Experimental Games on Networks: Underpinnings of Behavior and Equilibrium Selection*

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Abstract. We study behavior and equilibrium selection in network games. We conduct a series of experiments (with 580 participants) in which actions are either strategic substitutes or strategic complements, and participants have either complete or incomplete information about the structure of a random network. In our initial set of experiments on 5-person networks, we find a great deal of qualitative and quantitative support for the theoretical predictions of the Galeotti, Goyal, Jackson, Vega-Redondo, and Yariv (2010) model. The degree of equilibrium play is striking, in particular with incomplete information. There are intriguing patterns in our data, such as a taste for positive payoffs (but also security) when this supports the choice of one of the potential equilibria in a complete-information setting. To shed further light on the underpinnings of behavior and equilibrium selection in the laboratory, we study three more 5-person networks and test robustness by conducting sessions with three 20-person networks. Overall, we see strong evidence that choices and the equilibrium played depend on one's degree and the connectivity of the network, and suggestive evidence that choices also depend on the clustering in the network.

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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] Examples include 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). Network analysis is also useful for job search and labor-market issues, 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).

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. 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.[2] In this respect, controlled laboratory experiments are often viewed as the ideal tool for qualitatively testing theory (e.g., Falk and Heckman, 2009).

In this paper, we describe a series of laboratory experiments that implement specific examples of a more general network structure. Our starting point is the model in Galeotti, Goyal, Jackson, Vega-Redondo, and Yariv (2010), which considers general environments in which the agents' actions are either strategic complements or substitutes. Economic environments typically have a considerable degree of either 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. Strategic complements (positive network

[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." For an exhaustive review of social and economic networks, with particular attention to theoretical models, see Jackson (2008).
[2] Typical problems with field data are the use of idiosyncratic data sets, multiple simultaneous influences, and the issue of measurement error.

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.[3] 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 is choosing routes to avoid congested roads, since one certainly receives a greater benefit from choosing a route that has not been chosen much by others.

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 *et alii* (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 for 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 determine which equilibrium is likely to occur. 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 result that uncertainty about elements of the network tends to reduce the equilibrium multiplicity that arises under complete information, as shown by Galeotti *et alii* (2010). Another method for examining equilibrium selection is through experimental testing. This is our approach, as experimental work will provide empirical information regarding which of the multiple equilibria tends to actually prevail behaviorally and may even lead to clear insights *ex post*.

[3] 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.

In our first set of experiments, we consider a specific experimental environment that includes three different five-person networks. In the case of complete information, each person knows the network structure (which of the three networks is in play) 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.[4] The 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. We also do generally find support for a reduction in the multiple-equilibrium problem going from complete to incomplete information.

In the simpler case of *complete* information, we do not observe a multiplicity of equilibria. Behavior that is highly consistent with the same particular equilibrium is observed 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, since the efficient 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. 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. The frequency of active players increases with *connectivity* (the extent to which the

[4] 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 abstracted from 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.

nodes of the network are connected) 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.

Our experiment demonstrates that the theory in Galeoti *et alii* (2010) does remarkably well in predicting behavior in our initial networks in the incomplete-information scenario. However, these networks are not ideal for the purpose of studying equilibrium selection, and questions remained concerning the underpinnings. The model does predict that the connectivity (holding degree constant) increases activity in this environment, but this needed to be tested for robustness and applicability to other (potentially larger) networks. We also wished to study whether connectivity also increases activity levels in networks with complete information. Finally, we also suspected that the degree of *clustering* in the network[5] would be an important influence on behavior and equilibrium selection, since an increased level of clustering (increasing the probability that two neighbors of a player are also linked) reduces the independence of the equilibrium strategies of the neighbors.[6]

To test this and to examine the robustness of our findings to other networks, we conducted new treatments with another set of five-person networks and with a set of 20-person networks. In the first case, we focus on strategic complements (both with complete and incomplete information). In the second, we focus on strategic complements and incomplete information.[7] The data from these new treatments reinforces the evidence that connectivity is a key consideration for equilibrium selection, and also provides evidence that the degree of clustering does indeed have an effect on behavior and equilibrium selection.

We also consider a puzzle from the results in the first set of experiments: While people are able to form a three-person active clique[8] in one of the networks with strategic complements and complete information, the no-activity equilibrium is played when the chance that this

[5] A cluster is a fully-connected triple of nodes. One simple measure of the degree of clustering is the ratio between the number of closed triples and the number of potential closed triples.

[6] In equilibrium the strategies of linked individuals are correlated in the sense that are best responses to the strategies of the neighbors. Consider three players, A, B and C, where B and C are both neighbors of A and are not themselves neighbors. Their equilibrium strategy is a best response to the strategy of A and to strategies of other linked players. Now consider that A,B and C form a clique i.e. players B and C are neighbors between themselves. In such a case the equilibrium strategy of B (C) is a best response to the strategies of A, C (B) and others. Therefore, there is more correlation between the equilibrium strategies of B and C (neighbors of A).

[7] We only consider complements in this environment because this offers a multiplicity of equilibria in all scenarios. We only consider incomplete information in the large-network case because, with complete information, the number of equilibria would be very large, and each player's strategy would have a huge number (20) of components.

[8] A clique in a network is a group of three fully-interconnected nodes.

network is in force is 80%. Is this difference caused by uncertainty per se? It is true that the three-person clique seems difficult to sustain (the gain from being active is relatively small), so that certainty could be an important consideration. To test this, we change the probability that this particular network is in force to 95%. Here we see evidence that play in the 95% and 80% is converging to the no-activity equilibrium, while activity is fully sustained in the case of certainty, suggesting an important effect of uncertainty *per se* on behavior in network games.

All in all, people do largely behave in accordance with some simple principles and generally make very sensible choices in complex environments. First, behavior closely resembles the theoretical equilibrium when this is unique. Second, when there are multiple equilibria, there are general features of networks, such as connectivity, clustering, and the degree of the players, that predict informed behavior in the lab. Third, our evidence reveals some specific patterns. People have a strong attraction to efficiency and positive profits, so that the inactive equilibrium is rarely played when there is another equilibrium with activity; this is consistent with experimental work in which payoff dominance is a key consideration for equilibrium selection. And yet there are some moderating forces on the attraction to efficiency: 1) people seem content with capturing only the lion's share of the efficient profits in exchange for greater security, and 2) uncertainty about the network structure makes it considerably more difficult to coordinate on a demanding, but efficient, equilibrium that is typically implemented with complete information. We believe that our findings, while certainly not a full characterization, nevertheless offer considerable predictive power for behavior in games on networks.

The remainder of the paper is organized as follows. We discuss the relevant literature in section 2, and describe the experimental design and implementation in section 3. Our experimental results are given in section 4, and we offer a discussion of our results and their implications in section 5. We conclude in section 6, and propositions and proofs regarding our networks are given in the Appendix A.

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.

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. Nevertheless, networks in the field are typically endogenous, and moreover they evolve over time. Indeed, as Kirman (1997) argues, "the individuals in the economy learn, not only about the appropriate actions for them to take but also, about whom they should interact with. The network therefore evolves over time with the evolution of the players and there is a continual feedback from one to the other."

However, the (relative) rates at which networks and actions evolve depend very much on the specific economic context. While some networks are very volatile, many others are fairly stable over time (for example housing neighborhoods, networks of co-workers, particularly in countries with low levels of job mobility, insurance networks in developing countries, etc.). In the first case, interaction within the network evolves as fast as the network itself, but in the second case, the networks adjust very slowly, whereas interaction among the agents located in the network can be very frequent. In this sense, the study of agents' behavior under exogenous networks can be seen as a simplification of economic situations of the second kind, where players may be aware that at some point there will be chances to alter the network, but in the interim choose their actions taking the network as given.[9]

Regarding theoretical works, 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 and either complete or incomplete information.[10] Galeotti *et alii* (2010) was the starting point for our experimental design. They 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.

[9] There are also practical difficulties in allowing multi-player networks to develop endogenously; for example, there are a myriad of possible networks that can manifest and disappear, complicating the analysis and requiring more observations in the endogenous case.

[10] For the complete-information case, see for example Ballester, Calvó-Armengol and Zenou (2006), Bramoullé and Kranton (2007), Goyal and Moraga-Gonzalez (2001), and Calvó-Armengol and Jackson (2004). For the incomplete-information case, see Jackson and Yariv (2005), Sundararajan (2006), and Galeotti and Vega-Redondo (2011).

Our initial task was to adapt this theory to a distilled selection of networks that represented these possibilities and that differed from each other by only one link.

Overall, there is relatively little research in experimental economics on network games, particularly when one considers the wealth of theoretical contributions in this area.[11] 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.[12] 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) use a 3-person coordination game; in one treatment, each participant is connected to two neighbors on an 8-player circle, while in the other treatment, people play within closed 3-person groups. The 3-person group quickly coordinates on the payoff-dominant equilibrium while the circular group eventually coordinates on the risk-dominant equilibrium. Cassar (2007) compares 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.[13]

Fatas, Meléndez-Jiménez and Solaz (2010) consider network effects primarily in relation to the voluntary-contribution mechanism. They 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

[11] 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.

[12] Regarding experiments on coordination games in networks see also Berninghaus, Ehrhart and Keser (2002), Boun My *et alii* (2006) and Corbae and Duffy (2008). 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).

[13] 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.

and the circle. 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.[14]

Choi *et alii* (2011) study networks of three players in the lab. In each of three stages, each player must decide whether to contribute his unit of endowment to a public good (an irreversible decision) or to keep it. At each stage, each player can only observe the past decisions of his neighbors in the network. The public good is provided if and only if, after the third stage, at least two players have contributed. Each player earns his unit of endowment (in case he has not contributed it) plus two units (in case the public good is provided). There are multiple equilibria: inefficient ones (where no one contributes) and efficient ones (where two agents contribute). Choi *et alii* report that participants who are uninformed and are observed by others tend to contribute early, while informed ones tend to delay their contributions. They also observe significant differences in the levels of cooperation across networks and find evidence of coordination failures in networks where two participants are symmetrically situated. In their paper, in comparison to ours, the network only matters through the information received in the three stages. Furthermore, subjects' payoffs depend on own and global behavior, rather than depending only on own and neighbors' behavior, as in our case. Moreover, we study larger networks by considering five-player and 20-player networks with different structures.

Kearns *et alii* (2006, 2009) conduct experiments where players have a collective goal, studying how the capacity to achieve a common goal depends on the network structure. Kearns *et alii* (2006) consider a game of substitutes in which all players receive exactly the same payoff; it is more difficult to achieve success with networks generated by preferential attachment than with either "small-world" networks or networks based on cyclical structures.[15] Kearns *et alii* (2009) examine a game of complements, where the entire group aims to coordinate (vote) on a choice, and where there is heterogeneity in preferences. In contrast to these studies, the key aspect of our design is that earnings and optimal strategies are directly related to network

[14] 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. In a more recent paper, Carpenter *et alii* (2012) study the effects of punishment in VCM played in networks.

[15] Preferential attachment is a stochastic process generating random networks. A characteristic of this process is that the more connected a node is, the more likely it is to receive new links.

features, like the degree (in equilibrium, subjects with different degrees select different choices). Further, in our case players only care about their own choices and those of their neighbors. Additionally, we present a framework where one choice is safe and the other one is "risky" (providing a payoff related to the degree and the neighbors' choices). Hence, we have multiplicity of equilibria of very different natures (for instance, efficient but risky equilibrium vs. inefficient but safe one), which renders the equilibrium-selection problem a crucial issue. In sum, 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. Experimental design

The Game

In the experiments in this paper we focus on the two specific games that Galeotti *et alii* (2010) use 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). The player is located in a position within a network and her payoff depends both on her choice and on the choices of her neighbors.

- With ***strategic substitutes***, a player earns 100 if either she or at least one of her neighbors is active, and earns 0 otherwise. Being active costs 50, while inactivity is costless.
- With ***strategic complements***, if a player is inactive, she earns 50 and, if she is active she earns 33.33 times the number of neighbors that are active.[16]

The networks used in our experiments are shown in Figure 1:

[Figure 1]

Experiment 1: In this experiment we used the three networks displayed in the top panel: The *Orange*, *Green* and *Purple* networks. In the case of incomplete information, the value for p is the probability that the *Orange* network was in force (each of the other two networks was selected with probability (1-p)/2). Note that, since the *Orange* network has a higher connectivity than the other two ones (we can get the *Orange* network both by adding the link BD to the *Green*

[16] In our experimental design, in the case of strategic complements we have added 50 to all the payoffs as compared to the original game used by Galeotti *et alii* (2010) to avoid losses.

network and by adding the link CD to the *Purple* network) by parameter p we modulate the connectivity. We had 12 sessions with 20 participants in each. There were two sessions and thus 40 subjects in each of the six treatments below.

- 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.

The experimental instructions are provided in Appendix D.[17] 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, each network being equally likely) 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, the number of her neighbors who chose to be active, and the payoff resulting from her choice and those of her neighbors.[18]

Since behavior could potentially be affected by risk preferences, we also tested for these after the 40 periods 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

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

[18] Regarding the payoff transformations used in the sessions, during the experiment payoffs were given in ECUs (Experimental Currency Units), with 20 ECU = 1 Euro.

was kept. This method is easy for people to comprehend and gives a specific risk parameter, except for the few people who invest 0 or 100.

Based on the equilibrium analysis reported in Appendix A, we summarize the pure-strategy equilibrium predictions for each treatment of Experiment 1 in Table 1.[19]

[Table 1]

With complete information and strategic substitutes, all three networks have equilibria in in which two nodes are active and equilibria in which three nodes are active. The former are more efficient by having the lowest total cost, but the latter are more stable in the sense of Boncinelli and Pin (2012). In the case of strategic complements, we have a unique equilibrium in the green and purple networks, where all individuals are inactive; and there are two equilibria in the orange network: In addition to the full-inactivity (inefficient) equilibrium, there is an equilibrium in which the clique formed by positions B, C and D is active.

With incomplete information, Galeotti *et alii* (2010) show that the equilibria are defined by a threshold: In the case of strategic substitutes, those players with degree below (above) the threshold are active (inactive), and the threshold increases with connectivity. In the case of strategic substitutes, those players with degree above (below) the threshold are active (inactive) and the threshold decreases with connectivity. Thus, as depicted in Table 1, in the case of strategic substitutes, the theoretical prediction is that players with degree 1 (degree 3) are active (inactive) in both treatments, i.e., $p = 0.2$ and $p = 0.8$. Players with degree 2 are active only when $p = 0.8$. With strategic complements, the theoretical prediction is that no one will be active when $p = 0.2$, but that (in addition to the no-activity equilibrium) there is room for players with high degree (degrees 2 and 3) to be active in equilibrium when $p = 0.8$.

Comparing across informational regimes (Table 1), it becomes clear that the equilibrium multiplicity with complete information and strategic substitutes is fully resolved with incomplete information; this is also the case with strategic complements and $p = 0.2$, but not with $p = 0.8$, where multiple equilibria remain. Thus, by this design we can study if people are behaviorally responsive to the different network positions and the different level of information they have when the incentives are either fully complements or substitutes.

[19] We refer readers interested in the mixed-strategy equilibria to the working-paper version, Charness *et alii* (2012).

We conducted this initial set of 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. On average, a session lasted about 80 minutes, with an average payoff of 16 Euro per subject (including a 5 Euro show-up fee).

After conducting these sessions and seeing the results, we added an extra treatment to the Experiment 1 setting. In an effort to ascertain the dramatically-different behavior with strategic complements according to whether the orange network is known to be in force or is only 80% likely to be in force, we also ran two sessions with our initial networks and with the likelihood of p = 0.95 that the orange network being in force. The set of (pure-strategy) equilibria in this additional case coincides with the one for p = 0.8: There is one equilibrium in which all degrees are inactive and another one in which players with degree 1 are inactive and players with degrees 2 and 3 are active. A total of 40 new subjects participated in these sessions.

Experiment 2: After observing our results for Experiment 1 and receiving helpful comments, we designed a new experiment to study the issue of equilibrium selection in the lab in more detail. We focus on strategic complements in the new treatments.[20] The new treatments are:

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

In this experiment, we used the networks depicted in the middle panel of Figure 1: The *Blue*, *Red* and *Brown* networks. With incomplete information, the value for p is the probability that the *Blue* network was in force (each of the other two networks was selected with probability (1-p)/2). We created these three new networks by adding a link to each of the three initial networks used in Experiment 1 (with re-labeling to avoid visually-crossed lines).[21] We note that the red and brown networks have the same average connectivity but different clustering, with a

[20] This is so since, in the main context – of incomplete information – analyzed in Galeotti *et alii* (2010), there is multiplicity of equilibria in the case of strategic complements, whereas they find a unique equilibrium in the case of substitutes. In the complete information scenario, we also focus on the case of strategic complements in the new set of treatments.

[21] Specifically, we add the link CE to each of the networks, and then switch the labels of nodes D and F.

clustering coefficient of 1/3 for the red network and 0 for the brown network. The blue network has higher average connectivity, but also has a higher clustering coefficient.[22]

Table 2 shows the theoretical predictions for the network scenarios in Experiment 2, which are derived in the equilibrium analysis reported in Appendix A.

[Table 2]

Note that all treatments share two equilibria, one in which all subjects are inactive and another (efficient) one, in which the maximum number of players that can (profitably) coordinate on activity do so.[23] Then this design allows us to study the equilibrium selection and to relate it to the network characteristics. A comparison between the treatments with p = 0.2 and p = 0.8 allows us to test the prediction that an increase in the connectivity (and the same for the degree) should increase the probability that the efficient equilibrium is played, since the higher the connectivity, the higher the payoffs if the players are coordinated on the efficient equilibrium. Regarding clustering, Keser, Ehrhart and Berninghaus (1998) show that three-player cliques achieve more coordination than do 8-player circles, despite the same average connectivity.[24] Similarly, the results of Cassar (2007) also suggest that clustering increases the probability that agents coordinate on the payoff-dominant equilibrium. So our prediction is that clustering enhances the selection of the efficient equilibrium.

We ran the sessions of Experiment 2 in Innsbruck in November, 2012. There were two sessions of each of the treatments with the new 5-person networks, and thus 40 people in each of these treatments, yielding a total of 120 new participants.

