Coordination in Networks Formation: Experimental Evidence on Learning and Salience

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Abstract

Here, we have presented some experiments of non-cooperative games of network formation based on Bala and Goyal (2000). We have looked at the one-way and the two-way flow models, each for high and low link costs. The models came up with both multiple equilibria and coordination problems. We conducted the experiments under various conditions which also controlled for salient labeling and learning dynamics. We found that coordination on non-empty Strict Nash equilibria was not an easy task to achieve, even in the mono-directional model where the Strict Nash equilibria are wheels. We also found empty networks in the two-way flow model. We found that salient labels helped coordination, but also various other experimental frames contributed to enhance or lessen their effects. The evidence on learning behavior provided support for subjects that were choosing strategies in line with various learning rules, principally Reinforcement and Fictitious Play.

Keywords: Experiments, networks, behavioral game theory, salience, learning dynamics.

JEL classification: C92, C72, D83.

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1 Introduction

Networks play a crucial role in the formation of social and economic structures, in the circulation of information and in the emergence of competition and cooperation among individuals (see e.g. Mansky 2000, and Rauch and Hamilton 2001, for reviews).

The process of the emergence of social network has been rarely studied until recently. However, the issue has in the last few years become the object of a growing stream of research (Demange and Wooders 2005). An important question concerns the process of social network formation as experienced by the individual. Experimental economics is useful for this purpose and a number of studies have looked at this topic (see Kosfeld 2004, for a review).

This paper falls into this category, while also crossing various branches of related literature. The paper provides an experiment of one of the leading theories of endogenous network formation: the *non-cooperative* game by Bala and Goyal (2000). This model has also been investigated by Falk and Kosfeld (2003), Callander and Plott (2005) and, with some modifications, by Goeree *et al.* (2005) and Berninghaus *et al.* (2006). This paper differs from the previous experiments by drawing explicit attention to alternative decision processes individuals may follow by forming a network. In fact, this experiment is at the cornerstone of two major ideas on individual behavior in game playing, i.e., that of *salience* and *learning* (see Camerer 2003).

Bala and Goyal (2000) provided the leading model of endogenous network formation in a non-cooperative setting[1]. They considered a group of individuals, each endowed with a valuable piece of non-rival information with the possibility to create connections between them. Links to others are beneficial because they permit information transmission. However, direct connections are costly. Two specifications of information flow were considered: in the one-way or mono-directional model, an established link paid by i to j

[1]Another seminal paper on endogenous networks formation is by Jackson and Wolinsky (1996). They adopt a cooperative game-theoretical approach to examine whether efficient networks might be formed when self-interested individuals can choose to form and to severe connection-links. The cooperative approach by Jackson and Wolinsky, and the consequent process of unstructured negotiations among players (investigated experimentally by Vanin 2002), makes our aim of also studying strategic playing in networks formation difficult to pursue.

enables i to access j's information, but not vice versa. In the two-way or bi-directional case information flows in both directions.

The theory opens up various interesting issues. A major one is the problem of the multiplicity of equilibria and coordination. Bala and Goyal prove that in both the one-way and two-way models, several configurations of the Nash equilibrium can arise. Adopting a refinement based on the notion of the Strict Nash equilibrium, the sets are substantially restricted. In the mono-directional model, depending on link costs, the only Strict Nash networks are the empty network and wheel networks, while in the bi-directional model only the empty network and the center-sponsored star networks are Strict Nash equilibria.

The notion of Strict Nash, while reducing the number of equilibria, doesn't solve the question of whether any coordination can be achieved in practice. The networking games remain very complex indeed, further complicated by the fact that the wheel and center-sponsored star endorse different degrees of efficiency and payoff asymmetry.

As in most coordination games, experiments can help to shed some light on the issues involved. An interesting initial experiment of the Bala and Goya model was conducted by Falk and Kosfeld (2003) for a four person economy. Their findings support the Strict Nash refinement in the wheel case, but not in the case of the center-sponsored star of the two-way flow model. In fact, Falk and Kosfeld (2003) find that subjects in their experiments showed an impressive quick convergence towards the wheel equilibrium.

The study by Falk and Kosfeld (2003) uses A, B, C, D labels to identify subjects in the network. It also applies an experimental protocol in which subjects are invited at the start of the experiments to indicate the network ensuring the best possible flow of information and the maximum income for all group members. These features of the experimental procedure may have helped subjects to coordinate on the efficient wheel equilibrium, and to choose the naturally ordered wheel in which A connects to B, B to C, C to D and D back to A. In other words, subjects may have used letters to select an equilibria which was *salient* for them, in the classical sense of Schelling (1960)[2].

[2]See Bacharach (1993), Sugden (1995), Janssen (2001), for theoretical studies on salience; see Metha *et al.* (1994), Bacharach and Bernasconi (1997), Van Huyck *et al.* (1997), and the literature referred to in Camerer (2003), for various experimental studies. See Colman (2006) and Sugden and Zamarrón (2006), on other recent developments in this area.

An other interesting experiment on network formation has been conducted by Callander and Plott (2005). They only focus on the one-way flow model[3]. Among other things, these authors explicitly investigate the role of focalness in equilibrium selection. They find that various economies of their experiment converge to what is defined as a "salient" wheel in terms of their design (see the original paper and below for details).

A different approach to equilibrium selection in games is *learning dynamics*, namely equilibrium learning through repetitions (see Vega Redondo 2003, for an updated theoretical review). Bala and Goyal (2000) themselves develop a dynamic version of their network formation game. They show that when players follow a learning rule mixing inertia and Cournot Best Response, both the one-way and two-way economic networks converge to the Strict Nash equilibria.

The purpose of this paper is to investigate network formation controlled for salient labeling and different learning environments.

We have obtained several different results. We found that coordination on non-empty Strict Nash equilibria is not an easy task to achieve, even on the wheel equilibrium of the mono-directional model. We found that salient labels help coordination, but substantially less than reported by Falk and Kosfeld (2003). We found less evidence of convergence to wheel networks through learning dynamics, while we saw some emergence of empty networks in the bi-directional model.

We studied various learning rules which subjects could have used in the experiments. In particular we compared the 'Cournot Best Response hypothesis' with alternative learning rules based on models of Fictitious Play (as in Fudenberg and Levine 1998, and Cheung and Friedman 1997) and of Reinforcement learning (as in Roth and Erev 1995, and Mookherjee and Sopher 1994 and 1997). Evidence shows that subjects choose strategies consistent with various learning rules, which include Reinforcement and Fictitious Play as the main ones.

The paper is divided into several sections. Section 2 reviews the theoretical model of Bala and Goyal (2000). Section 3 discusses the many questions posed by the theory in

[3]Other recent experiments on networks formation include, e.g. Goeree *et al.* (2005) and Berninghaus *et al.* (2006). These experiments study modified theoretical predictions of the Bala and Goyal Model, and are therefore less relevant for the present paper.

terms of equilibrium selection, coordination, and previous experimental evidence. Section 4 presents our experimental design. Results are given in Section 5. In the conclusion (Section 6), we bring the various themes of the paper together to summarize the evidence.

2 The Bala and Goyal model: equilibrium theory

Let $N = \{1, ..., n\}$ be a set of agents, with $n \geq 3$. Bala and Goyal (2000) considered a non-cooperative model in which the payoff of an agent i from participating in a network is increasing in the number of agents directly or indirectly connected to i, and is decreasing in the number of links paid by i. Two alternative specifications are considered: in the mono-directional model, a link created by i to j only benefits agent i, in the bi-directional model a link created by i to j benefits both agents.

Thus, the payoff Π_i received by i depends on the type of informational flow, on the cost for creating the links and on the benefits of being connected to other members of the network. A basic payoff function considered by Bala and Goyal (2000) and adopted in our experiments is a linear function with no decay in the information transmission[4]. Denoting the constant marginal cost of creating a link $c > 0$, and with the marginal benefit from being connected to another agent normalized to 1, this can be written as:

$$\Pi_i = o_i - cd_i, \tag{1}$$

where o_i is the number of agents directly or indirectly connected to i, and d_i is the number of direct links that i is paying for.

For both flow games, Bala and Goyal (2000) described the Nash equilibria.

> **Nash networks.** *In the mono-directional model, a Nash network is either empty or minimally connected, in the sense that it has a unique component that splits apart as soon as a single link is severed (Bala and Goyal 2000, Proposition 3.1).*

[4] See Bala and Goyal (2000), Section 5, for the analysis in presence of decay.

In the bi-directional model, a Nash network is either empty or minimally bi-connected, meaning that it has a unique component, no cycle and no pair of agents build links with each other (Bala and Goyal 2000, Proposition 4.1).

Thus, in both models, a network is a Nash equilibrium if and only if, either, none or all individuals are connected with no redundant links. One problem is that, depending on the number of agents, the number of Nash networks can be quite large. For instance, Bala and Goyal calculate that with linear payoffs and $c < 1$, there are in the mono-directional model 5, 58, 1069, and more than 20000 Nash networks as n takes on the values 3, 4, 5 and 6, respectively; in the bi-directional model, when n has the same values and in the same order, the Nash networks are 12, 128, 2000 and 44352.

The notion of Strict Nash, where each individual plays their unique best response to the strategy profile of all the other agents, the set of equilibria is restricted.

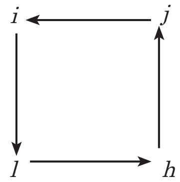
Strict Nash networks. *In the mono-directional model, a Strict Nash equilibrium is either the empty network or the wheel. In particular, if* $c < 1$*, the wheel is the unique Strict Nash network; if* $1 < c < n - 1$*, both the empty and the wheel are Strict Nash networks; if* $c > n - 1$*, the empty network is the unique Strict Nash equilibrium (Bala and Goyal 2000, Proposition 3.2) .*

In the bi-directional model, a Strict Nash equilibrium is either the empty network or the center-sponsored star, that is, the star where the agent located in the centre pays all links. In particular, the center sponsored star is the unique Strict Nash network if $c < 1$*, and the empty network is the unique Strict Nash equilibrium if* $c > 1$ *(Bala and Goyal 2000, Proposition 4.2).*

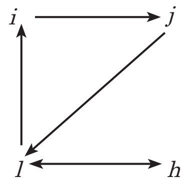
Thus, the notion of a Strict Nash network is quite successful in restricting the set of equilibria. Consider for example networks of 4 people: i, j, h, l. As noted, when $c < 1$, in the mono-directional case there are 58 Nash equilibria, which can be distinguished in four classes shown in Figure 2.1, where the arrows point in the direction of the information flow. In this figure, the set of Strict Nash corresponds to the networks of the wheel architecture. In particular, there are 6 equivalent wheels, which differ depending on the distribution of

Figure 1: Classes of Nash networks in 4 people economies

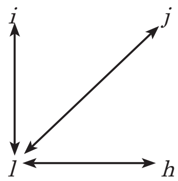
2.1 Classes of mono-directional Nash networks when c<1



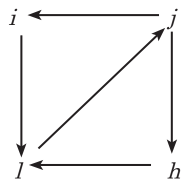
1) Wheel



2) Petal

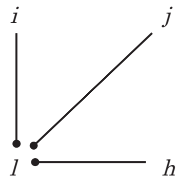


3) Star

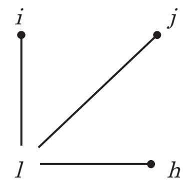


4) Two petals

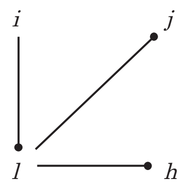
2.2 Classes of bi-directional Nash networks when c<1



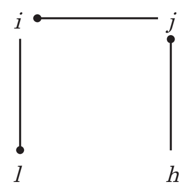
1) Center-sponsored star



2) Periphery-sponsored star



3) Mixed-sponsored star



4) Pipeline

the four players across the nodes of the network.

In the bi-directional model, for $c < 1$, there are 128 Nash equilibria, also of four general classes depicted in Figure 2.2, with dots indicating the agents paying the connection. The only Strict Nash networks are 4 center-sponsored stars, differing depending on who is the central agent.

With $1 < c < n - 1$ (and $n = 4$), the sets of Nash and Strict Nash in the mono-directional case coincide. These are the networks of the wheel architecture and the empty network. In the bi-directional case, the Nash equilibria are the empty network and a strict subset of 28 minimally bi-connected networks[5]. There is a unique Strict Nash equilibrium which is the empty network.

Bala and Goyal (2000) also consider the relations between Nash equilibria and efficiency, the latter measured by the sum of payoffs obtained by all the agents of a network.

> **Efficient networks.** *In the mono-directional model with linear payoffs, the wheel is the unique efficient network if* $c < n - 1$*, while the empty network is otherwise (Bala and Goyal 2000, Proposition 3.3).*
>
> *In the bi-directional model with linear payoffs, if* $c \leq n$*, a network is efficient if and only if is minimally bi-connected; while if* $c > n$*, the empty network is the unique efficient network (Bala and Goyal 2000, Proposition 3.3).*

3 Learning and salience in networks formation

The theory by Bala and Goyal (2000) raises non trivial questions regarding equilibrium selection and coordination. A network game may generate several networking configurations. For example, in a 4 people economy, every individual can choose between 2^3 strategies, giving rise to $(2^3)^4 = 4096$ possible networks. Depending on the level of costs, some strategies are dominated, restricting the number of "reasonable" strategies for the individuals to play. For instance, in the mono-directional model with $c < 1$, the strategy of

[5]This set in particular includes the 4 equivalent networks belonging to the periphery-sponsored star architecture, and 24 possible variants of a *restricted* pipeline network structure where any two different players both access the same third individual, while the remaining fourth is connecting to one of the former two subjects.

no link is strongly dominated and shouldn't be played. Furthermore, in both flow models with $1 < c < 3$, all strategies of more than one connection are dominated (by either the strategies of no link or of 1 link). However, even in this latter case, each individual is left with (2^2) different not-dominated strategies, with a total of $(2^2)^4 = 256$ possible emerging networks.

