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Equilibrium Selection in Experimental Games on Networks[*]

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Abstract. We study behavior and equilibrium selection in experimental network games. We vary two important factors: (a) actions are either strategic substitutes or strategic complements, and (b) subjects have either complete or incomplete information about the structure of a random network. Play conforms strongly to the theoretical predictions, providing an impressive behavioral confirmation of the Galeotti, Goyal, Jackson, Vega-Redondo, and Yariv (2010) model. The degree of equilibrium play is striking, even with incomplete information. We find that under complete information, subjects typically play the stochastically-stable (inefficient) equilibrium when the game involves strategic substitutes, but play the efficient one with strategic complements. Our results suggest that equilibrium multiplicity may not be a major concern. Subjects' actions and realized outcomes under incomplete information depend strongly on both the degree and the connectivity. When there are multiple equilibria, subjects begin by playing the efficient equilibrium, but eventually converge to the inefficient one.

JEL Codes: C71, C91, D03, D85

Keywords: Random networks; Incomplete information; Strategic substitutes; Strategic complements; Experiment

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1. Introduction

Social networks are a prominent feature of the economic landscape. A network is a non-market institution, but has important market-like characteristics. In a sense it can be considered to be an intermediate case between bilateral bargaining and matching in a large centralized market. Network structure affects choices in a wide variety of environments and network analysis has been applied to many important environments.[1] It has been applied, for example, to systems compatibility (Katz and Shapiro 1994), airline route design (Hendricks, Piccione and Tan 1995), matching markets (Gale and Shapley 1962, Kelso and Crawford 1982, Roth 1984, Crawford and Rochford 1986, Roth and Sotomayor 1989), bargaining (Kranton and Minehart 2001), and friendship (Currarini, Jackson and Pin, 2009). Job search and labor-market issues are also quite suitable for network analysis, since workers frequently find jobs through personal contacts and employers value the additional enforcement channel available through these personal intermediaries (Montgomery 1991, Calvó-Armengol 2004, Calvó-Armengol and Jackson 2004, 2007).[2]

A growing empirical literature has documented the effects of social networks on behavior; the information gleaned from these has motivated theoretical work. Since social networks are so prevalent in economic settings, modeling these networks is essential in order to understand how network structure affects behavior and which networks are likely to arise and be stable. However, it is very difficult (if not impossible) to cleanly test theoretical predictions using field data, since there are many confounding features in the environment.[3] In this respect, controlled laboratory experiments are often viewed as the ideal tool for qualitatively testing theory (e.g., Runkel and McGrath, 1972; Falk and Heckman, 2009).

In this paper, we design a laboratory experiment that implements specific examples of a more general network structure in which the agents' actions are either strategic complements or substitutes. Economic environments typically have a considerable degree of either

[1] Jackson (2010, p. 512) states that network structure "influences patterns of decisions regarding education, career, hobbies, criminal activity, and even participation in micro-finance. Beyond the role of 'social' networks in determining various economic behaviors, there are also many business and political interactions that are networked. Networks of relationships among various firms and political organizations affect research and development, patent activity, trade patterns, and political alliances."

[2] For an exhaustive review of social and economic networks, with particular attention to theoretical models, see Jackson (2008).

[3] Typical problems with field data are the use of idiosyncratic data sets, a snapshot of a static environment, or the issue of measurement error.

complementarity or substitutability, so that this notion applies to a wide variety of economic environments and includes perhaps most of the game-theoretic applications in the network literature.

In addition to the broad applicability of our setting, to the best of our knowledge we are the very first to experimentally study an environment in which the agents are uncertain about the precise network structure. This enhances the applicability and the external validity of our experiment, as there are many economic situations in which individuals have a good sense of the number of other people with whom they are interacting in some form of network, but know neither the identity of these others nor how these others are connected to still others. As examples for such situations, Galeotti, Goyal, Jackson, Vega-Redondo and Yariv (2010) mention choosing which languages to study before embarking on a career in diplomacy, researchers choosing software based on compatibility, and choosing whether to receive a vaccination.

A critical problem in relation to network theory is that even simple games have multiple equilibria, so that a great variety of outcomes are consistent with theoretical analysis. This naturally limits the predictive power of the theory and the scope of policy recommendations, since multiple equilibria make it difficult-to-impossible to offer definitive advice regarding how such labor markets, search markets, etc. should be organized. To make meaningful policy recommendations, it is very important to try to determine which of the equilibria are likely to occur. One way to achieve this is theoretical work. In fact, a central goal in network analysis is to refine the set of equilibria to be able to make better predictions about the likely outcomes; in some cases with networks on games, there is the rather surprising and non-intuitive result (at least at first sight) that uncertainty about elements of the network reduces the equilibrium multiplicity that arises under complete information, as shown by Galeotti *et alii* (2010). Another way to examine equilibrium selection is through experimental testing. This is our approach, since experimental work should be useful in identifying which of the multiple equilibria tends to actually prevail behaviorally.

Galeotti *et alii* (2010) mainly focus on two classes of games: strategic complements and strategic substitutes. Strategic complements (positive network externalities) arise when the benefit that an individual obtains from choosing an action is greater as more of her neighbors do the same. An example of strategic complements is human capital investment, whereby one’s own investment is more beneficial if others also make this investment.[4] Strategic substitutes arise when the benefit that an individual obtains from choosing an action is greater as more of her neighbors do the opposite. An example of strategic substitutes is that of a best-shot game, wherein it pays an individual to free-ride on the contributions or actions of others. Another example is choosing routes to avoid congested roads.

In our paper, we adapt the Galeotti *et alii* (2010) model to a specific experimental environment that includes three different five-person networks. In the case of complete information, each person knows the network structure and the node to which she has been assigned. In contrast, with incomplete information each person only knows the probability that each of the three possible networks has been randomly drawn and her degree (the number of connections to others). This probability is a treatment variable. Again, to the best of our knowledge this is the first experiment on networks to ever consider behavior under incomplete information and the concomitant increased complexity of the environment. In fact, a major challenge was to create a design that matched the Galeotti *et alii* (2010) theoretical model and yet was comprehensible for the participants. By explaining the game very carefully and by having participants play for 40 periods to allow – and control for – learning, we are confident that the participants understood the game quite well.

Our experimental results are striking. In fact, we find a great deal of support for every one of the theoretical predictions. Participants are, to a large extent, active in the network (which can be interpreted as purchasing a particular good) when the prediction is that they will be and they are inactive (not purchasing) when the prediction is that they won't be. In all scenarios, the modal behavior by every individual is consistent with the observed equilibrium outcome, and the overall rate of such equilibrium play is quite high.

In the simpler case of complete information, behaviorally we do not observe a multiplicity of equilibria. Behavior consistent with a unique equilibrium is seen in each and every independent group. With strategic substitutes and complete information, this equilibrium is not the efficient one, but in a certain sense it is 'risk dominant', as a deviation from the selected equilibrium is less harmful than a deviation from the efficient equilibrium. In other words, there is a trade-off between efficiency and the cost of a mistake (stability), since the efficient

[4] In fact, positive network externalities may be large enough to more than offset inferior quality or efficiency. A familiar example is that of the QWERTY keyboard; another is the general adoption of the VHS format over the Betamax format around 1980 despite the fact that the Betamax format was widely acknowledged to be superior.

equilibrium results in a higher cost for agents' errors. With strategic complements and complete information, the efficient equilibrium is selected. Remarkably, the predictions are borne out qualitatively for every node and quantitatively (within 10 percentage points of the extreme point-prediction) for most nodes, for both strategic substitutes and strategic complements.

With incomplete information, the only information provided is one's degree, so we do not distinguish amongst positions with the same degree. Despite the more complex game, subjects do seem to grasp the essential elements of play very well. As with complete information, the qualitative predictions of the model are supported for both strategic complements and strategic substitutes. As theory predicts, we observe that participants do use monotone (threshold) strategies. Regarding increased connectivity, the frequency of active players increases for degree 2 and 3 with both strategic substitutes and strategic complements. In scenarios where incomplete information induces a unique equilibrium, we see that participants make the choice that is consistent with this equilibrium an overwhelming majority of the time.

There is only one case with incomplete information where the theoretical prediction involves multiple equilibria, i.e., with strategic complements and a high degree of connectivity. In contrast to the parallel case with complete information, the efficient equilibrium is not played. We offer some possible explanations, relying on bounded rationality and subjects being forward looking, regarding the behavioral influences that could generate this asymmetry between complete and incomplete information in the case of strategic complements.

The remainder of the paper is organized as follows. We discuss the relevant literature in section 2, and present the equilibrium analysis for our set-up in section 3. The experimental design and implementation comprise section 4, and we present our experimental results in section 5. We offer a discussion of our results and their implications in section 6, and conclude in section 7.

2. Literature review

In this section we review related theoretical and experimental work. We refer the interested reader to Jackson (2008) for a comprehensive overview of theoretical work on and applications of social and economic networks.

2.1 Theoretical work

Our study relates to exogenous networks, as agents have no control over the structure of the network. Thus, we do not consider the issue of how networks were formed, but simply presume that the links are already in place due to some relationships that have (or had) value, and that the cost of (endogenous) change is prohibitive. In this sense, the networks we use are effectively stable.

A handful of papers show that the outcomes of games in general depend on the specific network structures, when there are either strategic substitutes or complements. In the case of complete information, Goyal and Moraga-Gonzalez (2001) analyze research collaboration when there is either rivalry or no rivalry amongst firms. Calvó-Armengol and Jackson (2004) develop a model in which agents receive information about job opportunities only through a network of social contacts. Ballester, Calvó-Armengol and Zenou (2006) consider the choice of committing a crime in a network setting with strategic complementarities, and Bramoullé and Kranton (2007) consider public-goods provision.

In the case of incomplete information, Jackson and Yariv (2005) show that diffusion depends on the network structure. Sundararajan (2006) presents a model of local network effects in which agents value the adoption of a product by a heterogeneous subset of neighbors, and have incomplete information about the structure and strength of adoption complementarities between all other agents; he finds that the symmetric Bayes-Nash equilibria of this network game are in monotone strategies. Galeotti and Vega-Redondo (2011) examine how local externalities affect behavior in a complex random network where agents choose investment levels that impose a payoff externality on neighbors; in the unique interior equilibrium, whether this externality is positive or negative depends on investment costs, while the investment strategy is increasing in degree.

Galeotti *et alii* (2010) obtain general results in games with incomplete information about the degrees of one's neighbors, where one's payoffs depend not only on one's action, but also on the actions of neighbors; they consider both strategic substitutes and strategic complements. The multiplicity present is substantially reduced under incomplete information.

2.2 Experimental work

Overall, there is a relative dearth of research in experimental economics on network games, particularly when one considers the wealth of theoretical contributions in this area.[5] Here we restrict our discussion of the literature in experimental economics to designs with exogenous networks (where the participants have no control of the network structure), as in our own environment.[6] Some research has examined the consequences of network structure on equilibrium selection in coordination games, which is relevant for our settings with a multiplicity of equilibria. Keser, Ehrhart and Berninghaus (1998) is the first paper in experimental economics to consider the effect of network structure. They use a 3-person coordination game. In one treatment, each participant is connected to two neighbors on an 8-player circle; in the other treatment, people play within closed 3-person groups. They find that the 3-person group quickly coordinates on the payoff-dominant equilibrium while the circular group eventually coordinates on the risk-dominant equilibrium. Berninghaus, Ehrhart and Keser (2002) modify the payoff function in the network coordination game, reducing the riskiness of the efficient equilibrium. They find that if the efficient Nash equilibrium becomes less risky, populations that interact locally on the circle also converge to efficient play in most cases. However, in contrast to these studies, Boun My, Willinger and Ziegelmeyer (2006) do not find that players who interact locally on the circle coordinate more frequently on the risk-dominant equilibrium.

Corbae and Duffy (2008) consider a two-player, 2x2 coordination game with groups of four people in three configurations: the complete network, the circle, and two isolated pairs. In their game, the efficient equilibrium is also the risk-dominant one; in almost every case the group achieved the efficient equilibrium. After 10 periods, the game is changed so that the efficient outcome is no longer risk dominant. Groups continue to play the efficient equilibrium, unless one player is obligated to play the risk-dominant strategy; in this case, there is convergence to the risk-dominant equilibrium when the interaction is more 'local' (the circle and the isolated pairs), but not as much with the global interaction of the complete network. Cassar (2007) compares

[5] Researchers in sociology have long been interested in studying networks in experiments (see the seminal studies by Stolte and Emerson, 1977, or Cook and Emerson, 1978; see also surveys of Willer, 1999, or Burt, 2000). Note, however, that sociologists have been in particular interested in studying the exercise of power in networks, something with which the literature in experimental economics has not yet been concerned.

[6] There are other experiments on networks in other environments, including buyer-seller networks (Charness, Corominas-Bosch, and Fréchette 2007), the prisoner's dilemma (Riedl and Ule 2002; Kirchkamp and Nagel 2007), and endogenous networks (Falk and Kosfeld 2003; Deck and Johnson 2004; Callander and Plott 2005; Berninghaus, Ehrhart, and Ott 2006; Berninghaus, Ehrhart, Ott, and Vogt 2007).

convergence to equilibrium across three different network structures: a local interaction network, a random network, and a "small-world" network (each link in the circle has a probability of being re-wired to a 'short cut' of a chord across the circle). She finds that participants converge to the efficient equilibrium in the small-world network, but less so in the other networks.[7]

To the best of our knowledge, there is only one experimental paper that considers network effects primarily in relation to the voluntary-contribution mechanism.[8] Fatas, Meléndez-Jiménez and Solaz (2010) have 4-person groups repeatedly play a standard VCM in four different network structures: the line, the circle, the star, and the complete network. Information about another person's contribution is only transmitted if and only if there is a direct link between the parties. Contributions are in fact affected by the network structure, with the complete network and the star leading to 30-40 percent higher contributions than with the line and the circle, which have similar contribution levels. It is clear that there is at least one person with a degree of three in each of the networks with higher contributions; such a person knows the contribution of every other player and every other player observes their choice, with this being common information. The degree of an individual does not appear to affect contributions, however.

Kearns *et alii* (2006, 2009) develop a series of experiments aimed to determine what strategies people use when they are given local information about a large network and are asked to work together, without communicating. Kearns *et alii* (2006) consider a game of substitutes (framed as a graph-coloring problem), and Kearns *et alii* (2009) examine a game of complements (framed as a voting game). The crucial difference between their design and ours is that in their case, the individual payoffs depend on the global performance of the network whereas in our case, only a subject's actions and those of her neighbors affect her payoff. Another difference is that Kearns *et alii* (2009) consider heterogeneity of preferences among players whereas in our

[7] Charness and Jackson (2007) frame a Stag Hunt as the choice of adding a link between two players in a pre-existing network, where this link can be added by either mutual consent or unilateral consent. Whether the payoff-dominant or the risk-dominant equilibrium prevails depends primarily on the degree of consent required.

[8] Carpenter (2007) mainly considers the issue of group size in the VCM, but also has treatments in which people are only allowed to punish their closest neighbors. He finds that, relative to not punishing at all, both the possibility to monitor either the complete or half of the group yields significantly more contributions, and the possibility to punish only a single player elicits significantly fewer contributions.

(complements) setup the preferences are homogeneous. In the case of substitutes, each action has a different cost in our design, whereas in Kearns *et alii* (2006) all the actions have the same cost.[9]

Our experiment can be seen as venturing into some new realms. We contrast strategic complements and strategic substitutes, considering both complete and incomplete information concerning aspects of the network structure.

3. Model and equilibrium analysis

3.1 The Game

In the experiment we focus on the two specific games that Galeotti *et alii* (2010) use in their Section 2 in order to introduce and motivate their results, which we now briefly summarize. Consider a player who can choose between being *active* (e.g., buying a product) or *inactive* (e.g., not buying the product). Being active has costs $c > 0$, while an inactive player bears no cost. For the following analysis, we will fix $c = 1/2$, as is the case in our experiment.

- In the case of ***strategic substitutes***, a player earns 1 if either she or at least one of her neighbors is active, and earns 0 otherwise. Note that she pays the cost c only in case she has been active.
- In the case of ***strategic complements***, if a player is inactive, she earns 0 and, if she is active she earns a scalar $\alpha > 0$ times the number of neighbors that are active, and pays the cost c.

3.2 Networks and connectivity

We consider the three five-player networks (g_O, g_G, and g_P – *Orange*, *Green* and *Purple*, respectively) presented in Figure 1. Since each of g_G and g_P can be obtained by deleting a single link from g_O, the *Orange* network has a higher connectivity than the other two. We analyze the cases of both complete and incomplete information about the network structure.

Figure 1 about here

[9] In a recent paper, Kovarik *et alii* (2011) analyze experimental anti-coordination games played in fixed networks. They find that the more-connected players are able to impose their preferred Nash equilibrium, which they rationalize using the fact that highly-connected players tend to have more stable best-responses.

For each player $i \in N = \{1, 2, 3, 4, 5\}$, let $N_i \subset N$ be the set of her neighbors in the realized network (g_O, g_G or g_P). Player i's action is denoted by $x_i \in \{0,1\}$, where $x = 1$ indicates being active ("buy"), while $x = 0$ stands for being inactive ("not buy").

3.3 Complete information scenario

There are five players arranged in one of the three networks defined in Figure 1. Initially, one of the three networks (g_O, g_G, or g_P) is randomly drawn with equal probability. Each player knows which network is in force (and knows it is the same network for all players) and the node (A, B, C, D, or E) to which she is assigned. Hence, she also knows her own degree (the number of neighbors she has, either 1, 2 or 3). With this information in hand, each player decides whether to be active (action 1) or inactive (action 0). Let a strategy profile be $s = (s_A, s_B, s_C, s_D, s_E)$, where s_i, with $i \in \{A, B, C, D, E\}$ denotes the probability that a player in position i is active.

We first examine the case of *strategic substitutes*. Player i's payoffs (assuming $c = 1/2$) are defined in equation (1):

$$\pi_i = I(x_i + \textstyle\sum_{j \in N_i} x_j \geq 1) - (\tfrac{1}{2}) \cdot x_i \qquad (1)$$

where $I(.)$ is an indicator function that takes value 1 if $x_i + \sum_{j \in N_i} x_j \geq 1$, and that takes value 0 otherwise. In Propositions 1, 2 and 3 we characterize the equilibria for the *Orange*, *Green* and *Purple* networks, respectively. All proofs of the propositions in this paper are in Appendix C.

Proposition 1. *Consider the scenario of strategic substitutes and complete information with network* g_O.

a) *There are three pure-strategy Nash equilibria*: (1,0,1,0,1), (1,0,0,1,0), and (0,1,0,0,1).
b) *The following strategy profiles, where agents use mixed strategies, are Nash equilibria:* $(m_A, 0.5, 1-\frac{0.5}{1-m_A}, 0, 1)$ *with* $m_A \in (0, 0.5]$, $(1, 0, 1-\frac{0.5}{1-m_E}, 0.5, m_E)$ *with* $m_E \in (0, 0.5]$, (0,0.5,0.5,0,1), (1,0,0.5,0.5,1), and (0,0.5,0,0.5,0).
c) *There are no other Nash equilibria*.

Proposition 2. *Consider the scenario of strategic substitutes and complete information with network g_G.*

a) *There are four pure-strategy Nash equilibria*: (1,0,1,0,1), (0,1,0,1,0), (1,0,0,1,0), and (0,1,0,0,1).

b) *The following strategy profiles, where agents use mixed strategies, are Nash equilibria*: $(m_A, 0.5, 1-\frac{0.5}{1-m_A}, 0, 1)$ *with* $m_A \in (0, 0.5)$, $(1, 0, 1-\frac{0.5}{1-m_E}, 0.5, m_E)$ *with* $m_E \in (0, 0.5]$, (0.5,0.5,0,0.5,0.5), (0.5,0.5,0,1,0), (0.5,0.5,0,0,1), (0,1,0,0.5,0.5), (1,0,0,0.5,0.5), (0,0.5,0.5,0,1), and (1,0,0.5,0.5,0).

c) *There are no other Nash equilibria*.

