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# To Share or Not to Share: An Experiment on Information Transmission in Networks*


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**Abstract**

We design an experiment to study how agents make use of information in networks. Agents receive payoff-relevant signals automatically shared with neighbors. We compare the use of information in different network structures, considering games in which strategies are substitute, complement and orthogonal. To study the incentives to share information across games, we also allow subjects to modify the network before playing the game. We find behavioral deviations from the theoretical prediction in the use of information, which depend on the network structure, the position in the network and the strategic nature of the game. There is also a bias toward oversharing information, which is related to risk aversion and the position in the network.



*JEL Classification:* C72, C91, C92, D82, D85
*Keywords:* networks, experiment, information sharing, strategic complements, strategic substitutes, pairwise stability


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# 1 Introduction

Information sharing is ubiquituous in our society. In many situations, people and organizations benefit from accessing others' information and, in return, they are required to disclose their own information to others. Recently, with the exponential rise of social networks, this phenomenon has become of special relevance. People form links, for example by proposing *friendships* in *Facebook* or *LinkedIn*, and access their friends' information, at the same time granting them access to their own information.

The information collected from social networks can be used for several purposes, and people may face different incentives to acquire and share information depending on the context. When different agents have a common interest, information provides ways to coordinate with others. For instance, friends may wish to choose the same leisure activity (a gig, a bar, a cinema), and at the same time they may want to learn from others which of the available options is the best. Other situations may display anti-coordination motives (representing, for instance, congestion effects). Alpinists may wish to know which mountain hut is the most convenient for a given route, but at the same time they may prefer not to select a hut where most other alpinists are expected to go, in order to avoid long queues or the risk of finding no vacancies once there. Of course, one can also envisage situations where there is no strategic interaction, and people only use the acquired information to support their decision making (for instance learning which car is the best buy on the market).

The importance of information sharing networks has motivated recent theoretical studies that address the incentives of economic agents to share information; these include Hagenbach and Koessler (2010), Galeotti et al. (2013), Currarini and Feri (2015, 2018), and Herskovic and Ramos (2015). In the present paper we report results from a controlled laboratory experiment, where subjects use private information in interactive decision making problems, and possibly decide with whom to share their private information (i.e., form links) before acting. Our objective is to understand how the strategic properties of the decision making problem affect the way in which subjects react to the information they observe from the network and their incentives to form links. The ultimate goal is to detect possible behavioral effects in either the use or the transmission of information.

In particular, our framework allows us to study behavioral effects of the network structure. We distinguish two main potential effects: First, the network determines the amount of information available to each agent. The degree of an agent represents the number of signals she is able to observe. Hence, the higher the degree, the higher the amount of information. On the other hand, the symmetry of the network determines relative concerns. In symmetric networks all agents have the same amount of information, whereas in asymmetric networks some agents are relatively more informed than others. In this respect, the literature on management has identified a behavioral phenomenon related to the information agents have. Zacharakis and Shepherd (2001) find that as more information becomes available to people, they become more overconfident, and overconfidence has a negative effect on their choices.[1] Likewise, Bernardo and Welch (2001) provide evidence suggesting that more overconfident actors have a propensity to overweight their private information relative to public information. In this line, in our experiment we may expect more informed agents (i.e., agents with a higher degree) to overweight their available information. Second, previous studies suggest that individuals have a (behavioral) preference for becoming informed, even if the information is useless or if they themselves believed they would be better off without it (see, for instance, van Dijk and Zeelenberg 2007, Kruger and Evans, 2009, Eliaz and Schotter, 2010, Sharot and Sunstein,2020, or Golman et al., 2020). Hence, regarding link formation, we may expect a (behavioral) tendency to form/maintain links even in case where theory predicts the opposite.

There has been an extensive theoretical effort to understand the acquisition and use of information in environments with fundamental uncertainty, even if mostly not with a network perspective.[2] Morris and Shin (2002) and Angeletos and Pavan (2007) study the optimal use of private and public information. Agents observe private signals (only revealed to them) and public ones (observed by all) and then play a game.[3] Public information plays the twofold role of revealing something about the state of the world and of allowing agents to coordinate with their rivals. Since this second incentive is socially irrelevant, agents tend to over-react to public signals compared to what would be socially optimal at the ex-ante stage. Myatt and Wallace (2015) show how this result is reversed in a context where strategies are substitutes (Cournot competition), so that more private signals tend to be used more intensively than more public ones.

The literature on information acquisition goes further by making the available information endogenously chosen by players (at a given cost). Hellwig and Veldkamp (2009), Myatt and Wallace (2012), Colombo, Femminis and Pavan (2014) and others show how the incentives to coordinate actions induce agents to also coordinate on which signals to acquire, thereby increasing the publicness of the acquired signals, and consequently exacerbating the inefficiency from the excessive use of public information. In a context of bilateral information transmission, Currarini and Feri (2015, 2018) and Herskovic and Ramos (2015) obtain similar insights studying information acquisition from peers, rather than from exogenous and impersonal sources. In Cur-

[1] Relatedly, Busenitz and Barney (1997) find that firm founders were significantly more overconfident than midlevel managers in their judgements, which as indicated by Hayward et al. (2006), reflects overconfidence in knowledge.

[2] In the framework of imperfect market competition, the analysis of the incentives of firms to share information before engaging in market competition dates back to the seminal contributions of Novshek and Sonnenschein (1982) and Vives (1985). One main insight from this body of literature is that incentives to share are associated with either strategic complementarity or weak substitutability, be it induced by products differentiation, by cost convexity or by price competition (see Vives, 1985, Kirby, 1988 and Raith, 1996).

[3] See also Cornand and Heinemann (2008), who introduce a concept of partial publicity by allowing for information that is provided to just a fraction of agents.

rarini and Feri (2015, 2018) players are assumed to share information by means of bilateral contract; in Herskovic and Ramos (2015) agents unilaterally acquire information from peers at a given cost. In these papers, the incentives to share and to acquire increase (decrease) with the degree of publicness of the signal received by the peer when the underlying game has coordination (anti-coordination) motives.

Our experimental design is based on the bilateral sharing structure of Currarini and Feri (2015). We will now therefore go more in the details of that paper before presenting our results. The structure of available information is determined by a network: each agent $i$ owns a piece of private information which is shared with all players linked to $i$ in the network. Each piece of information $i$ is therefore "public" to all agents linked to agent $i$. Consistent with the literature above, they find that the sensitivity of each player's strategy to each observed signal in the network depends on the strategic nature of the underlying game. Strategic complementarities induce agents to use more intensively those signals that are observed and used more intensively by other agents in the network. Opposite conclusions apply to games with strategic substitutes, where a congestion effect prevails and players tend to use less those pieces of information which are more "public". All the signals are instead treated symmetrically when players' strategies are orthogonal.

Having characterized the use of information in the network, Currarini and Feri (2015) study information transmission by looking at the endogenous formation of bilateral sharing agreements. The sharing technology is as follows: each pair of agents can commit ex-ante to "mutually" and "truthfully" disclose their own private information to each other, before playing a linear quadratic game. The ex-ante assumption rules out all signaling considerations from the analysis of sharing decisions. The assumption of truthful transmission avoids all the strategic considerations that are central to other recent studies of information sharing in networks, such as Galeotti et al. (2013) (where strategies are orthogonal) and Hagenbach and Koessler (2010) (where agents have a coordination motive). For the general class of linear quadratic games, Currarini and Feri (2015) characterize the set of pairwise stable information structures, defined as a set of bilateral sharing agreements where no pair of agents has an incentive to share additional information, nor to stop sharing. They find that the incentives to share information crucially depend on how sensitive payoffs are to the volatility of one's own action, on aggregate volatility, and on the covariance between the opponents' actions and the state of the world.[4]

In our experimental design we assume that each agent observes an independent signal in $\{-1, 1\}$, and that the state of the world is the sum of the signals observed by agents (this statistical model was used in Currarini and Feri (2018) to study information sharing with heterogeneous signals). We implement three treatments, that

[4]Currarini and Feri (2015) obtain that in the Beauty Contest game all the information is shared with all rivals. In the Cournot game (with linear costs and demand uncertainty) the absence of information sharing is a stable outcome, but network structures in which information is shared in fully connected components of increasing sizes are also stable.

correspond to three versions of the classical Keynes' Beauty Contest game (Morris and Shin, 2002, Hagenbach and Koessler, 2010), endowed with the three types of strategic interdependence: complementarity (COMP), substitutability (SUBS) and no interaction or orthogonal game (NOINT).[5]

In the first part of the experiment, the information network is exogenous, and our focus is on the way in which agents use their available information (the observed signals - that is their own signal plus those received by agents to which they are linked in the network). In the second part of the experiment we allow subjects to modify their information sharing links prior to playing the game.[6] In this second part we identify the architectures of pairwise stable networks for the three games described above.

Regarding the use of information, we find that the qualitative patterns of behavior in all the three games are consistent with equilibrium predictions. In particular, in the Beauty Contest game with strategic complements, i.e., our treatment COMP, the use of each piece of information becomes more intense as the number of subjects that observes that piece of information increases; an opposite pattern occurs in the Beauty Contest game with strategic substitutes (treatment SUBS), where a congestion effect prevails; in the orthogonal game (treatment NOINT), all signals are used with similar intensity. Despite these consistent qualitative patterns, we observe a systematic over-reaction to all signals in COMP, and a systematic under-reaction in SUBS and NOINT. Interestingly, we find that more connected (that is, more informed) subjects tend to react more to signals than less connected ones and that this effect is stronger in asymmetric networks. This effect is absent in equilibrium predictions where the only way in which the information network affects the coefficient applied to a given signal is the number of agents observing that given signal.

Regarding network formation, the observed behavior is consistent with equilibrium in both COMP and NOINT: all links are formed in all circumstances. There are however important departures from equilibrium predictions in SUBS. Here, the modal strategy is to form (or not to sever) a link even when it would be (theoretically) optimal not to do so. This apparent deviation from rationality may have a simple explanation: given the suboptimal reactions to signals observed in SUBS, the observed over-linking behavior would be optimal. Even after the anticipation of the actual suboptimal behavior is controlled for, we find that the residual departures from optimality is related to the degree of risk aversion: more risk-averse subjects tend to depart from equilibrium more often when this departure means forming or maintaining a link.