Experiment 3: With the aim to confirm the results previously observed, with regard to the equilibrium selection, we design a new experiment using a more complex environment. We

[22] The (global) clustering coefficient is defined as the effective number of cliques (triangles) divided by the number of potential cliques. For example, consider the blue network. Players C and E are neighbors of B and therefore there is a potential clique. Since players C and E are linked, the clique is effective. On the other hand, players A and E are neighbors of B (another potential clique). Since they are not linked, the clique is not effective.

[23] The scenario of incomplete information presents an additional Bayes-Nash equilibrium when p = 0.8, in which only players with degree 3 are active. However this equilibrium is weak, since players with degree 2 are indifferent between being active or inactive (see Appendix A for details). Indeed, in this equilibrium it is only because the remaining players with degree 2 are inactive, that a player with degree 2 has weak incentives to be inactive himself. It is an evanescent equilibrium since, in any dynamic setup, starting at this equilibrium, if one player with degree 2 switches from inactive to active (which is also a best response), then all the remaining players with degree 2 would have (strict) incentives to become active. Moreover, it is inefficient, as it is Pareto dominated by the (efficient and strict) equilibrium in which players with degrees 2 and 3 are active. By all these reasons, and because it has no behavioral support in our data –the frequency of activity of players of degree 2 in that scenario is close to 80%-, we barely mention this equilibrium throughout our analysis.

[24] Note that in our design it suffices for a 3-player clique to coordinate for activity to be optimal.

use the three different 20-person networks, shown in the bottom panel of Figure 1, under the incomplete-information regime. We consider only strategic complements for the same reasons mentioned above (cf. Footnote 20). In this case, we additionally focus on the incomplete-information scenario because the strategy space in the case of complete information would be very large.[25] Players know the network but not their position within the network. In each period, people are randomly allocated to the nodes of the network and are informed of their degree (color). They then make a choice between active or inactive. The network remained the same for all 40 periods. We had three treatments, one for each of the networks that, as explained below, differ in terms of connectivity and clustering. The experimental instructions (to the treatment corresponding to Network 1) are provided in Appendix D.

Table 3 gives a summary of network characteristics for these networks. Note that networks 2 and 3 are formed by adding seven links to network 1 (see Figure 1), that both networks 1 and 2 have zero clustering whereas there is positive clustering in network 3, and that networks 2 and 3 have the same level of connectivity and the same degree distribution. Hence both networks 2 and 3 are more connected than network 1, but additionally, network 3 presents a higher clustering.

[Table 3]

The equilibrium predictions (in pure strategies) are shown Table 4 (see Appendix A for a derivation of these results). As we can see, with this design, all three networks have the same set of (pure-strategy) equilibria: 1) An efficient equilibrium, in which players with degree higher than 1 are active, and 2) an inefficient equilibrium, in which all players are inactive.

[Table 4]

A comparison of networks 1 and 2 allows us to study the robustness of the connectivity effect on the selection of the efficient equilibrium in the large-network case, and the comparison of networks 2 and 3 allows us to study the effect of clustering. As in the former experiment our prediction is that clustering enhances the selection of the efficient equilibrium.

[25] In our design, the strategy of a player in the incomplete information scenario has four components (there are 4 possible degrees in the networks considered), whereas in the complete information scenario a strategy would have 20 components (we consider networks with 20 different positions).

For each of the three treatments (different 20-person networks), we conducted three sessions with 20 participants each at the University of Innsbruck in December 2012, having in total 180 new participants.

4. Results

4.1 Experiment 1

Measurement

We analyze our data 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 C.

The explanatory variables in the econometric model of the data from complete-information sessions are period, dummies for player position, all interactions between period and these dummies, and risk preference. 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 estimated probabilities to be active computed by player position, network, and treatment (see Table 5 below and Appendix C).

The explanatory variables in the econometric model of the data from incomplete-information sessions are period, a dummy for the connectivity (with $p = 0.2$ as benchmark), and dummies for a player's degree, interactions across these variables, and the measured level of risk aversion. The results of this model are summarized by the marginal probabilities computed with respect to connectivity and degree (see Table 6 below).

Complete information

Table 5 presents the summary statistics for behavior in the three networks for both substitutes and complements with complete information, as well as the estimated rate of activity. Figure 2 shows the evolution per network and position across the 40 periods.[26]

[Table 5 and Figure 2]

[26] 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.

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. There is strong support for this.[27] Averaging the absolute difference between the theoretical prediction and the observed behavior over all nodes, individual play is consistent with the equilibrium ACE/BD in 87.6 percent of all cases. There is no support for any of the other equilibria, so the problem of equilibrium multiplicity does not seem to be present behaviorally. In 52.5 percent of the observations the groups fully coordinate on this equilibrium; this is increasing over time (36.9 percent in the first 20 periods and 68.1 percent in the last 20 periods). In fact, the correlation coefficient between the period and the average frequency of equilibrium play is 0.724, with $p < 0.01$.

The econometric analysis confirms our previous impressions. In all networks (with strategic substitutes) the estimated activity probability for position A and for position E is close to 100 percent. On the other hand, the estimated activity probability for positions B and D is never more than 10 percent. While position C has a lower estimated activity rate than positions A in E in networks *Orange* and *Green*, being active is still by far the most likely outcome for position C. Thus, the equilibrium ACE/BD prevails in all networks. In Figure B.1 (in Appendix B), we see that this regularity is present in all groups 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 fully efficient, since three players pay the cost instead of two, with complete coverage in both cases (the net social benefit is 350, compared to the social benefit of 400 with only two purchases). However, it can be argued that the selected equilibrium ACE/BD is more stable than the equilibria where only two players are active. To see this, consider any of the three networks and the 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 50) and, from that configuration, only such a player would have incentives to switch his action (to become active again), leading back to the initial ACE/BD equilibrium. On the other hand, in the efficient equilibrium, after a deviation of a player to inactivity, at least two players would have incentives to become active, one of them being the deviator (for example, consider

[27] The weakest support is from player C in networks where he or she has degree 2. Even so, there is a strong trend over time towards C being active, as this rate increases from 58.7 percent in the first 20 periods to 76.6 percent in the final 20 periods with the Orange network and from 52.8 percent to 80.8 percent with the Green network. Similarly, player C's activity rate increases from 90.2 percent to 98.4 percent with the Purple network.

the equilibrium BE/ACD in the Orange network: if B deviates, each of A, B and C incur a loss of 50). Thus, from this configuration, there could be convergence to a different equilibrium that yields much lower payoffs.

Boncinelli and Pin (2012) provide support for this intuitive idea, as they 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.[28] Summarizing, there is a trade-off between efficiency and stability.

> ***Result 1:*** *With complete information and strategic substitutes, agents' behavior in all three networks is consistent with the inefficient, but stochastically-stable equilibrium ACE/BD. Coordination on this equilibrium increases over time.*

Strategic Complements

For complements, we see an impressive rate of play (96.1 percent) consistent with the unique equilibrium (no activity) in the *Green* and *Purple* networks.[29] The *Orange* network admits two equilibria, with either three active players (B, C, and D) or none. Here the play resembles the active equilibrium, as players B, C, and D are active 74.0 percent of the time, and players A and E remain inactive 95.6 percent of the time. This is also the efficient equilibrium, since players B, C, and D each earn more than with the inactive equilibrium. Thus, we find strong support for the theoretical predictions, with successful coordination by players in a clique to achieve the efficient equilibrium when this can involve a profit. At the group level (see Figure B2 in Appendix B), three of the four matching groups coordinate quite well on the efficient equilibrium. Over time, equilibrium play becomes more frequent, indicated by a correlation coefficient between the period and the frequency of equilibrium play of 0.622 (with $p < 0.01$).

The estimated probabilities of being active confirm this impression (Table 5). In all networks, the estimated probability of positions A and E choosing active is close to 0. This is also true for positions B, C, and D in the *Green* and *Purple* networks, while in the *Orange* network positions B, C and D are predominantly active (the estimated activity rates are respectively 0.843, 0.746 and 0.813). Interestingly this equilibrium is very robust since it is in

[28] The Equilibrium ACE/BD 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).

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

fact 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.

> ***Result 2:*** *With complete information and strategic complements, players in the Green and Purple networks play the unique equilibrium, while players in the Orange network behave consistently with the efficient equilibrium BCD/AE. There is increasing coordination on the equilibrium over time.*

Note the difference in outcomes between strategic substitutes and strategic complements: while people select the inefficient equilibrium with substitutes, with complements they select the efficient one. We can explain this difference by looking at the relation between efficiency and private incentives. With substitutes, efficiency is achieved when players B and D are active; but they strictly prefer the inefficient equilibrium ACE/BD that gives them a higher payoff. So they can implicitly coordinate on inactivity in order to force players A, C and E to be active. 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.

Finally we look at the role of risk aversion. Theoretically we could expect that a greater degree of risk aversion would be correlated with less activity in the case of strategic complements and more activity in the case of strategic substitutes. In Appendix C, we see that the marginal effect of risk aversion on the probability of being active is almost always insignificant, except for a modest difference (in the expected direction) for complements.

Incomplete information

Strategic substitutes

Table 6 presents the summary statistics for behavior with incomplete information and both strategic substitutes and complements under each probability regime, as well as the marginal effects on activity. Figure 3 shows the evolution per network and position across the 40 periods for both substitutes and complements.

[Table 6 and Figure 3]

For strategic substitutes we observe that, in each case ($p = 0.2$ and $p = 0.8$), modal play coincides with play in the unique equilibrium.[30] The correspondence is excellent for degrees 1

[30] The proportions are 94.8, 71.8 and 98.9 percent of the time, respectively, for degree 1, 2 and 3 when $p = 0.2$, and 92.9, 59.5 and 89.9 percent when $p = 0.8$.

and 3, but less so for degree 2. Overall, 87.6 percent of all choices were consistent with equilibrium play when $p = 0.2$ and 84.0 percent when $p = 0.8$.

Regarding the effect of connectivity within a particular degree (recall that higher values of p imply higher connectivity), Table 6 shows no significant difference in the behavior of players with degree 1 across the values of p. For players with degree 2, the probability of being active is significantly higher when $p = 0.8$, with a marginal effect of 0.547; for players with degree 3, this probability is marginally-significantly higher with $p = 0.8$, but the marginal effect is small (it is 0.024). Hence, our data are quite consistent with the equilibrium prediction.

Next we consider the effect of having different degrees. Participants with degree 2 are significantly less likely to choose to be active than those with degree 1; the decrease is quite large when $p = 0.2$ and much smaller when $p = 0.8$. People with degree 3 have a much lower and significantly different probability of choosing to be active than do people with degree 1, for both values of p. 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 $p = 0.8$ and a much lower one when $p = 0.2$.[31] All of the differences across the probability values are qualitatively in the direction of the theoretical prediction.[32] Hence, our analysis suggests that the expected effects of connectivity and degree are observed in the lab.

We can also examine behavior over the course of the 40 periods. 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 ½ when $p = 0.2$, and mostly above ½ when $p = 0.8$; this 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. Overall, the correlation coefficient between the period and the frequency of equilibrium play is 0.233 (not significant) with $p = 0.2$ and is 0.594 (p-value < 0.01) with $p = 0.8$.

[31] The marginal effects for degree 2 versus degree 1 are -0.816 and -0.273 for $p = 0.2$ and $p = 0.8$, respectively; for degree 3 versus degree 1, these are -0.980 and -0.961 for $p = 0.2$ and $p = 0.8$, respectively. Finally, the marginal effects for degree 3 versus degree 2 are -0.687 and -0.164 for $p = 0.2$ and $p = 0.8$, respectively.

[32] The fact that players with degree 2 play equilibrium strategies less frequently than players with degrees 1 and 3 may reflect their 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); (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 player with degree 2 is more likely to be linked to an active player), and we could expect more deviations from them.

Summarizing, 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 strong trend to the unique equilibrium and an increasing level of coordination.

> ***Result 3****: Under incomplete information, with strategic substitutes people play consistently the unique equilibrium and the probability of activity is decreasing with the degree and increasing with connectivity.*

Strategic complements

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 (98.0 and 82.1 percent). However, subjects with degree 3 are inactive only a bit more than half the time (55.6 percent). Still, in the aggregate, individual play is consistent with the equilibrium prediction six out of seven times. When $p = 0.8$, there are two pure-strategy equilibria. In one of these, no players are active, while in the other players of degree 2 and 3 are active. The latter equilibrium is the efficient one but it is also riskier. While the behavior of individuals with degree 1 is strongly consistent with these equilibria (98.2 percent, note they are inactive in both equilibria), the evidence on the behavior of individuals with degrees 2 and 3 is mixed, with activity rates of 31.0 and 51.0 percent respectively.

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. Players with degrees 2 and 3 are significantly more likely to choose to be active for the higher values of p, reflecting attempts by the players of higher degree to coordinate on activity.[33] However, these attempts are largely unsuccessful over time. The decline over the course of the session is faster when $p = 0.2$ (where activity is not present in any equilibrium) and slower when $p = 0.8$.

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 $p = 0.2$ (the marginal effects are 0.153 and 0.041, respectively). This is qualitatively in the direction of the theoretical prediction, since players with degree 2 are active in the efficient equilibrium when $p = 0.8$. Perhaps unsurprisingly, since players of degrees 2 and 3 make the same choice in either equilibrium in this environment, the same relationship holds

[33] The results are robust to the inclusion of risk attitudes, as the marginal effects are very small and insignificant.

between players with degrees 1 and 3, with higher marginal effects when $p = 0.8$ (0.562 versus 0.328 with $p = 0.2$). Finally, players of degree 3 are significant more likely to be active than players of degree 2, for all values of p. This evidence, not predicted by theory, may reflect the greater incentive for players of degree 3 to coordinate on the efficient equilibrium.

The pattern is revealing. It seems that subjects with higher degrees (particularly with degree 3) attempt to coordinate on being active and making some profits. But this more efficient play erodes over time, with low or very low rates of activity for everyone by the end of the session; the correlation coefficient between the period and the average frequency of equilibrium play is 0.926 for $p = 0.2$, and 0.639 for $p = 0.8$, with a significance level of one percent. 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.

Summarizing, 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 appears to converge to the inefficient equilibrium.

> ***Result 4****: Under incomplete information, with strategic complements the modal play coincides with the unique equilibrium with lower connectivity, while the probability of activity increases with the degree and connectivity.*

Finally we look at the role of risk aversion under incomplete information. In Appendix C, we see that, as it was the case with complete information, when there is incomplete information the marginal effect of risk aversion on the probability of being active is also almost always insignificant, except for a modest difference (in the expected direction) for complements.

Certainty versus uncertainty with strategic complements

We find a puzzling difference in play when it is certain that the *Orange* network is in force (complete information) and when this is only very likely ($p = 0.8$). The immediate question that arises is whether this difference is driven by there simply being *any* element of uncertainty regarding the network in force. Recall that the result with complete information is driven by the ability of the BCD clique (i.e., the positions with degree 2 or 3) to coordinate on activity, and that the potential benefit of such coordination is only one-third of the potential loss from trying. Perhaps even a tiny amount of uncertainty will make such coordination too difficult to achieve.

Accordingly, we conducted another treatment in which the probability that the Orange network is in force is 0.95. There are two equilibria: the efficient one where nodes with degree 2 and 3 are active (played when the Orange network was definitely in force) and a second one in which all players are inactive (the inefficient one, to which behavior converged in our treatment of incomplete information with $p = 0.8$).[34] If we observe differences between this environment and one with complete certainty, it indicates that coordination on efficient-but-risky equilibrium is too difficult without common knowledge of the precise network having been implemented. This explanation is in part based on the abundant experimental evidence that people are loss adverse and tend to overestimate small probabilities.

The aggregated activity rates observed for players with degree 2 or 3 (the activity rate for players of degree 1 is always negligible) with $p = 0.95$ look considerably closer to those found in the treatment of complete information when the Orange network was in force (hereafter we denote this environment by $p = 1$) than to those found with incomplete information and $p = 0.8$. The activity rates for players of degree 2 are 31.0, 67.9, and 72.8 percent for $p = 0.8$, 0.95, and 1, respectively, while the corresponding activity rates for players of degree 3 are 51.0, 75.7, and 74.6 percent. So at first glance it seems that there is no pure uncertainty effect. However, the patterns of play over time suggest otherwise:

[Figure 4]

Simple inspection of Figure 4 shows a clear negative trend in the rate of activity in both treatments of incomplete information ($p = 0.8$ and $p = 0.95$), but no evidence of decay with complete information ($p = 1$). Table 7 provides analytic evidence of this visual evidence:

[Table 7]

We report the estimated rates of activity by treatment and degree for the average period (20) and for the last period (40).[35] Comparing these rates in the two treatments with incomplete information, we find a clear and highly significant evidence of the connectivity effect for degrees 2 and 3. Comparing the estimated rates of activity in treatments $p = 0.95$ and $p = 1$ we find that, while in period 20 there is no significant difference, in period 40 the differences are significant at

[34] When $p = 0.95$, if players are coordinated in the efficient equilibrium, the probability of a loss when an agent has degree 3 is approximately 1%, while this probability is 7% when he has degree 2. Then, assuming coordination in the efficient equilibrium, over a total of 40 periods an individual would experience, on average, one period of losses.
[35] We estimated the probability of being active using a logit panel model with random effects.

5% in the direction of a higher activity rate with complete information. Table 7 also shows that the trend in the activity rate for degree 2 is significantly more negative with p = 0.95 than with complete information. Thus, it appears that there is indeed an effect of uncertainty *per se* over time, indicating that learning plays a role in how participants react to uncertainty. The trends indicate that the inefficient (no-activity) equilibrium will eventually predominate with incomplete information, while the efficient equilibrium prevails with complete information. Thus, there is evidence that uncertainty *per se* (regardless of the degree) is enough to derail attempts at coordination on the efficient equilibrium.

One may wonder why the effect of uncertainty does not appear until time has passed in the sessions. We suspect that this is a contagion effect in the coordination game. When players observe that some other players are inactive (together with the fact that they also face an uncertain context), they also become inactive. So we feel that the uncertainty matters together with the coordination context players face: Given the uncertainty, players may have different thresholds regarding how much perceived inactivity induces them to become inactive

> ***Result 5:*** *We see that even a very small amount of uncertainty about the network in force (p = 0.95) can lead to considerable differences over time with respect to behavior with certainty, derailing attempts to achieve the efficient equilibrium.*

4.2 Experiment 2

As mentioned earlier, we only consider strategic complements in Experiment 2, as these are better suited for testing equilibrium selection.

