Behavioural Patterns in Social Networks

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Abstract

In this paper, we focus on the analysis of individual decision making for the formation of social networks, using experimentally generated data. We analyse the determinants of the individual demand for links under the assumption of agents' static expectations and identify patterns of behaviour which correspond to three specific objectives: players propose links so to maximise expected profits (myopic best response strategy); players attempt to establish the largest number of direct links (reciprocator strategy); players maximise expected profits per direct link (opportunistic strategy). These strategies explain approximately 74% of the observed choices. We demonstrate that they are deliberately adopted and, by means of a finite mixture model, well identified and separated in our sample.

JEL classification: C33; C35; C90; D85

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1 Introduction

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 of 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 the seminal contributions by Myerson (1991), Jackson and Wolinsky (1996) and Bala and Goyal (2000). These papers take 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.[1]

Since the observed network structures are ultimately the outcome of individual linking decisions, one possible approach to overcome this difficulty is to investigate the process of network formation in order to identify patterns of individual behavior that can be resumed in prevailing linking strategies.

With this aim, we use data of a computerised experiment of network formation, where all connections are beneficial and only direct links are costly. The network formation protocol

[1] 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 (2012); for a negative result see Bernasconi and Galizzi (2012)), convergence is always problematic in frameworks where the prediction for the stable network is the star (Falk and Kosfeld (2012), Berninghaus et al. (2007), Goeree et al. (2009)). Falk and Kosfeld (2012) and Berninghaus et al. (2007) highlight the role of complexity and the lack of coordination in preventing convergence.

that we adopt, unlike the one used by most of the experimental literature that has focused 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, but a connection is made only when both players involved agree. We collect data from 9 groups of 6 participants each and a minimum of 15 rounds of network formation.

In this paper, we estimate a system of equations that model each player's decision on the opportunity to propose a link to any of her prospective partners in each round of the game. This approach allows us to take into account the fact that from a player's perspective the decision to propose a link to one of her opponents is not separate from the decision to propose or not a link to another opponent; therefore, decisions made by the player in each round of the game are the result of a joint valuation.

Relying on the results of such an analysis, we attempt to categorise players' systematic behaviour into a set of possible strategies adopted by the experimental subjects in our network formation game.

An obvious departing point to interpret these results is to consider myopic best response behavior, where players propose links so to maximise current profits while taking other players' link proposals as given. This is a useful benchmark because most of the theoretical literature on strategic network formation makes the assumption that agents behave according to myopic best response and focuses on Nash Equilibrium (and refinements of Nash Equilibrium) as the appropriate solution concept for the network formation game.

Given the payoff structure of the network formation game which we consider here, myopic best response requires subjects to propose (direct) links to all those that in the current network are not already reached through indirect connections. It is always advantageous, for example, to propose a link to an isolated node. On the other hand, redundant links (i.e. links to those nodes that are reached also through indirect connections) should be deleted. Also, given that links are only established if they are requested by both players involved, proposing a link to a player from which a link proposal has not been received is always a matter of indifference.

When all agents play according to myopic best response, the emerging network architecture is a minimal network, where no redundant links are active. The set of minimal networks contains also trivial network structures such as the empty network. The empty network is a Nash network (i.e. a network structure induced by agents who play myopic best response) because links have to be mutually agreed in order to form, hence not proposing while not being proposed is always a best response. To get more interesting and more focused predictions, the theoretical literature on network formation has proposed pairwise stable networks as a suitable refinement of Nash networks. A network is pairwise stable when it is: (1) Nash, and (2) such that all mutually profitable links have been activated. Pairwise stable networks are both minimal and connected, in that all nodes are connected and through the smallest number of links.

By accepting pairwise stability as the appropriate solution concept for the network formation game, most of the experimental literature has focused on whether convergence to a minimally connected network structure, such as the star, or the chain, obtains in the lab.

Minimally connected graphs are often reached in our experimental groups (21 out of 157, which correspond to a 13% of the total network configurations) but are typically unstable. Convergence to a minimally connected network is only observed in one out of the nine experimental groups (group 7), where the same minimally connected graph is reached and then kept for four rounds until the end of the session. Mostly we observed connected graphs which are not minimally connected (68 out of 157, which correspond to a 43% of the total network configurations).

We went on to speculate which behaviour, other than myopic best response, may concur in explaining the observed network architectures.

We start our analysis with a preliminary investigation of the determinants of individual linking decisions (see Section 3). In accordance with myopic best response behavior, we find that subjects are less likely to propose links to those that can already be reached through indirect connections. Moreover we find a tendency to reciprocate link proposals and a tendency to propose links to those who have the largest number of connections which is not necessarily in accordance with best response behaviour.

This observation motivates the two residual patterns of behaviour we consider in this study. Along with the myopic best response strategy, we consider the “reciprocator” and the "opportunistic" strategies.

A subject who follows the "reciprocator" strategy makes link proposals to all those from whom link proposals have been received. Other than maximising expected profits, a reciprocator aims to establish the largest number of direct links. As for best response behavior, reciprocators will not leave profitable linking opportunities unexploited; however, unlike best response behavior, they may keep redundant links. Reciprocators maximise revenues, rather than profits, and do not care about minimising the cost through which a high connectivity is obtained.

A subject who follows the "opportunistic" strategy only activates those links (among the ones which are feasible, in that proposals have been received by the other party involved) which are most profitable because bring the largest number of indirect connections. While this behavior may seem closer to profit maximisation because both costs and revenues of link formation are taken into account, it differs from myopic best response in that profitable link opportunities may be neglected (and at the same time there is no guarantee that redundant links will be avoided).

We then go on to verify from our data whether the identified strategies are well represented. Finally, in order to discriminate among these three types of systematic behaviour, we estimate a mixture model to establish if these strategies are well identified and separated in our sample.

We find that it is safe to assume that each subject in our sample belongs to one type, with mixing proportions approximately equal to 45%, 30% and 25% for best response, reciprocator and opportunistic types, respectively.

We notice that the payoffs achieved by the three types are not too dissimilar, with opportunists earning marginally less than myopic best responders and reciprocators.

Finally, we note that the propensity to adopt a certain strategy is group-driven, with subjects being more likely to best respond, to reciprocate and to behave opportunistically when others in the same group also do.

The fact that behavioural patterns (similar to, but) other than myopic best response behaviour are significantly represented in the population may explain why the observed network architecture fails to converge to a minimally connected graph as predicted by the theory. Myopic best response agents will always tend to include isolated nodes and delete redundant links, whereby pushing the network architecture to a minimally connected graph. If at any stage two reciprocators link up, then that link will not be deleted even when it is redundant, which may result in stable network configurations which are not minimal. Finally, the presence of opportunists along with myopic best response agents and reciprocators may favour, when prevalent, the emergence of asymmetric network configuration such as the star, over alternative architectures. For example, when there is a single myopic best response agent and everyone else is an opportunist, the network converges to a star (where the myopic best response agent is the hub). Hence the exact mix of strategies represented in the population can help us predict which network architecture will emerge in equilibrium.

