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An experimental study of partnership formation in social networks *

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Abstract

This paper reports on laboratory experiments on the formation of partnerships in social networks. Agents randomly request favors and turn to their neighbors to form a partnership where they commit to provide the favor when requested. The formation of a partnership is modeled as a sequential game, which admits a unique subgame perfect equilibrium resulting in the formation of the maximum number of partnerships. Experimental results show that a large fraction of the subjects (75%) play according to their subgame perfect equilibrium strategy and reveals that the efficient maximum matching is formed over 78% of the times. When subjects deviate from their best responses, they accept to form partnerships too early. The incentive to accept when it is optimal to reject is positively correlated with subjects' risk aversion, and players employ simple heuristics – like the presence of a captive partner – to decide whether they should accept or reject the formation of a partnership.

`JEL Classification Numbers: D85, C78, C91`

`Keywords: social networks, partnerships, matchings in networks, non-stationary networks, laboratory experiments`

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1 Introduction

1.1 The formation of partnerships in social networks

Bloch, Dutta and Manea (2018) (henceforth BDM) study the impact of network structures on the pattern of bilateral exchanges. Their setting is one in which individuals form partnerships to exchange *favors* with one another. Favors could be small – advice on a particular issue, a small loan, help on a school project or with baby-sitting, or large – sharing one's life with another person, or forming a professional partnership with other workers . The need for such favors arises randomly for any individual at any point of time. If an individual i needs a favor at any point, he turns to one of his neighbors j in the network to request the favor. The recipient of such a request can either grant the favor at some cost c (which is strictly less than the value of the favor v) or refuse to grant the favor. In the latter case, the link between i and j is broken. Individual i can then approach another neighbor to grant him the favor. If the favor is granted, the two players enter a reciprocal agreement to grant each other the favor and leave the network. The process is repeated in the next period when some individual chosen at random needs a favor.

It is not difficult to see that not all requests will be granted and that the network will grow sparser over time. Either an agent who requests a favor finds a partner, and the pair leaves the network with all their links or the agent is turned down by all his neighbors and ends up leaving the network as a a singleton. Exploiting this recursive structure (that the network grows sparser over time) BDM characterize the the unique subgame perfect equilibrium of the game. They establish that the unique optimal strategy of a player i is to accept the request of a player j if and only if, once the link ij is broken, player i does not belong to all maximum matchings of the graph $g \setminus ij$. It immediately implies that a maximum matching is obtained in equilibrium, as players will never break a link which reduces the number of matchings in the graph.

This paper is the experimental counterpart of BDM. We test whether players form efficient partnerships in social networks running a series of laboratory experiments. The experimental design mimics the game of partnership formation described above, but in a finite setting where, instead of receiving an expected discounted value, subjects obtain a fixed finite value when they form the partnership. [1] We consider five different settings with initial social networks of increasing complexity. We observe that a large fraction of the subjects (more than 75%) do indeed select the equilibrium action, and that the subjects' ability to compute and select the subgame perfect equilibrium action depends on the complexity of the network. We also note that, even when subjects do not employ their subject equilibrium strategy, the proportion of rounds for which the efficient maximum matching is obtained is very high – around 78% of all rounds.

[1] The value is computed so that the equilibrium behavior in the finite game is equal to the equilibrium behavior in the infinite game studied in BDM.

We analyze the systematic departures from equilibrium behavior and discover that subjects err by accepting too often. In addition, we see that subjects who are more risk averse (as measured by a classical questionnaire on risk aversion) accept more often, in the fear of being left isolated at the end of the game. One instance where we observe that agents correctly reject the requests is when they have access to 'captive' agents who are only linked to them. We show that this 'captive agents' heuristic works very well and that players with captive agents are much more likely to play their subgame perfect equilibrium strategy. Finally, we note that the complexity of the network – and in particular the presence of cycles – greatly complicates the computation of the equilibrium behavior and results in subjects making more mistakes.

1.2 Relation to literature

The model of partnership formation in social networks is related to two different strands of the literature. First, it has close connections to models of bargaining in networks, in particular models of bargaining in non-stationary networks where agents who leave the network are not replaced.[2] Second, because the value of a partnership is modeled through reciprocal exchange of favors, the model is related to the literature on favor exchange.[3] The paper by Abreu and Manea (2012) considers a model of bargaining which differs from ours in two dimensions. First agents bargain the division over a surplus whereas in our model agents cannot share the value of the partnership. Second, agents do not sever links if they do not reach agreement – a strong departure from our model which explains the difference in results in our paper and Abreu and Manea (2012). The paper in the literature on favor exchange which is closest to our model is the paper by Jackson, Rodriguez-Barraquer and Tan (2012). In this paper, pairs of agents are matched randomly in any period, with one of the agents requiring a favor from the other. Contrary to the BDM model, favors are link-specific and the agent can only obtain a favor form one of his neighbors. Pairs meet too infrequently to sustain bilateral exchange, However, the favor exchange network may be sustained through social pressures or punishments leading to possible loss of neighbors in the network. Despite the similarity in the settings, the primary focus of their model is very different from ours. In particular, very different forces sustain the socially efficient network in the two settings - social pressures in their case and individual incentives in the BDM case.

There is a growing literature on experiments in networks which is related to our paper.[4] To the best of our knowledge, our paper is the first to propose an experimental test of the model of partnership formation in non-stationary networks. The most closely related paper is the paper by Charness, Corominas-Bosch and Frechette (2007) who test the Corominas-Bosch bargaining model and observe that, as in our experimental study, the proportion of

[2] See Manea (2017) for a recent survey.

[3] This literature is surveyed in Möbius and Rozenblat (2017).

[4] See Choi, Gallo and Kariv (2016) for an up-to-date survey of this literature

efficient trade is very high and players' behavior seems to conform to the equilibrium behavior predicted by the theory.

2 The theoretical model

2.1 Partnerships

We start by giving a brief sketch of the theoretical model.

We consider a society of n agents who are organized in a social network g. The social network evolves over time, as agents will delete links and leave the network. At any discrete time $t = 1, 2, ..$, one agent is chosen with probability $\frac{1}{n}$ to request a favor from a neighbor. If the favor is granted, the agent who receives the favor obtains a flow payoff of v and the agent who grants the favor pays a flow cost c. All agents discount the future using the same discount factor δ. We define the *value* of a *partnership* as the expected discounted payoff obtained by an agent when he has found a partner with whom he *reciprocates* favors,

$$V = \frac{v - c}{n(1 - \delta)}.$$

Partnerships are formed according to the following decentralized procedure. Suppose that an agent i needs a favor at date t. Two situations may arise:

- Either agent i is already in a partnership
- Or agent i is not yet in a partnership

In the former case, the favor is offered by agent i's partner. In the latter case, agent i turns to his direct neighbors in the current social network g_t and asks them sequentially for a favor. The sequence in which he approaches his neighbors for the favor is exogenously given. If neighbor j is approached by agent i, he responds by Yes or No to the offer. If agent j rejects the request from i, the link ij is destroyed, the new social network is $g_t \setminus ij$, and agent i turns to the next neighbor in his chosen sequence. If all agents reject i's request, the network at next period is

$$g_{t+1} = g_t \setminus i,$$

the network obtained from g by deleting i and all his links.

