Transmission and use of information in network games*

Sergio Currarini
University of Leicester
and Università Ca' Foscari

Francesco Feri
Royal Holloway, University of London

Bjoern Hartig
Royal Holloway, University of London

Miguel A. Meléndez-Jiménez†
Universidad de Málaga

February 24, 2023

Abstract

We design an experiment to study how agents share and make use of information in networks. Agents receive payoff-relevant signals automatically shared with neighbours. 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 behavioural 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, behavioural biases

*We thank two anonymous referees and seminar participants the University of Exeter, the University of East Anglia, Universidad de Valencia, and the IV BiNoMa workshop on economics of networks in Belfast for helpful comments. Funding from BA/Leverhulme Small Research Grants (ref. SG142951), from Ministerio de Ciencia e Innovación, Spain (ref. RTI2018-097620-B-I00 and PID2021-127736NB-I00) and from the Regional Government of Andalusia-FEDER (ref. UMA18-FEDERJA-243 and P18-FR-3840) is gratefully acknowledged. The usual disclaimer applies.

†Currarini, sc526@leicester.ac.uk. Feri, Francesco.Feri@rhul.ac.uk. Hartig, Bjoern.Hartig@rhul.ac.uk. Meléndez-Jiménez, melendez@uma.es.

1 Introduction

Information sharing is ubiquitous 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, on Facebook people may use notification services to coordinate with their friends on some leisure activity (a gig, a bar, a cinema) and may, at the same time, read about their friends' feedback to learn which of the available options is the best. Similarly, people may discuss relevant issues with their friends and form an opinion based on the acquired information, with the twofold motive of forming the "correct" opinion and of conforming with the opinion that their friends form.

Other situations may display anti-coordination motives (representing, for instance, congestion effects). Alpinists may consult Facebook 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. Similarly, on LinkedIn people share information about job opportunities and may face a trade-off between acquiring more information from others and disclosing their own information (because of the increased competition this induces for the vacancies they get to know about).

Finally, 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 or connecting with people working in different sectors on LinkedIn).

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 (2020). In the present paper we report results from a controlled laboratory experiment, where subjects use private information in interactive decision making problems and decide with whom to share their private information (i.e., form links) before taking payoff relevant actions. In particular, we implement three treatments that 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).

The key theoretical prediction is that the use of (each piece of) information in equilibrium depends on how many agents observe it: In the COMP case, the more agents observe a particular information, the more intensely it is used, whereas the opposite occurs in the SUBS case. In the NOINT case, all the information is used equally. Regarding the incentives to share information prior to its use, equilibrium would predict that in treatments COMP and NOINT each agent shares information with all other agents (i.e., she forms/maintains each possible link), whereas in treatment SUBS each agent shares information (forms/maintains a link) only with agents that are less connected (i.e., have a lower degree).

Our goal in this paper is not only to test whether the observed behaviour corresponds to the theoretically predicted patterns, but ultimately to detect possible behavioural effects in either the use or the transmission of information, depending on the network structure.

Let us start with the use of information in a given and fixed network. Our results confirm the main theoretically predicted qualitative patterns of behaviour. Specifically, we find that in treatment COMP the use of each piece of information becomes more intense as the number of subjects observing that piece of information increases; an opposite pattern occurs in treatment SUBS, where a congestion effect prevails; in the orthogonal game (treatment NOINT), all signals are used with similar intensity. On top of these qualitative patterns, however, we observe a systematic over-reaction to all signals in COMP, and a systematic under-reaction in SUBS and NOINT.

To explain observed behaviour, we explore two potential behavioural effects that have been suggested in the literature, identifying a role for the degree of an agent and for the (a)symmetry of the network. Firstly, in the literature on management the amount of information available to an agent (the "degree" of an agent in our framework) has been shown to directly bear on that agent's behaviour. In particular, Zacharakis and Shepherd (2001) suggest that as more information becomes available, people 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. Secondly, it has been suggested that people tend to evaluate their situation relative to a reference point (see, e.g., Luttmer, 2005; White et al., 2006; Azmat and Iriberri, 2010; Blanes i Vidal and Nossol 2011). So, relatively better informed agents in asymmetric networks may overweight their available information to an even larger degree than agents with the same information in symmetric networks. In addition, asymmetric networks are more complex because they introduce heterogeneity, which tends to induce a lower frequency of equilibrium play (see, e.g., Dessi et al., 2016; Kovářík et al., 2018; Cortés-Corrales and Rojo-Arjona, 2021).

Our findings are somewhat consistent with these insights. First, we find that agents with higher degree (more informed agents) tend to respond more to the signals

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

they receive, ending up having a more variable behaviour. This pattern applies to all three games when the network is asymmetric, while in symmetric networks it only applies when strategies are complements. Asymmetry seems therefore to foster overconfidence by creating relative informational differences within the network.

Turning now to the incentives to share information (that is, to form the network links), we find that the link formation behaviour observed in the lab is consistent with equilibrium in both COMP and NOINT, where all links are formed in all circumstances. There are however important departures from equilibrium predictions in SUBS, where the modal strategy is to form (or not to sever) a link, even when this is not (theoretically) optimal. This is consistent with the empirical literature suggesting that agents are likely to show a behavioural preference for being better informed, even if this is not profitable (see, e.g., van Dijk and Zeelenberg, 2007; Kruger and Evans, 2009; Eliaz and Schotter, 2010; Cabrales et al., 2020; Golman et al., 2022; Sharot and Sunstein, 2020). Interestingly, we find that more risk-averse agents tend to depart from equilibrium more often when this departure means forming or maintaining a link. This points to a role of risk aversion in shaping the incentives to acquire information over and beyond what economic rationality would predict. Indeed, as suggested in Lipnowski and Sadler (2019), agents may form better predictions on their neighbours' actions and face an incentive to link to decrease strategic uncertainty.