Even when individuals have understood the game and perhaps try to play a Strict Nash equilibria, the chances of miss-coordination are very high. For example, in a one-way flow model with 4 persons, there are 6 equivalent wheels. Since there are three strategies of one link that each player has to choose between (one per each of the other players), the chances for players to coordinate in a single attempt are only $6/3^4 = 0.07$.

3.1 Learning dynamics

Learning dynamics is a possible way in which coordination and equilibrium selection can arise. This is the route considered by Bala and Goyal, who provide a model of equilibrium convergence for their games based on the following modified version of the Cournot Best Response dynamics[6].

The network formation game is repeated in each time period $t = 1, 2, ...$ In each period $t > 2$, each subject observes the network which has been formed in the previous period. Bala and Goyal assume that with some fixed probability $r_i \in (0, 1)$ agent i exhibits inertia maintaining the strategy chosen in the previous period. On the other hand, with probability $p_i = 1 - r_i$, the agent chooses a myopic pure best response strategy to the ones played by all the other agents in the previous period. In case there is more than one best response, each of them is chosen with positive probability.

Various theorems are given by Bala and Goyal showing that, for the case of linear payoff, these dynamics converge to the Strict Nash equilibria in both the mono-directional and bi-directional flow models and for any cost structure. Moreover, some simulations are run to test the speed of convergence. The simulations assume the same probability

[6] At the outset of their paper, Bala and Goyal (2000) note: "While these findings — those on Strict Nash equilibrium — restrict the set of networks sharply, the coordination problem faced by individuals in the network game is not entirely resolved... This leads us to study the process by which individuals learn about the network and revise their decisions on link formation, over time" (p. 1184).

Table 1: Rates of convergence to the Strict Nash equilibria when $n = 4$ for mixtures of inertia and Cournot best Responses (from Bala and Goyal 2000)

	Mono-directional $c < 1$	Mono-directional $1 < c < 3$	Bi-directional $c < 1$
$p = 0.2$	23.23(0.68)	11.52(0.38)	–
$p = 0.5$	12.71(0.37)	5.98(0.18)	318.23(22.93)
$p = 0.65$	–	–	71.34(4.93)
$p = 0.8$	13.14(0.42)	6.77(0.22)	17.55(1.02)
$p = 0.95$	–	–	14.83(0.53)

$p_i = p$ for all agents to choose a naive best response and assign equal probability to all best responses given a network. Table 1 shows the results of the simulations for a 4 people economy and various values of p. (The table reports averages from 500 simulations with standard errors in parentheses).

In the mono-directional models, the rates of convergence are relatively rapid regardless the structure of costs, reaching the wheel (when $c < 1$) and either the wheel or the empty network (when $1 < c < 3$) in at most 23 periods and often quicker than that. In the bi-directional model, the simulations are only provided for the case in which the Strict Nash is the center-sponsored star ($c < 1$). The results show that the rates of convergence are generally higher than in the mono-directional model.

Such results are interesting, though based on a very specific model of learning behavior, which in addition is assumed to be the same across all agents participating in a network. As however noted in the introduction, the literature on learning behavior in games is wider (Camerer 2003). Alternative learning rules may not necessarily lead to an equilibrium, and furthermore, evidence available from other games seems to point to quite heterogeneous behavior among people. Thus, the question about equilibrium convergence remains basically an empirical one.

3.2 Previous experiments and salient coordination

Previous experiments of the Bala and Goyal model have been conducted. A first interesting paper was by Falk and Kosfeld (2003), who studied network formation in four people economies. They run experiments for both the mono-directional and bi-directional models and with both cost structures $c < 1$ and $1 < c < 3$. In the experimental sessions, groups of four subjects interacted to form networks in three sequences of five periods each; groups were randomly formed at the beginning of each sequence.

The experiment by Falk and Kosfeld (2003) strongly supported the wheel-Strict Nash equilibrium in the mono-directional models: already in the first round of the first sequence, about 13% of the networks formed in the period were wheels (with little difference due to the cost structure), they were 25% in the first round of the second sequence, and 33% in the first of the third[7]. Both within and throughout the three sequences, the wheels increased steadily and were more than 60% by the end of the first sequence, around 75% by the end of the second, and 83% in the last round of the third. On the other hand, the notion of Strict Nash network was rejected in the bi-directional cases. In fact, neither were any center-sponsored star observed during the entire session run with $c < 1$, nor any empty network in those conducted for $1 < c < 3$.

Various arguments explain this evidence. Regarding the favorable results of the wheel in contrast to the failure of the center-sponsored star, an important argument considered by Falk and Kosfeld is based on the notion of *payoff asymmetry*. With this expression the authors refer to the fact that in the wheel equilibria every subject earns exactly the same payoff, while in the center-sponsored stars peripheral subjects earn much more than the central agents. Thus, fairness motives explain why the latter equilibria may be unappealing in the bi-directional model.

Payoff asymmetry is clearly an interesting point, but it doesn't fully explain the very high coordination rates observed in the one-way flow model[8]. A feature of Falk and

[7] To consider why these frequencies should be regarded as very high we should recall that, even when all individuals play the one-link strategies, the probability of coordinating on a wheel equilibrium in a one shot game (which is obviously also relevant for the first round of the various sequences) is only 7%.

[8] Falk and Kosfeld (2003) consider a second argument, referred to as *strategic asymmetry*, to explain the different evidence between the one-way and two-way flow model. With *strategic asymmetry*, Falk and Kosfeld refer to the fact that while the wheel in the mono-directional model is a symmetric equilibrium, where every subject chooses the same action, the centre-sponsored star is an asymmetric equilibrium, where one subject maintains all links and all other subjects maintain no link. This, according to the authors, may create more strategic uncertainty to determine who should be the central agent. We don't however consider this argument fully convincing, because even in a wheel, every player has to decide with which other agent to make a link, which also implies a high chance of miss coordination. In fact, by calculating the probabilities of equilibrium coordination, one could even argue the opposite, that it is easier coordinating

Kosfeld's experiments which may explain the latter point is that subjects were named in the experiments by ordered letters A, B, C, D. This may have been a coordination device for subjects in the experiment. In particular, amongst the six equivalent wheels which may be constructed with letters, subjects may have taken the one with A connecting to B, B to C, C to D and D to A (henceforth denoted by ABCD) as a focal point in the sense of Schelling (1960). Other details of the Falk and Kosfeld's experiment which may have contributed to this solution are considered below.

Callander and Plott (2005) is another experiment focused on the Bala and Goyal model. They studied various one-way flow economies with 6 agents; 12 of these economies fit exactly into the formal model of Bala and Goyal. The economies consisted of sequences of simultaneous linking-decisions by the subjects in each network, lasting for various rounds, with random stopping rules to minimize last round effects. Callander and Plott were interested in studying various possible coordination principles including focalness. In particular, in the economies run by Callander and Plott (2005), subjects were identified by 6 numbered locations in the laboratory, so that two obvious salient wheels could be identified: the clockwise - 1,2,3,4,5,6 - and counterclockwise - 6,5,4,3,2,1 - wheels. They found that 6 out of 12 economies converged to the salient wheels around, on average, round 11, four economies didn't converge even after numerous rounds (between 10 and 17), one converged to a nonfocal wheel (in round 17), and one to an inefficient weak Nash (in round 16).

The results of Callander and Plott are therefore quite interesting to show both that convergence to an equilibrium network is not necessarily certain and also that salience can help coordination. Their experiment however doesn't consider the role of learning independent of focalness. Our aim was to build on some of the insights obtained through the experiments of both Falk and Kosfeld (2003) and Callander and Plott (2005), and to further investigate the effect of learning and salience in both the one-way and two-way

in the asymmetric star case than in the symmetric wheel situation. This simply follows because in the mono-directional model there are six equivalent wheels and each subject has 3 possible strategies of one link to choose amongst, which gives an overall chance of coordinating on one of $6/3^4 = 0.07$. On the other hand, to set up a center-sponsored star, each subject has to choose between two strategies only, either no link or one link to each of the other players; with four possible center-sponsored stars, this gives a chance of $4/2^4 = 0.25$ of coordinating on one.

flow models of Bala and Goyal[9].

4 The Experiments

4.1 Design: three experimental waves

We ran the experiments implementing various versions of the network formation game proposed by Bala and Goyal. All the experiments looked at four people networks. We treated both the mono-directional and the bi-directional models with marginal benefit for each player from observing an information normalized at 1, as in equation (1), and with the two different costs of link formation, $c = 0.5$ and $c = 1.5$. Henceforth, we refer to the mono-directional experiments run under the two cost conditions as to $m0.5$ and $m1.5$, and to the bi-directional experiments as to $b0.5$ and $b1.5$. The predictions for all four models discussed in Section 2 are summarized in Table 2.

The subjects' payment for participating in the experiment were given by the payoff points accumulated across all the network formation stages in an experimental session, converted at a rate of 0.5 Euro per point.

The four models were tested under three main waves of experiments, differing in two main sets of parameters (see Table 3). The first set concerned the subjects' labels, while the second set considered the learning environments.

The first two waves were run to closely simulate the Bala and Goyal (2000) dynamic version of the networking games, namely repeated games with infinite horizon. Participants in these experiments were not allowed to know either how many periods the sessions were going to last, or which round was the last one. Following a standard practice to deal with infinite horizon games in the lab, subjects were simply told that they were interacting with the same group of subjects (though they didn't know the actual identity of the other

[9] In this respect, our approach is different from another interesting series of experiments on network formations which study slight modifications in the theoretical predictions of the Bala and Goyal model. For example, Goere et al. (2005) obtained some evidence of coordination in a two-way flow model by introducing individual heterogeneity (due to different linking costs or benefits from connections) which made the periphery-sponsored star (rather than the center-sponsored) as the (Bayesian) Nash network. Similar guidance for the periphery-sponsored star was found by Berninghaus et al. (2006) in an experiment of a two-way flow model where individuals had only limited access to their neighbors' information.

Table 2: Equilibrium and efficiency in the four network models

	$m0.5$	$m1.5$	$b0.5$	$b1.5$
Informational flow	Mono-directional	Mono-directional	bi-directional	bi-directional
Link cost	$c = 0.5$	$c = 1.5$	$c = 0.5$	$c = 1.5$
Nash networks	Minimally connected	Wheels, empty	Minimally bi-connected	Periphery-spons. stars, restricted pipelines, empty
Strict Nash networks	Wheels	Wheels, empty	Center-spons. stars	Empty
Efficient networks	Wheels	Wheels	Minimally bi-connected	Minimally bi-connected

people in the network) and that at some stage the game would end. As actual stopping device, we used a mechanism which was partly random and partly allowed to run the game for a significant number of rounds. Each treatment was automatically stopped with probabilities which were: a) 0 until no subject had gained at least 15 Euros for participating in the experiment; b) 0.25 when at least one subiect had gained 15 Euros, but no subject had gained more than 25 Euros; and c) 1 (hence we immediately stopped the game) when at least one subject had gained 25 Euros.

The main differences between the experiments conducted in the first two waves were the labels to identify subjects in the experiments. In particular, in the experiments of Wave 1 subjects in the networks were identified by the symbols @, #, $*$, %, which we considered neutral in that they do not provide subjects any clue when deciding to establish a link with another person in the group. With the Wave 2 experiments, we introduced the ordered letters A, B, C, D. The labels (letters or symbols) remained the same for the whole experiments and this was common knowledge.

We ran the experiments of Waves 1 and 2 with six groups of four individuals (in sessions of three groups each) for both the mono-directional and bi-directional models, and for both the low and high cost conditions. Table 3 summarizes for the various groups the length of interaction which resulted from the stopping device used to end the games.

Table 3: Experimental treatments

	Mono-directional flow	*Bi-directional flow*
Wave 1: *Long interaction / neutral label / no FK protocol*	$m0.5$: 3 groups × 18 periods, 3 groups × 17 periods $m1.5$: 3 groups × 22 periods, 3 groups × 19 periods	$b0.5$: 3 groups × 19 periods, 3 groups × 21 periods $b1.5$: 6 groups × 20 periods
Wave 2: *Long interaction / letter label / no FK protocol*	$m0.5$: 3 groups × 14 periods, 3 groups × 18 periods $m1.5$: 3 groups × 16 periods, 3 groups × 21 periods	$b0.5$: 3 groups × 17 periods, 3 groups × 18 periods $b1.5$: 3 groups × 12 periods, 3 groups × 17 periods
Wave 3: *Short interaction / neutral and letter labels / FK protocol*	$m0.5$, $m1.5$: 5 groups reshuffled every 3 sequences of 5 periods each	

On average, sessions lasted for 18 periods, the longest session lasted for 22 periods, the shortest for 12.

Detailed instructions were given and read aloud to subjects, both about the working of the networks and of the software used to run the experiments (a set of instructions and other material used to administer the experiments are given in Appendix A). Subjects could then make questions and answers were given, but no practice sections or control tests were conducted before the experiments began. This was because the main objective of these waves remained that of studying learning dynamics, simply defined as "an observed change in behavior owing to experience" (Camerer 2003, p. 265).

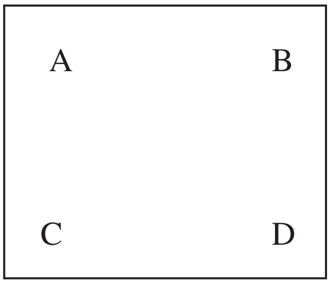
Wave 3 was conducted to reproduce more closely the environment used by Falk and Kosfeld (2003), while still controlling for the effect of salient labeling and separately identifying it from that of learning dynamics. For Wave 3, we shortened the period during which participants could interact within the same group, forcing subjects to change partners and labels every five periods. Furthermore, we adopted a protocol used by Falk and Kosfeld at the end of the instruction and before the experiments began. The protocol included two practice questions asking subjects to depict links in two network examples and a more theoretical question asking subjects "to depict the links ensuring the best flow of information and the maximum income for all group members" (see Figure 2 for the exact

Figure 2: The final question of Falk and Kosfeld (2003) protocol included in Wave 3 experiments

What links should, in your opinion, be formed to ensure the best possible flow of information and the maximum income for all group members?