The paper proceeds as follows. Section 2 describes the experimental design: the model and the experimental procedure. Section 3 presents and discusses the results of the model of link proposals described in Appendix A. Section 4 shows the characteristics of the three behavioural types that emerged from the analysis in Section 3. Section 5 analyses the data in the light of these three behavioural types. Section 6 develops the mixture model, and Section 7 concludes. The econometric model of link proposals is explained in Appendix A. The instructions (in their English translation) can be found in Appendix B.[2]

2 The Experimental Design

2.1 The Model

We model network formation as a non-cooperative simultaneous move game. As in Myerson (1991), 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 $i = 1, 2, \dots, n$. Each player i submits a

[2]The software used for the experiment has been developed by Andrea Lombardo and is available from the authors on request.

vector of intended links:

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

An intended link is $s_{ij} = \{-1, 1\}$ where $s_{ij} = 1$ means that player i intends to link to player j while $s_{ij} = -1$ 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

$$s = (s_1, s_2, \ldots, s_n)$$

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 $k_1, k_2, \ldots, k_m$ such that $g_{ik_1} = g_{k_1 k_2} = \cdots = g_{k_{m-1} k_m} = g_{k_m j} = 1$.

Denote by n_i^d the number of direct neighbours of player i, and by n_i the number of her 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 $N_i = \{j \mid$ there is a path in g from i 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 her position in the network g, is assumed to be equal to:

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

where b and c represent, respectively, the unitary benefit from (direct and indirect) connections and the unitary cost of direct links and are such that $b > c > 0$.

In this game, players simultaneously announce all the links they wish to form and the resulting network is formed by the mutually announced links. "This game is simple and intuitive. But, given that link creation requires the mutual consent of the two involved parties, a coordination problem arises. As such the game displays a multiplicity of Nash equilibria, and very different network geometries can arise endogenously." (Calvó-Armengol and Ilkilic (2009), page 2). For this reason we focus on pairwise equilibrium (or pairwise stable) networks as a refinement of Nash networks. Pairwise equilibrium networks are not only robust to unilateral deviations (all redundant links are deleted), but also to bilateral deviations which may make any two players coordinate on the formation of a new link so that no mutually beneficial links are left inactive.[3]

Formally:

Definition: *A network g is a pairwise equilibrium 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 (2006) show that all network architecture which are induced by a Nash equilibrium strategy profile (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 who can be reached both directly and indirectly. Agents 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 $b > c > 0$, all pairwise equilibrium networks are *both* minimal *and* connected (or minimally connected), i.e. there is one and only one path connecting any two agents.[4] The intuition behind this 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.

Examples of network architectures are in Figure 1. 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.

[3]See Goyal and Joshi (2006), Calvó-Armengol (2004) and Bloch and Jackson (2006) for applications of pairwise equilibrium networks.

[4]When $b < c$, the only pairwise equilibrium network (and the only Nash network) is the empty graph.

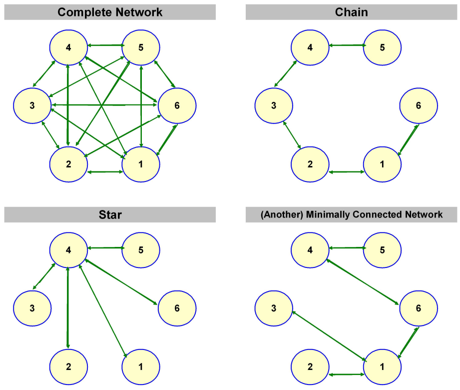


Figure 1: Examples of network architectures.

2.2 The Experimental Procedure

The experimental sessions were conducted in spring 2006 and 2008 at CESARE, LUISS University in Rome with a total of 54 participants.[5] Subjects were first-year Economics students. Each subject participated in only one session and none had previously taken part in a similar experiment. Each experimental sessions was made of 2/3 groups of 6 participants each, playing together in a network formation game. 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. They earned approximately €32 on average, on top of a €5 participation fee.

While in the sessions that were conducted in spring 2006 we implemented two alternative treatments, with different cost parameters, in the present paper we only analyse data from one of the two treatments, for which detailed parameters are given in the table below:[6]

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

[5]Here we re-analyse the data from Treatment 1 in Di Cagno and Sciubba (2008), plus some newly collected data. More in detail, of the 9 groups considered here, 7 coincide with those analysed for Treatment 1 in Di Cagno and Sciubba (2008) and were collected in spring 2006. In spring 2008 we collected data for 2 additional groups under the same experimental protocol used for the 2006 data. More independent observations than we had in 2006 were required for the econometric analysis conducted in this paper.

[6]Treatment 1 and Treatment 2 for which the data were originally collected are analysed in Di Cagno and Sciubba (2008). The econometric analysis that we conduct in the present paper is more sophisticated than in Di Cagno and Sciubba (2008) and requires more variation in the data than we had for Treatment 2. Also, the focus of the present paper is not on the role of the cost parameter, hence a single treatment suffices.

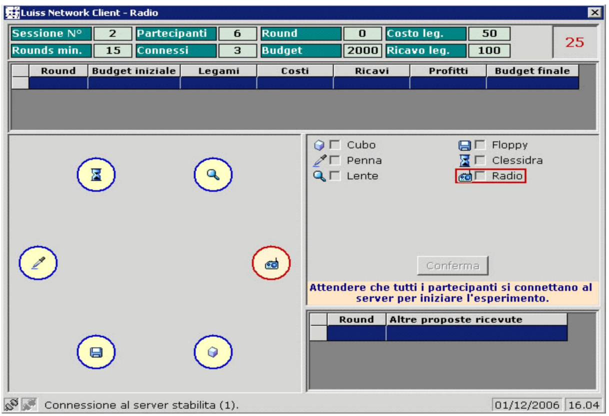


Figure 2: The initial screen

All relevant parameters were equal across participants and displayed on the screen at all 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.[7] 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 2.

Participants were represented on the screen by different symbols which we considered neutral in that they did not provide subjects with any particular clue when deciding to establish a link with another player in the group.[8] Subjects did not know their symbol (or the other participants' symbols) in advance and could identify themselves on the screen because their symbol was circled in red. In order to guarantee not only individual but also group anonymity, participants were invited to the lab in groups of eighteen, with three groups

[7]At the end of round 15 (and of each additional round after that), a lottery administered by the computer decided if an additional round had to be played. The probability of new rounds was fixed at 50%. The lottery was visualised on participants' screens by two flashing buttons, one red (with a NO sign) and one green (with a YES sign).

[8]In this setting we wanted to avoid any salient coordination device that induces coordination in a particular network. In the pilot study for this experiment (see Di Cagno and Sciubba (2008)), we labeled participants with A,B,C,D,E,F and we found that the alphabetical ordering explained most of the linking decisions. See also Bernasconi and Galizzi (2012) and Falk and Kosfeld (2012).