Our results provide insights into the use and acquisition of information in online social platforms. In particular, they relate agents' behaviour to two key characteristics of the network architecture: density and asymmetry. Consider first Facebook users, exchanging private information and opinions to infer some unknown aspect of the real world. The laboratory evidence suggests that when there are substantial concerns for comformism in opinions (or actions), then agents should be more prone to update their beliefs (and possibly their actions) in denser networks compared to sparse ones. We also learn that when congestion effects are relevant, such as on LinkedIn or in Facebook with anti-conformist users, asymmetry plays a crucial role for behaviour: well connected agents (hubs in the network) are expected to be more sensitive to newly acquired information compared to less connected agents, who remain more anchored to their initial prior. Our results also predict the formation of densely connected networks even when such congestion effects are prevalent. In such situations, the observed behavioural bias should allow agents to overcome the prisoner's dilemma type of inefficiency that would theoretically lead to sparse networks, and information about jobs and social events should therefore efficiently reach most participants.

The paper is organized as follows: Section 2 reviews the related literature. In Section 3, we present our theoretical framework, our experimental design, and the experimental hypotheses. Section 4 presents the results. Section 5 concludes the paper.

2 Related literature

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] In Morris and Shin (2002) and Angeletos and Pavan (2007), 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. In these models coordinating with other agents' actions (i.e. the second incentive) increases an agent's private payoff but is irrelevant from a social value perspective. As a consequence 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 (2020) obtain similar insights studying information acquisition from peers, rather than from exogenous and impersonal sources. In Currarini and Feri (2015, 2018) players are assumed to share information by means of bilateral contract; in Herskovic and Ramos (2020) 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), where 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.[4] In this context, a link provides two types of information: information about

[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.

[4]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

the state of the world and a more accurate prediction about others' actions. Indeed, this last feature is closely related to the concept of *peer confirming equilibrium* introduced by Lipnowski and Sadler (2019), which builds on the assumption that linked players have a perfect conjecture of each other action.

Within the experimental literature, Cornand and Heinemann (2014) study 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 restrict the analysis to the beauty contest game (strategic complements). They 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 neighbourhood), and the use of private information is potentially related to the possibility that agents share their private information before engaging in non-cooperative behaviour. 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).[5]

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).[6] 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

strategies are orthogonal, and Hagenbach and Koessler (2010), where agents have a coordination motive.

[5]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 behaviour 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.

[6]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.

(framed as a voting game).[7] 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 the length of such communication affects outcome and behaviour in a coordination context.

3 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 represent information sharing agreements. Thus, the signal received by one node is automatically shared with each linked 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 behavioural 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 move game where the individual payoff depends on the decisions of all players and on the realized value of a random variable θ (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).

[7] 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 behavioural characteristics of individual subjects (such as stubbornness) are strongly correlated with earnings.

3.1 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 θ 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 $r > 0$ there is strategic complementarity, when $r < 0$ strategic substitutability, and when $r = 0$ there is strategic independence. The state of the world θ 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.[8] 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.[9] 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.

[8]Therefore, our design constitutes the simplest case in which agents' signals are completely uncorrelated. Since correlation would introduce additional noise, the current design allows us a neater identification of departures from rationality as reflections of the hypothesized behavioural effects. As we discuss in Section 5, a (more complex) design with signal correlation may exacerbate the behavioural effects we find.

[9]This may happen, for instance, if there is a time dimension to the decision making, so information only travels to direct neighbours within the time frame in which players choose their actions.

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 θ. 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: $\frac{3}{7-n_j} \in \{0.5, 0.6, 0.75, 1\}$.

- **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 θ 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 $\frac{9}{1+2n_j} \in \{3, 1.8, 1.29, 1\}$.

- **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:

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

3.2 Network Formation

In the second part of the experiment, we allow agents to form and sever links to study network formation behaviour. 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 described 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 theoretical 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/maintain 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 Beauty Contest games 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 can therefore not be made conditional on the type of message one has received.

3.3 Experimental hypotheses

With respect to the *use of information* on a fixed given network, our experimental analysis will focus on three main questions:

1. How close is observed behaviour to equilibrium?
2. Do we observe the predicted qualitative relations between the degree of a signal and the use of that signal?
3. Are there other characteristics of the network, which are not relevant for equilibrium play, which nevertheless affect actual behaviour in the lab?

Starting with the first two questions, the analysis of equilibrium play performed in Section 3.1 leads to the following hypothesis.

Hypothesis 1. *The use of a signal is increasing in its degree in treatment COMP, decreasing in its degree in treatment SUBS and constant in treatment NOINT.*

We now consider the potential behavioural network effects on the use of a signal. As anticipated in the introduction, we will focus on the role played by the amount of available information to an agent and on the role of network asymmetry. Remember that in the present setting, the *degree* of an agent represents the amount of information available to her (the number of signals she sees). As we said, behavioural findings in the literature on management suggest that as agents have more information available, they become more overconfident and this has a negative effect on their choices (Zacharakis and Shepherd, 2001; Busenitz and Barney, 1997; Bernardo and Welch, 2001). In our context, the *overconfidence* associated to higher degrees (i.e. to more informed agents) would translate into these agents overweighting their available information. It is important, however, to distinguish between the sole effect of becoming more informed and the effect of feeling more informed than other agents in the network. Indeed, the *asymmetry of a network* may determine relative concerns, since some agents are relatively more informed than others. There is abundant experimental literature showing that agents evaluate their situation as compared to a reference point (see, e.g., Luttmer, 2005; White et al., 2006; Azmat and Iriberri, 2010;

Blanes i Vidal and Nossol, 2011). Hence, in asymmetric networks, subjects with a high (low) degree may have the perception that they are more (less) informed, as compared to the situation in which they have the same degree in a symmetric network. Moreover, we may also envisage that agents perceive asymmetric networks as more complex environments to play in. In a symmetric network all subjects are in an equivalent position and they only need to consider what is the optimal choice for that network position. In an asymmetric network they also need to consider the choices of opponents in different network positions.[10] We now pose our second hypothesis related to the third research question.

Hypothesis 2. *Agents with a higher degree (i.e. more informed) overweight their available information. This effect is more pronounced in asymmetric networks, in which a lower frequency of equilibrium play is expected.*

Let us now move to the *network formation* stage. Our theoretical results (Section 3.2), based on the backward induction logic postulating that agents will anticipate equilibrium play in the use of information when forming a link, lead us to pose the following hypothesis.