The following direct connections should be initiated:
Type A to:
Type B to:
Type C to:
Type D to:

Please insert these links in the follo wing diagram



What were your considerations?

display used in the latter question, and see Appendix A for the complete protocol used in Wave 3, henceforth referred to as the FK protocol). Obviously, answering the protocol may have helped subjects to understand the characteristics of the games better, while the type of networks subjects were asked to draw (that is, the one "ensuring the best flow of information and the maximum income for all group members") may have favored efficient solutions over alternative equilibria.

We used this environment only for the mono-directional specification, for both cost levels and types of labeling. All experiments in this treatment were run for five groups of four individuals and lasted for three sequences of five periods. Subjects knew the length of each sequence, but not the number of sequences in a session.

4.2 Running the experiment

The experiments were run at the lab of the University of Insubria, in Varese (Italy). A total of 272 subjects participated. All subjects were students of the second and third year of the undergraduate program in economics. No subjects participated in more than one session. As noted, subjects were paid according to the sum of payoff points earned in the whole treatment, with no showing-up fee. On average subjects received 18.4 Euros. A session, including reading of instructions, lasted about 1 and 3/4 hour on average.

Upon arrival at the lab, subjects were randomly seated in front of a terminal, given a set of instructions, a pen and a set of sheets of paper. Instructions were orally read by the instructor and time for questions was given. In the Wave 3 experiments subjects also performed the FK protocol.

During the experiments, subjects of one group were identified exclusively by labels (either the neutral @, #, $*$, %, or the ordered A, B, C, D). In any period and treatment, each subject could simultaneously form direct links to any other members of their group, including themselves, thus choosing to build from zero to four connections. The link formation stage was implemented with the help of a second computer screen, which displayed all the labels for the members in the group together with an empty box. To form a connection with a particular person of the same group, a subject had to fill in the box entering a 1 command, while entering 0 meant the subject didn't want to form a link with that person. The screen also reminded the unitary cost of forming the direct links.

After all subjects had decided their connections, a network formed and the computer program calculated all payoffs for each member of a group. A third screen then informed subjects about all the direct links in the network, with the payoff points gained in that period by each person of the group.

The screen didn't, however, provide any explicit figure for the networks formed. Subjects were encouraged to draw themselves the actual networks on sheets of paper provided for the purpose. More specifically, a typical sheet reported an empty table for the direct links similar to the one subjects saw on the screen. Participants were invited to report in the table the direct links and the payoffs of the round (also to check overall payments at the end of the experiment), and to draw the resulting network. This procedure was similar to, but lighter than the one employed by Falk and Kosfeld (2003), in which subjects were obliged to draw the networks in each round and the correct drawings represented a prerequisite for payment in the experiment[10].

After subjects had read the information and drawn the networks, they were asked to press an *OK* button on the screen. Once all the subjects had pushed that button, the terminal presented the screen for the next period. The session then proceeded in the same way until the treatment was interrupted.

We used the experimental software z-Tree (Fischbacher, 1999) to design and to run the experiments.

5 Experimental evidence

Below are the main findings from these experiments. We have split the analysis into two main parts. Firstly, we have shown the evidence on group behaviour and equilibrium selection in a static and in a dynamic perspective. We then analyze individual behaviour, to understand better the reasons behind the group evidence.

5.1 Group behaviour and equilibrium selection

Table 4 reports the overall frequencies of observed Nash, Strict Nash and Efficient networks, across the various treatments in a static perspective. The occurrence of Nash, Strict Nash and Efficient networks tended to be modest in all experiments: the highest proportion was 22.7% of Nash equilibria in the $m0.5$ game of Wave 3 with ordered labels. The lowest was 0 Strict Nash networks in the $b0.5$ experiments of both Waves 1 and 2. In the mono-directional games, the great majority of Nash networks were also Strict Nash, namely wheels, counting for 75 out of 83 Nash networks (90% of the instances). In the bi-directional model with low cost ($b0.5$), no Strict Nash (centered-sponsored star) network was observed in either treatment of Wave 1 and Wave 2, while Nash and efficient networks were observed without any regularity in the shape of the minimally bi-connected networks. In the bi-directional experiments with high cost ($b1.5$), the only Nash network observed with any regularity was the empty Strict Nash network, occurring in the aggregate of the

[10]Below we have reported the main evidence from our control and explain why we have avoided Falk and Kosfeld's stronger procedure, which we think can introduce certain distortions in subjects' behavior.

$b1.5$ treatments of Waves 1 and 2 with an overall frequency of 14.5% ((19+11)/(120+87)).

Comparing the equilibrium frequencies across treatments, we observe: *a)* in the neutral labeling experiments of Waves 1 and 3, the proportions of wheels in both the $m0.5$ and $m1.5$ experiments were very low in both waves (on the aggregate of the two cost models, they were 5.7% — 13/228 — in Wave 1, and 6.6% — 10/150 — in Wave 3); *b)* the frequencies of wheels increase in the ordered labeling treatments of Waves 2 and 3. The increase is more pronounced in Wave 3. On the sum of both the $m0.5$ and $m1.5$ experiments, the wheels account for 11.9% (26/219) of the observations in Wave 2 and 17.3% (26/150) in the ordered treatments of Wave 3. Both proportions are significantly greater than the proportion of wheels observed in the neutral treatments of the corresponding learning conditions[11]; *c)* the frequencies of empty networks in the $b1.5$ experiments were higher in Wave 1 with neutral labels (namely 15.8% of all networks) than in Wave 2 with ordered labels (12.6%), however the proportion differences are not significant.

Figure 3 shows how these equilibria were achieved dynamically by the different groups playing the games. In Wave 1, five groups coordinated in the mono-directional experiments on a wheel at some stage of their sessions. An issue here is the definition of subjects converging to an equilibrium. We considered as equilibrium convergence the evidence of a group playing an equilibrium in one round of a session, and then going on to play the same equilibrium for all rounds until the end of the session. With this definition, in the one-way flow games of Wave 1, two groups (namely, 4 and 6 in $m0.5$) converged to a wheel equilibrium between rounds 15 and 16. In the bi-directional model with low cost ($b0.5$), various non-Strict Nash equilibria were played, but they never became network configurations to which groups converged. In the $b1.5$ model, two groups (2 and 6) converged to the the empty Strict Nash equilibrium (in rounds 18 and 13, respectively).

Evidence in the bi-directional models of Wave 2 is similar, with the diagrams showing no convergence toward any equilibrium in the $b0.5$ case, while two groups (4 and 5) converging to the empty network in the $b1.5$. In the mono-direction treatments of Wave 2,

[11] In particular, 11.9% wheels in the aggregate of the $m0.5$ and $m1.5$ experiments of Wave 2 is significantly higher than 5.7% wheels in the corresponding neutral treatment of Wave 1 (with a $p < 0.01$). The evidence is stronger for the experiments of Wave 3, for the differences between the proportions 17.3% and 6.6% (with a $p < 0.001$), in the ordered and neutral labeling conditions, respectively.

Table 4: Overall frequencies of Nash, Strict Nash and efficient networks

Wave 1: Long interaction / neutral label / no FK protocol

	$m0.5$	$m1.5$	$b0.5$	$b1.5$
Nash networks	11 (10.5%) (10 w.; 1 pt.)	3 (2.4%) (3 w.)	23 (19.2%) (8 ps.; 10 p.; 5 msss.)	22 (18.3%) (19 Ø; 3 rp.)
Strict Nash networks	10 (9.5%) (10 w.)	3 (2.4%) (3 w.)	0	19 (15.8%) (19 Ø)
Efficient networks	10 (9.5%) (10 w.)	3 (2.4%) (3 w.)	23 (19.2%) (8 ps.; 10 p.; 5 mss.)	9 (7.5%) (5 p.; 4 mss.)
Total	105	123	120	120

Wave 2: Long interaction / ordered label / no FK protocol

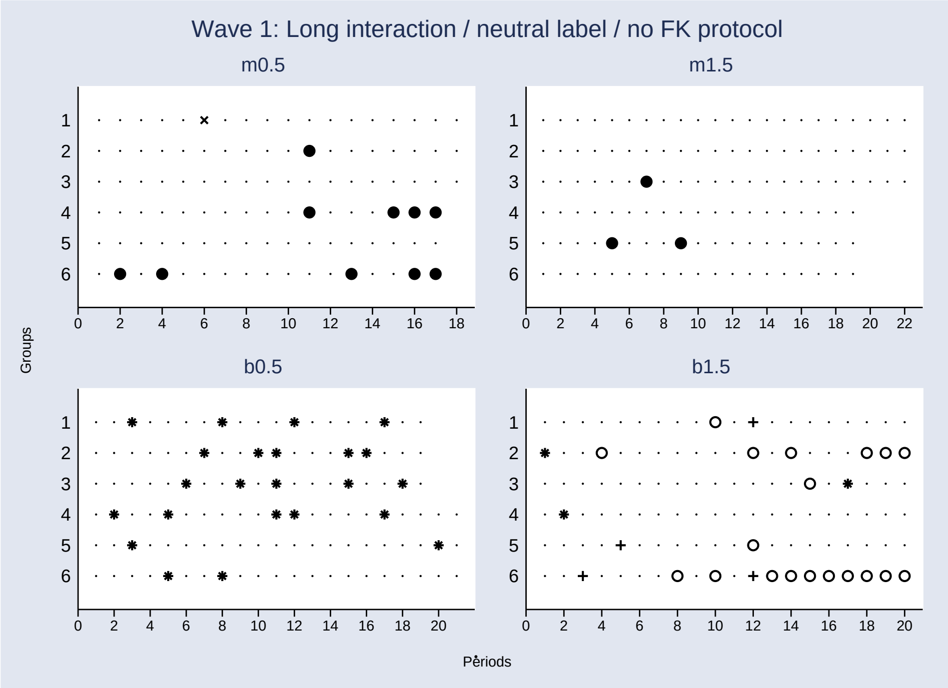
	$m0.5$	$m1.5$	$b0.5$	$b1.5$
Nash networks	15 (15.6%) (13 w.; 2 pt.)	13 (11.7%) (13 w.)	22 (21.0%) (10 ps.; 4 p.; 8 mss.)	15 (17.2%) (11 Ø; 4 rp.)
Strict Nash networks	13 (13.5%) (13 w.)	13 (11.7%) (13 w.)	0	11 (12.6%) (11 Ø)
Efficient networks	13 (13.5%) (13 w.)	13 (11.7%) (13 w.)	22 (21.0%) (10 ps.; 4 p.; 8 mss.)	7 (8.0%) (5 p.; 2 mss.)
Total	96	123	105	87

Wave 3: Short interaction / neutral & ordered label / FK protocol

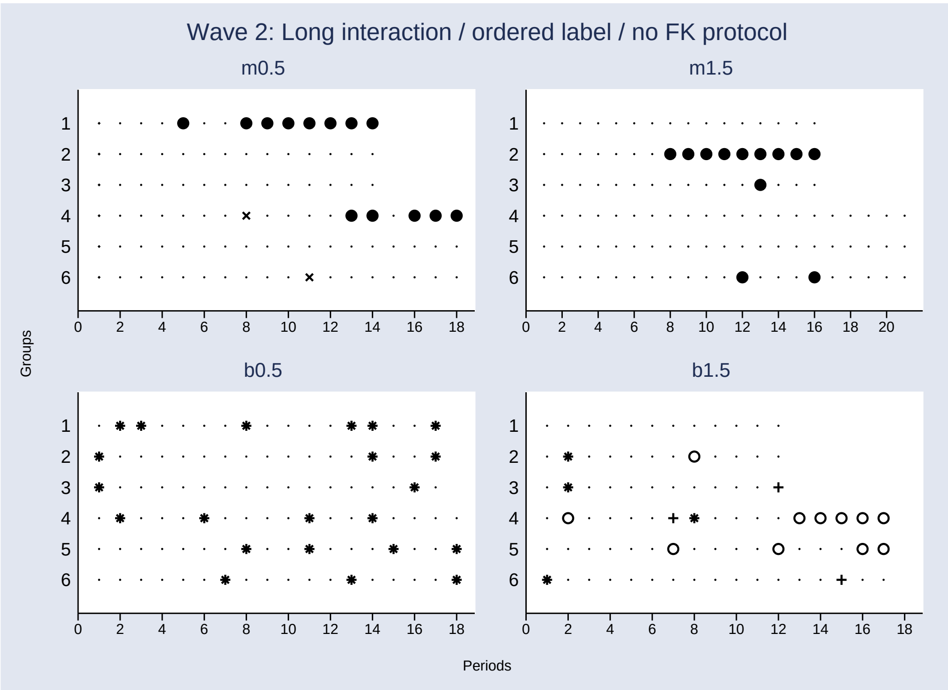
	Neutral label		Ordered label	
	$m0.5$	$m1.5$	$m0.5$	$m1.5$
Nash networks	4 (5.3%) (3 w.; 1 pt.)	7 (9.3%) (7 w.)	17 (22.7%) (13 w.; 3 pt.)	13 (17.3%) (13 w.)
Strict Nash networks	3 (4.0%) (3 w.)	7 (9.3%) (7 w.)	13 (17.3%) (13 w.)	13 (17.3%) (13 w.)
Efficient networks	3 (4.0%) (3 w.)	7 (9.3%) (7 w.)	13 (17.3%) (13 w.)	13 (17.3%) (13 w.)
Total	75	75	75	75

Legend: The numbers and letters in brackets show the shape of the networks. Letters stand for: w = wheel; pt=petal; tp=two-petals; mss=mixed-sponsored star; p=pipeline; ∅=empty; rp=restricted pipeline