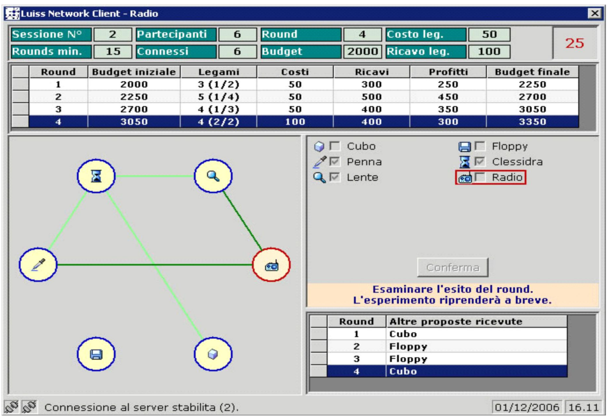


Figure 3: An example of the participants' screen at the end of a round

being matched at the same time. Participants were not told in which of the three groups of six they were playing, nor could they identify the group from their seating.[9]

The screen also displayed the relevant parameters for the session at play. After all subjects had confirmed their choice of network partners, the computer checked which links were mutually desired and activated them. At the end of each round, profits were computed and displayed on the screen. Great care was taken in making sure that all available information was provided to the experimental subjects in a user-friendly way. For this reason the graphical interface was designed such that actual links were visualised on the screen as a graph rather than a list of activated ties or as a matrix of $-1/1$ connections.

As an example, Figure 3 shows the players' 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 a round each subject was informed of those players who proposed a link to them but to whom they did not reciprocate. At any time during the experiment, subjects had access to a great deal of information on past history: by clicking on the bar corresponding to each round, they were able to visualise the graph of active links and the profits obtained in that round.

[9]While we always invited 18 subjects to the lab, in a few occasions we could only collect data for 2 groups of six. This was because not everyone who had registered for the experimental session showed up on time and, in one occasion, because the software for one of the 3 groups crashed.

3 The Model of Link Proposals

In this section, we analyse and discuss the determinants of link proposals. In doing so, we make the assumption of players having static expectations; that is, we assume that each player expects her opponents to make exactly the same choices in round t as in round $t-1$. This is in line with most of the theoretical literature on network formation; also, to a certain extent, such expectations are induced by the design of the experiment itself: the networks that result from choices in previous rounds are portrayed on the computer screen together with all the relevant information and made accessible throughout the game.[10]

Using the system of equations described in Appendix A, we estimate the probability of each subject i proposing a link to any of her prospective partners j, with $j = 1, \ldots, 5$, as a function of the position of i and j in the network reached in the previous round, which is represented graphically on the subject's screen. More in detail, we estimate the probability of subjects proposing a link as a function of a number of variables that can be classified into four categories: the characteristics of the relationship proposer-recipient, which, in particular, include the lagged dependent variable; the characteristics of the prospective partner; the characteristics of the proposer herself; the characteristics of the network of links observed in the previous round. We also control for experience.

This exercise is meant as a preliminary analysis aiming to verify whether there is systematic behaviour in players' link proposals that might be ascribed to the application of certain strategies and, consequently, to identify and to study such strategies.

3.1 Estimation Results

The estimation results of the 5-equation multivariate dynamic probit model derived in Appendix A are reported in Table 1.[11]

The relationship between i and her opponent, j, in $t-1$ is described by the first five

[10] In contrast to what we assume here, see Carrillo and Gaduh (2011) and Mantovani et al. (2011) for experimental evidence on farsighted behaviour in network formation.

[11] We have estimated several specifications of the model of link proposals, using many combinations of parameters and interaction terms as well as different proxies to represent subjects' and networks' characteristics. In Table 1, we report the selection of results that, in our opinion, gives the clearest picture of the main findings. All other results are available from the authors on request.

regressors. Let us start observing that the coefficient on the lagged dependent variable, s_{t-1}, is positive and strongly significant, which conveys the idea that subjects tend to build on what they did in the previous round. Given the strong statistical significance of the coefficient on 'j proposes a link to i', it seems more likely that a link is proposed if the recipient demanded a link to the proposer in the previous round. This could denote both a behavioural tendency to reciprocate and a rational response. In fact, under the assumption of static expectations (i.e. if players expect their opponents to make the same choices in round t as they did in round $t-1$), given that links have to be mutually agreed, a link can only be established by proposing a link to proposers in the previous round. The fact of i and j being linked directly plays no role here, in that the variable 'i and j directly linked', which is an interaction term between 's_{t-1}' and 'j proposes a link to i', shows not to be statistically significant in any specification. Anyhow, there is some evidence on the tendency to cut redundant links through the negative and statistically significant coefficient on the variable 'i and j are linked both directly and indirectly'. The attitude not to form redundant links is corroborated by the negativity and statistical significance of the coefficient on the variable 'i and j only indirectly linked', even if not in terms of all the specifications of the model. Therefore, the probability of proposing a link seems to diminish if i and j were previously linked both directly and indirectly and if they were already linked but only indirectly.

This first set of findings essentially describes the behaviour of a myopic best responder, as delineated in the Introduction, but there is something more. The coefficient on the variable 'j proposes a link to i in $t-1$' showed to be positive and strongly significant in any specification. This makes us conclude that, other than a tendency to best respond to the previously formed network, there might be subjects who simply reciprocate demanded links.

In our opinion, another possible motive of link formation can be extrapolated from the results regarding the probability of i proposing a link to j as a function of j's characteristics, which seem to portray the figure of a player acting in a rather opportunistic way. In effect, the estimation results disclose that players tend to propose links to those who have the largest number of connections and that demanding a link is more likely, the larger the number of

		(1)	(2)	(3)
$i-j$ relationship in $t-1$	s_{t-1}	0.560***	0.400***	0.400***
		(0.062)	(0.060)	(0.060)
	j proposes a link to i	0.467***	0.460***	0.459***
		(0.059)	(0.058)	(0.058)
	i and j directly linked	-0.089	0.130	0.127
		(0.079)	(0.091)	(0.091)
	i and j are linked both directly and indirectly	-0.238***	-0.191**	-0.221**
		(0.074)	(0.086)	(0.089)
	i and j only indirectly linked	-0.124***	-0.076	-0.075
		(0.045)	(0.056)	(0.056)
characteristics of j in $t-1$	number of j's redundant links	0.081***	0.069**	0.107**
		(0.031)	(0.032)	(0.046)
	= 1 if j is isolated	-0.086	-0.041	-0.049
	= 0 otherwise	(0.066)	(0.068)	(0.085)
	= 1 if j has the largest number of connections	0.126**	0.112*	0.115**
	= 0 otherwise	(0.056)	(0.058)	(0.059)
characteristics of i in $t-1$	number of i's redundant links	–	0.011	0.045
			(0.032)	(0.043)
	= 1 if j is isolated	–	-0.067	-0.078
	= 0 otherwise		(0.054)	(0.065)
	= 1 if i has the largest number of direct links	–	-0.034	-0.039
	= 0 otherwise		(0.041)	(0.041)
	number of links proposed – number of links activated	–	0.154***	0.154***
			(0.025)	(0.025)
network in $t-1$	number of redundant links in the group	–	–	-0.039
				(0.035)
	number of isolated nodes in the group	–	–	0.004
				(0.020)
error components	δ	0.029***	0.026**	0.027***
		(0.011)	(0.010)	(0.010)
	ρ	-0.196***	-0.205***	-0.205***
		(0.018)	(0.018)	(0.018)
	σ_i	0.246***	0.211***	0.208***
		(0.037)	(0.034)	(0.034)
	Log-likelihood	-2587.8	-2560.7	-2560.0
	number of observations	4440	4440	4440
	number of subjects	54	54	54
	number of groups	9	9	9

