST1*ANONYMOUS	-2.316**	-2.341**	0.152
	(0.829)	(0.810)	(1.213)
DIST2*NONANONYMOUS	-0.460	0.001	0.977
	(0.778)	(0.728)	(1.049)
DIST2*ANONYMOUS	-0.687	0.226	2.319†
	(0.879)	(0.841)	(1.247)
DIST3*NONANONYMOUS	-0.619	-0.277	-0.509
	(0.612)	(0.576)	(0.832)
DIST3*ANONYMOUS	0.038	-0.244	-0.156
	(0.694)	(0.669)	(1.002)
STRENGTH*NONANONYMOUS	-5.133*	-3.405†	-6.779*
	(2.099)	(2.028)	(2.806)
STRENGTH*ANONYMOUS	-1.079	-2.508	-6.607*
	(2.278)	(2.206)	(3.160)
ANONYMOUS	1.495**	2.633**	2.429**
	(0.499)	(0.474)	(0.701)
Intercept	22.062**	28.607**	29.096**
	(0.336)	(0.314)	(0.449)
N	1200	1077	759
R^2	0.074	0.105	0.086

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

The dependent variable is TOKENSHELD; standard errors are shown in paranthesis.

Figure 2: Distribution of types s_{ij} under anonymous interaction between allocator and recipient

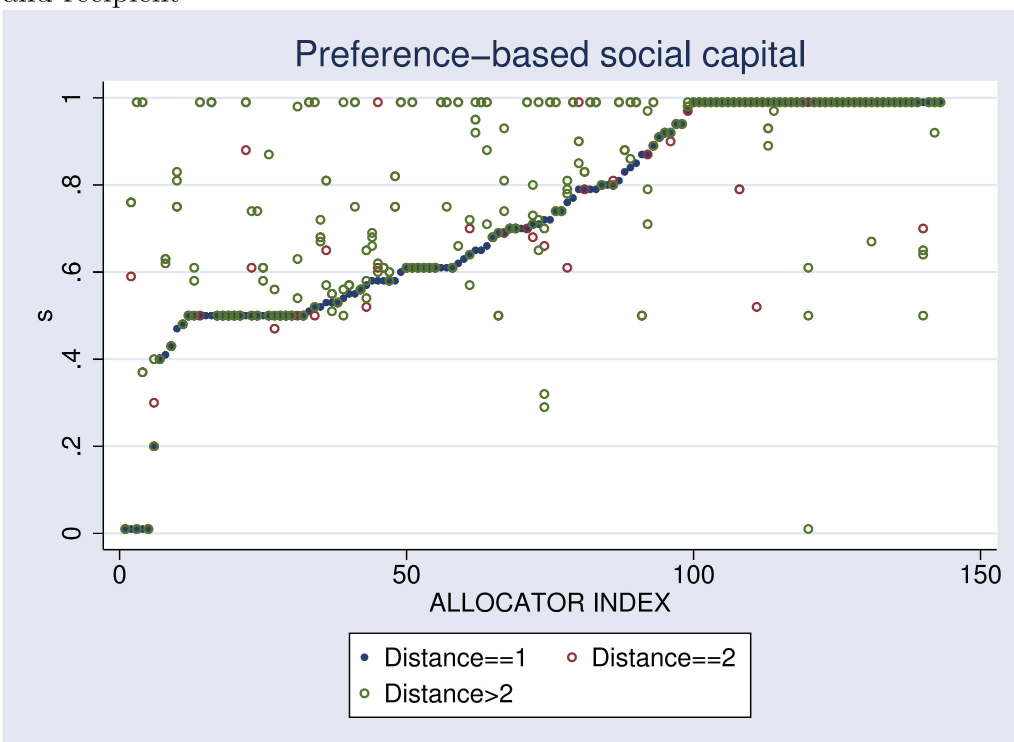

Figure 3: Distribution of types s_{ij} under non-anonymous interaction between allocator and recipient