ISSN 1745-8587

Birkbeck
UNIVERSITY OF LONDON

School of Economics, Mathematics and Statistics

Birkbeck Working Papers in Economics & Finance

BWPEF 0905

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June 2009

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Abstract

We run a computerised experiment of network formation where all connections are beneficial and only direct links are costly. Players simultaneously submit link proposals; a connection is made only when both players involved agree. We use both simulated and experimentally generated data to test the determinants of individual behaviour in network formation. We find that approximately 40% of the network formation strategies adopted by the experimental subjects can be accounted for as best responses. We test whether subjects follow alternative patterns of behaviour and in particular if they: propose links to those from whom they have received link proposals in the previous round; propose links to those who have the largest number of direct connections. We find that together with best response behaviour, these strategies explain approximately 75% of the observed choices. We estimate individual propensities to adopt each of these strategies, controlling for group effects. Finally we estimate a mixture model to highlight the proportion of each type of decision maker in the population.

Keywords: network formation, experiments, mixture models

JEL classification:

1 Introduction

In the era of virtual social networks such as Facebook, or LinkedIn, there is very little doubt that network membership is generally seen as a positive ingredient for personal achievement and increased chances of success.

The mesh of interpersonal and community relations which facilitate communication, information and exchange is part of what has been called "social

*This paper has benefited from useful comments and discussion by seminar participants at the Max-Planck Institute of Economics in Jena, University of Westminster in London, ESA 2008 in Lyon, IAREP 2008 in Rome, IMEBE 2009 in Granada, and LABSI 2009 in Florence.

capital". This is a nebulous concept and difficult to quantify but it is generally agreed that it strongly affects behaviour and individual outcomes. Given that personal success can be both the result and the pre-requisite of a large social network, any attempt to quantify the impact of social capital on outcomes has to take into account the process of network formation.

Individual strategies for network formation can be extremely complex. The main reason for this is that a network differs from a series of bilateral relationships because of the value that accrues to agents through indirect connections: any two economic agents who have to decide whether to establish a social tie take into account not only their own characteristics and the characteristics of the prospective partner, but also their (and the prospective partner's) position in the social network.

The theoretical literature on endogenous network formation stems from two seminal contributions by Jackson and Wolinsky (1996) and Bala and Goyal (2000). Both papers follow a game-theoretic approach to the formation of social ties where the main idea is that players earn benefits from being connected both directly and indirectly to other players and bear costs for maintaining direct links.

Predicted outcomes are typically not unique. Even for those cases where the stable network architecture is unique (for example, the star network in information communication models *à la* Bala and Goyal or Jackson and Wolinsky), the coordination problem of which agent occupies which position in the network still remains.

In presence of multiplicity of equilibria and coordination problems, it is hardly surprising that most experimental contributions on this topic have highlighted the difficulty in obtaining convergence to a stable network architecture as predicted by the theory. More in detail, while convergence may be more easily achieved in experimental settings where the stable network architecture is the wheel (for positive results see Callander and Plott (2005) and Falk and Kosfeld (2003); for a negative result see Bernasconi and Galizzi (2005)), convergence is always problematic in frameworks where the prediction for the stable network is the centre-sponsored star (Falk and Kosfeld (2003), Berninghaus et al (2004), Goeree et al. (2005)). Falk and Kosfeld (2003) and Berninghaus et al (2004) highlight the role of complexity and lack of coordination in preventing convergence. Deck and Johnson (2004) avoid coordination failures by introducing heterogeneity among agents and by constructing a framework where the stable network is indeed unique.

Even in absence of coordination, the observed network structures are ultimately the outcome of individual linking decisions. In this paper we focus on the analysis of individual decision making for the formation of social networks. In particular we ask which variables correlate with the propensity that agents have to behave optimally in a network formation game. When they do not, we ask which other strategies or rules of thumb may explain individual behaviour, and the proportion of individuals in the population behaving according to each of these strategies.

We run a computerised experiment of network formation, where all connections are beneficial and only direct links are costly. The network formation protocol that we adopt, unlike the one used by most of the experimental literature that has focussed on convergence, requires that links are not unilateral, but have to be mutually agreed in order to form. In particular, players simultaneously submit link proposals and a connection is made only when both players involved agree[1].

We run 9 sessions, with each session involving 6 participants and a minimum of 15 rounds of network formation. We use both simulated and experimentally generated data to test the underlying model of network formation.

When all agents are expected utility maximisers and form static expectations about what the other players will do, and under the assumption that the unitary cost of link formation is lower than the benefit obtained from each connection, the model admits non-trivial equilibrium network architectures. More in detail, any minimally connected network is stable.

Minimally connected graphs are often reached in our experimental sessions, but are typically unstable. Convergence to a minimally connected network is only observed in one out of the nine experimental sessions (session 7 displayed at page 9), where a minimally connected graph is reached and then kept for four rounds until the end of the session. However 40% of the individual choices are rational in that subjects take the current network as given and propose links by maximising expected payoffs (best response).

Best response requires individuals to reciprocate link proposals to those that they do not reach in the current network and to delete direct connections when inexpensive indirect connections are available (redundant links).

We compare the frequency of best responses for our experimental subjects to the likelihood of seemingly optimal behaviour in simulated samples where individuals choose at random. We find that in the experimental sample subjects follow best response behaviour a significantly higher proportion of time. Hence we conclude that best response behaviour is "conscious".

As for the remainder of the sample (60% of non-best response behaviour) we find that experimental subjects have a tendency to: propose links to those from whom they have received link proposals in the past and to propose links to those who have a large number of links. Also, we find that the actual profits obtained when following these alternative strategies of "almost best-response" are not very distant from best response profits. Together with best response behaviour these strategies explain approximately 75% of the observed choices.

We estimate individual propensities to adopt each of these strategies controlling for group effects. We find that group effects matter greatly when best response strategies are implemented, while individual effects play a major role when the other two strategies are adopted.

In order to discriminate among these three types of systematic behaviour, we estimate a mixture model to find that these strategies are well identified and separated in our sample.

The paper develops as follows. Section 2 describes the experimental design: the model and the experimental procedure. Section 3 and 4 present the results respectively for the experimental network architectures that we obtain, and for the individual linking strategies. Section 5 concludes the paper. The instructions (in their English translation) can be found in the appendix. The software used for the experiment is available from the authors upon request.[2]

2 The Experimental Design

2.1 The Model

We model network formation as a non-cooperative simultaneous move game. As in Goyal and Joshi (2006) we assume that players' strategies are vectors of intended links and that links are only formed when they are mutually agreed, i.e. desired by both parties involved. There are positive network externalities in that both direct and indirect connections are beneficial; however direct links are costly.

Consider a set N of $n \geq 3$ players, indexed by $i = 1, 2, ..., n$. Each player i submits a vector of intended links:

$$s_i = (s_{i1}, s_{i2}, ..., s_{in})$$

An intended link is $s_{ij} = 0, 1$ where $s_{ij} = 1$ means that player i intends to link to player j, while $s_{ij} = 0$ means that player i does not intend to link to player j. A link between i and j is formed if and only if $s_{ij} = s_{ji} = 1$. We denote the formed link by $g_{ij} = g_{ji} = 1$, while we represent the fact that there is no mutually agreed link between i and j by setting $g_{ij} = g_{ji} = 0$. A strategy profile for all players

$$s = (s_1, s_2, ..., s_n)$$

induces an (undirected) network of links $g = \{g_{ij}\}_{i,j \in N}$, where players are nodes and links are the edges between them. We say that i and j are connected in the graph g if there exists a path of adjoining nodes $k_1, k_2, ..., k_m$ such that $g_{ik_1} = g_{k_1 k_2} = ... = g_{k_{m-1} k_m} = g_{k_m j} = 1$.

Denote by n_i^d the number of direct neighbours of player i, and by n_i the number of his direct and indirect connections. More in detail, denote by n_i^d the number of elements of the set $N_i^d = \{j \mid g_{ij} = 1\}$ and by n_i the number of elements of the set $N_i = \{j \mid \text{there is a path in } g \text{ from } i \text{ to } j\}$. Notice that if i and j are directly linked, then there is a path between them (of length 1): hence necessarily $n_i \geq n_i^d$. Player i's payoff, given his position in the network g, is assumed to be equal to:

$$\pi_i(g) = b \cdot n_i - c \cdot n_i^d$$

where b and c are non-negative constants that represent respectively the unitary benefit from (direct and indirect) connections and the unitary cost of direct links.