Table 1: Estimation results of three specifications of the model of link proposals detailed in Appendix A. The coefficients on the group fixed effects, λ_g, are omitted.
$***$, $**$ and $*$ indicate a p-value < 0.01, < 0.05 and < 0.10, respectively.

the opponent's redundant links – an indicator of high connectivity.[12] If a player is instead isolated – that is, she has no connection of any sort – the other players do not seem to be willing to include her.

Among the variables that describe i in the previous round, we find strong evidence of the fact that the propensity to demand a link increases only if the breakdown rate in the previous

[12]Here again, the evidence is not extremely robust, making us suspect that only part of the population may adopt that kind of behaviour.

round – measured as the difference between the number of links proposed and the number of links activated – increases.[13]

We also estimate the propensity to propose a link as a function of the characteristics of the network of links that emerged in the previous round. Despite the large number of variables representing the network structure tested, none of them seem to play a significant role in subjects' decision. An example is reported in the third column of Table 1. It shows that neither the coefficient on the number of redundant links nor that on the number of isolated nodes in the group are statistically significant. We therefore conclude that players did not take into account the global structure of the network established in the previous round when expressing their willingness to demand a link and choosing the receiver of that proposal.

Table 1 also shows that the correlation coefficient ρ is precisely estimated to be about -0.20. It is also significantly different from zero and negative, as expected. This indirectly supports our reasons for dealing with individual link proposals as being jointly determined. The considerable magnitude of the standard deviation of the individual-specific propensity to demand links, σ_α, puts into evidence the heterogeneity of the population. Finally, the coefficient δ is estimated to be positive and significantly different from zero, so indicating that the noise diminishes, the higher the level of experience that players accumulate by playing the network game for several rounds.

Given these results, in what follows we study the distribution of three basic patterns of behaviour adopted by the experimental subjects in our sample:

- players who reciprocate to those who demanded a link in the previous round unless they can be reached otherwise through indirect connections (under the assumption of static expectations, this behaviour corresponds, in fact, to profit maximisation);
- players who act by simply reciprocating link proposals from the previous round;
- players who try to reach the largest number of nodes by reciprocating to those who exhibit a high connectivity.

[13] In our setting, reaching a node directly when it is already reached indirectly is always more beneficial than not reaching that node at all. Hence, we do not infer any particular behaviour from this finding.

As stated earlier, this exercise was meant to search for the leading motives of individual linking decisions, which essentially correspond to the maximisation of: expected profits; direct links; and expected profits per link. In what follows, we will delineate the behavioural rules which define these types of player, and we will try to establish whether these patterns of behaviour are deliberately and systematically adopted by the subjects in our sample and, if so, in which proportion of the observed sample the different types are represented.

4 Strategies of 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 example, a possible strategy of player 1 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.

Under the assumption of static expectations, each player expects the other 5 players to play the same strategy in round t that they played in round $t-1$. Hence, given these expectations on what the others will play, each player responds by selecting one of the strategies in the strategy set. In order to understand whether the behavioural patterns defined in the previous section are in fact represented in our sample, we have to define the specific characteristics required of a strategy such that it pertains to each of the behavioural types. The strategies eligible to be assigned to a type are the following:

- a strategy is of *myopic best response* type if it maximises the player's expected profit;
- a strategy is of *reciprocator* type if it maximises the player's expected number of direct links;
- a strategy is of *opportunistic* type if it only activates those link that provide the largest

expected profit per link.

Notice that a player who adopts a myopic best response strategy proposes a link to all those that cannot be indirectly reached (and does not reciprocate links to those that can be indirectly reached). Such a strategy maximises expected profits because, under our parametric assumptions, the benefit obtained by reaching a node is larger than the cost of a link. Hence, unless a node can be reached at zero cost through indirect connections, a proposal to connect directly should always be reciprocated. A myopic best response strategy activates all possible links, except the redundant ones.

A player adopting a reciprocator strategy reciprocates all link proposals that she has received in the previous round. Given that only links which are mutually agreed are activated, by reciprocating all link proposals a player is activating the largest possible number of direct links. The main difference between myopic best response and reciprocator strategies is that the latter activate all possible links, including the redundant ones.

A player following an opportunistic strategy does not reciprocate all link proposals, but only those which bring the largest profit. An opportunist that receives more than one link proposal always favors the link proposals received by those who have the largest number of connections. Unlike the reciprocator, an opportunist recognises the value of indirect connections. However, unlike expected profit maximisers, opportunists may miss out on a profit generating connection when, for example, they do not reciprocate a link proposal from a player that does not have any direct links. On the other hand, the fact that opportunists target highly connected individuals does not prevent them from maintaining redundant links.

While a reciprocator attempts to activate all possible direct links, the opportunist seems to recognize that larger profits can be obtained by restricting the number of direct links and by exploiting indirect connections. However, opportunists target the 'wrong' lot of links for deletion: rather than deleting redundant links (as an expected utility maximiser would do), they delete links to those with lower connectivity.

Given any network configuration, the strategies that fit our behavioural types are not unique. To start with, the fact that links have to be mutually agreed in order to be formed introduces some (trivial) multiplicity. For any of the three strategies outlined above, proposing links to any number of players from whom a link proposal has not been received in the previous round brings exactly the same result in terms of network configuration and profits as not proposing to them at all.

Moreover, for myopic best response behavior, there are non trivial ways in which expected profit maximising strategies are not unique. Consider, for example, the case of being linked to two agents who are also linked to one another. One of the two links is redundant; however a player would be indifferent as to which link to maintain and which link to delete. In this case, the fact that more than one strategy can be identified as a myopic best response is not trivial because such multiple strategies will correspond to the same payoff but to different network configurations.

Finally, there is clearly some overlap among the three strategy types. It may occur that the same strategy, for a given network configuration, can be classified as belonging to more than one type.

Consider, for example, the initial configuration of empty network where nobody is proposing any link. Under static expectations, no link proposals will be expected for the next round as well, hence all types will be indifferent as of making any link proposals or not. Any strategy choice, in this case, can be classified as a myopic best response, or as a reciprocator strategy, or as an opportunistic strategy.