Within the experimental literature, Cornand and Heinemann (2014) studies the use of public versus private information without a network approach. They design an experiment based on a two-player version of Morris and Shin's (2002) setup and, hence, restrict the analysis to the beauty contest game (strategic complements). They

[5]See for instance Ray and Vohra (1999).

[6]Our focus is on the incentives to share information at the ex-ante stage, as they result from the gains from acquiring and the possible losses from disclosing.

consider the case where each agent observes a private signal (only revealed to her) and a public signal (observed by both players). They measure the actual weights that subjects attach to public and private signals and find, in line with the theory, that subjects put larger weights on the public signal than on the private ones. However, the weights put on the public signal are smaller than theoretically predicted. They show that observed weights are distributed around the predictions from a cognitive hierarchy model, where players take into account that other players receive the same public signals, but neglect that other players also account for others receiving the same public signals. Differently to Cornand and Heinemann (2014), in our case each signal is public to a specific subset of agents (the neighborhood), and the use of private information is potentially related to the possibility that agents share their private information before engaging in non-cooperative behavior. We extend their findings for the COMP game by showing that to the extent that signals are "more public" (more observed in the network), subjects put more weight on them. Other experiments that explore the use of private versus public information are, for instance, Heinemann et al. (2004), Cornand (2006), and Cabrales et al. (2007).[7]

There are also experiments that consider games of different strategic nature in networks without fundamental uncertainty about the state of the world, like Kearns et al. (2006, 2009), Charness et al. (2014), and Choi and Lee (2014).[8] Kearns et al. (2006, 2009) develop a series of experiments where players located in a network aim to get a collective goal (subjects' payoffs depend on the global performance of the network) and study the capacity to achieve the common goal depending on the network structure. Kearns et al. (2006) consider a game of substitutes (framed as a graph-coloring problem), and Kearns et al. (2009) examine a game of complements (framed as a voting game).[9] Charness et al. (2014) conduct a series of experiments in which actions are either strategic substitutes or strategic complements, and participants have either complete or incomplete information about the structure of a random network. They study equilibrium selection and relate it to network characteristics like connectivity and clustering. Finally, Choi and Lee (2014) investigate how the interaction between the network structure of pre-play communication and

[7]Heinemann et al. (2004) design an experiment on the speculative-attack model by Morris and Shin (1998) and compare sessions with public and private information. The main differences in behavior between the two treatments are that with public information, subjects rapidly coordinate on a common threshold, attack more successfully, and achieve higher payoffs than with private information. Cornand (2006) extends the analysis of Heinemann et al. (2004) to allow for signals of different nature. Cabrales et al. (2007) study equilibrium selection in an experiment on a pure coordination game with uncertainty, where subjects receives noisy signals about the true payoffs.

[8]See also Fatas et al. (2010) that propose a public goods experiments in which a network determines the information subjects receive about others' prior choices.

[9]Kearns et al. (2006) find that networks generated by preferential attachment make solving the coloring problem more difficult than do networks based on cyclical structures, and "small worlds" networks are easier still. Kearns et al. (2009) find that in some networks the minority preference consistently wins globally, and that certain behavioral characteristics of individual subjects (such as stubbornness) are strongly correlated with earnings.

the length of such communication affects outcome and behavior in a coordination context.

The paper is organized as follows: Section 2 presents our three basic games and derives the theoretical predictions. Section 3 contains the experimental design. Section 4 presents the results. Section 5 concludes the paper.

# 2 Theoretical framework and experimental design

In this section, we introduce the theoretical framework, its equilibria, and the experimental design. We first describe the information sharing game for a fixed and exogenously given network. Here the links describe the open access for each of the two involved nodes to the signal received by the other node. A general analysis of this type of game is contained in Currarini and Feri (2015); we refer to the Appendix for all proofs of the equilibrium characterisation that apply to the present simpler version of the general class of games considered in that paper. We will consider three versions of such games, corresponding to alternative assumptions on the type of strategic interdependence between nodes/agents. We then describe the network formation game in which agents form and sever links in the attempt to induce the network structure that, if taken as given, maximises their expected payoff in the information sharing game. For these games we formulate the main theoretical hypothesis to be tested and suggest possible behavioral effect that may arise in the experiment. We then describe in full detail the experimental design.

In the experiment four subjects have to play a simultaneous game where the individual payoff depends on the decisions of all players and on the realized value of a random variable $\theta$ (state of the world). Before playing, each player receives some information about the state of the world. The experiment consists of two parts. In the first part four subjects are randomly allocated on a four nodes undirected network. Each player receives a signal giving some information about the state of the world. In addition to her private signal a player is able to see the private signals of all the players she is linked to. In the second part of the experiment, before receiving the private signal, subjects have the chance to modify the network (and thereby the number of signals they are able to see).

## 2.1 Use of information in an exogenous network

We consider a game with 4 agents, with generic agent $i \in N = \{A, B, C, D\}$. Each agent $i$ chooses an action $a_i \in R$. Agent $i$'s payoff is a function of her action $a_i$, of the sum of the other agents' actions $A_i = \sum_{j \neq i} a_j$, and of a parameter $\theta$ denoted as *state of the world*:

$$u_i(a_i, A_i, \theta) = 100 - w(a_i - \theta)^2 - r\left(a_i - \frac{A_i}{3}\right)^2. \tag{1}$$

where $w > 0$ and $r$ are parameters. When $r > 0$ the game has strategic complements, when $r < 0$ strategic substitutes, and when $r = 0$ there is strategic independence. The state of the world $\theta$ is a random variable of the form

$$\theta = 5 + \sum_{i \in N} y_i \tag{2}$$

where $y_i$ are i.i.d random variables taking either value 1 or $-1$ with equal probability. Each agent $i$ is privately informed of the realization of the random variable $y_i$, i.e., she receives a signal $m_i = y_i$.

Furthermore, the four agents are embedded in an undirected network. Link $ij$ means that player $i$ can see, in addition to his own message $m_i = y_i$, also the message $m_j$ privately received by player $j$; at the same time, player $j$ observes the message $m_i$ received by player $i$. In other words, the network structure defines the structure of private information in the game: each player observe his own signal and all signals received by his neighbours in the network. Note that a link between $i$ and $j$ only grants agent $i$ access to the signals *received* by $j$ and not to all signals *observed* by $j$ in the network. This assumption is consistent with the idea that all signals in all neighbourhoods are observed simultaneously after the primitive signals are received. For each agent $i$ we denote by $N_i^g$ the set of players that in network $g$ have a link with her, including herself. The degree of player $i$ is defined as $n_i^g = |N_i^g|$. The network structure and the position of the players on the network are common knowledge.

The elements just described define a game of incomplete information, in which the information set of each player is determined by her position in the network. With each possible *four nodes network* $g$ we associate the Bayesian Nash equilibrium of the game in which each agent $i$ sets her action $a_i$ in order to maximise her expected payoff, given the available information determined by $i$'s links in $g$ and given the optimal decisions of the other three agents.

We will study three versions of this basic game, corresponding to three different payoff functions, and capturing three alternative assumptions on the type of strategic inter-dependence: "strategic complements", "strategic substitutes" and "no interaction". All games share the structure of the Beauty Contest game, in which the optimal choice of an agent mediates between the desires of matching the true state of the world and the desire to stay close to (strategic complements) or far apart from (strategic substitutes) the actions of the other players. In case of no interaction, the agent only cares about matching the state of the world.

- **Beauty Contest with strategic complements (*COMP*)**

  We set parameters at $w = r = \frac{1}{2}$. Agent $i$'s payoff function is:

$$u_i = 100 - \frac{1}{2}\left((a_i - \theta)^2 + \left(a_i - \frac{A_i}{3}\right)^2\right)$$

This is the classic Keynes Beauty Contest game with strategic complements, where individuals try to coordinate their actions as well as to guess the correct value of $\theta$. This game belongs to the class of linear quadratic games, for which equilibrium strategies take the form of an affine function of the signals. Specifically, the equilibrium strategy of agent $i$ is:

$$a_i^* = 5 + \sum_{j \in N_i} \frac{3}{7 - n_j} m_j$$

Note that the coefficient $\frac{3}{7-n_j}$ applied by agent $i$ to the signal $j$ she observes has two key features:

1. It does not depend on $i$'s degree in the network, nor on any characteristic of other neighbours of $i$;
2. It is an increasing function of $j$'s degree in the network: the more agents observe $j$'s signal, the more agent $i$ responds to $j$'s signal.

The first feature of equilibrium depends on the specific way in which the structure of uncertainty was modelled - that is, on the assumption that signals are all independent and that the state of the world is the sum of the signals received by all agents. The second feature applies more generally to this type of games: the sensitivity of an agent's action to an observed signal increases with the degree of "publicness" of that signal. In other words, the informational content of a signal is higher the more it is observed in the network. This effect is a consequence of the coordination desire of agents: the more agents observe a signal, the more that signal is useful in coordinating with average play in the game.

Note finally that, for each signal $m_j$, $j \in N_i$, the equilibrium coefficient can take on the following values: $\frac{3}{7-n_j} \in \{0.5, 0.6, 0.75, 1\}$. The sensitivity to a signal is a convex function of that signal's degree.

- **Beauty Contest with strategic substitutes (*SUBS*)**

We set parameters at $w = \frac{1}{2}$ and $r = -\frac{1}{3}$. Agent $i$'s payoff function is:

$$u_i = 100 - \frac{1}{2} (a_i - \theta)^2 + \frac{1}{3} \left( a_i - \frac{A_i}{3} \right)^2$$

This variation of the classic Keynes Beauty Contest defines a game of strategic substitutes where individuals try to guess the correct value of $\theta$ and, at the same time, to stay as far as possible from the average play in the game. Equilibrium strategies are:

$$a_i^* = 5 + \sum_{j \in N_i} \frac{9}{1 + 2n_j} m_j$$

As for the case of complements, we highlight two features of equilibrium coefficients:

1. It does not depend on $i$'s degree in the network, nor on any characteristic of other neighbours of $i$;
2. It is a decreasing function of $j$'s degree in the network: the more agents observe $j$'s signal, the less agent $i$ responds to $j$'s signal.

The interpretation of the second feature is similar to the one discussed above: given the incentive to stay away from what other players do, each player wants to use less those signals that are observed by many other agents. This is a congestion effect that arises in more general versions of the present linear quadratic game and which is due to the strategic substitution property of the game.