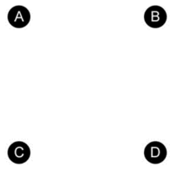
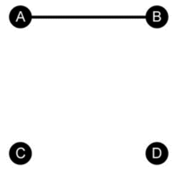
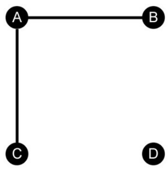
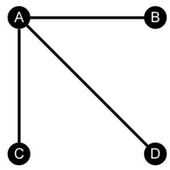
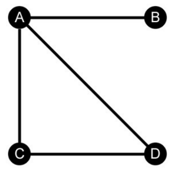
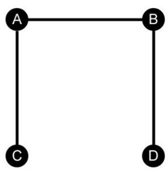
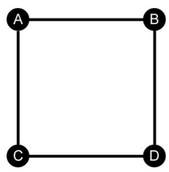
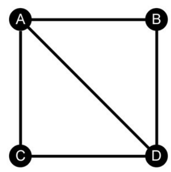
Hypothesis 3. *In treatments COMP and NOINT agents decide to form/maintain any possible link. In treatment SUBS agents only decide to form/maintain links with those agents with a lower degree than them.*

3.4 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 environment 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.

[10]Thus, there can be an effect of *complexity* associated to the asymmetry of the network, which is expected to induce a lower frequency of equilibrium play (see, e.g., Dessi et al., 2016; Kovářík et al., 2018; Cortés-Corrales and Rojo-Arjona, 2021).

Table 1: Network sets

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

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 four, then they are randomly assigned to one node of the (starting) network.

2. (Network modification phase. Part 2 only.) We apply the strategy method to the link formation stage. 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

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 θ 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 $[0, 10]$.[11] Furthermore, subjects have available on the computer screen a payoff calculator that allows them to explore how their payoffs depend on their choices, others' choices and the state of the world.

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

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)

[11] 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).

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.[12] 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.[13]

4 Results

We first analyse 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 formation decisions.

4.1 Use of the information across games

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.[14] 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.

[12]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.

[13]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.

[14]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) COMP		(2) NOINT		(3) SUBS		(4) COMP	(5) NOINT	(6) SUBS
S_1	0.616***	[0.50]	0.760***	[1.00]	1.178***	[3.00]	0.489***	0.902***	1.469***
	(0.032)		(0.036)		(0.073)		(0.075)	(0.084)	(0.167)
S_2	0.781***	[0.60]	0.854***	[1.00]	0.964***	[1.80]	0.533***	1.039***	1.312***
	(0.022)		(0.023)		(0.048)		(0.112)	(0.124)	(0.253)
S_3	0.919***	[0.75]	0.859***	[1.00]	0.961***	[1.29]	0.657***	0.984***	1.199***
	(0.017)		(0.019)		(0.040)		(0.119)	(0.132)	(0.269)
S_4	0.928***	[1.00]	0.828***	[1.00]	0.824***	[1.00]	0.655***	0.980***	1.100***
	(0.027)		(0.029)		(0.060)		(0.117)	(0.130)	(0.266)
Degree							0.083**	-0.029	-0.049
							(0.041)	(0.046)	(0.094)
Asymmetry							0.133	-0.319***	-0.596***
							(0.099)	(0.110)	(0.224)
D_Asym							-0.038	0.085**	0.166**
							(0.037)	(0.041)	(0.084)
Risk							0.001	-0.014	-0.084
							(0.023)	(0.025)	(0.051)
Constant	5.081***	[5.00]	5.136***	[5.00]	5.073***	[5.00]	5.080***	5.135***	5.073***
	(0.030)		(0.062)		(0.070)		(0.030)	(0.062)	(0.071)
Observations	3,600		3,600		3,600		3,600	3,600	3,600
Number of subjects	120		120		120		120	120	120
Marginal effect of *Degree* with:									
Asymmetry = 0							0.083**	-0.029	-0.049
							(0.041)	(0.046)	(0.094)
Asymmetry = 1							0.045**	0.056***	0.117***
							(0.018)	(0.020)	(0.041)
Marginal effect of *Asymmetry* with:									
Degree=1							0.095	-0.23***	-0.43***
							(0.065)	(0.072)	(0.147)
Degree=2							0.057	-0.149***	-0.264***
							(0.037)	(0.041)	(0.084)
Degree=3							0.020	-0.064*	-0.010
							(0.034)	(0.038)	(0.080)
Degree=4							-0.018	0.021	0.070
							(0.061)	(0.067)	(0.141)

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Theoretical predictions in square brackets

We first 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 (all the tests are reported in Table 4). In the NOINT game, the coefficients associated to signals observed by two, three, and four subjects (i.e., S_2, S_3, and S_4) are all very similar to each other (between 0.82 and 0.86), consistently with the theoretical predictions. However, the signals observed by only one subject (S_1) are significantly less used (coefficient 0.76) than the signals observed by two and three subjects (see Table 4), 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 weakly 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 qualitatively confirm the theoretical predictions, there are substantial and significant departures from equilibrium in the absolute levels of the estimated coefficients (see the lower panel of Table 4).

Table 4: Tests on the first set of regressions

	(1) COMP			(2) NOINT			(3) SUBS	
H_0	chi2 (df)	p-value	H_0	chi2 (df)	p-value	H_0	chi2 (df)	p-value
$S_1 = S_2$	17.91 (1)	0.0000		4.84 (1)	0.0278		6.89 (1)	0.0086
$S_2 = S_3$	25.14 (1)	0.0000		0.04 (1)	0.8505		0.00 (1)	0.9674
$S_3 = S_4$	0.07 (1)	0.7870		0.83 (1)	0.3628		3.65 (1)	0.0562
$S_1 = S_3$	68.53 (1)	0.0000		6.11 (1)	0.0135		7.83 (1)	0.0052
$S_1 = S_4$	54.40 (1)	0.0000		2.20 (1)	0.1379		15.35(1)	0.0001
$S_2 = S_4$	17.72 (1)	0.0000		0.47 (1)	0.4915		3.37 (1)	0.0665
All	86.84 (3)	0.0000		6.63 (3)	0.0846		15.39 (3)	0.0015
$S_1 = 0.50$	12.74 (1)	0.0004	$S_1 = 1.00$	45.26 (1)	0.0000	$S_1 = 3.00$	616.93 (1)	0.0000
$S_2 = 0.60$	69.66 (1)	0.0000	$S_2 = 1.00$	39.21 (1)	0.0000	$S_2 = 1.80$	300.63 (1)	0.0000
$S_3 = 0.75$	97.96 (1)	0.0000	$S_3 = 1.00$	57.08 (1)	0.0000	$S_3 = 1.29$	68.67 (1)	0.0000
$S_4 = 1.00$	7.02 (1)	0.0081	$S_4 = 1.00$	35.42 (1)	0.0000	$S_4 = 1.00$	8.65 (1)	0.0033
All	187.07 (4)	0.0000		177.61 (4)	0.0000		993.42 (4)	0.0000