Players aim at maximising their payoffs and can rationally form new links or sever existing ones to this aim. Goyal and Joshi (2006) characterise equilibrium networks by introducing the notion of pairwise stable networks. A pairwise stable network is such that there exists a Nash equilibrium strategy profile that induces the network (so that no agent has any incentive to deviate from his current vector of intended links) and such that no pair of agents have any incentive to form a new link. More in detail, for any two agents who are not linked in a pairwise stable network, if one of the two gains by establishing a new link, it must be the case the other player involved is made strictly worse off by the new link. Formally:

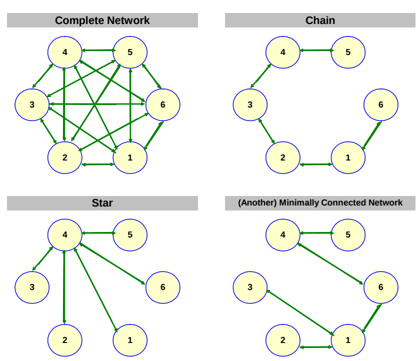
Definition: *A network g is a pairwise stable network if the following conditions hold:*

1. *there is a Nash equilibrium strategy profile* (s_i^*, s_{-i}^*) *that induces* g;
2. *for* $g_{ij} = 0$, *if* $\pi_i(g + g_{ij}) - \pi_i(g) > 0$ *then* $\pi_j(g + g_{ji}) - \pi_j(g) < 0$

Goyal and Joshi show that all Nash networks are minimal. A minimal graph is such that there is at most one path connecting any two agents: there are no redundant links. The intuition why this has to hold is that if there are redundant links then there are agents that can be reached both directly and indirectly. Players could obtain higher payoffs by deleting their (costly) direct links to all those nodes that they are able to reach indirectly through others.

As long as $b > c$, then all pairwise stable networks are *both* minimal *and* connected (or minimally connected), i.e. there is one and only one path connecting any two agents[3]. The intuition of why this is so is that if there is any isolated node, given that the benefit from an extra connection is higher than the cost of a direct link ($b > c$), then there are incentives for a new link to be formed between the isolated player and at least another node in the graph.

The complete network, where every node is directly connected to every other, is an example of connected graph. The complete network is clearly not minimal, as there are many redundant links. Examples of minimally connected graphs are the star and the chain.



Examples of network architectures.

2.2 The Experimental Procedure

The experimental sessions were conducted in Spring 2006 at CESARE, LUISS University in Rome. Subjects were first year Economics students and in total we had 54 participants. Each subject participated in only one session and none had previously participated in a similar experiment. We run 9 computerised experimental sessions, with 6 participants each. Each experimental session lasted between 30 and 45 minutes. Subjects total earnings were determined by the sum of the profits in each round and were paid using a conversion rate of 100 points per euro. Participants earned approximately 27 euros on average, on top of a 5 euros participation fee.

We implemented a single treatment, for which detailed parameters are in the table below:[4]

	Participants	Initial Endowment	Cost	Benefit
Sessions 1 - 9	6	500	90	100

All relevant parameters were equal across participants and displayed on the screen at any time throughout the experiment.

At the beginning of each session subjects were told the rules of conduct and provided with detailed written instructions, which were read aloud by the experimenters.

Sessions consisted of a minimum of 15 rounds, with a random stopping rule determining the end of the experiment.[5] In each round subjects were asked to submit (anonymously and independently) a vector of intended links. The initial screen for each participant is shown in figure 1.

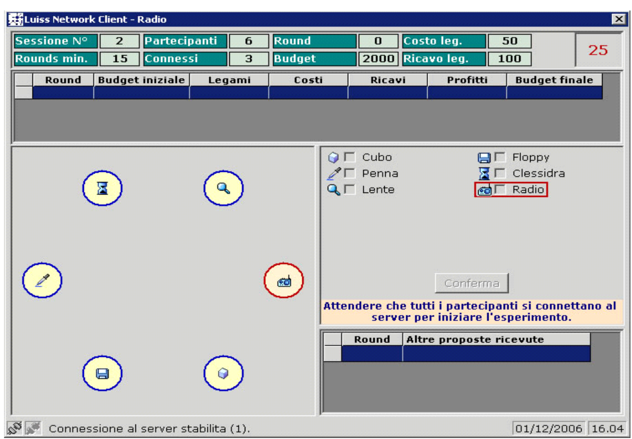


Figure 1: The initial screen.

Participants are represented on the screen by different symbols which we considered neutral in that they do not provide subjects any particular clue when deciding to establish a link with another player in the group.[6] Subjects do not know their symbol (or the other participants' symbols) in advance and can identify themselves on the screen because their symbol is circled in red. The screen also displays the relevant parameters for the session at play. After all subjects have confirmed their choice of network partners, the computer checks which links are mutually desired and activates them. At the end of each round profits are computed and displayed on the screen. Great care was put in making sure that all information available to experimental subjects was provided in a user-friendly way. For this reason the graphical interface was designed so that actual links are visualised on the screen as a graph, rather than as a list of activated ties, or as a matrix of 0/1 connections.

As an example, figure 2 shows the participants' screen at the end of round number 4. It displays the graph of all active links, total revenues, costs and profits in the round. It also provides information on past unmatched proposals: at the end of the round each subject is informed of those players who have proposed a link to them but whom they have not reciprocated. At any time during the experiment participants have access to a great deal of information on past history: by clicking on the bar corresponding to each round they are able to visualise the graph of active links and the profits obtained in that round.

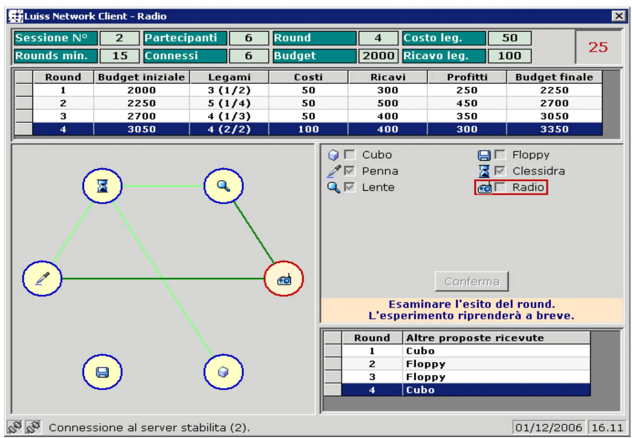


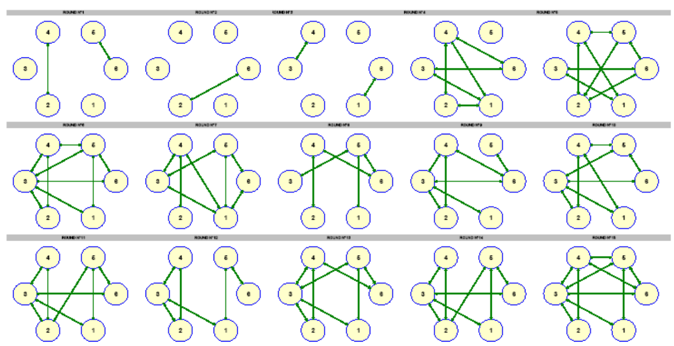
Figure 2: The participants' screen at the end of round 4.

3 Experimental Networks

Under our parametric assumptions any minimally connected graph is a pair-wise stable network. Minimally connected graphs are also efficient in that they maximise aggregate profits.

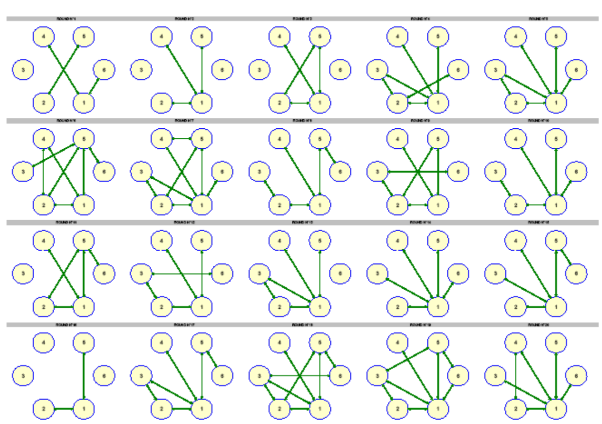
As typical examples of the observed experimental networks, we show below the outcome of sessions 1, 3 and 7.

In session 1 we notice that there is a tendency to inclusion, but not minimality: after the 3rd round, there are no isolated nodes, however many redundant links persist until the end of the session. Only once (in round 8) the network observed is minimally connected as predicted by the theory.



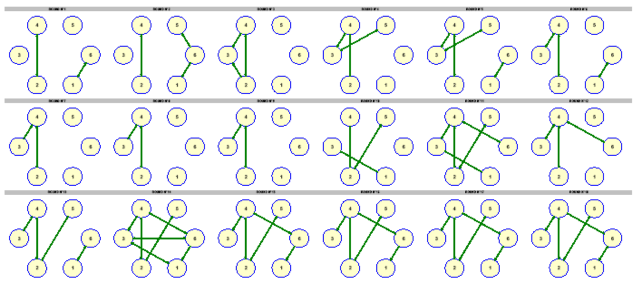
Session 1.

In session 3 we observe a tendency to both inclusion and minimality: in 75% of the rounds (15 out of 20) the obtained networks are connected; 27% of these connected networks are also minimally connected. In this particular session coordination on minimally connected networks is achieved through subject 1, who serves as a hub by accepting links with most of the others.



Session 3.