FIGURE 3: Dynamics of networks in the three experimental waves



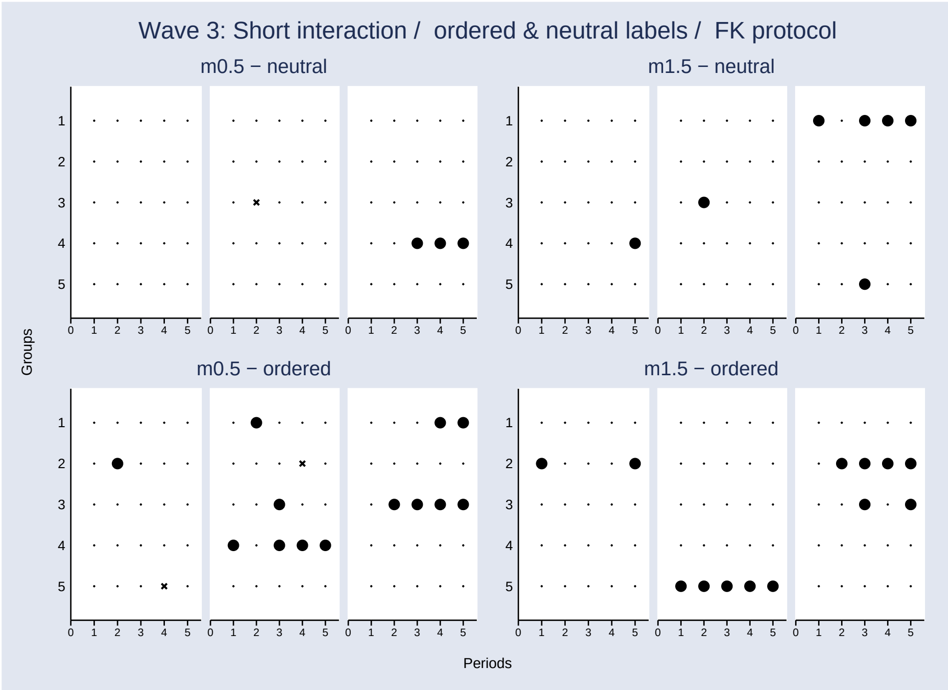
Symbols. • Wheel networks (Non-empty Strict Nash, only in $m0.5$ and $m1.5$); × Nash not-Strict and not-Efficient networks; ∗ Nash-Efficient networks (not-Strict); + Efficient not-Nash networks; ∘ Empty networks (Strict Nash only in $b1.5$)



Symbols as above. In $m0.5$ the wheels are of the following type: all 8 wheels of Group 1 are ADBC, all 5 wheels of Group 4 are ADCB; in $m1.5$ all 9 wheels of Group 1 are ACBD; the single wheel of Group 3 is ADCB; one wheel of Group 6 is ADBC, the other is ACBD.

Continued next page →

Figure 4: continued



Symbols as above. The wheels in the ordered treatments are of the following types: in $m0.5$, the single wheel of Group 1 in sequence 2 (at period 2) is ADBC, all other wheels are ABCD; in $m1.5$ all 13 wheels are ABCD.

three groups converged to a wheel. It is interesting that convergence occurred here slightly quicker than in Wave 1 (around on average repetition 10, rather than 16). Regarding this treatment, it is also important to look at the type of wheels formed by the groups (they are reported in the caption at the bottom of the Figure). Interestingly, none of the wheel established in the experiments is of the salient type ABCD, rather they occurred somehow randomly amongst all the other possible wheels.

In the mono-directional experiments of Wave 3, convergences occurred within two groups in the neutral labels treatment and within five groups in the ordered labels treatment. This difference in the convergence rates is small. It must however be emphasized that the actual significance of the term "convergence" in Wave 3 is restricted by the short interaction permitted to each group (only five rounds) of both treatments. Conversely, we have already noted that the frequencies of the total wheels played in the two treatments of Wave 3 was significantly larger in the ordered rather than in the neutral treatment.

We also notice that all but one of the 25 wheels in the ordered treatment of this Wave were the salient ABCD (see the caption at the bottom of the figure). The effect here is highly significant and cannot be attributed to pure chance[12]. Finally, it is also interesting to observe that all subjects in this treatment answered the FK protocol question about which network could ensure the best flow of information and the maximum income for all group members (see Fig. 2) by drawing the salient wheel ABCD.

5.2 Discussion

Overall, the results of group behaviour confirm the theoretical expectations that the Bala and Goyal games involve quite difficult coordination problems, in which equilibrium failure is clearly a possibility. The evidence from informational flow games also supports the intuition, first pointed out by of Falk and Kosfeld (2003), that coordination is nevertheless easier in the mono-directional model than in the bi-directional games, for which we also observed some empty networks.

Evidence from the mono-directional models also showed that coordination can occur under different learning and labeling conditions, as we found some albeit weak evidence of coordination across the different treatments of the various waves. We also found some evidence that salient labels can help coordination, mainly in the ordered treatment of Wave 3, after subjects went through the FK protocol. Even in this treatment, however, the rates of wheel networks observed were substantially lower than those reported by Falk and Kosfeld.

This, therefore, poses the interesting question on why, even in ordered treatment of Wave 3, subjects haven't more often played the salient wheel, which in addition all subjects identified in the FK protocol as the most efficient network. We have no a definite answer to this. Various explanations are possible, including explanations due to differences in the subject pools. Another may derive from other differences in the conduction of the two

[12] In particular, we conducted the following test. Consider the probability of observing one wheel of the salient type ABCD, when a group is playing a wheel equilibrium. The probability is 1/6. We observe 24 wheels of the salient type over 25 wheels. Since, however, some wheels are simply repetitions of wheels played in the previous period, for the test we only count wheels played at round t, when no wheel was played at round $t-1$. There are 13 of such wheels, of which 12 are salient. Their proportion is 0.92, which is significantly greater than 1/6 at $p < 0.001$ (one-tailed test based on the binomial distribution).

experiments. For example, we noticed that while we left subjects free to draw the networks from each round of the experiment, Falk and Kosfeld (2003) required that subjects to draw the correct networks in order to be paid[13]. This procedure could have made their subjects more reluctant than ours to try any strategy that was different from playing the salient wheel, which among other things subjects had already learned to draw from the protocol.

Another difference may be due to the perception of salience in relation to other attributes of the experiments. For example, various authors have emphasized that for salient coordination to arise, it is important that players somehow act cooperatively and see themselves more as members of a "team", rather than as strategic opponents in a non-cooperative game[14]. In this respect, we carefully checked ex-post for further differences between our experimental procedure and that followed by Falk and Kosfeld and noticed that their experimental frame was more favorable to generate cooperative behaviour among subjects, while ours was more focused on individuals. For example, while in our instructions we simply referred to subjects in the networks as participants, Falk and Kosfeld called them "group members". This might have induced our subjects to act more individualistically, perhaps also experimenting various strategies to check whether they could individually do better than in a wheel; whereas Falk and Kosfeld's subjects may have been satisfied to play the wheel network mainly for its efficiency properties.

Beyond the various possible explanations, the interesting point emerging from a comparison between our experiment and that conducted by Falk and Kosfeld (2003), or even that by Callander and Plott (2005), who also reported rather different rates of success in coordination (see Section 3.2), is that various subtleties may be involved in network formation, which can help or obstruct coordination.

To address the issue of coordination further, we will now move to analyse individual

[13]We nevertheless checked after the experiment the subjects' drawing sheets and verified that the great majority of subjects indeed drew the networks and they were correct.

[14]For example, in explaining how Schelling (1960) typically liked to use metaphors in presenting his theory of focal points, Sugden and Zamarrón (2006) note: "... another family of metaphors, used over and over again, implies that it is as if the players are engaged together in solving a 'riddle', jointly searching for what is variously called a 'clue', 'key', 'hint', 'message', 'signal', or 'suggestion' that is hidden in their decision problem" (p. 611). (See also the theories of "team reasoning" or "we thinking" by Sugden 1993, and Bacharach 1997, respectively; or the "Principle of Individual Team Member Rationality" by Gauthier 1975, and Janssen 2006).

behaviour which of course represents the ultimate driving force for the networks established in the experiment.

5.3 Individual behaviour

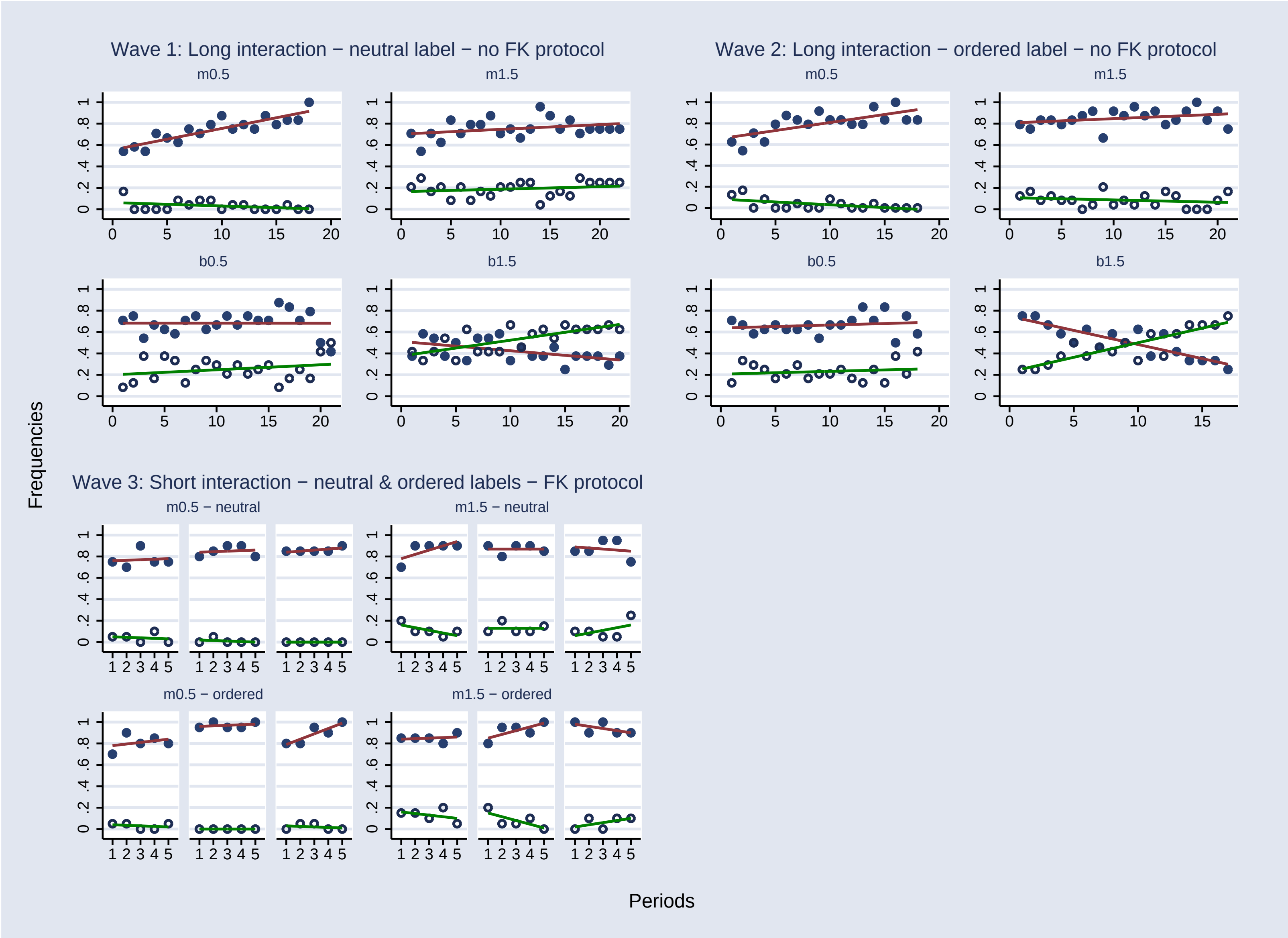
5.3.1 Link-strategies

An initial important question about individual behaviour is the number of links established by players across the various treatments. This is interesting because the strategies played may independently reveal the types of networks which subjects were attempting to form. For example, even if we haven't seen much convergence to the wheel equilibria in the mono-directional models, it is nevertheless interesting to check whether subjects at least attempted to play a wheel equilibrium, which first of all requires subjects to play one-link strategies.

Figure 4 shows the dynamics of the frequencies of one-link and zero-link strategies across the different treatments, with the frequencies of strategies with more than one link as complement to 1. The frequency of one-link strategies in the $m0.5$ treatment of Wave 1 was less than 60% at the beginning of the session and then increased steadily throughout the session, with an average frequency on the whole session of 74%. The frequency started at 70% in the $m1.5$ experiments of the same wave, and had a lower tendency to increase over the session (the average frequency on the whole session is 75%). In the $m0.5$ and $m1.5$ experiments of Wave 2 the patterns are similar, though the frequencies are a bit higher. The average proportions of one-link strategies were 79% in $m0.5$ and 85% in $m1.5$. In Wave 3, the frequencies of one-link strategies are a bit higher still: the average over all periods are 83% and 88% in the neutral treatments $m0.5$ and $m1.5$, respectively; and 89% in both the $m0.5$ and $m1.5$ ordered treatments.