Complete information

Table 8 presents the summary statistics for behavior in the three networks under complete information, as well as the marginal effects on activity. Figure 5 shows the evolution per network and position over time.

[Table 8 and Figure 5]

We see that the modal play corresponds to the efficient equilibria in all the three networks, but that the intensities of play vary. The results suggest that there is a positive effect of degree since within each network the frequencies of activity are higher for players with degree 3. There seems to be also a positive effect of clustering, as indicated by the fact that those players with degree 2 that should be active in the efficient equilibrium and those players with degree 3 are more likely to be active in the red network than in the brown network. Additionally, the more connected (also more clustered) blue network has higher rates of activity than do the red and brown ones. We do not observe any time trends for any position in any of the networks.

The econometric analysis (we estimate an econometric model analogous to that described in Experiment 1) for network and position (at the average period and average risk levels) shows that players in positions B, C, D and E have an activity rate that is significantly different from 0, although this probability is very small for players in position B of the *Red* network. These results confirm that the efficient equilibrium prevails for all three networks. Note that the only difference between the *Blue* and *Red* networks is one extra link in the Blue network; this extra link changes the probability that B players choose to be active from 92.86 percent to 18.52 percent, a highly-dramatic decrease which is consistent with the equilibrium prediction (in the efficient equilibrium, position B is active in the *Blue* network, but inactive in the *Red* one).

> ***Result 6****: Under complete information, the efficient equilibrium prevails for all three networks. There is a strong effect of degree on activity, as well as an effect of clustering.*

Incomplete information

Table 9 presents the summary statistics for behavior with incomplete information, as well as the marginal effects on activity. Figure 6 shows the evolution per degree over time.

[Table 9 and Figure 6]

Modal play for all degrees corresponds to the efficient equilibrium both when $p = 0.2$ and $p = 0.8$. In both treatments there is a positive effect of degree on activity levels (degree 3 is, respectively, 22.4 and 17.1 percentage points more active than degree 2). Regarding the effect of connectivity, there is no difference across values of p for players with degree 3, but there is a small difference for players with degree 2 (6.7 percentage points) that suggests a positive effect on the selection of the efficient equilibrium.[36] The main difference in time trends across the two values of p is that there is a clear negative trend for players with degree 2 when $p = 0.2$, while the trend with $p = 0.8$ is constant (or even slightly positive). There are no time trends for players of degree 1 (who are almost never active) or for players of degree 3 (who are almost always active).

[36] While a 6.73 percentage-point increase is certainly not large, it is nevertheless nearly one-quarter of the maximum 27.52 percentage-point increase possible from the activity rate with $p = 0.2$.

In order to check the significance of the effects for degree and connectivity, we report (in the bottom part of Table 9) the marginal effects for players of each degree estimated using an econometric model analogous to that described in Experiment 1. We see a significant degree effect on the likelihood one chooses to be active. Comparing rates for degree 1 and either other degree gives extremely large marginal effects, as predicted by theory. There is also a small but significant effect of degree with respect to players of degrees 2 and 3, which is not predicted in equilibrium. The increase in the (estimated) probability of being active is 5.2 and 9.3 percentage points when $p = 0.2$ and $p = 0.8$, respectively. Both marginal effects are significant at the 10% level with two-tailed tests.

Finally, in the middle of Table 9 we report the marginal effects of connectivity ($p = 0.8$ compared to $p = 0.2$) over the probability of being active, measured at the average risk levels. Since we have observed in Figure 6 a remarkable difference in trends across $p = 0.2$ and $p = 0.8$ for players with degree 2, we measure the marginal effect both at the average period (20) and at the final period (40).

At period 20, there are no significant differences for any degree. This is unsurprising for players with degree 3, since the frequency of activity is already close to full activity when $p = 0.2$. However, when we use period 40 to measure the marginal effect of connectivity for players with degree 2, we find significance at the 10% level on a two-tailed test.[37] Hence, there is an effect of connectivity on activity rates for players with this degree, but people need some periods of learning before this effect materializes. No difference is observed or predicted for players of degrees 1 or 3.[38]

Summarizing, we have:

> ***Result** 7: Under incomplete information, modal play corresponds to the efficient equilibrium for all probability values. Once again, there is a strong effect of degree and there is evidence that the probability of activity increases with the connectivity.*

4.3 Experiment 3

In Table 10, we display the frequencies of activity by degree and network, as well as the marginal effects on activity.

[37] The econometric analysis shows that, both for degree 2 and 3, the differences in the trends corresponding to treatments $p = 0.8$ and $p = 0.2$ (measured by the marginal effect of treatment on the marginal effect of period by degree) are positive and significant (at the 5% level for degree 2 and the 10% level for degree 3).

[38] Finally, we mention that, as in Experiment 1, the marginal effects (not reported here) of risk preference on the probability to be active are not significant for any degree or connectivity level.

[Table 10]

Players with degree 1 are rarely active, as we have seen in our other experiments with strategic complements (activity can never be profitable). We see a strong positive degree effect on the choice of being active, as the activity rates increase by degree in all three networks and for each degree. In networks 2 and 3, nearly every player with degree 3 or 4 is fully active.[39]

We find a clear connectivity effect when the behavior is compared across network 1 and either of networks 2 or 3. The activity rates in networks 2 and 3 are much higher than in network 1 for players with multiple connections. Regarding clustering, since players with degree 3 and 4 are already fully active in network 2, we can only consider players with degree 2 if we aim to identify a clustering effect; but even in this case, the activity rate in network 2 is very high (88.1%). We find that the probability of being active is only slightly higher in network 3 (92.9%), but the modest 4.8 percentage-point increase does represent more than 40 percent of the maximum 11.9 percentage-point increase possible from the activity rate with network 2.

In Figure 7 we observe the evolution of activity in each network (by degree). The results show convergence to the inefficient equilibrium in network 1 and clear adherence to the efficient equilibrium in networks 2 and 3. This shows a clear and strong connectivity effect.

[Figure 7]

In order to study the significance of these effects, as before we estimate a logit panel-data model with random effects and report the marginal effects across networks in relation to the probability of being active (measured at the average period and risk levels). The estimations show a significant connectivity effect on the choice of being active (the marginal effect for players of degrees 2, 3 and 4, comparing network 1 to either of networks 2 or 3). However, the clustering effect (marginal effect of network 3 over network 2, measured for players with degree 2) is not significant, perhaps due to the high activity rate in network 2 (ceiling effect).

[39] In the third session of network 3, we identified one person whose behavior was anomalous. This individual was always active when her degree was 2, whereas she was always inactive when her degree was 3 or 4. This pattern is in stark contrast to the incentive structure of the game and the behavior of all the other 179 subjects that played either in networks 1, 2 or 3. Thus, although we keep the data of this session for our analysis, we decided to remove the data from this specific anomalous individual throughout all our analysis. Consider that without this individual, we have completely full activity for players with degree 3 and 4, while this person is *never* active with degree 3 or 4 (but is active at a lower degree); furthermore, network 2 has full activity for players of degrees 3 and 4. Thus, if we include this individual and compare behavior in networks 2 and 3, we would find an odd "clustering" effect.

We do see some suggestive evidence of a clustering effect at the session level. In network 2, there is full activity for all players with degrees 3 and 4 and partial inactivity for degree 2 players in all three sessions. The pattern is different in network 3 for players with degree 2, who are fully active in two out of three sessions and in the other there is a partial degree of inactivity for degree 2 players. Summarizing, we have:

> ***Result 8****: Activity rates increase by degree in all three networks. We find a clear and strong connectivity effect across networks and suggestive evidence of a clustering effect.*

5. Discussion

In this section, we address issues of behavior with respect to equilibrium predictions. We first consider how well the experimental data fits the theoretical predictions, and then discuss the extent to which potential multiple equilibria manifest in each treatment and the issue of convergence over time. Finally, and perhaps most importantly, we examine the underpinnings of factors that appear to drive the selection of a particular equilibrium or equilibria.

5.1 Conformance of the experimental results to the theoretical predictions

Experiment 1

The results in Experiment 1 are quite consistent with the theoretical predictions for behavior in our games. These results provide not only very strong qualitative support, but also surprisingly strong quantitative support. With complete information and strategic substitutes, 87.6 percent of activity choices correspond to a stochastically-stable equilibrium in which everyone makes positive profits. When the game involves strategic complements, play corresponds to the predicted equilibrium 96.1 percent (100 percent in the last 10 periods) of the time when it is unique. Matters are a bit more complicated when there are two equilibria. While overall the efficient equilibrium is played 74 percent of the time by the players who should be active (82.6 percent over all players), one of the four 10-person groups converged to the no-activity equilibrium. In the last 10 periods of the session, the activity rate for players B, C, and D combined was 83.9 percent overall for three of the groups, but was only 11.1 percent for the other group.[40] So we see heterogeneity across groups.

The results with incomplete information are particularly striking, given the much greater complexity of this environment. With substitutes, play is consistent with the unique, no-activity equilibrium 87.6 percent of the time when $p = 0.2$ and 84.0 percent of the time when $p = 0.8$. Play in the last 10 periods is even more consistent with the equilibrium for both $p = 0.2$ (91.0 percent) and $p = 0.8$ (91.2 percent).[41] But 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 85.7 percent of the time (97.2 percent in the last 10 periods) when $p = 0.2$. When $p = 0.8$, there is an equilibrium with no activity, while players of degree 2 and 3 are active in the other. The overall activity rates are 31.0 percent for players with degree 2 and 51.0 percent for players of degree 3, painting a murky picture. However, these rates decline to 4.3 percent and 14.9 percent in the last 10 periods, so that behavior is converging to the no-activity equilibrium.

The effects of degree and connectivity on activity are entirely consistent with the theoretical predictions, which imply a negative relationship between degree and activity with strategic substitutes, but 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.[42]

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[40] Purely in terms of expected value, being active pays off for player B, C, or D if the chance that both of the other two players are also active is at least 2/3, which corresponds to 81.6 percent for each player without correlation. But a taste for social efficiency may lower this threshold.

[41] The rates in the last 10 periods for degrees 1, 2, and 3 with $p = 0.2$ are 99.5 percent, 72.7 percent, and 100 percent, respectively. The rates in the last 10 periods for degrees 1, 2, and 3 with $p = 0.8$ are 94.6 percent, 78.4 percent, and 95.2 percent, respectively.

[42] 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.

Experiment 2

The results of Experiment 2 are more mixed, but still provide strong qualitative and some quantitative support for the predictions. In this design, there is always an equilibrium with no activity and exactly one efficient equilibrium (not the same across networks) with activity by a proper subset of the players. With complete information (strategic complements), 81.2 percent of the overall choices correspond to the efficient equilibrium (76.2 percent for roles predicted to be active in the equilibrium). The overall percentage is highest for the *Blue* network, lower for the *Red* network, and lowest for the *Brown* network. Note that this pattern matches the number of 3-player cliques in each network, reflecting the difficulties in successful coordination on activity. All four groups coordinate on the efficient equilibrium with the *Blue* network, but one group in the *Red* network and two groups in the *Brown* network fail to do so.[43]

The equilibria with incomplete information (and complements) are the same for $p = 0.2$ and $p = 0.8$, with a no-activity equilibrium and one in which players with degrees 2 and 3 are active[44]; obviously, players of degree 1 should never be active. While activity rates are slightly higher for degree-2 players with more connectivity (79.21 percent versus 72.48 percent), for degree-3 players the activity rates are essentially the same with low and high connectivity (94.87 and 96.36 respectively). There is no overall time trend with the exception of degree-2 players and low connectivity, as the activity rate, respectively for degree-2 players and degree-3 players, in the last 10 periods is 62.14 and 93.86 percent when $p = 0.2$ and 78.95 and 98.06 percent when $p = 0.8$. Indeed with $p = 0.2$, while two groups completely converge to the efficient equilibrium (in the last 10 periods 99.38 percent activity for players with more than one degree), the other two groups do not (47.50 percent activity in the last 10 periods) and in fact seem to be headed toward the no-activity equilibrium.

In experiment 2, the effects of degree are consistent with the theoretical predictions, as there is more activity with higher degree with both complete and incomplete information. We also confirm the effect of connectivity in the case of incomplete information. Regarding complete information, we see that the increased connectivity and clustering in the *Blue* network

[43] The rate for players predicted to be active in the *Red* network is 83.5 percent for the three coordinating groups, but only 42.5 percent for the other group; the corresponding rates for the final 10 periods are 79.1 and 22.2 percent. By the same token, the rate is 86.1 percent for the two coordinating groups in the *Brown* network and is 38.2 percent for the two non-coordinating groups; the corresponding rates for the final 10 periods are 88.3 and 18.7 percent.

[44] Recall that there was also an additional evanescent (weak) equilibrium for $p = 0.8$, in which a player with degree 2 is not active. Yet, this equilibrium does not have any behavioral impact (cf. Footnote 23).

lead to higher activity rates (more groups coordinating on activity) than in the other networks. In addition, comparing behavior in the *Red* network to that in the *Brown* network allows us to identify a pure effect of clustering, holding connectivity constant. The last two rows of Table 8 show that for these players the activity rate in the *Red* network is higher than in the *Brown* network, with aggregate rates of 71.0 percent and 64.2 percent, respectively. Since the activity rate is higher in the *Red* network than in the *Brown* network for all four groups, a binomial test that conservatively considers each group to be only one independent observation, gives p = 0.062, on a (justified) one-tailed test. So there does appear to be an effect from clustering.

Experiment 3

In this difficult stress test with 20-person networks, the theoretical predictions do well. The activity rates increase steadily by degree, at least up to the point where the activity rate is near 100 percent (for degrees 3 and 4 in networks 2 and 3). All three networks had the same two equilibria, one featuring no activity and the other being the efficient equilibrium. We have predictions regarding connectivity and clustering that can be tested by comparing activity rates across network 1 and network 2 (change in connectivity, same clustering) and across network 2 and network 3 (same connectivity, change in clustering), respectively. Figure 7 indicates that there is a very high degree of conformance with the efficient equilibrium in networks 2 and 3, but considerable decay over time with network 1 for players with degrees 2, 3, and 4.

In fact, the pattern becomes much clearer by looking at the session-level data for network 1. In one session, rates were completely stable, with about 5 percent, 43 percent, 85 percent, and 100 percent for degrees 1, 2, 3, and 4, respectively, both on average and for the last 10 periods. There is sharp decay in activity rates in both of the other sessions, where the average activity rates in the last 10 periods are 0 percent, 2.5 percent, 17.5 percent, and 62.5 percent for degrees 1-4, respectively. While some hubs still cling to the possibility of gaining through activity, we speculate that they would eventually give up and the no-activity equilibrium would be reached.

So it seems that adding seven links to the 20 in network 1 greatly affects behavior. Activity rates are lower in each of the three sessions of network 1 than in any of the three sessions of either network 2 or network 3, and two of the three sessions with network 1 clearly converge to the no-entry equilibrium. Yet, for some reason, the efficient equilibrium is played in networks 2 and 3. This brings us to our next section.

5.2 Equilibrium selection

We find some strong and interesting patterns, and generally a strong adherence both qualitatively and quantitatively to the theoretical predictions. Nevertheless, a key issue for policy is that of equilibrium selection, where theory is typically silent and experimental work is particularly useful. Our results help to shed some light on this issue and perhaps allow us to reach some conjectures about equilibrium selection in games on networks.

Overall, there is a predominant tendency for a group to converge to one of the theoretical equilibra.[45] When there is a unique equilibrium, this is played almost universally. We again mention that this is the case in games of incomplete information, where players don't even know the network that has been drawn, let alone their position in it.

But there are definite patterns in the data that beg for an explanation. In Experiment 1, a particular near-efficient equilibrium is played in all three of the networks when we have strategic substitutes and complete information. With strategic complements, only the *Orange* network has an equilibrium involving positive activity. This equilibrium requires a high degree of coordination on activity amongst the members of a 3-person clique, as the potential loss from the attempt is three times the potential gain. This clique is successful in coordinating on the efficient equilibrium in three of the four groups, with an overall activity rate of 86.08 percent in the final 10 periods (11.11 percent activity rate in the other group). Yet, this equilibrium has vanished behaviorally (Figure 3) when the probability is 80 percent that the *Orange* network has been drawn. In Experiment 2, with complete information the efficient equilibrium is largely observed in two of the networks, but not so much in the network where there is no clique. However, with strategic complements and incomplete information, the efficient equilibrium is played even when there is only a 20 percent chance that the Blue network has been drawn. In Experiment 3, we see the efficient equilibrium played in two of the networks, but not in most sessions of the third.

One general tendency we see is that people have a strong taste for achieving coordination on efficient outcomes. There is substantial evidence that people like efficiency (e.g., Charness and Rabin 2002; Engelmann and Strobel 2004). This is in some sense similar to the taste for achieving payoff-dominant outcomes seen in the experimental literature (e.g., Charness, 2000).

[45] Throughout the paper, we have ignored the existence of mixed-strategy equilibra in our networks. But these don't seem to have behavioral impact.

But people are also concerned about the perceived risk/reward ratio and even uncertainty *per se*. For example, there is a clear thirst for achieving the payoff-dominant outcome in Charness and Jackson (2007), but playing Stag only predominates when the hurdle for successful coordination is lower. We see equilibrium selection as reflecting the underlying tastes of the individuals in a group for efficiency. If many people in the group are willing to take the chance on the efficient (but risky) equilibrium with positive activity, they may well be able to sustain the maximum payoff stream. Each group of players will have a particular taste for doing so and will essentially fall on either side of a threshold value that separates "basins of attraction". Certain conditions enhance the likelihood that the efficient equilibrium is selected.

We have seen that connectivity (how well a network is connected) often seems to influence the likelihood of activity, affecting which equilibrium emerges: the no-activity, zero-profit equilibrium or one featuring activity and positive profits.[46] When connectivity is higher with incomplete information and strategic substitutes in Experiment 1, a more active equilibrium occurs, although with strategic complements the more active equilibrium collapses over time. With complements and complete information, the extra link in the *Orange* network leads to successful coordination (in three groups out of four) on the active equilibrium. We see some evidence of a connectivity effect in Experiment 2 with incomplete information, as half of the groups converged on the no-activity equilibrium with $p = 0.2$, but no groups did with $p = 0.8$. Finally, there is a clear effect of connectivity when comparing behavior within networks 1 and 2 in Experiment 3 (complements and incomplete information).