In the COMP game, the signals observed by one, two, and three subjects are overweighted with respect to predictions, while the signals observed by four subjects are underweighted. In the NOINT game, all the signals are underweighted with respect to the theory. Also, in the SUBS game, we observe a large deviation from equilibrium, with all the signals being underweighted, especially those observed by one or two subjects.[15] 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, which gives support to Hypothesis 1. However, we observe a systematic underweighting of*

[15]These larger deviations in the SUBS scenario are in line with the results of Devetag and Warglien (2008), since this scenario is closer to what they define as a "mixed motive game", which is harder to represent for the experimental subjects.

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.

We now investigate whether our behavioural hypothesis 2 (on the potential roles of how informed an agent is and how symmetric the network is) find support in the data and potentially explain part of the quantitative departure from equilibrium coefficients. The amount of information available to an agent is measured by her degree (that is, the number of signals she observes); the level of (a)symmetry of the network is captured by a dummy that takes value 1 if the network is asymmetric (not all subjects have the same degree) and 0 otherwise. In the regression we use variables *Degree_s*, obtained as the product of the degree of the subject and the sum of all the signals she observes, and *Asymmetry_s*, obtained as the product of the asymmetry dummy and 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. We also consider the interaction of these two variables, denoted by *D_Asym*, which is constructed as the product of degree, asymmetry, and the sum of all the signals observed by the subject.

To control for a possible role of risk attitudes, we also add variable *Risk_s*, a dummy that takes value 1 if the subject has invested in the risky asset 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.

Our results are reported in the last three columns of the upper panel of Table 3. We first note that the estimates of the coefficients of variables S_1 - S_4 follow the same qualitative pattern as in the first set of regressions, consistently with equilibrium predictions. We also note that there is no significant effect of risk aversion in any of the three games. We then focus on the effects of degree and of asymmetry.

From the marginal effects reported in the lower panel of Table 3,[16] we first see that in asymmetric networks the marginal effect of *Degree_s* is positive and significant in all the three games, meaning that the number of signals that a subject is able to see enhances his reaction to these signals. In other words, more connected agents use their available information more than less connected ones. In symmetric networks, this is true only in games with strategic complements (COMP).

Result 2: *In COMP, there is a general tendency for the more informed players to react more to signals (overconfidence), while the asymmetry of the network does not play any role.*

[16]The marginal effect of *Degree_s* is computed as the sum of the coefficient of *Degree_s* and the product of the coefficient of *D_Asym* and variable *Asymmetry* (i.e., 0 or 1). The marginal effect of *Asymmetry_s* is computed as the sum of the coefficient of *Asymmetry_s* and the product of the coefficient of *D_Asym* and variable *Degree* (i.e., 1, 2, 3 or 4).

Result 3: *In SUBS and NOINT, overconfidence is observed only in asymmetric networks. In particular, asymmetry has the effect of weakening the reaction of low degree agents to signals, while it has no effect for high degree agents.*

These results seem to suggest that, apart from the case of COMP, the observed overconfidence effect has to do with the perceived informational advantage of very connected agents "relative" to less connected ones, rather than with the absolute amount of information that one has. This relative informational advantage comes not only due to a better knowledge about the state of the world, but also due to acquiring a higher accuracy for predicting others' actions, much in line with the arguments developed by Lipnowski and Sadler (2019), which, subsequently, may strengthen the overconfidence bias.

The evidence points therefore to an indirect channel through which the asymmetry of the network can affect the way in which signals are used. Whether asymmetry plays another, more direct, role that has to do with the complexity of decision making is difficult to assess.[17] While a robust analysis of the role of asymmetry and of decisional complexity is admittedly out of reach with the available data and is beyond the scope of the present paper, one possible hint in favor of some kind of direct effect may lie in the negative and significant effect of the variable *Asymmetry* in SUBS and NOINT. A significant negative value may suggest a (negative) shift in behaviour in such games (a uniform reduction in the use of signals), on top of the effect of degree, caused by asymmetry.

This shift would be consistent with the general under-reaction, compared to theoretical coefficients, observed in these two games). Moreover, it would suggest an interpretation of the marginal effects reported at the bottom of table 3 in terms of the composition of two forces: a general reduction in the use of information (due to asymmetry) and a more intense use of information for agents with high degree (that is, degree 3 or more), due to overconfidence. We leave a fully fledged analysis of the role of asymmetry for future research.

What lessons do we learn from these results for real world instances of information sharing? Let's think for instance of our original motivating examples of on-line social platforms. Result 2 tells us that Facebook users will update their choices and opinions more frequently to newly acquired information as the density of the network increases. Increased density may come as a result of an intensification of online activities (such as the world experienced during and after the COVID peak and the related lockdowns), with new friendships and channels of communication being created. Moreover, more popular people, with more friendships and more central to the network, are likely to update their choices and opinions more frequently and efficiently than their less connected friends. Therefore, at the periphery of the network we would expect to find more "stubborn" agents, little prone to a critical revision of their prior beliefs based

[17]We thank an anonymous referee for pointing out the possible interaction between overconfidence and asymmetry.

on newly acquired information. Therefore, our results suggest a new and unexplored relation between the position of an agent in the network and its characteristics in terms of the process of opinion formation.

Our Result 3 suggests that the hinted difference between central and peripheral agents also apply to games of substitutes, such as LinkedIn (where congestion effects are present) or Facebook when anti-conformism motives prevail. Here, as the network becomes more asymmetric (for instance, due to the formation or the growth of few and very connected hubs within a core-periphery structure) we should observe peripheral agents become more stubborn and averse to revising their opinions, possibly as a result of the increased complexity of updating and of interaction in a less predictable environment.

4.2 Network formation

Recall that in the second part of the experiment only one link (either existing or potential) is randomly selected to be modified and that 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 5, we show the frequency of strategies by the number of optimal decisions, by network, and by game.