Less trivially, it may, for example, occur that expected profit maximisation requires all link proposals to be reciprocated (imagine the initial network configuration is a minimal network), so that myopic best response strategies will coincide with reciprocator strategies. Similarly, it may occur that all agents who propose to a given player have the same number of connections, so that the strategy of reciprocating to only the most connected agents (opportunist) coincides with the strategy of reciprocating to all (reciprocator).

While it is easy to construct examples of overlap across strategies, in general the three types are distinct. In our experimental sample 39% of the strategy choices can be assigned to a single strategy type (see section 5 for more details).

5 Analysis of Experimental Data and Behavioural Types

In this section, we analyse the experimentally generated data in light of the behavioural types defined in the previous sections in order to verify whether the strategies, as defined in the previous section, are represented in our sample.

In our experimental sample, 360 out of 888 (40.54%) of the individual choices appear *as if* they were made by best responders. In order to assess whether this is a high percentage of choices or not, we compare it to the proportion of times a player who selects a strategy at random ends up selecting a best response strategy. We did this by determining, for each player in each round, the proportion of strategies which account for best response strategies, given the network of links arisen in the previous round. This comparison is particularly useful in our framework where the set of strategies that a best responder may wish to choose 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 half of the available strategies are of the best response type. In that case, even someone choosing a strategy at random would have a very good chance of selecting a best response strategy.

The result of this exercise shows that the average proportion of best response strategies in our sample, given the network emerged in the previous round, is 0.3195 (s.e. 0.0067). Consequently, the proportion of best responses effectively played in the sample (0.4054) is significantly larger than the proportion of best responses our players would have selected, had they picked one of the 32 strategies at random in each round, which establishes that a significant share of choices in our experiment correspond to a 'deliberate' desire to best respond.[14]

We repeat the exercise with the other two types. Both reciprocator and opportunistic strategies are well represented in our sample: 331 (0.3727) choices can be accounted for as being dictated by the reciprocator strategy; 357 (0.4020) choices can be accounted for as being dictated by the opportunistic strategy. By comparing these proportions with the probabilities players had to select a reciprocator strategy (an opportunistic strategy) by picking a

[14] As each strategy has 1/32 probability of being selected, the proportion of strategies which are of a certain type, given what happened in the previous round, can be interpreted as the probability a player has to select that type of strategy by picking one of the 32 strategies at random.

		strategy		
frequency	%	best response	reciprocator	opportunistic
107	12.05	✓	×	×
126	14.19	×	✓	×
112	12.61	×	×	✓
68	7.66	✓	✓	×
108	12.16	✓	×	✓
60	6.76	×	✓	✓
77	8.67	✓	✓	✓
230	25.90	×	×	×
tot. 888				

Table 2: The table shows the frequency of choices in our experimental sample explained by each of the three strategies alone and all possible overlaps. The tick indicates when a strategy is represented; the cross when it is not

strategy at random in each round, given the network arisen in the previous round, we notice that similarly to what observed in the case of best responders, reciprocators (opportunists) seem to be selecting their strategies deliberately. More in detail, the average proportion of choices which account for reciprocator choices is 0.2420 (s.e. 0.0071), compared to 0.3727 in our experimental sample; the average proportion of choices which account for opportunistic choices is, similarly, 0.2426 (s.e. 0.0071), compared to 0.4020 in our experimental sample.

Many choices can be explained by more than one strategy at a time both in the real and the simulated samples: there are instances when the reciprocator strategy coincides with a best response, an opportunistic strategy or both; there are other instances when reciprocator and opportunistic strategies coincide, or do not coincide, with best response behaviour, and so forth. Table 2 shows the overlap between the strategies arising from our experimental sample.[15] The table shows that almost 39% of all choices can be ascribed to only one behavioural type, the remainder being explained by none of the three types, two types at a time or three. It also reveals that 74% of all choices in our experimental sample can be explained in the light of one of our three behavioural types. This is quite a high proportion considering that in many cases playing a certain strategy in such a game might be rather difficult.

By comparing average profits obtained through each of the three strategies, we find that

[15] In table 2, the first row shows, e.g., that 107 (12.05%) choices in the experimental sample can be accounted for as best response, but not as reciprocator and/or opportunistic behaviour. Instead, the fourth row shows that 68 (7.66%) choices in the experimental sample can be accounted for as both best response and reciprocator behavior but not as opportunistic behaviour, and so forth.

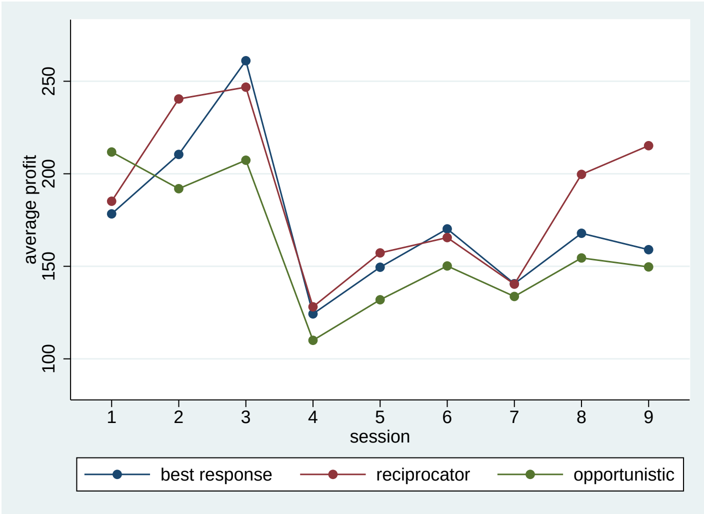


Figure 4: The figure shows average profits by strategy and by session.

the average profits obtained by best response choices are not significantly different from those obtained by reciprocators, but both best responders and reciprocators earned, on average, a profit larger than that earned by opportunists: best response choices yielded our experimental subjects an average of 175.056 (s.e. 7.901) experimental units, while reciprocators earned 182.931 (s.e. 7.433) and opportunists 158.655 (s.e. 7.344) experimental units. Figure 4 shows that this pattern holds not just on average, but also for most sessions. The fact that opportunists earned on average less than myopic best responders and reciprocators should not be too surprising. Given our parametric assumptions, connections are always profitable: indirect connections are more profitable than direct links, however both increase profits. The opportunist, by only targeting those connections that provide the highest payoff, may often miss out on linking opportunities by not reciprocating link proposals to those who would bring in a more modest, but still positive, payoff.

6 The Mixture Assumption

As seen in the last section, patterns of behaviour often overlap so that the choice of a particular strategy is compatible with more than one behavioural rule. For this reason, discriminating between subjects according to their behavioural type is rather difficult if one merely observes the strategies selected by them. In this section, we want to verify whether subjects systematically adopt one of the three patterns of behaviours under investigation so that the former can be framed alternatively within our definitions of the reciprocator type (RC), the best response type (BR) and the opportunistic type (OP). In order to assign subjects to these types, we estimate a finite mixture model (see McLachlan and Peel (2000)) that will allow us to verify if these strategies are well identified and separated in our sample.