If agent j responds Yes, the partnership $\{ij\}$ is formed, and the two partners leave the social network, deleting all their links. Thus, the partnership forms as soon as a favor is granted. We let

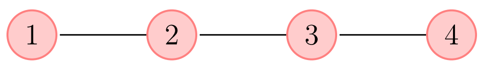
$$g_{t+1} = g_t \setminus i, j,$$

denote the network obtained after agents i and j have left. If j accepts i's request, but has not in the past approached i for a favor, then the network remains unchanged till the next period, when a possibly different agent needs a favor. A strategy for player j specifies, for any possible network g and any proposer i a decision to accept or reject the formation of a partnership. A subgame perfect equilibrium is a collection of strategies such that every agent plays his optimal strategy after every possible history.

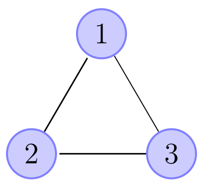
2.2 Matchings and essential nodes

In this subsection, we collect definitions in graph theory pertaining to matchings and bipartite graphs which will prove useful in our analysis.[5] Given a network g, a *matching* M is a collection of edges in g such that no pair of edges in M has a common vertex. A matching M is maximal if there is no matching $M' \supset M$ in g. A matching M is a *maximum matching* if there is no matching M' in g such that $|M'| > |M|$. For any graph g, we let $\mu(g)$ denote the *matching number* of graph g, i.e. the size of any maximum matching in g.

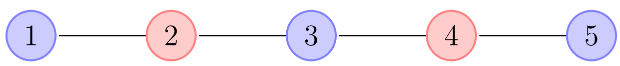
A node i in graph g is called *essential* if it belongs to *all* maximum matchings of the graph g. It is called *inessential* otherwise. Clearly, all nodes are essential in a perfect graph. As illustrated in Figure 2, all nodes are inessential in the odd cycle C_3, and in the line L_5, nodes 2 and 4 are essential, but not nodes 1, 3 and 5. In the line L_5, node 3 is the most central node according to all measures of node centrality, but is inessential. This example shows that there is no connection between centrality and essentiality of nodes in a graph.



The line L_4



The cycle C_3



The line L_5

[5]See Lovasz and Plummer (1986) for an excellent monograph on matchings and bipartite graphs.

Figure 1: Essential and inessential nodes

The following Proposition characterizes subgame perfect equilibrium strategies.

Proposition 2.1 *Suppose that j receives a request from i in the social network g. Then, in a subgame perfect equilibrium, j accepts the request if and only if j is inessential in $g \setminus i$ or $g \setminus i, k$ where k is the first agent (if any) to accept i's request if j refuses the requesr.*

Proof. We only give here a sketch of the proof. The full proof can be found in the companion paper (Bloch, Dutta and Manea (2018)).
We first make some observations on the characterization of essential nodes when the network evolves and becomes sparser:

1. If i is an essential node in g, there exists $ij \in g$, such that j is inessential in $g \setminus i$.

2. If i is not an essential node in g and $ij \in g$, j is an essential node in $g \setminus i$.

Any essential node i must be connected to some node which is inessential in $g \setminus i$. On the other hand, all neighbors of an inessential node i are essential in $g \setminus i$. When an inessential agent is removed from the network, all essential agents remain essential. When a pair of agents leaves the network, without disrupting the total number of matchings, all essential agents remain essential as well. This will lead us to show that in a subgame perfect equilibrium, all essential agents are guaranteed to find a partner whereas inessential agents may not find a partner with positive probability.
The proof is by induction on the number of agents in a connected component. For $n = 2$, both agents are essential and the statement is trivially satisfied. For $n = 3$, we show that the characterization is valid both in the line L_3 and in the circle C_3. The difficult part of the proof is to prove the inductive step. We do so by proving a sequence of assertions, noting that essential agents have no incentive to accept a proposal but inessential agents always accept.
■
We now use the characterization of equilibrium behavior to observe that when players are sufficiently patient, the maximum number of pairs are formed in equilibrium.

Theorem 2.2 *There exists $\overline{\delta} > 0$ such that for all $\delta \geq \overline{\delta}$, the maximum number of pairs is formed in a subgame perfect equilibrium.*

Proof. The complete proof is in BDM. The proof relies on the fact that, if an agent rejects the formation of a partnership, she must remain essential in the continuation game after the link ij has been deleted. But this implies that the matching number of the graph cannot drop after a rejection.
■

3 Experimental design

In order to test the behavior of agents in the game of partnership formation in social networks, we design a laboratory experiment in the model with costly favors.[6] The objective of the experiment is to check whether boundedly rational agents will play equilibrium strategies when facing incentives in real social-network interactions, and to what extent different networks support efficient outcomes.

Unlike the infinite process described in Section 2, the experiment must stop in finite time. We assume that once agents form partnerships and leave the network, they immediately collect the total value of the partnership and will not request or grant favors anymore. Only those agents who are not yet in a partnership are chosen with equal probability to request a favor from one of their neighbors. The process ends when no new partnership can be formed in the network. The value obtained by an agent in a partnership is either $v - c$ (if the agent grants the favor) or v (if he requests the favor). Agents who are not in a partnership at the end of the process receive a value of 0. We calibrate the values of v and c so that, in the particular networks we consider in the experiment, the equilibrium behavior in the finite game coincides with the equilibrium of the game of partnership formation of Section 2 when the discount factor δ converges to 1.

3.1 Initial social networks in the experiment

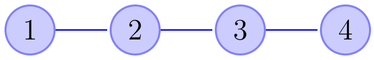
We choose five initial social networks in the experiment which are depicted in Figure 2. The number of nodes, links and complexity of the network structure increase from social network 1 to social network 5. The first two social networks are the lines L_4 and L_5. The other three social networks are more complex and involve cycles with four agents in social network 3, five agents in social network 4, and seven agents in social network 5.

In the experiment, subjects go through the initial social networks 1 to 5 in sequence. They play the game with each initial social network five times so play a total of 25 times. There are also 2 practice periods on social network 1 at the beginning of the experiment.

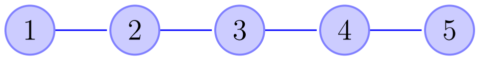
At the beginning of each period, subjects are randomly re-matched into groups. The network positions are also randomly assigned in each period. Given any initial network, each period starts with one agent, say i, being randomly chosen to request a favor from one of his neighbors, agent j. The sequence in which agent i approaches his neighbors is chosen at random by the computer.[7] Agent j then decides whether to accept the offer or not. If the offer is accepted, the partnership is formed and both agents leave the social network. If

[6] Behavior in the model of positive favors is obvious, so we do not feel that an experiment will be helpful there.