Table 5: 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 the game was COMP to 79% in the star network with NOINT. This is in line with the theoretical prediction that all links should be formed. In the SUBS game, the evidence is reverted, and the modal behaviour 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 are detrimental). Differently, in the star network the best responses depend on the player position. While the peripheral players should optimally sever the link with the center and not 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.

Table 6 sheds light on 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 6: 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 fourth result.

Result 4: *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 (hypothesis 3). However, 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.*

In SUBS, as argued above, we can interpret the tendency to overshare information as a general preference to be informed, or as an aversion to be uninformed. Such a tendency suggests a behavioural departure from optimality. This is consistent with abundant empirical literature that identifies an aversion towards remaining (relatively more) uninformed (than others), or a behavioural preference for being informed even if such information is not profitable per se (see, e.g., van Dijk and Zeelenberg, 2007; Kruger and Evans, 2009; Eliaz and Schotter, 2010; Cabrales et al., 2020; Golman et al., 2022; Sharot and Sunstein, 2020). We remark, however, that optimality in the link formation stage is defined here with respect to the (theoretically) optimal behaviour 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 behavioural 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 consistent with the observed behaviour in the second stage. This is indeed the case: by straight computations (see Table 10 in the Appendix) we find that, given the estimated coefficients in the second stage of the SUBS game, the observed link formation behaviour is optimal in almost all network positions.[18]

It must be stressed, however, that in order to support this interpretation of the observed behaviour at the link formation stage, one should assume that subjects not only anticipate their own "non-rational" behaviour in the second stage, but also the "non-rational" behaviour of their opponents. This seems a more stringent requirement than the anticipation of rational behaviour of others that is implicit in the notion of sequential rationality.

An alternative, or complementary explanation, could come from the role played by risk aversion and the possible behavioural effects that relate to the subjects' perception of risk.[19] 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:

[18]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.

[19]Note that by forming new links players reduce the uncertainty both about the state of the world and about others' actions. In this line, risk aversion may play a role on explaining oversharing in the network modification stage. Consistently with this role of risk aversion, oversharing of information could be rationalized in Lipnowski and Sadler's (2019) framework.

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 7 (marginal effects) and in Table 8 in the Appendix (full estimations).

Table 7: Determinants of network formation: marginal effects

	(1) COMP	(2) NOINT	(3) 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

First, note that 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 (but small) effect of the period and a significant effect of the degree. This evidence means that subjects located in nodes with high degree make optimal link decisions more frequently than subjects with lower degree. In SUBS we have the most interesting results. We find a negative and significant marginal effect of both the degree and the type of decision. This latter effect 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%. This is consistent with Result 4 above and with the observation that subjects may have an intrinsic incentive to be informed, far above what rationality would imply.

The results summarized in Table 7 provide one possible complementary determinant of the observed over-linking behaviour in SUBS (in addition to the optimality based on the observed use of information on the second stage of the game - cf. Table 10 in the Appendix), based on the way in which risk aversion affects the incentives to acquire information. Table 7 tells us that risk attitudes do not significantly affect the optimality of behaviour when the best response requires either to form a missing link or to maintain an existing one; 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*. In other words, more risk-averse subjects are less likely to make link-formation choices that are consistent with the theoretical prediction. This means that out-of-equilibrium behaviour prevails in those cases where equilibrium implies the absence of information sharing, pointing to a willingness to share which is not accounted for by the theoretical model.

In the present setting it is not easy to assess whether the effect of risk aversion on linking behaviour is consistent with pure rationality or stems instead from behavioural effects. The risk aversion that is embedded in subjects' preferences in the lab is not accounted for by the theoretical prediction, and the way in which incentives would be theoretically affected by imposing an extra layer of risk aversion on top of the linear quadratic payoff structure is not straightforward. It can be shown that the incentive to form a link 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 conjectured that higher degrees of risk aversion would therefore strengthen the incentives to acquire information, but determining the exact form in which this happens would require an extension of the model that would relax the assumption of linear quadratic payoffs and therefore make the computation of equilibria cumbersome. To obtain some insight on the role played by risk aversion on the incentive to share information, we develop in the Appendix the simple case of two players with the SUBS payoff function and "constant relative risk aversion" preferences. We measure the incentives of these two players to form a link (i.e., to share information). The results we obtain support the hypothesis that the incentives to form a link are increasing when risk aversion increases. More precisely, even if we find that for any level of risk aversion the absence of the link is preferred, we observe that the "cost" (in terms of certain payoff) of a deviation from the optimal behaviour (i.e. the cost of forming a link) decreases as the level of risk aversion increases. Therefore, our results suggest a behavioural effect, since subjects over-stress this rational incentive and end up forming links. In this sense, we conjecture that a behavioural model where the deviations from optimality in link formation are inversely correlated with their cost could explain the observed effect of risk aversion (for a graphical illustration, see Figure 1 in the appendix, section 6.3).

Summing up, the observed behaviour in the lab yields more information sharing than what is theoretically predicted; the evidence is consistent with an explanation in terms of the effect of risk aversion of subjects, which adds to the built-in concavity of designed payoff functions and is not captured by the theoretical equilibrium prediction. As we stressed, whether risk aversion is responsible for the whole observed bias or there are instead other behavioural effects that lead to an excess of information sharing (link formation) is difficult to assess, lacking reliable quantitative estimates of the effects of subjects' risk aversion on equilibrium choices. The regression reported in Table 7 also reveals behavioural effects stemming from the degree of the decision maker, with more connected subjects conforming to equilibrium less (more) frequently than less connected ones in SUBS (COMP).

A final question is whether risk aversion would play a role for the observed over-linking if subjects anticipated the "behavioural biases" in the use of information when they form links. As we have said, such expectation would rationalize the over-linking behaviour to a large extent. To address this question, in Appendix (Table 9) we report on an additional regression in which the dependent variable equals 1 if either a new link is formed or an existing one is not deleted (0 otherwise). This specification allows us to explore if there is a bias to share information in a model in which we do not impose the theoretical predictions about the use of information. Interestingly, in SUBS we find that the marginal effect of risk aversion on the probability to form/not to sever a link is positive and significant. This result confirms that the risk aversion explanation for the over-linking behaviour is complementary (rather than alternative) to the (optimal) reaction to the observed use of information in the second stage (cf. Table 10 in the Appendix).