Note that, for each $j \in N_i$, the coefficient applied to signal $m_j$ is $\frac{9}{1+2n_j} \in \{3, 1.8, 1.29, 1\}$: a decreasing and convex function of a signal's degree.

- **Beauty Contest without interaction (*NOINT*)**

  We set parameters at $w = \frac{1}{2}$ and $r = 0$. Agent $i$'s payoff function is:

$$u_i = 100 - \frac{1}{2}(a_i - \theta)^2$$

  Note that in this game the network structure is irrelevant, and each agent evaluates each signal only in terms of its informational value in guessing the state of the world. This implies that equilibrium strategies are neutral to the network structure and, given symmetry in signals' variances, all signals are applied the same coefficient of 1:

$$a_i^* = 5 + \sum_{j \in N_i} m_j$$

In line with the above discussion of equilibrium play, our experiment with a fixed given network will focus on three main questions:

1. How close observed behavior is to equilibrium?
2. Do we observe the qualitative relationship between the degree of a signal and the use of that signal? More precisely, are more observed signals used more under complements, less under substitutes, and just the same as less observed signals under no interaction?
3. Are there other characteristics of the network, which are not relevant for equilibrium play, which nevertheless affect actual behavior in the lab? In particular we will focus on the degree of the decision maker and on the degree of symmetry of the network.

## 2.2 Network Formation

In the second part of the experiment, we allow agents to form and sever links to study network formation behavior. The theoretical reference setting is the following. A two-stage process is in place: in the first stage, a network is formed as a result of the link formation decisions of players; in the second stage, players play one of the three Beauty Contest games describe in the previous section.

Solving the game backwards, we consider for the second stage the affine equilibrium strategies described in the previous section. Such strategies provide players with an expected payoff associated with each possible network structure arising in the first stage. For the first stage, we focus on "pairwise stable networks", that is, those networks satisfying the following two stability properties: no missing link would be willingly formed by the involved players; no existing link would be willingly severed by any of the involved players. Note that this is a "link-wise" solution concept: a stable network passes the stability test above for each missing or existing link being considered one at a time. In other words, no deviation based on the revision of more links at a time is possible. This makes pairwise stability a minimal stability requirement for any network formation process (See Jackson and Wolinsky, 1996).

We will now report on the theoretical predictions obtained by considering pairwise stability at the first decisional stage. Proofs can be found in the Appendix.

1. **Beauty Contest with strategic complements (*COMP*)**

   Here each existing link in any network is not severed, and any missing link in any network is formed. The unique pairwise stable network is therefore the complete network.

2. **Beauty Contest with strategic substitutes (*SUBS*)**

   Here the incentives to form and sever links are less straightforward. We have the following prediction. A player has no incentive to form a link with a player with the same degree or larger. This implies that a player has an incentive to delete an existing link with a player that has a degree not smaller than his degree. Finally, a player either has an incentive to form/mantain a link only with players with a smaller degree. These equilibrium features imply that only the empty network is a pairwise stable structure.

3. **Beauty Contest without interaction (*NOINT*)**

   The theoretical prediction is that players choose to create all possible new links and not to sever any link. The unique pairwise stable network is the complete network.

Note that at the link formation stage, incentives depend on the network in richer ways than in the game played at the second stage. In fact, at least for the case of strategic substitutes, the incentives of a player $i$ to form a missing link (or to sever an existing link) with player $j$ depend both on the degree of $i$ and on the degree of $j$. In particular, $i$'s incentives increase with $i$'s own degree and decrease with $j$'s degree. While the second feature is another instance of the congestion effect under strategic substitutes (also present in the second stage network game), the first feature is new and specific to the link formation problem.

We also remark that linking decisions are taken at the ex-ante stage, that is before receiving messages $m_i$. Decisions cannot therefore be made conditional on the type of message one has received.

## 2.3 Implementation and experimental procedures

In each session we used one of the games described in the previous subsection and one of the sets of networks in Table 1. Note that the networks in a set are *adjacent*, in the sense that we can move from the network structures in the central column - empty, star and circle networks - to those in the right (left) column by adding (deleting) one link. When set 1 is used, the session has 20 periods with exogenous networks (each of the two networks in the set is played 10 times) and 10 periods with a network modification phase in which the empty network is used as the starting network. When set 2 (3) is used, the session has 21 periods with exogenous networks (each of the three networks in the set is played 7 times) and 9 periods with a network modification phase in which the star (circle) network is used as the starting network. The motivation to design the experiment in two parts is to create an enviroment that promotes learning: In the first part (with exogenous networks) subjects experience the same networks a number of times; in the second part (with the network modification phase), the architecture of the (eventually) modified network has already been experienced several times in the first part of the experiment.

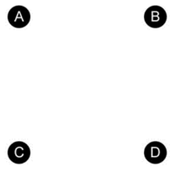
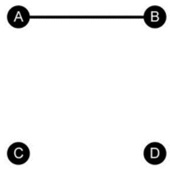
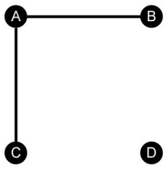
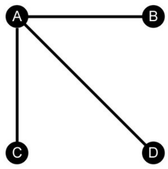
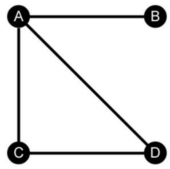
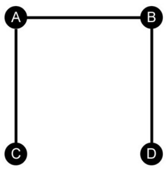
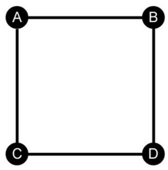
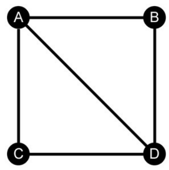
At the beginning of the experiment, subjects are divided into matching groups of eight individuals that remain fixed for all the 30 periods of the session. In each period we implemented the game according to the following timing:

1. Subjects are randomly assigned to a group of 4, then they are randomly assigned to one node of the (starting) network.

2. (Network modification phase. Part 2 only.) Subjects are asked, for each possible link (either existing or not) in which they are (potentially) involved, to simultaneously choose whether they want to maintain the status of the link or change it (i.e., sever an existing link or create a missing one).

3. (Part 2 only.) Then one of the six (possible) links is selected at random by the computer (with uniform probability), and the new status of the link is determined. The new status depends on the choices of the two subjects involved in the link: If the link was missing, it is created if and only if both players involved decided to create it in the network modification phase. An existing

Table 1: Network sets

| | | | |
|---|---|---|---|
| | | empty | empty + 1 |
| set 1 | |  |  |
| | star - 1 | star | star + 1 |
| set 2 |  |  |  |
| | circle - 1 | circle | circle + 1 |
| set 3 |  |  |  |

link is severed if and only if at least one of the two subjects involved decided to sever it.

4. The state of the world $\theta$ is generated according to (2) and each subject receives a signal and also sees the signals received by the subjects connected to her in the network.

5. Subjects simultaneously decide the action to play in the game (one of the three games described in the previous subsection). In order to simplify the game we constrain the actions to be in the interval $[0, 10]$.[10]

6. Subjects are informed about their round payoff and about all payoff relevant information.

[10]In SUBS, this constraint causes a small change in how subjects optimally use the information in networks star and star+1: In equilibrium, the agent with three links reacts slightly less to the signals she sees; the other agents react slightly more (the proof is available from authors upon request). However, in the experimental data we only find 3 observations in which the optimal decisions are on the boundaries of the interval (out of 17 predicted and 3624 total observations).

In the first part of the session (exogenous networks), steps 2 and 3 were omitted. Finally, at the end of each session, we implemented Charness and Gneezy's (2010) risk test, by allowing participants to choose which share (if any) of their show-up fee they want to invest in a risky asset (which provides 2.5 times the amount invested with probability 0.5 and the loss of the amount invested with probability 0.5).

Table 2: Treatments

| | Network set | Game | Sessions | Subjects |
|---|---|---|---|---|
| treatment 1 | 1 | COMP | 3 | 40 (24 + 8 + 8) |
| treatment 2 | 2 | COMP | 3 | 40 (16 + 16 + 8) |
| treatment 3 | 3 | COMP | 2 | 40 (24 + 16) |
| treatment 4 | 1 | NOINT | 2 | 40 (24 + 16) |
| treatment 5 | 2 | NOINT | 3 | 40 (16 + 16 + 8) |
| treatment 6 | 3 | NOINT | 3 | 40 (16 + 16 + 8) |
| treatment 7 | 1 | SUBS | 4 | 40 (16 + 8 + 8 + 8) |
| treatment 8 | 2 | SUBS | 3 | 40 (16 + 16 + 8) |
| treatment 9 | 3 | SUBS | 4 | 40 (16 + 8 + 8 + 8) |

Table 2 summarizes the treatments and sessions we run. The sessions were conducted at the ExpReSS laboratory at Royal Holloway, University of London, and at the LEXECON laboratory of the University of Leicester between March and November 2016. A total of 360 undergraduate and graduate students from all majors participated in 27 sessions. Sessions lasted for approximately 120 minutes and average earnings were £21 per subject including a show-up fee of £4.[11] We used the software z-Tree (Fischbacher, 2007). Subjects were provided with a sheet displaying the network architectures used in the first part of the session and, in the second part, subjects were provided with a sheet displaying all the possible modified networks. The experimental instructions are reported in the Appendix.[12]

[11] In order to increase the salience of the decisions, payments were computed summing up the payoffs from six randomly selected periods, four from the first part of the experiment and two from the second part.

[12] We provide the instructions for the COMP game and network set 1. The remaining cases only differ in the payoff function and in the set of networks, and are available from the authors upon request.

# 3 Results

We first analyze how subjects make use of the information (observed signals) in the three games of different strategic nature (COMP, SUBS, NOINT) and then analyze the link decisions.

## 3.1 Use of the information across games

Here we study how subjects use the information they receive through the links of a network. We perform a panel data analysis in which the unit of observation is a subject, observed for all the 30 periods of a session. We use a random effects Tobit model in which the dependent variable is the action chosen by the subject (censored in the interval [0, 10]). The regressors are the variables $S_x$, $x \in \{1, 2, 3, 4\}$, where we have denoted by $S_x$ the sum of all the signals that are observed by the subject and by other $x - 1$ subjects in the network. In other words, the various values of $x$ are the "degrees" of the nodes associated to the signals observed by the subject.[13] We estimate this model separately for each game, using the observations from both parts of the experiment. The results are reported in the first three columns of the upper panel of Table 3.