We proceed by assuming that a proportion π_{BR} of the population from which the experimental sample is drawn behaves according to the best response type; a proportion π_{RC} behaves according to the reciprocator type; and finally a proportion $\pi_{OP} = 1 - (\pi_{BR} + \pi_{RC})$ behaves according to the opportunistic type. Our mixture assumption is that each subject belongs to one of these types and that she cannot switch type across rounds. 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 then is:

$$L_{ig} = \pi_{BR} \times l_{ig}^{BR} + \pi_{RC} \times l_{ig}^{RC} + \pi_{OP} \times l_{ig}^{OP}, \tag{1}$$

where l_{ig}^{BR}, l_{ig}^{RC} and l_{ig}^{OP} are the likelihood contributions of individual i under the hypothesis of her belonging to the best response type, the reciprocator type and the opportunistic type, respectively. These are derived as follows.

We model the individual propensities to behave according to type $h \in (BR, RC, OP)$ in a very simple way, that is, by assuming that there is an average propensity, γ_g^h, to choose one of the strategies that comply with that type's rule which is common to all the subjects of that type. γ_g^h has a subscript g because we allow it to vary across groups in order to capture possible coordination effects (group-specific fixed effects). In other words, we test whether players are more likely to adopt a strategy if there are other players in her group of the same type. Thus individual i's propensity to choose one of the strategies that correspond to type

h is:

$$
\text{(2)} \qquad \begin{aligned} y_{ig,t}^{h^*} &= \gamma_g^h + \varepsilon_{ig,t}^h \qquad i = 1, \ldots, 6 \qquad g = 1, \ldots, 9 \qquad t = 1, \ldots, T_g \\ \varepsilon_{ig,t}^h &\sim N[0, 1] \end{aligned}
$$

Here, $\varepsilon_{ig,t}$ is an error term, distributed as a standard normal and independent of anything else in the model. $y_{ig,t}^{h^*}$ is a latent variable representing player i's attitude to act according to strategic type h. 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:

$$
\begin{aligned} y_{ig,t}^h &= 1 \qquad \text{if } s_{ig,t} \text{ complies with type } h\text{'s behavioural rules} \\ y_{ig,t}^h &= -1 \qquad \text{otherwise} \end{aligned}
$$

The likelihood contribution of subject i, conditional on being of type h, is

$$
\text{(3)} \qquad l_{ig}^h = L_{ig}^h \left(\gamma_g^h \mid s_{ig,1}, \ldots, s_{ig,T_g} \right) = \prod_{t=1}^{T_g} \Phi \left[y_{ig,t}^h \times \gamma_g^h \right],
$$

where $\Phi[\cdot]$ is the standard normal cumulative distribution function.

Results are displayed in Table 3. In specification 1, where all γ_g^h, with $h \in (BR, RC, OP)$, are estimated as common constants, we find that the predominant type is the best response type, followed by the reciprocator and the opportunistic type. Adding group fixed effects to the three types significantly increases the log-likelihood according to the likelihood-ratio test ($\chi^2_{24} = 80.010$, p-value< 0.0001). This makes again the best response type the most popular with a mixing proportion $\pi_{BR} = 0.452$, followed by the reciprocator type with a $\pi_{RC} = 0.296$ and the opportunistic type with a $\pi_{OP} = 0.252$. Compatible with these results, we observe that adopting a certain strategy seems group-driven (e.g., players are more likely to best respond if they are in a group where there are other players who do best response).

Given the estimates results of the mixture model, we can compute the posterior probabil-

	(1)	(2)
γ^{BR}	CC	GFE
γ^{RC}	CC	GFE
γ^{OP}	CC	GFE
π^{BR}	0.417	0.452
	(0.090)	(0.087)
π^{RC}	0.367	0.296
	(0.090)	(0.073)
π^{OP}	0.216	0.252
	(0.072)	(0.073)
Log-likelihood	-512.645	-472.640
observations	888	888
number of subjects	54	54
number of groups	9	9

Table 3: Estimation results of the mixture model. CC indicates that a common constant is estimated; GFE indicates that group fixed effects are estimated. The results are omitted.
All mixing proportions are statistically significant at 1% level.

ities of each experimental subject being of each type. Using Bayes' rule we have the following posterior probabilities:

$$\begin{aligned}\Pr\left[i \text{ is of type } h \mid s_{ig,1},\ldots,s_{ig,T_c}\right] &= \frac{\Pr\left[\text{type } h\right]\times\Pr\left[s_{ig,1},\ldots,s_{ig,T_c} \mid \text{type } h\right]}{\Pr\left[s_{ig,1},\ldots,s_{ig,T_c}\right]} \\ &= \frac{\pi_h\times\Pr\left[s_{ig,1},\ldots,s_{ig,T_c} \mid \text{type } h\right]}{\Pr\left[s_{ig,1},\ldots,s_{ig,T_c}\right]} = \frac{\pi_h\times l_i^h}{L_{ig}} \qquad (4)\end{aligned}$$

for $h \in \{BR, RC, OP\}$. Posterior probabilities are reported on the simplex displayed in Figure 5. The 54 subjects are represented by circles in the graph: small circles represent a single subject; larger circles cluster subjects concentrated in that area of the simplex (the larger the circle the more numerous the cluster). The closer a subject is to a vertex of the simplex the greater the posterior probability for that subject of being of the type represented on that vertex.[16] Subjects in the bottom left corner are of the best response type; subjects in the top corner are of the reciprocator type and, finally, those in the bottom right corner are of the opportunistic type. The majority of subjects are located very close to the vertices of the simplex, a minority to the edges and only three are in the middle. The yellow simplex in the centre represents a virtual area of "uncertainty over types" and is empty in the case under examination. This finding confirms that the mixture model clearly separates the three

[16]For producing the simplex, posterior probabilities have been rounded to the closest 0.05.