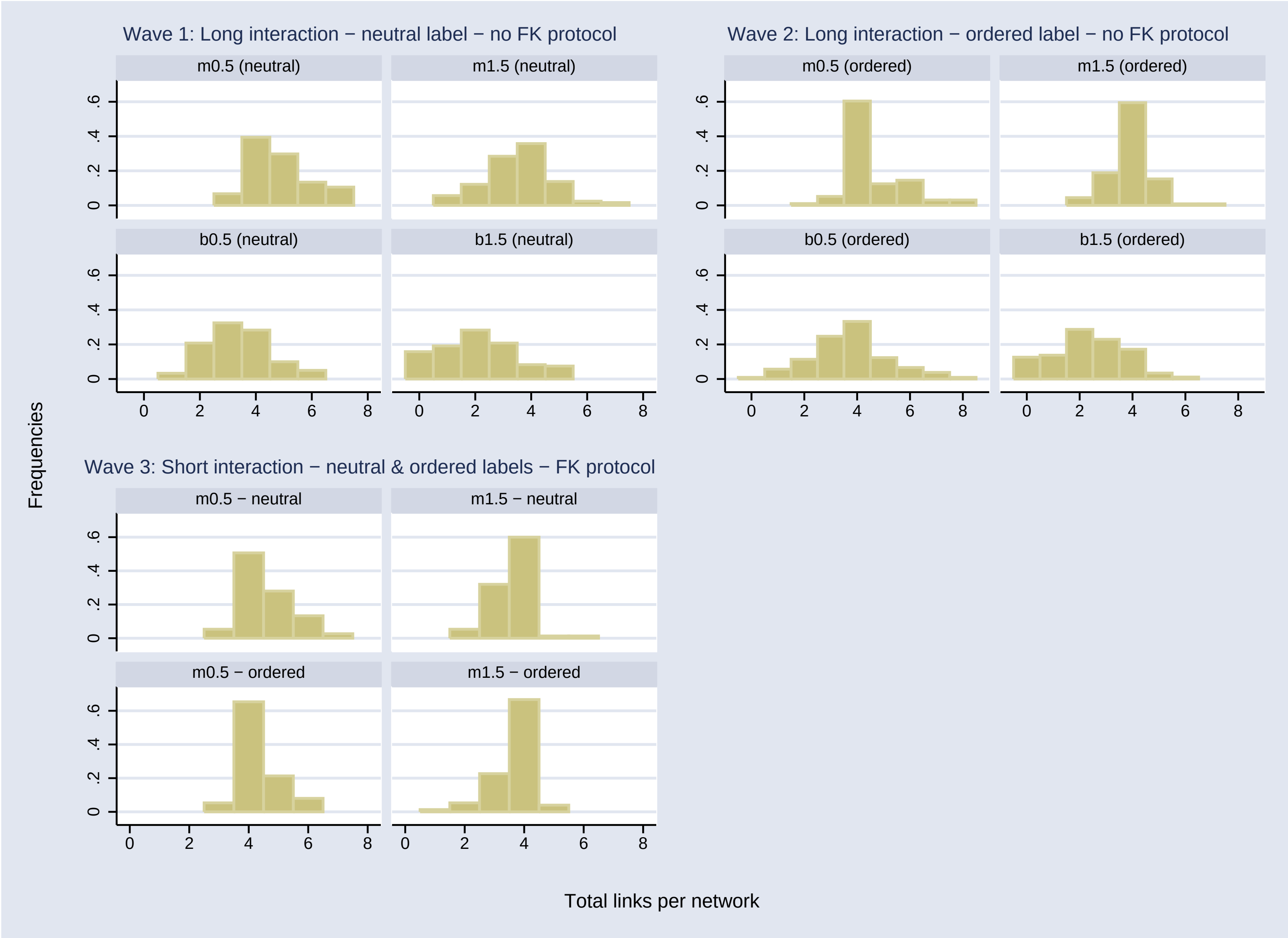
Also interesting in Figure 4, is the clear tendency in the $b1.5$ experiments of both Waves 1 and 2, for subjects to steadily reduce the number of one-link strategies, while increasing zero-link strategies. This may well explain the emergence of empty networks documented in Section 5.1 and the dynamics may indicate that with more repetitions, even more groups might have converged towards the empty networks in the $b1.5$ experiments.

FIGURE 4: Dynamic frequencies of link-strategies across treatments



Symbols. •: one-link strategies; ○ zero-link strategies (strategies with more than one link as a complement to 100%)

Figure 5: Frequencies of total links per network in the various experimental treatments



Values of Mann-Whitney tests for frequencies of 4-links per networks (only mono-directional models). Wave 1 vs. Wave 2. m0.5: z=-2.959 (p=0.0031); m1.5: z=-3.617 (p=0.0003). Wave 1 vs. Wave 3 - neutral. m0.5: z=-1.1361 (p=0.1361); m1.5: z=-4.212 (p=0.0000); Wave 2 vs. Wave 3 - ordered. m0.5: z=-0.657 (p=0.5110); m1.5: z=-0.074 (p=0.9414); Wave 3 neutral vs. Wave 3 - ordered. m0.5: z=-1.814 (p=0.0697); m1.5: z=-0.844 (p=0.3985)

The differences in the proportions of link strategies imply an impact for the type of network that groups could form across treatments. These are shown in Fig. 5. Most interesting here are the results of the mono-directional games. In Wave 1, the proportions of four-link networks were 39.4% in $m0.5$ and 35.8% in $m1.5$. In Wave 2 subjects showed a much better rate of success in playing four-link networks, 60.4% and 59.5% in $m0.5$ and $m1.5$, respectively. (See also the values of the Mann-Whitney tests reported in the caption at the bottom of Fig. 5). In the ordered treatment of Wave 3, the proportions were a bit higher, but not by that much, 65.3% in $m0.5$ and 66.7% in $m1.5$. In the neutral treatment of the same wave, the frequencies of four-link networks were still lower, 50.7% and 60% in the $m0.5$ and $m1.5$ treatments, respectively.

5.3.2 Salient plays

The question about why subjects in mono-directional games with ordered labels played four-link networks more often than subjects in games with neutral labels, but the same learning conditions (that is, subjects of Wave 2 versus subjects of Wave 1, and subjects of Wave 3 with ordered labels versus subjects of Wave 3 with neutral labels), is particularly interesting. A possible reason is that ordered labels may have simply induced more general confidence among subjects to coordinate in the experiments, which may have in turn generated more attempted links[15].

On the other hand, as emphasized throughout, in the mono-directional games, ordered labels may be used by subjects to solve the problem of multiplicity of equilibria and to coordinate on the salient wheel ABCD. The experimental evidence on equilibrium selection has shown weak convergence to the salient wheel, and only in the ordered treatment of

[15] This attitude could be explained in terms of the "variable frame theory of focal points" (Bacharach and Bernasconi 1997). The theory in particular entails a principle of game playing called 'Symmetry Disqualification'. This says that if two options are alike in all relevant respects, then a solution strategy for the player would be not to pick one option in preference to another (see also the similar Principle of Insufficient Reason in Bacharach 1993, and Janssen 2001 and 2006). Believing in such a principle, it is then possible that subjects playing with neutral labels were not able to find any reason to disqualify the symbols @, #, $*$, %, and hence found a zero-link strategy more salient. This is consistent with evidence that in the $m1.5$ treatment of Wave 1, there were both more zero-link strategies played by subjects and more networks with less than four links than in the corresponding treatment of Wave 2 (see again Figures 4 and 5); and similarly in the $m1.5$ neutral labels treatment of Wave 3 than in the treatment with ordered labels of the same wave.

Wave 3. However, it is still interesting to control the extent to which subjects in the ordered treatment of both Waves 2 and 3 at least tried to play salient strategies.

In Table 5 is the analysis data of the occurrence of salient play in the mono-directional experiments with ordered labels. The Table particularly gives the one-link strategies played by types A, B, C and D in the mono-directional ordered treatments of Waves 2 and 3. Since there were not significant differences between models $m0.5$ and $m1.5$ within each wave, the data were pooled.

The first block of data are for the whole sessions. The results of Wave 3 confirm that subjects played salient strategies, with in particular 62% of the one-link strategies of player A to B, 54% of player B to C, 58% of player C to D, and 64% of player D to A. We tested whether these frequencies were significantly different from 1/3 (see the note at the bottom of the table), which is the value one would expect when subjects (conditional on choosing the one-link strategy) connect to one of the other players at random. We see that they were highly significant. On the other hand, in Wave 2 we cannot reject the hypothesis that subjects choose to connect at random.

The other blocks of the Table show how the one-link strategies have been played over the three sequences of Wave 3 and on three period-subsets of Wave 2 (periods 1-5, periods 6-10, and periods 11 to the end of the various sessions). We see that in all sequences of Wave 3, subjects have to some extent played salient strategies, with also some tendency of the frequencies of salient strategies to increase over the three sequences. On the contrary, again we don't see any evidence of salient play in Wave 2, even across the three period-subsets.

We find this evidence quite interesting, particularly in contrast to the fact that the frequencies of one-link strategies increased through the period-subsets (which Table 5 confirms from the evidence already documented in Figure 4). More specifically, the intriguing result from Wave 2 is that if on the one side subjects seem to have learned through repetition the idea of playing one-link strategies (i.e. to possibly coordinate on a wheel), they don't seem to have learned to use letter labels to play salient coordination.

Table 5: One-link strategies per player-type in mono-directional ordered treatments (pooled models $m0.5$, $m1.5$)

	Wave 2 (Long interaction - ordered label - no FK protocol)							Wave 3 (Short interaction - ordered label - FK protocol)							
	Player type	Total plays	1 link strat.	to: A (as proportions of 1 link)	B	C	D	Player type	Total plays	1 link strat.	to: A (as proportions of 1 link)	B	C	D	
All periods	A	207	0.88	0.01	0.34	0.25	0.41	A	150	0.93	0.00	0.62***	0.15	0.23	All sequences
	B	207	0.86	0.35	0.00	0.39	0.26	B	150	0.87	0.23	0.00	0.54***	0.23	
	C	207	0.73	0.36	0.26	0.02	0.35	C	150	0.85	0.24	0.17	0.01	0.58***	
	D	207	0.82	0.27	0.42	0.31	0.00	D	150	0.90	0.64***	0.17	0.19	0.01	
	All	828	0.82					All	600	0.89					
Periods 1-5	A	60	0.80	0.02	0.33	0.27	0.38	A	50	0.90	0.00	0.64**	0.11	0.24	Sequence 1
	B	60	0.75	0.53	0.00	0.40	0.07	B	50	0.82	0.29	0.00	0.51	0.20	
	C	60	0.68	0.27	0.41	0.00	0.32	C	50	0.76	0.39	0.18	0.00	0.42	
	D	60	0.68	0.27	0.41	0.32	0.00	D	50	0.84	0.60**	0.17	0.24	0.00	
	All	240	0.73					All	200	0.83					
Periods 6-10	A	60	0.88	0.00	0.32	0.21	0.47	A	50	0.92	0.00	0.59**	0.17	0.24	Sequence 2
	B	60	0.90	0.26	0.00	0.33	0.41	B	50	0.88	0.27	0.00	0.45	0.27	
	C	60	0.73	0.43	0.27	0.02	0.27	C	50	0.92	0.17	0.11	0.02	0.70***	
	D	60	0.87	0.27	0.41	0.32	0.00	D	50	0.96	0.65**	0.19	0.17	0.00	
	All	240	0.85					All	200	0.92					
Periods 11-end	A	120	0.92	0.00	0.31	0.34	0.35	A	50	0.96	0.00	0.63**	0.17	0.21	Sequence 3
	B	120	0.88	0.33	0.00	0.42	0.25	B	50	0.92	0.13	0.00	0.65***	0.22	
	C	120	0.77	0.44	0.14	0.02	0.40	C	50	0.88	0.18	0.23	0.00	0.59**	
	D	120	0.87	0.29	0.40	0.32	0.00	D	50	0.90	0.67***	0.16	0.16	0.02	
	All	480	0.86					All	200	0.92					

Note: $*$, $**$, $***$ denote in the order statistical significance at 5%, 1% and 0.1% level, in a difference-of-proportion test that the frequency of one-link from type-row to type-column players is greater than 1/3 (one-tailed test based on standard normal distribution).

5.4 Models of learning dynamics

A final interesting question is the way in which subjects learned in the games. In Section 3.3, we recalled the specific model of learning dynamics centered on the Cournot Best Response taken by Bala and Goyal (2000) to predict equilibrium convergence in their networking games. While the equilibrium results had only weak evidence of convergence, it is still interesting to consider whether subjects' behaviour in any way followed the Cournot Best Response or some other learning rules.

Indeed, as it is well known, the Cournot Best Response is not the only possible way of learning in repeated games. Rather, it is the simplest version of a more general class referred to as belief learning models, where players form beliefs about what their opponents will do in the future based on past observation and best responds to such beliefs. In the Cournot Best Response players look only one period back. More articulated specifications in which players use longer history of observed play are known as models of Fictitious Play (as in Fudenberg and Levine 1998, or Cheung and Friedman 1997). A different approach is that of Reinforcement learning, which does not assume that players form beliefs about what others will do, but simply takes that players choose with higher probability strategies which achieved higher returns in the past (Roth and Erev 1995, and Mookherjee and Sopher 1994 and 1997).

The experimental evidence about how people actually learn in games is mixed (Camerer 2003). One problem is that, although individual learning models are conceptually different, they nevertheless point to similar predictions in several game situations. This seems a particularly serious drawback in the 2×2 normal form games often used to compare various approaches (Salmon 2001).

In order to trace possible learning dynamics in our more complex game situations we have proceeded as follows. Firstly, we calculated for each subject in each period of their session, the predictions of the three pure learning models of Reinforcement, Cournot Best Response, and Fictitious Play[16]. (The complete specifications of the various learning

[16] To obtain the predictions for Reinforcement, we adopted the most standard approach (Erev and Roth 1998), in which propensities to play the various strategies are adapted linearly by adding the latter payoffs to previous period's propensities. In regards to Fictitious Play, we considered both a model of

models are reported in Appendix B). Then, we constructed all possible combinations of mutually exclusive classes of the pure learning models: namely, the strategies consistent exclusively with Reinforcement (denoted as R), with Cournot Best Response (C), and with Fictitious Play (F); the classes consistent with pairs of learning models, namely Reinforcement *and* Cournot Best Response (*R&C*), Reinforcement *and* Fictitious Play (*R&F*), Cournot *and* Fictitious Play (*C&F*); and the class of strategies consistent with all three models at the same time (*R&C&F*). All remaining strategies were divided between two more classes, one for all other not-dominated strategies inconsistent with learning models (*others*), and one for dominated strategies (*dom.*).