In session 7 we obtain convergence to a minimally connected network: from the 15th round onwards (to round 18) a minimally connected network is achieved and remains stable. Although, as discussed above, in most of our sessions we can observe both a tendency to connectedness and minimality, session 7 is the only one in our sample where a definite convergence is obtained.



Session 7.

We believe that convergence to a minimally connected graph is made very difficult by two main factors. First of all, as it has been remarked by the literature (see Kosfeld (2004)), the game that agents play has multiple equilibria and players find it very difficult to coordinate on the same Nash equilibrium (clearly communication was prevented during the experiment). Secondly, subjects display some aversion to inertia and, whenever a minimally connected graph is reached in early rounds, it is often abandoned later (in same cases to be reached again) by subjects who cannot resist to the experimentation of new strategies.

The focus of this paper is not on convergence of experimental networks to a stable network architecture, but rather on individual linking strategies in network formation. In the next section we turn to this micro-level analysis. In particular, we attempt to identify individual behaviour that may lead to each of the three types of network architecture exemplified above:

1. networks where there is a tendency to inclusion but not to minimality, as in session 1;
2. networks where one or more subjects serve as hubs for a minimally connected network, although convergence may not occur, as in session 3;
3. networks where convergence to a minimally connected architecture is achieved, as in session 7.

4 Link Formation

In each round of link formation individuals have 32 available strategies. For each player a strategy is given by a 5-dimensional vector of 0s and 1s. For player 1, for example, a possible strategy is to propose a link to each of the other 5 players in the game:

$$(1,1,1,1,1)$$

Strategy $(0,0,0,0,0)$ corresponds to the choice of not proposing a link to any of the other players; while $(1,1,0,0,0)$ corresponds to the choice of proposing to the first two players (other than player 1) and not the other ones; and so forth.

More in detail, the set of strategies for each of the players is as follows:

$(0,0,0,0,0)$	$(1,0,0,0,0)$	$(0,1,0,0,0)$	$(0,0,1,0,0)$
$(0,0,0,1,0)$	$(0,0,0,0,1)$	$(1,1,0,0,0)$	$(1,0,1,0,0)$
$(1,0,0,1,0)$	$(1,0,0,0,1)$	$(0,1,1,0,0)$	$(0,1,0,1,0)$
$(0,1,0,0,1)$	$(0,0,1,1,0)$	$(0,0,1,0,1)$	$(0,0,0,1,1)$
$(1,1,1,0,0)$	$(1,1,0,1,0)$	$(1,1,0,0,1)$	$(1,0,1,1,0)$
$(1,0,1,0,1)$	$(1,0,0,1,1)$	$(0,1,1,1,0)$	$(0,1,0,1,1)$
$(0,1,1,0,1)$	$(0,0,1,1,1)$	$(1,1,1,1,0)$	$(1,1,1,0,1)$
$(1,1,0,1,1)$	$(1,0,1,1,1)$	$(0,1,1,1,1)$	$(1,1,1,1,1)$

Under the assumption of static expectations, each player expects the other 5 participants to play in round t the same strategy that they have played in round $t-1$. Hence given these expectations on what the others will play, each participant best respond by selecting the strategy (or the strategies) within the strategy set above whereby profits are maximised. Typically there will be more than one strategy that maximises profits. For example: if player 2 did not propose a link to player 1 in the previous round, player 1 will be indifferent between proposing or not proposing a link to him in the current round. Given that link proposals need to be reciprocated in order to generate payoffs, proposing to someone that does not propose to you yields exactly the same payoff as not proposing.

There are less trivial ways in which players may be indifferent between multiple best responses: suppose that in the previous round all other players were connected to each other and to player 1, so that a complete network was observed. Any of the following one-link strategies is a best response for player 1:

$$(1,0,0,0,0) \quad (0,1,0,0,0) \quad (0,0,1,0,0) \quad (0,0,0,1,0) \quad (0,0,0,0,1)$$

In other circumstances the best response for a player could be strict (i.e. unique). Suppose that in the previous round the observed network is a star where player 1 is the hub: all other players propose links to player 1 and to player 1 only. In the current round the best response of player 1 is unique and it is to propose to all other players:

$$(1,1,1,1,1)$$

4.1 Best Response Behaviour

4.1.1 Choices

In our sample 40% of the individual choices are best responses. In order to assess whether this is a 'high' percentage of choices or not, we need to compare it to the proportion of times that a player that selects a strategy at random would end up selecting a strategy that happens to be a best response, even though it is selected at random. This comparison is particularly useful in our framework where the set of best responses contains more than one strategy. Assume, for example, that in a typical round the experimental network that has been formed is such that for the next round a good half of the available strategies are best responses, then even someone choosing a strategy at random would have a very good chance of selecting a best response.

For sake of comparison, we assume that all individuals select strategies at random, with each of the 32 strategies having a probability equal to 1/32 of being selected. Under this assumption we simulate 1000 samples with the same number of sessions, rounds and participants as in our experiment. We find that in the simulated samples a best response is selected on average a significantly lower number of times than in the experimental sample (32%). More in detail, in the experimental sample 360 choices out of 888 conform to best response behaviour; in the simulated samples 284.38 choices on average can also be characterised as best responses (s.e. = 0.414).

Having established that a significant share of choices in our experiment correspond to a 'conscious' best response, we go on to examine the determinants of the propensity to best respond. In particular we examine the role of both group (session) and individual effects.

In order to highlight the individual propensity to best respond, we report in figure 3 the histogram of the proportion of best responses by individual. Many subjects follow best response behaviour more than 50% of the time. Most of the individuals do best response for 40% of their decisions. Figure 4 shows the cumulated frequency of the proportion of best response adoption by individual. We compare the cumulated distribution for the experimental sample to the average cumulated distribution resulting from the simulated samples where agents select strategies at random. To confirm the hypothesis that experimental subjects follow best response behaviour in a conscious manner, we find that the cumulated distribution of the experimental sample lies below the one obtained on average in the simulated samples. Hence there are more subjects who do best response more often in the experimental sample than they would if playing at random. In particular, while in the simulated samples an average of 95% of subjects conform to best response behaviour less than 50% of the times, in the experimental sample only 75% of subjects do best response less than 50% of the times. In other words, 25% of our experimental subjects do best response more than 50% of the time, while only 5% of the players in the simulated samples would do the same.

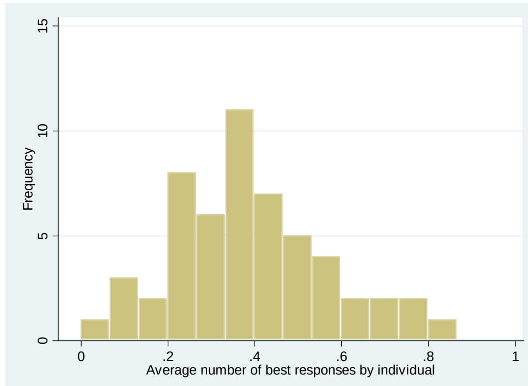


Figure 3: Histogram of the proportion of best responses by individual.

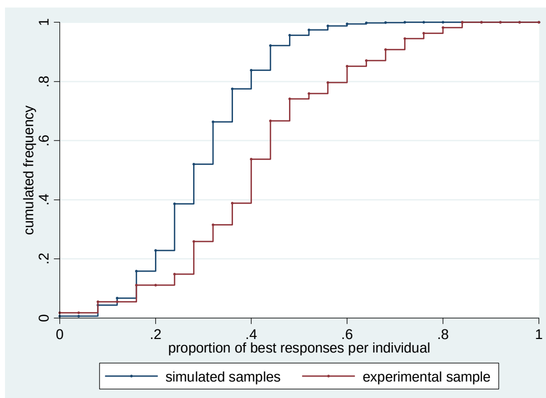


Figure 4: Cumulative distribution of the proportion of best responses by individual: experimental versus average simulated sample.

While the average number of best responses across sessions is 40%, a few sessions differ greatly from this average. In session 1 the proportion of best responses is very low (about 15%); by contrast, in session 7 almost 65% of the choices can be accounted for as best responses. In sessions 2, 3, 5 and 6 around 45% of choices correspond to best response behaviour. In sessions 4, 8 and 9 players appear to best-respond on 30% of occasions. Figure 5 shows the proportion of best responses by session, also displaying individual averages.

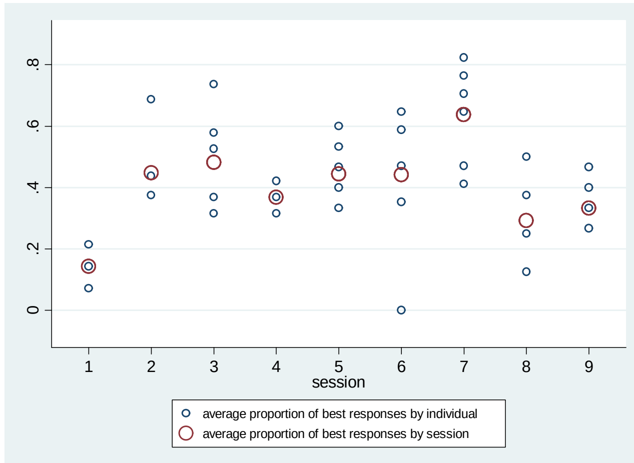


Figure 5: Average proportion of best response choices by session and by individual.