Note that in all the three games the average decision (captured by the constant) is very close to 5 (the theoretical prediction). Moreover, the estimates of the coefficients follow patterns that qualitatively match the theoretical predictions. In particular, in the COMP game the estimated coefficients for the variables $S_x$ are strictly increasing with respect to $x$, all the differences being statistically significant, with the exception of $S_3$ and $S_4$. In the NOINT game, the coefficients associated to signals observed by 2, 3, and 4 subjects (i.e., $S_2$, $S_3$, and $S_4$) are all very similar to each other (between 0.81 and 0.86), consistently with the theoretical predictions. However, the signals observed by 1 subject ($S_1$) are significantly less used (coefficient 0.76) than the signals observed by 2 and 3 subjects, suggesting that subjects tend to react differently to signals that are observed by some other player as compared to fully "private" signals, despite the fact that all of them are theoretically equivalent. (A Wald test rejects the null hypothesis that all four coefficients are equal.) Finally, in the SUBS game, we observe that the coefficients of variables $S_x$ are decreasing with respect to $x$, in line with the theoretical predictions, all the differences being significant with the exception of $S_2$ and $S_3$.

While these patterns are overall close to the theoretical predictions, there are substantial departures from equilibrium in the absolute levels of the estimated coefficients. In the COMP game, the signals observed by 1, 2, and 3 subjects are

[13] Consider a star with subject $A$ at the center and subjects $B$, $C$, and $D$ at the periphery. Signal $m_A$ is observed by all four subjects. Signals $m_B$, $m_C$ and $m_D$ are observed only by two subjects. Then for subject $A$, $S_1 = 0$, $S_2 = m_B + m_C + m_D$, $S_3 = 0$, and $S_4 = m_A$. For subject $j$, $j \in \{B, C, D\}$, $S_1 = 0$, $S_2 = m_j$, $S_3 = 0$, and $S_4 = m_A$.

Table 3: Regression models

| | (1) | | (2) | | (3) | | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|---|---|
| | COMP | | NOINT | | SUBS | | COMP | NOINT | SUBS |
| $S_1$ | 0.616*** | [0.50] | 0.760*** | [1.00] | 1.178*** | [3.00] | 0.621*** | 0.584*** | 0.838*** |
| | (0.0324) | | (0.0357) | | (0.0727) | | (0.0518) | (0.0577) | (0.122) |
| $S_2$ | 0.781*** | [0.60] | 0.854*** | [1.00] | 0.964*** | [1.80] | 0.666*** | 0.720*** | 0.712*** |
| | (0.0217) | | (0.0234) | | (0.0479) | | (0.0515) | (0.0558) | (0.117) |
| $S_3$ | 0.919*** | [0.75] | 0.859*** | [1.00] | 0.964*** | [1.29] | 0.789*** | 0.666*** | 0.604*** |
| | (0.0171) | | (0.0186) | | (0.0396) | | (0.0609) | (0.0667) | (0.138) |
| $S_4$ | 0.928*** | [1.00] | 0.828*** | [1.00] | 0.822*** | [1.00] | 0.787*** | 0.662*** | 0.497*** |
| | (0.0272) | | (0.0289) | | (0.0597) | | (0.0627) | (0.0684) | (0.142) |
| *Degree_s* | | | | | | | 0.0454** | 0.0562*** | 0.118*** |
| | | | | | | | (0.0181) | (0.0197) | (0.0411) |
| *Symmetry_s* | | | | | | | -0.133 | 0.319*** | 0.649*** |
| | | | | | | | (0.0988) | (0.110) | (0.224) |
| *DS* | | | | | | | 0.0376 | -0.0848** | -0.185** |
| | | | | | | | (0.0367) | (0.0408) | (0.0835) |
| *Risk_s* | | | | | | | 0.000501 | -0.0140 | -0.0836 |
| | | | | | | | (0.0233) | (0.0246) | (0.0510) |
| *Constant* | 5.081*** | | 5.136*** | | 5.073*** | | 5.080*** | 5.135*** | 5.073*** |
| | (0.0300) | | (0.0622) | | (0.0701) | | (0.0301) | (0.0623) | (0.0707) |
| Observations | 3,600 | | 3,600 | | 3,624 | | 3,600 | 3,600 | 3,624 |
| Number of subjects | 120 | | 120 | | 120 | | 120 | 120 | 120 |
| Marginal effect of *Degree_s* with: | | | | | | | | | |
| *Symmetry*=0 | | | | | | | 0.0454** | 0.0562*** | 0.118*** |
| | | | | | | | (0.0181) | (0.0197) | (0.0411) |
| *Symmetry*=1 | | | | | | | 0.0830** | -0.0286 | -0.0673 |
| | | | | | | | (0.0412) | (0.0456) | (0.0934) |
| Marginal effect of *Symmetry_s* with: | | | | | | | | | |
| *Degree*=1 | | | | | | | -0.0950 | 0.234*** | 0.463*** |
| | | | | | | | (0.0648) | (0.0722) | (0.147) |
| *Degree*=2 | | | | | | | -0.0575 | 0.149*** | 0.278*** |
| | | | | | | | (0.0367) | (0.0408) | (0.0836) |
| *Degree*=3 | | | | | | | -0.0199 | 0.0642* | 0.0928 |
| | | | | | | | (0.0345) | (0.0378) | (0.0803) |
| *Degree*=4 | | | | | | | 0.0177 | -0.0206 | -0.0925 |
| | | | | | | | (0.0610) | (0.0672) | (0.141) |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

significantly overweighted with respect to predictions, while the signals observed by 4 subjects are significantly underweighted. In the NOINT game, all the signals are underweighted with respect to the theory, which predicts a coefficient of 1 for all signals. Also, in the SUBS game, we observe a large deviation from equilibrium, with all the signals being underweighted, especially those observed by 1 or 2 subjects. This evidence is summarized in our first result.

**Result 1:** *With some noise, in all the three games, subjects respond to the information they receive with qualitative patterns that match the theoretical predictions. However, we observe a systematic underweighting of signals in both NOINT and SUBS (more so for signals observed by few subjects), as well as a systematic overweighting in the COMP game for signals that are not observed by all the subjects.*

To further investigate the systematic deviations observed in the previous analysis, we now examine the potential role of two structural features of the network: the degree of the subject (that is, the number of signals she observes) and the level of symmetry of the network, captured by a dummy that takes value 1 if the network is symmetric (all subjects have the same degree - i.e., empty and circle networks in Table 1) and 0 otherwise. Our aim in focusing on degree and symmetry is to check for behavioral effects in the use of information that might be triggered by how informed an agent is, both in absolute terms - the number of signals an agent observes - and in relative terms - that is, compared to how informed the other players are in the network. It is useful to remind here that the theoretical prediction for this second stage are that how informed an agent is, both in absolute and in relative terms, as well as how symmetric the network is, should not affect his or her use of the available pieces of information.

In the regression, the variable *Degree_s* measures the degree of the subject multiplied by the sum of all the signals she observes. Similarly, the variable *Symmetry_s* is given by the symmetry dummy multiplied by the sum of all the signals observed by the subject. Therefore, the coefficients of these variables measure the effect of the subject's degree and of the symmetry of the network on the sensitivity of actions to information.[14] We also consider the interaction of these two variables, denoted by *DS*, which is constructed as the product of degree, symmetry and the sum of all the signals observed by the subject, and whose role is to disentangle the effect of the degree in symmetric and asymmetric networks.

The third variable that we add to the regression, *Risk_s*, is a dummy that takes value 1 if the subject has invested in the risky asset strictly less than the median investment, and 0 otherwise, multiplied by the sum of all signals observed by the subject (like in the case of the previous variables). This variable allows us to test if risk attitudes play a role in the use of the information. The results are reported in the last three columns of the upper panel of Table 3.

Note that the estimates of the coefficients of variables $S_1$ - $S_4$ qualitatively confirm the evidence from the first regressions. Nevertheless, the estimated coefficients are smaller than the previous ones. This is due to the fact that the other independent variables in the regressions capture part of the reactions to the signals.

[14] We are taking the shortcut here to consider the sum of all signals, not taking into account how "observed" these signals are. Although we know that the latter characteristic of a signal affects the optimal reaction to it, we have chosen to multiply the degree (and the symmetry dummy) by the straight sum of signals, to avoid further enlarging the number of regressor.

Looking at the estimates of the additional variables, we first see that there is no significant effect of risk aversion in any of the three games. This means that the degree of risk aversion of subjects (not taken into account by the theoretical model, implicitely assuming that all subjects are risk neutral) does not affect the way in which agents use their available information on a fixed network.

We then turn to the effect of the degree of a subject and of the symmetry of the network. From the upper panel of Table 3 we see that: 1) the degree of the decision maker positively affects the sensitivity of actions of the observed signals (*Degree_s* is positive and significant in all games); 2) the symmetry of the network positively affects the sensitivity of actions of the observed signals in games NOINT and SUBS (*Symmetry_s* is positive and significant in these two games); 3) The interaction terms *DS* is negative and significant in games NOINT and SUBS, hinting to the fact that the effect of the degree on the use of information dies out when the network is symmetric. The lower panel of Table 3, recording the marginal effects of these variables, provides more information.[15]

Focusing on games NOINT and SUBS, we see that symmetry has a positive effect on less informed subjects only, and no effect on more informed subjects. This means that more informed subjects tend to behave roughly the same in symmetric and asymmetric networks. We also see that the effect of the degree is limited to asymmetric networks, where more information is associated with more intense use of each piece of information. We conclude that the effect of a subject's degree on his/her behavior seems to be triggered by the fact of being less informed than the other subjects in the game. This effect tends to induce less variability in the behavior of less informed subjects in asymmetric networks, compared to what these subjects would do, if similarly informed, in more symmetric networks. Summing up, behavior of more informed agents seems to be rather constant across networks, while less informed agents become more prudent when poorly informed compared to their rivals.

In game COMP, where incentives are totally aligned, there seems to be some positive effect of the degree in all networks, and symmetry seems to play no role in subjects' behaviour. We summarize these findings in the next result.

