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Network Structure and Strategic Investments: An Experimental Analysis

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Abstract

This paper experimentally analyzes the effect of network structures on individuals' decisions in a game of strategic substitutes. The theoretical basis for our experiment is the model of Bramoullé and Kranton (2007). As predicted, we find that individuals are able to coordinate on equilibria, but that this strongly depends on the network structure. Despite frequent coordination failures, equilibrium play seems easier on extreme network architectures with high (low) density and low (high) centrality. If play converges, it almost exclusively does so towards the predicted equilibria. Theoretical results with respect to welfare are also confirmed. Next to global graph structural properties we also explore the effects of local and individual factors. We find that behavior on networks is affected by the number of (direct) neighbors, but not by individuals' risk attitude. Apparently, the global and the local structure of a network does not leave much explanatory room for individual effects that pertain to risk-taking.

Keywords: Social networks, experiment, coordination, strategic substitutes, risk aversion

JEL classification: C91, D00, D81, D85, C72, H41

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1 Introduction

Although the traditional economics model yields a number of powerful insights about implications of rational decisions for resource allocation and welfare, it seems not to be able to explain some tenacious empirical regularities, like persistent inequalities, patterns of technology diffusion, or sociological phenomena like segregation of neighborhoods. In the recent past the traditional model of human activities, occurring within markets with anonymous and centralized interaction, has been further developed to also take into account the network in which the actors are embedded. In fact, the economics of social networks has gained increasing attention in the past decade, manifested in an explosion of game theoretical models on formation, stability and efficiency of networks, and the "wide variety of settings where social networks play a role [still] leads to an almost endless set of interesting avenues to investigate" (Jackson 2005, p.59).

As predictions from models proliferate, we need to confront these with rigorous empirical tests. We conduct the first of such a test for the well-known network model of Bramoullé and Kranton (2007). It pictures innovative activities and was motivated by the empirical analysis of Foster and Rosenzweig (1995), who study farmers' experimentations with a new technology. They find evidence of free riding as farmers tend to experiment less when their neighbors experiment more. Bramoullé and Kranton (2007) present a model in which individuals are part of a network and invest in the production of a local public good, as e.g. the farmers invest into the production of know-how. The underlying idea is that such innovative activities of individuals have positive externalities and that those externalities are strongest for those that are "closest" to the innovator. In general being "close" can have different meanings in different contexts: within organizations being "close" would refer to those who collaborate in the same project, in markets that could refer to all those that are part of an alliance, or to those who have access to the innovator's know-how due to, e.g., geographical or social proximity. All those interpretations are possible when explicitly considering the (social) network of the innovator.

Bramoullé and Kranton (2007) provide one of the first analysis of a game played on a network when actions are strategic substitutes. The model is characterized by two main features: agents are embedded in a fixed social network, and agents' payoffs are directly affected by their partners' actions. Most papers sharing these two assumptions look at positive social interactions and coordination games. In contrast, in their paper, Bramoullé and Kranton (2007) study a game with features of an anti-coordination game. Their analysis leads to several insights. First, they find that social networks can lead to specialization and that in any network there is an equilibrium where some individuals invest into innovative activity while others completely rely on the efforts of the innovators. Furthermore, "in many, particularly asymmetric, networks this extreme form of free-riding is the only equilibrium outcome. In all networks, such patterns are the only stable outcomes. Hence, an agent's position in a network can determine whether or not he contributes to the public good." (Bramoullé and Kranton (2007, p.479). Finally, they analyze the welfare effect of additional links. While an additional link increases access to the public good, it also reduces individual incentives to contribute, such that the overall effect depends on properties of the benefit function.

We design an experiment to test hypotheses on the effect of global graph structural properties of a network as predicted by the model of Bramoullé and Kranton (2007). For economics of social networks "[e]xperiments provide an important test bed for results which can be very difficult to pinpoint outside of the controlled environment of a laboratory" (Jackson 2005, p.60). First, we test whether individuals are indeed able to coordinate on equilibria. We find that individuals do play equilibrium strategies, but that the extent to which they are able to do this strongly depends on the network structure. For all structures coordination on equilibria is rather low, but much higher than predicted by chance. In general, coordination seems to be easier on extreme network architectures with combinations of high density and low centrality or vice versa, like the full and the star network. Moreover, local coordination with direct neighbors is six to seven times more frequent than coordination on network equilibria. Second, we test whether play converges to the theoretically predicted stable equilibria. For three of our experimental network structures theory predicts stable specialized equilibria. We find that stability is low, but if play converges it almost exclusively does so towards the predicted equilibria. Finally, we test for the welfare effects of network structures and of additional links. As expected, we find significant differences in total welfare between the network structures. Sparse networks, e.g., the star and the line, show the lowest average profits, while dense structures, e.g., the full, are found to be most profitable. Given our experimental setting, we expect a positive welfare effect of additional links, which our results confirm. But we also find that, across all networks, subjects' payoffs are, on average, 12.23% lower than efficient equilibrium payoffs.

As interactions on networks easily become complex it is not evident to what extent individual behavior is influenced by global graph structural properties of the network and to what extent by factors at the local or at the individual level. In a more explorative analysis we therefore test the effects of local and individual factors. At the local level we consider an agent's degree (the number of direct neighbors) as a possible influencing factor. Here, the results show that node degree centrality has a strong negative correlation with individual investments and a positive relation with individual profits.

A specific feature present in the model of Bramoullé and Kranton (2007) is the fact that all network structures support multiple equilibria, with a tendency that the denser and the more symmetric the structure the larger the number of equilibria. This adds a significant amount of strategic uncertainty to individual agents. At the level of the individual, we therefore hypothesize that personal risk attitudes also have an impact on strategic investment. Our analysis, however, reveals that the global graph structural properties of the network as a whole and the local features of a specific network position do not leave any room for individual effects that pertain to risk attitudes.

Altogether, our experimental study confirm the general predictions from the model of Bramoullé and Kranton (2007). But our study also indicates that strategic interaction on networks is prone to suffer from coordination failure, even on relatively small networks. Furthermore, the global network structure only partially determines behavior. Investment as well as coordination is significantly influenced by an agent's local position, specifically an agent's degree, while individual risk attitudes do not seem to play an important role.

The rest of the paper is structured as follows. In the next section we briefly relate our work to the existing literature. Section 3 presents the theoretical foundation and the development of the hypotheses for the experiment. In Section 4 we explain the experimental design. Section 5 reports the results and Section 6 concludes.

2 Literature

While theoretical research on economic networks has received extensive interest in the past 15 years, experimental work on networks in economics has been neglected until recently.[1] The existing experiments can broadly be grouped according to their focus on either the effect of network structures on equilibrium selection and on cooperation, or on link formation and the evolution of networks.

The first group of experiments is based on seminal work by Kandori, Mailath, and Rob (1993) and Young (1993), who have triggered intense interest in the question of equilibrium selection in coordination games. Berninghaus et al. (1998, 2002) present the first experiments that consider the role of the global structure of networks in coordination games. In their experiment, agents are located on a circle, and on a two-dimensional lattice, and while the size of an agent's neighborhood remains constant across treatments, the neighborhood structure differs. The authors find that play is more likely to converge to the risk-dominant equilibrium when agents interact on the lattice than on the circle. This result is rather striking since subjects were not informed about the precise global structure of the population in the two treatments. The authors conjecture that subjects observe individual play to be more changing in the lattice treatment than in the circle treatment and that therefore risk dominance as an individual motive has more power in the lattice treatment than in the circle treatment. Boun

[1] See Kosfeld (2004) for an interesting survey on experimental contributions in that field.

My et al. (2001) also analyze the effect of network structure on equilibrium selection. Using a setting similar to Keser et al. (1998), they compare the repeated play of a 2×2 coordination game under global and under local interaction with varied degrees of risk dominance of the inefficient equilibrium. In their setting the interaction structure itself does not seem to play a significant role in the convergence of play. In particular, contrary to the studies described above, Boun My et al. (2001) do not find that agents who interact locally on the circle coordinate more frequently on the risk-dominant equilibrium. Ellison (1993) and Morris (2000) analyze theoretically the role of local interaction networks in the spread of particular strategies in simple coordination games, showing how play converges to the risk-dominant equilibrium if agents are located on a circle and interact with their two nearest neighbors. Blume (1993) and Kosfeld (2002) prove empirically that under certain conditions there is convergence to the risk-dominant equilibrium in a population of players located on a d-dimensional lattice. Kovarik et al. (2010) study an anti-coordination game in which information on the network structure is endogenous. They find that local information about the network structure is as effective as full information in ensuring coordination and yields the same selection of Nash equilibria.

A second group of experiments focuses on cooperation on networks. Recently Kirchkamp and Nagel (2007) investigated the effect of local interaction on learning and cooperation in repeated prisoners' dilemmas. They compare interaction neighborhoods of different size and structure, and observe choices under different information conditions. Interestingly their experimental findings contradict the theoretical predictions of naive imitation models. Cassar (2007) studies coordination games and prisoners' dilemmas in local, random and small-world networks. She finds a tendency for coordination on the payoff-dominant equilibrium on all three networks. Her results suggest that local interactions do cause faster coordination than random interactions, but do so on the payoff-dominant equilibrium rather than on the risk-dominant equilibrium.[2] For the cooperation game, she finds insufficient cooperation on all three networks. Average cooperation is found to be lower in small-world networks than in random and local networks. This seems to support the prediction of Eshel et al. (1998) that local interactions offer a better ground for cooperation than other networks. More recently, Ballester et al. (2009) conducted an experiment to estimate subjects' bounded rationality in a network game with unique equilibrium predictions. They find evidence that subjects are boundedly rational in the sense that they only consider their neighborhood of distance two.

A third line of experiments investigates individual incentives for network formation. Goeree et al. (2009) analyze a pure network formation game and

[2] There is an interesting as well as promising link of research on coordination in social networks to recent theoretical and experimental studies on strategic uncertainty, e.g., by Heineman, Nagel and Ockenfels (2004) and (2009).

find that equilibrium predictions fail completely with homogeneous agents, while heterogeneity fosters the formation of an efficient structure over time. Buskens and Corten (2010) find some evidence that subjects will form networks that lead to play of the efficient Nash equilibrium in a simple coordination game, if they can choose their network partners themselves. Burger and Buskens (2009) test whether formation processes lead to predicted stable outcomes in different simple settings and find largely support of the theory. Van Dolder and Buskens (2009) find varying evidence for effects of social motives on network formation process.

Results of the experiments so far have shown that network configurations have important effects on economic outcomes, such as the convergence towards equilibria, the support of Pareto superior states, or the distribution of surplus among economic agents. We contribute to this research by focusing on the effect of network configurations on individual investment decisions in games with strategic substitutes.

3 Predictions for strategic investment in local public goods

In this section we briefly summarize the model and findings of Bramoullé and Kranton (2007) and translate them into testable hypothesis. Suppose there is a set of agents $N = \{1, ..., n\}$ and let $e_i \in \mathbb{R}^+$ denote agent i's level of effort spend on the production of a local public good.