In order to separate individual from group (session) effects, we model the individual propensities to best respond as a function of an individual effect, a session (cluster) effect and an error term. Let the jth individual in the overall sample be the ith subject in the cth session. Then individual i's propensity to best respond $y_{ict}^{BR^*}$ is:

$$\begin{array}{rcl} y_{ict}^{BR^*} & = & \alpha_c + \gamma_i + \varepsilon_{ict} \qquad i = 1, ..., 6 \qquad c = 1, ..., 9 \qquad t = 1, ..., T_c \quad (1) \\ \varepsilon_{ict} & \sim & N[0, 1] \qquad \gamma_i \sim N[0, \sigma_\gamma^2] \end{array}$$

Here there are two regression intercepts: the intercept γ_i varies across individuals (individual-specific random effect). We assume that γ_i is a normally distributed random variable that does not depend on any observable. In the network formation game that the experimental subjects play, individual decisions within a session may well be correlated because individuals are influencing each others' decisions. Such correlation may also arise because of unobservable common shocks to all individuals in the same session: for example, because all individuals observe the same sequence of graphs occuring during a session. Our method for controlling for dependence on unobservables within a session is to model the intercepts α_c as random unobservables (cluster-specific fixed effects model). Basically, we assume that the session-specific fixed effect α_c controls for any form of correlation within a session.

The available data is an unbalanced panel, since the number of rounds in each session (T_c) depends on a random stopping rule that decides, after round 15, whether or not to continue with another round of the game.

The observational rule is the following:

$$\begin{array}{rcl} y_{ict}^{BR} & = & 1 \qquad \text{if } s_{it} \text{ is a best response} \\ y_{ict}^{BR} & = & -1 \qquad \text{otherwise} \end{array}$$

The log-likelihood contribution of subject i is

$$ll_i^{BR} = LogL_i^{BR}(\alpha_c, \sigma_\gamma \mid s_{i1}, ..., s_{iT_c}) = \int_{-\infty}^{\infty} \prod_{t=1}^{T_c} \Phi[y_{ict}^{BR} \times (\alpha_c + \gamma)] f(\gamma, \sigma_\gamma) d\gamma \tag{2}$$

where $\Phi[\cdot]$ and $f(\cdot)$ are respectively the standard normal cumulative distribution function and the normal density function for the random variable γ_i. This model corresponds to an individual random effects probit model with session fixed effects. It is consistently estimated because the number of observations per session N_c is sufficiently large, with $N_c = T_c \times 6$ ranging between 84 and 114.[7]

Results are displayed in table 1. We find that session fixed effects matter greatly in determining the propensity to best respond. Individual unobserved heterogeneity does not seem to matter. This result suggests that the propensity to best respond may be increased by the fact that more subjects in the same group are also more likely to best respond.

Probit with individual random effects and session fixed effects of players' propensity to best respond
(players = 54; obs. = 888)

	specification	
	(1)	(2)
sess2	-	0.942***
		(0.226)
sess3	-	1.029***
		(0.221)
sess4	-	0.736***
		(0.222)
sess5	-	0.933***
		(0.229)
sess6	-	0.922***
		(0.225)
sess7	-	1.429***
		(0.226)
sess8	-	0.521**
		(0.230)
sess9	-	0.641***
		(0.231)
cons	-0.266***	-1.074***
	(0.068)	(0.658)
σ_i	0.378***	0.133
	(0.068)	(0.088)
LL	-587.563	-567.942

*** 1%significance level; ** 5%significance level.

Table 1.

4.1.2 Profits

We compare average profits obtained through best response and non-best response choices. Actual average profits obtained are not significantly different: best response choices yielded our experimental subjects an average of 175.056 (s.e. 7.901) experimental units, while non-best response choices earned them

179.091 (s.e. 5.506) experimental units. Actual average profits obtained in each of the sessions are displayed in figure 6.

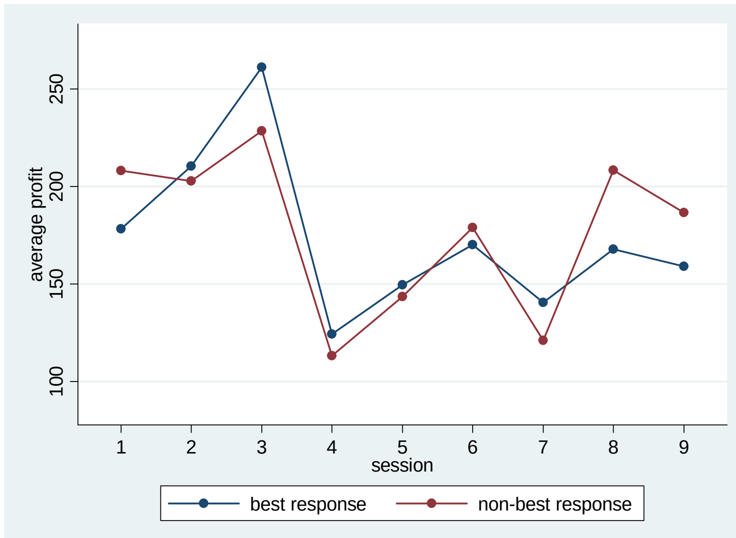


Figure 6: Average profits by session.

We can also compute expected profits under the assumption of static expectations. Not surprisingly for this case we find that expected returns from non-best response behaviour (153.921; s.e. 5.053) are significantly lower than expected returns from best responses (231.944; s.e. 7.559). If subjects had been correct in their static expectations, best response behaviour would have yielded higher profits by construction.

4.1.3 Distance from Best Response

The empirical analysis in this section is motivated by the observation that many individual choices that cannot be strictly accounted for as best responses are nevertheless 'close' to best response in terms of profits. With this in mind, we focus on a measure of distance from best response behaviour given by the difference between maximum attainable expected profit (i.e. profit that the agent would obtain by best responding) and the expected profit given the actual choice made.

More in detail, we propose an index of distance from best response obtained not in the domain of strategies, but in the domain of expected profits. Call s_{it}^* the best response strategy by agent i in round t. By definition of best response, strategy s_{it}^* maximises expected profits of agent i in round t, given that all other players are playing the same strategy in t as they did in $t-1$ (assumption of static expectations):

$$s_{it}^* = \arg\max_{s_i} E[\pi(s_i, s_{-i,t-1})]$$

Keeping the assumption of static expectations on the behaviour of others, expected profit to player i by choosing a non-best response strategy $\widehat{s}_{it}$ in round t is equal to:

$$E[\pi(\widehat{s}_{it}, s_{-i,t-1})]$$

As a measure of distance from best response we focus on the difference between these two expected payoffs, which we normalise with respect to the maximum payoff obtainable in each round (under our parametric assumptions, equal to 410) and which most importantly we penalise for the proportion of strategies within the strategy set of player i that correspond to best responses. The reason why we penalise for this proportion is that we want to put more weight to a discrepancy from best response that occurs in those cases where a large part of the strategy set corresponds to best response, than to those cases where only few strategies (possibly one) are best responses. In our framework it may occur that an agent in a given round has a large share of his available strategies that all constitute best responses (for example, 16 out of 32); in contrast it may also occur that only one (or very few) out of the 32 available strategies are best responses. We consider agent i to be *more* distant from a best response when he selects a non-best response strategy although many of his available strategies are best responses. The reason why we introduce this weighting is that we believe it may capture both the complexity of computing the best response and how consciously the subject deviates from it. If a large share of the available strategies are best responses, then identifying the vector of intended links that maximises profits is relatively easy. Hence we consider all those who do not follow best response behaviour in these circumstances as 'farther' away from best response behaviour compared to those who do not follow best response behaviour when this is (at least in probabilistic terms) more difficult to identify in the set of available strategies.

More in detail, the index of distance from the best response that we propose is the following:

$$d_{it} = \frac{(E[\pi(s^*_{it}, s_{-i,t-1})] - E[\pi(\widehat{s}_{it}, s_{-i,t-1})])/410}{(1-p_{it})^{\alpha}}$$

where p_{it} is defined as the proportion of strategies that constitute best responses (out of the available 32) for individual i in round t; $\alpha \geq 0$ is a parameter. For $\alpha = 0$, the index does not penalise for the proportion of strategies that correspond to best responses; larger values of α denote stronger penalisation. Clearly the proposed index is always non-negative and it is equal to zero only when the strategy chosen in round t by individual i is a best response. In what follows we assume $\alpha = 1.5$; alternative values for α do not affect our results from a qualitative point of view. With such a choice of the parameter α, d_{it} ranges from 0 to $d_{it}^{\max} = 2.8284$.

Figure 7 displays individual distances from best response by session. We notice that for each individual the distribution of distance from best response is rather concentrated, especially when the median is close to zero, as in sessions 5 and 7.