Table 6 shows the frequencies for the various classes so constructed. As a measure of the extent at which the different classes can explain behaviours, the various proportions are compared with frequencies (between brackets in the table) which should have been observed for each class in case subjects would be in fact picking at random over the entire set of not-dominated strategies. We also conducted formal tests for the statistical significance of the difference between the two proportions across the various models and treatments[17].

A first point which is worthwhile to emphasize is that subjects definitely favor strategies indicated by learning models. This is documented by the fact that, in all treatments, not-dominated strategies which are not also supported by some learning model (*others*) were chosen significantly less frequently than one would expect under random picking. Not all learning models seemed, however, to receive equal favor.

residual opponents, in which beliefs are formed to likelihoods of passed networks, and a model of individual opponents, where beliefs are formed to passed play of all other players. Having, however, found that the differences between the two variants of Fictitious Play don't produce significant differences in the findings, we have shown only results for the former specification.

[17]The difference-of-proportion tests were in particular derived for the null that participants are picking at random among not-dominated strategies. The tests are based on the statistics $d = \frac{h_1 - h_2}{\sqrt{\frac{h_1(1-h_1)}{n_1-1} + \frac{h_2(1-h_2)}{n_2-1}}}$, where h_1 is the proportion of observed choices consistent with the various learning models (calculated with respect to the overall choices N_1 of each treatment) and h_2 is the proportion of choices predicted by the models, computed with respect to the total number N_2 of non-dominated strategies which subjects could play under each treatment. Under the null, d is distributed as a standard normal. The results of the tests indicate that, with the exceptions of the Cournot Best Response model in $m1.5$ of Wave 1 and $b1.5$ of Wave 2, and of Fictitious Play in $m1.5$ of Wave 1, in all other cases observed frequencies are significantly higher than expected frequencies. More detailed results are not reported for brevity; results of tests conducted for mutually exclusive classes of learning models are reported below.

TABLE 6: Proportions of strategies across classes of learning models

	R	C	F	R&C	R&F	C&F	R&C&F	others	dom.	Tot.
Wave 1										
m0.5	0.07*	0.02	0.17	0.01	0.12***	0.15*	0.17***	0.25***	0.03	396
	(0.04)	(0.02)	(0.16)	(0.01)	(0.05)	(0.11)	(0.05)	(0.57)		
m1.5	0.11*	0.03	0.18	0.02	0.11	0.16	0.13**	0.20***	0.06	468
	(0.07)	(0.04)	(0.20)	(0.02)	(0.08)	(0.18)	(0.09)	(0.32)		
b0.5	0.08***	0.03	0.25	0.01	0.09**	0.21***	0.09**	0.25***	0.00	456
	(0.04)	(0.02)	(0.25)	(0.01)	(0.05)	(0.13)	(0.05)	(0.46)		
b1.5	0.08*	0.03	0.08	0.02	0.12***	0.15	0.32***	0.18***	0.01	456
	(0.06)	(0.05)	(0.17)	(0.01)	(0.06)	(0.20)	(0.12)	(0.33)		
Wave 2										
m0.5	0.09**	0.02	0.19	0.01	0.10***	0.12	0.20***	0.24***	0.03	360
	(0.05)	(0.02)	(0.21)	(0.01)	(0.04)	(0.12)	(0.04)	(0.50)		
m1.5	0.05	0.04	0.15	0.02	0.10*	0.15	0.26***	0.19***	0.04	420
	(0.05)	(0.04)	(0.17)	(0.01)	(0.07)	(0.14)	(0.12)	(0.41)		
b0.5	0.06**	0.01	0.26	0.01	0.11***	0.21***	0.12***	0.22***	0.00	396
	(0.03)	(0.01)	(0.26)	(0.00)	(0.05)	(0.14)	(0.06)	(0.44)		
b1.5	0.07	0.02	0.12	0.01	0.16***	0.18	0.22***	0.21***	0.01	324
	(0.06)	(0.04)	(0.17)	(0.01)	(0.08)	(0.22)	(0.12)	(0.30)		
Wave 3										
m0.5 neutr.	0.09*	0.01	0.07	0.00	0.13***	0.12	0.16***	0.41***	0.01	240
	(0.05)	(0.02)	(0.10)	(0.00)	(0.03)	(0.11)	(0.04)	(0.64)		
m1.5 neutr.	0.06	0.01	0.10	0.00	0.06	0.17	0.25***	0.34***	0.01	240
	(0.107)	(0.01)	(0.10)	(0.00)	(0.04)	(0.16)	(0.11)	(0.52)		
m0.5 order.	0.09**	0.00	0.08	0.00	0.08**	0.09	0.24***	0.40***	0.01	240
	(0.04)	(0.01)	(0.09)	(0.00)	(0.03)	(0.10)	(0.05)	(0.68)		
m1.5 order.	0.14**	0.01	0.03	0.01	0.05	0.15	0.25***	0.34***	0.01	240
	(0.08)	(0.01)	(0.08)	(0.00)	(0.03)	(0.15)	(0.10)	(0.54)		

Legend. The number in brackets are the frequencies expected for the classes of learning models when subjects choose randomly across not-dominated strategies.

$*$, $**$, $***$ denote in the order significance at 5%, 1% and 0.1% levels in a difference-of-proportion test in which the null hypothesis is that observed and expected choices when subjects choose randomly are not statistically different (see footnote 17 in the text; for the classes of learning model the alternative hypothesis is that observed choices are greater than expected. For the class of other not-dominated strategies the alternative is that observed choices are lower than expected. In either cases the tests are based on the one-tailed standard normal distribution).

Another aspect is that subjects are generally more prone to choose strategies consistent with various learning models, rather than supported by pure learning models. This is documented by the frequencies of choices consistent with the class combining all three learning models, namely R&C&F. In the aggregate of all treatments this accounted for almost three times the observations one would expect from random picking (19.8% of observed choices versus 7% expected). Given the relatively large number of undominated strategies that subjects could play, we emphasize that this result cannot be due to the fact that the three learning models collapsed under the same set of strategies.

Among the class of pure learning models, we finally notice that Reinforcement comes out more strongly, not only in combination with other models (in addition to the class *R&C&F*, also in the class with Fictitious Play, namely R&F), but also when it delivers exclusive predictions (class R). Cournot Best Response is instead the one least followed.

5.4.1 Probit regressions for subjects' strategies

As a final step to investigate behaviour which subjects may have followed in playing the game, we carried out some regression analysis on the role of learning rules, while also controlling for the effect of salient playing and inertia.

In Table 7 we report a summary of this evidence. The table shows results of probit regressions for the mono-directional experiments, conducted as follows[18]. We constructed standard dichotomous variables for the various strategies subjects could have played in the experiments. The variables take value one when a subject plays a given strategy and takes zero value otherwise.

The probit for which we report the results refer to the strategies of either zero or one link. The strategy of zero-link is indicated by vector (0000), the strategies of one-link are indicated by ordered vectors with three '0' and a '1' in the position of the player to which the link was directed to. For the ordered treatments, the positions of the 1's correspond to the ordered labels, for example, vector (1000) indicates the strategy of one link to player A, vector (0100) the strategy of one link to player B and so forth.

[18] Results from the bi-directional models are not reported for brevity. They are available upon request.

Table 7: Probit regressions for strategies of zero and one-links in mono-directional experiments (pooled models $m0.5$, $m1.5$)

	Neutral treatments of Waves 1 & 3					Ordered treatments of Wave 2					Ordered treatments of Wave 3				
	Strat. (0000)	Strat. (1000)	Strat. (0100)	Strat. (0010)	Strat. (0001)	Strat. (0000)	Strat. (1000)	Strat. (0100)	Strat. (0010)	Strat. (0001)	Strat. (0000)	Strat. (1000)	Strat. (0100	Strat. (0010)	Strat. (0001)
Inertia	0.140	0.192	0.045	0.110	0.010	0.026	0.161	0.072	0.068	0.416**	-0.229	-0.027	0.107	0.268	0.248
	(0.142)	(0.099)	(0.103)	(0.101)	(0.099)	(0.382)	(0.148)	(0.152)	(0.147)	(0.148)	(0.396)	(0.153)	(0.172)	(0.169)	(0.157)
R	1.086**	0.554**	0.547**	0.358	0.417*	1.232**	0.082	-0.014	0.713**	0.275	1.479**	0.419	0.209	0.362	0.535*
	(0.163)	(0.206)	(0.184)	(0.216)	(0.167)	(0.410)	(0.404)	(0.296)	(0.247)	(0.274)	(0.328)	(0.326)	(0.268)	(0.247)	(0.222)
C	-	-	0.388	0.025	0.236	0.677	0.897*	0.354	0.571	-0.200	-	-	-	-	0.073
			(0.327)	(0.288)	(0.265)	(0.458)	(0.446)	(0.294)	(0.342)	(0.565)					(0.599)
F	0.657**	0.259	0.188	0.178	0.336*	0.005	0.232	0.131	0.181	0.466*	-0.207	0.448	-0.499	-0.281	-0.362
	(0.194)	(0.134)	(0.133)	(0.128)	(0.135)	(0.365)	(0.187)	(0.182)	(0.202)	(0.190)	(0.489)	(0.233)	(0.308)	(0.262)	(0.410)
R&C	0.435	0.998*	0.546	0.272	0.772	-	0.711	0.632	-0.067	0.747	-	-	-	-	-
	(0.630)	(0.453)	(0.354)	(0.704)	(0.444)		(0.483)	(0.668)	(0.601)	(0.528)					
R&F	1.052**	0.867**	0.648**	0.288	0.887**	-	0.887**	0.490*	0.595*	0.413	-	0.910**	0.251	0.433	0.464
	(0.225)	(0.180)	0.175)	(0.170)	(0.159)		(0.230)	(0.244)	(0.244)	0.249)		(0.309)	(0.298)	(0.393)	(0.280)
C&F	0.276	0.221	0.191	0.440**	0.180	0.299	0.673**	0.235	0.193	0.181	0.386	0.302	0.165	-0.157	0.071
	(0.260)	(0.134)	(0.131)	(0.123)	(0.129)	(0.562)	(0.190)	(0.184)	(0.219)	(0.202)	(0.439)	(0.204)	(0.208)	(0.215)	(0.232)
R&C&F	1.045**	1.022**	0.969**	1.125**	0.915**	-	1.213**	1.000**	1.103**	0.977**	1.453	1.273**	0.828**	0.602**	0.936**
	(0.307)	(0.156)	(0.156)	(0.151)	(0.144)		(0.220)	(0.215)	0.219)	(0.231)	(0.899)	(0.240)	0.234)	0.232)	0.221)
Salience	-	-	-	-	-	-	-0.047	0.271*	0.089	-0.105	-	0.362*	0.605**	0.750**	0.557**
							(0.129)	(0.127)	(0.134)	(0.136)		(0.166)	(0.168)	(0.183)	(0.174)
c=0.5	-0.478**	0.120	0.035	0.009	-0.099	-0.289	-0.102	0.136	-0.127	0.090	-0.672**	0.078	0.045	0.120	-0.002
	(0.145)	(0.091)	(0.090)	(0.087)	(0.086)	(0.181)	(0.124)	(0.122)	(0.125)	(0.125)	(0.245)	(0.146)	(0.151)	(0.147)	(0.143)
Constant	-1.540***	-1.202**	-1.140**	-0.965**	-0.963**	-1.585**	-1.029**	-1.077**	-1.018**	-1.119**	-1.543**	-1.022**	-1.068**	-1.084**	-1.084**
	(0.095)	(0.117)	(0.109)	(0.105)	(0.101)	(0.125)	(0.157)	(0.139)	(0.173)	(0.173)	(0.144)	(0.158)	(0.152)	(0.147)	(0.149)
Obs.	1347	1001	1006	1005	1002	775	581	584	582	580	472	360	360	356	358
Pseudo R^2	0.187	0.076	0.065	0.060	0.065	0.083	0.102	0.067	0.80	0.085	0.190	0.128	0.136	0.161	0.167
LR	-329.0	-523.4	-533.1	-557.7	-579.5	-135.5	-289.3	-284.1	-284.6	-282.3	-91.1	-204.4	-187.5	-190.5	-197.1

Note: robust standard errors in brackets. $*$ and $**$ denote statistical significance at 5% and 1%, respectively. (Controls for classes of learning models are dropped when predict failure perfectly).

We studied the effect of the mutually exclusive classes of the learning models on the probability of subjects' playing various strategies. The regressions controlled for the impact of inertia. For each strategy, the variable inertia takes the value one if the strategy was played in the previous period and zero otherwise.

The regressions also controlled for the effect of salient playing. The variable salience is included only in the probit of the various one-link strategies of the ordered treatments[19].

The results in Table 7 are for the pooled models $m0.5$ and $m1.5$, distinguishing between the treatments with neutral labels (adding those of Waves 1 and 3), the treatments with ordered labels of Wave 2 and the treatments with ordered labels of Wave 3. To account for the difference in the cost of connections, the regressions include a dummy equals to 1 for the $m0.5$ experiments[20].

The regressions show the following. First of all, inertia has little effect in explaining the strategies chosen by subjects in this experiment. Conversely, learning models contribute to explain individual choice even after controlling for inertia. Furthermore, among the various learning models, the class consistent with predictions of all three learning rules, namely (R&C&F), is confirmed as the most effective to explain subjects' behaviour across all strategies. Reinforcement is also generally significant even when yielding to exclusive predictions.

Also interesting is the evidence concerning salient play. The regressions for the ordered treatment of Wave 2 confirm that, even after controlling for learning, subjects in this treatment failed to use ordered labels strategically in the experiments. Conversely, the results from the ordered treatment of Wave 3 show the impact of salient playing even after controlling for learning.