**Result 2:** *In games NOINT and SUBS, there is a general tendency for the less informed players to react less to signals than more informed ones in asymmetric networks. This effect is driven by little informed agents adopting a more conservative behavior when facing more informed ones than when facing similarly informed subjects, while more informed subjects tend to adopt the same behavior in all networks. When incentives are perfectly aligned as in COMP, more informed agents tend to react more to signals in all networks.*

[15] The marginal effect of *Degree_s* is computed as the sum of the coefficient of *Degree_s* and the coefficient of *DS* multiplied by variable *Symmetry* (i.e., 0 or 1). The marginal effect of *Symmetry_s* is computed as the sum of the coefficient of *Symmetry_s* and the coefficient of *DS* multiplied by variable *Degree* (i.e., 1, 2, 3 or 4).

Thus, our results suggest a behavioral effect of being more informed on the reaction to signals. Subjects react more when they have more information. However, this only operates in relative terms: it is not more information *per se* that triggers stronger reactions to signals, but rather the fact of being more informed than one's rivals in games where incentives are not perfectly aligned.

## 3.2 Information Sharing *via* Network formation

In this subsection we analyze the choice of link formation in the three games. Recall that in the second part of the experiment only one link (either existing or potential) is randomly selected to be modified. We apply the strategy method to the link formation stage, i.e., before playing the game, each player is asked to take three decisions, one for each of the existing or potential links she has. In Table 4, we show the frequency of strategies by the number of optimal decisions, by network, and by game.

Table 4: Frequency of strategies by network, game and number of optimal decisions (relative frequency in parenthesis)

| | | COMP | | | NOINT | | | SUBS | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Empty | Circle | Star | Empty | Circle | Star | Empty | Circle | Star |
| N. of optimal decisions | 0 | 28 | 7 | 19 | 36 | 25 | 6 | 264 | 215 | 198 |
| | | (7.00) | (1.94) | (5.28) | (9.00) | (6.94) | (1.67) | (66.00) | (59.72) | (51.56) |
| | 1 | 61 | 27 | 19 | 40 | 34 | 34 | 35 | 74 | 64 |
| | | (15.25) | (7.50) | (5.28) | (10.00) | (9.44) | (9.44) | (8.75) | (20.56) | (16.67) |
| | 2 | 37 | 42 | 39 | 34 | 34 | 35 | 46 | 55 | 56 |
| | | (9.25) | (11.67) | (10.83) | (8.50) | (9.44) | (9.72) | (11.50) | (15.28) | (14.58) |
| | 3 | 274 | 284 | 283 | 290 | 267 | 285 | 55 | 16 | 66 |
| | | (68.50) | (78.89) | (78.61) | (72.50) | (74.17) | (79.17) | (13.75) | (4.44) | (17.19) |
| Total | | 400 | 360 | 360 | 400 | 360 | 360 | 400 | 360 | 384 |

Note that in COMP and in NOINT the modal strategy is the one with three optimal (link) decisions, with a frequency ranging from 68% in the empty network when game was COMP to 79% in the star network with NOINT. We recall that, in these two games, it is optimal to form each link, and never to sever any. In the SUBS game, the evidence is reverted, and the most common behavior is to never play an optimal action, with a frequency ranging from 51% in the star network to 66% in the empty network. We recall that, in the circle and the empty network, the optimal decisions in this game are always either not to form a new link or to sever an existing one. The results in these two networks suggests that subjects have some preference to be informed per se (i.e. to create links - which provides them, but also others, with extra information, even if these links might be detrimental).

In the star network, optimal decisions in the game SUBS depend on the player's position. While the peripheral players should optimally sever the link with the center and not to form any additional link, the central player should maintain the links with the peripheral players. Hence, in this case we need a more detailed analysis in order to understand where the deviations mainly come from. We do this in Table 5, where we record the type of deviations from the theory that we observe in the star network under SUBS. The left panel reports the strategy of the central player by the number of links to sever (the optimal strategy is not to sever any link). The middle and the right panels report the strategies of the peripheral agents: the middle panel refers to the decision to sever (or not to sever) the unique link they have (the optimal decision is to sever this link), while the right panel refers to the decision to form (or not to form) the missing links (the optimal decisions is not to form any link).

Table 5: Frequency of strategies by position and type of decision in SUBS and star network (optimal strategies in bold)

| Central agent | | | Peripheral agents | | | | | |
|---|---|---|---|---|---|---|---|---|
| # links to sever | Freq. | % | # links to sever | Freq. | % | # links to form | Freq. | % |
| **0** | **63** | **65.63** | 0 | 240 | 83.33 | **0** | **29** | **10.07** |
| 1 | 14 | 14.58 | **1** | **48** | **16.67** | 1 | 44 | 15.28 |
| 2 | 7 | 7.29 | | | | 2 | 215 | 74.65 |
| 3 | 12 | 12.50 | | | | | | |
| Total | 96 | | | 288 | | | 288 | |

Note that the modal strategy of the central agent is consistent with the theoretical prediction of not severing any link (65%). Peripheral agents show instead consistent deviations from the theoretical prediction, as they decide to maintain the link that should be severed (83%), and to form new links when they should not (in 90% of the cases they form one or two new links), in line with the results observed for the circle and the empty network. This evidence is summarized in our third result.

**Result 3:** *In COMP and NOINT the modal strategy is to form all missing links and not to sever any of the existing ones, in line with the theoretical prediction. In SUBS the modal strategy is to form all the missing links and not to sever the existing ones, even for players whose optimal decision is to sever or abstain from forming a link according to the theoretical prediction.*

Let us then focus on the game SUBS where, as we have seen, there is a tendency to overshare information. This can be interpreted as a general preference to be informed or, equivalently, as an aversion to be uninformed - a behavioral departure from optimality. We will now discuss potential sources of such seemingly behavioral effects. A natural candidate is certainly the degree of subjects' risk aversion. We first note that the incentive to form a link theoretically depends on the difference in the variance of the equilibrium strategy of the decision maker, with and without that link: if forming a link causes a smaller equilibrium variance, then the link is (theoretically) formed. It can be therefore conjectured that higher degrees of risk aversion would strengthen the incentives to acquire information. Determining the exact form in which this happens would require an extension of the theoretical model where an additional layer of risk aversion in on top of the built in concavity of the employed linear quadratic payoff function, making the computation of equilibria rather cumbersome. It seems rather compelling, however, to support the hypothesis that some degree of risk aversion on the part of participants would (optimally) strengthen the incentives to form links, consistently with the general oversharing attitude observed in SUBS.

To assess the role of risk aversion in the link formation stage, we estimate the probability to take an optimal decision regarding a link (existing or potential), using a logit specification where the dependent variable equals 1 if the decision over that link is (theoretically) optimal. We also control for the degree of the decision maker, for the symmetry of the network, and for learning effects. Thus, the regressors are:

1. *Period*: the period in which the decision is taken;
2. *Type of decision*: a dummy that takes value 1 if the optimal decision is either to sever an existing link or not to form a new one, and 0 otherwise;
3. *Risk*: a dummy that takes value 1 for those subjects that invested in the risky asset less than the median investment, and 0 otherwise;
4. *Degree*: the number of signals that a subject observes;
5. *Asymmetric network*: a dummy that takes value 1 if the network is the star, and 0 otherwise;
6. *DR*: the interaction term between Type of decision and Risk.

We estimate this model separately for each game. The results are reported in Table 6 (marginal effects) and in Table 7 in the Appendix (full estimations).

In NOINT, none of the independent variables has a significant effect on the probability to take an optimal link decision; in COMP we observe a significant effect of the degree, suggesting that more informed subjects make optimal link decisions more frequently than less informed ones. Let us then turn to the game SUBS, where most departures from equilibrium predictions are observed. Firstly, we find a negative and significant marginal effect of the type of decision. This means that it is less likely to observe an optimal link decision if this implies either to delete an existing link or not to form a potential one. This effect is quite substantial, as the decrease in the probability to play equilibrium (when moving from one type of decision to the other) is around 65%. All this is consistent with Result 3 above and with the observation that

Table 6: Determinants of network formation: marginal effects

| | (1)<br>COMP | (2)<br>NOINT | (3)<br>SUBS |
|---|---|---|---|
| $Type\,of\,decision$ | | | -0.648*** |
| | | | (0.049) |
| $Risk\,(Type\,of\,decision = 0)$ | -0.0285 | 0.0269 | 0.0639 |
| | (0.0340) | (0.0426) | (0.1219) |
| $Risk\,(Type\,of\,decision = 1)$ | | | -0.0765*** |
| | | | (0.0294) |
| $Degree$ | 0.0578*** | 0.0385 | -0.0438** |
| | (0.0175) | (0.0251) | (0.0198) |
| $Asymmetric\,network$ | 0.0113 | 0.0442 | -0.0503 |
| | (0.0333) | (0.0448) | (0.0329) |
| $Period$ | 0.00561** | 0.00111 | -0.0035 |
| | (0.00228) | (0.00194) | (0.0038) |
| Observations | 3,360 | 3,360 | 3,432 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

subjects may have an intrinsic incentive to be informed, far above what rationality would imply.

Let us then turn to the effect of risk aversion. Table 6 tells us that risk attitudes do not significantly affect the optimality of behavior when the best response requires either to form a missing link or to maintain an existing one (Type of decision=0); however, the marginal effect of risk aversion on the probability to play according to equilibrium is negative and significant *when the best response requires either the deletion of an existing link or not forming a new one* (Type of decision=1). In other words, more risk-averse subjects are less likely to make link-formation choices that are consistent with the theoretical prediction when this prescribes to sever or not to form a link. Again, whether this comes from a purely rational reaction to one's own (unobserved) risk aversion, or from a behavioral prudence triggered by risk aversion, is difficult to assess. Looking at the magnitude of the marginal effect of risk aversion, however, we note that the latter accounts for roughly 7% of the over-linking behavior, to be compared with the out-of-equilibrium behavior in SUBS by peripheral agents, who play according to equilibrium only 10% of the time when it comes to sever links, and 16% of the time when it comes not to form a link. We must therefore conclude that although risk aversion plays a role in the over-linking observed behavior, it does not account for the full magnitude of the phenomenon.