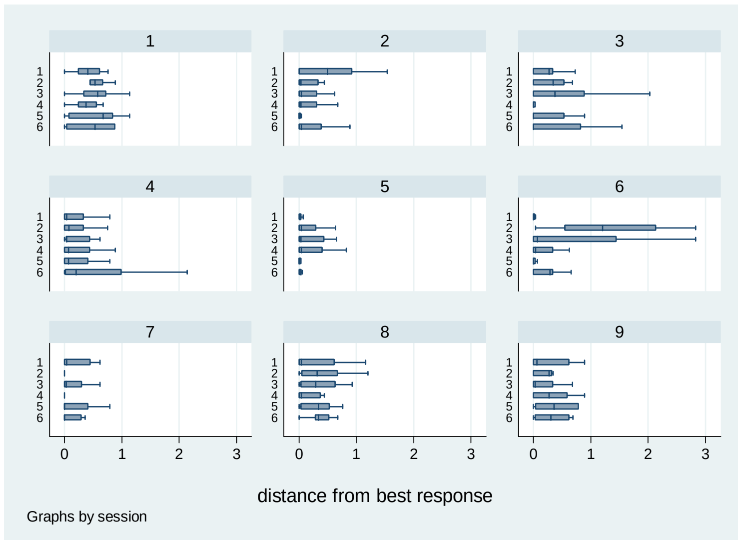


Figure 7: Boxplot for distance from best response, by subject.

The distribution of our measure of distance from best response for our experimental sample is displayed in figure 8: it seems to follow an exponential distribution and we will model it as such. The exponential distribution is characterised by a single parameter referred to as the rate parameter: the larger the rate parameter, the more concentrated towards zero is the distribution. Figures 7 and 8 suggest us to model each individual as characterised by his own ideal distance from the best response; they also suggest that this individual distance is exponentially distributed over the population. The observed $\widetilde{d}_{it}$ is the result of subject i own distance from the best response in round t plus a normally distributed random error:

$$\widetilde{d}_{ict} = \theta_i + u_{ict} \qquad \theta_i \sim Exp(1/\lambda) \qquad u_{ict} \sim N[0, \sigma_c^2] \tag{3}$$

Here we consider statistical inference under the assumption of intra-session heteroschedasticity. By doing so we take into consideration common shocks that may affect all subjects in the same session. We want the model to take into account that there is a mass, actually a small mass, at $d_{ict}^{\max}$ that is a clear manifestation of upper censoring. Since the maximum possible distance from the best response is 2.8284, the observed d_{ict} is the result of the following censoring rule:

$$\begin{aligned} d_{ict} &= \widetilde{d}_{ict} \qquad \text{if } \widetilde{d}_{ict} < 2.8284 \\ d_{ict} &= 2.8284 \qquad \text{if } \widetilde{d}_{ict} < 2.8284 \end{aligned}$$

Let us define the censoring indicator

$$\begin{aligned} s_{it} &= 0 \qquad \text{if } \widetilde{d}_{ict} < 2.8284 \\ s_{it} &= 1 \qquad \text{if } \widetilde{d}_{ict} < 2.8284 \end{aligned}$$

Then, the likelihood contribution of subject i is:

$$LogL_i(\lambda, \sigma_c) = \ln \int_0^{\infty} \prod_{t=1}^{T_i} \left[(1 - s_{it})\phi(\frac{d_{ict} - \theta}{\sigma_c}) + s_{it}\Phi(\frac{\theta - 20284}{\sigma_c}) \right] f(\theta; \lambda) d\theta$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are respectively the standard normal density function and cumulative distribution function, and $f(\theta; \lambda)$ is the exponential density function for the random variable θ_i.

By estimating model (3) on the data from our experimental sample, we obtain that the rate parameter λ is rather precisely estimated to equal 3.438 (s.e. 0.275).[8]

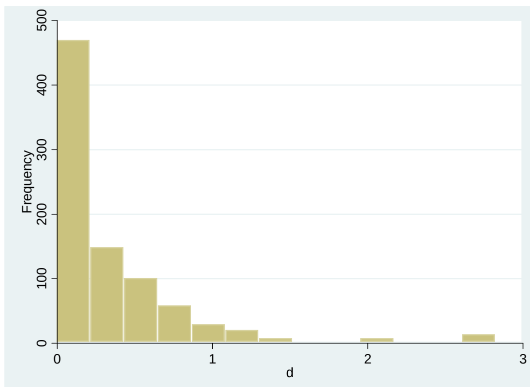


Figure 8: Histogram of the distance from the best response d_{ict}.

We also estimate the rate parameter λ for each of the simulated samples. Summary statistics are reported in table 2. We find that the rate parameter for the experimental sample is significantly larger than the one obtained in the simulation. This confirms that the experimental sample is more concentrated towards best response behaviour than if players were playing at random.

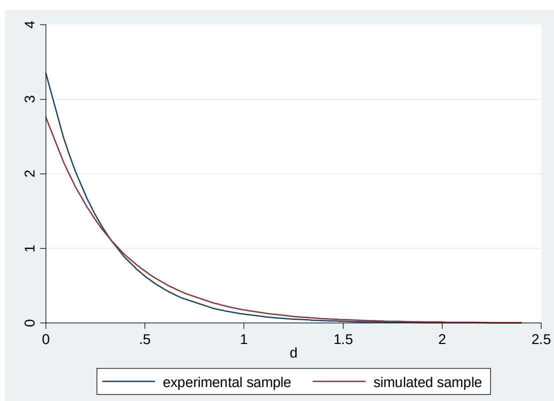


Figure 9: Estimated probability density functions distance from best response experimental sample/simulated sample.

Summary statistics of estimated scale parameter from the distance from best response model (controlling for intra-cluster heteroschedasticity)

	$\hat{\lambda}$
1000 simulated samples (*N* = 54)	
(LL = -726.2642)	
Mean	2.755
(Standard error)	0.008
Median	2.784
Standard deviation	0.240
Minimum	1.718
Maximum	3.328

average number of observations per subject = 15.78

Table 2

The λ so obtained is a parameter that is able to summarise the distribution of our measure of distance from best response. We have tested if λ decreases over time through learning, to find that time does not play a role here.[9] Only in sessions 2 and 7 the average distance from best response eventually reduces (see figure 10).

These findings confirm the analysis described in the previous section.

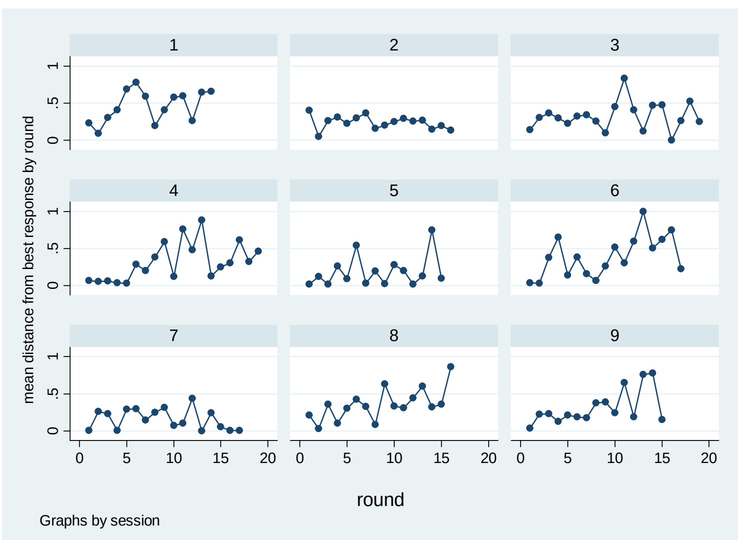


Figure 10: Average distance from best response, by round.

4.2 Other-than-Best Response Behaviour

4.2.1 Choices

In the previous section we showed that 40% of individual choices can be accounted for as best responses. As for the remaining 60%, our analysis of distance from best response showed that they are not very far from best response behaviour. In this section we ask whether there are 'nuances' of best response that may explain in a systematic fashion individual behaviour other than best response.

First, we speculate that subjects may act as to maximise the number of direct links in the game, as a proxi for maximising profits. A subject who maximises links rather than profits is someone who does not recognize that he could be making more money by deleting redudant links, i.e. links to those nodes that can be reached indirectly through connections put in place by others. Someone who plays the network formation game with the aim of maximising direct links, under the assumption of static expectations, always proposes a link back to those from whom he has received a link proposal in the previous round. We call this strategy the 'reciprocator'. Second, we speculate that some subjects may have attempted a rule of conduct that is somehow complementary to reciprocator in providing a best response: rather than maximising the number of direct links, some subjects may indeed have attempted to maximise the number of indirect connections achieved through a single link. A subject who follows this rule adopts the strategy to propose links to those that had the maximal number of direct links in the previous round. We call this strategy 'opportunistic'.

Both reciprocator and opportunistic strategies are well represented in our sample: 37% of choices can be accounted for as being dictated by the reciprocator strategy; 34% of choices can be accounted for as being dictated by the opportunistic strategy.