[19]The variable is defined in the obvious way: namely, in the probit for strategy (1000), the variable salience is one to identify player D, otherwise is zero; in the probit for strategy (0100), salience is one for player A and 0 otherwise; and so forth.

[20]Regressions on the individual treatments do not add to the evidence. They are available on request.

6 Final discussion and summary

The results of individual behaviour helps to focus the various points of the paper better. We started from the very neat theory of Bala and Goyal (2000) about network formation in a non-cooperative setting. We conducted experiments of various versions of the model and under various experimental conditions. At a very general level, we saw some emergence of equilibrium networks, but neither particularly strong, nor homogeneous under the different conditions.

We studied in more detail two behavioural rules of game playing applied to networks: salient play and learning dynamics. Regarding salient playing, we saw that using ordered letter labels A, B, C, D rather than neutral labels to identify subjects in the networks, had a general positive effect in helping subjects to better focus on the games and increasing their performance in the networks. Quite interestingly however, we also saw that ordered labels were not enough to induce salient coordination in the mono-directional model (meaning that subjects take part in a wheel in which A connects to B, B to C, C to D, and D to A). But other conditions are also important. In our experiments, we saw some tendency of salient play only in Wave 3, after subjects went through a common protocol which may have helped them to synchronize their minds on the strategic role which labeling could have for coordination.

We saw that learning dynamics can sometimes also lead to equilibrium convergence, both to the wheel networks in the mono-directional model and to the empty networks in the bi-directional one. In neither case, however, convergence appeared to be quick or general. We studied more specific models of learning dynamics and found little evidence of subjects playing the Cournot Best Response, which was the basic learning rule used by Bala and Goyal (2000) to predict convergence to the Strict Nash equilibria in both flow models. In fact, we found more support for subjects playing strategies jointly sustained by a combination of learning rules, including Reinforcement and Fictitious play as the main ones.

Compared to evidence from previous experiments on networks formations, this paper provides some confirmation and some qualifications. The main confirmation is that even if the wheel and the center-sponsored star rest on equivalent equilibrium notions from a purely game theoretic perspective, the latter network in Bala and Goyal bi-directional model seems definitively affected by a too large payoff asymmetry to be chosen by subjects in the experiments (Falk and Kosfeld 2003). Some more recent experiments have shown that slight modifications in the structure of incentives, due for example to heterogeneity in the linking costs or in the benefits from connecting to neighbors, can contribute to solve the coordination problems arising in the two-way flow models (see, e.g. Goere et al. 2003, and Berninghaus et al. 2006). Important qualifications concern the evidence from the one-way flow models previously studied in the experiments conducted by Falk and Kosfeld (2003) and by Callander and Plott (2005). Although both our investigation and the previous two focus on models with identical game theoretic predictions, each experiment reported rather different rates of equilibrium convergence.

Throughout the paper we have pointed out various differences in the procedures, frames and conductions of the experiments, which in addition to the obvious differences in subject pools, can contribute to explain the differences in findings. More generally, we believe that the differences among the various experimental results also confirm that network formation is a very fascinating, but challenging theme for experimental research, since even slight differences in experimental conditions may cause significative difference in results.

Obviously, if this occurs in the lab, the impact of labels, frames, people's mental attitudes can be even more important for the formation of social networks in the real world. Neglecting considerations of such psychological aspects may produce serious drawbacks in our understanding of circumstances which may favor social networks in the real world.

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Appendix

A Example of instructions for the experiment

The experiments were conducted in Italian. Here is a translation of the instructions for the experiment on the mono-directional flow model with low cost ($m0.5$) conducted in Wave 1. The instructions for the other treatments were changed accordingly.

Welcome to an experiment in economic decision-making

This experiment is devoted to the study of network formation processes in which valuable information is transmitted.

The experiment consists of a series of periods in which you should make decisions.

If you follow the instructions carefully and make good decisions, you can earn a considerable amount of money, which will be paid in cash at the Bank ... of the Università dell'Insubria. . . .

In the room there are instructors to whom you can clarify any doubts. If you have any questions, raise your hand and wait for an instructor to contact you.

An experiment on information transmission

In this experiment you will always interact with three other participants. During the whole experiment these participants will remain the same. During the experiment you are asked not to speak in any way with the other participants.

Each participant is represented by one of the following symbols: @, #, *, %. You will only be informed about your symbol at the beginning of the experiment. Your symbol will only be known to yourself. Do not communicate your identity to anyone else.

In the experiment, each participant has some information that only he is aware of. The exact nature of the information is irrelevant to gain in the experiment. What is important is that the information owned by each participant is worth 1 point. This value is the same for each participant.

You have immediate access to your information, without having to take any action.

However, to access the information owned by other participants, you have to communicate with them.

You can only access the information held by another participant if there exists a connection that allows the information transmission between you and him.

Be aware that you can access the information held by another participant, both through a direct connection (for instance, you are @ and # is directly connected with you) or through a connection chain (for instance you, @, are connected with * while * is connected with #).

It is important to remember that the information is transmitted in just one direction. If you are, directly or indirectly, connected with #, the information held by # will arrive to you but not the other way round. In fact, if # wants to observe your information, he or she has to be connected with you, either directly or indirectly.

Remember that the value of the information you accede does not depend on the number of connections that allow you to observe it.

Connection Cost

To open a connection is costly.

If you decide to establish a direct connection with another participant you must spend an amount equivalent to 0,5 points.

Your total costs amount to 0,5 points times each direct connection you establish.

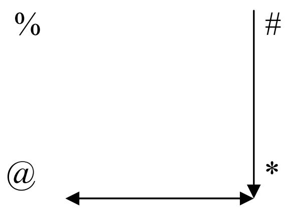
If you decide not to open a connection with anyone you do not have to pay anything. Remember that you observe your own information automatically without the need of any connection.

An example

You can think of the connections between you and the others as arrows from them to you. The arrow indicates that the information of the others is flowing in your direction. The arrows form a network which shows the information flows between the players.

The arrows of the network can also show which player has created a connection. Indeed, for each arrow, the player to which the arrow is pointing toward is the one that has created that connection, bearing the cost.

Try to observe the information transmission and the connection costs of the following network:



First of all observe the number of connections opened by each player.

You can see the number of direct connections established by a player simply by counting the number of arrows pointing in his or her direction. Hence, you can see that

% has not established any connections,
neither has # established any connections,
@ has established just one connection (with *),
* has established two connections (one with # and another with @).

You can now calculate the total cost of the connections made by each player, multiplying by 0,5 points the number of connections he has established:

% does not spend anything,
# does not spend anything,
@ spends 0,5 points
* spends 1 point

Now think it how the information is transmitted in this network. Remember that the information circulate in the same direction as the arrows.

This means that the information of # flows in a direct way to * , but not vice versa.

Moreover, from the moment that there exists an arrow from * to @, it means that * directly observes also the information from @.

Note that in this case, @ is really able to observe the information of * from the moment that he has decided to establish a connection with *.

You also have to consider how the information is transmitted through indirect connections. As a matter of fact, through *, @ can also have access indirectly to the information of #. However you can see that the opposite is not true.

Player % is isolated, as he or she has not established any connection. Nevertheless, remember that each player always observes his or her own information.

Thus, to summarize the number of information observed by each player through the network, we can say that,

only observes his or her own information

* and @ each observe 3 information (their own and those from the other two players) through direct or indirect connections.

% only observes his or her own information

Profit

The experiment of network formation will be repeated several times.

What you will earn from participating in the experiment depends on the type of network formed in each period.

In particular, the profit of each participant on each period will be given by the value of all information observed by him or her in that period through direct and indirect connections, minus the total cost of the direct connections established by him or her.

The profit of each player in each period will then be calculated by counting the information observed and attributing to each 1 point. To this amount 0,5 points will be subtracted for each direct connection established by him or her.

In the above example it is easy to calculate the points obtained by each participant:

% earns 1 point: observes only one piece of information, his or her own, and does not bear any cost.

also earns 1 point: observes only his or her own information and does not spend anything.

* earns 2 points: he or she observes 3 pieces of information and spends 1 point for the two connections.

@ earns 2,5 points: he or she observes 3 pieces of information and spends 0,5 points in one connection.

The total amount for participating in the experiment will then be given by the sum of all points obtained in each period, converted into euro.

In particular, in each period the points earned will be converted into euro through the following rule:

Euro = (Points)*0.5

The payment for the participation in the experiment will be done after the experiment ends.

Computer support for the experiment

Hence, the experiment consists of deciding on the connections to be established with the other participants in a sequence of periods. To assist you with your decisions, we have prepared some computer support.

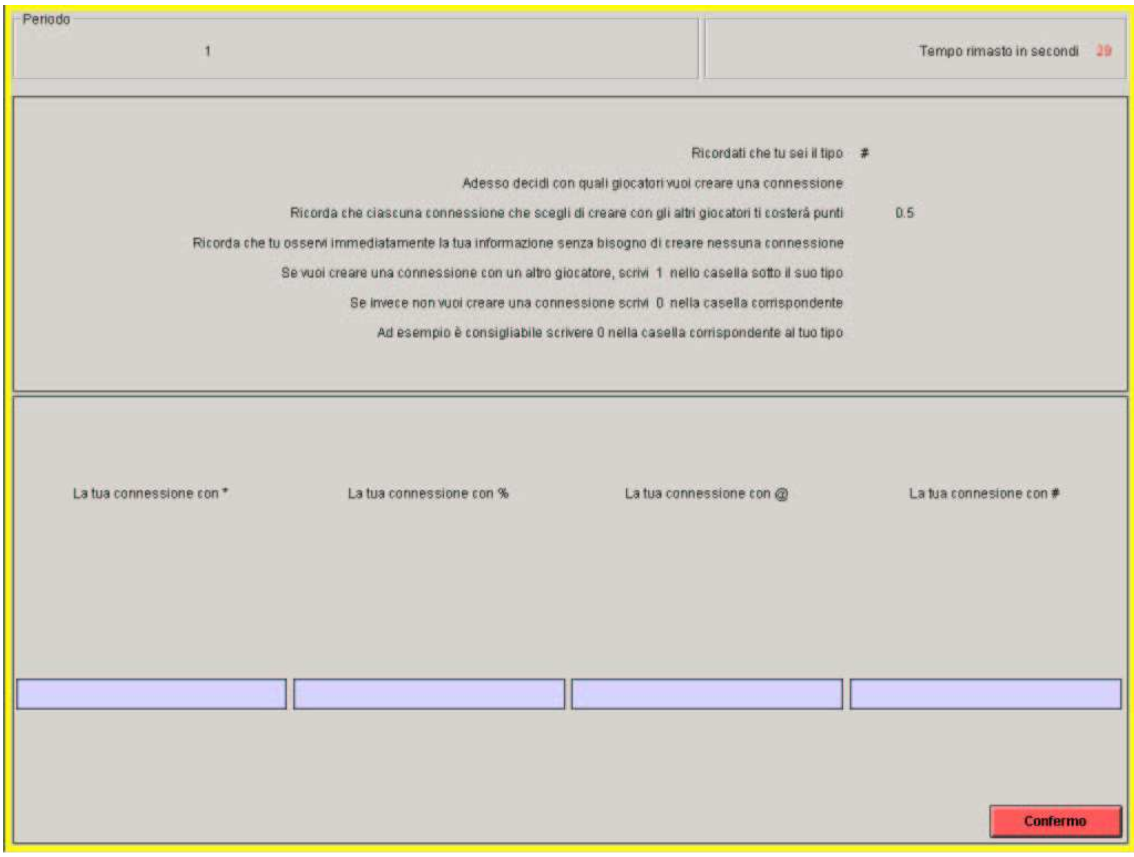
At the beginning of the experiment, an initial screen will communicate whether you are @ , # , * or %. This identity will remain the same during the whole experiment. Thus, the proper and true experiment will be started with the period sequence.

In each period, you will be given two successions of screens: in the first you should make your choice, in the second you will be communicated the network structure and the earned points in that period.

The screen for your choice in the experiment

In each period of the experiment you will be asked to decide whether to establish a direct connection and with whom of the other participants you want to establish a direct connection. To make your choices you will have up to 2 minutes in each period.

You can make your choice by using one computer screen in front of you. Figure 1 represents a typical screen to make your choice.



The screen reminds you who you are (@ or # or * or %), it is numbered according to the period you are in and it indicates the remaining time to make your choice. For example, the figure refers to a hypothetical player #, in period 1, that still has 29 seconds to make his or her own choice.

On the top of the screen you will find the most important information to have in mind when you make your choice, i.e. that each connection costs 0,5 points and that you observe your own information automatically without needing any connection.

The screen reminds you that it is not advisable to activate a connection with yourself.

On the bottom of the screen, there are four cells with a similar label: Your connections to *, Your connections to %, Your connections to @, Your connections to #. Underneath each of these cells there is an empty space to introduce your choice.

In particular,

If you intend to establish a connection with a specific player you should insert “1” in the empty space under the cell that corresponds to his symbol.