A potential source of deviations from the theoretical predictions at the link formation stage is the observed quantitative bias in the use of information at the second stage of the game. More precisely, optimality in the link formation stage in tables

5 and 6 is defined with respect to the (theoretically) optimal behavior in the second stage, where agents use the acquired information to play the SUBS game. As we have seen in the previous section, in SUBS the use of information in the second stage only qualitatively follows the theoretical prediction (there is a general tendency to underuse information, i.e., the estimated coefficients are below the equilibrium ones - cf. Result 1) and displays behavioral effects that relate to the degree of the decision maker and the symmetry of the network. Rationality in the link-formation stage could therefore still be partly restored if we assumed that subjects anticipate the observed behavior in the second stage rather than the theoretical one. It turns out that this is indeed the case: by straight computations (see Table 8 in Appendix 5.2) we find that, given the estimated coefficients in the second stage of the SUBS game, the observed link formation behavior is optimal in almost all network positions.[16] It must be stressed, however, that in order to support this interpretation of the observed behavior at the link formation stage, one should assume that subjects not only anticipate their own "non-rational" behavior in the second stage, but also the "non-rational" behavior of their opponents. This seems a more stringent requirement than the anticipation of rational behavior of others that is implicit in the notion of sequential equilibrium. As we show in Table 9 (in Appendix 5.2), however, risk attitudes still play a role for the incentives to form links, even if actual behavior at the second stage was anticipated by subjects. In fact, the coefficient for risk aversion is still significant, and still supports the hypothesis that more risk averse subjects (and, in this specifica case, periphery subjects in the star network) are prone to form links (or not sever links) even when this is not optimal given the expected behavior in the second stage.

**Result 4:** *There is a general tendency to share information beyond what is implied by theoretical predictions. Part, but not all, of the over-sharing behavior can be explained by subjects risk aversion. Most of the over-sharing behavior disappears if one assumes that subjects anticipate the behavioral biases in the use of information at the second stage. The residual over-sharing can be explained by risk aversion. Other behavioral effects persist, as sharing behavior also depends on how informed an agent is.*

# 4 Conclusion

We study how people make use of available information in the laboratory, depending on who observed which piece of information (the information sharing network) and on the strategic nature of interaction (strategic complements, substitutes, and orthogonal strategies). We then investigate the information sharing network originates through

[16]In particular, this is true with the sole exception of agents with degree 2 which slightly benefit from severing a link with agents with degree 4. Specifically, in a star network the peripheral player has a small incentive to sever the link with the central player.

the subjects' decisions to establish information sharing agreements (links) prior to interaction in these contexts.

We find that the use of information in the laboratory qualitatively follows the theoretical predictions in each case; however, we also observe quantitative deviations from equilibrium. We associate these deviations to behavioral effects related to network characteristics, which are in line with previous findings in the literature of management suggesting that more informed agents become overconfident (see, e.g., Zacharakis and Shepherd, 2001). For instance, we find a general tendency of more informed (i.e., higher degree) agents to weight their information more. Also, high degree subjects make use of information more intensively in asymmetric networks, in which their amount of available information is above others'.

Regarding the decision to share information, we observe that people's behavior is consistent with the theoretical predictions in the games of strategic complements and when strategies are orthogonal - cases where the incentives to create/maintain links are aligned across agents. In contrast, deviations are observed in the case of strategic substitutes, where subjects tend to create/maintain links, even when this goes against rationality and theoretical predictions. We trace part of this over-sharing behavior to the degree of risk aversion of subjects. We also find that most of the over-sharing behavior can be accounted for if players react, at the link formation stage, to the suboptimal use of information in the second stage of the game. Even after controlling for this possibility, risk aversion play a role.

The effect of risk aversion on the incentive to share information may reflect a behavioral bias, an aversion towards remaining (relatively more) uninformed (than others) - or a behavioral preference for being informed, in line with findings of previous studies (see, e.g., van Dijk and Zeelenberg 2007, Kruger and Evans, 2009, Eliaz and Schotter, 2010, Sharot and Sunstein,2020, and Golman et al., 2020). However, its relation to risk aversion cannot be properly assessed lacking analytical results on the effects of subjects' risk aversion on equilibrium choices. This suggests that more theoretical developments are needed in order to gain a better understanding of this interesting phenomenon.

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# 5 Appendix

## 5.1 Theoretical model and predictions

### Use of information

We derive the Bayesian Nash Equilibrium of the game for a given four nodes network $g$ and for the generic payoff function (1) The vector of signals observed by $i$ in network $g$ is denoted by $\mathbf{m_i^g} = \{m_j : j \in N_i^g\}$. We denote by $a_i(\mathbf{m}_i^g)$ the equilibrium strategy of player $i \in N$ in network $g$.

Each agent $i$ maximizes her expected payoff given the equilibrium strategies of the opponents. The expected payoff is:

$$E\left[u_i(a_i, A_i, \theta)|\mathbf{m}_i^g\right] =$$

$$100 - w\left(a_i^2 + E(\theta^2|\mathbf{m}_i^g) - 2a_i E(\theta^2|\mathbf{m}_i^g)\right) - r\left(a_i^2 + \frac{E(A_i^2|\mathbf{m}_i^g)}{9} - 2a_i\frac{E(A_i|\mathbf{m}_i^g)}{3}\right) \quad (3)$$

Taking the first order derivative w.r.t. $a_i$ we get:

$$a_i(\mathbf{m}_i^g) = \frac{wE(\theta|\mathbf{m}_i^g)}{r+w} + \frac{rE(A_i|\mathbf{m}_i^g)}{3(r+w)} \quad (4)$$

yielding:

$$a_i(\mathbf{m}_i^g) = \frac{w}{r+w}(5 + \sum_{k\in N_i^g} m_k) + \frac{r}{3(r+w)}\sum_{j\neq i} E(a_j(\mathbf{m}_j^g)|\mathbf{m}_i^g)$$

Standard results (see Radner,1962, Angeletos and Pavan, 2007, Currarini and Feri 2015) can be used to establish the existence of a unique Bayesian Nash Equilibrium for networks $g$, with the equilibrium strategies affine in the observed signals, i.e.:

$$a_j(\mathbf{m}_j^g) = \alpha_j^g + \sum_{k\in N_j^g} \beta_{jk}^g m_k. \quad (5)$$

Replacing this functional form in the FOC for player $i$ , using the fact that signals have zero mean and are i.i.d., we obtain:

$$a_i(\mathbf{m}_i^g) = \frac{w}{r+w}(5 + \sum_{k\in N_i^g} m_k) + \frac{r}{3(r+w)}\sum_{j\neq i}(\alpha_j^g + \sum_{k\in N_j^g\cap N_i^g} \beta_{jk}^g m_k)$$

which can be rewritten as:

$$a_i(\mathbf{m}_i^g) = \frac{5w}{(w+r)} + \frac{r}{3(w+r)}\sum_{j\neq i}\alpha_j^g + \frac{w}{(w+r)}\sum_{k\in N_i^g} m_k + \frac{r}{3(w+r)}\sum_{k\in N_i^g}\sum_{j\in N_k^g\setminus i}\beta_{jk}^g m_k$$

It follows that

$$\alpha_i^g = \frac{5w}{(w+r)} + \frac{r}{3(w+r)} \sum_{j \neq i} \alpha_j^g$$

$$\beta_{ik}^g = \frac{w}{(w+r)} + \frac{r}{3(w+r)} \sum_{j \in N_k^g \setminus i} \beta_{jk}^g \ \forall k \in N_i^g$$

From the above expressions (that apply to all $i$) it directly follows that: 1) $\alpha_i^g = \alpha_j^g$ $\forall i, j$ ; 2) $\beta_{ik}^g = \beta_{jk}^g$ $\forall i, j$ and $k \in N_j^g \cap N_i^g$ (any common neighbour $k$). Then we can write $\alpha^g = \alpha_i^g$ $\forall i$ and $\beta_k^g = \beta_{ik}^g$ ∀i. We obtain:

$$\alpha^g = \frac{5w}{(w+r)} + \frac{r}{(w+r)} \alpha^g \beta_k^g = \frac{w}{(w+r)} + \frac{r(n_k^g - 1)}{3(w+r)} \beta_k^g$$

from which we obtain

$$\alpha^g = 5 \qquad \beta_k^g = \frac{3w}{3(w+r) - r(n_k^g - 1)} \tag{6}$$

It can be checked that in our game of complements (COMP), where $w = r = \frac{1}{2}$, this yields the equilibrium strategy:

$$a_i(\mathbf{m}_i^g) = 5 + \sum_{j \in N_i^g} \frac{3}{7 + n_j^g} m_j$$

In our game of substitutes (SUBS), where $w = \frac{1}{2}$ and $r = -\frac{1}{3}$, this yields:

$$a_i(\mathbf{m}_i^g) = 5 + \sum_{j \in N_i^g} \frac{9}{1 + 2n_j^g} m_j.$$

When there is no interaction (NOINT), so that $r = 0$ (and letting $w = \frac{1}{2}$) we obtain:

$$a_i(\mathbf{m}_i^g) = 5 + \sum_{j \in N_i^g} m_j \tag{7}$$

**Network formation**

We study the incentives to share information at the ex-ante stage. For each network $g$, we denote by $u_i^e(g)$ the ex-ante expected payoff for agent $i$, assuming all agents playing the Bayesian Nash Equilibrium strategy (note that $g$ describes the information structure of the Bayesian game played at the interim stage). The payoff $u_i^e(g)$ is obtained by taking the expectation of interim payoff (3) over all possible realisations of $\mathbf{m}_i^g$ and assuming $a_i(\mathbf{m}_i^g)$ $\forall i$. With abuse of notation we denote $a_i(\mathbf{m}_i^g)$

by $a_i^g$ and $A_i^g = \sum_{j \neq i} a_j^g$. Factorizing the righ hand side and using (4), the agent i's interim expected payoff (3) can be written as:

$$E\left[u_i(a_i^g, A_i^g, \theta)|\mathbf{m}_i^g\right] = 100 + (w+r)(a_i^g)^2 - wE[\theta^2|\mathbf{m}_i^g] - \frac{rE[(A_i^g)^2|\mathbf{m}_i^g]}{9} \quad (8)$$

Using the expression (5) we can write:

$A_i^g = \sum_{j \neq i}\left(5 + \sum\limits_{k \in N_j^g} \beta_k^g m_k\right) = 15 + \sum\limits_{k \in N_i^g} (n_k^g - 1)\beta_k^g m_k + \sum\limits_{k \notin N_i^g} n_k^g \beta_k^g m_k$