By comparing these percentages with those obtained from the simulated samples where individuals choose at random, we notice that reciprocator and opportunistic behaviour occur less often than in our experimental sample. More in detail: only 192.86 (s.e. 0.332) choices are explained by reciprocator in the simulated samples, compared to 331 in our experimental sample; only 212.35 (s.e. 0.461) choices are explained by opportunistic in the simulated samples, compared to 305 in our experimental sample.

Many choices can be explained by more than one strategy at a time: there are occurrences when the best response strategy coincides with reciprocator, or opportunistic, or both; also there are occurrences when reciprocator and opportunistic strategies coincide, while not coinciding with best response behaviour.

Table 3 shows the overlap between the strategies and compares it to what arises from our simulated samples (theoretical distribution under the hypothesis that all agents are selecting strategies at random). The Pearson's chi-square test shows that the frequency distribution of the experimental sample differs from the distribution of the simulated samples (p-value < 0.001).

Number of choices		Explained by		
Treat. 1	Theoretical distribution	best respondent	reciprocator	opportunist
146	166.828 (.345)	√	x	x
120	103.539 (.288)	x	√	x
135	115.963 (.365)	x	x	√
110	48.620 (.208)	√	√	x
69	55.687 (.224)	√	x	√
66	27.453 (.159)	x	√	√
35	13.245 (.113)	√	√	√
207	356.665 (.469)	x	x	x
Tot. 888 χ^2-stat = 241.6739 (p-value=0.000)				

Table 3.

Similarly to the analysis in section 4.1.1 we examine the individual propensities to adopt reciprocator and opportunistic strategies through a probit model with individual random effects and session fixed effects. The distributional assumptions are the same as in the probit model for best response behaviour (see equation (1)). Here the observational rules for reciprocator and opportunistic behaviour are the following:

$$\begin{aligned} y_{ict}^{RC} &= 1 \quad \text{if } s_{it} \text{ is a reciprocator choice} \\ y_{ict}^{RC} &= -1 \quad \text{otherwise} \end{aligned}$$

$$\begin{aligned} y_{ict}^{OP} &= 1 \quad \text{if } s_{it} \text{ is an opportunistic choice} \\ y_{ict}^{OP} &= -1 \quad \text{otherwise} \end{aligned}$$

As a result, the log-likelihood contributions of subject i are respectively:

$$ll_i^{RC} = LogL_i^{RC}(\alpha_c, \sigma_\gamma \mid s_{i1}, ..., s_{iT_c}) = \int_{-\infty}^{\infty} \prod_{t=1}^{T_c} \Phi[y_{ict}^{RC} \times (\alpha_c + \gamma)] f(\gamma, \sigma_\gamma) d\gamma \tag{4}$$

$$ll_i^{OP} = LogL_i^{OP}(\alpha_c, \sigma_\gamma \mid s_{i1}, ..., s_{iT_c}) = \int_{-\infty}^{\infty} \prod_{t=1}^{T_c} \Phi[y_{ict}^{OP} \times (\alpha_c + \gamma)] f(\gamma, \sigma_\gamma) d\gamma \tag{5}$$

The results of our analysis are in table 4. We find that group effects (as measured through session fixed effects) are not significant[10], while unobserved heterogeneity matters greatly. This is in stark contrast with our results for the propensity to adopt best response, where group effects were the only determinant. Figures 11 and 12 compared to figure 5 illustrate this point: there appears to be much more dispersion around the session average for non-best response behaviour than for best responses; also, in contrast with best response behaviour, for reciprocator and opportunistic most of the heterogeneity is across individuals rather than across sessions.

Probit with individual random effects and session fixed effects of players' propensity to reciprocate and to behave opportunistically
(players = 54; obs. = 888)

	reciprocator		Opportunistic	
	(1)	(2)	(1)	(2)
session fixed effects	no	yes	no	Yes
σ_i	0.607***	0.542***	0.647***	0.519***
	(0.084)	(0.080)	(0.090)	(0.079)
LL	-545.629	-540.930	-524.214	-514.728

***1% significance level

Table 4.

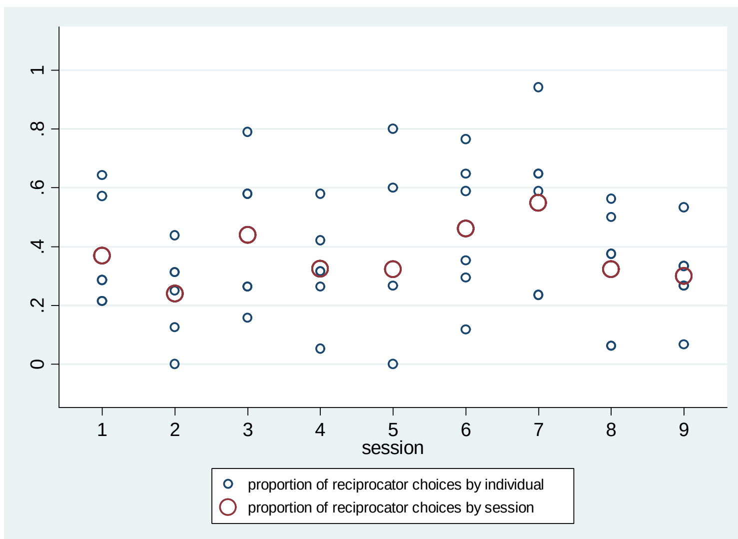


Figure 11: Average proportion of reciprocator choices, by session and by individual.

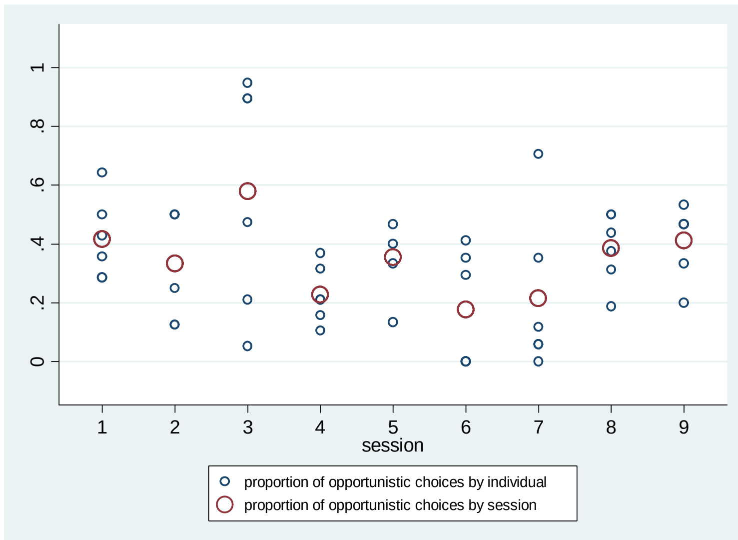


Figure 12: Average proportion of opportunistic choices, by session and by individual.

Figures 13 and 14 show respectively the cumulated frequency of the proportion of reciprocator and opportunistic behaviour by individual. In each case we compare the cumulated distribution for the experimental sample to the average cumulated distribution resulting from the simulated samples where agents select strategies at random. To confirm the hypothesis that experimental subjects follow reciprocator or opportunistic behaviour in a conscious manner, we find that, with the exception of very low proportions, the cumulated distribution of the experimental sample lies below the one obtained from the simulated samples. Hence there are more subjects who reciprocate (or are opportunistic) more often in the experimental sample than they would if playing at random.

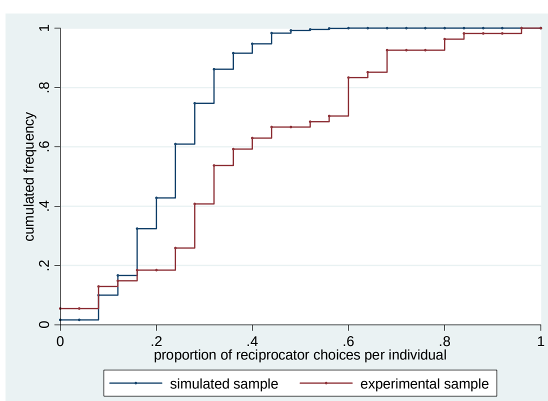


Figure 13: Cumulative distribution of the proportion of reciprocator choices by individual: experimental versus average simulated sample.

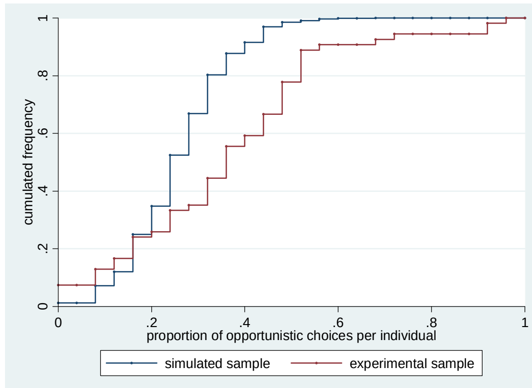


Figure 14: Cumulative distribution of the proportion of opportunistic choices by individual: experimental versus average simulated sample.