Agents are arranged on a network, which is represented by an undirected network g, that is: $g_{ij} \in \{0, 1\}, g_{ij} = g_{ji}$, for all $j \in N$. If $g_{ij} = 1$, agent j benefits directly from agent i's production, and $g_{ij} = 0$ otherwise. Agent i benefits from his own effort, thus $g_{ii} = 1$. Let $N_i = \{j \in N \backslash \{i\} : g_{ij} = 1\}$ be the set of agents with whom agent i has a link in the network g, and let $\eta_i(g) = |N_i(g)|$ denote the cardinality of this set. We refer to $\eta_i(g)$ as *agent i's degree* and to N_i as the *neighbors* of agent i that benefit directly from i's effort. A network is *regular* if every agent has the same number of links, i.e., $\eta_i(g) = \eta(g) \forall i \in N$. We refer to $\eta(g)$ as the *density of the network (average degree)* and to $\eta(g^c)$ as the number of links that are maximally possible in the set of agents N. Each agent receives a benefit $u_i(e_i, ..., e_n; g) = b(e_i + \sum_{j \in N_i} e_j)$ with $b(0) = 0$ and $b' > 0$ and $b'' < 0$. Marginal costs of effort are constant and equal to c and we assume $b'(0) > c$ to avoid trivial cases.

Given this set-up, Bramoullé and Kranton (2007) study which investment levels form equilibria given a network structure. Let e^* denote the effort level at which to an individual agent, marginal costs are equal to marginal benefits. Bramoullé and Kranton (2007) model the investment decisions on a given network as a non-cooperative game. All individuals simultaneously decide how much to spend on the production of the local public good. It is straightforward to show that a profile e is a Nash equilibrium if and only if for each agent i either (1) $\sum_{j \in N_i} e_j \geq e^*$ and $e_i = 0$, or (2) $\sum_{j \in N_i} e_j \leq e^*$ and $e_i = e^* - \sum_{j \in N_i} e_j$. Obviously, levels of effort are strategic substitutes: the less one agent invests, the more his direct neighbor invests. In general, the equilibrium distribution of effort will lie in-between two extremes: either a profile e is such that for all agents i either $e_i = 0$ or $e_i = e^*$. This will be called a *specialized* profile, and furthermore we will call an agent who invests e^* a *specialist* and an agent investing $e = 0$ a *free-rider.* The other extreme is that all agents i invest some effort such that $0 < e_i < e^*$. This will be called a *distributed* profile.

The hypotheses are formulated under the assumption that agents behave perfectly rational in the sense that they are aware of the entire network structure and that their behavior is influenced by the *graph structural properties at the group level.*

For our analysis the following general result of Bramoullé and Kranton (2007, Theorem 1 and footnote 10, p. 483) is of direct interest: *For any structure* g, *there exists a profile* e *that constitutes a Nash equilibrium, and for any structure* g, *there exists a specialized profile* e *that constitutes a Nash equilibrium.* This result implies that we can characterize best-response functions as well as equilibria for specific network structures. Since pure strategy equilibria exist for all network structures, we can hypothesize that in each network structure individuals are able to find, and thus are able to coordinate on, pure strategy equilibria.

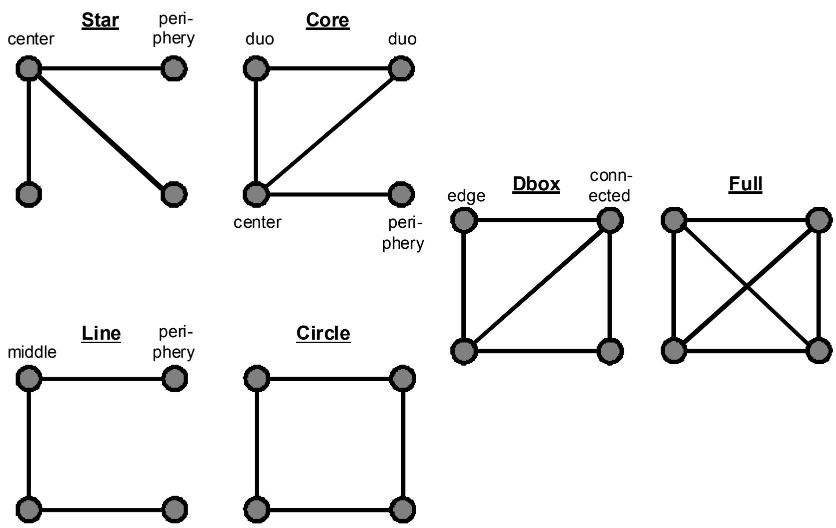
(H1) In any network structure individuals are able to coordinate on pure strategy equilibria.

Bramoullé and Kranton argue that for any graph (except the empty network), there are potentially many Nash equilibria, ranging from specialized to distributed. Using a simple notion of stability based on Nash tâtonnement, Bramoullé and Kranton (2007, Theorem 2, p. 484) identify stable structures: *For any social structure* g, *an equilibrium is stable if and only if it is specialized and every non specialist is connected to at least two specialists.* A consequence of the multiplicity of equilibria is that coordination becomes an issue. This second result implies that if a network structure allows for an equilibrium as specified in the theorem, play should converge towards this equilibrium. Coordination should thus be easier on network structures in which stable equilibria exist and investment profiles should be characterized by more specialization.

(H2) Equilibria in which every non-investing agent is connected to at least two specialists are played for a higher number of consecutive rounds than other equilibria.

For further predictions consider connected graphs of size $N = 4$. All possible connected graphs are depicted in Figure 1. For each of these network structures, we can characterize the full set of Nash equilibria: on the line network there are only two types of Nash equilibria: (i) either the agents at the periphery of the line each invest e^* and the other two (middle) agents invest nothing, or (ii) one agent at the periphery and his neighbor in the middle invest in total e^*, the other middle agent contributes nothing and the remaining peripheral agent invests e^*. On the circle network the following strategy profiles constitute Nash equilibria: (i) $(e^*, 0, e^*, 0), (0, e^*, 0, e^*)$ and (ii) $(\frac{e^*}{3}, \frac{e^*}{3}, \frac{e^*}{3}, \frac{e^*}{3})$. Out of these 3 equilibria, the first two are stable. On the diagonal box (dbox) network there are also only two types of Nash equilibria: (i) either the two agents that are connected to all others invest in total e^*, and the other two agents (on the edge) invest nothing, or (ii) the edge agents not connected to all others each invest e^*, and the other (connected) agents do not invest anything. The second equilibrium is stable, the other equilibria are not stable. On the core-periphery (core) network there are also only two types of Nash equilibria: either the agent in the periphery invests e^*, the core-center agent linked to this agent does not invest and the remaining core-duo agents invest in total e^*, or only the core-center invest e^* and all other agents do not invest anything. None of the equilibria is stable. On the star network there are only two Nash equilibria: either the center is a specialist and the agents at the periphery do not invest (center sponsored), or the agents at the periphery are specialists and the center does not invest (periphery sponsored). The latter equilibrium is stable. Finally, on the full network any profile such that $\sum_{i \in N} e_i = e^*$ constitutes an equilibrium which is not stable.

Figure 1: Network structures in the experiment



Bramoullé and Kranton (2007) furthermore investigate the conditions under which specialization can be beneficial in equilibrium. While no Nash equilibrium is efficient, we can investigate which Nash equilibria and which network structures yield the highest welfare. Due to the fact that individual efforts are strategic substitutes, the level of total effort sustainable in equilibrium has an upper bound. If agents specialize in equilibrium, more effort is sustainable. When specialists are well-located on the graph, social benefits increase through the benefit premium, i.e. the benefits of those agents that do not exert effort but rely on specialists. Their benefits are equal to $\sum_{j:e_j=0}[b(\bar{e}_j) - b(e^*)]$, where the summation is over all agents j who do not exert effort, and $\bar{e}_j = \sum_{i \in N_j} e_i$ is the sum of investment of j's neighbors. Bramoullé and Kranton (2007) introduce a measure $\sigma = (b(ne^*) - b(e^*))/c(n-1)e^*$ for the benefit function that captures the trade-off between benefit premia and effort costs. If we consider a benefit function with a high σ, which allows the benefit premium to outweigh additional costs, for all connected graphs with $N = 4$ we can rank all equilibria according to the welfare they generate. Following Bramoullé and Kranton we define an equilibrium profile e to be *second-best* for a given graph g if and only if there is no other equilibrium profile e' such that total welfare $W(\mathsf{e}'; g) > W(\mathsf{e}; g)$. Consider a graph g and two agents i and j who are not linked in g. Denote by $g + ij$ the graph obtained by connecting i and j in g. A link leads to a 'gain in welfare' when the second-best level of welfare for graph $g + ij$ is higher than that for g. In this case we can rank adjacent graphs according to the welfare the agents earn in the second best equilibrium on the graph: for specific benefit functions, adding a link should not reduce welfare if we move from the star to the core to the dbox, or if we move from the line to the circle to the dbox.

(H3) Adjacent networks (except the full network) can be ranked with respect to increasing welfare (average profits).

From a more explorative perspective it is interesting to investigate to what extent individual behavior is influenced by global graph structural properties of the network and to what extent by factors at the local or at the individual level. For the specific subgroup of connected graphs with $N = 4$ that are tested in this paper local features of an agent's network position can be expected to have an influence on investment decisions. From the model we can conclude that an agent's equilibrium investment depends on his *degree* $\eta_i(g)$ (or *degree centrality* $\eta_i(g)/\eta(g^c)$). On the one hand, if agents are coordinating on a distributed profile (if it exists), a higher number of neighbors should lead to lower individual investment. On the other hand, if agents are coordinating on a specialized profile, then stability (if a stable equilibrium exists) implies that the agents with fewer neighbors are likely to become the specialists. This leads us to formulate the following hypothesis:

(H4) The higher an agent's degree, the lower his investment.

Moreover, the model predicts multiple equilibria for all network structures. Hence, if we abstract from situations where stability arguments (as explained above) lead to unique predictions, agents will be confronted with *strategic uncertainty,* since they cannot assign probabilities to any outcome by relying only on deductive reasoning. As all outcomes are consistent with optimizing behavior and rational expectations neoclassical theory cannot help to predict behavior. Furthermore, if we do not want to rely on arguments of efficiency considerations we may refer to individual risk attitudes to predict which agents will specialize and which will free ride in equilibrium. Suppose agents consider only equilibrium behavior in the sense that they assume that all (non-unique stable) equilibria are played with equal probability.

Concavity of the benefit function $b(e_i + \sum_{j \in N_i} e_j)$ with $b(0) = 0$ and $b' > c$ and $b'' < 0$, implies for the variance that $Var[b(0, \tilde{e}_j)] > Var[b(e^*, \tilde{e}_j)]$, with $\tilde{e}_j$ being the expected sum of equilibrium investments of agent i's neighbors. If, at the same time, $Exp[b(0, \tilde{e}_j)] < Exp[b(e^*, \tilde{e}_j) - ce^*]$ any rational agent would choose $e_i = e^*$. On the other hand, if $Exp[b(0, \tilde{e}_j)] > Exp[b(e^*, \tilde{e}_j) - ce^*]$ sufficiently risk averse agents would still prefer $e_i = e^*$ over $e_i = 0$, while less risk averse agents may choose $e_i = 0$. This leads us to our final hypothesis.

(H5) The less risk averse, the lower an agent's investment.

4 Design of the Experiment

4.1 Experimental game

The aim of our experimental design is to test the hypotheses developed in the previous section. In order to keep the number of treatments manageable, we have chosen to focus on the specific networks used for the development of Hypotheses 3-5. Thus, as depicted in Figure 1, our main experimental treatment variable consists of six different network configurations.