Replacing it in (8) and taking the expectation over all possible realisations of $\mathbf{m}_i^g$, we get the ex-ante expected payoff in network $g$:

$$u_i^e(g) = 100 + (w+r)E\left[\left(5 + \sum_{k \in N_i^g} \beta_k^g m_k\right)^2\right] - wE\left[\left(5 + \sum_{k \in N} m_k\right)^2\right] - \frac{r}{9}E\left[\left(15 + \sum_{k \in N_i^g} (n_k^g - 1)\beta_k^g m_k + \sum_{k \notin N_i^g} n_k^g \beta_k^g m_k\right)^2\right]$$

Using the fact that signals $m_i$ have zero mean and are i.i.d we write the ex-ante payoff as follows:

$$u_i^e(g) = 100 + (w+r)\left(25 + \sum_{k \in N_i^g} (\beta_k^g)^2\right) - 29w - \frac{r}{9}\left(225 + \sum_{k \in N_i^g} (n_k^g - 1)^2(\beta_k^g)^2 + \sum_{k \notin N_i^g} (n_k^g)^2(\beta_k^g)^2\right)$$

Now we can compute the agent i's incentive to sever the link $ij$ as the difference in the ex-ante expected payoffs of networks $g$ and $g' = g - ij$:

$$u_i^e(g) - u_i^e(g') = (w+r)\left[(\beta_i^g)^2 + (\beta_j^g)^2 - (\beta_i^{g'})^2\right] - \frac{r}{9}\left[(n_i^g - 1)^2(\beta_i^g)^2 + (n_j^g - 1)^2(\beta_j^g)^2 - (n_i^g - 2)^2(\beta_i^{g'})^2 - (n_j^g - 1)^2(\beta_j^{g'})^2\right] \quad (9)$$

Replacing the expression of $\beta$ given in (6) we get:

$$
\begin{aligned}
&u_i^e(g) - u_i^e(g') = \\
&(w{+}r)\left[\left(\frac{3w}{3(w+r)-r(n_i^g-1)}\right)^2 + \left(\frac{3w}{3(w+r)-r(n_j^g-1)}\right)^2 - \left(\frac{3w}{3(w+r)-r(n_i^g-2)}\right)^2\right] \\
&\qquad - \frac{r}{9}\left[\left(\frac{3w(n_i^g-1)}{3(w+r)-r(n_i^g-1)}\right)^2 + \left(\frac{3w(n_j^g-1)}{3(w+r)-r(n_j^g-1)}\right)^2\right] \\
&\qquad\qquad + \frac{r}{9}\left[\left(\frac{3w(n_i^g-2)}{3(w+r)-r(n_i^g-2)}\right)^2 + \left(\frac{3w(n_j^g-1)}{3(w+r)-r(n_j^g-2)}\right)^2\right] \quad (10)
\end{aligned}
$$

In the game of complements (COMP), $w = r = \frac{1}{2}$ expression (9) becomes:

$$
\begin{aligned}
u_i^e(g) - u_i^e(g') = &\left(\frac{3}{7-n_i^g}\right)^2 + \left(\frac{3}{7-n_j^g}\right)^2 - \left(\frac{3}{8-n_i^g}\right)^2 \\
&- \frac{1}{2}\left[\left(\frac{n_i^g-1}{7-n_i^g}\right)^2 + \left(\frac{n_j^g-1}{7-n_j^g}\right)^2 - \left(\frac{n_i^g-2}{8-n_i^g}\right)^2 - \left(\frac{n_j^g-1}{8-n_j^g}\right)^2\right]
\end{aligned}
$$

which is strictly positive for all $n_i^g$ and $n_j^g$. This implies that each existing link is not severed and any missing link is formed.

In the game of no interaction (NOINT), $w = \frac{1}{2}$ and $r = 0$ expression (9) becomes:

$$
u_i^e(g) - u_i^e(g') = \frac{1}{2}
$$

This implies that each existing link is not severed and any missing link is formed.

In the game of strategic substitutes (SUBS), $w = \frac{1}{2}$ and $r = -\frac{1}{3}$ expression (9) becomes:

$$
\begin{aligned}
u_i^e(g) - u_i^e(g') = &\frac{1}{6}\left[\left(\frac{9}{2n_i^g+1}\right)^2 + \left(\frac{9}{2n_j^g+1}\right)^2 - \left(\frac{9}{2n_i^g-1}\right)^2\right] \\
&+ 3\left[\left(\frac{n_i^g-1}{2n_i^g+1}\right)^2 + \left(\frac{n_j^g-1}{2n_j^g+1}\right)^2 - \left(\frac{n_i^g-2}{2n_i^g-1}\right)^2 - \left(\frac{n_j^g-1}{2n_j^g-1)}\right)^2\right]
\end{aligned}
$$

This is positive only in the following cases: a) $n_i^g = 3$ and $n_j^g = 2$, b) $n_i^g = 4$ and $n_j^g = 2$, c) $n_i^g = 4$ and $n_j^g = 3$ This implies that there is an incentive to form/not to delete links only with agents with strictly lower degree.

## 5.2 Statistics and econometrics

In Table 7 we report the (full) estimations of the probability to take an optimal decision regarding a link (existing or potential), from which the marginal effects in 6 are computed.

Table 7: Determinants of network formation: estimates

| | (1) COMP | (2) NOINT | (3) SUBS |
|---|---|---|---|
| $Type\,of\,decision\,=\,0$, $Risk\,=\,1$ | -0.230 | 0.211 | 0.531 |
| | (0.267) | (0.329) | (0.962) |
| $Type\,of\,decision\,=\,1$, $Risk\,=\,0$ | | | -2.726*** |
| | | | (0.726) |
| $Type\,of\,decision\,=\,1$, $Risk\,=\,1$ | | | -3.205*** |
| | | | (0.736) |
| $Degree$ | 0.475*** | 0.299 | -0.265** |
| | (0.144) | (0.214) | (0.122) |
| $Asymmetric\,network$ | 0.0932 | 0.344 | -0.304 |
| | (0.273) | (0.312) | (0.196) |
| $Period$ | 0.0461** | 0.00862 | -0.0213 |
| | (0.0213) | (0.0148) | (0.0231) |
| $Constant$ | -0.355 | 0.637 | 2.806*** |
| | (0.492) | (0.467) | (1.013) |
| Observations | 3,360 | 3,360 | 3,432 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 8, for SUBS, we report on the incentives to create/form or sever/not form links, given the observed behavior in the second stage of the game. To this aim, we compute the incentives of player $i$, with degree $n_i$, to create a new link with player $j$, with degree $n_j$. In each row, the left part corresponds to network $g'$, in which $i$ and $j$ are not linked. The middle part corresponds to network $g'$ in which a link between $i$ and $j$ is added to network $g$ (hence the degree of both $i$ and $j$ increases by 1). In the right part we compute the payoff increase for player $i$ from moving from $g'$ to $g$, using equation (9), in which as $\beta_i$ and $\beta_j$ we use the corresponding coefficients estimated in model (3) of Table 3. If such a difference is positive (negative), player $i$ has an incentive to create (not create) the link to $j$. Note that we can also use Table 8 to analyze the incentives to remove a link, by moving from network $g$ to $g'$. In this case, the last column represents a payoff decrease for player $i$ from removing the link.

Table 8: Empirical network formation in substitute

| g' | | g | | |
|---|---|---|---|---|
| $n_i$ | $n_j$ | $n_i$ | $n_j$ | $U_i(g) - U_i(g')$ |
| 1 | 1 | 2 | 2 | 0.10 |
| 1 | 2 | 2 | 3 | 0.11 |
| 1 | 3 | 2 | 4 | -0.01 |
| 2 | 1 | 3 | 2 | 0.24 |
| 2 | 2 | 3 | 3 | 0.26 |
| 2 | 3 | 3 | 4 | 0.13 |
| 3 | 1 | 4 | 2 | 0.18 |
| 3 | 2 | 4 | 3 | 0.20 |
| 3 | 3 | 4 | 4 | 0.07 |

In Table 9 we report an additional regression for SUBS. The dependent variable equals 1 if the decision is optimal given the observed behavior in stage 2 (use of information, see Table 8). In the last row of the table, we report the marginal effect of risk aversion.

Table 9: Determinants of network formation: robustness SUBS

| | |
|---|---|
| *Period* | 0.007 |
| | (0.019) |
| *Risk* | 0.472*** |
| | (0.144) |
| *Degree* | 0.337*** |
| | (0.096) |
| *Asymmetric network* | -0.784*** |
| | (0.158) |
| *Constant* | 0.144 |
| | (0.577) |
| Marginal effects | |
| *Risk* | 0.089*** |
| | (0.027) |
| Observations | 3,432 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## 5.3 Experimental instructions

We only provide the instructions for the COMP game and network set 1. The remaining cases only differ in the payoff function and in the set of networks, and are available from the authors upon request.

**INSTRUCTIONS**

The aim of this experiment is to study how individuals make decisions in certain contexts. The instructions are simple. You first receive the instructions for Part 1 of the experiment, after which you will receive instructions for a second part that is independent of Part 1. If you follow the instructions carefully you will earn a non-negligible amount of money in cash (£) at the end of the experiment. During the experiment, your earnings will be accounted in ECU (Experimental Currency Units). Individual payments will remain private, as nobody will know the other participants' payments. Any communication among you is strictly forbidden and will result in an immediate exclusion from the experiment.

**1.-** Part 1 of the experiment consists of 20 periods. In each period you will be randomly assigned to a group of 4 participants. In this room, there are 8 participants (including yourself) that are potential members of your group. At the beginning of each period your group of 4 participants is selected at random among these 8 participants, each of them being equally likely to be in your group. You will not know the identities of any of these participants and they will not know yours.

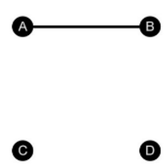
**2.-** At each period, the computer selects a **network for your group**. The network is **selected from the two networks depicted in the additional sheet** provided to you, entitled NETWORKS. Note that, in this sheet, each network is identified by a number, 1 and 2. Each of the two networks will be selected ten times (that is, in ten periods) during Part 1 of the experiment, and the order at which the networks are selected is randomly determined at the beginning of the experiment.