The *manner* in which the network is connected also seems to matter; we consider the clustering coefficient, which reflects the number of cliques (groups of fully-connected agents) in the network. There is no direct way to test for clustering effects in Experiment 1, since the *Orange* network differs from the others by having both an extra link and a corresponding clique that appears. Nevertheless, the success in coordinating on the efficient equilibrium in the *Orange* network with complements and complete information is suggestive that clustering may have an effect. In Experiment 2, we do find a small-but-significant clustering effect with both complete

[46] The formal definition in graph theory refers to the minimum number of elements (nodes or edges) that must be removed to disconnect the remaining nodes from each other.

and incomplete information. In Experiment 3, there is a modest increase in the activity rate for players with degree 2 when cliques are present.[47]

A third factor that feeds into equilibrium selection is the degree of uncertainty. To some extent, this may help to explain why cliques are more effective, since there is in some sense more "certainty" when a group is fully connected. And even when it is very probable (p = 0.95) that a clique is present, the efficient equilibrium that predominates with complements and certainty in Experiment 1 has collapsed into the no-activity equilibrium in half the groups. It is not so easy to coordinate among three people when the loss from failure is thrice the gain from success, and any degree of uncertainty exacerbates the difficulty considerably. With known positions, there may be a flavor of common knowledge or even tacit communication, as each individual in the clique knows that the other individuals in the clique, etc., know the situation. Perhaps the awareness of a shared fate makes people more confident about the likelihood of successful coordination. The efficient equilibrium is usually played with incomplete information in Experiment 2, and is also consistently played in the two networks in Experiment 3 with higher connectivity.

Thus, while people have a taste for efficiency, the hurdle appears to be too high for some coordination problems. And we have also seen that groups are willing to absorb some cost to participate in the near-efficient equilibrium in Experiment 1 (positions A, C, and E active) with complete information and substitutes, rather than one of the equilibria with full efficiency (one less active player). As we have discussed, the near-efficient equilibrium is stochastically-stable and yields 87.5 percent of the total payoffs received in an efficient one. Our view is that this represents a group awareness of the riskiness of having only two active players. This is not unfamiliar in other coordination games. For example, even though there is an extremely high level of coordination on the payoff-dominant outcome in Charness (2000) when there is simple, one-way communication, the risk-dominant equilibrium prevails without communication; it seems that communication moves beliefs sufficiently to cross the threshold value.

Summarizing, we see a number of intertwining factors that combined determine which equilibrium is selected in games on networks. Higher connectivity and more clustering increase activity rates and facilitate coordination on efficient outcomes. Uncertainty (incomplete

[47] Players of degree 3 or 4 are fully active even without any cliques (network 2), so this can't increase by introducing cliques (network 3) and in fact it remains the same.

information) is a negative influence on activity rates, but can be overcome when the coordination problem is less severe or when the active equilibrium is unique. There is also a strong taste for efficiency, but people will invest a modest amount for "insurance" that they will still earn profits if one other person deviates from the equilibrium. No one of these factors is determinative, but can be seen as reinforcing or weakening beliefs in the likelihood of successful coordination. That said, nearly every single group has largely converged to an equilibrium by the end of the 40 periods in the session.

6. Conclusion

Networks are a ubiquitous 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 how games with strategic substitutes or complements, which are general to many economic environments, are played on a variety of networks. We include the case of incomplete information in our experimental design, and 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.

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. Our principal objectives in conducting our experiments were to test theoretical predictions with complete and incomplete information and to provide empirical evidence that sheds light on factors that influence which equilibrium will actually prevail in practice in network settings. In fact, our results suggest that the problem of equilibrium multiplicity may in practice not be so severe. This is particularly true with complete information and substitutes in Experiment 1, where people seem to be willing to trade a relatively small difference in potential gain for an increased likelihood of actually receiving a gain. We find that a number of factors help to mediate which equilibrium prevails. There are higher rates of activity (and so higher profitability) with higher connectivity and clustering, and people have a definite taste for efficiency when there is not much uncertainty and risk is limited.

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. While even in early periods subjects' play is remarkably close to equilibrium predictions, this further improves in later periods, indicating that people learn over time to avoid mis-coordination. 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 for almost every group. In the case of incomplete information, we also find strong qualitative support for the predicted relationships between degree and activity and connectivity and activity. Our results are robust to a variety of smaller networks and larger networks.

Overall, we feel that experimental research such as this will be quite 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, further experimental research that incorporates incomplete information and uncertainty would certainly seem worthwhile. While we have taken a first step in identifying the effects of uncertainty, probabilities are often unknown in practice. Likewise, we consider it as interesting to examine how communication between players in a network may have an impact on equilibrium selection. Our results have shown a remarkable degree of equilibrium play and coordination on a particular equilibrium without any communication, but it seems promising to study whether communication may even further improve successful coordination on the efficient equilibrium. Finally, it would be valuable to develop experiments involving endogenous network formation with multiple players. One major difficult is that a large number of networks are possible, making it difficult to get enough data to draw even tentative conclusions. One approach is to provide an existing framework with some specified options, as in Charness and Jackson (2007), but that is just a start.

Improved behavioral network theory may well be the result of the knowledge gleaned from this and future laboratory experiments.

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Tables and Figures

Table 1: Equilibria in Experiment 1

I) 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

II) With incomplete information

	Probability of the Orange network	Active degrees	Inactive degrees
Substitutes	0.2	1	2, 3
	0.8	1, 2	3
Complements	0.2	-	1, 2, 3
	0.8	-	1, 2, 3
		2, 3	1
	0.95 (addendum to Experiment 1)	-	1, 2, 3
		2, 3	1

Table 2: Equilibria in Experiment 2

I) With complete information

Network	Active nodes	Inactive nodes
Blue	B, C, D, E	A
	-	A, B, C, D, E
Red	C, D, E	A, B
	-	A, B, C, D, E
Brown	B, C, D, E	A
	-	A, B, C, D, E

II) With incomplete information

Probability of the Blue network	Active degrees	Inactive degrees
0.2	-	1, 2, 3
	2, 3	1
0.8	-	1, 2, 3
	2, 3	1
	3	1, 2 (weak equilibrium)

Table 3: Network Characteristics in Experiment 3

		Network 1	Network 2	Network 3
Degree distribution (# nodes)	degree = 1	8	4	4
	degree = 2	6	4	4
	degree = 3	4	6	6
	degree = 4	2	6	6
Number of links		20	27	27
Clustering		0	0	>0

Table 4: Equilibria in Experiment 3

Network	Active degrees	Inactive degrees
Network 1	-	1, 2, 3, 4
	2, 3, 4	1
Network 2	-	1, 2, 3, 4
	2, 3, 4	1
Network 3	-	1, 2, 3, 4
	2, 3, 4	1

Table 5: Complete information in Experiment 1

Frequencies of activity by treatment, network and player position

		Orange		Green		Purple	
		Active ***(%)***	*Total*	Active ***(%)***	*Total*	Active *(%)*	*Total*
Substitutes	A	88 (94.62)	*93*	96 (91.43)	*105*	113 (92.62)	*122*
	B	8 (8.60)	*93*	16 (15.24)	*105*	6 (4.92)	*122*
	C	63 (67.74)	*93*	70 (66.67)	*105*	115 (94.26)	*122*
	D	10 (10.75)	*93*	18 (17.14)	*105*	22 (18.03)	*122*
	E	85 (91.40)	*93*	99 (94.29)	*105*	112 (91.80)	*122*
	Total	254 (54.62)	*465*	299 (56.95)	*525*	368 (60.33)	*610*
Complements	A	4 (3.51)	*114*	1 (0.95)	*105*	1 (0.99)	*101*
	B	85 (74.56)	*114*	4 (3.81)	*105*	13 (12.87)	*101*
	C	83 (72.81)	*114*	11 (10.48)	*105*	1 (0.99)	*101*
	D	85 (74.56)	*114*	2 (1.90)	*105*	5 (4.95)	*101*
	E	6 (5.26)	*114*	1 (0.95)	*105*	1 (0.99)	*101*
	Total	263 (46.14)	*570*	19 (3.62)	*525*	21 (4.16)	*505*

Estimated activity rates by treatment, network and player position
(at period = 20 and average risk level)

	Substitutes			*Complements*		
Position	Orange	Green	Purple	Orange	Green	Purple
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)
B	0.011 (0.008)	0.048* (0.025)	0.013 (0.009)	0.843*** (0.050)	0.007 (0.006)	0.050* (0.027)
C	0.767*** (0.076)	0.754*** (0.079)	0.990*** (0.008)	0.746*** (0.067)	0.010 (0.009)	0.000 (0.000)
D	0.023 (0.014)	0.091** (0.039)	0.097** (0.040)	0.813*** (0.057)	0.001 (0.002)	0.006 (0.007)
E	0.978*** (0.014)	0.987*** (0.010)	0.970*** (0.016)	0.000 (0.001)	0.001 (0.002)	0.000 (0.000)

***, **,* denote significance at 1%, 5% and 10% levels, respectively, two-tailed tests

Table 6: – Incomplete information in Experiment 1

Frequencies of activity by connectivity (p) and degree

		p = 0.2		*p* = 0.8	
		Active (%)	Total	Active (%)	Total
Substitutes	degree = 1	731 (94.81)	771	628 (92.90)	676
	degree = 2	156 (28.16)	554	225 (59.52)	378
	degree = 3	3 (1.09)	275	55 (10.07)	546
	Total	890 (55.63)	1600	908 (56.75)	1600
Complements	degree = 1	15 (1.97)	763	12 (1.76)	681
	degree = 2	107 (17.89)	598	116 (31.02)	374
	degree = 3	106 (44.35)	239	278 (51.01)	545
	Total	228 (14.25)	1600	406 (25.37)	1600

Marginal effects of connectivity (p) by treatment and degree
(*p* = 0.8 vs. *p* = 0.2 *at period 20 and average risk level)*

	Substitutes	*Complements*
degree = 1	0.004 (0.009)	-0.000 (0.001)
degree = 2	0.547*** (0.083)	0.111** (0.056)
degree = 3	0.024** (0.010)	0.233* (0.132)

Marginal effects of degree by treatment and connectivity (p)
(at period 20 and average risk level)

		Substitutes	Complements
degree = 2 vs. degree = 1	*p* = 0.2	-0.816*** (0.041)	0.041** (0.017)
	p = 0.8	-0.273*** (0.064)	0.153*** (0.053)
degree = 3 vs. degree = 1	*p* = 0.2	-0.980*** (0.007)	0.328*** (0.091)
	p = 0.8	-0.961*** (0.009)	0.562*** (0.095)
degree = 3 vs. degree = 2	*p* = 0.2	-0.164*** (0.045)	0.287*** (0.079)
	p = 0.8	-0.687*** (0.063)	0.409*** (0.061)

***, **,* denote significance at 1%, 5% and 10% levels, respectively, two-tailed tests

Table 7. Experiment 1

Estimated activity rates by connectivity (p), degree and period (at average risk level)

		p = 0.80	*p* = 0.95	*p* = 1
degree = 2	period = 20	0.153*** (0.053)	0.805 (0.072)	0.746 (0.067)
	period = 40	0.007*** (0.004)	0.416 (0.131)	0.747** (0.102)
degree = 3	period = 20	0.563*** (0.095)	0.919 (0.034)	0.828 (0.045)
	period = 40	0.012*** (0.006)	0.388 (0.117)	0.685** (0.090)

Estimated trends of activity rates by connectivity (p) and degree (at period 20 and average risk level)

	p = 0.80	*p* = 0.95	*p* = 1
degree = 2	-0.008 (0.003)	-0.014 (0.004)	0.000*** (0.000)
degree = 3	-0.047*** (0.008)	-0.011 (0.004)	-0.006 (0.002)

***, **,* denote significant difference respect to treatment p=0.95 at 1%, 5% and 10% levels, respectively, two-tailed tests

Note that p = 1 means the orange network in the treatment of complete information.

Table 8. Complete Information in Experiment 2

Frequencies of activity by network and player position

	Blue		Red		Brown	
Position	Active (%)	Total	Active (%)	Total	Active (%)	Total
A	0 (0.00)	112	1 (0.93)	108	2 (2.00)	100
B	104 (92.86)	112	20 (18.52)	108	79 (79.00)	100
C	109 (97.32)	112	92 (85.19)	108	62 (62.00)	100
D	85 (75.89)	112	70 (64.81)	108	60 (60.00)	100
E	108 (96.43)	112	68 (62.96)	108	56 (56.00)	100
Degree 2^	85 (75.89)	112	138 (63.88)	216	178 (59.33)	300
Degree 3	321 (95.54)	336	92 (85.19)	108	79 (79.00)	100

Estimated activity rates by network and player position
(at period 20 and average risk level)

	Blue	Red	Brown
A	0.000 (.)	0.000 (.)	0.000 (.)
B	0.989*** (0.007)	0.065** (0.034)	0.913*** (0.042)
C	0.996*** (0.003)	0.992*** (0.005)	0.581*** (0.120)
D	0.882*** (0.052)	0.753*** (0.091)	0.668*** (0.109)
E	0.999*** (0.001)	0.785*** (0.085)	0.674*** (0.110)
Degree 2^	0.882*** (0.052)	0.769*** (0.080)	0.641*** (0.091)
Degree 3	0.995*** (0.003)	0.992*** (0.005)	0.913*** (0.042)

***, **,* denote significance at 1%, 5% and 10% levels, respectively, two-tailed tests
^ Here we are only referring to those players with degree 2 active in the efficient equilibrium.

Table 9. Incomplete information in Experiment 2

Frequencies of activity by connectivity (p) and degree

	p = 0.2		*p* = 0.8	
	Active (%)	Total	Active (%)	Total
degree = 1	25 (7.81)	320	23 (7.19)	320
degree = 2	603 (72.48)	832	339 (79.21)	428
degree = 3	425 (94.87)	448	821 (96.36)	852
Total	1053 (65.81)	1600	1183 (73.94)	1600

Marginal effect of connectivity (p) by degree and period
(p = 0.8 vs. p = 0.2 at average risk level)

	period = 20	period = 40
degree = 1	0.001 (0.005)	-0.001 (0.002)
degree = 2	-0.041 (0.060)	0.272* (0.151)
degree = 3	-0.000 (0.001)	0.004 (0.004)

Marginal effect of degree by connectivity (p)
(at period 20 and average risk level)

degree = 2 vs. degree = 1	p = 0.2	0.943*** (0.030)
	p = 0.8	0.900*** (0.049)
degree = 3 vs. degree = 1	p = 0.2	0.995*** (0.003)
	p = 0.8	0.994*** (0.004)
degree = 3 vs. degree = 2	p = 0.2	0.052* (0.031)
	p = 0.8	0.093* (0.051)

***, **,* denote significance at 1%, 5%, 10% levels, respectively, two-tailed tests

Table 10. Experiment 3

Frequencies of activity by network and degree

	Network 1		Network 2		Network 3	
	Active (%)	Total	Active (%)	Total	Active (%)	Total
degree = 1	26 (2.71)	960	16 (3.33)	480	34 (7.17)	474
degree = 2	177 (24.58)	720	423 (88.13)	480	434 (92.93)	467
degree = 3	291 (60.62)	480	720 (100)	720	707 (99.58)	710
degree = 4	195 (81.25)	240	719 (99.86)	720	709 (100)	709

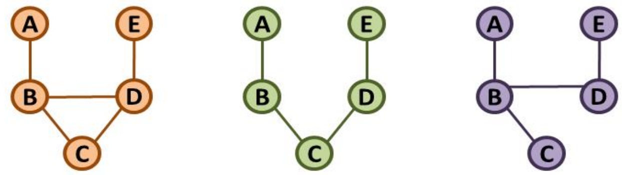
Marginal effect of network by degree (at period 20 and average risk level)

	Network 2 vs. Network 1	Network 3 vs. Network 1	Network 3 vs. Network 2
degree = 1	0.004 (0.004)	0.010* (0.006)	0.006 (0.006)
degree = 2	0.832*** (0.038)	0.836*** (0.037)	0.004 (0.014)
degree = 3	0.284*** (0.060)	0.284*** (0.060)	-0.001 (0.000)
degree = 4	0.051*** (0.019)	0.051*** (0.019)	0.000 (0.000)

***, **,* denote significance at 1%, 5% and 10% levels, respectively, two-tailed tests

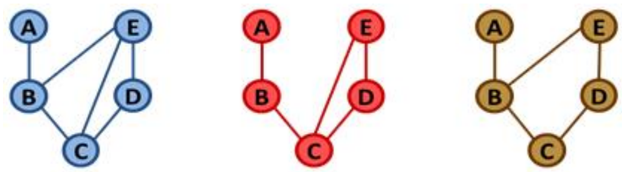
Figure 1: The networks

Experiment 1



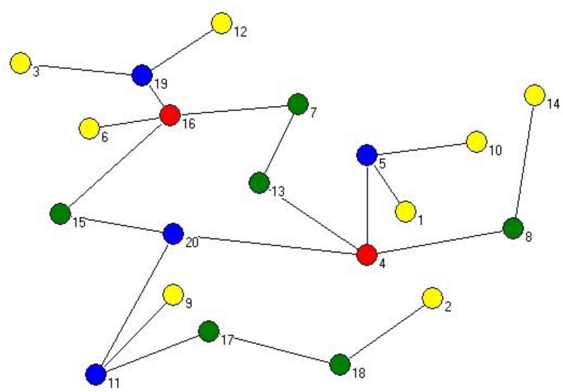
Orange network   Green network   Purple network