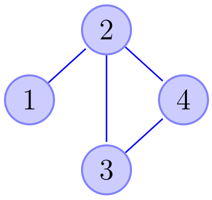
[7] In the theoretical model, the proposer chooses the sequence in which neighbors are approached. But



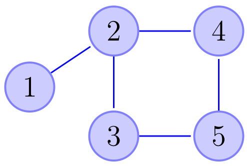
Social network 1



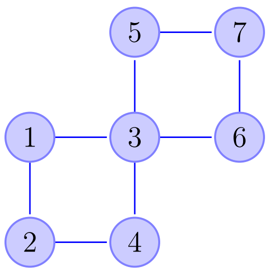
Social network 2



Social network 3



Social network 4



Social network 5

Figure 2: Initial social networks 1-5 in the experiment

this agent decides to reject the offer, the link between i and j is destroyed. Agent i then requests a favor from his next neighbor in the sequence. If all neighbors reject his request, agent i will be cut off from the social network. Once agents leave or are cut off from the social network, the computer will then randomly select the next agent from the remaining social network and the same process is executed again. The social network evolves until each agent either has a partner or is isolated. Each period thus involves a sequence of decisions, with each decision made in a specific network by the selected subject. For each decision, subjects who made it and who proposed the request are informed of the result and their respective payoffs, and others in their group are shown the changes in the social network on the computer screen.

3.2 Individual difference tests

Belief elicitation
Subjects should make decisions in the game according to their beliefs about the rationality and the behavior of other agents in the social network. In order to take into account these beliefs in the analysis of decisions, we have asked subjects about the decision of other agents in a simple situation. In the context of the 3-agent line L_3, subjects are asked to give an estimate of the proportion of central agents who actually accepted the request from one of the extreme nodes. In this situation, the agent should always reject the request, as he obtains either v or $v - c$ after the rejection. The actual proportion of acceptance from central agents is 14.6%. The average estimated proportion of acceptance is 20.8%, and half of the subjects believe that it is smaller than 10%. In addition, only 15.6% of subjects estimate that the proportion of acceptance is equal to or higher than 50%. This question is not incentivized in our experimental design.[8]

Cognitive ability
In our experiment, cognitive abilities are elicited with the CRT test (Frederick, 2005). This test is designed to assess an individual's ability to move from an intuitive and spontaneous wrong decision to a reflective and deliberative right one. Subjects are asked to answer three questions in the CRT test, which are listed as follows:

- Question 1: A bat and a ball cost €11. The bat costs €10 more than the ball. How much does the ball cost?

whether the sequence is chosen endogenously or exogenously does not affect the equilibrium response of the agents. Since the analysis focuses on equilibrium responses and matchings formed, the two models with endogenous and exogenous sequences are equivalent.

[8]This is not a true elicitation of subjects' beliefs about other agents' behavior as the answer to this question depends also on the rationality of the subject questioned. Nevertheless, the answer to this question may explain deviation from the equilibrium strategy.

- Question 2: If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
- Question 3: In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

Although the CRT test is relatively short and simple to perform compared to other cognitive tests, its results are positively related with rational thinking performance (Toplak, West and Stanovich, 2011). On average, 1.75 questions are answered correctly by subjects in the CRT test for this study.

Risk elicitation
Rejection is a risky decision when the acceptance of the request gives $v - c$ for sure. So, acceptance and rejection decisions should be related to subjects' attitudes towards risk. We elicited this attitude following a procedure introduced by Eckel *et al* (2012). The procedure consists of a choice among six lotteries in the form of a coin flip that gives a low or a high payoff with equal probability. The lotteries are arrayed from a safe one with a certain payoff of 18 experiment points to a highly risky one with a high payoff of 54 points and a negative low payoff of -2 points. Expected return increases along with higher variance as one moves from the safest to the riskiest lottery. The variance that a subject is willing to accept gives a proxy of his risk preference. Therefore, we can estimate each subject's level of risk attitude by looking at his choice among six lotteries: lottery 1 through 4 represent decreasing levels of risk aversion, lottery 5 indicates risk neutrality, and lottery 6 corresponds to risk seeking individuals.

Table 1: Six lotteries in risk test

Lottery	Payoff (experiment points)				Risk Preference	Percentage
	Low (50%)	High (50%)	Expected	Variance		
1	18	18	18	0	Highly risk averse	20.14%
2	14	26	20	36	Very risk averse	22.86%
3	10	34	22	144	Risk averse	17.1%
4	6	42	24	324	Slightly risk averse	7.49%
5	2	50	26	576	Risk neutral	15.31%
6	-2	54	26	784	Risk loving	17.1%

3.3 Experimental procedure

In each experimental session, subjects are randomly assigned ID numbers and seats in front of the corresponding terminal in the laboratory. The experimenter reads the instructions aloud.

Subjects are given the opportunities to ask questions, which are answered in private. We check the subjects' understanding of the instructions by asking them to answer 7 incentivized review questions at their own pace. After answering one review question, each subject is shown whether his answer is correct, as well as the right answer. After going over all review questions, subjects go through 27 periods in the social-network experiment, including 2 practice periods. Afterwards, subjects are asked to report their beliefs on other agents' behaviors, and take the CRT and risk tests. At the end of the experiment, each subject fills out a demographic survey on the computer, and is then paid in private. Each session lasts approximately 80 minutes, with 15 minutes devoted to the instructions. The experiment is programmed in Java.

In the experiment, we set the parameters at $v = 20$ experimental points and $c = 8$ points. Therefore, in a given period, a subject will obtain a payoff of 20 points by requesting a favor or 12 points by granting a favor. If the subject has no partner, he will earn 0 points. There are 21 subjects in each session. As there are 4 or 5 subjects per group from the initial social networks 1 to 4, for the corresponding period one subject will be randomly chosen not to play and be paid 10 points. At the end of the experiment, 10 out of 25 periods are randomly chosen to be paid. In addition, a subject could earn 2 points per review question and per CRT question answered correctly. He will also earn the payoff resulting from the draw for the lotteries he chose in the risk test. The exchange rate is 10 experiment points for €1 for all sessions. Each subject also receives a participation fee of €3. The average earning (including participation fee) is equal to €21.

All sessions were conducted in French at GATE-LAB, the Experiment Economics Laboratory in Lyon between April and September 2015. The subjects are students from an engineering department, Ecole Centrale de Lyon, a business school EM Lyon, and the University of Lyon. No one participated more than once. We ran 6 independent sessions. In total, 126 subjects participated in the experiment and we collected 1842 decisions. The English translations of the experimental instructions can be found in the Appendix.

4 Results

In this section, we analyze the results of the experiment, focusing on two main questions. First, we study individual behavior and analyze whether agents play the subgame perfect equilibrium strategy, which is also referred to as risk-neutral best response (BR) here. We also identify which factors could explain the deviation from the best response behavior. Second, we analyze whether, at the aggregate level, the social interaction among real agents results in efficient outcomes in different social networks.

4.1 Individual behavior

To check whether subjects choose the BR, we consider all networks which may arise during the experiment and break down behavior in the various networks, defining different situations that subjects are faced with when making decisions in each graph.[9] Overall, there are 28 possible graphs and 105 possible situations in the experiment.