In our experimental set-up we implemented a finitely repeated version of the game proposed and analyzed by Bramoullé and Kranton (2007).[3] Throughout the experiment we had groups of $N = 4$ individuals that formed a connected network g. In the game individuals' pure strategies at each stage are investment levels e. Investment is discrete and can be any positive number with two decimals in the interval $[0, 1]$. This implies that each

[3] Note that all static equilibria continue to be equilibria also in the finitely repeated version. In symmetric regular structures players can alternatively play additional equilibrium strategies, such as a trigger strategy, to achieve cooperation in the first stages. This would imply that all players coordinate on a rewarding equilibrium (a distributed profile) in the last stage(s), if all players cooperated or, if one player deviates, the others punish by playing a less favorable equilibrium (they free-ride on the defector). Our empirical analysis reveals that subjects were hardly able to coordinate their play on such a sophisticated level.

agent's action set contains $s = 101$ different actions. Payoffs at each stage are calculated using the following benefit function from profile e in graph g:

$$u_i(\mathsf{e}, \mathsf{g}) = a \ln(1 + e_i + \sum_{j \in N_i} e_j) - ce_i$$

with $a, c > 0$ and $c = \frac{1}{2}a$. This implies that $e^* = 1$ and that in equilibrium $e_i = \max\{0, 1 - \sum_{j \in N_i} e_j\}$.[4] For this benefit function, Table 1 shows a summary of all equilibria with corresponding investment levels and profits. Given the discrete investment and the characterization of equilibria above, we can calculate the total number of equilibria for each structure: on the line network there are $2s$ equilibria, on the circle there are 3 equilibria, on the diagonal box (dbox) network as well as on the core-periphery network there are $s + 1$ equilibria. On the star there are 2 equilibria and on the full network there are $\frac{1}{4}s^3$ equilibria. Relating these numbers to the total number of possible investment profiles, which in our experiment is $s^4 = 101^4$, leads to the probability to reach an equilibrium randomly. For the specific values and their discussion refer to Table 4 in the results section.

Table 1: Theoretical investments and profits in equilibrium

network	(equil.)	investment (in equilibrium)				Ø invest	profit (in equilibrium)				Ø profit
Star		periph	periph	center	periph		periph	periph	center	periph	
	(S1)^{s}	1	1	0	1	.75	13.93	13.93	100	13.93	35.45
	(S2)*	0	0	1	0	.25	50	50	13.93	50	40.98
Core		duo	duo	center	periph		duo1	duo2	center	periph	
	(Co1)*	0	0	1	0	.25	50	50	13.93	50	40.98
	(Co2)	sum=1		0	1	.5	13.93-50		79.25	13.93	39.28
Line		periph	middle	middle	periph		periph	middle	middle	periph	
	(L1)**	sum=1		0	1	.5	13.93-50		50-79.25	13.93	31.97-39.28
	(L2)**	1	0	sum=1		.5	13.93	50-79.25	13.93-50		31.97-39.28
Circle		node1	node2	node3	node4		node1	node2	node3	node4	
	(Ci1)$^{*+,s}$	1	0	1	0	.5	13.93	79.25	13.93	75.25	46.59
	(Ci2)	.33	.33	.33	.33	.33	37.74	37.74	37.74	37.74	37.74
Dbox		conn.	conn.	edge	edge		conn.	conn.	edge	edge	
	(D1)^{*,s}	0	0	1	1	.5	79.25	79.25	13.93	13.93	46.59
	(D2)	sum=1		0	0	.25	13.93-50		50	50	40.98
Full		node1	node2	node3	node4		node1	node2	node3	node4	
	(F1)*	sum=1				.25	13.93-50				40.98

* second best equilibrium; ** second best are only (0,1,0,1) and (1,0,1,0); $^{+}$ or (0,1,0,1); ^{s} stable equilibrium

4.2 Risk attitudes

We measure risk attitudes in two different ways. First, we register subjects' decisions in a lottery treatment with a sequence of nine decisions between two alternatives A and B. Alternative A provides a secure payoff that ranges from €10 to €90 in steps of €10. Alternative B is a lottery where the payoff is either €100 or €0 with equal probability (determined by a coin toss at the end of the experiment). The sequence of the nine decisions was ordered according to an increasing safe payment while the expected payment of the

[4]In the experiment we set $a = 72,13$ and $c = 36,07$ (motivated by expositional reasons), which lead to the payoff table in Appendix 2.

lottery remained constant. An agent's level of risk aversion should determine at which decision he is indifferent between the two alternatives. For any further decision, he should prefer the safe alternative. The instructions in Appendix 1 show a sample screen of the lottery setup.

As an alternative measurement, we combine the experiment with a questionnaire containing Zuckerman's (1994) Sensation Seeking Scale V (SSSV).[5] This measure is based on the notion that risk taking could be linked to factors that are trans-situational, such as personality traits. The fundamental concept central to most trait theories is that traits are life-long and relatively consistent (Allport, 1961). Risk propensity could thus be more a characteristic of an individual than of the situation. In this area, sensation seeking is found to be of particular importance. Since Zuckerman's et al. (1964) pioneering study, a stream of research has confirmed sensation seekingness as a highly consistent predictor of various kinds of risk taking (see, e.g., Zuckerman and Kuhlman, 2000; Zaleskiewicz, 2001) with a high reported internal reliability coefficient (Cronbach's alpha ranges from .85 to .90 for all scales).

The SSSV data is gathered via a questionnaire using 40 forced choice items, assessing the respondents' sensation seekingness on four sub-scales: experience seeking (ES), thrill and adventure seeking (TAS), disinhibition (DIS), and boredom susceptibility (BS). The Sensation Seeking Scale V (SSSV) currently is the most widely used form of the sensation seeking scale with the largest volume of normative data supporting it (Zuckerman, 1994). The four sub-scales each have a score range of 0-10 points, with 10 being high. The total scale score is the sum of the sub-scales scores. The thrill and adventure seeking sub-scale examines the respondents' appeal to activities of physical danger or risk taking. In the experience seeking sub-scale desires for new experiences are assessed. Sub-scale items include the desire for exotic travel or association with unusual friends. Items in the disinhibition sub-scale examine respondents' desire to exhibit uninhibited/unrestrained behaviors. These include behaviors considered high risk, such as heavy drinking, drug use, or having a variety of sexual partners. The final sub-scale, boredom susceptibility, assesses an individual's dislike of repetitive experiences or predictable experiences.

4.3 Procedural details

In total sixteen sessions were run at the experimental laboratory ELSE at Utrecht University. The experiment was conducted in two parts: eight sessions in June 2007 (first part) and eight sessions in September 2009 (second part). Participating subjects came from the subject pool that mainly re-

[5] We include this well validated questionnaire as an alternative measure, because the predictive validity of expected utility-based assessments of risk attitudes has been questioned, especially when decisions concern low stakes as in experiments. See Harrison et al. (2005) for a systematic review of instruments that measure risk propensity.

cruits students of Utrecht University from all faculties. Participants in the first part of the experiment were not invited to the second part. The procedure during the sixteen sessions was kept the same. All sessions were computerized, using a program written with z-tree (Fischbacher, 2007). Altogether 300 subjects participated (148 and 152) and were seated in a random order at PCs. The instructions (see Appendix 1) were then read aloud and questions were answered in private. Before starting the experiment, subjects had to answer a few questions concerning their understanding of the rules. The experiment started, when all subjects gave the correct answers to these questions. Throughout the sessions subjects were not allowed to communicate and could not see others' screens.

In the first part of the experiment, each of the eight sessions contained five treatments: an initial lottery treatment (described above), administered to each student individually, followed by four network treatments with a sequence of 20 decision rounds (also referred to as periods) each. Each of the four network treatments is characterized by a specific network structure: the star, circle, core-periphery, or full network. After each sequence of 20 decisions, subjects were asked to look at the next network structure. We administered the lottery treatment first to prevent that the payoffs from the network treatments affect individuals' lottery decisions. Also, as the payoffs of the lottery treatment were determined and revealed at the very end of the session, we do not expect payoff effects from the lottery on the network decisions. In the second part of the experiment, the sessions contained two network treatments with 20 decision rounds each, followed by one network treatment with 40 decision rounds. In this part we administered the remaining two network structures, line and dbox, with 20 decision rounds, and a robustness check of the circle and the full network over 40 periods.[6] In total, each subject took 80 network decisions: 4x20 in the first eight sessions and 2x20+40 in the second eight sessions of the experiment. For the exact sequencing of the network treatments in all sessions, please see Appendix 3.[7]

Before the start of the first network treatment in each session, subjects were randomly assigned to groups of size $N = 4$ without knowing who the other members of their group were. At the beginning of each network treatment, subjects were informed about their random position on the network and that all agents will keep the same network position over all decision rounds played on the network structure. We decided for such a partner (within-subjects) design to ensure completely independent observations at

[6] After the first part of the experiment, the circle and the full showed a particularly strong deterioration of profits over 20 periods (also see the results section and Appendix 6). We therefore decided to check this development over a longer sequence.

[7] After the analysis of the first part of the experiment, we found very similar results for the SSSV and the lottery measure (also see the results on Hypothesis 5 in this paper). We therefore optimized our experimental budget by excluding the lottery from the second part and adding the robustness check of 40 decision rounds.

the group level. Within the group of four subjects we ensured that no subject was allocated to a central position (i.e., star-center or core-center) in more than one treatment. In each period subjects decided how much to invest, with investments being any positive number with two decimals in the interval $[0, 1]$. These investments generated payoffs in Experimental Currency Units (ECU) that ranged from 0 to 100 (see Appendix 2) with an exchange rate of 0.6 Eurocent per ECU. After each period, the investments and payoffs of all four subjects in a group were revealed to each other and thus became common knowledge within the network.

We chose to administer at least 20 periods per network structure to allow for the coordination of strategies and also to ensure a sufficient number of independent observations on the network level. Although this design is not a direct translation from the original static theoretical setting, we favoured the aspect that it facilitates coordination in this rather complex environment.[8] There is a trade-off, however, because much longer treatments may increase collusive behavior. In fact, while we find only one case of collusion in the 20-period-treatment, the robustness check with 40 periods shows a higher collusion rate between three or four players (primarily on the full network, but also on the circle). Once we exclude these cases, we find no significantly different behavior between 20 or 40 periods.[9]

At the end of each session each subject answered a questionnaire asking for personal data and the SSSV. In the first part of the experiment, one of the nine alternatives of one of the participants in the room was randomly selected after the questionnaire in order to determine the payoff of the lottery treatment. The duration of the sessions ranged from 90 to 120 minutes. Subjects that could not participate because the lab was full received a show-up fee of €5. The average payoff in the experiment across both parts was €17.63 per subject, with minimum earnings of €6.85 and maximum earnings of €120.90 including lottery winnings (of €100) and of €28.50 when excluding lottery winnings.

5 Empirical Analysis and Results

Excluding the robustness check (network treatments with 40 periods), this section analyses the behavior of 300 students, who played 20 periods on two or four of the six network structures, resulting in 17920 investment decisions (observations). As we treat the first five periods as trial rounds, the actual

[8] In December 2005 we conducted a pilot experiment with networks of six subjects in a random stranger design. With the exception of our result on risk, where we found a negative relation between risk attitudes and investments, all results reported in this paper replicate those of the pilot, which indicates that subjects did not play dynamic strategies in the finitely repeated design.