4.2.2 Strategies, Networks and Returns

Figure 15 reports percentages of strategies adoption by session. Session 7 is characterised by the fact that a large majority of experimental subjects played according to best response. Recall that session 7 (illustrated in section 3) is the only session where convergence to a minimally connected network has been obtained. Session 3 is characterised by a large majority of opportunistic choices. Recall that in this session subject 1 served as a hub for the experimental network with most other subjects linking to him (session 3 is illustrated in section 3). Session 1 is an example of a session where best response behaviour was particularly scarce. In this session redundant links were not eliminated and convergence was not obtained (session 1 is illustrated in section 3).

By comparing average profits obtained through each of the three strategies, we find that average profits obtained by best response choices are not significantly different from those obtained by reciprocators: best response choices yielded our experimental subjects an average of 175.056 (s.e. 7.901) experimental units, while reciprocators earned 182.930 (s.e. 7.433) experimental units. By contrast, opportunistic choices lead to significantly higher profits (221.180; s.e. 7.595) both with respect to best response and with respect to reciprocator. Figure 16 shows that this pattern applies not just on average, but also for most sessions. In particular, opportunistic behaviour seems to earn a premium over the other two strategies in sessions 6 and 7. Sessions 6 and 7 are characterised by the fact that many individuals adopted the reciprocator strategy (see figure 15). This may explain why opportunistic behaviour was particularly profitable in these sessions.

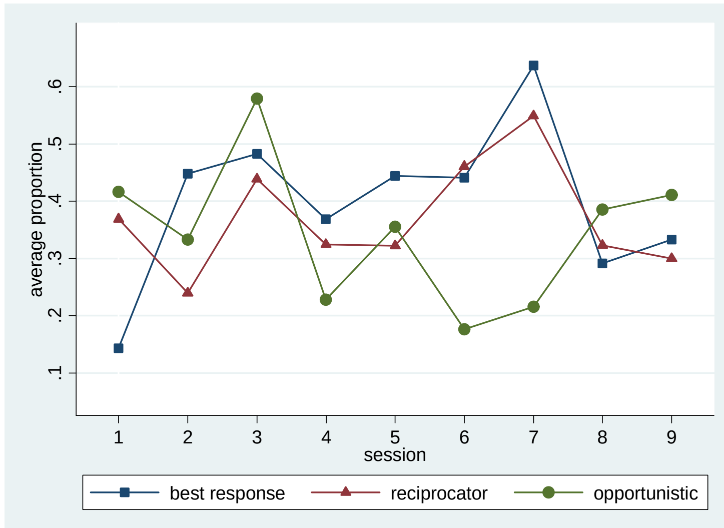


Figure 15: Percentages of strategies adoption, by session.

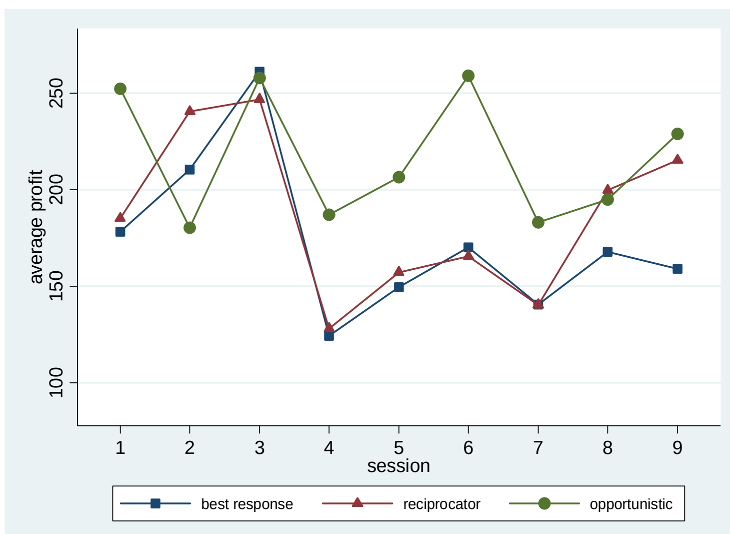


Figure 16: Average profits, by strategy and session.

We also ask how average profits vary with the frequency with which subjects adopt each of the three different strategies. More in detail, figure 17 shows the average profit obtained by individuals who followed each of the strategies for a given percentage of choices. We see that the highest profits across all sessions is achieved by those (few) who follow an opportunistic strategy more than 80% of the time. By contrast, the lowest levels of average profits are achieved by the only player who follows the reciprocating strategy for more than 90% of the times. Average profits obtained by those who follow best response do not seem to vary greatly as the percentage of choices in which best response itself is adopted increases. For the range of proportions of strategy adoptions where most of individuals lie (i.e. in the range 10% to 40%) we observe that average profits obtained by following best response are not too dissimilar from average profits obtained by adopting the reciprocator strategy. For the same range, the average profit of those who have followed the opportunistic strategy were lower.

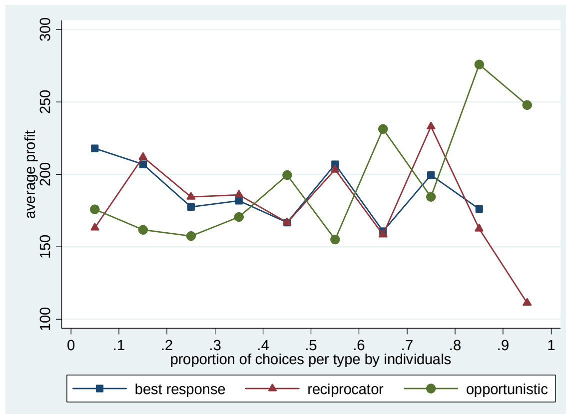


Figure 17: Average profits by strategy adoption.

4.3 The Mixture Assumption

Taking into account the fact that different individuals may behave differently in network formation, we adopt the solution of using a mixture model (see McLachlan and Peel (2000)). We restrict attention to the three candidate strategies that we have described above and we assume that each subject is of one type: best response, reciprocator or opportunistic. We proceed by assuming that a proportion π_{BR} of the population from which the experimental sample is drawn behaves according to best response; a proportion π_{RC} behaves according to reciprocator; and finally a proportion $\pi_{OP} = 1 - (\pi_{BR} + \pi_{RC})$ behaves according to opportunistic.

The parameters $(\pi_{BR}, \pi_{RC}, \pi_{OP})$ are known as the mixing proportions and are estimated along with the other parameters of the model.

The likelihood contribution of subject i is then:

$$LogL_i = \pi_{BR} \times ll_i^{BR} + \pi_{RC} \times ll_i^{RC} + \pi_{OP} \times ll_i^{OP}$$

where ll_i^{BR}, ll_i^{RC} and ll_i^{OP} have been defined respectively in equations (2), (4) and (5) above.

As displayed in table 5, we find that 31% of the population does best response; 27% behaves as a reciprocator; 42% behaves as a opportunistic. In accordance with our findings in the probit regressions (see tables 1 and 4), we find that while best response behaviour is not affected by individual specific attitudes but only by group effects, for the reciprocator and the opportunistic types session fixed effects are only slightly significant with most of the action being played by individual attitudes.

Mixture model of the three different types of behaviour; each individual is one type. (players = 54; obs. = 888)			
specification 1			
	best response	Reciprocator	opportunistic
session fixed effects	No	No	No
σ_i	0.293	0.442**	0.911***
	(0.218)	(0.205)	(0.197)
mixing proportions	0.220***	0.305***	0.474***
	(0.080)	(0.084)	(0.088)
LL		-452.637	

specification 2			
	best response	reciprocator	opportunistic
session fixed effects	Yes	Yes	Yes
σ_i	2.76e-10	0.000	0.589***
	(.)	(0.089)	(0.149)
mixing proportions	0.314***	0.268***	0.417***
	(0.080)	(0.068)	(0.082)
LL		-426.057	

Table 5.

Having estimated a mixture model, one obvious thing to do is to compute the posterior probabilities of each experimental subject being of each type. Using Bayes' rule we have the following posterior probabilities:

$$\begin{aligned}\Pr[\text{type } k \mid s_{i1},...,s_{iT_c}] &= \frac{\Pr[\text{type } k] \times \Pr[s_{i1},...,s_{iT_c} \mid \text{type } k]}{\Pr[s_{i1},...,s_{iT_c}]} \\ &= \frac{\pi_k \times \Pr[s_{i1},...,s_{iT_c} \mid \text{type } k]}{\Pr[s_{i1},...,s_{iT_c}]} = \frac{\pi_k \times ll_i^k}{LogL_i}\end{aligned}$$

for $k \in \{BR, RC, OP\}$.

Posterior probabilities are depicted in figure 18. Each of the 54 subjects is represented by a single point in the graph. Subjects who are in the bottom left corner are of the opportunistic type; subjects who are in the bottom right corner are of the best response type; finally those who are in the top left corner are of the reciprocator type. The vast majority of subjects are located very close to one of the vertices of the triangle, a minority is close to the lower edge and virtually nobody is in the middle. This finding confirms that the mixture model segregates the three types of individuals well, with most of them being of a particular type. Only for a small number of subjects we cannot determine if they are best response or opportunistic, or if they are best response or reciprocator. This technique has been previously been used by Conte et al (2009).