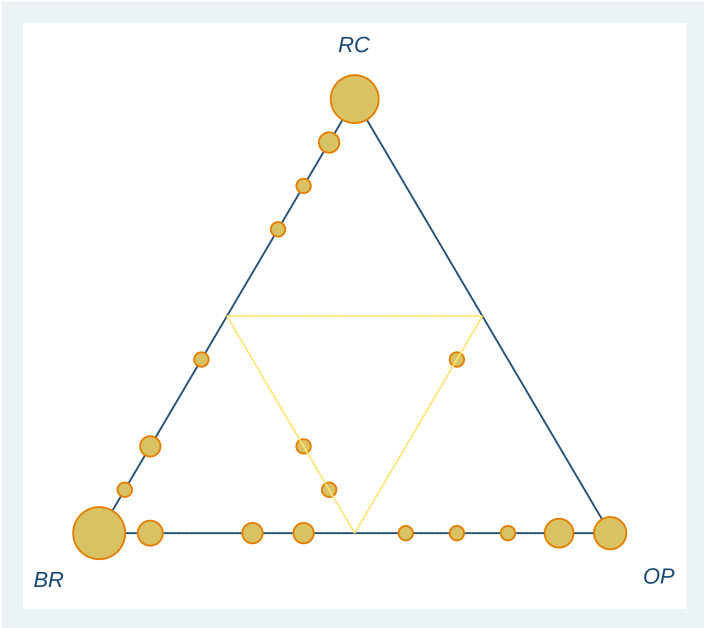


Figure 5: Posterior probability of types from estimation results in Table 3, specification 2.

types of individuals, with most of them being assigned to a particular type with quite a high posterior probability.[17]

7 Conclusions

In this paper we use experimentally generated data to analyse individual linking strategies in a network formation game.

By a system of equations modelling players' link proposals in each round of the game, we are able to distinguish between strategies that we name of the reciprocator type, of the myopic best response type and of the opportunistic type.

We find that approximately 40% of the network formation strategies adopted by the experimental subjects can be accounted for as myopic best response strategies, 37% as reciprocator strategies and 40% as opportunistic strategies. Adding myopic best response, reciprocator and opportunistic behaviour, we are able to explain approximately 74% of the observed choices. We show that each of these types of behaviour is 'deliberate' in that we have obtained shares

[17]This technique has been previously used by Conte and Levati (2014) and Conte and Moffatt (2014).

of each behaviour that are significantly different from what we would have obtained if agents had selected links at random.

Given that there is overlap between strategies, we have tested 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 45%, 30% and 25% for best response, reciprocator and opportunistic types, respectively.

We observe that the average profits obtained by subjects following each of the strategies are not too dissimilar, with opportunists earning marginally less. We argue that this is because, by targeting only the links which have the highest connectivity, opportunists may miss out on profitable connections.

Finally, we discover that the individual attitude to adopt a certain strategy is heavily group-driven, with agents being more likely to best respond, for example, when others in the same group also do so.

The latter finding has very interesting policy implications. By having more subjects who have an individual propensity toward a certain behaviour, we increase the attitude to adopt that kind of behaviour of other members of the same group. Hence by controlling the group composition in behavioural types one could favour some network outcomes as opposed to others.

In this paper, we present the reciprocator and the opportunist as behavioural strategies other than myopic best response behaviour. If agents are myopic and have static expectations, anything other than myopic best response is 'irrational'. In a more complex model, where agents are farsighted and averse to strategic uncertainty, rational behaviour may share features with the strategies that we have outlined here. A rational farsighted agent may attempt to establish her reputation as a reliable connection by always reciprocating link proposals. Equally, an agent who is averse to strategic uncertainty may choose to keep redundant links. We do not attempt such modelling here, but acknowledge the possibility that in a more general model of network formation the behavioural patters we outline here may indeed stem from expected utility maximisation. This is a topic for future research.

Appendix A. The econometric model of link proposals

In each round of the game, each subject submits a vector of choices concerning the opportunity to propose or not propose a link to any of her opponents. From a player's perspective, the decision to propose a link to one of her opponents is not separate from the decision to propose or not propose a link to another opponent. For this reason, all decisions made by a player in a round are not independent but they are the result of a joint evaluation and need to be analysed as such.[18]

Let us consider a set of 6 players, indexed by $i = 1, \dots, 6$. Each player i in round t submits a 5-dimensional vector of intended links:

$$s_{ig,t} = (s_{i1g,t}, \dots, s_{ijg,t}, \dots, s_{i5g,t}) \, .$$

Here, $j = 1, \dots, 5$ represents i's prospective players; groups of opponents are indexed by g, with $g = 1, \dots, 9$; $t = 2, \dots, T_g$ indicates the round number. The final round number, T_g, may differ by group because of a random stopping rule that decides, after round $t = 15$, whether or not to continue with another round of the game. $s_{ijg,t}$ equals 1 if subject i expresses his willingness to be linked to j; it equals -1 otherwise.

The vector of intended links s_{igt} is the result of a complex decision process. In making her decisions, i needs to jointly evaluate the opportunity to propose a link to each of her 5 prospective players. In other words, i needs to consider the following system of equations:

$$\begin{aligned} s^*_{ijg,t} \;\; &= \;\; \alpha_i + \lambda_g + \beta^{'}_w W_{ijg,t-1} + \beta^{'}_x X_{jg,t-1} + \beta^{'}_y Y_{ig,t-1} + \beta^{'}_z Z_{g,t-1} + \frac{u_{ijg,t}}{(1 + \delta \, (t-2))}, \\ &\quad\;\; \text{for} \quad j = 1, \dots, 5 \quad \text{and} \quad j \neq i. \end{aligned} \tag{5}$$

Here, $W_{ijg,t-1}$ is a vector of explanatory variables describing the characteristics of the relationship between i and j in the previous round, including the lagged dependent variable, $s_{ijg,t-1}$; $X_{jg,t-1}$ is a vector of characteristics of j as shown by the network that emerged in the previous round; $Y_{ig,t-1}$ is a vector of explanatory variables related to i's position in the net-

[18]Cf. Di Cagno and Sciubba (2008), who disregard this characteristic of players' decisions, deal with each player's link proposals to her prospective partners as independent choices.

work in the previous round; the explanatory variables in $Z_{g,t-1}$ describe the main features of the network resulting from players' link proposals in the previous round. There are also two regression intercepts, α_i and λ_g. Intercept α_i varies across individuals (individual-specific time-invariant random effect) and is assumed to be common to all equations in (5). We also assume that it does not depend on any observable. It represents the individual-specific propensity to demand links and is assumed to be distributed normal across the population: $\alpha_i \sim N\left(0, \sigma_\alpha^2\right)$. In a network formation game, individual decisions within a group may well be correlated because of unobservable common shocks to all individuals in the same group – for example, because all individuals observe the same sequence of graphs occurring during a session. Our method of controlling for dependence on unobservables within a session is to model the intercepts λ_g as random unobservables (group-specific fixed effects). The term $(1 + \delta(t-2))$ is introduced in order to capture the effect of experience on players' decisions. A positive (negative) δ implies that subjects' choices eventually become less (more) noisy.[19] $s^*_{ijg,t}$ – the latent dependent variable representing subject's i propensity to demand a link to j – and $s_{ijg,t}$, the observed binary outcome variable, are related by the following observational rule:

$$s_{ijg,t} = \begin{cases} 1 & \text{if } s^*_{ijg,t} \geq 0 \\ -1 & \text{else} \end{cases}.$$

Since players in each round jointly evaluate the opportunity to propose a link to any of their opponents, we expect that the choice of proposing a link to one of the prospective partners reduces the probability of proposing a link to the others. In other words, we expect to observe a negative correlation across the equations in (5).[20] i's decision in each round can be framed within the class of M-equation multivariate dynamic probit models. Anyhow, we need to place some restrictions on the variance-covariance matrix of the errors and the

[19] A positive δ would eventually reduce the error variance (that is constrained to be equal to 1 in round 2 for identification purposes), consequently making the role of the stochastic disturbance less and less relevant in players' decisions and, in this sense, highlighting the role of experience accumulated throughout the game.