Result 5: *There is a general tendency to share information beyond what is implied by theoretical predictions in SUBS. This is consistent with an explanation in terms of the effect of subjects' risk aversion on their link formation incentives. However, there are also behavioural effects, since more connected subjects conform to the equilibrium prediction with a lower frequency than less connected ones in SUBS, whereas the opposite holds in COMP.*

What does all this imply for real world instance of information sharing? Let as turn again to our motivating examples of Facebook and LinkedIn social platforms. Our laboratory evidence suggests that dense networks should be the rule both in Facebook, when the prevalent motive is one of coordinating actions, and in LinkedIn, where congestion effects prevail. And while in the first case it is individually rational to coordinate with as many friends as possible, in the second case we should see risk averse agents form dense networks of connections, beyond what it would be individually rational for them to do. Being such situations characterized by prisoner's dilemma types of inefficiencies (the socially optimal structure being the complete network), we should expect the intrinsic desire to be connected to cause a wide dissemination of socially useful information, in what we could consider a beneficial effect of behavioural traits. In this sense, the overlinking bias may help to overcome social dilemmas. Moreover, the role played by risk aversion implies interesting and counter-intuitive predictions about who will take which position on the network. In particular, our results for SUBS suggest that in the LinkedIn network more risk averse agents should be located in more central and connected positions. This implies, together with our previous results on overconfidence in the use of information, that more risk averse online users will update their behaviour more frequently and more intensely than less risk averse and less connected agents.

Looking beyond its implications for economic motives, developing a better understanding of the apparent bias for oversharing could also be an important contribution to the treatment of mental health issues caused or aggravated by social media use. Indeed, as Braghieri et al. (2022) report, the introduction of Facebook at colleges had a negative effect on student mental health. Recent research in psychology suggests that revealing more personal information can cause distress (Radovic et al., 2017) through, e.g., attention seeking and social media addiction, and it invites cyberbullying (Aizenkot, 2020) or other forms of abuse (Chan et al., 2021) like identity theft. Similarly, gathering excessive information can increase anxiety, e.g., about Covid-19 (Shabahang et al., 2020). If, as we found, more risk-averse individuals are indeed more prone to excessively share and acquire information, this could help identify individuals most at risk in social media (by attending to indicators about risk attitudes). And considering that risk-aversion is possibly not the only cause of the bias, but only correlated to it, social scientists may want to identify other bio-social markers affecting information sharing behaviour (cf. Zuckerman and Kuhlman, 2000).

5 Conclusion

We have studied how people make use of information in the laboratory depending on the observability of such information (determined by an information sharing network) and on the strategic nature of interaction (strategic complements, substitutes, and orthogonal strategies). In these contexts, we also investigate the decisions to establish information sharing agreements (links) prior to interaction.

Even if agents' use of information qualitatively follows the theoretical predictions, we find strong behavioural effects that depend on network characteristics and on the position of agents in the network. These behavioural effects induce quantitative deviations from the equilibrium predictions. We find a general tendency of more connected (i.e., higher degree) agents to weight their information more and of a less intensive use of information in asymmetric networks, with larger departures from equilibrium.

Regarding information sharing agreements, we observe a general tendency to create/maintain links, even when this goes against the theoretical prediction. This pattern may reflect a behavioural bias against being relatively less uninformed than those with whom one interacts strategically. We also find that aversion towards risk plays a role, with more risk averse subjects creating/maintaining more links.

There are several questions that deserve further study and empirical investigation. Firstly, we have used a simple and stylized design where signals' correlation is structurally ruled out. A more general design allowing for unconditional or conditional correlation may provide interesting insights on the effect of correlation on the observed behavioural biases. For instance, correlation may reinforce overconfidence by providing very connected agents with a feeling of information advantage, coming both from the information directly acquired from their links and from the inference on unlinked agents behaviour that signals' correlation allows for. As shown by Currarini and Feri (2015), conditional correlation of signals does indeed generate (rational) incentives to form links. Secondly, further research and lab evidence is needed to ascertain the role played by network asymmetry in determining behavioural biases. In particular, research is needed to assess the extent to what the complexity of decision making, also coming from the asymmetry of network relations, may lead agents to rationally ignore some of the acquired information and play significantly away from equilibrium as a result and whether such phenomenon wears out as the game is repeated. Finally, we have considered a stylized setup in which agents are informed of the expected average of signals (in our case, it is set to zero). However, in many real world situations individuals who look at social networks may not have a clear prior about the state of the world, and they only learn it over time from the observation of the information disclosed by their contacts in their social network. This information can indeed be biased, since individuals may extrapolate the local information acquired from their neighbourhood to the whole network. For example, people can evaluate the unemployment rate, the state of the economy, or the average political opinion looking only at their contacts, disregarding the specific characteristics of their neighbourhood. Further investigation would be useful to study how these biases may affect both the use of information and information sharing in networks. We leave these questions for future research.

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6 Appendix

6.1 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 maximises her expected payoff given the equilibrium strategies of the opponents. The expected payoff is:

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

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 $\beta_k^g = \beta_{ik}^g$ $\forall$i. We obtain:

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

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 right hand side, agent i's interim expected payoff (3) can be written as:

$$E\left[u_i(a_i^g, A_i^g, \theta)|\mathbf{m}_i^g\right] = 100 - (a_i^g)^2(w+r) - wE(\theta^2|\mathbf{m}_i^g) - r\frac{E((A_i^g)^2|\mathbf{m}_i^g)}{9} + 2a_i^g\left(wE(\theta|\mathbf{m}_i^g) + r\frac{E(A_i^g|\mathbf{m}_i^g)}{3}\right)$$

From the (4) we get

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

replacing it into (**??**), we get

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

Using the expression (5) we can write:

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

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 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 β given in (6) we get:

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

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

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

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:

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

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.

6.2 Statistics and econometrics

In Table 8 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 Table 7 are computed.

Table 8: 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 9 we report on an additional regression in which the dependent variable equals 1 if either a new link is formed or an existing one is not deleted (0 otherwise). Since in COMP and NOINT the dependent variable coincides with the optimal decision regarding a link (and hence the results are already reported in 9) we focus on SUBS. In the last row of the table, we report the marginal effect of risk aversion.