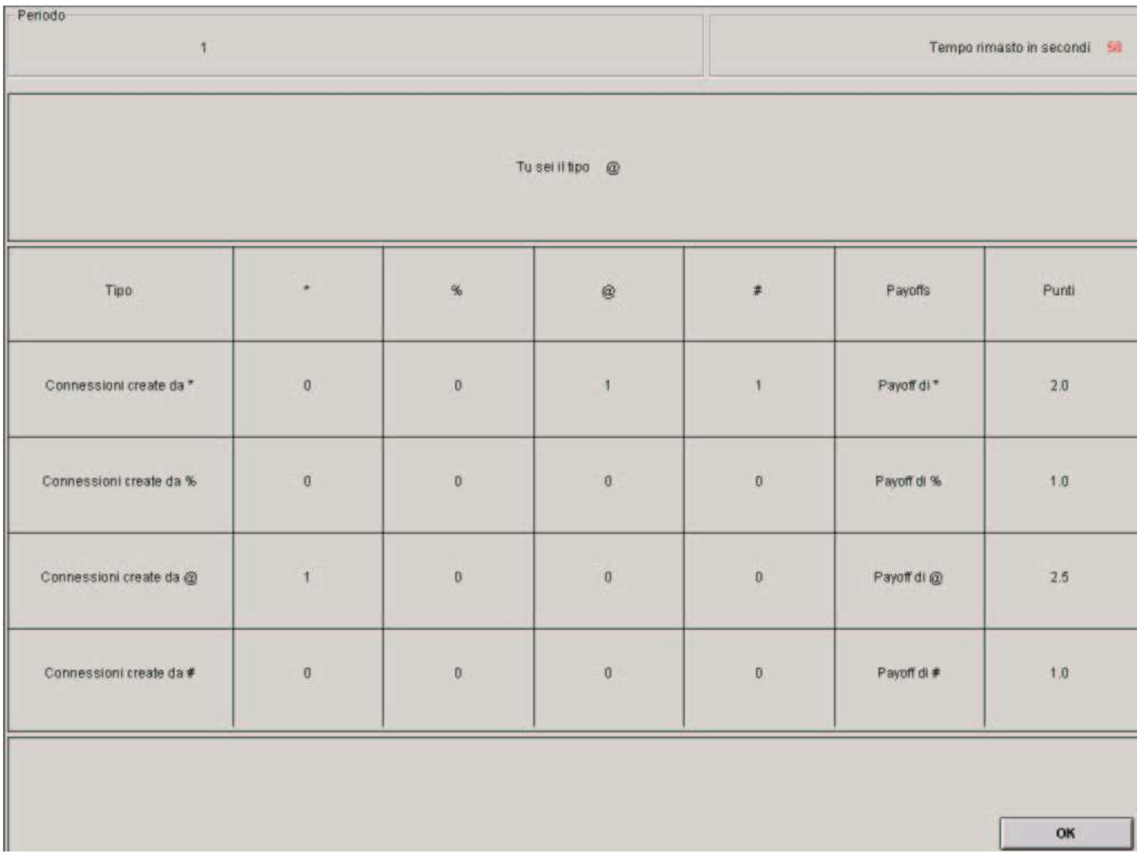
If instead you intend to create no connections with a specific player you should insert “0” in the empty space under the cell that corresponds to his symbol.

0 and 1 are the only accepted characters. If you insert any other character an error message will show up.

You can always modify your choice until time expires. When you have decided definitely on all connections, you have to confirm your choice by pressing the button Confirm.

The results screen, with the network structure and the profits

After having made your decision, you will receive a waiting message. When all participants have taken their decisions on the direct connections, the network will be formed. The computer will then show a screen with the network formation and the points earned by each player. This will occur with a screen like the one on Figure 2.



Tipo	*	%	@	#	Payoffs	Punti
Connessioni create da *	0	0	1	1	Payoff di *	2.0
Connessioni create da %	0	0	0	0	Payoff di %	1.0
Connessioni create da @	1	0	0	0	Payoff di @	2.5
Connessioni create da #	0	0	0	0	Payoff di #	1.0

The screen shows a table. Each row of this table corresponds to one of the four players: * , % , @ , # .

All rows have cells.

If inside a cell there is 1, it means that the player of that row has decided to establish a connection with the player represented in the column.

If inside a cell there is 0, it means that the player of that row has decided not to establish a connection with the player represented in the column.

The connections made by you and by the other players of the group determine the structure of the network and the payoff points earned by each player. These are shown in the last column on the right of the connections table.

Figure 2 refers for example, to a period in which a network was formed with the following characteristics:

Player * has established a connection with # and one with @. His profit is 2 points

Player % hasn't established any connection with any of the other players. His profit is 1 point.

Player @ has established one connection with *. His profit is 2,5 points.

Player # hasn't established any connection with any of the other players. His profit is 1 point.

Please note that these are the same characteristics of the network represented with the graph of the previous example. In fact, the network is the same.

The screen does not show the network graph. You will find next to your computer sheets of paper to draw the graph of the network (see Figure 6). You can also copy the direct links formed by you and the other players in the empty table, with the points earned by each in the period.

This operation will among other things be useful to control your total profit for all periods in the experiment.

How the experiment continues

After you have seen the structure of the network and the earned points for a sufficient amount of time, the experiment will go into the successive period. Again all participants should make decisions, a network will be formed and will give profits that will be communicated by the computer through a new screen of results.

End of the experiment

The experiment will go on for a number of periods, until a different screen appears. On this screen you will be asked to fill in some information useful for your payment.

The computer will then calculate the amount you have earned for participating in the experiment, converting the total scored points in euro through the formula previously indicated.

You can withdraw your payment for the participation in the experiment in the office of Bank... of the Università dell'Insubria, address...

Figure 6: The sheet to report results and draw the network

Copy the screen of the results with the point-payoffs earned by each player,

	@	%	#	*	Payoff-points
Links formed by @ to:					Payoff earned by @:
Links formed by % to:					Payoff earned by %:
Links formed by # to:					Payoff earned by #:
Links formed by * to:					Payoff earned by *:

Draw the graph of the network resulting from the screen of the results. Consider the direction of the arrows.

@	%
#	*

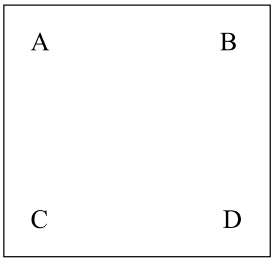
A.1 Control protocol along the style of Falk and Kosfeld (2003) - included only in the ordered and neutral treatments of Wave 3

Please answer the following questions. Your answers bear no consequences on your payment. They serve only to verify if you have understood the instructions. Please raise your hand when you have done.

Question 1. The following direct links were formed:

Type A to: B, C
Type B to: A
Type C to: B
Type D to: A, B

Please insert the links from these decisions in the following diagram. Consider the direction of the arrows.



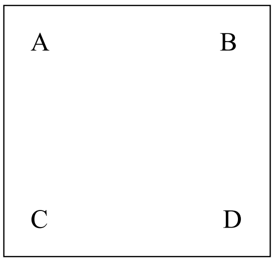
Calculate the cost, the information observed by each member of the network, the payoff-points earned by each member.

Type	Cost	Information observed (of other members)	Points earned
Type A			
Type B			
Type C			
Type D			

Question 2. The following direct links were formed:

Type A to: B, C, D
Type B to: C, D
Type C to: B, D
Type D to: A, B

Please insert the links from these decisions in the following diagram. Consider the direction of the arrows.



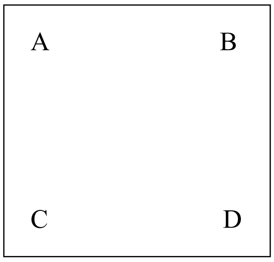
Calculate the cost, the information observed by each member of the network, the payoff-points earned by each member.

Type	Cost	Information observed (of other members)	Points earned
Type A			
Type B			
Type C			
Type D			

Question 3. What links should, in your opinion, be formed to ensure the best possible flow of information and the maximum income to all group members?

The following direct connections should be initiated:
Type A to: B, C
Type B to: A
Type C to: B
Type D to: A, B

Please insert these links in the following diagram.



What were your considerations?

B Models of learning

B.1 Reinforcement (R)

In the *Reinforcement* model, in the first period each player $i = 1, ..., I$ has an initial *propensity* to play any n of her N_i strategies. Such a propensity is represented by $q_{in}(t)$ for any period of time t. Strategies with higher propensity are played with higher probability. The probability of player i choosing strategy n at time t can be found using $p_{in}(t) = \frac{q_{in}(t)}{\sum_m q_{im}(t)}$. It is usually assumed that all initial propensities are strictly positive, so that at all times there is a positive probability of a strategy being picked.

In all our experimental games, $I = 4$, and the set of strategies is the same for all agents, $N_i = N$ for any i, with $|N| = 16$. Moreover, in order to guarantee that the propensities stayed always strictly positive even in the (unlikely) case of repeated plays of a dominated strategy with a negative payoff, we assumed that in any game $\forall i$, $q_{in}(1) = 22 \times 2.5 = 55$. Any other choice would only re-scale the quantitative findings with no substantial effects.

Any learning model also needs an updating rule. In this paper, we only focused on the standard basic *reinforcement* model, where the propensities are updated by adding the payoff x received in period t by playing strategy n to the previous propensity. Formally, the updating rule is

$$\begin{cases} q_{in}(t+1) = q_{in}(t) + x & \text{if } n \text{ is played at } t \\ q_{im}(t+1) = q_{im}(t) & \forall m \neq n \end{cases},$$

that is, only nth propensity is changed. The reason for this is that, since actions other than n were not chosen, the payoff they would have received could not be observed. Also note that the parameterization of the initial propensity $q_{in}(1) = 55$ takes care of the existence of negative payoffs in the experimental games and rules out the technical problem of possibly negative propensities as well as of undefined probabilities by introducing a difference between reinforcements and payoffs in the spirit of Erev and Roth (1998).

B.2 Belief learning

A standard formalization of belief learning is commonly used for the case of two-player games, $I = 2$. Each subject i's beliefs about his/her opponent's actions can be represented by a vector v_i containing a number of elements equal to the rank of the particular payoff matrix used in the game. Each element represents the weight player i places on opponent choosing each pure strategy. Thus $v_{in}(t)$ represents the weight that player i gives to his/her opponent playing pure strategy n in period t. It is easy to sort out the probability with which player i believes his/her opponent will play strategy n by calculating $\pi_{in}(t) = \frac{v_{in}(t)}{\sum_m v_{im}(t)}$. The player then chooses the pure strategy that is a best response to the probability distribution. In case of a tie, the player is assumed to choose randomly between all the possible best response strategies.

Two possible extensions to the more general case of $I > 2$ players are possible. The first it is to calculate an $n \times (I-1)$ matrix $V_i(t)$ for each player i, containing the weight i is placing on each of his/her $I-1$ opponents playing each pure strategy. In such an *individual opponent belief learning,* player i is then choosing that particular strategy which is a best response to the combination of the most probable pure strategies by each of his/her opponents. In our network formation games this formally implies, first, identifying the highest element $\overline{v_{inj}}\,(t)$ for each j column of the matrix, and then selecting i's best response to a network formed by the other 3 opponents each playing their most probable strategies $\overline{v_{inj}}\,(t)$.

Note, however, that this generalization of belief learning to our four-player games implies that subjects would experience not only a relatively time-consuming effort on computational operations, but also a rather sophisticated kind of learning. Indeed, given that the network to which best respond is exclusively formed by the opponents' most probable strategies, it may well be that that particular network has never been seen in the past. In other words, being mainly an abstract procedure (based on joint probability distributions), which in theory should respond purely to virtual networks, makes individual opponent belief learning not particularly appealing in terms of understanding real subjects' behaviour.

On the contrary, an alternative generalization of belief learning with I players, is based on the idea that subjects can see the structures formed in the past and may easily see how often a particular residual network has emerged. That is, the *residual opponent belief learning* assumes that in four-players games, for instance, each subject only keeps track of the observed combinations of the pure strategies played by all three his/her opponents and behaves by facing and reacting exclusively to residual networks. Formally, in such a case a $\left(n^{I-1}\right) \times 1$ vector $v_{i(-i)}\,(t)$ needs to be compiled by each player: any element $v_{i(n,m,\dots,l)(-i)}\,(t)$ represents the weight that player i gives to the possible residual network formed when his/her opponents are playing respectively pure strategies $n, m, ..., l$ in period t.

This generalization would also be rather demanding in terms of calculation time, as it would require each subject filling all the $(16)^3 = 4096$ elements of the vector. It should be underlined, however, that the calculation only occurs with strategy combinations corresponding to residual networks seen in the past. Thus, while all unobserved residual networks simply get zero weight, players are only supposed to keep track of one structure for a given period of time, which in standard experiments seems to be a reasonable requirement.

In the data analysis of our four-person experimental games, we have calculated both the generalizations of belief learning for each subject. However, having found that, with extremely few exceptions, they perfectly overlap the same probability distributions, we only refer to vector formulation of the residual opponent model.

The belief learning variants typically differ only on the way they model how the belief vector $v_{i(-i)}\,(t)$ is updated.

B.2.1 Fictitious play (F)

The pure deterministic *Fictitious Play* learning model that we adopted, begins with setting zero weights on any combination of strategies and residual networks, $v_{i(-i)}\,(0) = [0]$. Therefore, subjects choose randomly in the first period. For all subsequent periods, let $y^* = [n^*, m^*, ..., l^*]$ be the choices of all player i's opponents in period $t-1$. The Fictitious Play learning model updates the belief vector by setting

$$\begin{cases} v_{iy^*(-i)}\,(t) = v_{iy^*(-i)}\,(t-1) + 1 & \text{with } y^* = [n^*, m^*, ..., l^*] \text{ chosen at } t-1 \\ v_{ix(-i)}\,(t) = v_{ix(-i)}\,(t-1) & \forall x \neq y^* \end{cases}.$$

Thus, a player who learns according to the Fictitious Play model uses the entire history of opponents' past strategies to form her beliefs. Subjects' beliefs are simply the observed frequency with which all opponents have simultaneously used each combination of individual strategies.

B.2.2 Cournot Best Response (C)

Alternatively, the *Cournot Best Response* model assumes that players update their belief setting

$$\begin{cases} v_{iy^*(-i)}(t) = 1 & \text{with } y^* = [n^*, m^*, ..., l^*] \text{ chosen at } t-1 \\ v_{ix(-i)}(t) = 0 & \forall x \neq y^* \end{cases}.$$

In other words, a player learning according to the Cournot Best Response uses only the most recent period observation to form beliefs. We can immediately see that this type of learning, by treating each subject as assuming opponents will play the same combination of strategies as they did in the previous period, corresponds to what Bala and Goyal call 'naive best response dynamics'.