Proposition 3. *Consider the scenario of strategic substitutes and complete information with network g_P.*

a) *There are three pure-strategy Nash equilibria*: (1,0,1,0,1), (1,0,1,1,0), and (0,1,0,0,1).

b) *The following strategy profiles, where agents use mixed strategies, are Nash equilibria*: $(m_A, 0.5, 1-\frac{0.5}{1-m_A}, 0, 1)$ *with* $m_A \in (0, 0.5)$, $(1, 0, 1-\frac{0.5}{1-m_E}, 0.5, m_E)$ *with* $m_E \in (0, 0.5]$, (0,0.5,0,0.5,0), *and* (1,0,1,0.5,0.5).

c) *There are no other Nash equilibria*.

We next examine the case of *strategic complements*. Consistent with our experimental design (cf. Section 4), we assume α = 1/3. Hence, player i's payoffs (assuming c = 1/2) become:

$$\pi_i = \left(\frac{\sum_{j \in N_i} x_j}{3} - \frac{1}{2}\right) \cdot x_i \qquad (2)$$

In Proposition 4 we characterize the equilibria for the *Orange* network, and in Proposition 5 we characterize the equilibria for the *Green* and *Purple* networks.

Proposition 4. *Consider the scenario of strategic complements and complete information with network g_O.*

a) *There are two pure-strategy Nash equilibria*: (0,0,0,0,0), and (0,1,1,1,0).

b) *The following strategy profiles, where agents use mixed strategies, are Nash equilibria*: (0,1,0.5,0.5,0), (0,0.5,1,0.5,0), (0,0.5,0.5,1.0), *and* (0,0.75,0.75,0.75,0).

c) *There are no other Nash equilibria*.

Proposition 5. *Consider the scenario of strategic complements and complete information. If the network is either g_G or g_P, there is a unique Nash equilibrium*: (0, 0, 0, 0, 0).

3.4 Incomplete-information scenario

Again, there are five players arranged in one of the three networks defined in Figure 1. We modulate the connectivity through a parameter $p \in (0,1)$. Initially one of the three networks (g_O, g_G, or g_P) is randomly drawn, where $\Pr(g_O) = p$ and $\Pr(g_G) = \Pr(g_P) = (1-p)/2$. Note that, since g_O is more connected than g_G and g_P, by increasing parameter p we increase the expected connectivity of the network. In our design, in the sessions with incomplete information either $p = 0.2$ or $p = 0.8$.

The five players are then randomly allocated (with uniform probability) to the five nodes of the resulting network. Players are not informed about which network has been drawn, but they know their own degree (the number of neighbors they have, either 1, 2 or 3). With this information in hand, each player decides whether to be active (action 1) or not (action 0).[10] Since each player only learns her degree (and the prior p), she can only condition her behavior on this information. In this sense, a (symmetric) strategy profile is represented by a vector $s = (s_1, s_2, s_3)$, where $s_k \in [0,1]$ is the probability such that the agent with degree $k \in \{1,2,3\}$ chooses action 1.

We first consider strategic substitutes, with payoffs defined in equation (1) above. In the following proposition we analyze the equilibria.

[10] Note that connectivity is modulated in a different way in the examples proposed by Galeotti *et alii* (2010). In their case, each potential link between two players is formed independently with probability p (Erdös-Rényi network), so several different networks can arise. Our approach leads to the same theoretical predictions (meaning that players use threshold strategies and that the effects of connectivity go in opposite directions in strategic substitutes and strategic complements), but is considerably easier to understand for experimental participants.

Proposition 6. *Let p* ∈ (0,1). *In the scenario of strategic substitutes and incomplete information there exists an equilibrium* $(1, s_2^*(p), 0)$, *where*

$$s_2^*(p) = \begin{cases} 0 & if\ p \le \frac{1}{2} \\ 1 - \sqrt{\frac{2-3p}{1-p}} & if\ \frac{1}{2} < p < \frac{2}{3} \\ 1 & if\ p \ge \frac{2}{3} \end{cases}$$

Moreover, there are no other pure-strategy equilibria and, if p ≥ 0.2, *the equilibrium* $(1, s_2^*(p), 0)$ *is unique.*[11]

The proof is in Appendix C. Note that function $s_2^*(p)$ is continuous and (weakly) increasing in *p*. Hence, our equilibrium is in line with Galeotti *et alii*'s (2010) general result: In the case of strategic substitutes, there exists an equilibrium that involves monotone (symmetric) strategies where the equilibrium actions are non-increasing in players' degrees; and by increasing the connectivity, the set of degrees for which players are active increases.

We next turn to the case of strategic complements, with payoffs defined in equation (2) above. In the following proposition we characterize the equilibria.

Proposition 7. *Let* $p' = (\sqrt{105} + 13)/32$, *and consider the scenario of strategic complements and incomplete information.*[12] *If p*<1/2, *there is a unique equilibrium:* (0, 0, 0). *If* $p \ge 1/2$, *there are three equilibria:* (0, 0, 0), (0, 1, 1) and $(0, s_2'(p), s_3'(p))$, where

$$s_2'(p) = \begin{cases} \dfrac{5-6p}{4(1-p)} & if\ p < p' \\ \dfrac{3-30p+51p^2}{2(5p-1)^2} & otherwise \end{cases} \quad and \quad s_3'(p) = \begin{cases} 1 & if\ p < p' \\ \dfrac{3p+9p^2}{(5p-1)^2} & otherwise \end{cases}$$

The proof is in Appendix C. We observe that by increasing the connectivity from p < 1/2 to p ≥ 1/2, there are new equilibria in which the set of degrees with which players are active

[11] For $p < 0.2$, additional mixed-strategy equilibria can be found.
[12] Note that $p' = 0.72647 > 1/2$ and that both $s_2'(p)$ and $s_3'(p)$ are continuous for $p > 1/2$.

increases. In equilibrium, the probability that a player is active is increasing in the degree, in line with the Galeotti *et alii* (2010) results.

4. Experimental design

4.1 Predictions

In our design, we vary the information scenario (complete and incomplete), the game (substitutes and complements) and, in the incomplete information scenario, the connectivity (p = 0.2 or p = 0.8). Based on the results of Propositions 1-7, we summarize the equilibrium predictions for each case in Tables 1 and 2. In the case of complete information, given the considerable multiplicity of mixed-strategy Nash equilibria, in Table 1 we only report the pure-strategy ones.

Table 1 and Table 2 about here

Regarding the case of complete information and strategic substitutes (Table 1), there are equilibria in which two nodes are active and equilibria in which three nodes are inactive. The former are more efficient by having the lowest total cost, but the latter are stochastically stable.

With incomplete information and strategic substitutes (Table 2), the theoretical prediction is that players with low degree will be active and those with high degree will be inactive; furthermore, the threshold should increase (from degree 1 to degree 2) when we increase p from 0.2 to 0.8. With incomplete information and strategic complements, the theoretical prediction is that no one will be active when p = 0.2, but that there is room for players with high degree (degrees 2 and 3) to be active when p = 0.8.[13] We can also compare across strategic substitutes and complements. Players with low degree (degree 1) should always be active with substitutes, but should never be active with complements. Moreover the equilibrium moves in different directions for substitutes and complements when p increases; with substitutes the prediction is that an increase in p increases the threshold, while with complements the prediction is reversed.

Comparing across Tables 1 and 2, it becomes clear that the equilibrium multiplicity with complete information and strategic substitutes is fully resolved with incomplete information; this

[13] New equilibria appear such that the threshold can decrease from degree 3 to degree 1.

is also the case with strategic complements and p = 0.2, but not with p = 0.8, where multiple equilibria remain.

4.1 Implementation and experimental treatments

We conducted our computerized experimental sessions at the University of Innsbruck in March of 2011, using the software zTree (Fischbacher 2007). A total of 240 undergraduate students from various academic disciplines were recruited with the help of ORSEE (Greiner 2004) from a pool of 3,800 students registered for experiments. No subject was allowed to participate in more than one session. We had 12 sessions with 20 participants in each. There were two sessions and thus 40 subjects in each of our six treatments that were as follows:

- strategic substitutes with complete information;
- strategic complements with complete information;
- strategic substitutes with incomplete information and p = 0.2;
- strategic substitutes with incomplete information and p = 0.8;
- strategic complements with incomplete information and p = 0.2;
- strategic complements with incomplete information and p = 0.8.

In each session, the 20 participants were split randomly into two matching groups of 10 subjects, and this was common information to the participants. In each of 40 periods (plus five unpaid trial periods), the members of a matching group were randomly assigned to groups of five subjects who played the stage game of a given treatment. On average, a session lasted about 80 minutes, with an average payoff of 16 Euro per subject (including a 5 Euro show-up fee).

The experimental instructions are provided in Appendix D.[14] In treatments with complete information, participants were always informed at the beginning of a period about the chosen network (which was re-drawn each period) and the participant's position in it. At the end of a period, each person received feedback about her neighbors' decisions and the payoff resulting from her choice and those of her neighbors. Before a new period began, participants also received the respective feedback for all prior periods. In treatments with incomplete information, subjects were informed about their degree at the beginning of a period. At the end of the period, each person received information about the actual network that was in effect, her position in it,

[14] We only provide the instructions for "complete information – substitutes" and "incomplete information – complements – p = 0.8". The remaining cases are analogous.

the number of her neighbors who chose to be active, and the payoff resulting from her choice and those of her neighbors.[15]

Since behavior could potentially be affected by risk preferences, we also tested for these after the 40 rounds of play, using the method described in Charness and Gneezy (2010). Each person received an endowment of 100 tokens and could invest as many of these as desired in a risky asset. This asset had a 50 percent chance of success, in which case it paid 2.5 times the number of tokens invested; the investment was lost if the asset failed. Whatever was not invested was kept. This method is easy for people to comprehend and gives a specific risk parameter, except for people who invest 100, since both risk-neutral and risk-seeking subjects should fully invest.[16]

5. Results

5.1 Measurement

The data are analyzed with an econometric model to control for robustness of our stated results. We estimate the probability of being active as a logistic function of explanatory variables listed below. We have arranged the data as a panel where the unit of observation is a participant who is observed for 40 periods. The models are estimated using random effects and are shown in Appendix A.

For the analysis of the data from complete information sessions, the explanatory variables of the econometric model are period, dummies for player position and network, all interactions between period and these dummies, and the measured level of risk aversion. One model is estimated using data from sessions with substitutes and another model is estimated using data from sessions with complements. The results are summarized by the marginal probabilities computed relative to position A in each network (see Table 4 below and the underlying models in Appendix A).

[15] Regarding the payoff transformations used in the sessions, during the experiment payoffs were given in ECUs (Experimental Currency Units). In order to facilitate calculations by the participants, in the cases of strategic substitutes, the payoffs in ECUs corresponded to those in equations (1) and (2) of section 3, but multiplied by 100. In the cases of strategic complements, in addition to multiplying payoffs by 100, we also added 50 ECUs to all the payoffs in order to avoid the possibility of losses (so that we do not need to control for loss aversion). Note that these linear transformations on the payoffs have no effects at all on the equilibrium predictions.

[16] Previous work has indicated that the proportion of risk-seeking people in experiments is 10 percent or less (e.g., see Holt and Laury, 2002).

For the analysis of the data with incomplete-information sessions, the explanatory variables of the econometric model are period, a dummy for the connectivity (with p = 0.2 as benchmark), dummies for a subject's degree and all interactions across these variables; moreover each model is estimated a second time adding the measured level of risk aversion as an explanatory variable. The results of this model are summarized by the marginal probabilities computed with respect to connectivity, degree, and risk aversion (see Table 6 below and the underlying models in Appendix A).

5.2 Complete information

Table 3 presents the summary statistics for behavior in the three networks under complete information and Figure 2 shows the evolution per network and position across the 40 rounds.[17]

Table 3 about here

For strategic substitutes the main observation is that the equilibrium where A, C and E are active, and B and D inactive (denoted ACE/BD henceforth) is focal in all networks. We observe that participants in positions A and E are active more than 90 percent of the time in all networks. Subjects in position C are active almost 70% of the time (note that position C has degree 2, in comparison to positions A and E, which have degree 1). Participants in positions B and D are inactive with a frequency higher than 80 percent in all networks. Averaging across nodes the absolute difference between the theoretical prediction and the observed behavior, individual play is consistent with the equilibrium ACE/BD in 87 percent of all cases. There is clearly no support for any of the other equilibria, so that it appears that the problem of equilibrium multiplicity is not present in a behavioral sense. In 52.5 percent of the observations the groups coordinate on this equilibrium (with a 54.1 percent rate of perfect coordination across all equilibria).

Figure 2 and Table 4 about here

[17] There are eight subjects in each network position in this treatment. Thus, the maximum number of observations behind each circle in Figure 2 is eight.

The econometric analysis confirms our previous impressions. Table 4 provides, for each network, the estimated probability that the player in position A chooses active (Prob_p_A) and the estimated difference of probabilities of choosing active between the remaining positions and position A (Dif_p_i-p_A). In all networks with strategic substitutes the estimated probability of position A choosing active is close to 100 percent and the differences from position E are never significant (see row Dif_p_E-p_A). Moreover positions B and D have a significantly lower probability of being active in all cases, with a difference of more than 90 percent. Position C has a significantly lower probability than position A in networks *Orange* and *Green*, but the difference is much lower (around 20 percent) and hence, being active is still the most likely outcome in position C. Thus, the equilibrium ACE/BD prevails in all networks. In Figure B.1 (in Appendix B), we observe that this regularity is present in all groups of subjects participating in the experiment.

Note that, across all different possible equilibria, ACE/BD is the equilibrium that involves a maximum number of active players; i.e. it is not efficient, since three people pay the cost instead of two, with complete coverage in both cases (the net social benefit is 3.5, compared to the social benefit of 4.0 with only two purchases). However, in this context a deviation from the selected equilibrium is much less harmful (and thus safer) then a deviation from the efficient equilibrium. To see this, consider any of the three efficient networks and the inefficient (but stable) equilibrium ACE/BD. If any player who is active, i.e. A, C or E, deviates to inactive, only the deviating player incurs a loss (of 1/2). On the other hand, in the efficient equilibrium more people benefit from an active agent, so that a deviation to inactive is more costly. For example, consider the equilibrium BE/ACD: If B deviates, each of A, B and C incur a loss of 1/2; therefore, a deviation is more deleterious on average.

Summarizing, there is a trade-off between efficiency and the cost of a mistake (stability). The efficient equilibrium results in a higher cost of agents' errors. Interestingly, the equilibrium ACE/BD is also the stable one in a (perturbed) dynamic set-up.[18] Boncinelli and Pin (2011) show that in Best Shot Games, the equilibrium that involves a maximum number of active players is the unique stochastically stable one. This result applies directly to our set-up.

[18] It is the *only* stable one in the *Orange* and *Green* networks, and there is an additional stable equilibrium in the *Purple* network: ACD/BE (which is also inefficient).

For complements (see the lower part of Figure 2 and the lower part of Table 3), we see an impressive rate of play (96 percent) consistent with the unique equilibrium (nobody is active) in the *Green* and *Purple* networks.[19] The *Orange* network admits two equilibria, with either three active players (B, C, and D) or none. Here the play resembles the former equilibrium, as players B, C, and D are active about 74 percent of the time, and players A and E remain inactive over 95 percent of the time. This is also the more efficient equilibrium, since players B, C, and D each earn a positive amount (1/6). Overall, the rate of play consistent with this equilibrium is over 90 percent. All the five agents jointly coordinate on the efficient equilibrium 42 percent of the time. Thus, we find strong support for the theoretical predictions, with successful coordination by players at three nodes to achieve the efficient equilibrium in the one case where this can involve a profit. Refining this analysis at the group level (see Figure B2 in Appendix B), we observe that three of the four matching groups coordinate quite well on the efficient equilibrium; however, the other group, although it first tries to coordinate on this equilibrium, finally fails to do so: in the last periods all subjects choose inactive. In general we conclude that the majority of groups playing in the *Orange* network coordinate on the efficient equilibrium (in which subjects with more than one link become active).

The marginal effects in Table 4 (computed by estimating the econometric model in Appendix A) confirm our previous impressions. In all networks the estimated probability of position A choosing active is close to 0 and the differences to position E in the *Orange* network and to positions B, C, D, and E in the other networks are never significant. In the *Orange* network, positions B, C and D show a much higher probability of being active (respectively 83, 73 and 80 percent, and significant at the 1% level).[20] Interestingly this equilibrium is very robust since it is not only a Nash equilibrium but also a strong Nash equilibrium (it is immune to deviations from any coalition of players). In contrast, the other equilibrium (all inactive) is clearly not strong Nash. We summarize these findings in our first result:

RESULT 1: *In the game of substitutes, agents' behavior in all three networks is consistent with the inefficient, but stochastically-stable and relatively riskless, equilibrium ACE/BD. In the game of complements, players in the Green and Purple*

[19] Of course, A and E will never wish to be active, since the maximum possible gain is less than the cost.

[20] A Wald test cannot reject the null hypothesis that $Dif\_p_B\text{-}p_A = Dif\_p_C\text{-}p_A = Dif\_p_D - p_A$. This suggests that players B, D, and D are equally likely to play the efficient strategy.

networks play in accordance with the unique equilibrium. In the Orange network subjects behave consistently with the efficient equilibrium BCD/AE.

Note the difference in outcomes between the two treatments: while in substitutes subjects select the inefficient equilibrium, in complements they select the efficient one. We can explain this difference by looking at the relation between efficiency and private incentives. In the game of substitutes, efficiency is achieved when players B and D are active; however, they strictly prefer the inefficient equilibrium ACE/BD that provides them a higher payoff. So they can implicitly coordinate on inactivity in order to force players A, C and E to be active.[21] With complements the private incentives are more in line with efficiency, given that the efficiency gains are earned from those subjects who are active in producing the efficient outcome.

We also explore whether equilibrium play becomes more frequent over time. In Figure 3, we plot across periods the average frequency of equilibrium play. At each period, we measure the frequency of groups such that all the members are coordinated on an equilibrium. We observe that this frequency has a positive tendency over time. For substitutes (complements) the correlation coefficient between the period and the average frequency of equilibrium play is 0.724 (0.622), with a significance level of one percent in both cases. In other words, coordination failure becomes much less frequent in later periods.

Figure 3 about here

Finally we look at the role of risk aversion. Examining all previous econometric results, we can see that they are robust to the inclusion of risk aversion. Theoretically we could expect that in both treatments, a greater degree of risk aversion is correlated with less activity in the case of strategic complements and more activity in the case of strategic substitutes. In Appendix A, we see that the marginal effect of risk aversion on the probability of being active is significant (and in the right direction) only for complements. This yields our next result:

[21] The reverse is also true: players A, C and E could implicitly coordinate on the inactivity to force players B and D to be active. But the implicit coordination could be more difficult to get across three subjects than across two, as evidence from coordination games suggests that coordination is less likely in larger groups (Weber, 2006). Note that in this set-up (strategic substitutes with complete information), the more-connected players tend to have more stable best-responses, as defined by Kovarik *et alii* (2011), which also indicates that the preferred equilibrium of the more-connected agents is played.