Experiment 2

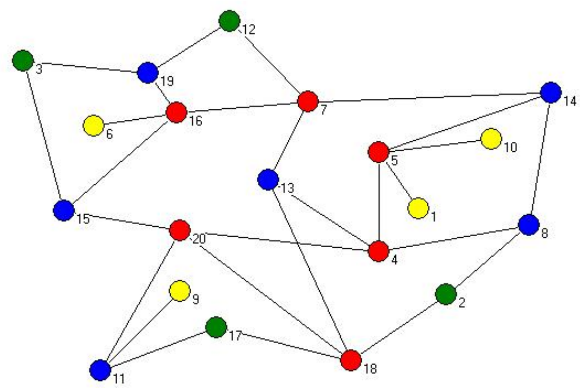


Blue network   Red network   Brown network

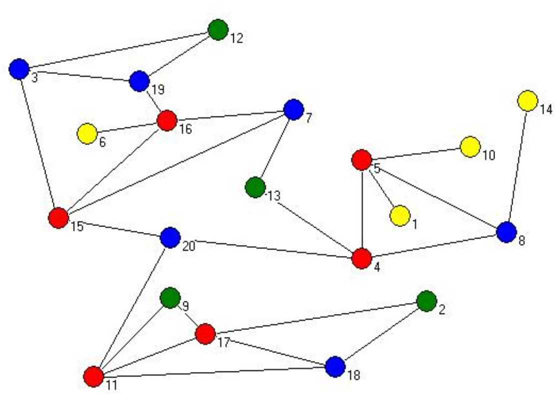
Experiment 3



Network 1



Network 2

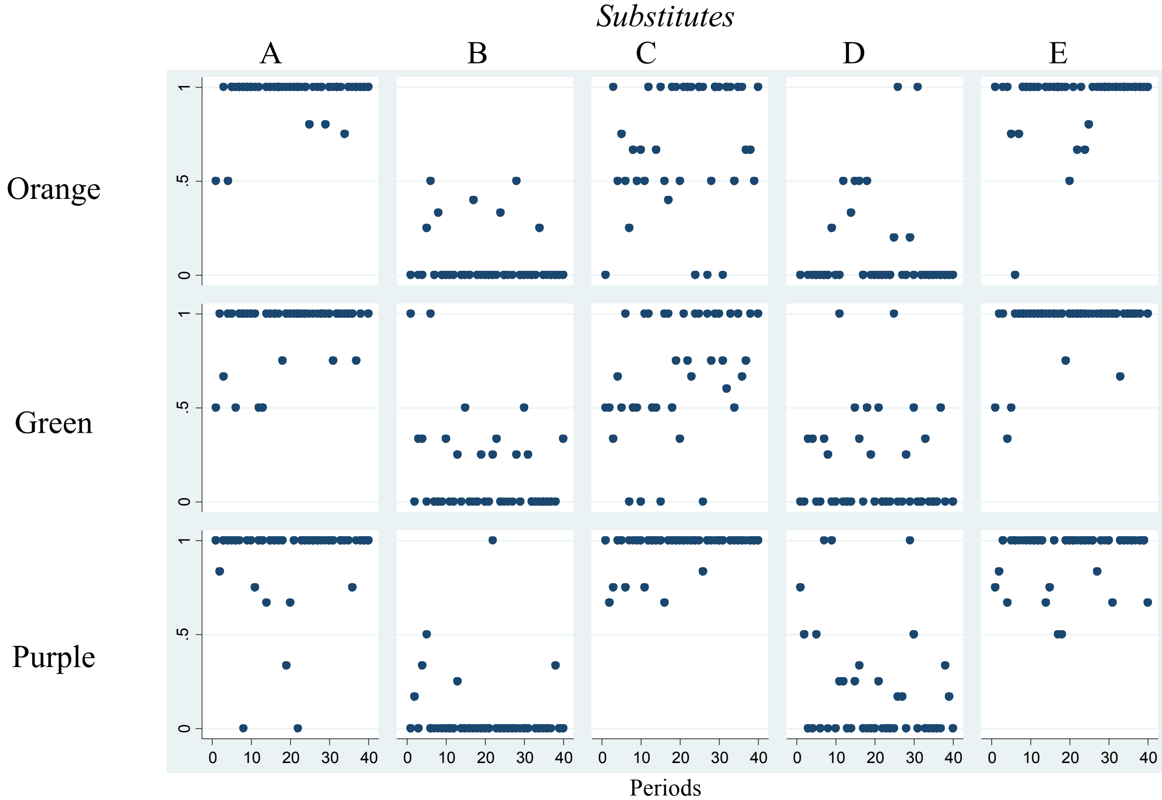


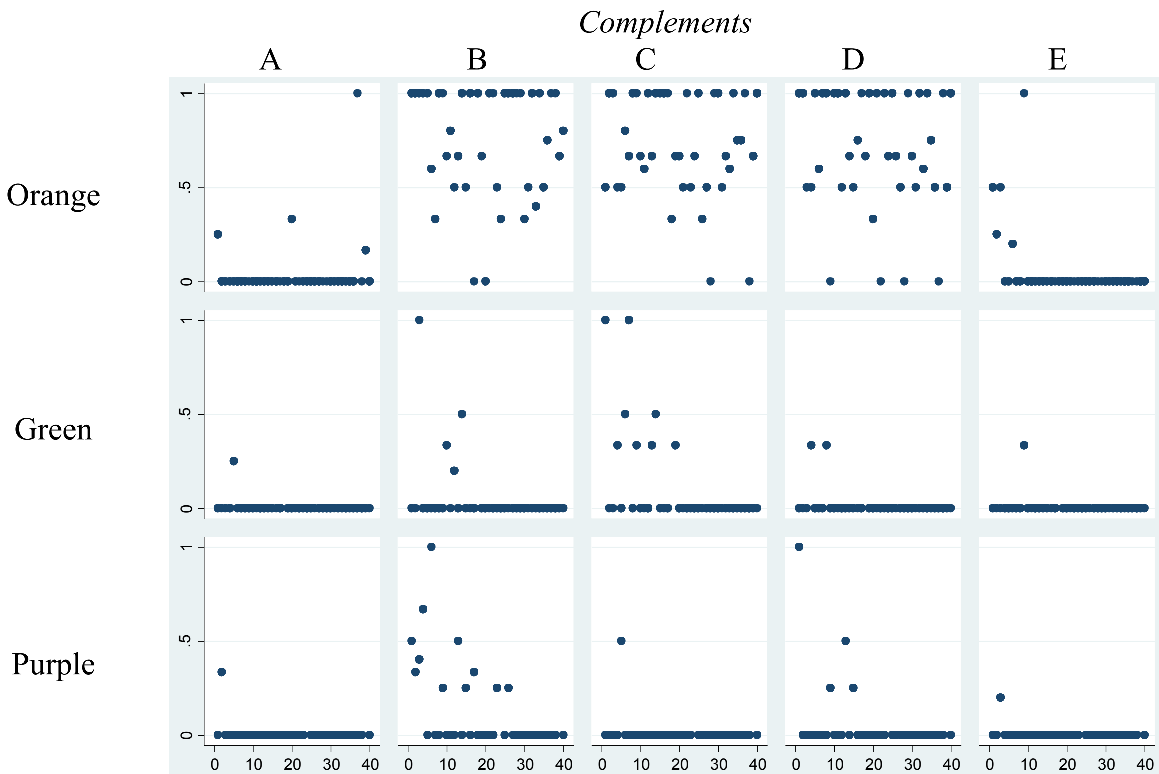
Network 3

Network 2 = Network 1 + links 3-15, 7-12, 7-14, 5-14, 2-8, 13-18, 18-20

Network 3 = Network 1 + links 3-15, 3-12, 7-15, 5-8, 9-17, 2-17, 11-18

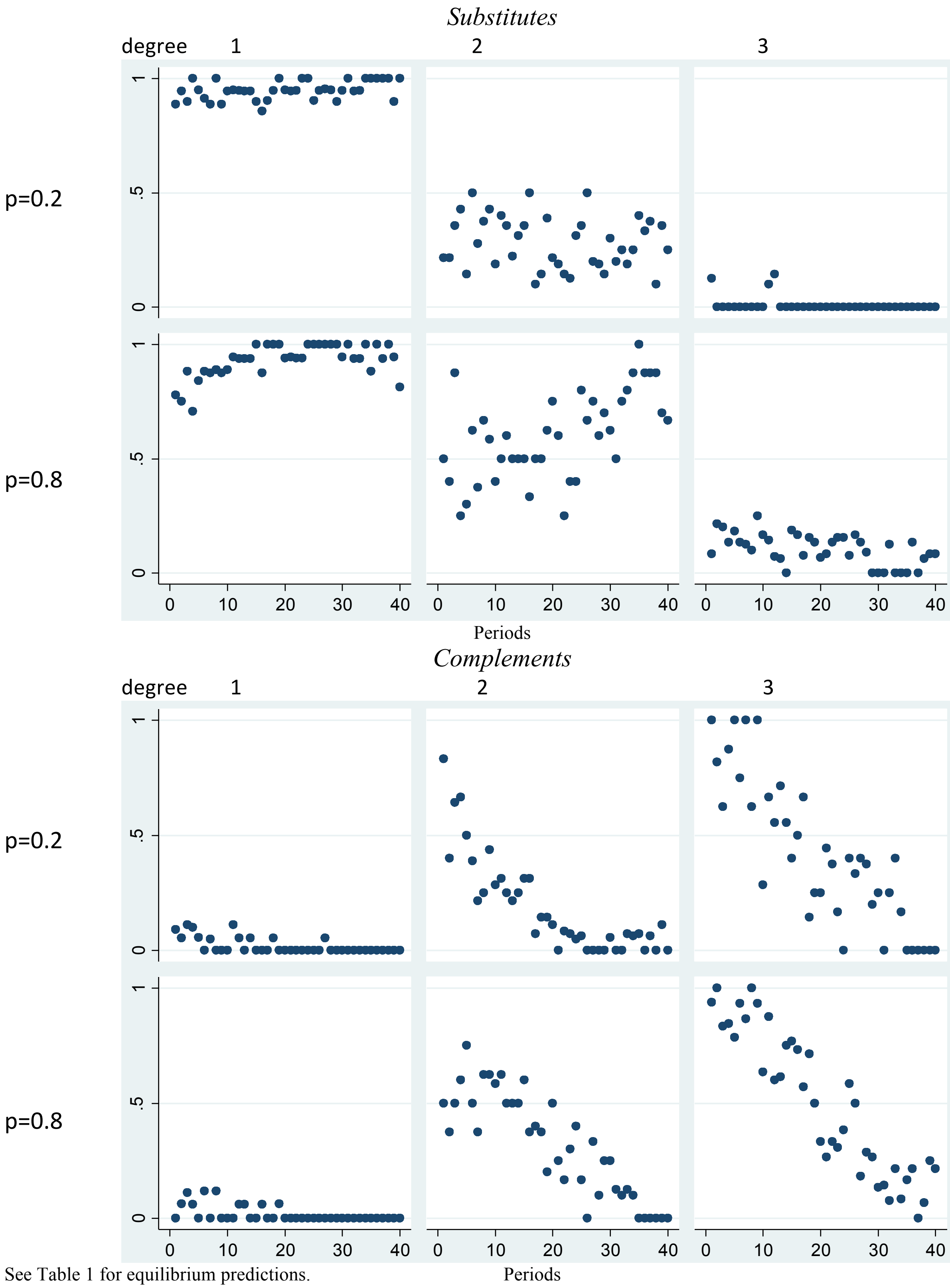
Figure 2: Relative frequency of active choices across periods, by network player position and treatment – Experiment 1, Complete information





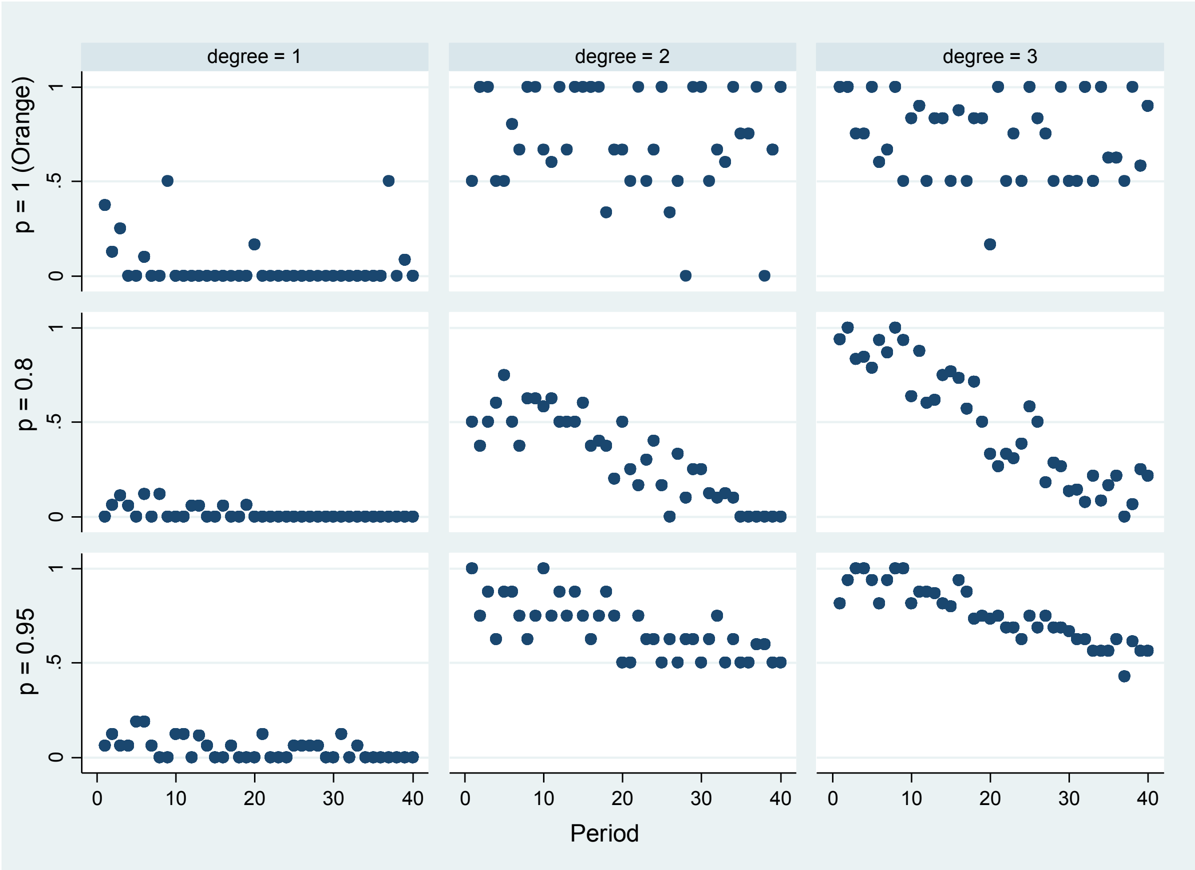
See Table 1 for equilibrium predictions. Periods

Figure 3: Relative frequencies of choices by degree, games, and *p*
Incomplete information, Experiment 1



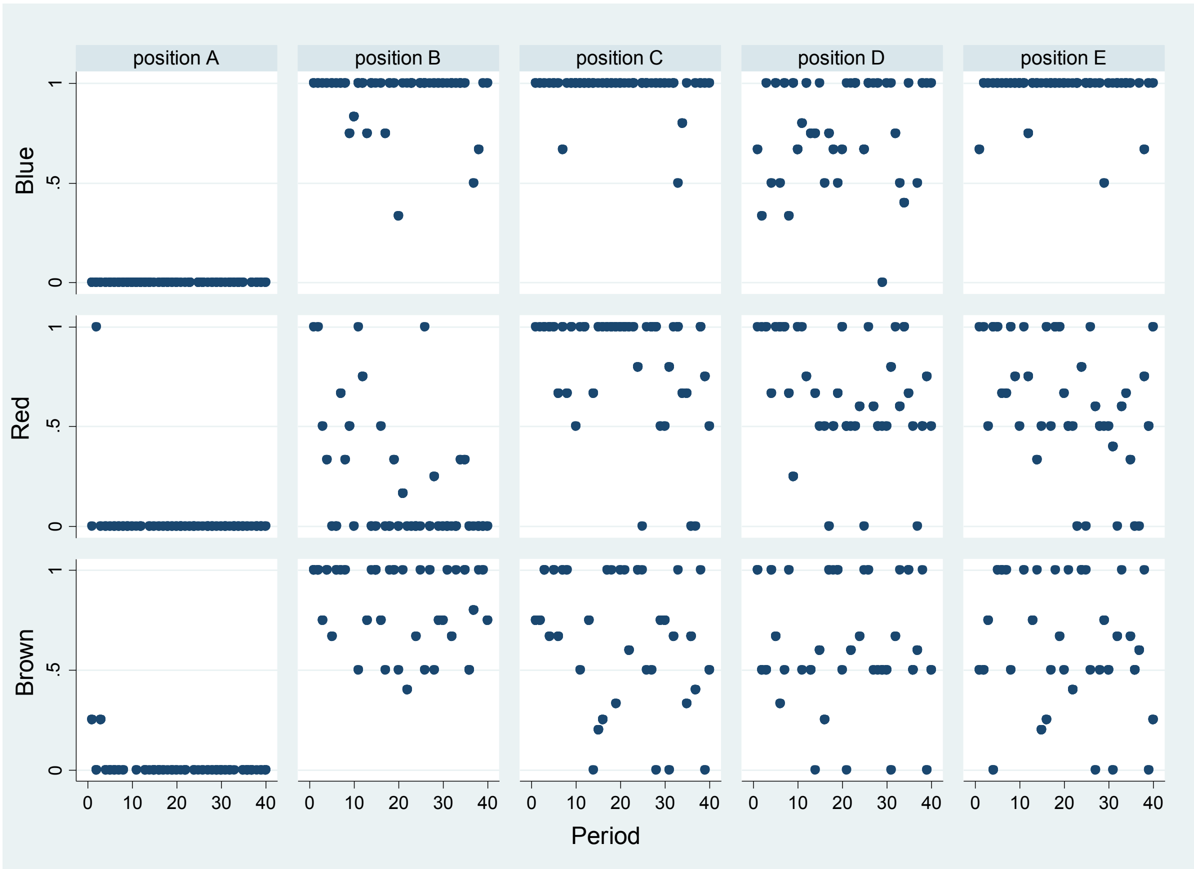
See Table 1 for equilibrium predictions.