For each situation, we compute the BR of the agent using the characterization results of Section 2. We also calculate the expected value of acceptance, which is always 12 with certainty, and the expected value of rejection for each situation. For example, in Figure 2, suppose that agent 2 in the initial social network 1 receives a request from agent 3. Agent 2 can make the following calculation using backward induction. He will earn 12 for sure by accepting the request; however, if agent 2 declines the offer, the link between agents 2 and 3 will be destroyed, and agent 3 would make a request to agent 4, who is expected to accept the offer. The network would then evolve to L_2 where agent 2 has 50% chance of earning 20 by making a request that should be accepted by a rational agent 1, and 50% chance of earning 12 by accepting the request from agent 1. The expected value is thus $0.5 \times 20 + 0.5 \times 12 = 16$. Hence agent 2 should reject the offer. Generally, the difference between the expected values of rejection and acceptance is defined as follows:

$$\text{EV.difference} = \text{Expected value of rejection} - \text{Expected value of acceptance.}$$

Note that when EV.difference > 0, BR is to reject, and when EV.difference < 0, BR is to accept.[10]

Due to strategy uncertainty, subjects may not behave according to the expected value difference calculated under the assumption that other agents play BR. For instance, in the previous example, it is possible that agent 1 mistakenly rejects the offer, making the payoff after rejection equal to $0.5 \times 0 + 0.5 \times 12 = 6$ for agent 2. Considering the possibility of agent 1's mistake, agent 2 may instead accept the offer as he earns less than 12 by rejection. We thus decided to check if subjects make decisions based on the difference between the actual payoffs after rejection and acceptance. The actual payoff after rejection is computed, for each situation, as the average actual payoff after rejection. The difference between actual payoff after rejection and acceptance is therefore defined as follows:

$$\text{Real.difference} = \text{Real gain of rejection} - \text{Real gain of acceptance.}$$

Finally, in order to assess the complexity of each situation, we compute the steps of reasoning a person has to consider when making the decision, i.e. the number of successive decisions

[9] For instance, in the initial network 1 or line L_4, there are 3 different situations: one where an extreme agent requests a favor from a central agent, one where a central agent requests a favor from an extreme agent and one where a central agent requests a favor from the other central agent.

[10] Given our design, we did not have any situation with indifference in the experiment.

in the longest path of the extensive form game starting from this situation.[11] For instance, when agent 2 receives a request from agent 3 in the previous example, the complexity for agent 2 is equal to 2. We also calculate the complexity of the social network by taking the average of complexity in all possible situations at a given initial graph, and find that the complexity increases from 2 steps of reasoning on average for the initial social network 1 to 8 steps of reasoning for the initial social network 5.

4.1.1 Basic findings

We first examine whether subjects behave according to the subgame perfect equilibrium of the partnership formation game. Overall, we find that the proportion of best responses is equal to 79.5%. Even if we exclude the simple situations where the decision maker only has one link, the proportion of best response remains as high as 66.7%. Table 2 presents the proportions of rejection for EV.difference > 0 (Real.difference > 0) and EV.difference < 0 (Real.difference < 0) in each session, respectively. On average, the proportion of rejection is as high as 67.2% (59.5%) when EV.difference > 0 (Real.difference > 0) and as low as 12.8% (26.5%) when EV.difference < 0 (Real.difference < 0) (the proportion of acceptance is 87.2% (73.5%) correspondingly). In other words, a majority of subjects play equilibrium strategies, with 67.2% of rejection when BR is to reject and 87.2% of acceptance when BR is to accept.

Table 2: Proportions of rejection

	EV.difference > 0	EV.difference < 0	Real.difference> 0	Real.difference < 0
Session 1	0.691	0.106	0.583	0.263
Session 2	0.703	0.148	0.588	0.297
Session 3	0.655	0.089	0.556	0.239
Session 4	0.528	0.140	0.492	0.231
Session 5	0.768	0.143	0.708	0.290
Session 6	0.683	0.139	0.646	0.273
Average	0.672	0.128	0.595	0.265

Even though subjects generally conform to the theoretical prediction, we find that their choices vary greatly in different situations. Table 3 presents some graphs which arise frequently during the experiment. These graphs are ordered from the simple two-agent line

[11] Other measures of complexity of the situation can also be computed, such as the total number of nodes in the extensive form of the game or the total number of terminal nodes, etc. We find that all of these measures are highly correlated with each other.

to the most complex seven-agent network, labeled as $g_1, \ldots g_8$ in sequence. In each graph, we compute the expected value difference, real earning difference, the proportion of best response as well as the number of observations for each possible situation. It can be seen from Table 3 that subjects perform differently when the social networks are lines (e.g. 85.7% of best response for g_1 to g_3) and when social networks have cycles (e.g. 24% and 51.3% of best responses in g_4 and g_5, respectively). Their rational reaction also changes with different positions in a given graph (e.g. in g_6, 88.9% of best response when agent 3 or 4 requests to 1 and 50% conversely) or when different neighbors place requests (e.g. in g_7, 80% of rational acceptance for agent 2 when 3 requests a favor and 44.4% when 1 makes the request).

In particular, we observe that subjects tend to follow two behavioral patterns, which are presented in Figure 3.

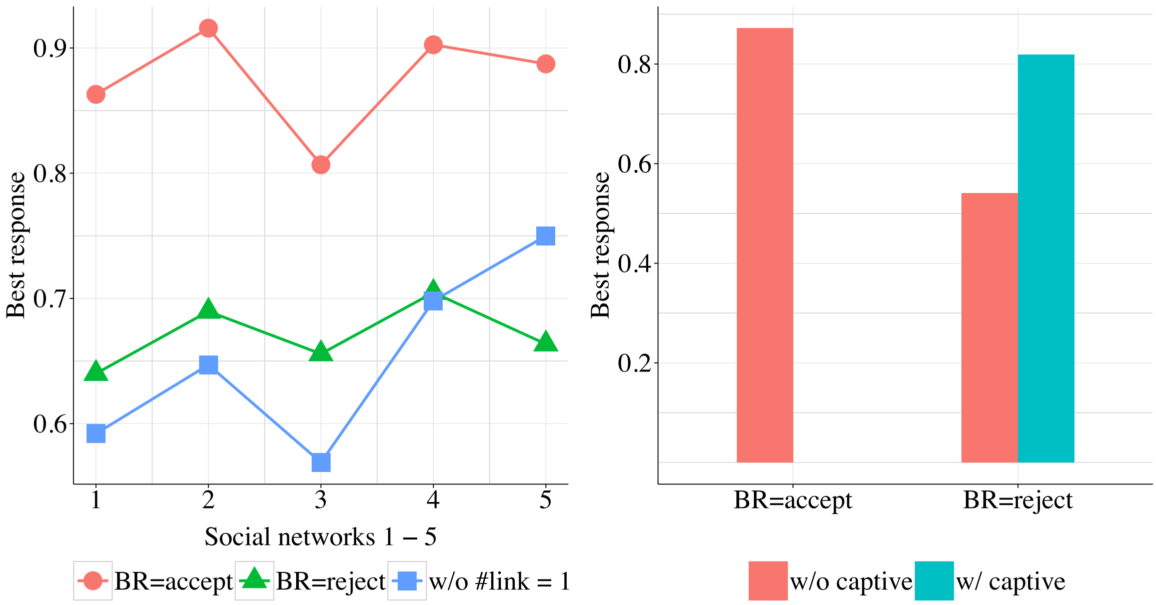
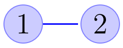
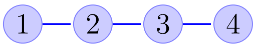
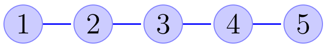
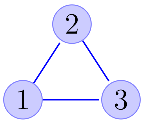
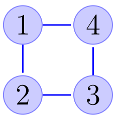
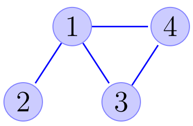
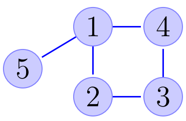
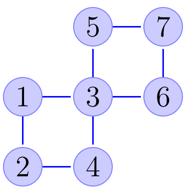