Table 9: Determinants of network formation: robustness SUBS

Period	0.0164
	(0.0222)
Risk	0.471**
	(0.204)
Degree	0.220*
	(0.113)
Asymmetric network	0.145
	(0.175)
Constant	0.137
	(0.665)
Marginal effects	
Risk	0.0780**
	(0.0344)
Observations	3,432

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

In Table 10, for SUBS, we report on the incentives to create/form or sever/not form links, given the observed behaviour 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 β_i and β_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 10 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 10: 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

6.3 Analysis of the effects of risk aversion on link formation with two players

Consider two players, with the CRRA utility function $U(m) = \frac{(m)^\rho}{\rho}$, with $\rho \in (0,1]$, where $(1-\rho)$ measures the RRA parameter.

We will formulate the conditions for a Bayesian equilibrium for the empty network (i.e., if the two players are not linked) and for the complete network (i.e., if they get linked). We characterize the optimal actions and compute the incentives to form the link using the SUBS payoff function. Since the game is fully symmetric, we focus on a single player.

The strategy is a map from the set of signals to an action in response to the signal that is received. In the empty network the set of signals is $\{-1,1\}$, while in the complete network the set of signals is $\{-1,1\} \times \{-1,1\}$.

Empty Network. We denote by a_L and by a_H the optimal actions when observing the signals -1 and $+1$, respectively. A Bayesian equilibrium is characterized by the following system of FOCs:

$$\begin{aligned}
&\frac{\rho}{2}\left(100 - \frac{1}{2}(a_L+2)^2 + \frac{1}{3}(a_L - a_L^{-i})^2\right)^{\rho-1}\left(-(a_L+2) + \frac{2}{3}(a_L - a_L^{-i})\right) + \\
&\quad \frac{\rho}{2}\left(100 - \frac{1}{2}(a_L)^2 + \frac{1}{3}(a_L - a_H^{-i})^2\right)^{\rho-1}\left(-(a_L) + \frac{2}{3}(a_L - a_H^{-i})\right) = 0; \\
&\frac{\rho}{2}\left(100 - \frac{1}{2}(a_H)^2 + \frac{1}{3}(a_H - a_L^{-i})^2\right)^{\rho-1}\left(-(a_H) + \frac{2}{3}(a_H - a_L^{-i})\right) + \\
&\frac{\rho}{2}\left(100 - \frac{1}{2}(a_H-2)^2 + \frac{1}{3}(a_H - a_H^{-i})^2\right)^{\rho-1}\left(-(a_H-2) + \frac{2}{3}(a_H - a_H^{-i})\right) = 0; \\
&a_L = a_L^{-i} \text{ and } a_H = a_H^{-i}.
\end{aligned}$$

The first condition refers to the expected (ex-ante) utility given a signal $s_i = -1$. The second refers to the expected (ex-ante) utility given a signal $s_i = 1$. The last two conditions exploit symmetry of the network and of the game. In the first two conditions we have used the assumption that signals are drawn with uniform probability.

In Table 11, we report the optimal actions in the empty network for different values of the relative risk aversion coefficient: $\rho = 0.2$, $\rho = 0.4$, $\rho = 0.6$, $\rho = 0.8$ and $\rho = 1$, being the risk aversion decreasing in ρ (the case $\rho = 1$ coincides with the case of risk neutrality considered in the paper so far).

Table 11: Equilibrium Actions in the Empty Network

ρ	a_L	a_H
0.2	-2.92	2.92
0.4	-2.94	2.94
0.6	-2.96	2.96
0.8	-2.98	2.98
1	-3	3

We can then compute the players' welfare in the empty network by taking the (ex-ante) expected utility given these optimal actions. Remember that we are assuming that agents decide whether to form a link at the ex-ante stage, that is before getting to know their own private signal. The ex-ante utility level is given by:

$$\frac{1}{4\rho}\left(100-\frac{1}{2}(a_L+2)^2+\frac{1}{3}(a_L-a_L^{-i})^2\right)^{\rho}+\frac{1}{4\rho}\left(100-\frac{1}{2}(a_L)^2+\frac{1}{3}(a_L-a_H^{-i})^2\right)^{\rho}+$$
$$\frac{1}{4\rho}\left(100-\frac{1}{2}(a_H)^2+\frac{1}{3}(a_H-a_L^{-i})^2\right)^{\rho}+\frac{1}{4\rho}\left(100-\frac{1}{2}(a_H-2)^2+\frac{1}{3}(a_H-a_H^{-i})^2\right)^{\rho}$$

Complete Network. In the complete network we need to denote an optimal action for each one of the possible realizations of signals: a_{LL}, a_{LH}, a_{HL} and a_{HH}. A Bayesian equilibrium is characterized by the following first order conditions:

$$\begin{aligned}
\frac{\rho}{4}\left(100-\frac{1}{2}(a_{LL}+2)^2+\frac{1}{3}(a_{LL}-a_{LL}^{-i})^2\right)^{\rho-1}\left(-(a_{LL}+2)+\frac{2}{3}(a_{LL}-a_{LL}^{-i})\right) &= 0;\\
\frac{\rho}{4}\left(100-\frac{1}{2}(a_{LH})^2+\frac{1}{3}(a_{LH}-a_{LH}^{-i})^2\right)^{\rho-1}\left(-(a_{LH})+\frac{2}{3}(a_{LH}-a_{LH}^{-i})\right) &= 0;\\
\frac{\rho}{4}\left(100-\frac{1}{2}(a_{HL}-2)^2+\frac{1}{3}(a_{HL}-a_{HL}^{-i})^2\right)^{\rho-1}\left(-(a_{HL})+\frac{2}{3}(a_{HL}-a_{HL}^{-i})\right) &= 0;\\
\frac{\rho}{4}\left(100-\frac{1}{2}(a_{HH}-2)^2+\frac{1}{3}(a_{HH}-a_{HH}^{-i})^2\right)^{\rho-1}\left(-(a_{HH})+\frac{2}{3}(a_{HH}-a_{HH}^{-i})\right) &= 0;\\
a_{LL}=a_{LL}^{-i},\ a_{HH}=a_{HH}^{-i},\ a_{HL}=a_{HL}^{-i}\ \textit{and}\ a_{LH}=a_{LH}^{-i}.
\end{aligned}$$

In Table 12 we report the optimal actions in the complete network for the same set of values of the relative risk aversion coefficient used in Table 11.