Figure 4. Observed activity probabilities, by degree and *p*, Experiment 1



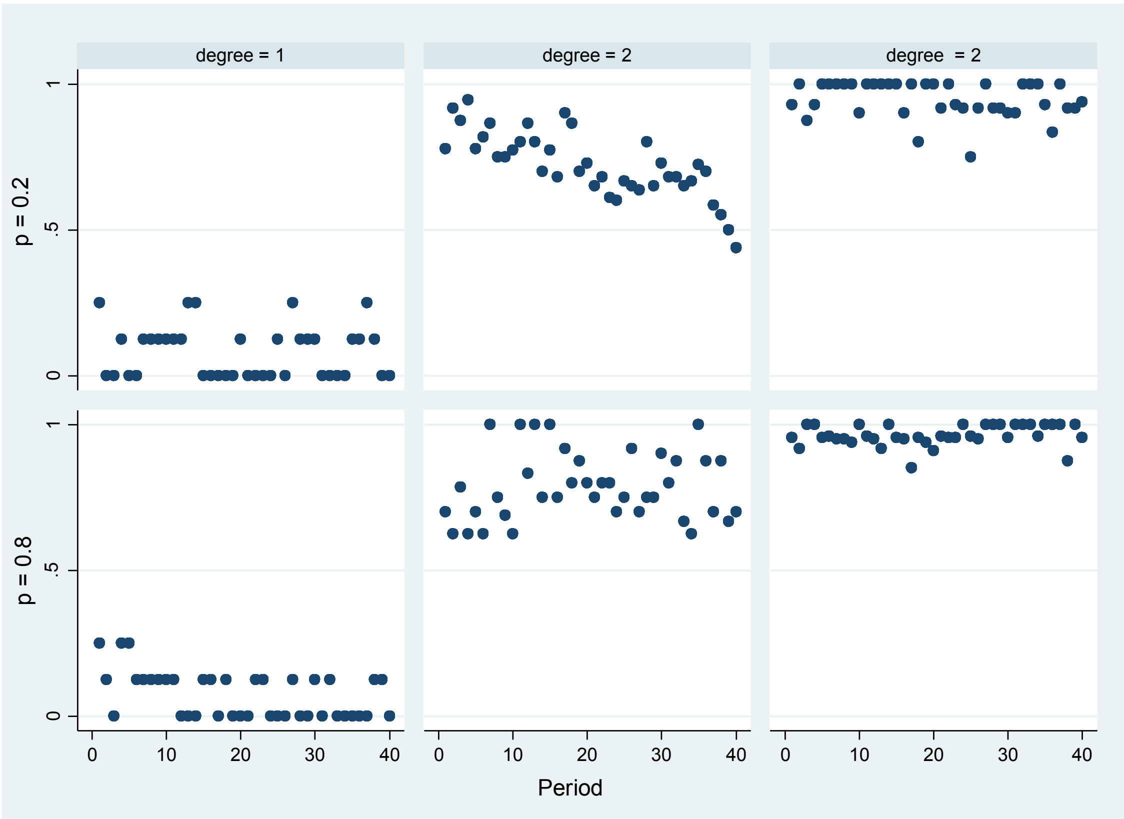
See Table 1 for equilibrium predictions.

Figure 5. Observed probabilities of being active, by network and position in Experiment 2, Complete information



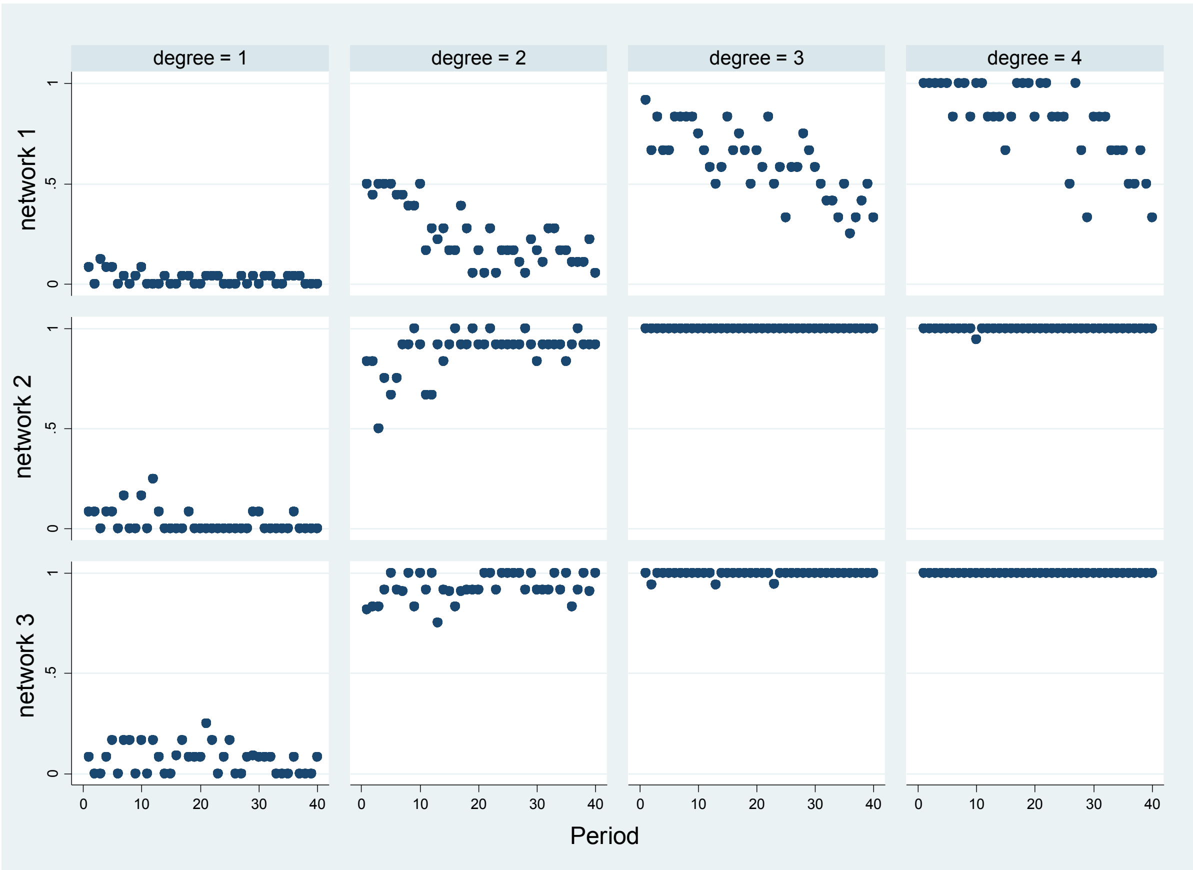
See Table 2 for equilibrium predictions.

Figure 6. Observed probabilities of being active, by connectivity and degree
Experiment 2



See Table 2 for equilibrium predictions.

Figure 7. Observed probabilities of being active, by network and degree
Experiment 3



See Table 4 for equilibrium predictions.

Appendix A: Proofs

Complete information, 5-player networks

Let $s_i \in \{0,1\}$ $i \in \{A, B, C, D, E\}$ be the action of the player in position i where 1 means to be active 0 means to be inactive. Then a strategy profile is give by $s = (s_A, s_B, s_C, s_D, s_E)$. Let be N_i the set of player that have a link to player i and $n_i = |N_i|$. Let $\pi_i(s_i, s_{-i})$ be the expected payoff of the player in position *i*.

Proposition 1. *Consider the scenario of strategic substitutes and complete information of Experiment* 1. *In the Orange network the pure-strategy Nash equilibria are*: (1,0,1,0,1), (1,0,0,1,0), and (0,1,0,0,1). *In the Green network the pure-strategy Nash equilibria* are (1,0,1,0,1), (0,1,0,1,0), (1,0,0,1,0), and (0,1,0,0,1). *In the Purple network the pure-strategy Nash equilibria* are (1,0,1,0,1), (1,0,1,1,0), and (0,1,0,0,1). *All these equilibria are strict.*

Proof: It suffices to prove the following claim: In a Nash equilibrium (i) $s_i = 1$ if and only if, $\forall j \in N_i, s_j = 0$; and (ii) $s_i = 0$ if and only if $\exists j \in N_i \; s.t. s_j = 1$. Then the result directly follows. To prove the claim, assume a Nash equilibrium where $\forall j \in N_i, \; s_j = 0$. Then the best response of player i is $s_i = 1$ because $\pi_i(0, s_{-i}) = 0$ and $\pi_i(1, s_{-i}) = 50$. Assume a Nash equilibrium where $\exists j \in N_i \; s.t. \; s_j = 1$, then the best response of player i is $s_i = 0$ because $\pi_i(0, s_{-i}) = 100$ and $\pi_i(1, s_{-i}) = 50$. Assume a Nash equilibrium where $s_i = 1$ and $\exists j \in N_i \; s.t. \; s_j = 1$, then the best response of player i is $s_i = 0$ because $\pi_i(0, s_{-i}) = 100$ and $\pi_i(1, s_{-i}) = 50$, a contradiction. Assume a Nash equilibrium where $s_i = 0$ and $\forall j \in N_i, \; s_j = 0$, then the best response of player i is $s_i = 1$ because $\pi_i(0, s_{-i}) = 0$ and $\pi_i(1, s_{-i}) = 50$, a contradiction. It is straightforward to see that all the equilibria are strict. QED

Proposition 2. *Consider the scenario of strategic complements and complete information of Experiment* 1. *In the Orange network there are two pure-strategy Nash equilibria*: (0,0,0,0,0), and (0,1,1,1,0). *In the Green and Purple networks there is a unique Nash equilibrium*: (0,0,0,0,0). *All these equilibria are strict.*

Proof: We first prove the following claim: $s_i = 1$ is a best response if and only if $\sum_{j \in N_i} s_j \geq 2$. To this aim, suppose a strategy profile where $\sum_{j \in N_i} s_j \geq 2$. Then, the best response of player i is $s_i = 1$, since $\pi_i(0, s_{-i}) = 50$ and $\pi_i(1, s_{-i}) \geq 66.66$. Suppose now a strategy profile where $s_i = 1$ is a best response and $\sum_{j \in N_i} s_j < 2$. Then, $\pi_i(0, s_{-i}) = 50$ and $\pi_i(1, s_{-i}) \leq 33.33$, a contradiction. Thus, the claim follows. The claim implies that, in all Nash equilibria, $s_i = 0 \; if \; n_i = 1$.

Consider the Orange network. Since players A and E choose 0 in all Nash equilibria ($n_A = n_E = 1$), in a pure-strategy Nash equilibrium either $s_B = s_C = s_D = 1$ or $s_B = s_C = s_D = 0$. Consider the Green and the Purple Network. Players *A* and *E* in the Green network, and players *A*, *C* and *E* in the Purple network choose 0 in all Nash equilibria (all of them have $n_i = 1$). Hence, in a Nash equilibrium, players B and D in the Green network and player D in the Purple network also choose action 0, since they have $n_i = 2$ and one of their neighbors has $n_i = 1$ (and, therefore, chooses action 0). It follows that, in a Nash equilibrium, also player C in the Green network and player B in the Purple network choose action 0, since all their neighbors also choose 0. It is straightforward to see that all the equilibria are strict. QED

Incomplete information, 5-player networks

In Incomplete information scenario 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). 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 $s_j \in \{0,1\}$ is the action chosen by an agent with degree $j \in \{1,2,3\}$. There are 8 strategy profile candidates to be a pure – strategy Nash equilibrium: $s^{\mathrm{I}} = (0,0,0)$, $s^{\mathrm{II}} = (1,0,0)$, $s^{\mathrm{III}} = (0,1,0)$, $s^{\mathrm{IV}} = (0,0,1)$, $s^{\mathrm{V}} = (1,1,0)$, $s^{\mathrm{VI}} = (1,0,1)$, $s^{\mathrm{VII}} = (0,1,1)$ and $s^{\mathrm{VIII}} = (1,1,1)$. Let $\pi_i^j(x_i, x_{-i})$ be the payoff of an agent (indexed by $i \in N$) with degree $j \in \{1,2,3\}$.

Proposition 3. *In the scenario of strategic substitutes and incomplete information of Experiment* 1 *there exists a unique pure-strategy Bayes-Nash equilibrium:* $(1, s_2^*, 0)$, *with* $s_2^* = 0$ *if* $p = 0.2$ *and* $s_2^* = 1$ *if* $p = 0.8$. *All these equilibria are strict.*

Proof. We first define some conditional probabilities that shall be useful in the proof. Let $q_1(j)$ be the expected probability for an agent that, conditional on having degree 1, her neighbor has degree *j*. By applying Bayes' rule we get $q_1(2) = \frac{3(1-p)}{5(1-p)+4p}$ and $q_1(3) = \frac{2(1-p)+4p}{5(1-p)+4p}$. Let $q_2(j_1,j_2)$ 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 $q_2(1,2) = \frac{2(1-p)}{4(1-p)+2p}$, $q_2(2,2) = \frac{1-p}{4(1-p)+2p}$, $q_2(1,3) = \frac{1-p}{4(1-p)+2p}$ and $q_2(3,3) = \frac{2p}{4(1-p)+2p}$. Let $q_3(j_1,j_2,j_3)$ 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 $q_3(1,1,2) = \frac{1-p}{1+3p}$ and $q_3(1,2,3) = \frac{4p}{1+3p}$.

First, we 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 $\pi_i^1(0, x_{-i}^I) = 0 < 50 = \pi_i^1(1, x_{-i}^I)$.

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., $q_1(2) \geq \frac{1}{2}$ and $\frac{1}{2} \geq q_2(1,2) + q_2(2,2)$, 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., $q_2(1,3) + q_2(3,3) \geq \frac{1}{2}$ and $\frac{1}{2} \geq q_3(1,2,3)$, but these inequalities are incompatible for all $p \in (0,1)$.
For all $p \in (0,1)$, s^{VI} is not an equilibrium, since $\pi_i^3(1, x_{-i}^{VI}) = 50 < 100 = \pi_i^3(0, x_{-i}^{VI})$.
For all $p \in (0,1)$, s^{VII} is not an equilibrium, since $\pi_i^2(1, x_{-i}^{VII}) = 50 < 100 = \pi_i^2(0, x_{-i}^{VII})$.
For all $p \in (0,1)$, s^{VIII} is not an equilibrium, since $\pi_i^1(1, x_{-i}^{VIII}) = 50 < 100 = \pi_i^1(0, x_{-i}^{VIII})$.

Finally, we prove that candidates s^{II} is an equilibrium if and only if $p \leq \frac{1}{2}$, and that s^{V} is an equilibrium if and only if $p \geq \frac{2}{3}$. Let us start with s^{II}. First, we observe that, for all $p \in (0,1)$, $\pi_i^1(1, x_{-i}^{II}) = 50 > 0 = \pi_i^1(0, x_{-i}^{II})$ and $\pi_i^3(0, x_{-i}^{II}) = 100 > 50 = \pi_i^3(1, x_{-i}^{II})$. 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., $q_2(1,2) + q_2(1,3) \geq \frac{1}{2}$, which simplifies to $p \leq \frac{1}{2}$. Thus, if $p = 0.2$, s^{II} is a strict equilibrium and, if $p = 0.8$, it is not an equilibrium. Consider now s^{V}. First, we observe that, for all $p \in (0,1)$, $\pi_i^3(0, x_{-i}^{V}) = 100 > 50 = \pi_i^3(1, x_{-i}^{V})$. 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., $\frac{1}{2} \geq q_1(2)$ and $\frac{1}{2} \geq q_2(1,2) + q_2(2,2) + q_2(1,3)$. The second inequality implies the first one, and the equilibrium condition simplifies to $p \geq \frac{2}{3}$. Thus, if $p = 0.2$, s^{V} is not an equilibrium and, if $p = 0.8$, it is a strict equilibrium. QED

Proposition 4. *In the scenario of strategic complements and incomplete information of Experiment* 1, *if* $p = 0.2$ *there is a unique Bayes-Nash equilibrium*: (0,0,0); *if* $p \in \{0.8, 0.95\}$, *there are two pure-strategy Bayes Nash equilibria*: (0,0,0) and (0,1,1). *All these equilibria are strict.*

Proof. The conditional probabilities $q_1(j)$, $q_2(j_1,j_2)$ and $q_3(j_1,j_2,j_3)$ are defined in the proof of Proposition 3. 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}, s^{V}, s^{VI} and s^{VIII} are not equilibria, since $\pi_i^1(1, x_{-i}^{II}) \leq \frac{100}{3} < 50 = \pi_i^1(0, x_{-i}^{II})$.
For all $p \in (0,1)$, s^{III} is not an equilibrium, since $\pi_i^2(1, x_{-i}^{III}) = \frac{100}{3}(q_2(1,2) + 2(q_2(2,2)) < 50 = \pi_i^2(0, x_{-i}^{III})$. 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., $\frac{100}{3} q_3(1,2,3) \geq 50$. However, the inequality does not hold since, for any $p \in (0,1)$, $q_3(1,2,3) < 1$.

We now prove that candidates s^{I} is an equilibrium for all $p \in (0,1)$, and that candidate s^{VII} is an equilibrium if and only if $p \geq 1/2$. We start with candidate s^{I}. For all $p \in (0,1)$, and $k \in \{1,2,3\}$,

$\pi_i^k(0, x_{-i}) = 50 > 0 = \pi_i^k(1, x_{-i})$. Hence s^{I} is a strict equilibrium. Now consider candidate s^{VII}. First, we observe that, for all $p \in (0,1)$, $\pi_i^1(0, x_{-i}^{VII}) = 50 > 100/3 = \pi_i^1(1, x_{-i}^{VII})$. 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.,

$\frac{100}{3}(q_2(1,2) + q_2(1,3) + 2q_2(2,2) + 2q_2(2,3)) \geq 50$ and

$\frac{100}{3}(q_3(1,1,2) + 2q_3(1,2,3)) \geq 50$.

The first inequality simplifies to $p \geq 1/2$ and the second one simplifies to $p \geq 1/5$. Hence, if $p = 0.2$, s^{VII} is not an equilibrium and, if $p = 0.8$ it is a strict equilibrium (since both inequalities strictly hold). QED

Proposition 5. *In the scenario of Experiment* 2 (*strategic complements and incomplete information*), (i) *if* $p = 0.2$, *there are two pure-strategy Bayes-Nash equilibria*: (0,0,0) *and* (0,1,1); *these equilibria are strict*. (ii) *If* p=0.8 *there are two pure-strategy strict Bayes-Nash equilibria*: (0,0,0) *and* (0,1,1); *and there is a pure-strategy weak Bayes-Nash equilibria*: (0,0,1).