Figure 3: Two behavior patterns in the experiment

First, subjects are more likely to accept than to reject (left panel of Figure 3). On average, 65.6% of requests are accepted by subjects. We also find a higher rate of rational acceptance (acceptance when BR is to accept), which is 87.2%, compared to 67.2% for rational rejection (rejection when BR is to reject). However, the high rate of acceptance is probably due to the fact that rational acceptance includes the simple situations where the decision maker has only one link. If we exclude these situations, the proportion of rational acceptance is only 64.7%.

Table 3: Proportions of best response in selected graphs

#	Graph	Situation	EV.diff.	Real.diff.	BR	# of obs.
g_1:		1 (2) → 2 (1)	-12	-12	0.983	478
g_2:		1 (4) → 2 (3)	-4.7	-4.44	0.649	154
		2 (3) → 3 (2)	4	3.82	0.733	60
		2 (3) → 1 (4)	-12	-12	1	63
g_3:		2 (4) → 3	-4.7	-0.27	0.7	20
		1 (5) → 2 (4)	4	1.57	0.529	87
		3 → 2 (4)	4	3.2	0.769	26
		2 (4) → 1 (5)	-12	-12	1	27
g_4:		2 (3) → 1	4	-1.33	0.24	25
g_5:		2 (4) → 1	4	1.6	0.513	39
g_6:		2 → 1	-1.33	-4	0.39	41
		3 (4) → 1	4	1.33	0.889	27
		3 (4) → 4 (3)	-4.7	-4	0.676	37
		1 → 3 (4)	4	3.5	0.5	32
		1 → 2	-12	-12	1	13
g_7:		5 → 1	4	-0.52	0.784	37
		2 (4) → 1	4	0.57	0.824	34
		3 → 2 (4)	-4.7	0.8	0.8	35
		1 → 2 (4)	-0.35	0.8	0.444	18
		2 (4) → 3	4	-0.11	0.359	39
		1 → 5	-12	-12	1	12
g_8:		1 (4, 5, 6) → 3	4	0.76	0.8	30
		2 (7) → 1, 4 (5, 6)	- 3.34	1.14	0.667	24
		3 → 1 (4, 5, 6)	-1.8	-1.71	0.714	7
		1, 4 (5, 6) → 2 (7)	4	0.95	0.414	29

We conduct probit regressions to control for this fact,[12] and still find a significantly higher rate of rational acceptance than rational rejection.[13] There are two plausible explanations for this tendency to accept: (1) to reject is a risky choice and subjects tend to accept because of risk aversion; (2) there is a cognitive cost to calculate expected value of rejection, and so subjects will make the immediate acceptance decision instead. We will explore these two explanations in the next subsection.

Second, subjects tend to rationally reject when they have a *captive agent* not making the request (right panel of Figure 3). An agent is said to be a *captive agent* if he has only one connection in the social network. So one should expect that a captive agent will always accept the request from his only neighbor. When a subject has a captive agent he should reject the current offer as he is guaranteed to earn 20 by requesting a favor from his captive agent. We find that 81.9% of requests are rationally rejected when subjects have captive agents not making the request, compared to 54.1% of rational rejection by subjects who do not have captive agents. (This effect is proved to be significant through regression results in the next subsection).

4.1.2 Determinants of behavior

We now analyze in detail departures from equilibrium behavior related to the characteristics of the current social network and situation. We also control for factors related to individuals. In order to systematically check how these factors affect the strategies of the subjects, we conduct probit regressions. The results are presented in Table 4 and Table 5. The dependent variable is the probability of best response when BR is to reject (in Table 4) and when BR is to accept (in Table 5), respectively. Independent variables include "EV.difference", the difference between expected value after rejection and acceptance in specifications (1) through (3), "Real.difference", the difference between actual payoffs after rejection and acceptance in specifications (4) through (6). Specifications (1) and (4) only include variables related to the characteristics of the social network and situation: a dummy variable "Steps of reasoning" which is equal to 1 if an agent has to consider more than 3 steps of reasoning in the extensive form of the game he faced, a dummy variable "Cycle" which is equal to 1 if subject is in the cycle. In the case of the regressions when BR is to reject (in Table 4), we add an additional dummy variable "Captive" which is equal to 1 if the subject has a captive agent who is not the one who requests a favor from him. Specifications (2) and (5) control for individual

[12] In the regressions, the dependent variable is the probability of best response. The primary independent variable is the dummy variable "BR Reject" which is equal to 1 if BR is to reject. Control variables include the dummy variable "One link" which is equal to 1 if the subject has only one link, the absolute difference between expected value and actual value after rejection and acceptance, as well as other variables introduced in the regressions in the next subsection. The regression results are presented in Table **??** in Appendix.

[13] In Table **??**, the coefficients for dummy variable "BR Reject" are negative and significant at $p < 0.01$ or $p < 0.05$.

differences: the measure of "Risk" preference for a subject where smaller value indicates higher level of risk aversion, the number of correct answers in the "CRT" test, and the proxy for the subject's "Belief" about other agents' rationality where a lower percentage represents a higher estimation of the rationality of other agents. Finally, specifications (3) and (6) add individual ”Experience", the number of decisions the subject has already made, in order to capture a learning effect.

Table 4: Probit regressions: Probability to best respond when BR is to reject

	(1)	(2)	(3)	(4)	(5)	(6)
EV.difference	-0.030	-0.029	-0.043			
	(0.115)	(0.117)	(0.112)			
Real.difference				-0.007	-0.008	-0.001
				(0.010)	(0.008)	(0.009)
Steps of Reasoning	-0.168***	-0.177***	-0.143***	-0.175***	-0.184***	-0.145***
	(0.043)	(0.044)	(0.041)	(0.038)	(0.039)	(0.034)
Cycle	0.010	0.005	-0.033	0.016	0.011	-0.032
	(0.062)	(0.058)	(0.059)	(0.066)	(0.061)	(0.063)
Captive	0.400***	0.397***	0.395***	0.404***	0.401***	0.394***
	(0.040)	(0.041)	(0.042)	(0.037)	(0.040)	(0.040)
Risk		0.016**	0.018**		0.016**	0.018**
		(0.007)	(0.007)		(0.007)	(0.007)
CRT		0.014	0.011		0.014	0.011
		(0.021)	(0.021)		(0.020)	(0.021)
Belief		-0.002**	-0.002***		-0.002**	-0.002***
		(0.001)	(0.001)		(0.001)	(0.001)
Experience			0.014***			0.014***
			(0.003)			(0.004)
No. of observations	724	724	724	724	724	724

Note: standard errors in parentheses are clustered at the session level; coefficients are marginal effects. *** p<0.01, ** p<0.05, * p<0.1.