[9] This also applies to the deterioration of profits mentioned above: per network, the average profits in the first and in the last period of the 20-period-treatment are similar to those in the 40-period-treatment. Detailed results can be obtained from the authors.

sample for analysis consists of 13440 observations.[10] None of the results presented in this paper change qualitatively when we include the first five trial periods in the analyses.

5.1 Sample description

Table 2 describes the most important variables of the sample and reports their pairwise correlation. On average, the subjects contributed 0.39 units (with a maximum contribution of 1.0) per period across all sessions and network structures. 63% of the subjects were female, 26% did not have the Dutch nationality, 34% had at least one friend in the same session, and the average age was 22 years. To correct for these and other unobserved individual characteristics we use the variables (4)-(7) as controls and include random effects for all 300 subjects in our estimations.

Table 2: Descriptive statistics and pairwise correlations of subject variables

	mean	s.d.	min	max	1	2	3	4	5	6
1 contribution[1]	0.39	0.34	0.03	1.00	1.00					
2 lottery	40.36	14.14	10.00	70.00	0.10	1.00				
3 SSSV	5.15	1.51	1.00	9.25	-0.05	0.18*	1.00			
4 female[2]	0.63	0.48	0.00	1.00	-0.09	-0.15	-0.06	1.00		
5 foreign[2]	0.26	0.44	0.00	1.00	0.01	0.06	-0.06	-0.03	1.00	
6 age	21.65	3.88	16.00	59.00	0.02	0.14	-0.12*	-0.06	0.18*	1.00
7 friends[2]	0.34	0.48	0.00	1.00	-0.08	0.10	0.04	-0.05	0.21**	-0.12*

* p<0.05, ** p<0.01, *** p<0.001 (300 subjects, except lottery with 148 subjects)
[1] moments based on 13440 decisions; average per subject (300 obs.) in pairwise correlation
[2] female=1, non-Dutch=1, at least one friend in same session=1

As Table 2 also shows, the risk measurement from the lottery treatment ('lottery') and the sensation seeking score from the questionnaire ('SSSV') are positively correlated with each other ($\beta = 18\%$) at a statistically significant level of $< 5\%$. This corroborates our choice of these two variables as related but nevertheless alternative measurements of behavior towards risk.[11]

The subjects in our experiment are on average risk averse as their choice to switch to fixed payments averages at €40.36, while the risk-neutral, expected value of the lottery is €50. This corresponds with the sensation seeking measurement (SSSV), which has a slightly lower average value of 5.15 compared with the normative sample from Zuckermann (1994) of 5.32. Table 3 reports for every sensation seeking dimension how our sample scored

[10] In the first (second) part, 148 (152) students played 20 periods on 4 (2) networks: $(148\times4+152\times2)\times20 = 17920$. Excluding the five trial periods generates $15/20\times17920 = 13440$ observations.

[11] This confirms prior findings that there is indeed a relation between the psychological measurement of risk with the SSSV and economic risk taking (see, e.g., Zuckerman and Kuhlman (2000), Zaleskiewicz (2001)).

in comparison with the normative sample of Zuckermann (1994) (adjusted to the same ratio of women and men).[12]

Table 3: Sensation seeking values (SSSV scores)

	mean (normative)	mean (sample)	s.d. (sample)
SSSV-TAS	7.01	6.84	2.55
SSSV-ES	5.13	5.86	2
SSSV-BS	3.39	3.05	2.01
SSSV-DIS	5.76	4.86	2.48
SSSV (avg)	5.32	5.15	1.51

5.2 Testing of Hypotheses

5.2.1 Do agents coordinate on equilibria?

In order to test Hypothesis 1 we compute the percentage of individual investment *decisions* with which the players *reached an equilibrium.* To account for the possibility that subjects make mistakes - due to the large number of equilibrium actions and overall complexity - we also identify *'fuzzy' equilibria.* These allow for some deviation ε in individual i's contribution e_i, with $e_i \leq \varepsilon$ or $|e^* - e_i| \leq \varepsilon$ for specialized equilibria, and $\left|\frac{e^*}{N_i+1} - e_i\right| \leq \varepsilon$ and $|e^* - (e_i + \bar{e}_i)| \leq \varepsilon$ for distributed equilibria respectively. For robustness, we accept fuzzy values within a band of $\varepsilon = \pm 0.1$.

For the same reason, we also consider two alternative measures of coordination. i) In contrast to equilibria, which involve the whole network, *coordination* may be reached more *locally* by only some subjects. To test this, we first identify all direct neighbors N_i of a subject i. For each period we then code all decisions where subjects locally coordinate their own investments e_i to $\bar{e}_i$, the sum of their neighbors' contributions, such that $e_i + \bar{e}_i = e^*$. If the neighborhood of subject i invests $\bar{e}_i > e^*$, we only code nodes with $e_i = 0$. Analogously, we also code *fuzzy local coordination* for nodes where $|e^* - e_i| \leq \varepsilon$, and for nodes that contribute $e_i = 0$ if their direct neighbors invest $\bar{e}_i > e^* + \varepsilon$.

ii) Analogously to local coordination, we also compute *exact and fuzzy myopic best reply.* Here, we identify all situations where the sum of a subject's current investment and all direct neighbors' investments in the previous period, $e_{i_t} + \bar{e}_{i_{t-1}}$, is equal to e^* (exact), or where $\left|e_{i_t} + \bar{e}_{i_{t-1}} - e^*\right| \leq \varepsilon$ (fuzzy). Again, if $\bar{e}_{i_{t-1}} > e^*$ (exact) or $\bar{e}_{i_{t-1}} > e^* + \varepsilon$ (fuzzy), we only code directly linked nodes with $e_{i_t} = 0$.

Table 4 reports, for all six network structures, the percentage of individual investment decisions that would reach an exact equilibrium by chance

[12] The normative sample (age range of 17-23 years) for the SSSV consisted of 410 male and 807 female undergraduate students from the University of Delaware.

and the observed percentage of decisions that lead to a specific type of equilibrium or to local coordination on the network. We find that, on all six network structures, subjects succeed to coordinate on equilibria and also to coordinate locally with their direct neighbors. In support of Hypothesis 1, subjects coordinate on equilibria with a much higher frequency than they would by chance. This result applies to all networks.[13] In addition, nearly all types of equilibria are reached at least once, with the exception of the center-sponsored star (S2: second best, but unstable) and the distributed circle (Ci2: neither second best nor stable). Across all networks, 2.4% (5.4%) of all decisions lead to exact (fuzzy) equilibria and 17% (30.6%) to local coordination. It seems that coordination is easier on structures that are characterized by extreme network architectures (for measures see Table 6), expressed in combinations of high density and low network centrality or vice versa (the full and the star), while coordination failure is more persistent on networks with intermediate combinations.

Table 4: Frequency of equilibria, local coordination and myopic best reply

			equilibria			local coordination		myopic best reply	
network (type)	equilibrium (type)	N (decisions)	chance (% of N)	exact (% of N)	fuzzy (% of N)	exact (% of N)	fuzzy (% of N)	exact (% of N)	fuzzy (% of N)
	$S1^{s}$	2220		4.7%	5.8%				
Star	S2*	2220		0.0%	0.0%				
	S1+S2	2220	$1.9\text{x}10^{-6}$%	4.7%	5.8%	29.3%	42.1%	16.4%	25.2%
	Co1*	2220		0.2%	0.5%				
Core	Co2	2220		1.1%	2.9%				
	Co1+Co2	2220	$9.8\text{x}10^{-5}$%	1.3%	3.4%	15.9%	29.8%	15.7%	26.1%
Line	L1**+L2**	2280	$1.9\text{x}10^{-4}$%	0.5%	2.1%	11.8%	27.0%	9.9%	18.7%
	$Ci1^{*,s}$	2220		0.4%	1.8%				
Circle	Ci2	2220		0.0%	0.0%				
	Ci1+Ci2	2220	$2.9\text{x}10^{-6}$%	0.4%	1.8%	11.7%	26.7%	13.6%	27.1%
	$D1^{*,s}$	2280		1.4%	1.8%				
Dbox	D2	2280		0.9%	1.6%				
	D1+D2	2280	$9.8\text{x}10^{-5}$%	2.3%	3.3%	16.5%	29.3%	17.4%	30.6%
Full	F1*	2220	0.2%	5.4%	16.0%	17.3%	28.9%	21.4%	35.0%
Total	all	13440	0.05%	2.4%	5.4%	17.0%	30.6%	15.7%	27.1%

* second best equilibrium; ** includes second best; ^{s} stable equilibrium

For a closer inspection of the behavior in and out-of-equilibrium, Appendix 4 shows the distribution of contributions per node type. As shown in Figure 1, we can identify eleven node types, which are distinctively different from each other. The investment profiles in Appendix 4 complement Table 4 in analyzing equilibrium play at the network level.

The full network has the highest percentage of equilibrium decisions: 5.4% (exact) and 16% (fuzzy). We observe a high free-riding behavior on

[13] Note that a systematic relation between the number of potential equilibria and the number of equilibrium observations is difficult to establish. On the one hand it may be easier to coordinate if there are less equilibria, e.g., on the star network. On the other hand, a higher number of potential equilibria may increase the chance to be in an equilibrium by pure coincidence, e.g., on the full network.

the full network: 35.7% of all contributions are 0, while we observe 29.1%, 27.9%, 21.8%, 17.2%, and 16.0% of free-riding on the dbox, core, circle, line and star, respectively. At the same time 12.4% of all contributions on the full are equal to e^*.[14] This leads to several equilibria with specialists (see Appendix 4). In fact, out of 30 periods (with 120 individual decisions) with exact equilibria on the full network (5.4% of 555 periods and 2220 decisions), 19 periods involve specialists $(0, 0, 0, 1)$, one a near-specialist $(0, 0, 0.1, 0.9)$ and ten periods show truly distributed contributions of two or more players.

Excluding the full network, the frequency of equilibria (exact and fuzzy) is highest on the star network, followed by the dbox, core, line and circle. On the star, all 19 (37) exact (fuzzy) equilibria are periphery-sponsored (S1). Similarly, on the core network, only one (three) exact (fuzzy) equilibrium is center-sponsored (Co1). All other six (16) equilibria have free-riding centers (Co2). Four (10) of these equilibria are distributed, since both nodes in the duo invest more than 0 (0.1). In contrast to the star and core, the dbox displays a more balanced occurrence of its equilibrium types: of the 13 (19) exact (fuzzy) equilibria, five (six) are sponsored by the connected nodes (D2), of which one (three) is distributed. On the line, two (six) of the exact (fuzzy) equilibria are specialized and one (six) distributed. On the circle, all equilibria (two exact and ten fuzzy) are specialized.

It seems that, in general, coordination on specialized equilibria is easier than on distributed equilibria. This particularly applies to specialized equilibria for which total investment is above e^*, as equilibrium S1 on the star, Co2 on the core, and D1 on the dbox. On these irregular structures, subjects that are in positions that allow them to receive a benefit premium in one of the equilibria could be a driving force because of their strong incentive to free ride. They seem to be able to pursue their preferred equilibrium such that subjects in periphery positions more frequently specialize if linked to these free-riders. This combination may also explain why, across all networks, local coordination is roughly six (fuzzy) to seven (exact) times more frequent than equilibrium play. Compared with the frequency ranking of equilibrium play the most significant change is that the full network does not have the highest percentage of coordination anymore.[15] Instead, the star shows most exact (fuzzy) local coordination with 29.3% (42.1%) of all decisions. This does not apply, however, to myopic best reply. The full network, the dbox and the circle seem to be more conducive to myopic best replies, because on these networks they occur more frequently than local coordination. In contrast, the networks with peripheral nodes as the star, core, and

[14] The respective values for the other networks are: star (27.2%), line (13.5%), circle (13.2%), core (11.9%), and dbox (8.3%).