RESULT 2: *Both treatments of substitutes and complements display increasing coordination over the time. The effect of the level of risk aversion is small and significant only for complements.*

5.3 Incomplete information

Table 5 presents the summary statistics for behavior with incomplete information and strategic substitutes or complements under each probability regime. In strategic substitutes we observe that, in each case (p = 0.2 and p = 0.8), modal play coincides with play in the unique equilibrium. The proportions are 94.81 percent, 71.84 percent and 98.91 percent of the time, respectively, for degree 1, 2 and 3 when p = 0.2, and 92.90 percent, 59.52 percent and 89.93 percent when p = 0.8. The correspondence is excellent for degrees 1 and 3, but less so for degree 2. Overall, 87.56 percent of all choices were consistent with equilibrium play when p = 0.2 and 84.00 percent when p = 0.8.

Table 5 and Table 6 about here

This descriptive evidence is confirmed by the econometric analysis that is summarized in Table 6. It reports marginal effects (full estimations are in Appendix A). First, regarding the effect of connectivity within a particular degree (recall that the *Orange* network has higher connectivity, so the higher value of p implies higher connectivity), the behavior of players with degree 1 does not significantly differ across the values of p. For players with degree 2, the probability of being active is significantly higher with the higher value of p, with a marginal effect of 0.547 (in the model including controls for risk aversion). Finally, the probability of being active for players with degree 3 is marginally-significantly higher with the higher value of p, but the marginal effect is close to 0 (it is 0.024). Hence, our data are quite consistent with the equilibrium prediction.

Next we consider the effect of having different degrees. Having degree 2 significantly reduces the probability of being active with respect to degree 1, but the decrease is quite large when p = 0.2 (the marginal effect is -0.816), and much smaller when p = 0.8 (the marginal effect is -0.273). People with degree 3 have a significantly lower probability of choosing to be active than do people with degree 1, with a very large difference both when $p = 0.2$ (the marginal effect is -0.980), and when $p = 0.8$ (the marginal effect is -0.961). Comparing degree 3 to degree 2 we find a significantly lower probability of choosing to be active for people with degree 3, with a large difference when $p = 0.8$ (the marginal effect is -0.687), and a much lower one when $p = 0.2$ (the marginal effect is -0.164). All of the differences across the two probability values are qualitatively in the direction of the theoretical prediction. Hence, our analysis suggests that the expected effects of connectivity and degree are observed in the lab. The first two columns in Table 6 show that including risk aversion as an independent control variable leaves the estimated marginal effects of different degrees and connectivity almost identical. The risk-aversion parameter itself shows that more risk-averse subjects are less likely to be active, although the marginal effects are only marginally significant or non-significant. We summarize these findings in the following result:

> **RESULT 3***: In the game of strategic substitutes under incomplete information: a) subjects play consistently with the unique equilibrium; b) the probability of being active is decreasing with the degree and increasing with the connectivity.*

One reason why subjects with degree 2 play equilibrium strategies less frequently than subjects with degrees 1 and 3 may be due to the fact that they have a lower cost from deviating: (I) Consider the case $p = 0.2$, where players with both degree 2 and degree 3 are inactive in equilibrium. A player with degree 3 has more chances of being linked with an active player than does a player with degree 2 (i.e. the cost of deviation for a player with degree 2 is lower).[22] In this sense, if the frequency of deviation is inversely related to the cost of deviation, we expect more deviations of players with degree 2. (II) Consider the case $p = 0.8$. Here players with both degree 2 and degree 1 are active in equilibrium. Similarly, in this case, the cost of deviating to become inactive is lower for players with degree 2 than for players with degree 1 (a deviating

[22] In this case, the expected value of being inactive in equilibrium for player with degree 3 is 100 (note that he is always linked with a player with degree 1) whereas the expected value of being inactive for a player with degree 2 is lower than 100. Note that a deviating player (with degree either 2 or 3) always earns 50.

player with degree 2 is more likely to be linked to an active player), and we could expect more deviations from them.[23]

Now consider the case of strategic complements. When p = 0.2, there is a unique equilibrium (all inactive), and play by people with degrees 1 and 2 is strongly consistent with the equilibrium prediction (98.03 percent and 82.11 percent). However, subjects with degree 3 are inactive only a bit more than half the time (55.65 percent), the greatest deviation from equilibrium play that we see in all of our treatments. Still, in the aggregate, individual play is consistent with the equilibrium prediction six out of seven times. When p = 0.8 there are three equilibria, with two of these in pure strategies. Players with degree 1 are never active; in one pure-strategy equilibrium, players with both degrees 2 and 3 are active, while in the other pure-strategy equilibrium these players are inactive; in other words, it is worthwhile for players of higher degrees to coordinate on activity. The high-activity equilibrium is the efficient one, with players of higher degree making positive profits in expectation, but it is also riskier. Perhaps the tension between these two equilibria leads to only two-thirds of the overall choices being consistent with this equilibrium.

Attending to the econometric model on the right hand side of Table 6, regarding the effect of connectivity within a particular degree, the behavior of players with degree 1 does not significantly differ across the values of p. For players with degrees 2 and 3, the probability of being active is significantly higher with the higher value of p. Most likely this reflects the presence of other equilibria involving activity when p = 0.8, so that it appears that some players try to coordinate, although without much success, on the efficient equilibrium. The results are robust to the inclusion of risk attitudes, as the marginal effects are very small and insignificant. Thus, risk attitudes do not appear to play much of a role here.

Concerning the effect of the degree we see that a person with degree 2 is significantly more likely to be active than a person of degree 1, but the increase is considerably higher with p = 0.8 than with p = 0.2 (respectively the marginal effects are 0.153 and 0.041). This is qualitatively in the direction of the theoretical prediction (in contrast to the case p = 0.2, p = 0.8

[23] In this case, a player with degree 2 is located in the *Orange* network with a probability of 2/3 and in this case, if she deviates, she earns 0, whereas with a probability 1/3 if she deviates, she earns 100. On the other hand, if a player with degree 1 deviates, with a probability of 18/21, she earns 0 and with a probability of 3/21, she earns 100. Note that a non-deviating player (with degree 1 or 2) always earns 50. Hence, if a player with degree 1 deviates she switches a fixed payoff of 50 to an expected payoff of 100*3/21; whereas if a player with degree 2 deviates, she switches a fixed payoff of 50 to an expected payoff of 100*1/3. Thus the cost of deviating is lower for a player with degree 2 than for a player with degree 1.

allows for players with degree 2 to be active in equilibrium). Perhaps unsurprisingly, since players of degrees 2 and 3 make the same choice in either of the pure-strategy equilibria in this environment, the same relationship holds between subjects with degrees 1 and 3, with a higher marginal effect (0.562 versus 0.328) when $p = 0.8$. Finally we find significant evidence in both treatments that players of degree 3 are more active than players of degree 2. This evidence, not predicted by theory, could be explained by the greater incentive for players of degree 3 to get coordination on the efficient equilibrium. We summarize this evidence in our next result.

> **RESULT 4:** *In the game of strategic complements under incomplete information: a) with lower connectivity the modal play coincides with the unique equilibrium; b) the probability of being active increases with the degree and connectivity.*

We now analyze the evolution of average behavior across the 40 periods. Figure 4 suggests that, for substitutes, behavior is quite stable for players with degrees 1 and 3 (and very close to the equilibrium prediction). The frequency of choosing to be active for players with degree 2 is always below 1/2 when $p = 0.2$, and mostly above 1/2 when $p = 0.8$, which qualitatively follows the equilibrium prediction, although deviations are observed. We note that when $p = 0.8$, players of degree 2 display a convergence to the equilibrium. For complements the pattern is revealing. It seems that subjects with higher degrees attempt to coordinate on being active and making some profits; this is particularly true for players of degree 3. But this more efficient play erodes over time, with low or very low rates of activity for everyone by the end of the session. So it seems that the inefficient (but safe) equilibrium would prevail in the long run. Our interpretation is that coordination problems lead participants to eventually play the risk-dominant equilibrium. In any event, modal play (in the aggregate) corresponds to this no-activity case.

Figure 4 and Figure 5 about here

In Figure 5 we examine whether there is a trend over time toward equilibrium play. We plot across periods the average frequency of equilibrium play. At each period, we measure the frequency of groups such that all the members are coordinated on an equilibrium. We observe that this frequency is significantly positive over time, which suggests movement towards equilibrium.[24] We can state our final result:

> **RESULT 5:** *a) When players face a game of strategic substitutes with low connectivity, individual play and the level of coordination is stable over time. With higher connectivity there is a trend to the unique equilibrium and an increasing level of coordination. b) When players face a game of strategic complements, individual play with low connectivity converges to the unique equilibrium with an increasing level of coordination; individual play with higher connectivity converges to the inefficient equilibrium with an increasing level of coordination.*

6. Discussion

In this section, we address the extent to which the experimental data fits the theoretical prediction, the equilibrium selection in the different scenarios and how convergence to the equilibrium evolves over time.

6.1 Conformance of the experimental results to the theoretical predictions

Our experimental results are quite consistent with the theoretical predictions for behavior in network games. These results not only provide very strong qualitative support, but also surprisingly strong quantitative support. With complete information, subjects on average make choices that correspond to a specific equilibrium 87 percent of the time when the game involves strategic substitutes, even though there are theoretically multiple equilibria for each of the three networks. When the game involves strategic complements, play corresponds to the same specific equilibrium 96 percent of the time when there is a unique equilibrium and 74 percent of the time when there are two equilibria (overall, more than 90 percent of the time). In this latter case, the equilibrium is the efficient one. If we consider only the last 10 periods of the sessions, play corresponds to the efficient equilibrium in the *Orange* network 81 percent of the time, and to the unique equilibrium in the other networks a full 100 percent of the time (see Table 7).

[24] For substitutes the correlation coefficient between the period and the average frequency of equilibrium play is 0.233 (and non significant) with $p = 0.2$ and it is 0.594 (with a significance level of one percent) with $p = 0.8$. For complements the correlation coefficient between the period and the average frequency of equilibrium play is 0.926 with $p = 0.2$ and 0.639 with $p = 0.8$, with a significance level of one percent in both cases.

Table 7 about here

With incomplete information and substitutes, play is consistent with the unique equilibrium 89 percent of the time when p = 0.2 and 81 percent of the time when p = 0.8. These percentages are relatively low for subjects with degree 2, as there is a substantially lower expected cost if one deviates from equilibrium play. With incomplete information and complements, play is consistent with the unique equilibrium 79 percent of the time when p = 0.2 and with the same equilibrium 72 percent of the time when p = 0.8 and there are multiple theoretical equilibria (in this case the equilibrium is inefficient). However, these rates with complements are much higher if we consider only the last 10 periods of the sessions, as there is strong convergence to this equilibrium over time (95 percent and 94 percent consistency for p = 0.2 and p = 0.8, respectively; see Table 7). These results with incomplete information are particularly striking, given the far greater complexity of this environment.

In addition, the effects of degree and connectivity on activity are entirely consistent with the theoretical predictions. Proposition 6 predicts a negative relationship between degree and activity with strategic substitutes, while Proposition 7 predicts a positive relationship with strategic complements. Furthermore, activity rates for agents with degrees 2 or 3 are higher for both complements and substitutes with higher connectivity (agents with degree 1 should never be active with complements for either p-value, but should always be active with substitutes for either p-value). Indeed, these qualitative predictions are borne out by the data, as can be seen in Table 5.[25] Thus, we find that the main regularities derived from theory (in line with Galeotti *et alii* 2010), both within treatments and across treatments are confirmed by the experimental data.

6.2 Equilibrium selection

A key issue for policy is that of equilibrium selection, where theory is typically silent and experimental work is particularly useful. In our setup, we have multiplicity of equilibria in five

[25] Summarizing, the activity rates for degrees 1, 2, and 3, respectively, the rates with substitutes drop from 95 to 28 to 1 percent with p = 0.2 and from 93 to 60 to 10 percent for p = 0.8. The activity rates with complements increase from 2 to 18 to 44 percent with p = 0.2 and from 2 to 31 to 51 percent for p = 0.8. Concerning connectivity, the comparisons with substitutes across p = 0.2 and p = 0.8 are 28 versus 60 percent for degree 2 and 1 versus 10 percent for degree 3; the respective comparisons with complements are 18 versus 31 percent for degree 2 and 44 versus 51 percent for degree 3.

scenarios:[26] (i) complete information + substitutes + *Orange* network, (ii) complete information + substitutes + *Green* network, (iii) complete information + substitutes + *Purple* network, (iv) complete information + complements + *Orange* network, and (v) incomplete information + complements + p = 0.8. While the *in*efficient equilibrium (which is less risky and stochastically stable) is prominently played in the lab in cases (i), (ii), (iii) and (v), we observe that most groups adhere to the efficient equilibrium in case (iv).

These results raise the question of what reasons lie behind the observed asymmetry between complete and incomplete information in the case of complements –i.e., between cases (iv) and (v)– that is not addressed by the theory (and so is behavioral in nature). Note that in both cases, there is an efficient equilibrium (where players with degrees 2 and 3 are active) and an inefficient one (where all players are inactive). However, if subjects know with certainty that they are in the *Orange* network –case (iv)– , they mostly play the efficient equilibrium whereas, if we introduce a little bit of uncertainty –case (v)– and they are in the *Orange* network with high probability (p = 0.8), the pattern of play converges to the inefficient equilibrium.[27] Hence, stochastic stability does not work to capture these differences in behavior (in both cases it would select the inefficient equilibrium). A closely related equilibrium concept proposed by Charness and Jackson (2007), that relies on stochastic stability but considers more sophisticated players (robust belief equilibrium), does not capture these observed differences in behavior.[28]

In order to find a logic that explains the sharp difference in behavior across both scenarios, we need to rely on bounded memory (or rationality) and the ability of agents to be

[26] The theoretical multiplicity problem is not (behaviorally) present with *complete information*. Even though there are at least three equilibria for each network in the case of strategic substitutes, only one of these receives any support. This appears to be the result of pragmatic decision-making:. While the ACE/BD equilibrium provides a slightly smaller social surplus than those with only two active players (3.5 versus 4.0), it is less risky to be active in the ACE/BD network. With respect to strategic complements, only the *Orange* network has multiple equilibria. In this case, the efficient equilibrium is reached in three of the four matching groups.

[27] Although, in the first 10 periods, the activity rate for subjects with degree 2 is 55 percent and an impressive 89 percent for subjects with degree 3, this decreases precipitously to 4 percent and 15 percent, respectively, in the last 10 periods. Thus, the ambiguity regarding one's position in the network appears to erode one's belief in the possibility of coordination, so that the initial optimism about coordination on the efficient equilibrium does not last.

[28] In a robust-belief equilibrium, basically, agents incorporate the possibility that others make errors in their best responses. This assumption may reduce the number of absorbing sets or the number of states in an absorbing set and, as a consequence, the stochastically-stable states can change. However, in our setup, both in incomplete and complete information (with complements), this refinement does not cause any reduction in the number of absorbing sets nor in the number of states in each absorbing set and, therefore, the robust-belief equilibrium and the stochastically- stable state coincide: no one becomes active.

forward looking (at least to some extent).[29] Regarding bounded memory and rationality, we can observe that, if players are not completely Bayesian and update their payoff using past experience, in case (v) the efficient (and risky) equilibrium is not an absorbing state. To see this, note that in this treatment (with incomplete information) subjects can get payoffs below the secure payoff of 50 provided by inactivity, even if all players are fully coordinated on the efficient equilibrium.[30] If subjects have limited memory and update their expected payoffs with past (and recent) experiences, a few periods of experiencing payoffs below 50 suffice to move to coordination on the inefficient (and less risky) equilibrium (without the necessity of mistakes or mutations).[31] Hence, when individuals are fully coordinated on the inefficient (and less risky) equilibrium, the bounded memory is not enough to move out from this equilibrium without the presence of mutations. This could explain why we observe the convergence to the inefficient equilibrium in the treatment with complements and p = 0.8 (incomplete information).

However, in case (iv) –complete information– the efficient equilibrium is not affected by bounded memory, and it is absorbing. This happens because the efficient equilibrium is not risky (if players are not making mistakes) and, when individuals are fully coordinated on some equilibrium, individuals never experience payoffs below 50. Therefore, with complete information (in the *Orange* network) both equilibria are absorbing, which raises the question of why people coordinate more on the efficient equilibrium. We put forward two explanations:

First, there is substantial evidence that people in experiments like efficiency/payoff dominance (e.g., Charness and Rabin 2002; Engelmann and Strobel 2004), particularly without uncertainty.[32] Relatedly, note that in the *Orange* network the efficient equilibrium just requires the coordination of three individuals in a game with only two actions, and there is experimental evidence that shows that small groups of individuals coordinate more often on the efficient

[29] Indeed, an estimation of an EWA learning model (Camerer and Ho, 1999) using our experimental data (not reported here, but available upon request) suggests that: (i) individuals consider the foregone payoffs as well as the realized ones in their updating process (they are not completely stuck to their strategy), and (ii) individuals use a limited number of past experience in their updating process.

[30] It could happen, for example, to a player with degree 3 when the *Purple* network is realized.

[31] Note that, even if p = 0.8, this is not a really unlikely event. In equilibrium, although for players with degree 3 it happens only six percent of the times, for players with degree 2 there is a 25 percent chance of payoffs below 50. With a bit of noise, this percentage rises rapidly. Moreover, we also observe evidence of this in the data. It seems that subjects skip from active to inactive after some experience of low payoffs. For example, if we look at the average payoff in the rounds before subjects skip from active to inactive, their payoffs are around 21-22 (50 is the sure payoff from inactivity).

[32] Under complete information, everyone knows that everyone else knows the network structure and one's position in it (and with respect to the *Orange* network, knowing one's degree is equivalent to knowing one's position) and this induces a higher comfort level for making risky attempts at coordination.

equilibria than large groups, and that efficient coordination is more likely the fewer the number of available strategies (e.g., Weber, 2006; Feri, Irlenbusch and Sutter, 2010). Moreover, even though there is anonymity in both case (iv) and case (v), complete information has more of a feel of being in a known group, perhaps triggering a sense of group membership.[33] In some sense, there may be a parallel with the effectiveness of anonymous communication in achieving the payoff-dominant equilibrium (Cooper, DeJong, Forsythe, and Ross, 1992; Charness, 2000). Here tacit 'communication' may be present with known positions, but not otherwise.

A second, and complementary, explanation relies on the consideration that, to some extent, individuals are forward looking (i.e., not completely myopic), which may have a significant impact when studying stochastic stability, as proposed by Mengel (2011).[34,35] For example consider a coordination game with three players, two actions and suppose that the efficient action is preferred only if all players are fully coordinated on it. These are the elementary ingredients of case (iv), in which the players with degrees 2 and 3 are those who can coordinate on being active.

Consider first the traditional stochastic-stability analysis: If players are fully coordinated on the inefficient equilibrium, at least two mutations are needed to transit to the efficient equilibrium. On the contrary, if players are coordinated on the efficient equilibrium, one mutation is enough to transit to the inefficient one. Therefore the inefficient equilibrium is a stochastically-stable state. Suppose now that players are forward looking and believe that others are myopic. Assume first that there is full coordination on the inefficient state. If an agent mutates to the efficient action, the best response of a forward looking agent is to change her action, because she knows that the best response of the subsequent players will be to play the efficient action as well (provided there are two players playing it). Therefore one mutation is enough to move the system to the efficient equilibrium. With the same kind of reasoning we can state that one mutation is not enough to move the system from the efficient equilibrium to the inefficient one. Hence, the introduction of forward-looking considerations allows for the selection of the efficient equilibrium.

[33] See, for example, Goette, Hufmann and Meier (2006), Charness, Rigotti, and Rustichini (2007) and Chen and Li (2009).