Proof. We first redefine the conditional probabilities for the case of Experiment 2. By applying Bayes' rule we get $q_1(2) = \frac{1-p}{2}$, $q_1(3) = \frac{1+p}{2}$, $q_2(2,2) = \frac{1-p}{2(p+3(1-p))}$, $q_2(1,3) = \frac{1-p}{2(p+3(1-p))}$, $q_2(2,3) = \frac{2(1-p)}{p+3(1-p)}$, $q_2(3,3) = \frac{p}{p+3(1-p)}$, $q_3(1,2,2) = \frac{1-p}{2(3p+(1-p))}$, $q_3(2,2,2) = \frac{1-p}{2(3p+(1-p))}$, $q_3(1,3,3) = \frac{p}{3p+(1-p)}$, and $q_3(2,3,3) = \frac{2p}{3p+(1-p)}$.

For all $p \in (0,1)$, s^{II}, s^{V}, s^{VI} and s^{VIII} are not equilibria, since $\pi_i^1(1, x_{-i}) \leq \frac{100}{3} < 50 = \pi_i^1(0, x_{-i})$. For all $p \in (0,1)$, s^{III} is not an equilibrium, since $\pi_i^2(1, x_{-i}^{III}) = \frac{100}{3}(2q_2(2,2) + q_2(2,3)) < 50 = \pi_i^2(0, x_{-i}^{III})$.

We now prove that candidate s^{I} is an equilibrium for all $p \in (0,1)$, and that candidate s^{VII} is an equilibrium if and only if $p \geq 1/2$. We start with candidate s^{I}. For all $p \in (0,1)$, and $k \in \{1,2,3\}$, $\pi_i^k(0, x_{-i}) = 50 > 0 = \pi_i^k(1, x_{-i})$. Hence s^{I} is a strict equilibrium. Now consider candidate s^{VII}. First, we observe that, for all $p \in (0,1)$, $\pi_i^1(0, x_{-i}^{VII}) = 50 > 100/3 = \pi_i^1(1, x_{-i}^{VII})$. 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 $\pi_i^3(1, x_{-i}^{VII}) \geq \pi_i^3(0, x_{-i}^{VII})$, i.e.,

$\frac{100}{3}(2q_2(2,2) + q_2(1,3) + 2q_2(2,3) + 2q_2(3,3)) \geq 50$ and

$\frac{100}{3}(2q_3(1,2,2) + 3q_3(2,2,2) + 2q_3(1,3,3) + 3q_3(2,3,3)) \geq 50$.

It can be directly verified that both inequalities (strictly) hold for any $p \in (0,1)$ and, therefore, s^{VII} is a strict equilibrium.

Finally, consider s^{IV}. First, we observe that, for all $p \in (0,1)$, $\pi_i^1(0, x_{-i}^{IV}) = 50 > 100/3 = \pi_i^1(1, x_{-i}^{IV})$. Hence, in order to be an equilibrium, it requires both $\pi_i^2(0, x_{-i}^{IV}) \geq \pi_i^2(1, x_{-i}^{IV})$ and $\pi_i^3(1, x_{-i}^{IV}) \geq \pi_i^3(0, x_{-i}^{IV})$, i.e.,

$50 \geq \frac{100}{3}(q_2(1,3) + q_2(2,3) + 2q_2(3,3))$ and

$\frac{100}{3}(2q_3(1,3,3) + 2q_3(2,3,3)) \geq 50$.

The first inequality simplifies to $p \leq 0.8$ and the second one simplifies to $p \geq 0.5$. Therefore, s^{IV} is not an equilibrium if $p = 0.2$, and it is a weak equilibrium if $p = 0.8$. QED

Incomplete information, 20-player networks

In this scenario players are informed about which network is in place but they do not know the specific position they have in the network. They know only their own degree (the number of neighbors they have, either 1, 2, 3 or 4). With this information in hand, each player decides whether to be active (action 1) or not (action 0). Since each player only learns her degree, she can only condition her behavior on this information. In this sense, a (symmetric) strategy profile is represented by a vector $\mathrm{s} = (\mathrm{s}_1, \mathrm{s}_2, \mathrm{s}_3, \mathrm{s}_4)$, where $\mathrm{s}_\mathrm{j} \in \{0, 1\}$ is the action chosen by an agent with degree $\mathrm{j} \in \{1, 2, 3, 4\}$.

Proposition 6. *In the scenario of Experiment* 3 *in the three 20-player networks there are two pure-strategy Bayes-Nash equilibria:* $(0, 0, 0, 0)$ *and* $(0, 1, 1, 1)$. *Both equilibria are strict.*

Proof. Let $\pi_i^j(x_i, x_{-i}) \equiv \pi_i^j(x_i)$ be the payoff of an agent (indexed by $i \in N$) with degree $j \in \{1,2,3,4\}$ from action x_i when other players choose x_{-i}. Note that (i) in all Nash equilibria, $s_1 = 0$ because $\pi_i^1(0, x_{-i}) = 50$ and $\pi_i^1(x_i, x_{-i}) \leq \frac{100}{3}$; (ii) the strategy profile $(0, 0,0, 0)$ is a strict Bayes-Nash equilibrium in all networks because a deviation to action 1 produces a payoff of 0 (against a payoff of 50 from action 0). Then there are 7 strategy profiles candidates to be a pure-strategy Bayes-Nash equilibrium: all possible combinations of s_2, s_3, s_4 in s excluding $(0, 0,0, 0)$.

Consider Network 1. Strategy $(0,1,0,0)$ is not an equilibrium because $\pi_i^2(1, x_{-i}) = 22.22 \leq 50 = \pi_i^2(0, x_{-i})$. Strategy $(0,0,1,0)$ is not an equilibrium because $\pi_i^3(1, x_{-i}) = 16.66 < 50 = \pi_i^3(0, x_{-i})$. Strategy $(0,0,0,1)$ is not an equilibrium because $\pi_i^4(1, x_{-i}) = 0 < 50 = \pi_i^4(0, x_{-i})$. Strategy $(0,1,1,0)$ is not an equilibrium because $\pi_i^4(1, x_{-i}) = 116.66 > 50 = \pi_i^4(0, x_{-i})$. Strategy $(0,1,0,1)$ is not an equilibrium because $\pi_i^2(1, x_{-i}) = 44.44 < 50 = \pi_i^2(0, x_{-i})$. Strategy $(0,0,1,1)$ is not an equilibrium because $\pi_i^3(1, x_{-i}) = 41.66 < 50 = \pi_i^3(0, x_{-i})$. Finally, strategy $(0,1,1,1)$ is a strict equilibrium because $\pi_i^4(1, x_{-i}) = 116.66 > 50 = \pi_i^4(0, x_{-i})$, $\pi_i^3(1, x_{-i}) = 58.33 > 50 = \pi_i^3(0, x_{-i})$, and $\pi_i^2(1, x_{-i}) = 55.55 > 50 = \pi_i^2(0, x_{-i})$.

Consider Network 2. Strategy $(0,1,0,0)$ is not an equilibrium because $\pi_i^2(1, x_{-i}) = 0 \leq 50 = \pi_i^2(0, x_{-i})$. Strategy $(0,0,1,0)$ is not an equilibrium because $\pi_i^3(1, x_{-i}) = 11.11 < 50 = \pi_i^3(0, x_{-i})$. Strategy $(0,0,0,1)$ is not an equilibrium because $\pi_i^4(1, x_{-i}) = 44.44 < 50 = \pi_i^4(0, x_{-i})$. Strategy $(0,1,1,0)$ is not an equilibrium because $\pi_i^2(1, x_{-i}) = 41.66 < 50 = \pi_i^2(0, x_{-i})$. Strategy $(0,1,0,1)$ is not equilibrium because $\pi_i^2(1, x_{-i}) =$

$25 < 50 = \pi_i^2(0, x_{-i})$. Strategy $(0,0,1,1)$ is not equilibrium because $\pi_i^2(1, x_{-i}) = 66.66 > 50 = \pi_i^2(0, x_{-i})$. Strategy $(0,1,1,1)$ is a strict equilibrium because $\pi_i^4(1, x_{-i}) = 116.66 > 50 = \pi_i^4(0, x_{-i})$, $\pi_i^3(1, x_{-i}) = 94.44 > 50 = \pi_i^3(0, x_{-i})$, and $\pi_i^2(1, x_{-i}) = 66.66 > 50 = \pi_i^2(0, x_{-i})$.

Consider Network 3. Strategy $(0,1,0,0)$ is not an equilibrium because $\pi_i^2(1, x_{-i}) = 0 \leq 50 = \pi_i^2(0, x_{-i})$. Strategy $(0,0,1,0)$ is not an equilibrium because $\pi_i^3(1, x_{-i}) = 11.11 < 50 = \pi_i^3(0, x_{-i})$. Strategy $(0,0,0,1)$ is not an equilibrium because $\pi_i^4(1, x_{-i}) = 33.33 < 50 = \pi_i^4(0, x_{-i})$. Strategy $(0,1,1,0)$ is not an equilibrium because $\pi_i^2(1, x_{-i}) = 33.33 < 50 = \pi_i^2(0, x_{-i})$. Strategy $(0,1,0,1)$ is not an equilibrium because $\pi_i^2(1, x_{-i}) = 33.33 < 50 = \pi_i^2(0, x_{-i})$. Strategy $(0,0,1,1)$ is not an equilibrium because $\pi_i^2(1, x_{-i}) = 66.66 > 50 = \pi_i^2(0, x_{-i})$. Strategy $(0,1,1,1)$ is a strict equilibrium because $\pi_i^4(1, x_{-i}) = 116.66 > 50 = \pi_i^4(0, x_{-i})$, $\pi_i^3(1, x_{-i}) = 94.44 > 50 = \pi_i^3(0, x_{-i})$, and $\pi_i^2(1, x_{-i}) = 66.66 > 50 = \pi_i^2(0, x_{-i})$. QED

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.

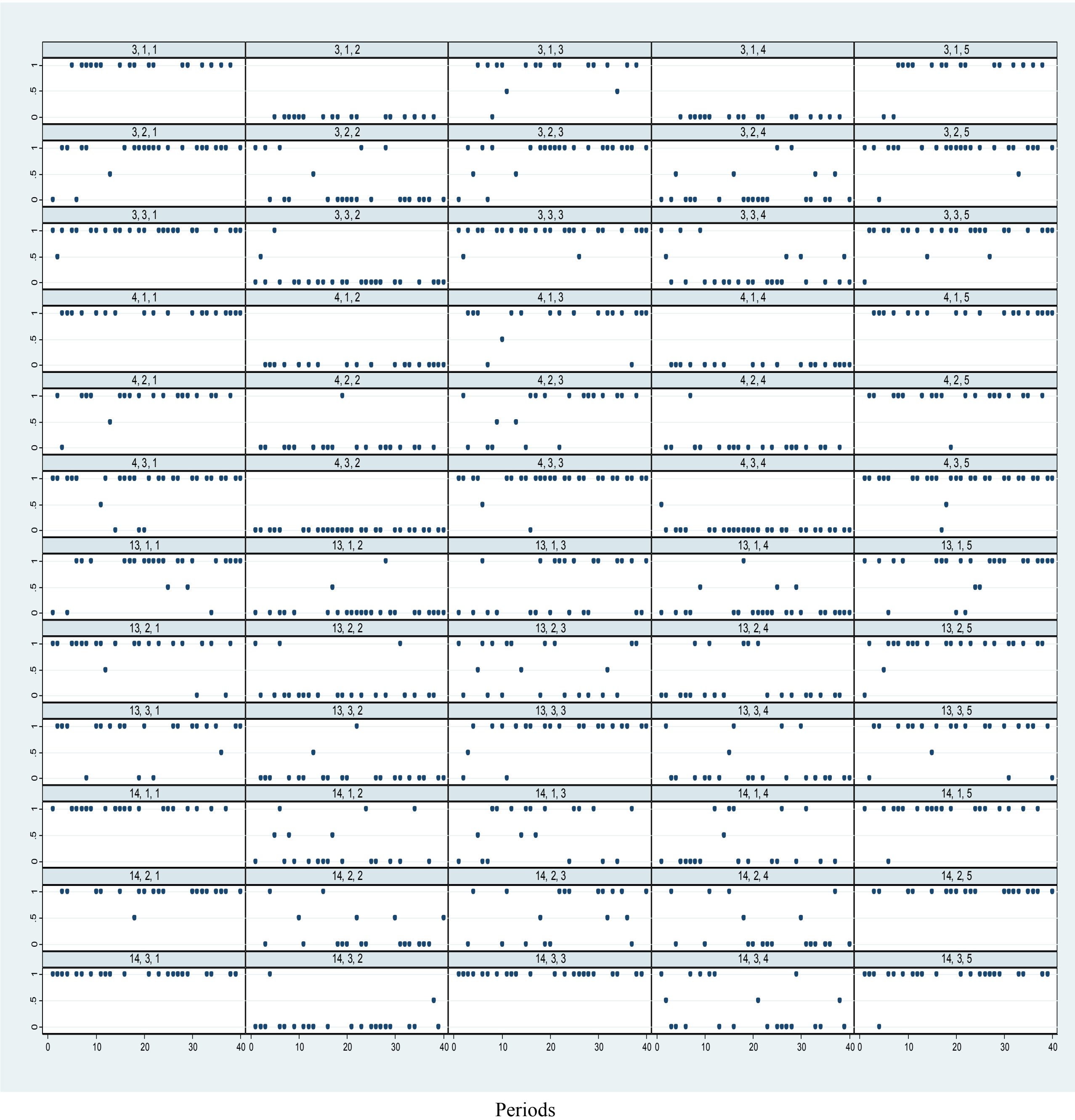
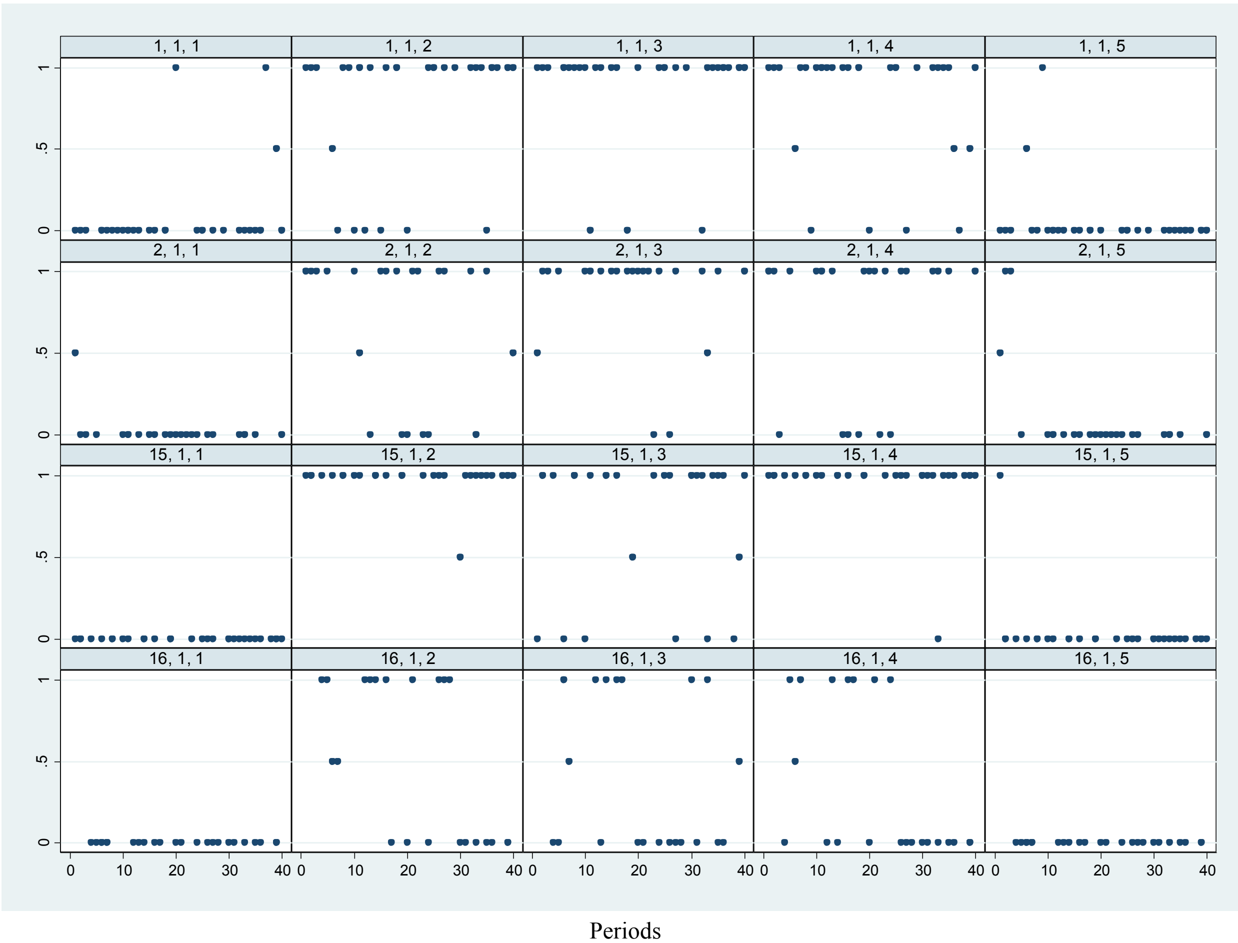


Figure B.2: Complete information and complements: Relative frequencies of active choices across periods, by group and position in the Orange network.