[15] This is partially an artefact of the special situation that all nodes are direct neighbors of each other on the full network. Because of this, any local coordination on a joint investment of 1 is always identical to global coordination and therefore cannot add to the number of equilibria. Only if the joint investment is greater than one, we can identify out-of-equilibrium local coordination for nodes that invest nothing.

line display less myopic best reply than local coordination. In the absence of peripheral nodes, on which subjects more frequently specialize, coordination seems more difficult, even locally. On these structures, coordination appears to be more a result of myopic best reply.

Appendix 5 shows the development of coordination success over time (20 periods). A visual inspection suggests the existence of some learning, although this is limited to specific networks. In fact, point-biserial correlation tests between the period (as a trend variable) and a dummy for fuzzy equilibria show a positive correlation only for the full and the star network (statistically significant at the 95% confidence level).[16] Regarding fuzzy local coordination we find positive correlations for the full, star, and the dbox.[17]

5.2.2 Does play converge to stable equilibria?

To test Hypothesis 2 we compute the frequency of 'converging equilibria' in different network structures. In analogy to Callander and Plott (2005) we define convergence as staying in the *same* equilibrium for at least three consecutive periods, as opposed to the above definition of reaching an equilibrium, that is playing it at least in one period. Note that this is a very demanding requirement in comparison to other studies (e.g., Goeree et al., 2009).

Table 5 shows the frequency of convergence to equilibrium play (no. eq.) as well as the number of periods played in converged equilibria (no. per.). In support of Hypothesis 2, we only find convergence in equilibria where every non-investing agent is connected to at least two specialists, with one exception (for fuzzy equilibria) on the full network. Convergence in exact equilibria is limited to the stable equilibria on the star (S1) and the dbox (D1). For fuzzy equilibria, we detect convergence in all three stable equilibria (S1, Ci1, D1) and in a quasi-stable equilibrium on the core (Co2), where a free-riding center is connected to a specialist at the periphery and to a specialist (and a free-rider) in the duo. The only exception to the support for Hypothesis 2 is a fuzzy equilibrium on the full network that is played for three periods in a row (Period 13-15) before it collapsed.

Most of the convergence takes place towards the end of the treatments. On the core and the dbox, one group converged on each network in the last three and eight periods, respectively. On the star, one group converged twice

[16] If learning to coordinate on (fuzzy) equilibria takes place on the full network, it seems to be restricted to the first 20 periods. A robustness check with the data over 40 decision rounds (last treatment in second part of the experiment) reveals no positive correlation in the last 20 periods.

[17] The point biserial correlation is a special case of the Pearson product-moment correlation (for a continuous variable and a true dichotomy) and therefore the same assumptions apply. We use indicators for fuzzy coordination, because some networks (e.g., line and circle) do not have sufficent observations of exact coordination success for reliable test statistics.

(Period 8-10 and 14-16) and two groups converged in the last seven and eight periods. Of all theoretically stable equilibria, only convergence on the circle (Ci1) always collapsed before the end of the treatment (Period 6-12 and 15-17). In the robustness check over 40 periods we find the same pattern for the circle: there is only one group that converges to the (specialized) equilibrium from Period 33 to 35 and then the equilibrium collapses well before the end of the treatment.

Table 5: Frequency of converging equilibria

network (type)	equilibrium (type)	N (periods)	convergence *exact* equilibria (no. eq.)	(no. per)	(% of N)	convergence *fuzzy* equilibria (no. eq.)	(no. per)	(% of N)
Star	$S1^{s}$	555	4	19	3.4%	4	21	3.8%
	S2*	555	0	0	0.0%	0	0	0.0%
	S1+S2	555	4	19	3.4%	4	21	3.8%
Core	Co1*	555	0	0	0.0%	0	0	0.0%
	Co2	555	0	0	0.0%	1	3	0.5%
	Co1+Co2	555	0	0	0.0%	1	3	0.5%
Line	L1**+L2**	570	0	0	0.0%	0	0	0.0%
Circle	$Ci1^{*,s}$	555	0	0	0.0%	2	10	1.8%
	Ci2	555	0	0	0.0%	0	0	0.0%
	Ci1+Ci2	555	0	0	0.0%	2	10	1.8%
Dbox	$D1^{*,s}$	570	1	8	1.4%	1	8	1.4%
	D2	570	0	0	0.0%	0	0	0.0%
	D1+D2	570	1	8	1.4%	1	8	1.4%
Full	F1*	555	0	0	0.0%	1	3	0.5%
Total	all	3360	5	27	0.8%	9	45	1.3%

* second best equilibrium; ** includes second best; ^{s} stable equilibrium

As predicted, we do not find any convergence on the line. The other two networks without theoretically stable equilibria, the core and the full, only show convergence at the bare minimum level: for fuzzy equilibria only and for exactly three periods, once. Although this is theoretically expected, it is particularly striking for the full network, because it shows the highest number of equilibria (see Table 4). Some of these equilibria survive for two periods in a row, but most have a lifetime of only one.[18]

5.2.3 What is the welfare effect of extra links?

Hypothesis 3 predicts that welfare increases in the number of links in adjacent networks (excluding the full network). To test this hypothesis we compute the average profit per network (for each group and period) and conduct two-sample tests between all network types.[19] Table 6 reports the average

[18] Similarly, in the robustness check, we detect the convergence of only one (specialized) equilibrium on the full, lasting for five periods. In line with previous indications that learning may be restricted to the earlier periods, this convergence occurs in Periods 6 to 10.

[19] We use paired tests (within-subject) except for pairwise comparisons that involve network types from both the first and the second part of the experiment (between-subject).

profits and contributions at both the node and the network level. Further, it characterizes the node types with their degree as a fraction of the maximally possible degree, $\eta_i(g)/(N-1)$ (Freeman's actor level degree centrality). At the network level, Table 6 shows the total number of links and the standard deviation of all nodes' degree centrality, $\sqrt{\sum_i \left(\left(\eta_i(g) - \eta(g)\right)/N\right)^2}/(N-1)$ (Freeman's network centrality).

Table 6: Structural measures, contribution and profits per network and node type

network/node	N	links/ [degr.]	centrality network	centrality node	mean contr.	mean profit	% deviation from 2nd best	% deviation from minimum
star	2220	3	0.29		0.50^a	34.41^c	-16.03^d	-2.94^d
center	555	[3]		1.00	0.34^b	65.53^b	370.41^d	-34.47^d
periph.	1665	[1]		0.33	0.56^b	24.04^b	-51.93^d	72.55^d
core	2220	4	0.24		0.39^a	36.75^c	-10.31^d	-6.43^d
center	555	[3]		1.00	0.33	53.71^b	285.54^d	-32.23^d
duo	1110	[2]		0.67	0.34	34.94^b	-30.12^d	9.30^d
periph.	555	[1]		0.33	0.56^b	23.43^b	-53.14^d	68.19^d
line	2280	3	0.17		0.45^a	34.15^c	-13.06^d	6.82^d
middle	1140	[2]		0.67	0.39^b	43.01^b	-7.69^d	-13.99^d
periph.	1140	[1]		0.33	0.51^b	25.29^b	-20.87^d	81.59^d
circle	2220	4	0.00	0.67	0.36^a	37.48^c	-19.56^d	-0.70
dbox	2280	5	0.17		0.34^a	39.95^c	-14.24^d	-2.50
conn.	1140	[3]		1.00	0.30^b	47.41^b	-40.17^d	48.32^d
edge	1140	[2]		0.67	0.37^b	32.50^b	133.28^d	-35.01^d
full	2220	6	0.00	1.00	0.29^a	40.95^c	-0.08	-0.08
total (netw.)	13440				0.39	37.28	-12.23^d	-0.94

[a] significantly different from all other networks (p<0.01)
[b] significantly different from all other node types within the network (p<0.01)
[c] significantly different from all other networks (p<0.01) exc. full/dbox, circle/core, star/line
[d] significantly different from zero (p<0.01)

An inspection of the average profit levels in Table 6 reveals significant differences in total welfare between the six network structures. Sparse networks, e.g., the star and the line, show the lowest average profits, while denser structures, e.g., the full and the dbox, are the most profitable. As predicted in Hypothesis 3 we indeed find increasing profits along the two 'adjacency paths' from the star to the dbox and from the line to the dbox: the star has the lowest average profit (34.41), followed by the adjacent core (36.75), and the dbox (39.95); similarly, the line has lower profits (34.15) than the adjacent circle (37.48), followed by the dbox (39.95). The differences in profits are statistically significant along the two 'adjacency paths'.[20]

[20] For robustness, we administer several two-sample tests: the Student's mean comparison test (accounting for equality of sample size and of variance), as well as Wilcoxon's signed-rank test (paired) and the Mann-Whitney-Wilcoxon test (unpaired). The latter two tests analyze the equality of population medians and do not assume normal distributions.

Interestingly, across 'adjacency paths', network pairs with the same number of links, i.e. star-line and core-circle, do not differ significantly in their welfare.

Although Hypothesis 3 assumes equilibrium play, it does not depend on reaching the efficient equilibrium payoff (second best): it predicts a change in welfare and not its absolute level. Indeed, a look back at the theoretical profit levels in Table 1 shows that Hypothesis 3 also holds for the least efficient equilibrium payoff. When inspecting the empirical results in more detail, we find that the percentage deviation from the second best welfare level is substantial. Across all networks, subjects' payoffs are, on average, 12.23% lower than efficient equilibrium payoffs. In fact, on all networks (except on the full), the welfare level is closer to that in the least efficient equilibrium.[21] Also, as shown in Table 6, the average payoff does not significantly deviate from the minimum equilibrium payoff on, e.g., the circle and the dbox, but also across all networks.

In discussing why the welfare levels are so low, we can divide the networks into three groups: one, where the stable equilibria are least efficient (star and core); a second, where no stable equilibria exist (line and full); and a third, where the equilibria are both stable and efficient (circle and dbox). In the first group, one of the reasons for the low welfare level may be our previous finding that stable equilibria are reached more often. On both the star and the core we find more periphery-sponsored equilibria and convergence (see Tables 4 and 5). These equilibria are stable (or quasi-stable for the core), but also least efficient. The periphery-sponsored investment profile of the average contributions per node type on the star and the core (as displayed in Table 6) serves as another indication that stability serves as a coordination device. In the second group, the absence of stable equilibria may allow subjects to better coordinate on efficiency. In support of this, Table 6 shows that the line is the only network where subjects earn significantly more than in the least efficient equilibrium and the full is the only network where we do not see a lower welfare than predicted (Table 6). In the third group, consisting of the dbox and the circle, the efficient equilibria are also stable. Accordingly, these equilibria occur and converge more often than the less efficient equilibria (see Tables 4 and 5). Also, the connected players on the dbox invest significantly less than the edges (see Table 6 and Appendix 4), which points towards the stable and efficient equilibrium. Despite all this, Table 6 shows that the average payoffs on the dbox and the circle are far below second best and statistically not distinguishable from the least efficient equilibrium. The least efficient equilibria, however, are not reached more often, which suggests miscoordination as another reason for low welfare. This notion is supported by the fact that the circle has the lowest percentage of equilibrium play and of local coordination (Table 4).