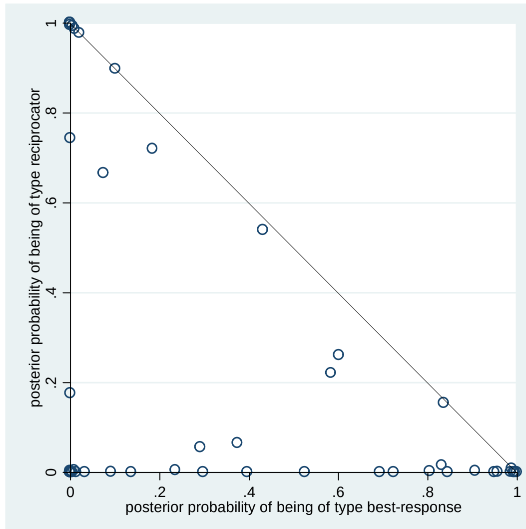


Figure 18: Posterior probabilities.

5 Conclusions

Our empirical results provide an explanation for individual behaviour in the network formation game.

Approximately 40% of the network formation strategies adopted by the experimental subjects can be accounted for as best responses. The individual attitude to best respond is heavily group driven, with agents being more likely to best respond when others in the same session also do, while individual effects are not significant.

We link such empirical findings to the fact that there is a multiplicity of equilibria around which the group needs to coordinate.

We also observe that many of the experimental subjects' choices which cannot be strictly accounted for as best responses are nevertheless 'close' to best response. With this in mind, we focus on a measure of distance from best response behaviour given by the difference between maximum attainable expected profit (i.e. profit that the agent would obtain by best responding) and the expected profit given the actual choice made.

We compare the empirical distributions of such distance from the best response to the theoretical ones obtained in a simulation where all subjects are assumed to play randomly. We find that the empirical distributions are significantly different from the ones in which subjects are assumed to play at random. Moreover the empirical distributions are much more concentrated towards the best response than the theoretical ones.

For this 'close' to best reponse behaviour we go farther and attempt to identify regularities in the way in which experimental subjects behave. First, we speculate that subjects may indeed act as to maximise the number of direct links in the game, as a proxi for maximising profits. A subject who maximises links rather than profits is someone who does not recognize that he could be making more money by deleting redudant links, i.e. links to those nodes that can be reached indirectly through connections put in place by others. Someone who plays the network formation game with the aim of maximising direct links, under the assumption of static expectations, always proposes a link back to those from whom he has received a link proposal in the previous round. We call this strategy 'reciprocator'. Second, we speculate that some subjects may have indeed attempted a rule of conduct that is somehow complementary to reciprocator in providing a best response: rather than maximising the number of direct links, some subjects may have attempted to maximise the number of indirect connections achieved through a single link. A subject who follows this rule adopts the strategy to propose links to those that had the maximal number of direct links in the previous round. We call this strategy 'opportunistic'.

Given that there is obviously some overlap across best response behaviour and each of these strategies, we go on to test econometrically if a mixture assumption can be validated for our sample. We find that it is safe to assume that each individual belongs to one type, with mixing proportions approximately equal to 42%, 31% and 27% for opportunistic (the leading type), best response, and reciprocator respectively.

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Appendix
Instructions (English Translation)

Welcome

This is an experiment on the formation of links among different subjects. If you make good choices you will be able to earn a sum of money that will paid to you in cash immediately at the end of this session.

You are one of the 6 participants to this experiment; at the very beginning the computer will randomly assign to you an initial budget (equal across participants). Also, the computer will randomly assign to you an icon (**Dropper**, **Radio**, **Cube**, **Floppy disk**, **Hand lens**, **Hour glass**) that will identify you throughout the experiment and will assign you an initial budget (equal across participants). The icon that identifies you is circled in red on your screen.

The experiment consists of a random number of rounds: there will be at least 15 rounds, after which a lottery administered by the computer will determine whether there is any further round or the experiment is over.

Each participant to this experiment represents a node. At the beginning of the experiment all nodes are isolated. In each round the computer will ask you whether you want to propose any link and to whom. You can propose 0, 1 or more links. *The computer will collect the proposals from all participants and will activate only the links which are desired by both subjects involved (reciprocated proposals).*

Your screen will show the graph of active links. The box at the bottom right of your screen will show you who has proposed you a link in the previous round and whom you have not reciprocated.

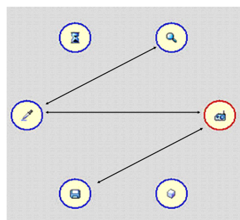
Each link that you manage to activate has a cost (equal across participants) that is indicated on the screen. In each round the computer may reject your link proposals if they entail an expenditure that is higher than your budget for that round.

Your revenues in each round are automatically computed and are given by the product by the revenue per node (equal across subjects and indicated on your screen) and the number of nodes that you manage to reach both through your direct links and the links activated by other participants.

Computing costs and revenues

Example: subject **Radio** is directly linked to **Floppy disk** and **Dropper** and indirectly, that is through **Dropper**, to **Hand lens**.

Unitary revenue: 10
Cost of each connection: 3



The profit of **Radio** is:

total revenues – total costs

total revenues = number of nodes reached (directly and indirectly) x revenue per node = 3 x 10 = 30

total costs = direct connections x cost of each connection = 2 x 3 = 6

profit = 24

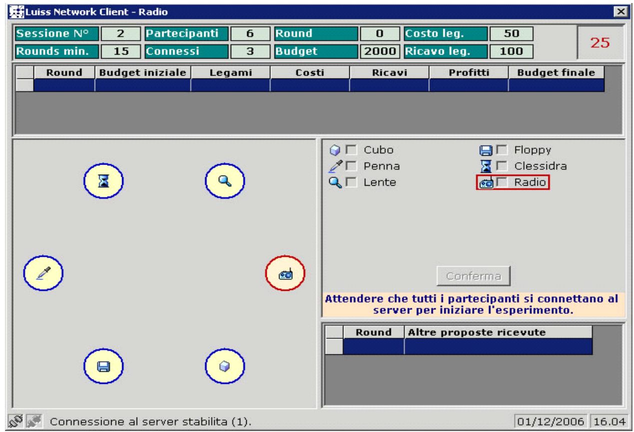
In each round the computer will work out your profit and will display it on your screen. The overall profit from the experiment is given by the sum of your revenues in all rounds. At the end of the experiment you will be paid in cash an amount in euros equivalent to 10% of your total profit.

More in detail

At the beginning of the experiment please wait for instructions from the experimenters without touching any key.

When the experimenter will ask you to do so, please double-click only once on the "Network Client" icon on your desktop.

The following screen will appear:

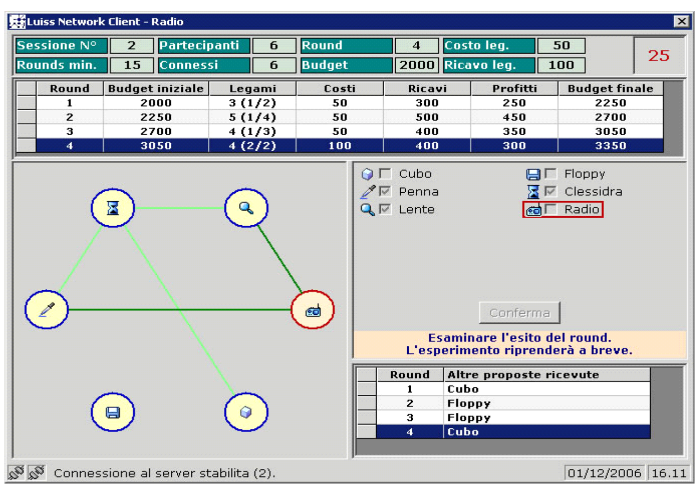


The screen gives you all the information regarding the round that you are about to play.

Be careful: each round has a maximum time duration given by the number of seconds indicated in red at the top-right corner of your screen. If you have not managed to make your choice by then, the computer will immediately proceed to the next round.

Your screen shows all the relevant data useful for the current round (available budget, costs and revenues) as well as the results that you have obtained from each of the previous rounds.

At the end of each round, the graph will show the links which have been activated by you and the other participants (as shown above). Moreover the table that summarises your performance in the current round will be updated. You will have the possibility to review the situation of previous rounds by clicking on the corresponding bar in the same table. The table at the bottom right of your screen gives you additional information on proposals that you have received but not matched in the previous rounds.



When the message "Round is now active" appears at the bottom of your screen, you can make your choice by ticking the boxes corresponding to the icons that you want to propose a link to. When you are done, press “Confirm”. When all participants have confirmed their choices, the computer will show the results of the round on the screen.

You will be advised of the beginning of a new round by a "New Round" message. Be careful: after the 15th round, red and green lights will flash on the screen. If the lights stop as green, you will play another round; if they stop as red, the experiment is over.

It is very important that you make choices independently and that you do not communicate with other participants during the experimental session.

At the end of the last round the experiment is over and you will be paid in cash for a sum corresponding to your profit during the course of the whole experiment.

For any problem, please contact the experimenters.

Enjoy.

May 2006

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