Appendix C: Econometric model (Variables and Estimations)

Experiments 1 and 2

Network:

Experiment 1
Orange = 1,
Green = 2,
Purple =3
Experiment 2
Blue = 1,
Red = 2,
Brown =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_degree3: 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.

risk_0_1: marginal effect of risk when d1=0 and degree==1
risk_0_2: marginal effect of risk when d1=0 and degree==2
risk_0_3: marginal effect of risk when d1=0 and degree==3
risk_1_1: marginal effect of risk when d1=1 and degree==1
risk_1_2: marginal effect of risk when d1=1 and degree==2
risk_1_3: marginal effect of risk when d1=1 and degree==3

Experiment 1

Complete information - Strategic Substitutes

Log likelihood = -388.50483						
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

Marginal effects of risk

	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Risk	.0083711	.01168	0.72	0.474	-.014525	.031267

Complete information - Strategic Complements

Log likelihood = -280.54602						
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

Marginal effects of risk

	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Risk	.0274705	.00797	3.45	0.001	.011846	.043095

Incomplete information - Strategic Substitutes

Log likelihood = -835.0852

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

Marginal effect of risk

risk_0_1	-.0002897	.0001697	-1.71	0.088	-.0006223	.0000429
risk_0_2	-.0021784	.0010144	-2.15	0.032	-.0041666	-.0001901
risk_0_3	-.0000198	.0000251	-0.79	0.431	-.000069	.0000294
risk_1_1	-.0002272	.0001254	-1.81	0.070	-.0004729	.0000185
risk_1_2	-.0032382	.0014454	-2.24	0.025	-.0060711	-.0004052
risk_1_3	-.0003819	.0002303	-1.66	0.097	-.0008333	.0000695

Incomplete information - Strategic Complements

Log likelihood = -708.07396

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

Marginal effect of risk

risk_0_1	-2.75e-06	.0000119	-0.23	0.817	-.000026	.0000205
risk_0_2	-.0000811	.0003397	-0.24	0.811	-.000747	.0005848
risk_0_3	-.0004371	.0018246	-0.24	0.811	-.0040132	.0031391
risk_1_1	-2.02e-06	8.78e-06	-0.23	0.818	-.0000192	.0000152
risk_1_2	-.0002572	.0010765	-0.24	0.811	-.002367	.0018527
risk_1_3	-.0004869	.0020325	-0.24	0.811	-.0044706	.0034969

Incomplete information - Strategic Complements - p = 0.95

Log likelihood = -412.52192

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Period	-0.06831	0.020013	-3.41	0.001	-0.10754	-0.02909
degree2	6.656791	0.632275	10.53	0	5.417555	7.896027
degree3	8.786581	0.654056	13.43	0	7.504655	10.06851
deg2_period	-0.01938	0.026316	-0.74	0.461	-0.07096	0.032195
deg3_period	-0.07553	0.025416	-2.97	0.003	-0.12535	-0.02572
Risk	0.00991	0.014227	0.7	0.486	-0.01798	0.037794
_cons	-3.95017	0.878676	-4.5	0	-5.67234	-2.228

Experiment 2

Complete information

Log likelihood = -403.98366

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Period	-0.78131	0.953394	-0.82	0.412	-2.64993	1.087306
d212	7.296092	2.976187	2.45	0.014	1.462872	13.12931
d213	8.593323	3.199112	2.69	0.007	2.323179	14.86347
d214	4.512357	2.864328	1.58	0.115	-1.10162	10.12634
d215	10.06287	3.512437	2.86	0.004	3.178619	16.94712
d222	3.465771	2.897039	1.2	0.232	-2.21232	9.143864
d223	12.1354	3.286807	3.69	0	5.69338	18.57743
d224	5.38125	2.878885	1.87	0.062	-0.26126	11.02376
d225	5.527497	2.895627	1.91	0.056	-0.14783	11.20282
d231	3.632378	3.391387	1.07	0.284	-3.01462	10.27937
d232	6.245805	2.889733	2.16	0.031	0.582033	11.90958
d233	4.87267	2.872389	1.7	0.09	-0.75711	10.50245
d234	5.146739	2.86956	1.79	0.073	-0.4775	10.77097
d235	4.783574	2.871477	1.67	0.096	-0.84442	10.41156
t212	0.797173	0.954438	0.84	0.404	-1.07349	2.667836
t213	0.783776	0.955599	0.82	0.412	-1.08916	2.656715
t214	0.810881	0.953742	0.85	0.395	-1.05842	2.68018
t215	0.774828	0.957463	0.81	0.418	-1.10177	2.651421
t222	0.629482	0.953886	0.66	0.509	-1.2401	2.499064
t223	0.576057	0.954651	0.6	0.546	-1.29503	2.44714
t224	0.72249	0.953831	0.76	0.449	-1.14699	2.591964
t225	0.724289	0.953799	0.76	0.448	-1.14512	2.593701
t231	-0.43954	1.189874	-0.37	0.712	-2.77165	1.89257
t232	0.74131	0.953731	0.78	0.437	-1.12797	2.610588
t233	0.708418	0.953723	0.74	0.458	-1.16084	2.57768
t234	0.713307	0.953636	0.75	0.454	-1.15578	2.582398
t235	0.732869	0.953727	0.77	0.442	-1.1364	2.602138
Risk	0.027857	0.012704	2.19	0.028	0.002958	0.052755
_cons	-4.34676	2.900478	-1.5	0.134	-10.0316	1.338073

Marginal effects of risk

	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Risk	0.027857	0.0127	2.19	0.028	0.002958	0.052755

Incomplete information

Log likelihood = -564.68216						
Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Period	-0.03954	0.028585	-1.38	0.167	-0.09557	0.016485
d1	2.246575	1.169403	1.92	0.055	-0.04541	4.538561
degree2	9.844207	0.898926	10.95	0	8.082345	11.60607
degree3	13.70468	1.303205	10.52	0	11.15045	16.25892
d1_period	-0.0962	0.04866	-1.98	0.048	-0.19157	-0.00083
d1_degree2	-5.43655	1.117169	-4.87	0	-7.62616	-3.24694
d1_degree3	-4.86144	1.554457	-3.13	0.002	-7.90813	-1.81476
deg2_period	-0.07148	0.032004	-2.23	0.026	-0.13421	-0.00875
deg3_period	-0.05	0.043899	-1.14	0.255	-0.13604	0.036042
deg2_per_d1	0.224834	0.053274	4.22	0	0.120419	0.329249
deg3_per_d1	0.222774	0.06418	3.47	0.001	0.096984	0.348565
Risk	0.011876	0.012558	0.95	0.344	-0.01274	0.036489
_cons	-5.29965	1.047908	-5.06	0	-7.35351	-3.24579

Marginal effect of risk

Choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
risk_0_1	4.66E-05	5.96E-05	0.78	0.435	-7E-05	0.000164
risk_0_2	0.000597	0.000709	0.84	0.4	-0.00079	0.001986
risk_0_3	9.11E-06	1.29E-05	0.7	0.482	-1.6E-05	3.45E-05
risk_1_1	6.41E-05	0.000082	0.78	0.434	-9.7E-05	0.000225
risk_1_2	0.001013	0.00118	0.86	0.391	-0.0013	0.003326
risk_1_3	9.90E-06	0.000014	0.71	0.481	-1.8E-05	3.74E-05

Experiment 3

n2 = 1 if network=2, 0 otherwise
n3 = 1 if network=3, 0 otherwise
d2 = 1 if player's degree=2, 0 otherwise
d3 = 1 if player's degree=3, 0 otherwise
d4 = 1 if player's degree=4, 0 otherwise
d2n2: interaction between d2 and n2
d2n3: interaction between d2 and n3
d3n2: interaction between d3 and n2
d3n3: interaction between d3 and n3
d4n2: interaction between d4 and n2
d4n3: interaction between d4 and n3
n2p: interaction variable between n2 and period
n3p: interaction variable between n3 and period
d2p: interaction variable between d2 and period
d3p: interaction variable between d3 and period
d4p: interaction variable between d4 and period
d2n2p: interaction variable between d2, n2 and period
d2n3p: interaction variable between d2, n3 and period
d3n2p: interaction variable between d3, n2 and period
d3n3p: interaction variable between d3, n3 and period
d4n2p: interaction variable between d4, n2 and period
d4n3p: interaction variable between d4, n3 and period

risk_1_1: marginal effect of risk when network 1 and degree==1
risk_1_2: marginal effect of risk when network 1 and degree==2
risk_1_3: marginal effect of risk when network 1 and degree==3
risk_1_4: marginal effect of risk when network 1 and degree==4
risk_2_1: marginal effect of risk when network 2 and degree==1
risk_2_2: marginal effect of risk when network 2 and degree==2
risk_2_3: marginal effect of risk when network 2 and degree==3
risk_2_4: marginal effect of risk when network 2 and degree==4
risk_3_1: marginal effect of risk when network 3 and degree==1
risk_3_2: marginal effect of risk when network 3 and degree==2
risk_3_3: marginal effect of risk when network 3 and degree==3
risk_3_4: marginal effect of risk when network 3 and degree==4

Log likelihood = -1047.914						
choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
period	-0.05858	0.024295	-2.41	0.016	-0.10619	-0.01096
n2	1.332241	0.784154	1.7	0.089	-0.20467	2.869154
n3	0.423339	0.780118	0.54	0.587	-1.10566	1.952342
d2	4.759135	0.528128	9.01	0	3.724024	5.794246
d3	7.331392	0.573277	12.79	0	6.207789	8.454995
d4	10.60647	0.856568	12.38	0	8.927626	12.28531
d2n2	0.174066	0.832004	0.21	0.834	-1.45663	1.804763
d2n3	2.272886	0.879686	2.58	0.01	0.548733	3.997039
d3n2	21.21926	4313.574	0	0.996	-8433.23	8475.669
d3n3	2.881053	1.292484	2.23	0.026	0.347831	5.414274
d4n2	1.109566	2.070312	0.54	0.592	-2.94817	5.167304
d4n3	17.64513	4942.264	0	0.997	-9669.02	9704.305
n2p	-0.02345	0.038179	-0.61	0.539	-0.09828	0.051381
n3p	0.051894	0.031444	1.65	0.099	-0.00973	0.113522
d2p	-0.03878	0.026727	-1.45	0.147	-0.09117	0.013601
d3p	-0.03067	0.027	-1.14	0.256	-0.08359	0.022246
d4p	-0.09452	0.034091	-2.77	0.006	-0.16134	-0.02771
d2n2p	0.216455	0.044848	4.83	0	0.128555	0.304354
d2n3p	0.089878	0.039223	2.29	0.022	0.013002	0.166754
d3n2p	0.101249	194.1649	0	1	-380.455	380.6575
d3n3p	0.109483	0.068038	1.61	0.108	-0.02387	0.242834
d4n2p	0.277924	0.140703	1.98	0.048	0.002151	0.553697
d4n3p	0.099375	213.2344	0	1	-417.832	418.0312
risk1	0.014794	0.005353	2.76	0.006	0.004303	0.025285
_cons	-5.35813	0.596135	-8.99	0	-6.52653	-4.18973

Marginal effect of risk

choice	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
risk1_1_1	4.47E-05	2.52E-05	1.77	0.076	-4.72E-06	9.42E-05
risk1_1_2	0.001786	0.000759	2.35	0.019	0.000298	0.003274
risk1_1_3	0.003011	0.001138	2.65	0.008	0.000781	0.00524
risk1_1_4	0.000718	0.000351	2.04	0.041	2.97E-05	0.001406
risk1_2_1	0.000163	0.000133	1.23	0.22	-9.7E-05	0.000423
risk1_2_2	0.003687	0.001344	2.74	0.006	0.001052	0.006322
risk1_2_3	8.74E-13	.	.	.	.	.
risk1_2_4	5.34E-05	9.63E-05	0.55	0.58	-0.00014	0.000242
risk1_3_1	7.17E-05	5.58E-05	1.29	0.199	-3.8E-05	0.000181
risk1_3_2	0.002873	0.001327	2.17	0.03	0.000273	0.005473
risk1_3_3	0.000179	0.000196	0.91	0.361	-0.00021	0.000563
risk1_3_4	9.74E-12	.	.	.	.	.

Appendix D: Experimental instructions

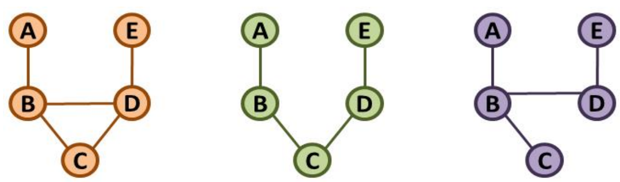
I) Complete Information - Substitutes (Experiment 1)

[Note: The corresponding instructions for Experiment 2 are analogous (it just changes the three networks)]

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 periods. In each period you will be randomly assigned to a group of 5 participants. This group is determined randomly at the beginning of the period. Therefore, the group you are assigned to changes at each period. In this room, there are 10 participants (including yourself) that are potential members of your group. That is, at every period 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 period, the computer selects randomly a **network for your group**: the **orange network**, the **green network** or the **purple network**:



Orange network **Green network** **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 period, you are equally likely to be located in each of the 5 positions. At each period, 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 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 period 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 period, 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 period 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 period payoff is **50 ECU** for sure [100 – 50]
- If you choose to be **INACTIVE** your period 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 period, you will get information about current and past periods. 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 (period) payoff.

5.- Payoffs. At the end of the experiment, you will be paid the earnings that you achieved in 4 periods, that will be randomly selected across the 40 periods of play (all periods 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 €**.

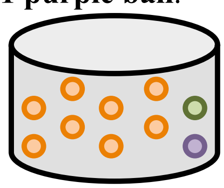
II) Incomplete Information – Complements – p=0.8 (Experiment 1)

[*Note: The case p=0.2 is analogous (it just changes the virtual urn composition). The corresponding instructions for Experiment 2 are also analogous (it just changes the three networks)*]

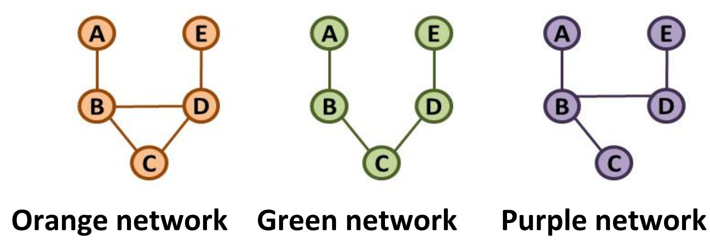
The aim of this Experiment is to study how individuals make decisions in certain contexts. The instructions are simple. If you follow them carefully you will earn a non-negligible amount of money in cash (Euros) at the end of the experiment. During the experiment, your earnings will be accounted in ECU (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 periods. In each period you will be randomly assigned to a group of 5 participants. This group is determined randomly at the beginning of the period. Therefore, the group you are assigned to changes at each period. In this room, there are 10 participants (including yourself) that are potential members of your group. That is, at every period 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 period, 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 period 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 period, you are equally likely to be located in each of the 5 positions. At each period, 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 period 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 period, 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 period 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 period, 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 period 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 period payoff is 50 ECU. If you choose to be ACTIVE, your period 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 period payoff can be:
  - $\mathbf{100,00}$ **ECU** if 3 participants linked to you choose to be ACTIVE $\left[\frac{100+100+1003}{}\right]$, 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 period payoff is $\mathbf{50,00}$ **ECU** for sure.

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

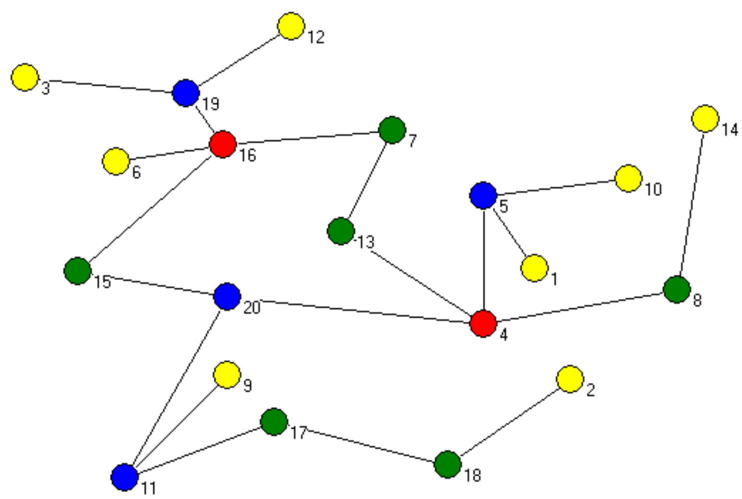
- The selected network.

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

6.- Payoffs. At the end of the experiment, you will be paid the earnings that you achieved in 4 periods, that will be randomly selected across the 40 periods of play (all periods 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 €**.

III) Network 1 (Experiment 3)
[*Note: The corresponding instructions for Network 2 and Network 3 are analogous (it just changes the figure of the network)*]
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 periods**, and there are **20 participants**, including yourself. The participants will remain the same throughout the experiment. At each period, you and each of the remaining nineteen participants will be assigned one position of the following **NETWORK**. The **positions in the network** are numbered from 1 to 20.



2.- In the network, a link is represented by a line (connection) between two positions. For example, **position 16** has four links: it is linked to **positions 6**, **7, 15** and **19** (but it is not linked to the remaining positions).

Note that there are **four classes of positions** in the network, identified by **different colors**.

- There are eight **yellow positions**: Those positions **with one link** (1, 2, 3, 6, 9, 10, 12 and 14).
- There are six **green positions**: Those positions **with two links** (7, 8, 13, 15, 17 and 18).
- There are four **blue positions**: Those positions **with three links** (5, 11, 19 and 20).
- There are two **red positions**: Those positions **with four links** (4 and 16).

3.- At each period, you (and the other participants) are randomly assigned by the computer to a **position from 1 to 20 in the network**, all of them being equally likely. The assignment process is random: At each period, you are equally likely to be located in each of the 20 positions of the network.

3.- At each period, **you will only be informed of the color of your position**, that is, you will know how many links your assigned position has: **1 link (yellow)**, **2 links (green)**, **3 links (blue)** or **4 links (red)**. However, **you will not be informed of which is your exact position**.

For example, if at a particular period you are informed that your position has 3 links (blue), then you know that you can be in position 5, 11, 19 or 20, and that you can be in any of them with the same probability. Note that, in such a case, you also know that you cannot be in yellow, green or red positions.
Your earnings of the period can only be affected by your decisions and the decisions of those participants located in positions that are linked to yours, as specified below.

4.- At each period, 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 period will depend on your choice and on the choices of those participants located in positions linked to yours. If you choose to be INACTIVE, your period payoff is 50 ECU. If you choose to be ACTIVE, your period 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 period payoff can be:
  - **133,33 ECU** if 4 participants linked to you choose to be ACTIVE $\left[\frac{100+100+100+100}{3}\right]$, or
  - **100,00 ECU** if 3 participants linked to you choose to be ACTIVE $\left[\frac{100+100+100}{3}\right]$, or
  - **66,66 ECU** if 2 participants linked to you choose to be ACTIVE $\left[\frac{100+100}{3}\right]$, or
  - **33,33 ECU** if 1 participants linked to you choose to be ACTIVE $\left[\frac{100}{3}\right]$, or
  - **0,00 ECU** if no participant linked to you choose to be ACTIVE.
- If you choose to be **INACTIVE** your period payoff is **50,00 ECU** for sure.

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

6.- Payoffs. At the end of the experiment, you will be paid the earnings that you achieved in 4 periods, that will be randomly selected across the 40 periods of play (all periods 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 €.