We first check the relation between best response and expected value difference as well as real earning difference. Figure 4 presents the proportion of rejection in each situation for each expected value difference (left panel) and real earning difference (right panel), respectively.

Table 5: Probit regressions: Probability to best respond when BR is to accept

	(1)	(2)	(3)	(4)	(5)	(6)
EV.difference	-0.033***	-0.033***	-0.032***			
	(0.002)	(0.002)	(0.003)			
Real.difference				-0.024***	-0.024***	-0.024***
				(0.002)	(0.002)	(0.002)
Steps of Reasoning	-0.101***	-0.109***	-0.074*	-0.034	-0.048	0.011
	(0.033)	(0.030)	(0.038)	(0.042)	(0.044)	(0.060)
Cycle	-0.062	-0.068	-0.058	-0.028	-0.040	-0.018
	(0.048)	(0.044)	(0.045)	(0.044)	(0.045)	(0.050)
Risk		-0.008***	-0.009***		-0.007**	-0.007***
		(0.002)	(0.002)		(0.003)	(0.003)
CRT		0.016**	0.015**		0.016**	0.016*
		(0.008)	(0.008)		(0.008)	(0.008)
Belief		-0.001	-0.001		-0.001	-0.001
		(0.000)	(0.000)		(0.001)	(0.001)
Experience			0.005**			0.009***
			(0.003)			(0.003)
No. of observations	1,118	1,118	1,118	1,104	1,104	1,104

Note: standard errors in parentheses are clustered at the session level; coefficients are marginal effects. *** p<0.01, ** p<0.05, * p<0.1.

For risk neutral rational agents, the proportion of rejection should be equal to zero when EV.difference < 0 and equal to one when EV.difference > 0.

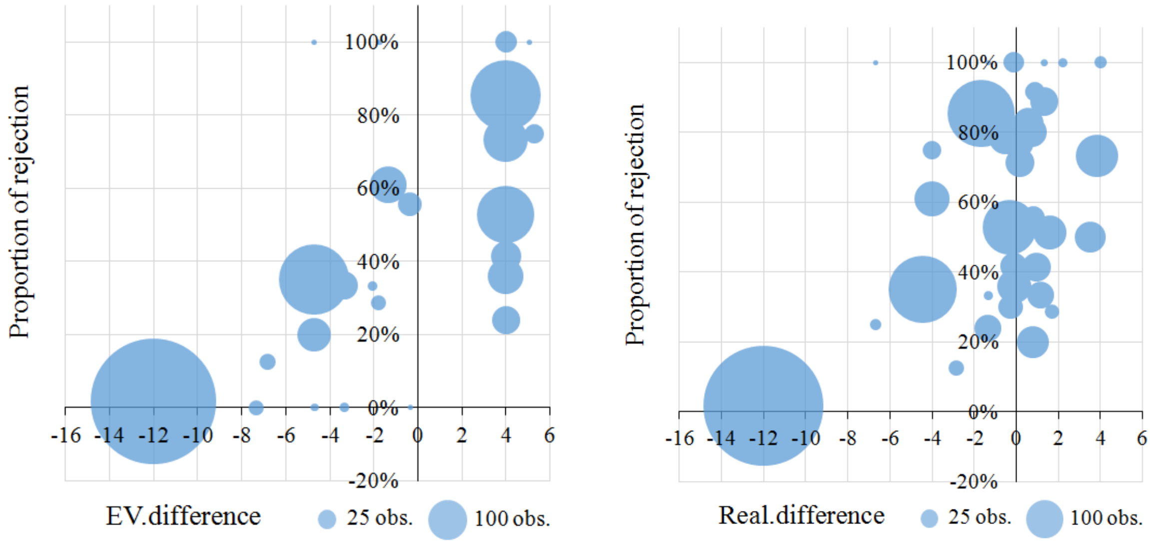


Figure 4: Proportion of rejection in each situation by EV.difference and Real.difference

It can be seen from Figure 4 that although subjects do not play completely according to the theoretical prediction, they are more likely to reject when the expected value difference or the real earning difference increases. In particular, this relation is almost linear when EV.difference < 0 and Real.difference < 0.

Regression results in Table 5 support this finding. A subject's probability of playing a best response (acceptance) will significantly decrease by about 3.2 percentage points when the expected value difference increases by 1 unit ($p < 0.01$ for coefficients "EV.difference"), and will significantly decrease by about 2.4 percentage points when the real earning difference increases by 1 unit ($p < 0.01$ for coefficients "Real.difference"). We note that when BR is to accept, the expect value difference is negative (EV.difference < 0). So the subject's best response significantly increases with the absolute value difference between rejection and acceptance, indicating that subjects tend to play equilibrium strategies when the cost of deviation from rational acceptance increases.

However, Figure 4 shows that when BR is to reject (EV.difference > 0), there is a striking heterogeneity among subjects' best responses according to different decision situations, even for situations with the same expected value difference. In fact, the coefficients of "EV.difference" in specifications (1) through (3) and the coefficients of "Real.difference" in specifications (4) through (6) in Table 4 are all negative and insignificant. This indicates that other characteristics of the situation, such as complexity of the network or the structure of the network are likely to play a role in situations when BR is to reject.

We next present in Figure 5 the proportion of best responses as a function of the steps of reasoning when BR is to accept or to reject (left panel), and when the decision maker is in a line or in a cycle (right panel).