[21]Note that, on the full network, all equilibria have the same payoff (40.98 in our experiment).

Taking a more explorative perspective, a dynamic analysis of the average profits reveals significant changes across periods. Appendix 6 shows the profit development per network along the two adjacency paths. We detect a strong deterioration of welfare on the full and the dbox from more than 50 ECU in the first period to less than 35 ECU in the last period, a medium deterioration on the core and the circle (from over 40 to less than 35 ECU), and only a weak deterioration on the star and the line (from above 35 to below 35 ECU). The development seems to be particularly strong in the first and the last five periods, suggesting trial-round and end-round effects at the beginning and the end of the treatment, respectively.[22] In fact, in Period 15 most average profit levels are close to one of the theoretically predicted equilibrium values, ranging from 43.67 to 34.43 ECU.[23] In period 20, however, all average profits are statistically on or even below 34 ECU.

When we re-run the two-sample tests reported in Table 6 for the sub-sample of the last five periods we find only partial support for Hypothesis 3. On the adjacency path 'line-circle-dbox', welfare on the dbox is still higher compared with the circle (mean $\Delta = 2.37$ ECU with $p = .086$) and with the line (mean $\Delta = 3.77$ ECU with $p = .004$), but welfare on the latter two networks is statistically equal (mean $\Delta = 1.4$ ECU with $p = .227$). On the adjacency path 'star-core-dbox', the star and the dbox are the only two networks that still have statistically different welfare levels (dbox higher with mean $\Delta = 3.45$ ECU with $p = .005$).

To inspect the reasons for this in more detail, Appendix 7 shows a break-up of the contributions per node and their development over time (separated along the two adjacency paths). On both adjacency paths we can detect a sharp decline in investments in the last five periods for almost all nodes with more than one degree. A Pearson product-moment correlation between the last five periods (as a trend variable) and the investments of all nodes with more than one degree is negative and statistically highly significant ($\rho = 0.10$; $p = 0.00$). This is different for peripheral nodes with only one degree. Here, subjects do not only invest at a higher level, but jointly also show no end-round effect ($\rho = 0.02$; $p = 0.21$). This diverging investment behavior in the last five periods has different welfare effects. On the star, where the stable equilibrium is periphery-sponsored, the end round effect at the center works into the direction of the stable equilibrium and does not automatically lead to lower profits. In all other networks, however, the end round effect for nodes with more than one degree can lead to miscoordination. For example, on the core periphery, the core duo nodes decrease their investment to approximately the same level as the core-center (0.287

[22] The robustness checks over 40 periods for the full and the circle show a very similar pattern. The results can be requested from the authors.

[23] On the full, for example, the mean profit in Period 15 (43.67) does not differ statistically (two-tailed t-test with $p = 0.28$) from its theoretical value (40.98 ECU, see Table 1). The same applies to the star (34.43 v. 35.45 ECU; $p = 0.42$), the core (38.90 v. 39.28 ECU; $p = 0.86$), and the dbox (37.63 v. 40.98 ECU; $p = 0.13$).

and 0.263, respectively), while the theoretical investment for the periphery-sponsored equilibrium is, on average, 0.5 per duo node. Similarly, on the dbox, where all nodes have more than one degree, both the connected nodes and the edges decrease their investments in the last periods.

5.2.4 Is individual behavior influenced by local degree?

Hypothesis 4 predicts a negative relation between node degree centrality and investment. To test this hypothesis we run panel estimations with subjects' individual contributions as the dependent variable and their node degree centrality as the explanatory variable of interest. As the experimental design only allows contributions between 0 and 1 (although they could theoretically also be higher or lower than that) we use a Tobit panel model.[24] As the unit of observation is a subject's individual decision, we include some demographics (gender, nationality, age, no. of friends in the lab) as well as random effects at the subject level. In order to capture unobserved characteristics at the group level, we include 75 (minus one) fixed effects, one for each group of four subjects within the partner design. In addition, we use the period (sequence) as a trend control and also specify 16 (minus one) session fixed effects.

Table 7 shows the results of the estimations with and without fixed effects for the different network structures (Model 1 and 2, respectively). As expected, we find a strong and highly significant negative correlation between individual investments and node degree centrality, irrespective whether network effects are included (Model 2) or not (Model 1). As discussed in connection with Hypothesis 3 (above), these results could be driven by periphery nodes with only one degree. Model 3 therefore includes dummies for each level of degree centrality: 0.33 (one degree), 0.67 (two degrees), and 1.00 (three degrees), with the degree centrality of 0.67 as the reference case. The results show that the negative relation between node degree and investment is supported at all levels of node centrality: periphery nodes on the star, core, and line (with a centrality of 0.33) jointly invest significantly more than the core-duo, line-middle, and dbox-edge (centrality: 0.67), while the star-center, core-center, dbox-connected and the nodes in the full (centrality: 1.00) invest significantly less.

Looking back at the average profits per node type in Table 6, it is interesting to note that players with higher degree centrality not only invest less, but also earn higher profits than others on the network. This positive relation holds specifically for the star and the core, where the central players seem to be able to pursue their preferred equilibrium. On the dbox,

[24] For robustness we also estimated (i) ordinary least squares panel regressions with the same specification and Huber/White sandwich estimators of variance, as well as (ii) multilevel mixed-effects linear regressions with random effects both at the individual level and at the group level. The qualitative results for all Tobit estimations reported in this paper remain unchanged.

however, the less central players (edge) earn significantly higher profits than predicted by the more central players' most favourable equilibrium. Here, the subjects on the edge of the dbox seem to benefit from the fact that there is more than one central player.

Unique stable equilibria tend to be a basin of attraction. It is therefore possible that the results of Model 3 in Table 7 are driven by investment behavior on the star and the dbox. As a robustness check, we therefore exclude the star and the dbox from the sample and re-estimate the specification of Model 3. As shown in Model 4, the results support Hypothesis 4 also in the absence of network structures with unique stable equilibria.

Table 7: Node degree and contribution

dep.var.: contribution	Model 1	Model 2	Model 3	Model 4
centrality [node]	-0.534***	-0.513***		
	[-31.769]	[-19.767]		
centrality [node]=0.33			0.247***	0.235***
			[15.264]	[11.386]
centrality [node]=1.00			-0.098***	-0.066*
			[-6.263]	[-2.542]
sequence (per.)	-0.007***	-0.007***	-0.007***	-0.008***
	[-7.450]	[-7.456]	[-7.466]	[-7.736]
female	-0.034	-0.035	-0.032	-0.036
	[-1.319]	[-1.338]	[-1.231]	[-1.350]
foreign	0.009	0.009	0.012	-0.009
	[0.265]	[0.284]	[0.361]	[-0.256]
age	-0.004	-0.004	-0.004	-0.005
	[-1.098]	[-1.095]	[-1.143]	[-1.270]
friends	-0.036*	-0.036*	-0.037*	-0.024
	[-2.376]	[-2.363]	[-2.440]	[-1.492]
star		0.048**	0.046**	
		[2.574]	[2.448]	
core		-0.017	0.019	0.044
		[-1.081]	[1.077]	[1.949]
circle		-0.050**	0.022	0.053
		[-3.155]	[1.092]	[1.861]
line		0.161	0.174	0.440**
		[1.170]	[1.191]	[3.027]
dbox		0.167	0.182	
		[1.221]	[1.254]	
session fixed effects	y	y	y	y
group fixed effects	y	y	y	y
constant	1.018***	0.840***	0.608***	0.228
	[8.069]	[6.549]	[3.814]	[1.819]
obs. (N)	13440	13440	13440	8940
no. of subjects	300	300	300	300
Wald Chi2	1187	1247	1279	584.34
prob > Chi2	0.000	0.000	0.000	0.000

Tobit panel estimation with random effects per subject

* p<0.05, ** p<0.01, *** p<0.001; t-values in parentheses

5.2.5 What is the effect of risk attitudes on individual investment?

Hypothesis 5 predicts that, on a given node position, risk and sensation seeking subjects invest less. To test this we run panel Tobit regressions with individual contributions as the dependent and with risk and sensation seeking measures as independent variables. Higher values of the two proxies imply higher risk attitudes. To control for all structural effects associated with a subject's network position we include fixed effects for the eleven (minus one) idiosyncratic node types defined in Figure 1 and Table 6. The rest of the econometric specification is identical to the models in Table 7.

Table 8: Risk attitude and contribution

dep.var.: contribution	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
lottery	0.002		0.002		0.001	
	[1.464]		[1.440]		[0.615]	
SSSV		-0.003		-0.008		-0.001
		[-0.294]		[-0.895]		[-0.103]
sequence (per.)	-0.007***	-0.007***	-0.010***	-0.008***	-0.012***	-0.010***
	[-5.912]	[-7.465]	[-7.666]	[-7.735]	[-9.460]	[-10.668]
female	-0.069*	-0.035	-0.042	-0.047*	-0.052	-0.008
	[-1.829]	[-1.316]	[-1.109]	[-1.730]	[-1.293]	[-0.249]
foreign	0.006	0.010	-0.023	-0.012	0.007	0.010
	[0.131]	[0.310]	[-0.480]	[-0.362]	[0.140]	[0.257]
age	-0.003	-0.004	-0.005	-0.005	-0.003	-0.004
	[-0.781]	[-1.128]	[-1.213]	[-1.256]	[-0.751]	[-0.935]
friends	-0.045	-0.036*	-0.029	-0.019	-0.029	-0.040*
	[-1.881]	[-2.377]	[-1.214]	[-1.183]	[-1.136]	[-2.250]
node fixed effects	y***	y***	y***	y***	y***	y***
session fixed effects	y	y*	y	y	y	y
group fixed effects	y	y	y	y	y	y
constant	0.684***	0.816***	0.487***	0.940***	0.338*	0.584***
	[4.394]	[5.516]	[3.407]	[6.396]	[2.011]	[3.713]
obs. (N)	8880	13440	6660	8940	6660	10080
no. of subjects	300	300	300	300	300	300
Wald Chi2	887459	1290260	404414	594820	243959	377436
prob > Chi2	0.000	0.000	0.000	0.000	0.000	0.000

Tobit panel estimation with random effects per subject
* p<0.05, ** p<0.01, *** p<0.001; t-values in parentheses

The results in Table 8 show that the risk attitude measure from the lottery treatment (Model 1) has no association with individual investment levels. The same applies when we use sensation seeking as a proxy for risk attitudes (Model 2).[25] As mentioned in the previous section, it is possible

[25] The difference in the number of observations between Model 1 and 2 is due to the fact that the lottery variable was only measured in the first part of the experiment (with 8880 observations on four network structures).

that unique stable equilibria act as a basin of attraction and bias the results. When re-estimating Models 1 and 2 without the star and the dbox (analogous to Model 4 in Table 7), the coefficients for either measure of risk attitude stay insignificant.

In the framework of our experiment the investment behavior of periphery players with only one degree may be independent of their risk attitude. This is because these players face both higher expected profits and a lower variance when investing e^* instead of nothing, if they assume that their neighbors play all (non-unique stable) equilibria with equal probability. As this may blur our results, we re-estimate Models 1 and 2 without the investment decisions of the periphery players, i.e. without the star-, core-, and line-periphery nodes. The results of the respective Models 5 and 6, once again, do not show any significant relationship between individual risk attitudes and investment.