Once the network is selected, you (and the other members of your group) are randomly assigned to a **player position**: **A**, **B**, **C** or **D**, all of them being equally likely. At each period, you will be informed of the selected network (from 1 to 3) and of your player position (you will be player A, B, C or D).

In a network, a link is represented by a line (connection) between two players.

For example, consider **network 2** (depicted in the right)

- **Player A** has one link: he/she is linked to **player B** (but not linked to **players C** and **D**).
- **Player B** has one link: he/she is linked to **player A** (but not linked to **players C** and **D**).
- **Player C** has no links.
- **Player D** has no links.

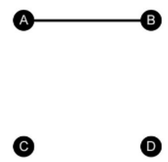



**3.-** At each period, **the computer randomly selects a signal for each of the four players (A, B, C and D)**. The signal of a player can be **either +1 or –1**, and each of these two possibilities (+1 and –1) is equally likely (that is, each player gets the signal +1 with a probability of 50% and gets the signal –1 with a probability of 50%). The computer selects the signal of each player separately, and independently, meaning that the signals that you and the other players of your group receive are unrelated.

At each period, each player will be informed of his/her own assigned signal for the period, and also of the signals assigned to those players to whom he/she is linked in the network:

If, for example, **network 2** (depicted in the right) is selected in a period, then:

- **Player A** will observe his/her signal and the signals of player B.
- **Player B** will observe his/her signal and the signals of player A.
- **Player C** will observe only his/her signal.
- **Player D** will observe only his/her signal.




**4**.- As explained in the next points, your earnings in a period will depend on the realized value of "**the state of the world**" (a number ***X***). The state of the world *X* is obtained by adding 5 to the sum of the signals of all players.

Therefore, **the state of the world *X* can take the following values**:

- ***X* = 1**, when all the four signals are –1 (*X* = – 4 + 5),
- ***X* = 3**, when three signals are –1 and one signal is +1 (*X* = – 2 + 5),
- ***X* = 5,** when two signals are –1 and two signals are +1 (*X* = 0 + 5),
- ***X* = 7,** when one signal is –1 and three signals are +1 (*X* = 2 + 5) and
- ***X* = 9,** when all the four signals are +1 (*X* = 4 + 5).

How accurately a player is informed about *X* depends on the network (that is, on how many signals he/she observes).

**For example, consider again network 2** and suppose that player A is informed of the fact that his/her signal is –1 and that the signals of player B is +1. In such a case, what player A knows about *X* is that it can be either 3 or 5 or 7 (depending on whether the sum of the signals of players C and D is –2, 0 or +2) respectively with probability 0.25, 0.5 and 0.25.

**5**.- At each round, being informed of the selected network, your player position, your signal and the signals of the players to whom you are linked in the network, you will be asked **to choose a number between 0.00 and 10.00 (with two decimal positions)**.

**Your earnings of the round** will depend on your decision, on the sum of the decisions of the other three players of your group, and on the state of the world *X*, as follows:

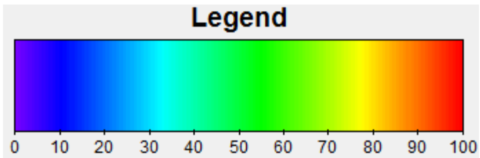
$$100 - \frac{1}{2}(Your\ decision - X)^2 - \frac{1}{2}\left(Your\ decision - \frac{Sum\ of\ the\ others'decisions}{3}\right)^2$$

Given this expression, your earnings result from subtracting *a loss* from 100 ECU. *This loss* is the average of the squared difference between your decision and *X* and the squared difference between your decision and the average of the other three players' decisions. This means that your earnings are higher the closer your decision is to *X* and to the average of the other three players' decisions. We recommend that you take some time to become familiar with the way in which your earnings depend on the various elements of the above expression.

**6**.- In order to allow you to precisely calculate the earnings that your choices can provide you, at each period, you will be provided with a **payoff calculator** in your screen. To use the payoff calculator, you first need to select a state of the world, by clicking in one of the buttons of the upper part of the screen: I (*X*=1), II (*X*=3), III (*X*=5), IV (*X*=7) or V (*X*=9). Immediately, a "**color map**" appears where different colors correspond to different earnings, computed for the chosen value of the state of the world in the expression shown at point 5. You can select coordinates by clicking inside this map. The selected horizontal coordinate represents a value for the sum of the other three players' decision (from 0 to 30) and the selected vertical coordinate represents the value for your decision that you are exploring (from 0 to 10).

Once you click inside the map, in the lower part of the screen you can see the **earnings (resulting payoff)** that you *would* obtain for:
- The selected state of the world (*X*)
- The selected value for sum of the other three players' decision (horizontal coordinate)
- The selected value for your decision (vertical coordinate)

You can explore as many possibilities as you wish in order to familiarize with the payoff scheme, just by clicking in different points of the map (note that you can *fine tune* the selected points by clicking on the appropriate buttons below the map). The colors in the map provide the direction in which earnings vary. The legend below the map provides an approximate idea of the earnings that corresponds to each point in the color map.




At any moment, you can change the state of the world that you want to explore in the payoff calculator by clicking on a new button of the upper part of the screen: I (*X*=1), II (*X*=3), III (*X*=5), IV (*X*=7) or V (*X*=9). When you select another button, a new "color map" appears (the one corresponding to the selected value of *X*). Then you can learn the earnings that correspond to different coordinates (combinations of your choice and the sum of other choices) under such a state of the world.

While you are using the payoff calculator, you will see the signals that you were informed of in the upper-right part of the screen. At any moment, you can also recall the selected network of the period by clicking on the button "Show Network Info" in the lower-right part of the screen.

**7.-** Once you are ready to take **your decision for the period**, you can introduce it using the scroll bar in your screen (note that you can *fine tune* by clicking on the appropriate buttons below the scroll bar). Then, click on "Confirm decision".

**8.-** When all players have taken their decision, you will get information about the current period. The information consists of:
- The selected network
- Your player position in the network,
- The sum of the other players' decisions,
- The signals of all the players,
- The state of the world (*X*) and
- Your (period) earnings.

**9.-** Payoffs. At the end of the experiment, you will be paid the earnings that you achieved in 4 periods, that will be randomly selected across the 20 periods of play (all periods selected will have the same probability). These earnings are transformed to cash at the exchange rate of **40ECU = 1£**. In addition, just by showing up, you will also be paid a fee of **4£**.

## PART 2 OF THE EXPERIMENT

**1.-** Part 2 of the experiment consists of 10 periods. In each period you will be randomly assigned to a group of 4 participants. This group is determined randomly at the beginning of the period (among the same 8 participants than in part 1).

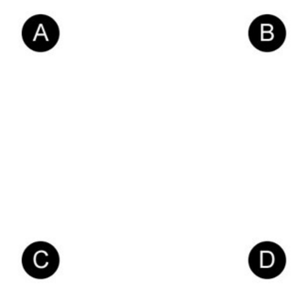
**2.-** At each period, **network 1** (depicted in the sheet provided to you in part 1 of the experiment, entitled NETWORKS) assumes the role of **original network** of the period, which may be modified by you and the other members of your group as explained below.

You (and the other members of your group) are randomly assigned to a **player position**: **A**, **B**, **C** or **D**, all of them being equally likely. At each period, you will be informed of your player position (you will be player A, B, C or D).

**3.-** Network modification (I). The novelty of part 2 of the experiment is that, prior to being informed of the signals, you and the other players of your group have **the possibility to modify the original network**. Only one link of the network can be added. The link that can be added (AB, AC, AD, BC, BD or CD) will be randomly selected by the computer.

The process is as follows. Knowing the original network and their positions, but before knowing which link can be added, all the four players simultaneously decide whether they consent to added each one of their links (in case it is the link selected by the computer).

- **Player A** will have to answer YES or NO to the following questions:
  (i) *Do you want the link AB to be added to the network?*
  (ii) *Do you want the link AC to be added to the network?*
  (iii) *Do you want the link AD to be added to the network?*
- **Player B** will have to answer YES or NO to the following questions:
  (i) *Do you want the link AB to be added to the network?*
  (ii) *Do you want the link BC to be added to the network?*
  (iii) *Do you want the link BD to be added to the network?*
- **Player C** will have to answer YES or NO to the following questions:
  (i) *Do you want the link AC to be added to the network?*
  (ii) *Do you want the link BC to be added to the network?*
  (iii) *Do you want the link CD to be added to the network?*
- **Player D** will have to answer YES or NO to the following questions:
  (i) *Do you want the link AD to be added to the network?*
  (ii) *Do you want the link BD to be added to the network?*
  (iii) *Do you want the link CD to be added to the network?*




**4.-** Network modification (II). Once all these decisions are made, **the computer randomly selects one link (AB, AC, AD, BC, BD or CD)**, all of them being equally likely**.** The selected link is the only link from the original network that can be added**.** Whether the link is added or not depends on the decisions formerly taken by the two players involved. For example, if the selected link is BD, the decisions taken by players B and D determine whether the link is added or not.

The rules for the network modification are the following: The creation of a new link requires the consent of both players involved. This means that the **current network** (resulting from the network modification stage) is determined as follows:

- The link is created if both players involved answered YES to the question of *whether they want this particular link to be added to the network*. In such a case, the current network is the original one plus the selected link.
- If at least one of the players involved answered NO, then the link is not created. In such a case, the current network is equal to the original one.

The current network will be one of the 7 networks depicted in the new sheet entitled NETWORKS (PART 2) that we have provided to you. These are the initial 2 networks (that are the first 2 networks of this sheet) plus all the possible networks that arise by creating one link from **network 1** (the **original network** of the period).

**5.-** Then, all the four players are informed of:
- The original network.
- The link randomly selected by the computer to be potentially added.
- Whether there was or was not consent (by the players involved) to add the selected link.
- The current network.

**6.-** From that point on, **the current network is the relevant one for the period**. Then, as in part 1 of the experiment, the computer randomly selects a signal (+1 or –1) for each of the four players (A, B, C and D), and the current network determines which signals each player observes. Then, the game proceeds exactly as in part 1 of the experiment.

**7.-** Payoffs from this part. At the end of the experiment, you will be paid the earnings that you achieved in 2 periods, that will be randomly selected across the 10 periods of play of part 2 (all periods selected will have the same probability). As in Part 1 the exchange rate is: **40 ECU = 1£**.