[34] Note that this presumes a different kind of sophistication for best-responders in the analysis of the stochastic stability than Charness and Jackson (2007): Instead of assuming that agents incorporate the possibility that others make errors in their best responses, it presumes that players are forward-looking but believe that others are myopic.

[35] In a recent experiment, Mantovani *et alii* (2011) show that, in a network formation setup, agents are forward-looking rather than myopic.

6.3 Convergence towards equilibrium

A final important point is that the rate of conformance to the equilibrium increases dramatically over time. Perhaps the data would match the theoretical predictions even more closely over a longer number of periods. Table 7 shows the deviation rates in the last 10 periods from the predicted equilibrium in every treatment.

Play conforms very closely to what would be expected in the equilibrium that we observe in each case. Remarkably, there are absolutely no deviations from equilibrium play in 12 of the 30 cells for complete information, and in three of the 12 cells for incomplete information. The *Orange* network has a high average deviation rate of about 19 percent, mainly because of one group (out of four) who largely played the inefficient equilibrium. Overall, the rate of conformance with the claimed equilibrium is 94 percent in the final 10 periods with complete information and complements and 93 percent with complete information and substitutes. A real surprise is that this rate of conformance is equally as high with incomplete information, at 95 percent with complements and 91 percent with substitutes.

7. Conclusion

Networks are a very prevalent feature of the social and economic landscape, with important applications in the areas of bargaining, job search, political interactions, and systems compatibility, among others. The question of how network structure affects behavior is a vital one for business decisions and governmental policy. We conduct an experiment designed to test the theoretical predictions (adapted from Galeotti *et alii* 2010) for behavior in the cases of strategic complements and strategic substitutes, which are general to many economic environments. We include the case of incomplete information in our experimental design, as theory predicts this should ameliorate the problem of equilibrium multiplicity. In fact, to the best of our knowledge, we are the first to consider experimentally the challenging case of uncertainty regarding aspects of the network structure. In our view, there is almost always a degree of uncertainty concerning the prevailing network structure in the field, so this is a very relevant design choice.

We find that play conforms very strongly to the qualitative and quantitative theoretical predictions for whether agents are active or inactive. The degree to which this is true is impressive with complete information, and is somewhat startling with incomplete information, considering the cognitive challenges of making decisions under uncertainty. When we restrict our attention to the more 'settled' behavior in the last 10 periods of the sessions, we observe strong convergence to an equilibrium. In the case of incomplete information, we also find strong qualitative support for the predicted relationships between degree and activity and connectivity and activity.

A central issue in network theory is that of equilibrium selection, since it is more difficult to make informed policy decisions when one cannot predict the effects of network structure on outcomes. Considerable theoretical research has been conducted on trying to refine these or to gain insight into how to predict which of a multiplicity of equilibria actually prevails. Galeotti *et alii* (2010) refine away some more delicate equilibria by considering the case of incomplete information, while others, such as Boncinelli and Pin (2011), consider selection based on concepts such as stochastic stability. In fact, our results suggest that the problem of equilibrium multiplicity may in practice not be so severe. Even with the numerous pure-strategy equilibria with substitutes and complete information, there is a strong adherence to a specific equilibrium in each of three different networks. While this equilibrium is not the most efficient one, it is much more stable.

Thus, people seem to choose to trade off a relatively small difference in potential gain against the likelihood of actually receiving a gain. In the case of complements, there is multiplicity just in the *Orange* network scenario. In this case, the equilibrium selected is the efficient one, which can be rationalized relying on bounded memory and forward looking arguments, along with the fact that people in experiments are attracted by payoff dominance, particularly without uncertainty. With incomplete information, when there is more than one equilibrium (in the case of strategic complements), the prevailing one is the stochastically-stable (inefficient) equilibrium.

Overall, we feel that experimental research such as this shall be extremely useful in making pragmatic choices regarding which network structure to implement and in predicting outcomes for an already-existing network structure. Given the uncertainty in the field environment, incorporating incomplete information and uncertainty will certainly increase the external validity of such research. Improved behavioral network theory may well be the result of the knowledge gleaned from laboratory experiments. We encourage others to pursue this research as well.

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Tables and Figures

Table 1: Equilibria with complete information

	Network	Active nodes	Inactive nodes
Substitutes	Orange	A, C, E	B, D
		B, E	A, C, D
		A, D	B, C, E
	Green	A, C, E	B, D
		B, D	A, C, E
		B, E	A, C, D
		A, D	B, C, E
	Purple	A, C, D	B, E
		A, C, E	B, D
		B, E	A, C, D
Complements	Orange	B, C, D	A, E
		-	A, B, C, D, E
	Green	-	A, B, C, D, E
	Purple	-	A, B, C, D, E

Table 2: Equilibria with incomplete information

	Probability of g_O	Degree profile
Substitutes	0.2	(1, 0, 0)
	0.8	(1, 1, 0)
Complements	0.2	(0, 0, 0)
	0.8	(0, 0, 0)
		(0, 1, 1)
		(0, 0.65, 0.91)

Note: (x, y, z) represents the probability that participants with degree 1, 2, or 3, respectively, are active.

Table 3: Frequencies (and relative frequencies, %) of choices by network and position – Complete information

		Orange Total Choices	Orange Active (%)	Green Total Choices	Green Active (%)	Purple Total Choices	Purple Active (%)
Substitutes	A	93	88 (94.62)	105	96 (91.43)	122	113 (92.62)
	B	93	8 (8.60)	105	16 (15.24)	122	6 (4.92)
	C	93	63 (67.74)	105	70 (66.67)	122	115 (94.26)
	D	93	10 (10.75)	105	18 (17.14)	122	22 (18.03)
	E	93	85 (91.40)	105	99 (94.29)	122	112 (91.80)
	Total	465	254 (54.62)	525	299 (56.95)	610	368 (60.33)
Complements	A	114	4 (3.51)	105	1 (0.95)	101	1 (0.99)
	B	114	85 (74.56)	105	4 (3.81)	101	13 (12.87)
	C	114	83 (72.81)	105	11 (10.48)	101	1 (94.26)
	D	114	85 (74.56)	105	2 (1.90)	101	5 (18.03)
	E	114	6 (5.26)	105	1 (0.95)	101	1 (0.99)
	Total	570	263 (54.62)	525	19 (3.62)	505	21 (4.16)

Table 4: Marginal effects by player position, network and treatment – Complete information

	Substitutes			*Complements*		
	Orange	Green	Purple	Orange	Green	Purple
Prob_p_A	0.989*** (-0.007)	0.975*** (-0.014)	0.977*** (-0.013)	0.010 (-0.007)	0.000 (0.000)	0.000 (0.000)
Dif_ p_B-p_A	-0.978*** (-0.010)	-0.927*** (-0.026)	-0.965*** (-0.014)	0.833*** (-0.050)	0.007 (-0.007)	0.050* (-0.027)
Dif_p_C-p_A	-0.222*** (-0.074)	-0.221*** (-0.074)	0.012 (-0.013)	0.736*** (-0.066)	0.01 (-0.009)	0.000 (0.000)
Dif_p_D-p_A	-0.967*** (-0.015)	-0.884*** (-0.037)	-0.880*** (-0.037)	0.803*** (-0.056)	0.001 (-0.002)	0.006 (-0.007)
Dif_p_E-p_A	-0.001 (-0.014)	0.012 (-0.015)	-0.007 (-0.016)	-0.010 (-0.007)	0.001 (-0.002)	0.000 (0.000)

Notes: Prob_p_A is the estimated probability that position = A chooses active. Dif_p_i-p_A is the estimated difference (position i - position A) of probabilities of choosing active, standard errors are reported in parenthesis.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, two-tailed tests.

Table 5: Frequencies (and relative frequencies, %) of choices by connectivity (p) and degree – Incomplete information

	Degree	p = 0.2		p = 0.8	
		Total Choices	Active (%)	Total Choices	Active (%)
Substitutes	1	771	731 (94.81)	676	628 (92.90)
	2	554	156 (28.16)	378	225 (59.52)
	3	275	3 (1.09)	546	55 (10.07)
	Total	1600	890 (55.63)	1600	908 (56.75)
Complements	1	763	15 (1.97)	681	12 (1.76)
	2	598	107 (17.89)	374	116 (31.02)
	3	239	106 (44.35)	546	278 (51.01)
	Total	1600	228 (14.25)	1600	908 (25.37)

Table 6: Marginal effects on the choices of connectivity, degree and risk – Incomplete information

	Substitutes		*Complements*	
	(I)	(II)	(III)	(IV)
p = 0.8 and degree = 1	0.002 (.009)	0.004 (0.009)	-0.000 (0.001)	-0.000 (0.001)
p = 0.8 and degree = 2	0.521*** (0.087)	0.547*** (0.083)	0.111** (0.056)	0.111** (0.056)
p = 0.8 and degree = 3	0.021** (0.009)	0.024* (0.010)	0.233* (0.132)	0.233* (0.132)
degree 2 (compared to degree 1) and p = 0.2	-0.805*** (0.045)	-0.816*** (0.041)	0.041** (0.017)	0.041** (0.017)
degree 2 (compared to degree 1) and p = 0.8	-0.287*** (0.068)	-0.273*** (0.064)	0.152*** (0.053)	0.153*** (0.053)
degree 3 (compared to degree 1) and p = 0.2	-0.981*** (0.007)	-0.980*** (0.007)	0.328*** (0.091)	0.328*** (0.091)
degree 3 (compared to degree 1) and p = 0.8	-0.962*** (0.009)	-0.961*** (0.009)	0.562*** (0.095)	0.562*** (0.095)
degree 3 (compared to degree 2) and p = 0.2	-0.176*** (0.049)	-0.164*** (0.045)	0.287*** (0.079)	0.287*** (0.079)
degree 3 (compared to degree 2) and p = 0.8	-0.675*** (0.067)	-0.687*** (0.063)	0.409** (0.061)	0.409*** (0.061)
Marginal effect of risk aversion when *p* = 0.2 and degree = 1		-0.000* (0.000)		-0.000 (0.000)
Marginal effect of risk aversion when *p* = 0.2 and degree = 2		-0.002** (0.001)		-0.000 (0.000)
Marginal effect of risk aversion when *p* = 0.2 and degree = 3		-0.000 0.000)		-0.000 (0.002)
Marginal effect of risk aversion when *p* = 0.8 and degree = 1		-0.000* (0.000)		-0.000 (0.000)
Marginal effect of risk aversion when *p* = 0.8 and degree = 2		-0.003** (0.001)		-0.000 (0.001)
Marginal effect of risk aversion when *p* = 0.8 and degree = 3		-0.000* (.000)		-0.000 (0.002)

Notes: standard errors are reported in parenthesis, ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, two-tailed tests

Table 7: Deviation rates in last 10 periods from primary equilibrium

	Substitutes						*Complements*					
	Position						Position					
	A	B	C	D	E	Avg.	A	B	C	D	E	Avg.
Orange	0.05	0.05	0.27	0.05	0.00	0.08	0.06	0.30	0.27	0.30	0.00	0.19
Green	0.07	0.07	0.20	0.10	0.03	0.09	0.00	0.00	0.00	0.00	0.00	0.00
Purple	0.04	0.04	0.00	0.07	0.07	0.04	0.00	0.00	0.00	0.00	0.00	0.00
	Degree						Degree					
	1	2	3	Avg.*			1	2	3	Avg.*		
$p = 0.2$	0.02	0.27	0.00	0.10			0.00	0.04	0.10	0.03		
$p = 0.8$	0.05	0.22	0.05	0.09			0.00	0.04	0.15	0.06		

Notes: The average is calculated by weighting the rates with the number of observations in each cell.

Figure 1: The networks

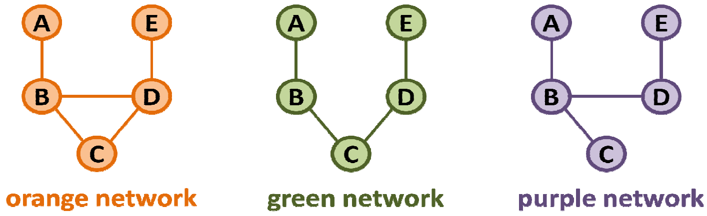


Figure 2: Relative frequency of active choices across periods, by network player position and treatment – Complete information

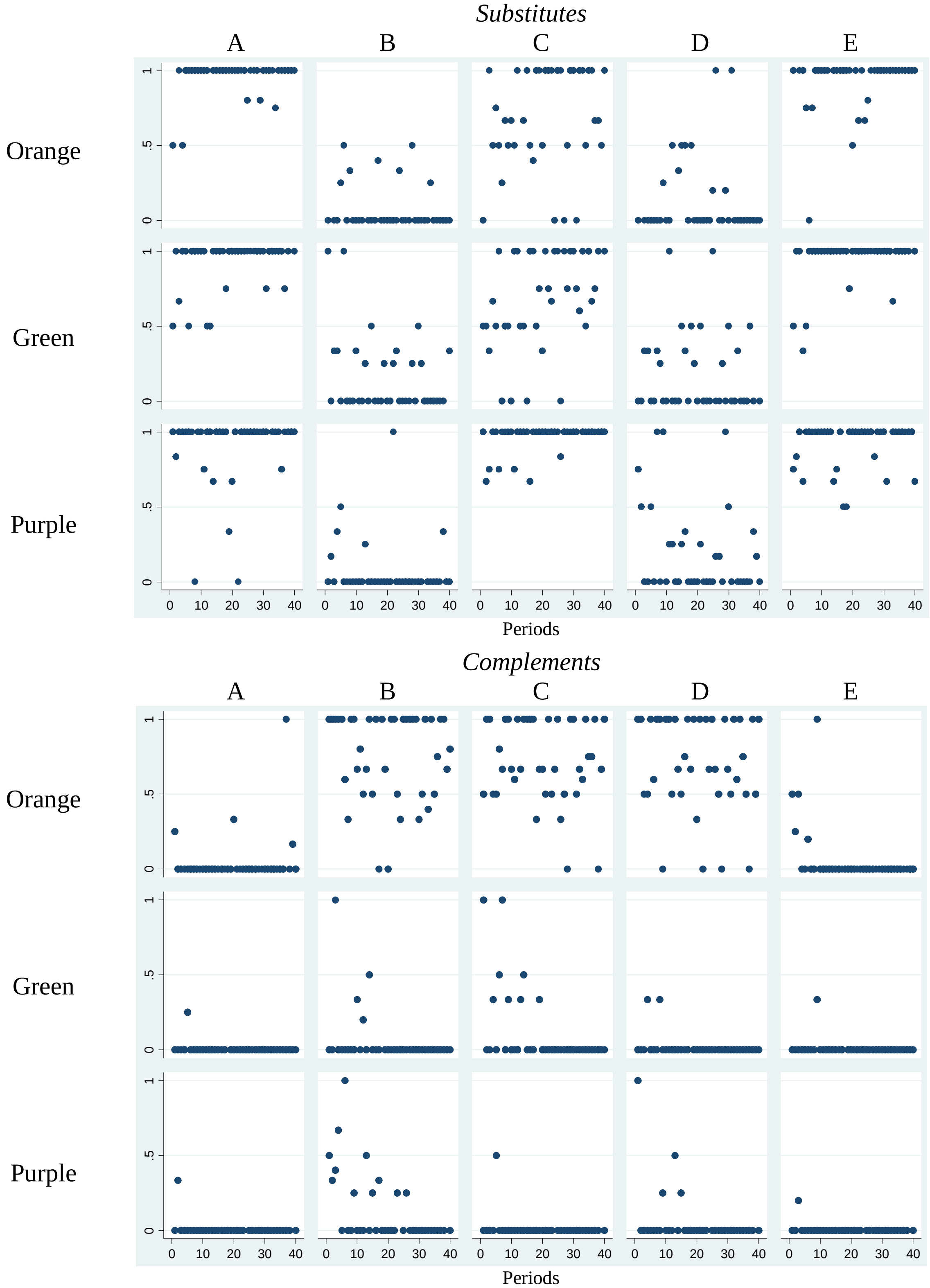


Figure 3: Relative frequency of equilibrium play across period by treatment – Complete information

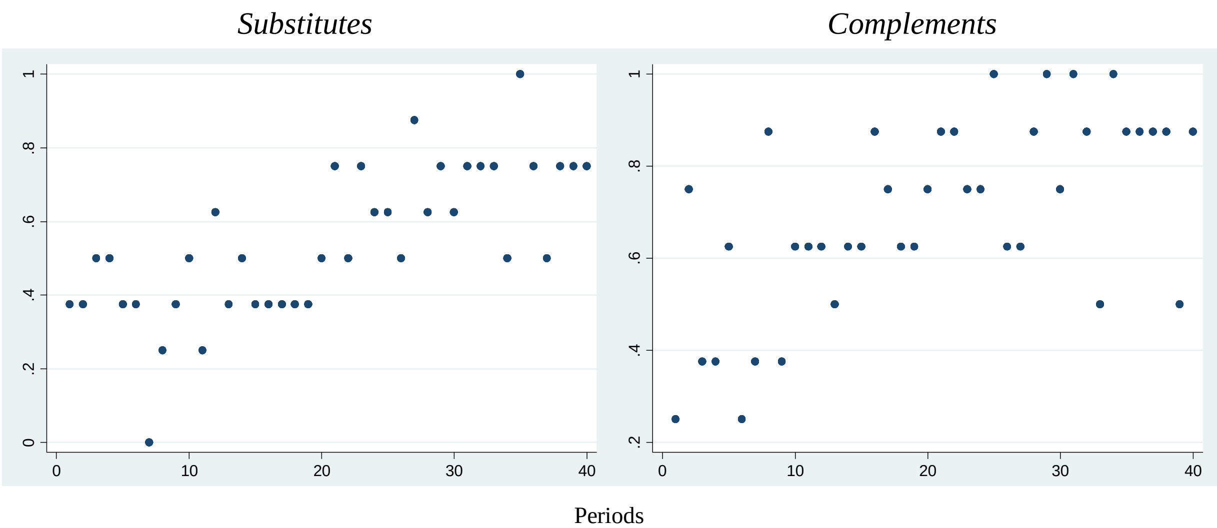


Figure 4: Relative frequencies of choices by degree, games, and connectivity (*p*) – Incomplete information