Table 12: Equilibrium Actions in the Complete Network

ρ	a_{LL}	a_{HH}	a_{HL}
0.2	-2	2	0
0.4	-2	2	0
0.6	-2	2	0
0.8	-2	2	0
1	-2	2	0

The expected utility level in the complete network is computed by replacing the equilibrium actions in the following utility function:

$$\frac{1}{4\rho}\left(100-\frac{1}{2}(a_{LL}+2)^2+\frac{1}{3}(a_{LL}-a_{LL}^{-i})^2\right)^{\rho}+\frac{1}{4\rho}\left(100-\frac{1}{2}(a_{LH})^2+\frac{1}{3}(a_{LH}-a_{LH}^{-i})^2\right)^{\rho}+$$
$$\frac{1}{4\rho}\left(100-\frac{1}{2}(a_{HL})^2+\frac{1}{3}(a_{HL}-a_{HL}^{-i})^2\right)^{\rho}+\frac{1}{4\rho}\left(100-\frac{1}{2}(a_{HH}-2)^2+\frac{1}{3}(a_{HH}-a_{HH}^{-i})^2\right)^{\rho}$$

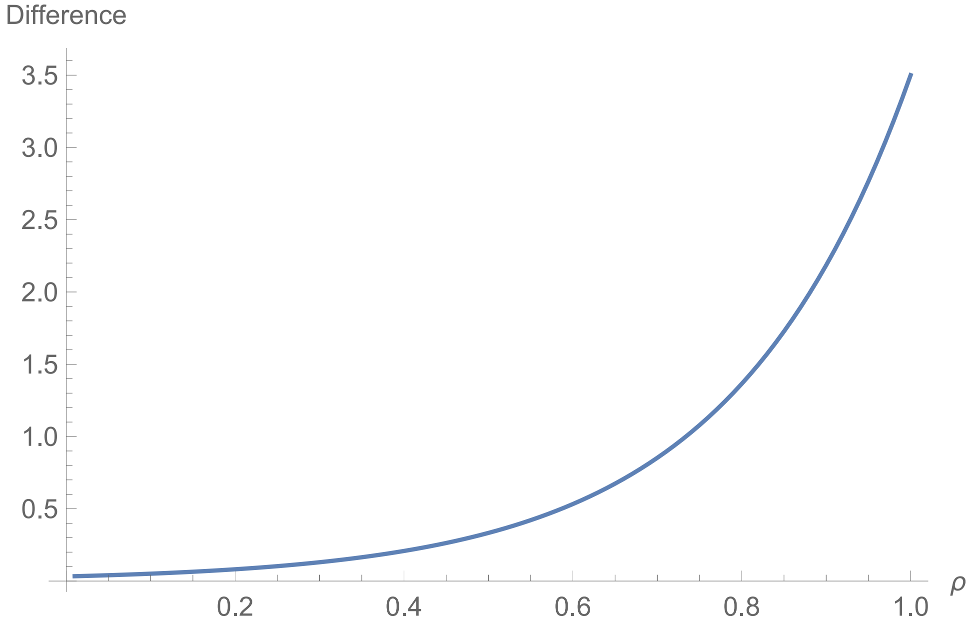
Incentives to Form the Link. We denote by U_c and by U_e the expected utility levels in the complete and empty networks and by CE_c and by CE_e we denote the respective certainty equivalents. Table 13 reports the expected utility levels and the certainty equivalents in the Bayesian equilibrium for the two network architectures, using the considered set of levels of ρ.

Table 13: Ex-ante Expected Utility: Complete and Empty Networks

ρ	U_c	U_e	CE_c	CE_e	$CE_c - CE_e$
0.2	12.56	12.64	100	103.28	-3.26
0.4	15.77	15.98	100	103.33	-3.33
0.6	26.41	26.95	100	103.38	-3.38
0.8	49.76	51.13	100	103.44	-3.44
1	100	103.5	100	103.5	-3.5

The comparison of certainty equivalents provides us with a measure of the incentives to form the link that overcomes the scaling problems inherent in the comparison of utilities. Our results show that, as risk aversion increases (i.e., ρ decreases, moving gradually from $\rho = 1$ to $\rho = 0.2$), the incentives to form the link remain negative, but increase monotonically (see Figure 1 for a graphical representation of these incentives in the form $U_e - U_c$). In other words, although agents prefer not to form (or sever) the link even for high levels of risk aversion, the cost of deviating from the optimal behaviour (i.e., of forming a link) shrinks as risk aversion increases. This result can explain why the deviations from optimal behaviour in the link formation stage (i.e. the over-linking behaviour observed in the SUBS game) depend positively on the level of risk aversion.

Figure 1: Utility difference between the empty and the complete network



6.4 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.

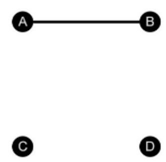
2.- At each period, the computer selects a **network for your group**. The network is **selected from the two networks depicted in the additional sheet** provided to you, entitled NETWORKS. Note that, in this sheet, each network is identified by a number, 1 and 2. Each of the two networks will be selected 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 2) 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.

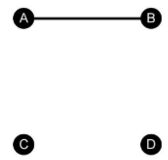


3.- At each period, **the computer randomly selects a signal for each of the four players (A, B, C and D)**. The signal of a player can be **either +1 or –1**, and each of these two possibilities (+1 and –1) is equally likely (that is, each player gets the signal +1 with a probability of 50% and gets 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:

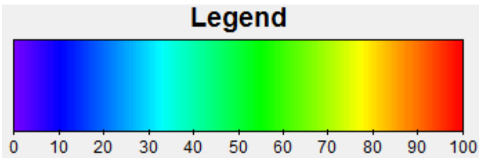
$$100 - \frac{1}{2}(Your\ decision - X)^2 - \frac{1}{2}\left(Your\ decision - \frac{Sum\ of\ the\ others'decisions}{3}\right)^2$$

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).

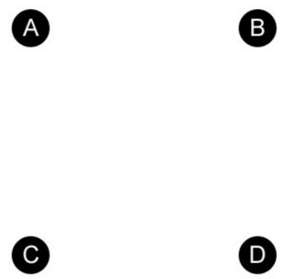
2.- At each period, **network 1** (depicted in the sheet provided to you in part 1 of the experiment, entitled NETWORKS) assumes the role of **original network** of the period, which may be modified by you and the other members of your group as explained below.

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£**.