Although not reported in Table 8, we also conducted many additional robustness checks. First, as in the previous section, we used other estimation methods, in particular panel OLS regressions and multilevel mixed-effects estimations. Second, we amended the econometric specifications in Table 8 with the following variables: the neighbors' cumulative investment, the neighbors' average risk attitude, and the interaction between a player's contribution and these two variables. Third, we tried different samples. To exclude possible end round effects, all models in Table 8 were re-estimated without the observations of the last five periods. Further, we re-estimated Models 1 and 2 for each of the eleven node positions separately. In all these additional tests, however, the coefficients for our measures of risk attitude remain statistically insignificant. Hence, none of the results support Hypothesis 5. Overall they rather indicate that network structure leaves little explanatory room for individual effects that pertain to risk preferences.

6 Conclusion

This paper experimentally tests predictions from a model introduced by Bramoullé and Kranton (2007). The primary aim is to gain better understanding of how individuals' decisions in a game of strategic substitutes (a local public good game) depend on the global graph structural properties of the network. Furthermore, we explore the effects of the local structure of the neighborhood that the subjects are positioned in and to what extent individual factors, like risk attitudes, have an effect.

Our main treatment variable in the experiment is the structure of the underlying network. We focus on networks with four agents and consider all possible connected graphs. We find that individual behavior is significantly affected by the network characteristics both at the global and at the local level. In our local public good setting, individuals find it difficult to coordinate on equilibria, but it seems that coordination on specialized equilibria is easier than on distributed equilibria. While network centrality, in general, exhibits no clear pattern, we observe most free-riding behavior on the full network. Moreover, it seems that coordination is easier on structures that are characterized by extreme network architectures with combinations of high density and low network centrality, or vice versa. Coordination failure is more persistent on networks with intermediate combinations.

If play converges to an equilibrium it mostly converges to the theoretically predicted equilibria. We find significant differences between network structures in total welfare and, as predicted, increasing profits along 'adjacency paths' of additional links. But we also find that, across all networks, subjects' payoffs are lower than efficient equilibrium payoffs. At the local level, a larger neighborhood (higher degree) leads to more free riding, which is in line with findings of experiments on cooperative behavior that neglect the neighborhood structure. This concurs with a positive relation between a subject's degree centrality and his profits. Finally, we find that individual risk attitudes do not have an effect on investments.

In general, these findings confirm the theoretical predictions of Bramoullé and Kranton (2007). But at the same time, they also show that interaction on networks is characterized by frequent coordination failure when individual decisions become more complex. We provide evidence that, next to the global network structure, the local degree strongly affects decision making. This result relates to recent work by Galeotti et al. (2010). For games with strategic substitutes in which agents have incomplete information about the network structure, Galeotti et al. (2010) predict that an agent's degree is negatively related to his investment and positively to his profit. This is exactly what we find in our experiment.

Although all subjects had complete information about the whole network structure and although these structures were quite simple, the subjects often seem to behave as if they were only partially informed about the global picture. This finding may indicate that, in order to fully understand behavior on networks, theory should focus on models with incomplete information about the global structure, such as, e.g., Galeotti et al. (2010). Berninghaus et al. (1998, 2002), Ballester et al. (2009) and Kovarik (2010) provide first experimental evidence in this direction. These studies suggest that valuable insights can be gained from the analysis of very simple structures as the basic building blocks of more complex networks.

Appendix 1

Instructions for the first part of the experiment
(instructions for the second part are analogous)

Thank you for participating in this research project. Your earning depends on your decisions and the decisions of the other participants. From now on until the end of the experiment you are not allowed to communicate with each other. If you have some question, raise your hand and one of the instructors will answer the question in private. Please, do not ask aloud. Thank you very much.

The rules are equal for all the participants.

The project consists of 3 phases. In the first phase you will have to decide between different risky or riskless options. The second phase consists of 4 situations. Each situation is independent of the other. In each situation you have to make a sequence of 20 decisions. Your payment at the end depends on these decisions. In the third phase we ask you to fill out a questionnaire.

The Experiment

Phase I

In the first phase you will have to decide between 9 pairs of alternatives. As you see below, for each pair, one of the alternatives is a safe payment (A), the other is a lottery (B). After the experiment, one of the 9 alternatives of one of the participants in the room will be selected at random and the chosen type of payment will be executed.

CHOICE A: **safe payment**	CHOOSE BETWEEN A and B	CHOICE B: **lottery (flipping a coin)**
receive €10,- as safe payment	A ○ ○ B	win €100 or €0, with 50% chance each
receive €20,- as safe payment	A ○ ○ B	win €100 or €0, with 50% chance each
receive €30,- as safe payment	A ○ ○ B	win €100 or €0, with 50% chance each
receive €40,- as safe payment	A ○ ○ B	win €100 or €0, with 50% chance each
receive €50,- as safe payment	A ○ ○ B	win €100 or €0, with 50% chance each
receive €60,- as safe payment	A ○ ○ B	win €100 or €0, with 50% chance each
receive €70,- as safe payment	A ○ ○ B	win €100 or €0, with 50% chance each
receive €80,- as safe payment	A ○ ○ B	win €100 or €0, with 50% chance each
receive €90,- as safe payment	A ○ ○ B	win €100 or €0, with 50% chance each
		OK

Thus, for EACH of the 9 alternatives (rows) shown, please decide between a safe payment (choice A: "safe") and flipping a coin for €100,- (choice B:

"lottery"). If you start with choice B ("lottery"), please look carefully at which row you are switching to choice A ("safe").

After this first phase we will announce the beginning of the following second phase:

Phase II

In the second phase you will be in four different “situations” for 20 periods each. Each situation is represented by a specific network structure that will be shown to you. After 20 periods you will be asked to look at the next network structure. Altogether, you will be in four *different network structures* and you will have to make *80 decisions*.

During this second phase you will be playing with three other randomly chosen participants. In the beginning of each situation you will be informed about your position in the network and you will keep the same network position over all 20 periods played in a network structure. All other members will also not change their identity and positions in the network. Although the network structure and the network positions of the individual players change after each sequence of 20 periods, the persons within your network remain the same over all 80 periods.

The procedure for all 80 periods and all situations/networks is the following:

1. On the computer screen you will be asked to look at a network structure with a specific number, which you will find in the handout. You will also see on the computer screen which player (node number = position) you are in that network. Look carefully at the entire network structure!

2. Each player can produce know-how that will earn him or her Experimental Currency Units (ECUs). You have to decide how much to contribute to the production of know-how. For this you have to type in your “contribution” as any number between 0 and 1, e.g. 0,1 or 0,25 or 0,3 or 0,33 or 0,5 or 0,75, or 0,8. . . etc. up to 1.

3. IMPORTANT: Your know-how is available to your direct neighbors, and the know-how of your direct neighbors will be available to you. Your direct neighbors are players with a direct connection to you. On the basis of this total know-how (yours and your direct neighbors’) your and your neighbors’ ECUs are calculated.

4. Thus, the number of ECUs that you can receive from “know-how” production in each period depends not only on your own contribution but also on the contribution of your direct neighbors. Please have a

look at Table 1 to see how the ECUs you can earn change with the contribution of yourself and your direct neighbors.

Payment:

At the end of the experiment, your ECUs earned in the experiment will be converted into Eurocents with an exchange rate of 0,6. Hence, 100 ECUs will be 60 Eurocents. All information which leads to the calculation of your payment will be made transparent.

Phase III (Questionnaire)

In the third phase we ask you to fill in a questionnaire. All data will be treated confidential and are only used for research. To prove our spending in case of financial investigation, we must ask you for your name and address. These data will be stored separately from the others.
Once you completed the questionnaire, we pay you the amount that you earned in the experiment.

To make sure that everybody understands the rules of the game, we ask you some questions about the game.

Quiz

Before the experiment started, subjects had to answer a few questions on the experimental setup and rules.

Appendix 2

Payoff matrix in the hand-out for the experiment:

		Your own contribution												
		0.00	**0.10**	**0.20**	**0.25**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.75**	**0.80**	**0.90**	**1.00**
Sum of your neighbors' contribution	**0.00**	0.00	3.27	5.94	7.08	8.11	9.84	11.21	12.26	13.03	13.32	13.55	13.84	**13.93**
	0.10	6.88	9.54	11.71	12.63	13.45	14.82	15.87	16.64	17.15	17.33	17.45	**17.54**	17.45
	0.20	13.15	15.32	17.06	17.79	18.43	19.48	20.24	20.76	21.05	21.12	**21.15**	21.06	20.81
	0.25	16.10	18.04	19.59	20.23	20.79	21.70	22.33	22.74	22.93	**22.95**	22.93	22.76	22.43
(neighbors = players with a direct link to you)	**0.30**	18.93	20.66	22.03	22.60	23.08	23.85	24.37	24.66	**24.75**	24.73	24.67	24.41	24.01
	0.40	24.27	25.64	26.69	27.11	27.46	27.97	28.27	**28.36**	28.27	28.17	28.02	27.62	27.08
	0.50	29.25	30.30	31.06	31.35	31.58	31.87	**31.97**	31.88	31.63	31.45	31.23	30.69	30.03
	0.60	33.90	34.67	35.19	35.36	35.48	**35.57**	35.49	35.23	34.83	34.58	34.30	33.64	32.86
	0.70	38.28	38.79	39.09	39.16	**39.18**	39.09	38.84	38.44	37.90	37.59	37.24	36.46	35.58
	0.75	40.37	40.77	40.96	**40.98**	40.96	40.79	40.46	39.99	39.39	39.05	38.67	37.84	36.90
	0.80	42.40	42.69	**42.79**	42.76	42.70	42.45	42.05	41.51	40.85	40.47	40.07	39.19	38.20
	0.90	46.30	**46.39**	46.31	46.20	46.05	45.65	45.12	44.46	43.68	43.25	42.79	41.81	40.73
	1.00	**50.00**	49.91	49.66	49.48	49.26	48.72	48.06	47.28	46.40	45.92	45.42	44.34	43.18
	1.50	**66.10**	65.32	64.43	63.95	63.45	62.38	61.21	59.97	58.66	57.97	57.27	55.82	54.30
	2.00	**79.25**	78.01	76.69	76.00	75.30	73.85	72.33	70.76	69.13	68.29	67.45	65.71	63.93
	2.50	**90.37**	88.79	87.16	86.33	85.48	83.75	81.97	80.14	78.27	77.32	76.36	74.41	72.43
	3.00	**100.00**	98.17	96.31	95.36	94.40	92.45	90.46	88.44	86.39	85.35	84.30	82.18	80.03

Appendix 3

Sequence of network treatments (with number of periods in brackets):