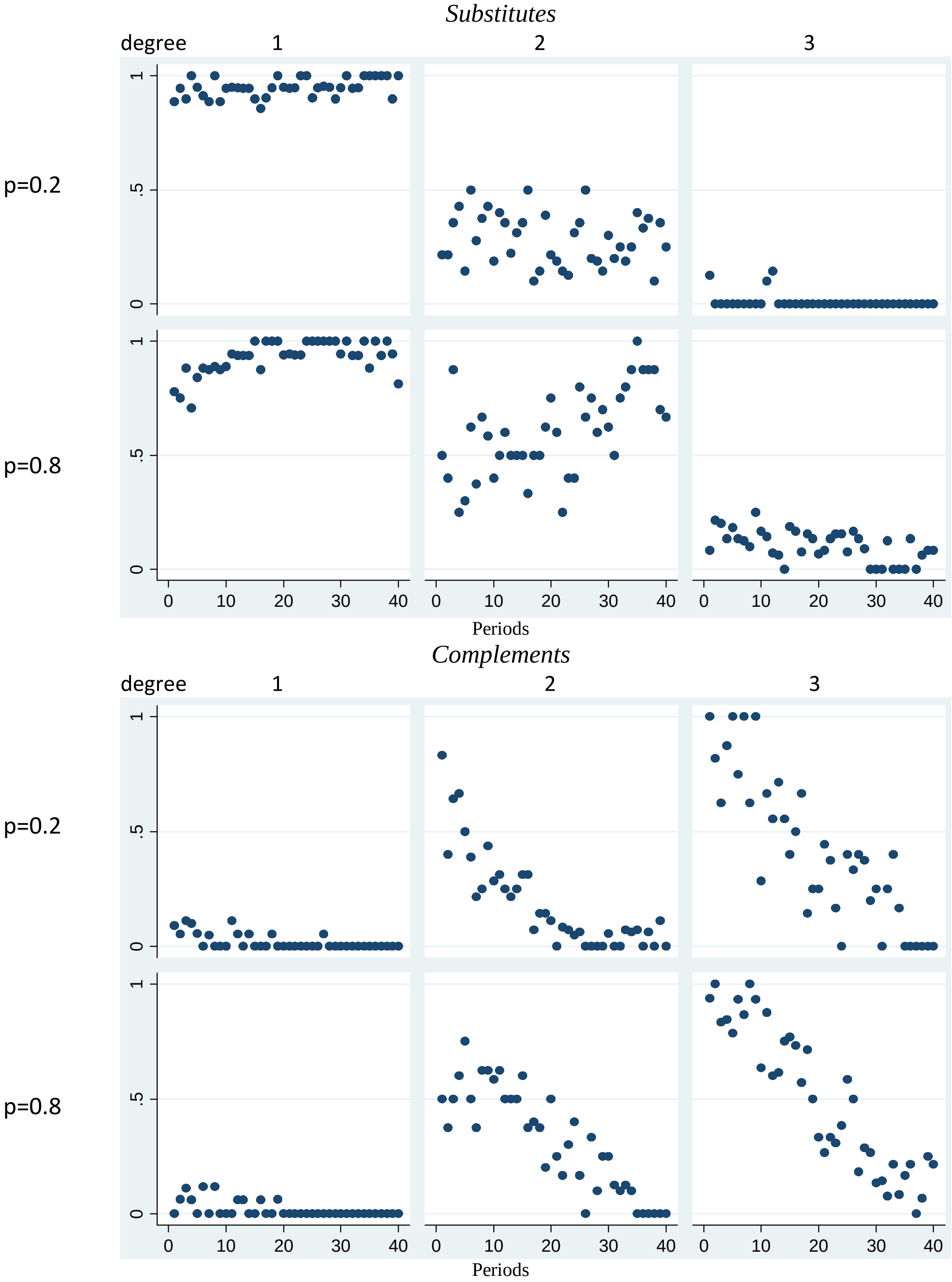
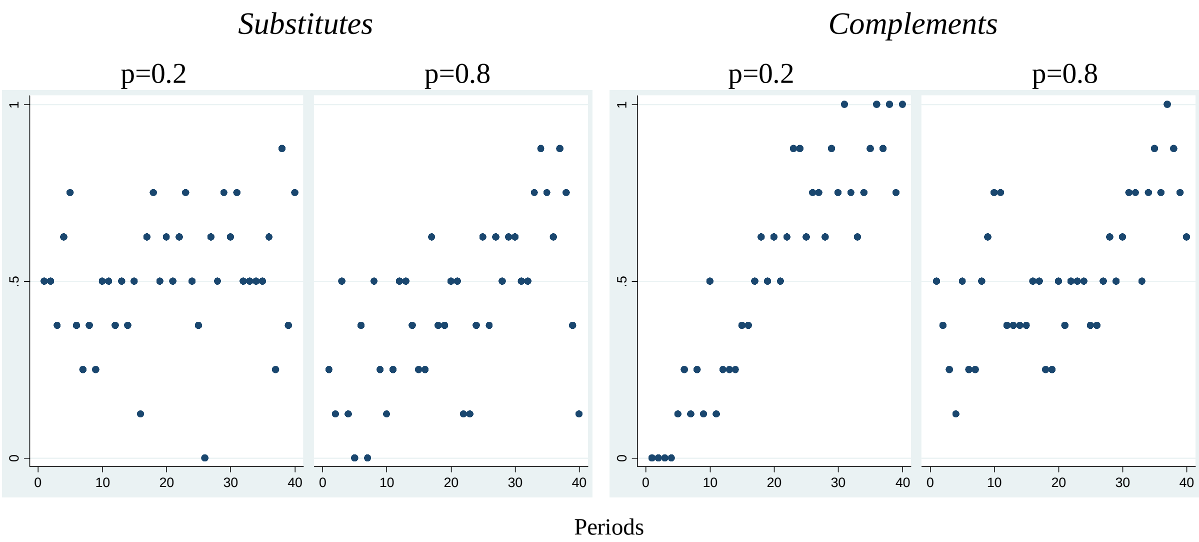


Figure 5: Relative frequencies of equilibrium play across periods by game and connectivity – Incomplete information



Appendix A: Econometric model (Variables and Estimations)

Network:

Orange = 1,
Green = 2,
Purple =3

Position:

A = 1,
B = 2,
C = 3,
D = 4,
E = 5.

Complete information

dij = 1 if network=i and position = j , 0 otherwise
tij: interaction between dij and period

Incomplete information

d1=1 if p=0.8, 0 otherwise
degree2 = 1 if player's degree=2, 0 otherwise
degree3 = 1 if player's degree=3, 0 otherwise
d1_period: interaction between period and d1
d1_degree2: interaction between d1 and degree2
d1_degree2: interaction between d1 and degree3
deg2_period: interaction between degree2 and period
deg3_period: interaction between degree3 and period
deg2_per_d1: interaction between degree2, period and d1
deg3_per_d1: interaction between degree3, period and d1.

d1_degree1: marginal effect of d1 when degree=1
d1_degree2: marginal effect of d1 when degree=2
d1_degree3: marginal effect of d1 when degree=3
degree2_d1_0: marginal effect of degree 2 (with respect to degree 1) when d1=0 (p=0.2)
degree2_d1_1: marginal effect of degree 2 (with respect to degree 1) when d1=1 (p=0.8)
degree3_d1_0: marginal effect of degree 3 (with respect to degree 1) when d1=0 (p=0.2)
degree3_d1_1: marginal effect of degree 3 (with respect to degree 1) when d1=1 (p=0.8)
degree32_d1_0: marginal effect of degree 3 (with respect to degree 2) when d1=0 (p=0.2)
degree32_d1_1: marginal effect of degree 3 (with respect to degree 2) when d1=1 (p=0.8)

risk_0_0_0: marginal effect when d1=0 and degree==1
risk_0_1_0: marginal effect when d1=0 and degree==2
risk_0_0_1: marginal effect when d1=0 and degree==3
risk_1_0_0: marginal effect when d1=1 and degree==1
risk_1_1_0: marginal effect when d1=1 and degree==2
risk_1_0_1: marginal effect when d1=1 and degree==3

Complete information - Strategic Substitutes

Random-effects logistic regression			Number of obs		=	1600
Group variable: id			Number of groups		=	40
Random effects u_i ~ Gaussian			Obs per group: min		=	40
			avg		=	40
			max		=	40
			Wald chi2(30)		=	375.7
Log likelihood = -388.50483			Prob > chi2		=	0

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.Interval]	
Period	0.030663	0.047141	0.65	0.515	-0.06173	0.123057
d12	-8.40485	1.7711	-4.75	0	-11.8761	-4.93356
d13	-3.90144	1.265561	-3.08	0.002	-6.38189	-1.42098
d14	-6.95259	1.5288	-4.55	0	-9.94899	-3.9562
d15	-1.80211	1.416295	-1.27	0.203	-4.578	0.973777
d21	-2.43685	1.350567	-1.8	0.071	-5.08391	0.210213
d22	-5.75513	1.357171	-4.24	0	-8.41514	-3.09512
d23	-4.33103	1.260564	-3.44	0.001	-6.80169	-1.86037
d24	-5.59522	1.326514	-4.22	0	-8.19514	-2.9953
d25	-1.22466	1.440592	-0.85	0.395	-4.04816	1.598853
d31	-0.87704	1.366207	-0.64	0.521	-3.55476	1.800676
d32	-6.18386	1.418038	-4.36	0	-8.96316	-3.40455
d33	-2.10023	1.34226	-1.56	0.118	-4.73101	0.530551
d34	-4.85752	1.249787	-3.89	0	-7.30706	-2.40798
d35	-1.86108	1.328373	-1.4	0.161	-4.46464	0.742488
t12	-0.03139	0.073418	-0.43	0.669	-0.17528	0.112509
t13	0.02826	0.053593	0.53	0.598	-0.07678	0.133299
t14	-0.06707	0.065325	-1.03	0.305	-0.19511	0.060959
t15	0.053105	0.068362	0.78	0.437	-0.08088	0.187091
t21	0.078902	0.061831	1.28	0.202	-0.04228	0.200088
t22	-0.0878	0.059385	-1.48	0.139	-0.20419	0.028597
t23	0.046098	0.053475	0.86	0.389	-0.05871	0.150906
t24	-0.0617	0.05645	-1.09	0.274	-0.17234	0.048942
t25	0.050011	0.074264	0.67	0.501	-0.09554	0.195565
t31	0.005485	0.061208	0.09	0.929	-0.11448	0.125452
t32	-0.13539	0.06704	-2.02	0.043	-0.26678	-0.00399
t33	0.106867	0.072718	1.47	0.142	-0.03566	0.249391
t34	-0.09514	0.05377	-1.77	0.077	-0.20053	0.010246
t35	0.040081	0.058256	0.69	0.491	-0.0741	0.154262
Risk	0.008371	0.011682	0.72	0.474	-0.01453	0.031267
_cons	3.491075	1.312174	2.66	0.008	0.919263	6.062888
/lnsig2u	1.384996	0.274943			0.846118	1.923875
sigma_u	1.998702	0.274765			1.526624	2.616761
Rho	0.548385	0.068092			0.414661	0.675469

Likelihood-ratio test of rho=0: chibar2(01) = 275.78 Prob >= chibar2 = 0.000

Marginal effects

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Period	.0003294	.0005634	0.58	0.559	-.0007748	.0014336
t12	-7.84e-06	.0006102	-0.01	0.990	-.0012038	.0011882
t13	.0106987	.0051008	2.10	0.036	.0007014	.0206961
t14	-.0008184	.0011067	-0.74	0.460	-.0029874	.0013507
t15	.0018897	.0012482	1.51	0.130	-.0005567	.0043361
t21	.0028018	.0014995	1.87	0.062	-.0001372	.0057408
t22	-.0025522	.0017662	-1.45	0.148	-.0060138	.0009095
t23	.0145285	.0055472	2.62	0.009	.0036562	.0254007
t24	-.0025986	.0027381	-0.95	0.343	-.0079652	.002768
t25	.0011056	.0007921	1.40	0.163	-.000447	.0026582
t31	.000818	.0008963	0.91	0.361	-.0009386	.0025747
t32	-.0013675	.0008659	-1.58	0.114	-.0030645	.0003296
t33	.0015022	.0008646	1.74	0.082	-.0001923	.0031968
t34	-.0054927	.0025946	-2.12	0.034	-.010578	-.0004075
t35	.0021455	.0013144	1.63	0.103	-.0004306	.0047217
Risk	.0083711	.01168	0.72	0.474	-.014525	.031267

Complete information - Strategic Complements

Random-effects logistic regression			Number of obs	=		1600
Group variable: id			Number of groups	=		40
Random effects u_i ~ Gaussian			Obs per group: min	=		40
			Avg	=		40
			Max	=		40
			Wald chi2(30)	=		234.49
Log likelihood = -280.54602			Prob > chi2	=		0
Choice	Coef.	Std. Err.	z	P>z	[95% Conf.Interval]	
Period	0.012517	0.045182	0.28	0.782	-0.07604	0.101071
d12	7.203613	1.407627	5.12	0	4.444714	9.962512
d13	5.912277	1.359848	4.35	0	3.247023	8.57753
d14	7.21883	1.402497	5.15	0	4.469987	9.967673
d15	4.015273	1.500287	2.68	0.007	1.074765	6.955781
d21	1.862151	2.698071	0.69	0.49	-3.42597	7.150273
d22	2.566745	1.610425	1.59	0.111	-0.58963	5.723119
d23	5.055612	1.463772	3.45	0.001	2.186673	7.924552
d24	2.257243	1.837471	1.23	0.219	-1.34413	5.85862
d25	1.806821	2.147597	0.84	0.4	-2.40239	6.016034
d31	4.098842	2.678017	1.53	0.126	-1.14998	9.347658
d32	4.726608	1.400217	3.38	0.001	1.982232	7.470983
d33	1.841959	2.148467	0.86	0.391	-2.36896	6.052878
d34	3.49502	1.504369	2.32	0.02	0.546511	6.443529
d35	3.505376	2.435331	1.44	0.15	-1.26779	8.278537
t12	-0.04634	0.051205	-0.9	0.365	-0.1467	0.05402
t13	-0.01217	0.050444	-0.24	0.809	-0.11104	0.086698
t14	-0.05783	0.050785	-1.14	0.255	-0.15737	0.041705
t15	-0.35341	0.138617	-2.55	0.011	-0.62509	-0.08172
t21	-0.36076	0.413782	-0.87	0.383	-1.17175	0.450241
t22	-0.1474	0.088299	-1.67	0.095	-0.32047	0.025659
t23	-0.25116	0.083561	-3.01	0.003	-0.41494	-0.08738
t24	-0.23798	0.174672	-1.36	0.173	-0.58033	0.104369
t25	-0.2018	0.16164	-1.25	0.212	-0.51861	0.115004
t31	-0.97318	0.975	-1	0.318	-2.88415	0.93778
t32	-0.15397	0.062666	-2.46	0.014	-0.2768	-0.03115
t33	-0.31792	0.270881	-1.17	0.241	-0.84884	0.212999
t34	-0.20028	0.090852	-2.2	0.027	-0.37835	-0.02222
t35	-0.61405	0.566495	-1.08	0.278	-1.72436	0.496265
Risk	0.027471	0.007972	3.45	0.001	0.011846	0.043095
_cons	-6.23145	1.347641	-4.62	0	-8.87277	-3.59012
/lnsig2u	0.778799	0.325834			0.140176	1.417423
sigma_u	1.476094	0.240481			1.072602	2.031372
Rho	0.398421	0.078097			0.259096	0.556403
Likelihood-ratio test of rho=0: chibar2(01) = 75.62 Prob >= chibar2 = 0.000						

Marginal effects

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Period	.0001233	.0004298	0.29	0.774	-.0007191	.0009658
t12	-.0044179	.0031186	-1.42	0.157	-.0105302	.0016944
t13	.0000659	.0042203	0.02	0.988	-.0082058	.0083375
t14	-.0067972	.0034897	-1.95	0.051	-.0136368	.0000424
t15	-.0001938	.0003237	-0.60	0.549	-.0008283	.0004407
t21	-.0000199	.0000978	-0.20	0.838	-.0002117	.0001718
t22	-.0009829	.0006546	-1.50	0.133	-.0022659	.0003002
t23	-.0027501	.0017791	-1.55	0.122	-.0062372	.0007369
t24	-.0002091	.0003588	-0.58	0.560	-.0009123	.0004941
t25	-.0002263	.0003052	-0.74	0.458	-.0008244	.0003719
t31	-3.47e-09	.	.	.	.	.
t32	-.0071486	.0028674	-2.49	0.013	-.0127686	-.0015287
t33	-.0000395	.0001264	-0.31	0.755	-.0002873	.0002084
t34	-.001237	.00095	-1.30	0.193	-.003099	.0006249
t35	-1.29e-06	.0000114	-0.11	0.910	-.0000236	.000021
Risk	.0274705	.00797	3.45	0.001	.011846	.043095

Incomplete information - Strategic Substitutes

I) Non including the risk variable

Random-effects logistic regression			Number of obs	=		3200
Group variable: id			Number of groups	=		80
Random effects u_i ~ Gaussian			Obs per group: min	=		40
			Avg	=		40
			Max	=		40
			Wald chi2(11)	=		668.46
Log likelihood = -837.60775			Prob > chi2	=		0
Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Period	.0353394	.0157828	2.24	0.025	.0044056	.0662731
d1	-.8188269	.6459138	-1.27	0.205	-2.084795	.4471409
degree2	-4.566573	.4437865	-10.29	0.000	-5.436379	-3.696767
degree3	-7.386604	1.027127	-7.19	0.000	-9.399737	-5.373472
d1_period	.0466305	.0242528	1.92	0.055	-.0009042	.0941651
d1_degree2	1.648846	.6139654	2.69	0.007	.4454959	2.852196
d1_degree3	2.438584	1.149082	2.12	0.034	.1864249	4.690743
deg2_period	-.050013	.0189049	-2.65	0.008	-.0870659	-.0129601
deg3_period	-.1621972	.0830486	-1.95	0.051	-.3249694	.000575
deg2_per_d1	.0305168	.0289488	1.05	0.292	-.0262219	.0872555
deg3_per_d1	.0142048	.0874948	0.16	0.871	-.1572819	.1856914
_cons	3.323875	.4665528	7.12	0.000	2.409449	4.238302
/lnsig2u	1.337087	.1957578			.9534084	1.720765
sigma_u	1.951393	.1910002	1.610757	2.364065	sigma_u	1.951393
Rho	.5364948	.0486787	.4409175	.6294639	rho	.5364948
Likelihood-ratio test of rho=0: chibar2(01) = 490.93 Prob >= chibar2 = 0.000						

Marginal effect

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
d1_degree1	.0018477	.0090151	0.20	0.838	-.0158217	.0195171
d1_degree2	.5206969	.0873879	5.96	0.000	.3494198	.691974
d1_degree3	.0213193	.0093988	2.27	0.023	.002898	.0397405
degree2_d1_0	-.8054548	.0451776	-17.83	0.000	-.8940012	-.7169084
degree2_d1_1	-.2866056	.067589	-4.24	0.000	-.4190775	-.1541336
degree3_d1_0	-.9811888	.0065618	-149.53	0.000	-.9940496	-.9683279
degree3_d1_1	-.9617172	.008591	-111.95	0.000	-.9785552	-.9448792
degree32_d1_0	-.175734	.0488696	-3.60	0.000	-.2715167	-.0799512
degree32_d1_1	-.6751116	.0667504	-10.11	0.000	-.8059401	-.5442832

II) Including the risk variable

Random-effects logistic regression			Number of obs	=		3200
Group variable: id			Number of groups	=		80
Random effects u_i ~ Gaussian			Obs per group: min	=		40
			Avg	=		40
			Max	=		40
			Wald chi2(12)	=		669.38
Log likelihood = -835.0852			Prob > chi2	=		0
Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Period	.0353746	.0157977	2.24	0.025	.0044117	.0663375
d1	-.6814024	.6378184	-1.07	0.285	-1.931503	.5686988
degree2	-4.581403	.4443026	-10.31	0.000	-5.45222	-3.710586
degree3	-7.392577	1.027527	-7.19	0.000	-9.406494	-5.37866
d1_period	.0466369	.0242576	1.92	0.055	-.0009071	.094181
d1_degree2	1.671407	.6139628	2.72	0.006	.4680618	2.874752
d1_degree3	2.461545	1.148353	2.14	0.032	.210815	4.712274
deg2_period	-.0500117	.0189244	-2.64	0.008	-.0871029	-.0129206
deg3_period	-.162495	.0831316	-1.95	0.051	-.32543	.0004399
deg2_per_d1	.0302095	.0289505	1.04	0.297	-.0265325	.0869514
deg3_per_d1	.0148065	.0875422	0.17	0.866	-.1567731	.1863861
Risk	-.0158006	.0069383	-2.28	0.023	-.0293993	-.0022018
_cons	4.136116	.5870075	7.05	0.000	2.985603	5.28663
/lnsig2u	1.261315	.1973897	.8744378	1.648191	/lnsig2u	1.261315
sigma_u	1.878845	.1854324	1.548395	2.279818	sigma_u	1.878845
Rho	.5176095	.0492862	.421551	.6123839	rho	.5176095
Likelihood-ratio test of rho=0: chibar2(01) = 453.07 Prob >= chibar2 = 0.000						