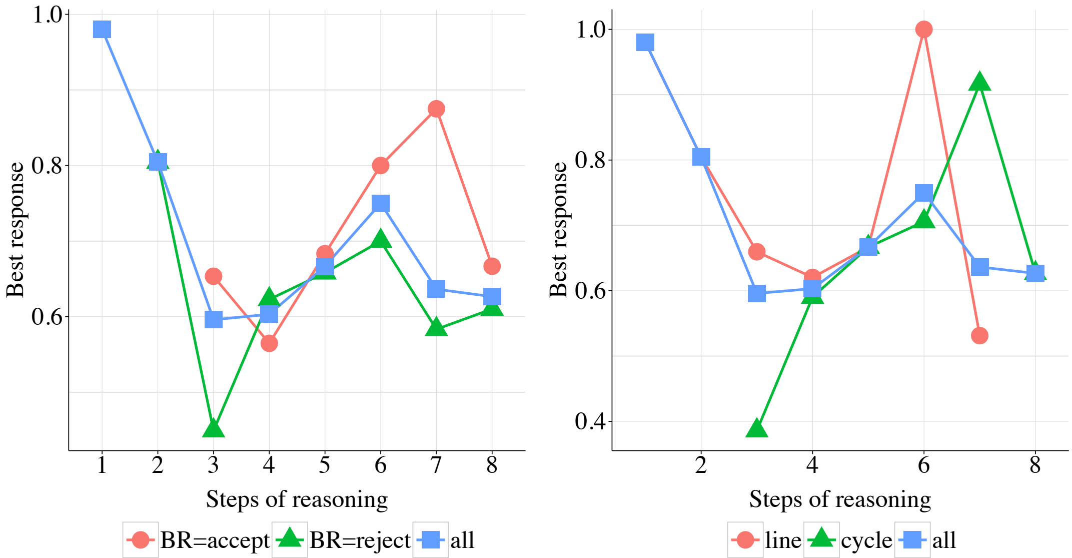


Figure 5: Proportion of best response by situation complexity

It can be seen from Figure 5 that the proportion of best response decreases with the complexity at first and then increases slightly when the number of steps of reasoning is higher than 3. We also observe a high volatility of best responses for some steps of reasoning. This is probably due to the small number of observations, especially when the situation becomes more complex -we only have a third of the total observations corresponding to situations where the number of steps of reasoning is higher than 3. Overall, we find that the proportion of best responses is high when the situation is less complex. The proportion of rational rejections is 73.1% (91.8% of rational acceptance) when the number of steps of reasoning is smaller than 3, and is 62.9% (64.1% of rational acceptance) otherwise. Results of the regressions in Table 4 and Table 5 further show that when it takes more than 3 steps of reasoning, the probability of best responses significantly decreases by at least 14.3 percentage points when BR is to reject ($p < 0.01$ for coefficients "Steps of Reasoning" in Table 4) and by about 7.4 percentage points when BR is to accept. However, the effect is only significant if we do not control for learning effect and real earning difference ($p < 0.01$ in specifications (1) and (2) in Table 5).

On average, it takes 5 steps for a subject to figure out his subgame perfect equilibrium strategies when he is in a cycle, but it only requires 2 steps in a line. However, when we control for the complexity of the situation, the network structure - whether the subject is in a line or in a cycle - has no significant effect on the probability of best response (coefficients for "Cycle" are insignificant in Table 4 and Table 5). On the other hand, when facing the same level of complexity, the probability of best response significantly increases by at least 39.4 percentage points if the subjects have captive agents when BR is to reject ($p < 0.01$ for coefficients "Captive" in Table 4). This result further supports the previous finding that this heuristics helps subjects adopt equilibrium strategies.

We next argue that risk aversion, cognitive ability, subject's belief about other participants' rationality can also help explain behavior heterogeneity. Regression results show that subjects with higher levels of risk aversion are significantly less likely to rationally reject (the coefficients for "Risk" are 0.016 to 0.018 at $p < 0.05$ in Table 4) and are significantly more likely to rationally accept the favor (the coefficients for "Risk" are -0.009 to -0.007 at $p < 0.05$ in Table 5). That is, risk aversion makes subjects more likely to accept, especially in situations when BR is to reject. Even in the "safe rejection" situations when subjects will earn at least 12 by rejection, highly risk averse subjects- those who choose low but certain payoff in the risk test- still tend to accept (56.6% of rejection by high risk averse subjects v.s. 70.3% of rejection by other types of subjects).

On the other hand, subjects have to invest their cognitive abilities and cognitive efforts to calculate the expected value of rejection so as to find out their optimal choices. We use the number of correct answers in the CRT test as the proxy for subjects cognitive abilities and cognitive efforts. We find that subjects with a better answer in the CRT test are more likely to play equilibrium strategies. However, this effect is only significant ($p < 0.05$ for coefficient "CRT" in Table 5) and sometimes marginally significant ($p < 0.1$ for coefficient "CRT" in specification (3) of Table 5) when BR is to accept.

Subjects' beliefs about others' rationality may also affect their tendency to best respond. Regression results in Table 4 and Table 5 show that the coefficients of variable "Belief" are negative in all specifications, and in particular, they are significant when BR is to reject ($p < 0.05$ for coefficients "Belief" in Table 4). The result indicates that subjects holding a stronger belief about strategy uncertainty (i.e. weaker belief about others' rationality) are more likely to choose the safe "acceptance", when rejection is in fact their subgame perfect equilibrium strategies under the assumption of rationality for other agents.

Lastly, as the experiment is repeated for 25 periods, from the simple social network to the complex ones, it is interesting to ask whether previous experiences affect individual choices, and more importantly, whether subjects learn to best respond over time. We check the effect of a subject's own decision experience on best response by controlling for situation characteristics as well as individual difference, and find a significant learning effect. It can be seen from Table 4 and Table 5 that on average, with one more decision a subject has made, the probability of best response significantly increases by 1.4 percentage points when BR is to reject ($p < 0.01$ for coefficients "Experience" in Table 4), and by at least 0.5 percentage points when BR is to accept ($p < 0.05$ for coefficients "Experience" in Table 5).

4.2 Aggregate outcomes

In this subsection, we analyze whether aggregate behavior leads to efficient outcomes in the experiment. We first look at the number of matched pairs for each of the five initial social networks formed in the experiment. If all subjects follow the subgame perfect equilibrium strategies, as shown in Section 2, the maximum number of matches in the initial social network will be achieved. We therefore compute an efficiency index (EI) as follows:

$$\text{EI} = \frac{\text{Number of actual matched pairs}}{\text{Maximum number of matched pairs}}.$$

Notice that, in some social networks, the maximum number of matched pairs can still be formed when agents do not play their equilibrium strategies. For example, in the social network 5, even when some agents make mistakes by accepting the offer when they should reject, there will still be 3 matches formed at the end. On the contrary, in social network 1, if any of the agents does not play his best response, the efficient outcome cannot be achieved. As a result, social networks differ by the sensitivity of the number of matches formed as a function of the behavior of agents. Taking this fact into account, we consider random agents who randomly reject and accept the request in each situation with equal probability, and compute the number of matched pairs formed by these random agents. This gives us a benchmark with which to compare the efficiency level obtained by real agents. We compute a relative efficiency index (REI) as follows:

$$\text{REI} = \frac{\text{Number of actual matched pairs - Number of randomly matched pairs}}{\text{Maximum number of matched pairs - Number of randomly matched pairs}}.$$

Table 6 presents the outcome efficiency for each of five initial social networks, including the number of actual matched pairs, the number of randomly matched pairs, the maximum number of matched pairs, the efficiency index as well as the relative efficiency index. The proportion of best response is also computed for each initial social network. On average, the efficiency index is as high as 0.90 and the relative efficiency index is 0.75. We also find

Table 6: Outcome efficiency for initial social networks

Period	Network 1	Network 2	Network 3	Network 4	Network 5
1	1.63	1.96	1.53	1.96	2.78
2	1.73	1.92	1.53	1.88	2.89
3	1.60	1.96	1.63	1.96	2.94
4	1.63	1.88	1.53	1.96	2.89
5	1.77	1.88	1.57	1.96	3.00
Average	1.67	1.92	1.56	1.94	2.90
Random agents	1.09	1.41	1.13	1.51	2.25
Max.# of pairs.	2	2	2	2	3
EI	0.84	0.96	0.78	0.97	0.97
REI	0.64	0.86	0.49	0.88	0.87
Best response	0.828	0.821	0.756	0.804	0.774

that 78% of times (493 out of 630 total outcomes) the maximum number of matched pairs is achieved. More interestingly, in the most complex seven-agent social network, all groups achieve efficient outcomes in the last period. For each initial social network, the number of matched pairs established by random agents is also lower than that achieved by real agents.