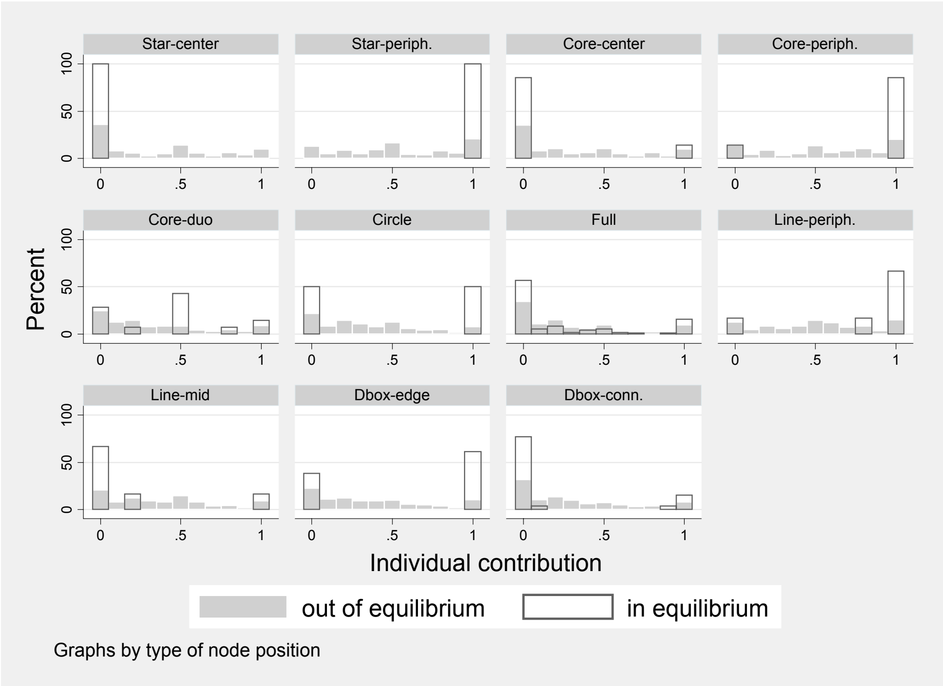
First part of experiment				
session	treatment 1	treatment 2	treatment 3	treatment 4
1	circle (20)	full (20)	star (20)	core (20)
2	core (20)	star (20)	full (20)	circle (20)
3	full (20)	core (20)	circle (20)	star (20)
4	star (20)	circle (20)	core (20)	full (20)
5	core (20)	circle (20)	star (20)	full (20)
6	full (20)	star (20)	circle (20)	core (20)
7	circle (20)	full (20)	core (20)	star (20)
8	star (20)	core (20)	full (20)	circle (20)

Second part of experiment			
session	treatment 1	treatment 2	treatment 3
9	line (20)	dbox (20)	full (40)
10	dbox (20)	line (20)	full (40)
11	line (20)	dbox (20)	circle (40)
12	dbox (20)	line (20)	circle (40)
13	line (20)	dbox (20)	full (40)
14	dbox (20)	line (20)	full (40)
15	line (20)	dbox (20)	circle (40)
16	dbox (20)	line (20)	circle (40)

Within each part of the experiment, the sequencing of the network treatments with 20 periods satisfies the following properties: (1) all network structures are administered equally frequently on each treatment position (2 times in 1st part and 4 times in 2nd part); (2) each network structure precedes each other network structure equally often (2 times in 1st part and 4 times in 2nd part).

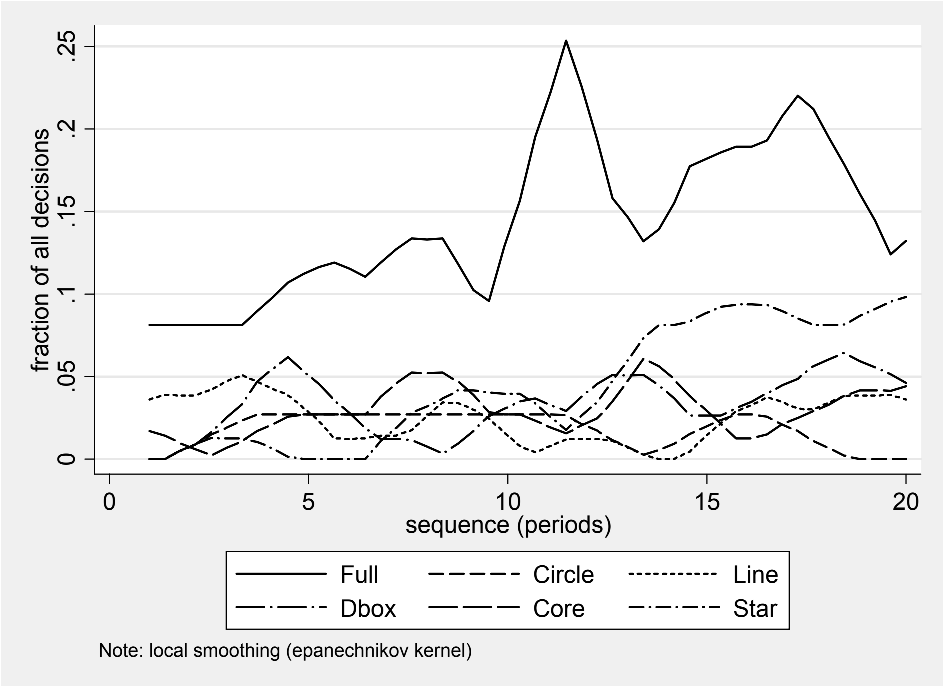
Appendix 4

Contributions per node in and out of equilibrium (15 periods)

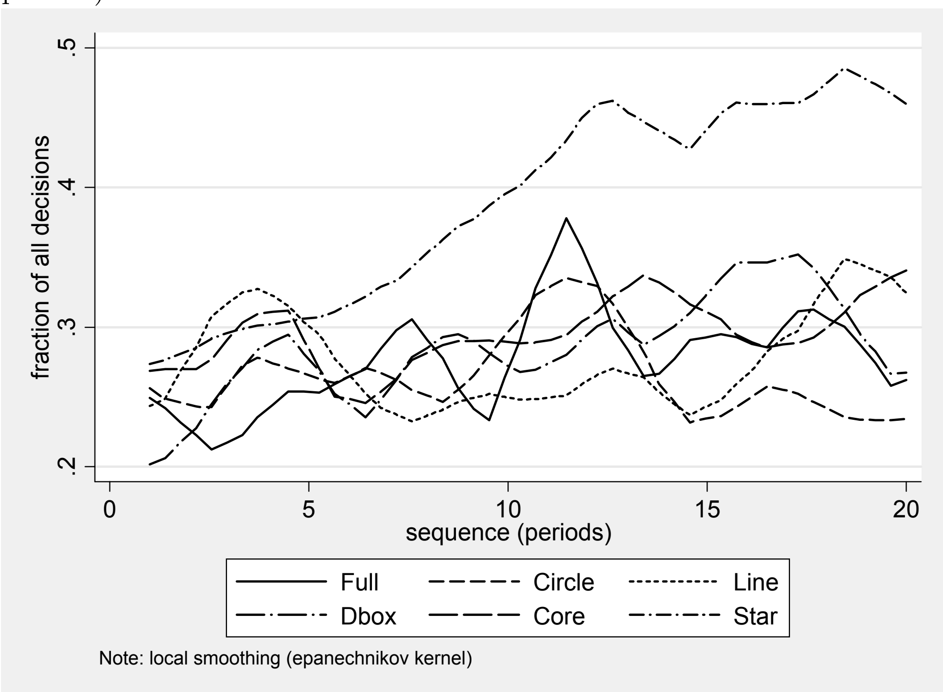


Appendix 5

Graph A: Fraction of (fuzzy) equilibria per network over time (20 periods)

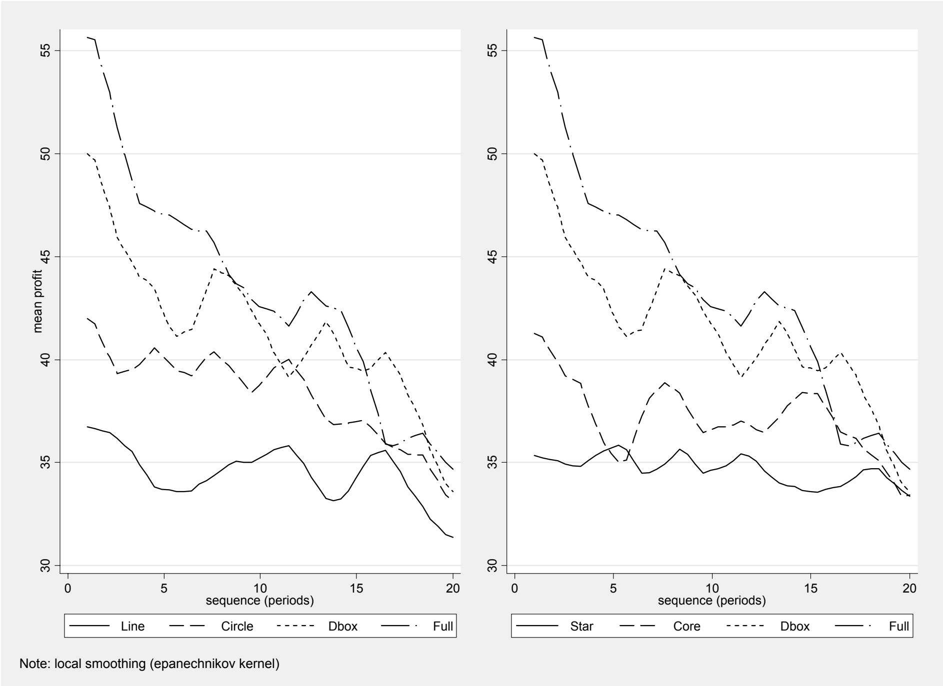


Graph B: Fraction of (fuzzy) local coordination per network over time (20 periods)



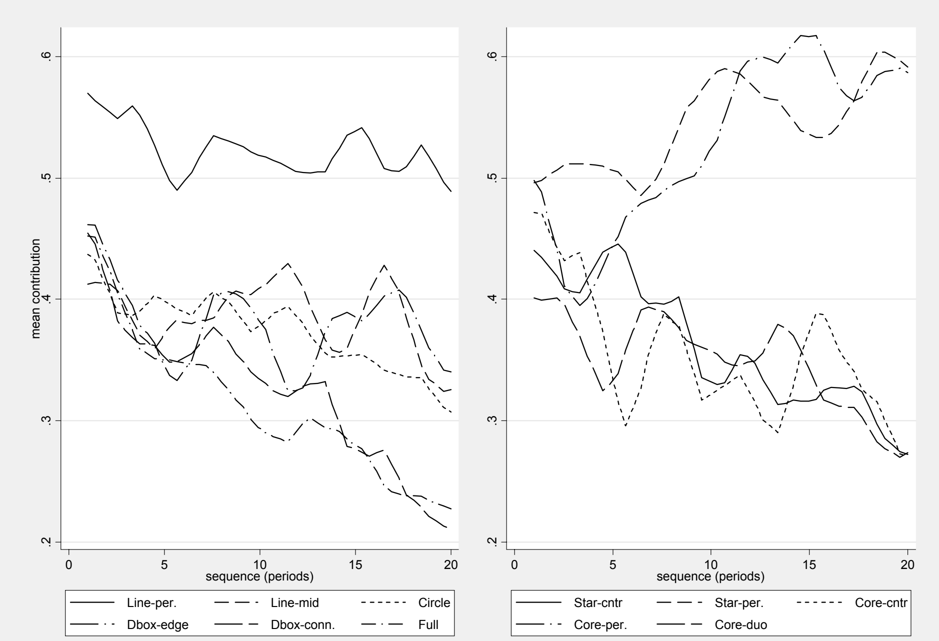
Appendix 6

Average profit per adjacent network over time (20 periods)



Appendix 7

Average contribution per node type over time (20 periods)



Note: local smoothing (epanechnikov kernel)

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