Marginal effect

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
d1_degree1	.004092	.0089446	0.46	0.647	-.0134391	.0216232
d1_degree2	.5471342	.0826837	6.62	0.000	.3850772	.7091913
d1_degree3	.0235348	.0099948	2.35	0.019	.0039455	.0431242
degree2_d1_0	-.8161774	.0414533	-19.69	0.000	-.8974244	-.7349305
degree2_d1_1	-.2731352	.0642068	-4.25	0.000	-.3989783	-.1472921
degree3_d1_0	-.980062	.0068608	-142.85	0.000	-.9935089	-.9666151
degree3_d1_1	-.9606192	.0090874	-105.71	0.000	-.9784301	-.9428083
degree32_d~0	-.1638846	.0451955	-3.63	0.000	-.252466	-.0753031
degree32_d~1	-.687484	.0628339	-10.94	0.000	-.8106361	-.5643318
risk_0_0_0	-.0002897	.0001697	-1.71	0.088	-.0006223	.0000429
risk_0_1_0	-.0021784	.0010144	-2.15	0.032	-.0041666	-.0001901
risk_0_0_1	-.0000198	.0000251	-0.79	0.431	-.000069	.0000294
risk_1_0_0	-.0002272	.0001254	-1.81	0.070	-.0004729	.0000185
risk_1_1_0	-.0032382	.0014454	-2.24	0.025	-.0060711	-.0004052
risk_1_0_1	-.0003819	.0002303	-1.66	0.097	-.0008333	.0000695

Incomplete information - Strategic Complements

I) Non including the risk variable

Random-effects logistic regression			Number of obs		=	3200
Group variable: id			Number of groups		=	80
Random effects u_i ~ Gaussian			Obs per group: min		=	40
			avg		=	40
			max		=	40
			Wald chi2(11)		=	453.63
Log likelihood = -708.10264			Prob > chi2		=	0

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Period	-0.14473	0.040886	-3.54	0	-0.22487	-0.0646
d1	-0.50301	0.892839	-0.56	0.573	-2.25295	1.246919
degree2	4.341164	0.587702	7.39	0	3.18929	5.493038
degree3	7.213044	0.756647	9.53	0	5.730044	8.696044
d1_period	0.00959	0.059068	0.16	0.871	-0.10618	0.12536
d1_degree2	1.386266	0.881645	1.57	0.116	-0.34173	3.114258
d1_degree3	1.891964	1.030358	1.84	0.066	-0.1275	3.911429
deg2_period	-0.04366	0.044415	-0.98	0.326	-0.13071	0.043393
deg3_period	-0.0674	0.047183	-1.43	0.153	-0.15988	0.025075
deg2_per_d1	0.01618	0.063925	0.25	0.8	-0.10911	0.141471
deg3_per_d1	-0.03096	0.065662	-0.47	0.637	-0.15966	0.09773
_cons	-3.67977	0.62245	-5.91	0	-4.89975	-2.45979
/lnsig2u	1.645845	0.207959			1.238252	2.053437
sigma_u	2.277145	0.236777			1.857304	2.791889
Rho	0.611827	0.049389			0.511849	0.703201
Likelihood-ratio test of rho=0: chibar2(01) = 459.91 Prob >= chibar2 = 0.000						

Marginal effect

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
d1_degree1	-.0003723	.0012022	-0.31	0.757	-.0027285	.0019839
d1_degree2	.1106046	.0557568	1.98	0.047	.0013234	.2198859
d1_degree3	.232949	.1322903	1.76	0.078	-.0263352	.4922333
degree2_d1_0	.0414475	.0172073	2.41	0.016	.0077219	.0751732
degree2_d1_1	.1524245	.0528636	2.88	0.004	.0488137	.2560353
degree3_d1_0	.3283258	.0912503	3.60	0.000	.1494784	.5071731
degree3_d1_1	.5616471	.0949516	5.92	0.000	.3755454	.7477488
degree32_d~0	.2868782	.0791469	3.62	0.000	.1317532	.4420032
degree32_d~1	.4092226	.0609084	6.72	0.000	.2898443	.5286009

II) Including the risk variable

Random-effects logistic regression			Number of obs	=		3200
Group variable: id			Number of groups	=		80
Random effects u_i ~ Gaussian			Obs per group: min	=		40
			Avg	=		40
			Max	=		40
			Wald chi2(12)	=		453.60
Log likelihood = -708.07396			Prob > chi2	=		0

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Period	-.1447516	.0408935	-3.54	0.000	-.2249014	-.0646018
d1	-.5010158	.8928432	-0.56	0.575	-2.250956	1.248925
degree2	4.341514	.5878049	7.39	0.000	3.189437	5.49359
degree3	7.213081	.7566286	9.53	0.000	5.730116	8.696045
d1_period	.0096085	.0590735	0.16	0.871	-.1061734	.1253905
d1_degree2	1.385479	.8816709	1.57	0.116	-.3425639	3.113522
d1_degree3	1.891547	1.03034	1.84	0.066	-.1278814	3.910976
deg2_period	-.0436345	.0444213	-0.98	0.326	-.1306986	.0434297
deg3_period	-.0674082	.047188	-1.43	0.153	-.1598949	.0250785
deg2_per_d1	.016171	.0639297	0.25	0.800	-.1091288	.1414708
deg3_per_d1	-.0309548	.0656667	-0.47	0.637	-.1596591	.0977496
Risk	-.0019786	.0082606	-0.24	0.811	-.0181691	.0142118
_cons	-3.559826	.797559	-4.46	0.000	-5.123013	-1.996639
/lnsig2u	1.645359	.2079661	1.237753	2.052965	/lnsig2u	1.645359
sigma_u	2.276592	.236727	1.856841	2.791231	sigma_u	2.276592
Rho	.6117114	.0493962	.5117242	.7031029	rho	.6117114
Likelihood-ratio test of rho=0: chibar2(01) = 459.57 Prob >= chibar2 = 0.000						

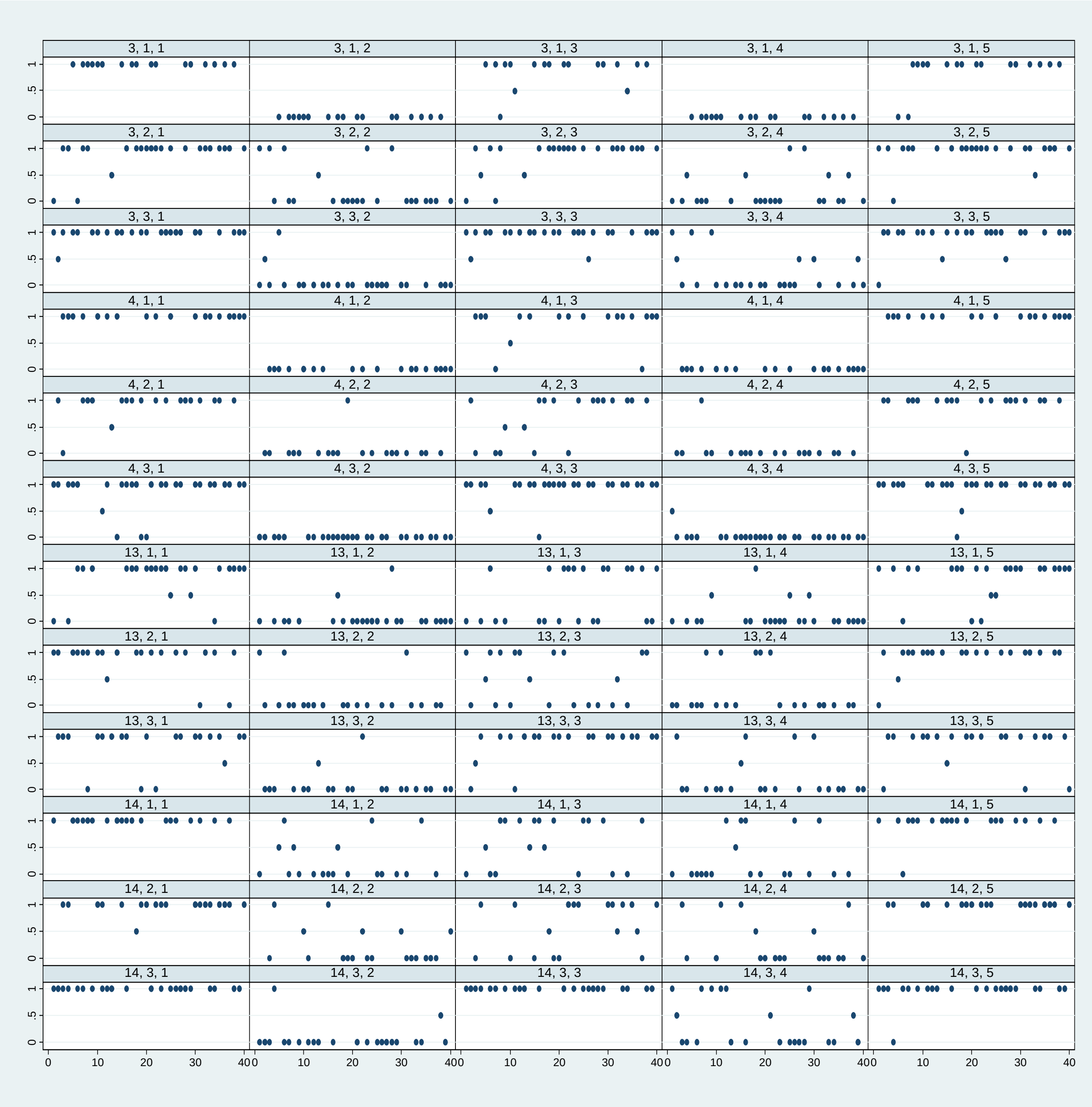
Marginal effect

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
d1_degree1	-.0003694	.0012015	-0.31	0.759	-.0027243	.0019855
d1_degree2	.1107319	.0557719	1.99	0.047	.0014209	.2200429
d1_degree3	.2334398	.1322453	1.77	0.078	-.0257562	.4926359
degree2_d1_0	.0414237	.0171952	2.41	0.016	.0077216	.0751257
degree2_d1_1	.1525249	.0528829	2.88	0.004	.0488763	.2561735
degree3_d1_0	.3279842	.0911988	3.60	0.000	.1492378	.5067307
degree3_d1_1	.5617934	.0949291	5.92	0.000	.3757358	.7478511
degree32_d~0	.2865606	.0791045	3.62	0.000	.1315186	.4416025
degree32_d~1	.4092685	.0608862	6.72	0.000	.2899337	.5286033
risk_0_0_0	-2.75e-06	.0000119	-0.23	0.817	-.000026	.0000205
risk_0_1_0	-.0000811	.0003397	-0.24	0.811	-.000747	.0005848
risk_0_0_1	-.0004371	.0018246	-0.24	0.811	-.0040132	.0031391
risk_1_0_0	-2.02e-06	8.78e-06	-0.23	0.818	-.0000192	.0000152
risk_1_1_0	-.0002572	.0010765	-0.24	0.811	-.002367	.0018527
risk_1_0_1	-.0004869	.0020325	-0.24	0.811	-.0044706	.0034969

Appendix B: Figures by groups

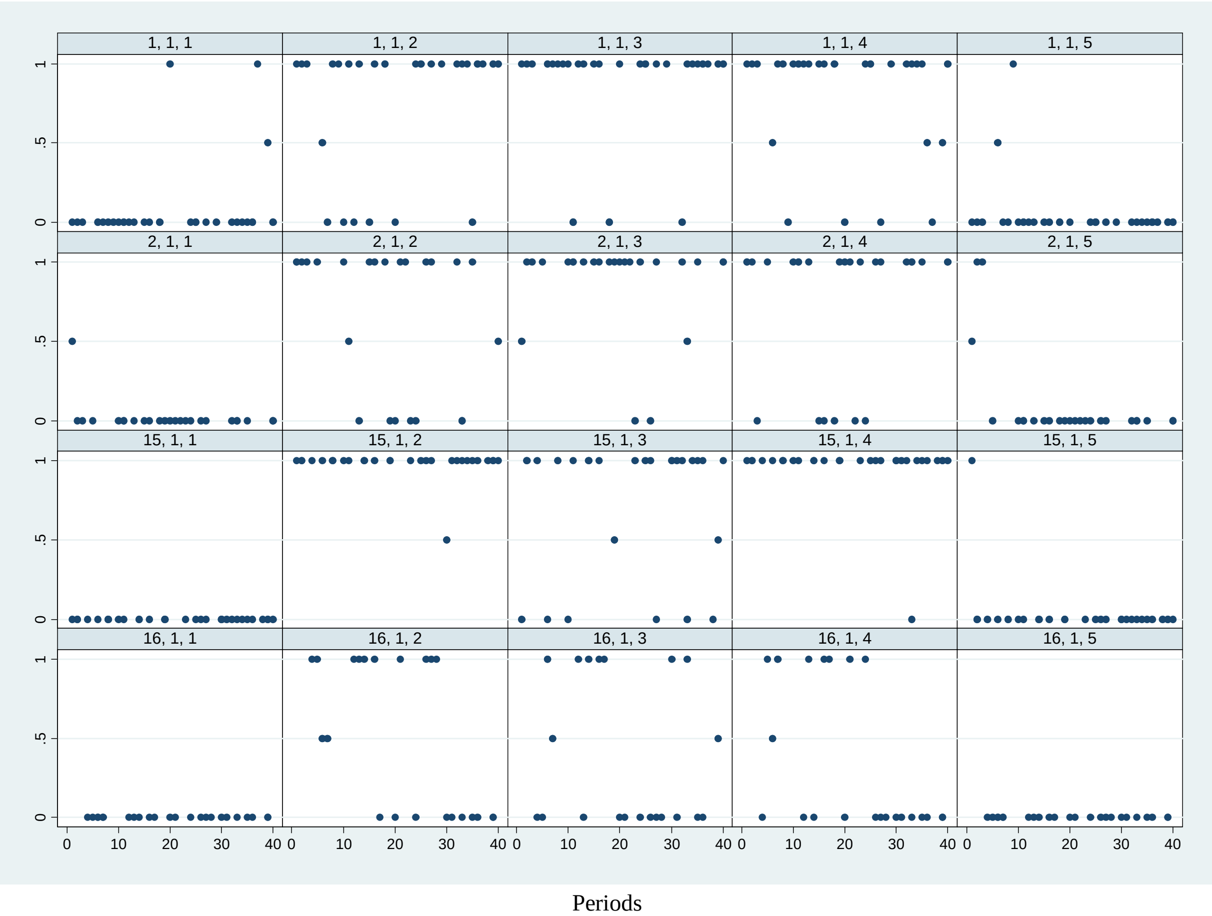
(x,y,z) means group x, network y position z where **Network:** Orange = 1, Green = 2, Purple =3 **Position:** A = 1, B = 2, C = 3, D = 4, E = 5.

Figure B.1: Complete information and substitutes: Relative frequencies of active choices across periods, by group, network and position.



Periods

Figure B.2: Complete information and complements: Relative frequencies of active choices across periods, by group and position in the Orange network.



Appendix C: Proofs

Complete information scenario – Strategic substitutes

For each $i \in \{A, B, C, D, E\}$, Let $m_i \in [0,1]$ be the probability to be active of the player in position i. Let $n_i = |N_i|$.

A Nash equilibrium in mixed strategies is described by $\sigma \equiv (m_A, m_B, m_C, m_D, m_E)$. We first state and prove some lemmas that shall be latter used in the proofs of Propositions 1, 2 and 3.

Lemma 1. *Consider the scenario of strategic substitutes and complete information. In a Nash equilibrium either* $m_i \in [0, 0.5]$ *or* $m_i = 1$.

Proof: Assume $m_i \in (0.5, 1)$; then for all $j \in N_i$ the best response of player j is $m_j = 0$, because $E_j(0) > 0.5$. However, in this case, the best response of player i implies that $m_i = 1$, a contradiction. QED

Lemma 2. *Consider the scenario of strategic substitutes and complete information. In a Nash equilibrium*

a) *If* $m_i \in (0, 0.5]$, *then,* $\prod_{j \in N_i}(1 - m_j) = 0.5$ *and, for all* $\in N_i$, $m_j \in [0, 0.5]$.
b) $m_i = 1$ *if and only if, for all* $j \in N_i, m_j = 0$.
c) $m_i = 0$ *if and only if* $\prod_{j \in N_i}(1 - m_j) \leq 0.5$

Proof: Part (*a*). The condition $E_i(0) = E_i(1) = 0.5$ must hold. Hence, $E_i(0) = (1 - \prod_{j \in N_i}(1 - m_j)) = 0.5$, and the claim follows. Part (*b*). It directly follows from the best response of players j, given that $E_j(0) = 1$ and $E_j(1) = 0.5$. Part (*c*). It must be the case that $E_i(0) = (1 - \prod_{j \in N_i}(1 - p_j)) \geq 0.5$. Hence, the claim follows. QED

The following remark describes some special cases of Lemma 2.

Remark 1. *Let* $n_i = 1$, *in a Nash equilibrium*:

a) *If* $m_i \in (0, 0.5]$ *and* $j \in N_i$, *then* $m_j = 0.5$.
b) *If* $m_i = 0$ *and* $j \in N_i$, *then* $m_j = 1$.

Lemma 3. *Let* $j \in N_i$ *and* $n_j = 1$. *In a Nash equilibrium, if* $m_i \in (0, 0.5]$, *then* $m_i = 0.5$.

Proof: Let $m_i \in (0, 0.5)$, the best response of player j implies $m_j = 1$. Therefore, the best response of player i implies $m_i = 1$, a contradiction. QED

In the following proofs (Propositions 1-3), in order to compute the Nash equilibria in mixed strategies (the proofs are constructive), we start by assuming a Nash equilibrium where one player is using a mixed strategy. Then, we explore all strategy profiles consistent with a Nash equilibrium. Note that, when we are assuming that (in a Nash equilibrium) a player i is playing a mixed strategy, by Lemma 1 we know that $m_i \in (0, 0.5]$.

Proof of Proposition 1.

The characterization of the pure strategy Nash equilibria directly follows from part (*b*) of Lemma 2. In order to characterize the mixed strategy equilibria, we analyze three cases (the other ones are symmetric): $m_A \in (0, 0.5], m_B \in (0, 0.5]$, and $m_C \in (0, 0.5]$.

Case 1: $m_A \in (0, 0.5]$.
By part (*a*) in Remark 1, we have that $m_B = 0.5$ and, by part (*a*) in Lemma 2,

(3) $\quad (1 - m_A)(1 - m_C)(1 - m_D) = 0.5 \text{ } and \text{ } m_A, m_C, m_D \in [0, 0.5]$

By Lemmas 2 and 4, $m_D \in \{0, 0.5\}$. Assume $m_D = 0$, by (3) we have that $m_C = 1 - \frac{0.5}{1-m_A}$ and by part (*b*) of Remark 1, $m_E = 1$. Hence, the following set of strategy profiles are Nash equilibria: $(m_A, 0.5, 1 - \frac{0.5}{1-m_A}, 0, 1)$ with $0 < m_A \leq 0.5$. By symmetry, the following set of strategy profiles are also Nash equilibria: $(1, 0, 1 - \frac{0.5}{1-m_E}, 0.5, m_E)$ with $0 < m_E \leq 0.5$. Assume now $p_D = 0.5$. Then, condition (3) is not satisfied.