In addition, the efficiency index (relative efficiency index) is 0.84 (0.64) and 0.78 (0.49) in social networks 1 and 3, lower than those in social networks 2, 4 and 5. We also observe that the efficiency level achieved by random agents is also lower in these two networks. In fact, social networks 1 and 3 have an even number of agents, whereas the rest has an odd number of agents. Therefore, the low level of efficiency in these two networks is partly due to the fact that they are more sensitive to mistakes in the agents' behavior. As a result, even though the proportion of best response in social network 1 is higher than that in all other networks, the efficiency level is lower.

5 Conclusion

This paper analyzes the formation of partnerships in social networks. Agents randomly request favors and turn to their neighbors to form a partnership where they commit to provide the favor when requested. The formation of a partnership is modeled as a sequential game, which admits a unique subgame perfect equilibrium resulting in the formation of the maximum number of partnerships. Experimental results show that a large fraction of the subjects (75%) play according to their subgame perfect equilibrium strategy and reveals that the efficient maximum matching is formed over 78% of the times. When subjects deviate from their best responses, they accept to form partnerships too early. The incentive to accept when it is optimal to reject is positively correlated with subjects' risk aversion, and players employ simple heuristics – like the presence of a captive partner – to decide whether they should accept or reject the formation of a partnership.

We are aware of a number of limitations of our model and experimental study and would like to focus our attention to two important questions in future work. First, we would like to extend the model to the study of partnerships of more than two agents. While this extension does not pose any conceptual difficulty, it requires to define generalized matchings of more than two agents, and requires to use more complex tools from graph theory. The second extension is to allow for heterogeneity in the value of partnerships, letting the value of the partnership depend on the pair ij, v_{ij}. Computing the optimal behavior of agents in non-stationary networks with heterogeneous values is a complex task. It will introduce a new dimension of heterogeneity (beyond the location in the network) in experiments. However, we believe that this is an important avenue for future research.

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A Experimental Instructions

We would like to thank you for having agreed to participate in this economics experiment. During this experiment, you will earn a certain sum of money. Your earnings are stated in experimental currency unit (ECU). At the end of the session they will be converted to euros using the following rate of conversion :

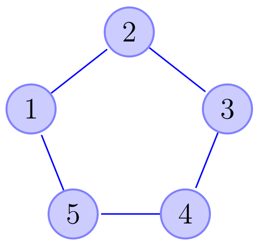
1 ECU = 0,1 Euros

So **10 ECU= 1 Euros**

Besides the earnings you will make during the experiment, you will receive a 3 Euros participation fee. Your earnings will be paid using a bank transfer during a maximum of 4 weeks . All the decisions which you will take during this experiment are anonymous. You will never have to identify yourself on the computer.

The experiment consists of several periods. At the beginning of every period the groups of players are randomly formed. The links between the members of the same group are represented in the form of a graph. In a graph a player can form a pair with his direct neighbors but not with the other players. The number of players and the structure of the graph change every five periods. The first two periods of the first sequence are trial periods which are not taken into account to determine your earnings. This experiment contains a total of 27 periods.

Example 1 :



In this group of 5 players, player #1 can form a pair with players #2 and #5 but not with players #3 and #4.

A player is chosen randomly among every group to be the claimant. All the players in the graph have an equal chance to be chosen. A neighbor chosen randomly among the neighbors of the claimant is requested to form a pair with the claimant. All the neighbors of the claimant have an equal chance to be chosen.

If this chosen neighbor accepts to form a pair with the claimant, then:

- The pair leaves the graph: all the links that linked the pair to the rest of the graph are deleted. The period ends for the two players of the pair.

- The claimant earns 20 ECU.

- The neighbor that accepted to form the pair with the claimant earns 20 - 8 ECU, so 12 ECU.

- If there is another possibility of forming a new pair in the remaining graph, another player is chosen randomly among the remaining players to be the new claimant.

If this chosen neighbor refuses to form a pair with the claimant, then:

- The link that linked the claimant to this neighbor is deleted.

- A neighbor is chosen randomly among the remaining neighbors to form a pair with the claimant.

- If the claimant has no remaining neighbors, then if there is another possibility of forming a new pair in the remaining graph, another player is chosen among the remaining players to be the new claimant.

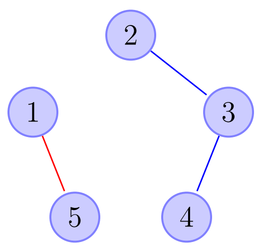
Example 2 : In the graph of example 1. We suppose that player #5 is chosen to be the claimant. We suppose that among the neighbors of player #5 (in this case player #1 and #4), player #1 is chosen to form a pair with player #5.
If player #1 accepts to form the pair with player #5.

- Players #1 and #5 are no longer linked to the remaining graph.

- Player #5 earns 20 ECU for this period.

- Player #1 earns 12 ECU for this period.

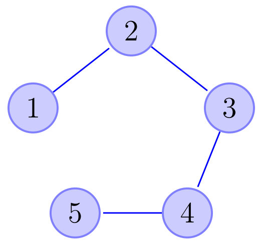
- A new claimant is randomly chosen among the players of the remaining graph formed by players #2, #3 and #4.



If player #1 refuses to form a pair with player #5.

- Players #1 and #5 are no longer linked in the graph.

- Player #4 has the opportunity to form a pair with player #5.



In the end, a claimant that forms a pair earns 20 ECU. A neighbor player who was chosen to form a pair and he accepts, earns 12 ECU. A player that doesn't belong to any pair at the end of a period, earns 0 ECU.
After the last period of the last sequence, 10 periods will be drawn randomly among the periods except the trial periods. The earnings obtained for these 10 periods will determine your earnings for this experiment. Every period has an equal chance to be drawn.
You are 21 participants in the room. When the number of players in the group is 4 or 5, there is then a participant that is randomly chosen, that won't be able to participate during one period. In this case, his earning for this period is 10 ECU.
It is totally forbidden to communicate between each other during the experiment. Any communication may cause the exclusion of the participant from the experiment without compensation. We kindly ask you to reread carefully these instructions and answer the questionnaire which is going to appear on your screens. Every correct answer to this questionnaire will yield a profit of 2 ECU . If you have questions - now or during the experiment, kindly call us by pressing your call button. We shall come to answer you in private.
A series of questions will be given to you after the 27 periods of the experiment. Some of these questions will allow you to win additional earnings