[20] Suppose player i's decisions are uncorrelated. Then, the probability that i proposes a link to both player 1 and player 2 is 25%. A correlation of -0.25 reduces this probability to about 21%, a correlation of -0.5 to about 17%, and so on. A positive correlation would obviously increase such probability.

coefficients on the system's variables. In particular, the joint distribution of the error terms is assumed to take the form:

$$V\begin{pmatrix} u_{i1g,t} \\ \vdots \\ u_{ijg,t} \\ \vdots \\ u_{i5g,t} \end{pmatrix} = \begin{pmatrix} 1 & \cdots & \rho & \cdots & \rho \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \rho & \cdots & 1 & \cdots & \rho \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \rho & \cdots & \rho & \cdots & 1 \end{pmatrix}. \tag{6}$$

Here, error variances on the leading diagonal of V have values of 1 and the off-diagonal elements are all equal to ρ. This hypothesis of equi-correlation of the error terms of the system of behavioural equations (5) follows from the fact that there is no reason to assume that a certain pair of equations in (5) are more or less correlated than another pair. Further, we assume that the coefficients on the variables in system (5) do not vary across equations.

Estimation of the dynamic system (5) requires an assumption about the initial observations $s_{ijg,1}$. Since players do not know anything about their opponents and the group of players as a whole before the graph of the network resulting from round 1 link proposals is shown to them, we can safely assume that the initial condition $s_{ijg,1}$ is completely random.

Let us define player i's likelihood contribution as:

$$L_{ig} = \int_{-\infty}^{\infty} \prod_{t=1}^{T_g} \Phi_5\left(\mu_{ig,t};\Omega\right) f\left(\alpha; 0, \sigma_\alpha^2\right) \mathrm{d}\alpha, \tag{7}$$

where $\mu_{ig,t} = (s_{i1g,t} \times \mu_{i1g,t}, \ldots, s_{ijg,t} \times \mu_{ijg,t}, \ldots, s_{i5g,t} \times \mu_{i5g,t})$ and $\mu_{ijg,t} = (1 + \delta\,(t-2)) \times \left(\alpha_i + \lambda_g + \beta_w^{'} W_{ijg,t-1} + \beta_x^{'} X_{jg,t-1} + \beta_y^{'} Y_{ig,t-1} + \beta_z^{'} Z_{g,t-1}\right)$, with $j = 1, \ldots, 5$; Ω is a symmetric 5×5 matrix whose elements on the leading diagonal are equal to 1 ($\sigma_{jj} = 1$ for $j = 1, \ldots, 5$) and are equal to $\sigma_{jk} = s_{ijg,t} \times s_{ikg,t} \times \rho$ (for $j, k = 1, \ldots, 5$ and $j \neq k$) somewhere else; $f\left(\alpha; 0, \sigma_\alpha^2\right)$ is the normal density function with mean 0 and variance σ_α^2 evaluated at α.

The multivariate normal cumulative distribution function $\Phi_5\,(.)$ is evaluated by the Geweke-Hajivassiliou-Keane (GHK) algorithm.[21] The likelihood function is maximised using 20-point

[21] This is implemented in Stata 12 by the **mvnp()** function; see Cappellari and Jenkins (2006).

Gauss-Hermite quadrature.[22]

Appendix B. Experimental instructions

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 after the end of this session.

You are one of 6 participants to this experiment; at the very beginning the computer will randomly assign to you an initial budget (equal across participants). The computer will also 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 identifying 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 will be a 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 may propose 0, 1 or more links. *The computer will collect the proposals from all participants and activate only the links desired by both of the two subjects involved (reciprocated proposals).*

Your screen will show the graph of active links. The box at the bottom right corner of your screen will show you who has proposed a link to you in the previous round and to 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.

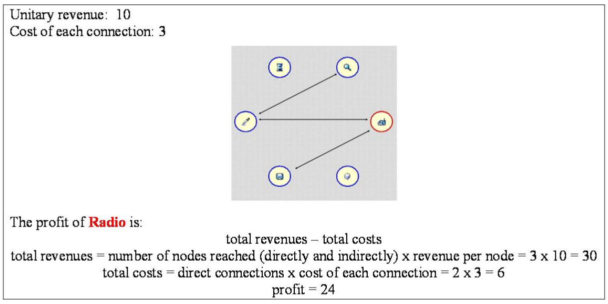
Your revenues in each round are automatically computed and are given by the product by the revenue per node (equal across subjects and indicated on your screen) and the number

[22] The programme is available from the authors on request.

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**.



In each round, the computer calculate out your profit and 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 before touching any key.

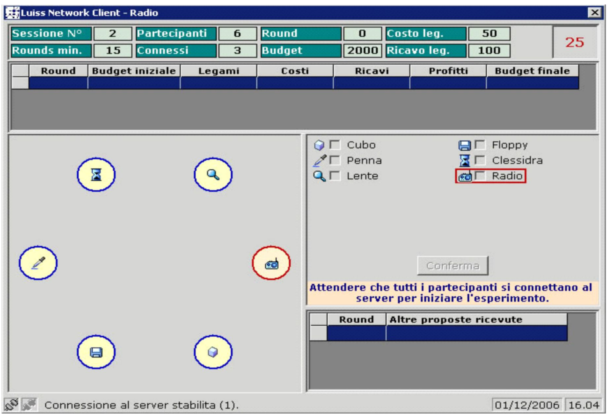
When the experimenter asks you to do so, please double-click only once on the "Network Client" icon on your desktop.

The following screen will appear:

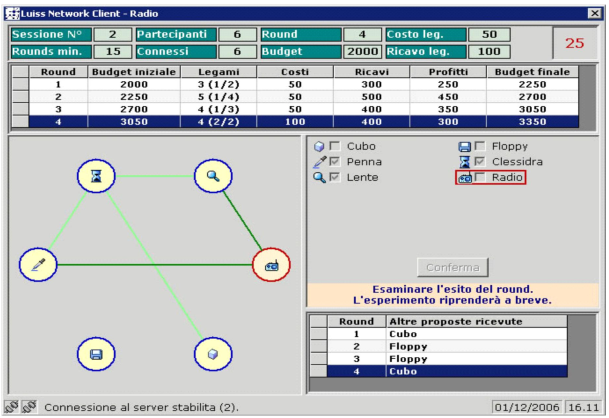
The screen gives you all the information regarding the round that you are about to play.

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 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 corner of your screen gives you additional information on proposals that you have received but not reciprocated 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 on green, you will play another round; if they stop on 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 a sum in cash 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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