Case 2: $m_B \in (0, 0.5]$.
By Lemma 3, $m_B = 0.5$. The case $m_A \in (0, 0.5]$ is discussed above. By part (*a*) of Lemma 2 we only need to discuss the case $m_A = 0$. Moreover, by Lemmas 2 and 4, $m_D \in \{0, 0.5\}$. Assume $m_D = 0$, by (3) we have that $m_C = 0.5$ and, by part (*b*) of Remark 1, $m_E = 1$. Hence, $(0, 0.5, 0.5, 0, 1)$ is a Nash equilibrium. By symmetry, also $(1, 0, 0.5, 0.5, 0)$ is a Nash equilibrium. Assume now $m_D = 0.5$. By (3), $m_C = 0$ and, from part (*a*) of Lemma 2, $m_E = 0$. Hence, $(0, 0.5, 0, 0.5, 0)$ is a Nash equilibrium.

Case 3: $m_C \in (0, 0.5]$.
By part (*a*) of Lemma 2, $m_B, m_D \in [0, 0.5]$ and, by Lemma 3, $m_B, m_D \in \{0, 0.5\}$. By part (*a*) of Lemma 2, $m_B = m_D = 0$ and $m_B = m_D = 0.5$ are not part of a Nash equilibrium. On the other hand, assuming either $p_B = 0.5 \text{ } and \text{ } p_D = 0$, or $p_B = 0 \text{ } and \text{ } p_D = 0.5$, we obtain the equilibria described in Case 1. This concludes the equilibrium characterization. QED

Proof of Proposition 2.

The characterization of the pure strategy Nash equilibria directly follows from part (*b*) of Lemma 2. In order to characterize the mixed strategy equilibria, we analyze three cases (the other ones are symmetric): $m_A \in (0, 0.5], m_B \in (0, 0.5]$, and $m_C \in (0, 0.5]$.

Case 1: $m_A \in (0, 0.5]$.
By part (*a*) of Remark 1, we have that $m_B = 0.5$ and, by part (*a*) of Lemma 2,

(4) $(1 - m_A)(1 - m_C) = 0.5$ *and* $m_A, m_C, m_D \in [0, 0.5]$

By condition (4), we have that $m_C = 1 - \frac{0.5}{1-m_A}$. If $m_A = 0.5$, then $m_C = 0$. Hence, $(0.5, 0.5, 0, 0.5, 0.5)$, $(0.5, 0.5, 0, 1, 0)$, and $(0.5, 0.5, 0, 0, 1)$ are Nash equilibria. By symmetry, $(0, 1, 0, 0.5, 0.5)$ and $(1, 0, 0, 0.5, 0.5)$ are also Nash equilibria. If $m_A \in (0, 0.5)$, then $m_C > 0$. Then, by part (*a*) of Lemma 2, $m_D = 0$ and, by part (*b*) of Remark 1, $m_E = 1$. Hence, the following set of strategy profiles are Nash equilibria: $(m_A, 0.5, 1 - \frac{0.5}{1-m_A}, 0, 1)$ with $0 < m_A < 0.5$. By symmetry, the following set of strategy profiles are also Nash equilibria: $(1, 0, 1 - \frac{0.5}{1-m_E}, 0.5, m_E)$ where $0 < m_E < 0.5$.

Case 2: $m_B \in (0, 0.5]$.
By Lemma 3, $m_B = 0.5$. The case $m_A \in (0, 0.5]$ is discussed above. By part (*a*) of Lemma 2, we only need to discuss the case $m_A = 0$. By Lemma 2, $m_C = 0.5$ and $m_D = 0$. Moreover, by part (*b*) of Remark 1, $m_E = 1$. Hence, $(0, 0.5, 0.5, 0, 1)$ is a Nash equilibrium. By symmetry, $(1, 0, 0.5, 0.5, 0)$ is also an equilibrium.

Case 3: $m_C \in (0, 0.5]$.
By part (*a*) of Lemma 2, $m_B, m_D \in [0, 0.5]$ and, by Lemma 3, $m_B, m_D \in \{0, 0.5\}$. By part a in Lemma 2, $m_B = m_D = 0$ and $m_B = m_D = 0.5$ cannot be part of a Nash equilibrium. Assuming either $m_B = 0.5$ *and* $m_D = 0$, or $m_B = 0$ *and* $m_D = 0.5$, we obtain the same equilibria described in the previous case. This concludes the equilibrium characterization. QED

Proof of Proposition 3.

The characterization of the pure strategy Nash equilibria directly follows from part (*b*) of Lemma 2. In order to characterize the mixed strategy equilibria, we analyze four cases (the remaining one is symmetric): $m_A \in (0, 0.5], m_B \in (0, 0.5]$, $m_D \in (0, 0.5]$, and $m_E \in (0, 0.5]$.

Case 1: $m_A \in (0, 0.5]$.
By part (*a*) of Remark 1, $m_B = 0.5$ and, by part (*a*) of Lemma 2:

(5) $\quad (1-m_A)(1-m_C)(1-m_D) = 0.5 \textit{ and } m_A, m_C, m_D \in [0, 0.5]$

By Lemma 3, $m_D \in \{0, 0.5\}$. Assume $m_D = 0.5$. Condition (5) implies that $m_A = 0$, a contradiction. Assume now $m_D = 0$. By condition (5), $m_C = 1 - \frac{0.5}{1-p_A m_A}$ and, by part (*b*) of Remark 1, $m_E = 1$. Hence, the following set of strategy profiles are Nash equilibria: $(m_A, 0.5, 1 - \frac{0.5}{1-m_A}, 0, 1)$ with $0 < m_A < 0.5$. By symmetry, the following set of strategy profiles are also Nash equilibria: $(1 - \frac{0.5}{1-m_C}, 0.5, m_C, 0, 1)$ with $0 < m_C < 0.5$.

Case 2: $m_B \in (0, 0.5]$.

By Lemma 3, $m_B = 0.5$ and $m_D \in \{0, 0.5\}$. If $m_D = 0$, by part (*b*) of Remark 1, $m_E = 1$ and, by part (*a*) of Lemma 2, $m_C = 1 - \frac{0.5}{1-m_A}$ with $m_A \in [0, 0.5]$. Then, the following set of strategy profiles are Nash equilibria: $(m_A, 0.5, 1 - \frac{0.5}{1-m_A}, 0, 1)$ with $m_A \in [0, 0.5]$. By symmetry, the following set of strategy profiles are also Nash equilibria: $(1 - \frac{0.5}{1-m_C}, 0.5, m_C, 0, 1)$ where $m_C \in [0, 0.5]$. (Note that these equilibria include the ones found in previous case). If $m_D = 0.5$, by part (*a*) of Lemma 2, $p_A = 0$, $p_C = 0$ and $p_E = 0$. Hence, $(0, 0.5, 0, 0.5, 0)$ is a Nash equilibrium.

Case 3: $m_D \in (0, 0.5]$.

By Lemma 3, $m_D = 0.5$. By part (*a*) of Lemma 2,

(6) $\quad (1-m_B)(1-m_E) = 0.5 \textit{ and } m_B, m_E \in [0, 0.5]$

By Lemma 3, $m_B \in \{0, 0.5\}$. Assume $m_B = 0$. By part (*b*) of Remark 1, $m_A = m_C = 1$. Then, by (6), $m_E = 0.5$. Hence, $(1, 0, 1, 0.5, 0.5)$ is a Nash equilibrium. Assume now $m_B = 0.5$. By (6), $p_E = 0$. Then, by part (*a*) of Lemma 2, $p_A = 0$ and $p_C = 0$. Hence, $(0, 0.5, 0, 0.5, 0)$ is a Nash equilibrium.

Case 4: $m_E \in (0, 0.5]$.

By part (*a*) of Remark 1, $m_D = 0.5$. Then, by part (*a*) of Lemma 2,

(7) $\quad (1-m_B)(1-m_E) = 0.5.$

Since $m_E > 0$, condition (7) implies $m_B < 0.5$. Then, by Lemma 3, $m_B = 0$ and, by part (*b*) of Lemma 2, $m_A = m_C = 1$. Finally, (7) implies $m_E = 0.5$. Hence, $(1, 0, 1, 0.5, 0.5)$ is a Nash equilibrium. This concludes the equilibrium characterization. QED

Complete information scenario – Strategic complements

Proof of Proposition 4.

For each $i \in \{A, B, C, D, E\}$ such that $n_i = 1$, i's best response implies $m_i = 0$, since her payoff from choosing action 1 is $1/3 - 1/2 < 0$. Hence, in all Nash equilibria, $m_A = m_E = 0$.

We first, characterize the pure strategy Nash equilibria. For each of the players B, C and D, in order to find optimal to choose action 1, it is requires that at least two of their neighbors also choose 1, otherwise they prefer action 0. Since A and E choose 0, in a pure-strategy Nash equilibrium either $m_B = m_C = m_D = 1$ or $m_B = m_C = m_D = 0$.

Since $m_A = m_E = 0$, in order to characterize the mixed strategy equilibria, we just need to analyze one case (the remaining ones are symmetric): $m_D \in (0, 1)$.

Case 1: $m_D \in (0, 1)$. To be in a Nash equilibrium the following condition must be satisfied: $\big((1 - m_C)m_B + (1 - m_B)m_C\big)\frac{1}{3} + m_B m_C \frac{2}{3} = \frac{1}{2}$, that simplifies to:

$$(8) \qquad \frac{1}{3}(m_B + m_C) = \frac{1}{2}$$

Hence, $m_B, m_C > 0$. By (8), $m_B = m_C = 1$ can not hold. Suppose $m_B = 1$, then, by (8), $m_C = 0.5$. A similar computation yields $m_D = 0.5$. Hence, $(0, 1, 0.5, 0.5, 0)$ is a Nash equilibrium. By symmetry, $(0, 0.5, 1, 0.5, 0)$, $(0, 0.5, 0.5, 1, 0)$ are also Nash equilibria. Suppose now $m_B < 1$. If $m_C = 1$, we obtain one of the previous equilibria. Hence, assume $m_C < 1$. Then, the following conditions must hold:

$$(9) \qquad \frac{1}{3}(m_A + m_C) = 0.5$$

$$(10) \qquad \frac{1}{3}(m_A + m_B) = 0.5$$

Conditions (8), (9), and (10) imply $m_B = m_C = m_D = 0.75$. Hence, $(0, 0.75, 0.75, 0.75, 0)$ is a Nash equilibrium. QED

Proof of Proposition 5.

For each $i \in \{A, B, C, D, E\}$ such that $n_i = 1$ (A and E in g_G, and A, C and E in g_P), i's best response implies $m_i = 0$, since her payoff from choosing action 1 is $1/3 - 1/2 < 0$. Hence, in a Nash equilibrium, players B and D in g_G and player D in the g_P also choose action 0, since they have degree 2 and one of their neighbors has degree 1 (and, therefore, chooses action 0). It follows that, in a Nash equilibrium, also player C in g_G and player B in g_P choose action 0, since all their neighbors also choose 0. QED

Incomplete information scenario

We first define some conditional probabilities that shall be useful in the proofs of Propositions 6 and 7. Let $q_1(j;\, p)$ be the expected probability for an agent that, conditional on having degree 1, her neighbor has degree j. By applying Bayes' rule we get[36]

$$q_1(2;\, p) = \frac{3(1-p)}{5(1-p)+4p} \text{ and } q_1(3;\, p) = \frac{2(1-p)+4p}{5(1-p)+4p}$$

Let $q_2(j_1,j_2;\, p)$ be the expected probability for an agent that, conditional on having degree 2, her neighbors have degrees j_1 and j_2. By applying Bayes' rule we get

$$q_2(1,2;\, p) = \frac{2(1-p)}{4(1-p)+2p},\ q_2(2,2;\, p) = \frac{1-p}{4(1-p)+2p},\ q_2(1,3;\, p) = \frac{1-p}{4(1-p)+2p} \text{ and } q_2(3,3;\, p) = \frac{2p}{4(1-p)+2p}.$$

Let $q_3(j_1,j_2,j_3;\, p)$ be the expected probability for an agent that, conditional on having degree 3, her neighbors have degrees j_1, j_2 and j_3. By applying Bayes' rule we get

$$q_3(1,1,2;\, p) = \frac{1-p}{1+3p} \text{ and } q_3(1,2,3;\, p) = \frac{4p}{1+3p}.$$

Let $\pi_i^j(x_i, x_{-i})$ be the payoff of an agent (indexed by $i \in N$) with degree $j \in \{1,2,3\}$.

Proof of Proposition 6.

We start checking for pure strategy equilibria. There are 8 candidates: $s^{\mathrm{I}} = (0,0,0)$, $s^{\mathrm{II}} = (1,0,0)$, $s^{\mathrm{III}} = (0,1,0)$, $s^{\mathrm{IV}} = (0,0,1)$, $s^{\mathrm{V}} = (1,1,0)$, $s^{\mathrm{VI}} = (1,0,1)$, $s^{\mathrm{VII}} = (0,1,1)$ and $s^{\mathrm{VIII}} = (1,1,1)$. We first prove that candidates s^{I}, s^{III}, s^{IV}, s^{VI}, s^{VII} and s^{VIII} cannot be equilibria:

- For all $p \in (0,1)$, s^{I} is not an equilibrium, since $\pi_i^1(0, x_{-i}^I) = 0 < 1/2 = \pi_i^1(1, x_{-i}^I)$.
- Regarding s^{III}, in order to be an equilibrium, it would require $\pi_i^1(0, x_{-i}^{III}) \geq \pi_i^1(1, x_{-i}^{III})$ and $\pi_i^2(1, x_{-i}^{III}) \geq \pi_i^2(0, x_{-i}^{III})$, i.e., $q_1(2;\, p) \geq \frac{1}{2}$ and $\frac{1}{2} \geq q_2(1,2;\, p) + q_2(2,2;\, p)$, but these inequalities are incompatible for all $p \in (0,1)$.
- Regarding s^{IV}, in order to be an equilibrium, it would require $\pi_i^2(0, x_{-i}^{IV}) \geq \pi_i^2(1, x_{-i}^{IV})$ and $\pi_i^3(1, x_{-i}^{IV}) \geq \pi_i^3(0, x_{-i}^{IV})$, i.e., $q_2(1,3;\, p) + q_2(3,3;\, p) \geq \frac{1}{2}$ and $\frac{1}{2} \geq q_3(1,2,3;\, p)$, but these inequalities are incompatible for all $p \in (0,1)$.
- For all $p \in (0,1)$, s^{VI} is not an equilibrium, since $\pi_i^3(1, x_{-i}^{VI}) = 1/2 < 1 = \pi_i^3(0, x_{-i}^{VI})$.
- For all $p \in (0,1)$, s^{VII} is not an equilibrium, since $\pi_i^2(1, x_{-i}^{VII}) = 1/2 < 1 = \pi_i^2(0, x_{-i}^{VII})$.
- For all $p \in (0,1)$, s^{VIII} is not an equilibrium, since $\pi_i^1(1, x_{-i}^{VIII}) = 1/2 < 1 = \pi_i^1(0, x_{-i}^{VIII})$.

[36] Recall that with probability p, the orange network is selected whereas each of the other two networks is selected with probability $(1-p)/2$. Then the five players are randomly allocated in the network with uniform probability.

We now prove that candidates s^{II} and s^{V} are equilibria when $p \leq \frac{1}{2}$ and $p \geq \frac{2}{3}$, respectively:

- Candidate s^{II} = (1,0,0). First, we observe that, for all $p \in (0,1)$, $\pi_i^1(1, x_{-i}^{II}) = 1/2 > 0 = \pi_i^1(0, x_{-i}^{II})$ and $\pi_i^3(0, x_{-i}^{II}) = 1 > \frac{1}{2} = \pi_i^3(1, x_{-i}^{II})$. Hence, in order to be an equilibrium, it requires $\pi_i^2(0, x_{-i}^{II}) \geq \pi_i^2(1, x_{-i}^{II})$, i.e., $q_2(1,2;\, p) + q_2(1,3;\, p) \geq \frac{1}{2}$, which simplifies to $p \leq \frac{1}{2}$.
- Candidate s^{V} = (1,1,0). First, we observe that, for all $p \in (0,1)$, $\pi_i^3(0, x_{-i}^{V}) = 1 > \frac{1}{2} = \pi_i^3(1, x_{-i}^{V})$. Hence, in order to be an equilibrium, it requires both $\pi_i^1(1, x_{-i}^{V}) \geq \pi_i^1(0, x_{-i}^{V})$ and $\pi_i^2(1, x_{-i}^{V}) \geq \pi_i^2(0, x_{-i}^{V})$, i.e., $\frac{1}{2} \geq q_1(2;\, p)$ and $\frac{1}{2} \geq q_2(1,2;\, p) + q_2(2,2;\, p) + q_2(1,3;\, p)$. The second inequality imply the first one, and the equilibrium condition simplifies to $p \geq \frac{2}{3}$.

Thus, we have shown that, when $p \in \left(0, \frac{1}{2}\right] \cup \left[\frac{2}{3}, 1\right)$, the strategy profile (1, $s_2^*(p)$, 0) is an equilibrium, and that for all $p \in (0,1)$, there are no other pure strategy equilibrium.

We now check for equilibria where players use mixed strategies. First, consider a strategy profile $s^{\mathrm{IX}} = (1, m, 0)$, with $m \in (0,1)$, i.e., players with degree 2 mix, and players with degrees 1 and 3 choose actions 1 and 0, respectively. For s^{IX} to be an equilibrium, it is required that $\pi_i^2(1, x_{-i}^{IX}) = \pi_i^2(0, x_{-i}^{IX})$, i.e., $\frac{1}{2} = q_2(1,2;\, p) + q_2(1,3;\, p) + (m^2+2m(1-m))\, f_2(2,2;\, p)$, which simplifies to $m = \frac{1-p-\sqrt{(2-3p)(1-p)}}{1-p}$, i.e., $m = 1 - \sqrt{\frac{2-3p}{1-p}}$. We get that m is a real number lying in the interval (0,1) when $\frac{1}{2} < p < \frac{2}{3}$.[37] Note that, for all $p \in (0,1)$, $\pi_i^3(0, x_{-i}^{IX}) = 1 > \frac{1}{2} = \pi_i^3(1, x_{-i}^{IX})$. Thus, in order to show that, for all $p \in \left(\frac{1}{2}, \frac{2}{3}\right)$, s^{IX} is an equilibrium, we just require that $\pi_i^1(1, x_{-i}^{IX}) \geq \pi_i^1(0, x_{-i}^{IX})$, i.e., $\frac{1}{2} \geq m\, q_1(2;\, p)$. Since $m < 1$, $q_1(2;\, p)$ is decreasing in p, and $q_1(2;\, 1/2) = 1/3$, we get that when $p \in \left(\frac{1}{2}, \frac{2}{3}\right)$, the strategy profile (1, $s_2^*(p)$, 0) is an equilibrium. Finally, using the software *Mathematica* we have checked that, if $p \geq 0.2$, there is no other mixed strategy equilibrium.[38] QED

[37] When solving for m (a second degree equation), we select the root that provides $m < 1$. The condition $p < 2/3$ is obtained from imposing that the argument of the square root is positive, and $p > 1/2$ is obtained from imposing $m > 0$.

[38] To check it analytically would be cumbersome, since it requires to check for various simultaneous inequalities, and there are a number of candidates: $(m_1,0,0)$, $(m_1,1,0)$, $(m_1,0,1)$, $(m_1,1,1)$, $(0,m_2,1)$, $(1,m_2,1)$, $(0,0,m_3)$ $(1,0,m_3)$, $(0,1,m_3)$, $(1,1,m_3)$, $(m_1,m_2,0)$, $(m_1,m_2,1)$, $(m_1,0,m_3)$, $(m_1,1,m_3)$, $(0,m_2,m_3)$, $(1,m_2,m_3)$ and (m_1,m_2, m_3). The *Mathematica* file is available from the authors upon request [for the referees' convenience, it is included in the technical document – not intended for publication].

Proof of Proposition 7.

We start checking for pure strategy equilibria. There are 8 candidates: s^{I} = (0,0,0), s^{II} = (1,0,0), s^{III} = (0,1,0), s^{IV} = (0,0,1), s^{V} = (1,1,0), s^{VI} = (1,0,1), s^{VII} = (0,1,1) and $\mathrm{s}^{\mathrm{VIII}}$ = (1,1,1).

We first prove that candidates s^{II}, s^{III}, s^{IV}, s^{V}, s^{VI}, and s^{VIII} cannot be equilibria:

- For all $p \in (0,1)$, s^{II} is not an equilibrium, since $\pi_i^1(1, x_{-i}^{II}) = -1/2 < 0 = \pi_i^1(0, x_{-i}^{II})$.
- For all $p \in (0,1)$, s^{III} is not an equilibrium, since $\pi_i^2(1, x_{-i}^{III}) = \frac{1}{3}(q_2(1,2;\, p) + 2(q_2(2,2;\, p)) - \frac{1}{2} < 0 = \pi_i^2(0, x_{-i}^{III})$.
- Regarding s^{IV}, in order to be an equilibrium, it would require $\pi_i^3(1, x_{-i}^{IV}) \geq \pi_i^3(0, x_{-i}^{IV})$, i.e., $\frac{1}{3}q_3(1,2,3;\, p) - \frac{1}{2} \geq 0$. However, the inequality does not hold since, for any $\in (0,1)$, $q_3(1,2,3;\, p) < 1$.
- Regarding s^{V}, in order to be an equilibrium, it would require $\pi_i^1(1, x_{-i}^{V}) \geq \pi_i^1(0, x_{-i}^{V})$, i.e., $\frac{1}{3}q_1(2;\, p) - \frac{1}{2} \geq 0$. However, the inequality does not hold since, for $\in (0,1)$, $q_1(2;\, p) < 1$.
- Regarding s^{VI}, in order to be an equilibrium, it would require $\pi_i^1(1, x_{-i}^{VI}) \geq \pi_i^1(0, x_{-i}^{VI})$, i.e., $\frac{1}{3}q_1(2;\, p) - \frac{1}{2} \geq 0$. However, the inequality does not hold since, for $\in (0,1)$, $q_1(2;\, p) < 1$.
- For all $p \in (0,1)$, s^{VIII} is not an equilibrium, since $\pi_i^1(1, x_{-i}^{VIII}) = -1/6 < 0 = \pi_i^1(0, x_{-i}^{VIII})$.

We now prove that candidates s^{I} is an equilibrium for all $p \in (0,1)$, and that candidate s^{VII} is an equilibrium for all $p \geq 1/2$.

- Candidate s^{I} = (0,0,0). For all $p \in (0,1)$, and $k \in \{1,2,3\}$, $\pi_i^k(0, x_{-i}) = 0 > -1/2 =$ *πik1,x−i*. Hence s^{I} is an equilibrium.
- Candidate s^{VII} = (0,1,1). First, we observe that, for all $p \in (0,1)$, $\pi_i^1(0, x_{-i}^{VII}) = 0 > -1/6 = \pi_i^1(1, x_{-i}^{VII})$. Hence, in order to be an equilibrium, it requires both $\pi_i^2(1, x_{-i}^{VII}) \geq \pi_i^2(0, x_{-i}^{VII})$ and $\pi_i^2(1, x_{-i}^{VII}) \geq \pi_i^2(0, x_{-i}^{VII})$, i.e.,
  $\frac{1}{3}(q_2(1,2;\, p) + q_2(1,3;\, p) + 2q_2(2,2;\, p) + 2q_2(2,3;\, p)) - \frac{1}{2} \geq 0$ and
  $\frac{1}{3}(q_3(1,1,2;\, p) + 2q_3(1,2,3;\, p)) - \frac{1}{2} \geq 0$.
  The first inequality simplifies to $p \geq 1/2$ and the second one simplifies to $p \geq 1/5$. Since both conditions are necessary, the result follows.

We now check for equilibria where players use mixed strategies. First note that, in any equilibrium profile, players with degree 1 necessarily choose the pure strategy 1, since $\pi_i^1(1, x_{-i}) \leq \frac{1}{3} - \frac{1}{2} < 0 = \pi_i^1(0, x_{-i})$. Hence, assuming $m_2 \in (0,1)$ and $m_3 \in (0,1)$, the equilibrium candidates are s^{X} = (0, m_2, 0), s^{XI} = (0, m_2, 1), s^{XII} = (0, 0, m_3), s^{XIII} = (0, 1, m_3) and s^{XIV} = (0, m_2, m_3).

We first prove that candidates s^{X}, s^{XII} and s^{XIII} cannot be equilibria:

- Since, in s^{III} = (0,1,0), for all $p \in (0,1)$, $\pi_i^2(1, x_{-i}^{III}) < 0 = \pi_i^2(0, x_{-i}^{III})$, s^{X} can neither be an equilibrium.
- For all $p \in (0,1)$, s^{XII} is not an equilibrium, since $\pi_i^3(1, x_{-i}^{XII}) \leq \frac{1}{3} - \frac{1}{2} < 0 = \pi_i^3(0, x_{-i})$ and, therefore, players with degree 2 cannot optimally mix.
- Regarding s^{XIII}, in order to be an equilibrium, it would require that $\pi_i^3(1, x_{-i}^{XIII}) = \pi_i^3(0, x_{-i}^{XIII})$, i.e., $\frac{1}{3}$ (f_3(1,1,2; p) + (1–m_3) f_3(1,2,3; p) + 2m_3 f_3(1,2,3; p)) $-\frac{1}{2} = 0$, which simplifies to $m_3 = \frac{1+3p}{8p}$. Since $m_3 > 1$, it is needed that p > 1/5. Additionally, for s^{XIII} to be an equilibrium, we would need that $\pi_i^2(1, x_{-i}^{XIII}) \geq \pi_i^2(0, x_{-i}^{XIII})$, i.e., $\frac{1}{3}$ (f_2(1,2; p) + 2f_2(2,2; p) + m_3 f_2(1,3; p) + 2(m_3)² f_2(3,3; p) +2m_3(1–m_3) f_2(3,3; p)) $-\frac{1}{2} \geq 0$. If we substitute $m_3 = \frac{1+3p}{8p}$, we obtain that the inequality is satisfied if and only if $p \in \left(0, 5 - 2\sqrt{6}\right) \cup \left(5 + 2\sqrt{6}, \infty\right)$. Since $5 - 2\sqrt{6} < 1/5$, there is no $p \in (0,1)$ such that s^{XIII} is an equilibrium.

We finally prove that candidate s^{XI} = (0, m_2, 1), with $m_2 = \frac{5-6p}{4(1-p)}$, is an equilibrium if $p \in \left(\frac{1}{2}, \frac{13+\sqrt{105}}{32}\right)$; and that s^{XIV} = (0, m_2, m_3), with $m_2 = \frac{3-30p+51p^2}{2(5p-1)^2}$ and $m_3 = \frac{3p+9p^2}{(5p-1)^2}$ is an equilibrium if $p \geq \frac{\sqrt{105}+13}{32}$.

- Candidate s^{XI} = (0, m_2, 1). In order to be an equilibrium, it requires that $\pi_i^2(1, x_{-i}^{XI}) = \pi_i^2(0, x_{-i}^{XI})$, i.e., $\frac{1}{3}$ (m_2 f_2(1,2; p) + 2(m_2)² f_2(2,2; p) + 2m_2(1–m_2) f_2(2,2; p) + f_2(1,3; p) + 2f_2(3,3; p)) $-\frac{1}{2} = 0$, which simplifies to $m_2 = \frac{5-6p}{4(1-p)}$. Since we require $m_2 \in (0,1)$, it is needed that $p \in \left(\frac{1}{2}, \frac{5}{6}\right)$. Additionally, for s^{XI} to be an equilibrium, we need that $\pi_i^3(1, x_{-i}^{XI}) \geq \pi_i^3(0, x_{-i}^{XI})$, i.e., $\frac{1}{3}$ (m_2 f_3(1,1,2; p) + (1–m_2) f_3(1,2,3; p) + 2m_2 f_3(1,2,3; p)) $-\frac{1}{2} \geq 0$. If we substitute $m_2 = \frac{5-6p}{4(1-p)}$, we obtain that the inequality is satisfied if and only if $p \in \left(\frac{13-\sqrt{105}}{32}, \frac{13+\sqrt{105}}{32}\right) \cup (1, \infty)$. Since $\frac{13-\sqrt{105}}{32} < \frac{1}{2}$ and $\frac{13+\sqrt{105}}{32} < \frac{5}{6}$, we get that s^{XI} is an equilibrium if $p \in \left(\frac{1}{2}, \frac{13+\sqrt{105}}{32}\right)$.
- Candidate s^{XIV} = (0, m_2, m_3). In order to be an equilibrium, it requires that both $\pi_i^2(1, x_{-i}^{XIV}) = \pi_i^2(0, x_{-i}^{XIV})$ and $\pi_i^3(1, x_{-i}^{XI}) = \pi_i^3(0, x_{-i}^{XI})$, i.e.,
  $\frac{1}{3}$ (m_2 f_2(1,2; p) + 2(m_2)² f_2(2,2; p) + 2m_2(1–m_2) f_2(2,2; p) + $m_3 f_2$(1,3; p) + 2(m_3)² f_2(3,3; p) + 2m_3(1–m_3) f_2(3,3; p)) $-\frac{1}{2} = 0$ and
  $\frac{1}{3}$ (m_2 f_3(1,1,2; p) + (m_3(1–m_2)+ m_2(1–m_3)) f_3(1,2,3; p) + 2$m_3 m_2$ f_3(1,2,3; p)) $-\frac{1}{2} = 0$.
  Solving for the system of equations, we get that $m_2 = \frac{3-30p+51p^2}{2(5p-1)^2}$ and $m_3 = \frac{3p+9p^2}{(5p-1)^2}$. Finally, we get that $m_2 \in (0,1)$ and $m_3 \in (0,1)$ if and only if $p > \frac{13+\sqrt{105}}{32}$. QED

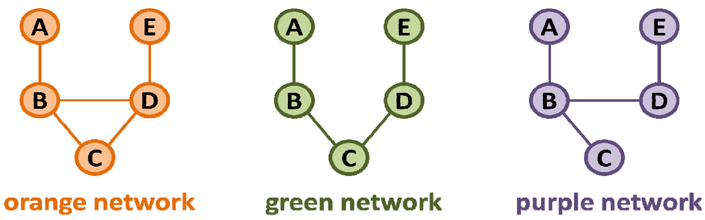
Appendix D: Experimental instructions

I) Complete Information - Substitutes

The aim of this Experiment is to study how individuals make decisions in certain contexts. The instructions are simple. If you follow them carefully you will earn a non-negligible amount of money in cash (Euros) 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.- The experiment consists of 40 rounds. In each round you will be randomly assigned to a group of 5 participants. This group is determined randomly at the beginning of the round. Therefore, the group you are assigned to changes at each round. In this room, there are 10 participants (including yourself) that are potential members of your group. That is, at every round your group of 5 participants is selected among these 10 participants, each of them being equally likely to be in your group. You will not know the identities of any of these participants.

2.- At each round, the computer selects randomly a **network for your group**: the **orange network**, the **green network** or the **purple network**:



Once a network is selected, you (and the other members of your group) are randomly assigned to a **position**: **A**, **B**, **C**, **D** or **E**, all of them being equally likely. The assignment process is random: At each round, you are equally likely to be located in each of the 5 positions. At each round, you will be informed of the selected network (color) and of your position (letter).

In a network, a <u>link</u> is represented by a line (connection) between two positions. For example, in the **orange network**, **position B** has <u>three links</u>: it is linked to **positions A**, **C** and **D** (but it is not linked to **position E**). Summarizing:

- In the **orange network** there are two positions with <u>1 link</u> (**positions A** and **E**), one position with <u>2 links</u> (**position C**), and two positions with <u>3 links</u> (**positions B** and **D**).
- In the **green network** there are two positions with <u>1 link</u> (**positions A** and **E**), three positions with <u>2 links</u> (**positions B**, **C** and **D**), and no position with <u>3 links</u>.
- In the **purple network** there are three positions with <u>1 link</u> (**positions A**, **C** and **E**), one position with <u>2 links</u> (**position D**), and one position with <u>3 links</u> (**position B**).

You can notice that both the **green** and the **purple** network have <u>one link less</u> that the **orange** one: In the **green network positions B** and **D** are <u>not linked</u>, and in the **purple network positions C** and **D** are <u>not linked</u>.

Your earnings of the round can only be affected by your decisions and the decisions of those participants located in positions that are linked to yours, as specified below.

3.- At each round, knowing the selected network and your position, you will be asked to make a choice: to be **ACTIVE** or **INACTIVE** (the other participants are asked to make the same choice). Your payoff of the round will depend on your choice and on the choices of those participants of your group located in positions linked to yours: You earn 100 ECU if either you or at least one of the participants located in positions linked to yours choose to be ACTIVE. Being active has a cost of 50 ECU. Hence,

- If you choose to be **ACTIVE** your round payoff is **50 ECU** for sure [100 – 50]
- If you choose to be **INACTIVE** your round payoff can be:
  - **100 ECU** if at least one participant linked to you choose to be ACTIVE, or
  - **0 ECU** if no participant linked to you choose to be ACTIVE.

4.- At the end of every round, you will get information about current and past rounds. The information consists of:
- The selected network.
- Your position in the network.
- Your choice (ACTIVE or INACTIVE).
- The number of participants linked to you that chose to be ACTIVE.
- Your (round) payoff.

5.- Payoffs. At the end of the experiment, you will be paid the earnings that you achieved in 4 rounds, that will be randomly selected across the 40 rounds of play (all rounds selected will the same probability). These earnings are transformed to cash at the exchange rate of **20 ECU = 1 €**. In addition, just by showing up, you will also be paid a fee of **5 €**.

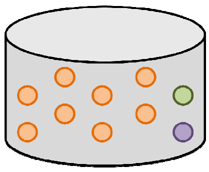
II) Incomplete Information – Complements – p=0.8

[Note: The case p=0.2 is analogous (it just changes the virtual urn composition)]

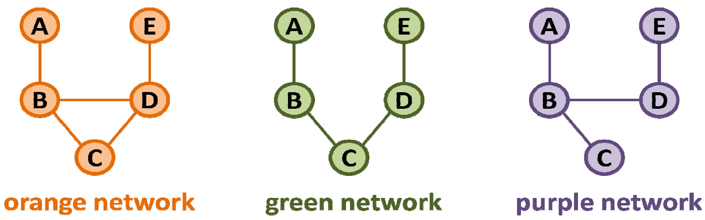
The aim of this Experiment is to study how individuals make decisions in certain contexts. The instructions are simple. If you follow them carefully you will earn a non-negligible amount of money in cash (Euros) at the end of the experiment. During the experiment, your earnings will be accounted in ECU (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.- The experiment consists of 40 rounds. In each round you will be randomly assigned to a group of 5 participants. This group is determined randomly at the beginning of the round. Therefore, the group you are assigned to changes at each round. In this room, there are 10 participants (including yourself) that are potential members of your group. That is, at every round your group of 5 participants is selected among these 10 participants, each of them being equally likely to be in your group. You will not know the identities of any of these participants.

2.- At each round, the computer selects one color from a virtual urn. The virtual urn contains 10 balls: **8 orange balls**, **1 green ball** and **1 purple ball**.



All the 10 balls of the virtual urn are equally likely to be selected by the computer. The **color** of the selected ball determines a **network for your group**: the **orange network**, the **green network** or the **purple network**. Once the network has been selected, the ball is returned to the virtual urn. Thus, in each round the color selection process is identical (there are always 8 orange balls, 1 green ball and 1 purple ball, and one of them is randomly picked by the computer). The three possible networks are:



Once a network is selected, you (and the other members of your group) are randomly assigned to a **position**: **A**, **B**, **C**, **D** or **E**, all of them being equally likely. The assignment process is random: At each round, you are equally likely to be located in each of the 5 positions. At each round, you will neither be informed of the selected network (color) nor of your position (letter).

In a network, a link is represented by a line (connection) between two positions. For example, in the **orange network**, **position B** has three links: it is linked to **positions A**, **C** and **D** (but it is not linked to **position E**). Summarizing:

- In the **orange network** there are two positions with 1 link (**positions A** and **E**), one position with 2 links (**position C**), and two positions with 3 links (**positions B** and **D**).
- In the **green network** there are two positions with 1 link (**positions A** and **E**), three position with 2 links (**positions B**, **C** and **D**), and no position with 3 links.
- In the **purple network** there are three positions with 1 link (**positions A**, **C** and **E**), one position with 2 links (**position D**), and one position with 3 links (**position B**).

You can notice that both the **green** and the **purple** network have one link less that the **orange** one: In the **green network positions B** and **D** are not linked, and in the **purple network positions C** and **D** are not linked.

Your earnings of the round can only be affected by your decisions and the decisions of those participants located in positions that are linked to yours, as specified below.

3.- At each round, you will only be informed about how many links your assigned position has (1 link, 2 links or 3 links) in the selected network, but you will neither know with certainty which is the selected network nor your exact position.

For example, if at a particular round you are informed that your position has 3 links, there are different paths that could lead to this outcome: It may be the case that the selected network is the **orange network** and you have been assigned to **position B** or **D**, or it may be the case that the selected network is the **purple network** and you have been assigned to **position B**.

4.- At each round, knowing the selected network and your position, you will be asked to make a choice: to be **ACTIVE** or **INACTIVE** (the other participants are asked to make the same choice). Your payoff of the round will depend on your choice and on the choices of those participants of your group located in positions linked to yours. If you choose to be INACTIVE, your round payoff is 50 ECU. If you choose to be ACTIVE, your round payoff is calculated as follows: First, add 100 ECU per participant linked to you that also chooses to be ACTIVE; then, divide the result by 3. Hence,

- If you choose to be **ACTIVE** your round payoff can be:
  - $\mathbf{100,00}$ **ECU** if 3 participants linked to you choose to be ACTIVE $\left[\frac{100+100+100}{3}\right]$, or
  - $\mathbf{66,66}$ **ECU** if 2 participants linked to you choose to be ACTIVE $\left[\frac{100+100}{3}\right]$, or
  - $\mathbf{33,33}$ **ECU** if 1 participants linked to you choose to be ACTIVE $\left[\frac{100}{3}\right]$, or
  - $\mathbf{0,00}$ **ECU** if no participant linked to you choose to be ACTIVE.
- If you choose to be **INACTIVE** your round payoff is $\mathbf{50,00}$ **ECU** for sure.

5.- At the end of every round, you will get information about current and past rounds. The information consists of:

- The selected network.
- Your position in the network.
- Your choice (ACTIVE or INACTIVE).
- The number of participants linked to you that chose to be ACTIVE.
- Your (round) payoff.

6.- Payoffs. At the end of the experiment, you will be paid the earnings that you achieved in 4 rounds, that will be randomly selected across the 40 rounds of play (all rounds selected with the same probability). These earnings are transformed to cash at the exchange rate of **20 ECU = 1 €**. In addition, just by showing up, you will also be paid a fee of **5 €**.