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by

Niels D. Grosse

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Impressum:

Friedrich Schiller University Jena
Carl-Zeiss-Str. 3
D-07743 Jena
www.uni-jena.de

Max Planck Institute of Economics
Kahlaische Str. 10
D-07745 Jena
www.econ.mpg.de

Experimenting with Strategic Experimentation: Risk Taking, Neighborhood Size and Network Structure

Niels D. Grosse

Friedrich-Schiller-University Jena

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Abstract

This paper investigates the effects of neighborhood size and network structure on strategic experimentation. We analyze a multi-arm bandit game with one safe and two risky alternatives. In this setting, risk taking produces a learning externality and an opportunity for free riding. We conduct a laboratory experiment to investigate whether group size and the network structure affect risk taking. We find that group size has an effect on risk taking that is qualitatively in line with equilibrium predictions. Introducing an asymmetry among agents in the same network with respect to neighborhood size leads to substantial deviations from equilibrium play. Findings suggests that subjects react to changes in their direct neighborhood but fail to play a best-response to their position within the network.

Keywords: strategic experimentation, experiment, bandit game, risk taking

JEL-Code: C91, D81, D85, O33

1 Introduction

The adoption of new technologies is acknowledged to be of outstanding importance for economic development. Early adopters are often confronted with substantial risks that are involved in trying out new technologies. Especially in developing countries, there is strong evidence that diffusion depends crucially on the information that is provided through the experience by the social environment (Foster and Rosenzweig, 1995; Conley and Udry, 2009). This paper analyzes experimentally how the structure of the neighborhood influences risk taking in the presence of information externalities.

In situations with information externalities, the problem arises that individuals might strategically delay the adoption of new technologies until others have taken the risk and gathered the necessary information. This problem of strategic delay has received considerable attention in the theoretical literature (Chamley and Gale, 1994; Kapur, 1995; McFadden and Train, 1996). This paper follows Bolton and Harris (1999), Keller et al. (2005) and Klein and Rady (2008) by investigating strategic experimentation as a multi-arm bandit model. In this model the payoffs of the arms depend on the state of the world. Individuals can choose between a "safe" arm whose payoff does not depend on the state and two "risky" arms whose payoffs vary with the state. In a first period, experimentation with risky arms is costly in terms of expected value. However, risk taking provides an opportunity for revealing the state and, subsequently, obtaining higher payoffs in a second period. If actions and payoffs of neighbors are observable, a strategic interaction with multiple equilibria emerges with an incentive to free-ride on the experimentation of others.

Observations in the field by Bandiera and Rasul (2006) suggest that the size of individuals' neighborhood affects experimentation with new technologies. Consistent with considerations of strategic experimentation, individuals in neighborhoods with more adopters wait with their utilization of new technologies. However, one striking feature of many communication networks relevant for the diffusion of new technologies is the unequal distribution of individuals' degree, i.e. their number of neighbors (Rogers, 2003). Individuals differ with respect to the size of their neighborhood. Combining learning with incentives for strategic behavior in larger social networks with heterogeneous agents results in theoretically very complex settings. These settings are tractable only by assuming that agents are either partially informed about the network structure or situated in very simple networks (Bala and Goyal, 1998; Galeotti et al., 2009). This paper uses three simple network settings - a pair, a fully connected network of four and a star network of four - to identify whether subjects care about the structure of the network or base their decision solely on their degree. The results of the experiment suggest that strategic experimentation does take place in the laboratory setting. Neighborhood size, indeed, has a negative effect on experimentation in the first period. Finally, decision makers with the same degree behave similarly in different network structures although this structure is common knowledge. This behavior leads to very different results from theoretical equilbrium predictions in which individuals would fully account for their position in the network.

Besides allowing for the analysis of very simple networks, laboratory experiments have the advantage that social network and available information about neighbors is tightly controlled. Additionally, network structures and the position within networks are exogenously imposed. In empirical data, positions within networks are likely to be correlated with unobservable factors. For example, Glaeser et al. (2000) finds field evidence that th enumber of individuals' social connections are correlated with trusting and trustworthy behavior. An emerging experimental literature has used this advantage of exogenous network structures to disentangle effects of network formation from incentive effects of network structure.[1] Keser et al. (1998) and Berninghaus et al. (2002) look at equilibrium selection in coordination games and vary the openness of the neighborhood, i.e. whether individuals' neighbors also play together. They find that coordination converges less on the payoff-dominant equilibrium in open neighborhoods. Kirchkamp and Nagel (2007) look at the effect of neighborhoods' openness and size in a prisoner dilemma game and find evidence for less cooperation in larger neighborhoods. Very few studies have looked at networks in which subjects differ with respect to their neighborhood structure. Cassar (2007) departs from the homogeneity of subjects by introducing perturbations in the structure in coordination and prisoner's dilemma games. Again coordination depends on the openness of the neighborhood and cooperation is easier in local structures. To our knowledge, Rosenkranz and Weitzel (2008) and Choi et al. (2009) are the only studies that look at irregular network structures in a systematic way by using games that combine public good and coordination aspects. Both find that irregular network structures can help to facilitate coordination by making strategies salient. We contribute to this literature by showing that individuals react strongly to changes in their neighborhood but fail to recognize the implications of the global network structure.

The early experimental literature on multi-arm bandit games mostly focused on individual learning. Only recently, experimentalists became interested in the case in which different alternatives do not have independent distributions but a common state like in our model. In situations with a common state, Charness and Levin (2005) find evidence that players persistently ignore newly generated information by previous choices and undervalue the information generated by their actions. Players who make errors are more likely to ignore data that is in dissonance to their beliefs leading to imperfect learning. Strategic interaction has only recently caught attention in bandit models. Boyce et al. (2008) look

[1]The experimental literature on network formation will not be discussed in this context. See Kosfeld (2004) for an overview.

at simplified two-period adaption of the Bolton and Harris (1999) model while varying the payoffs for the safe and the risky arm. They find that experimental subjects indeed behave strategically in this environment and respond to the information that is provided by them consistent with (imperfect) reinforcement learning. Our results are consistent with these previous experiences. Subjects behave strategically and respond to information that is made available by others, however, imperfectly. This experiment shows that strategic interaction and adoption decisions are strongly influenced by characteristics of the neighborshood. We do not find evidence that decision making errors confound our results.

This paper proceeds as following: in section 2 we describe the theoretical model and the resulting conjectures. Section 3 describes the experimental implementation whose results are reported in section 4. The final section concludes.

2 Model

This model follows the two-arm bandit model by Keller et al. (2005) and Klein and Rady (2008) with one safe and one risky arm with uncertain states and combines it with basic games on networks (e.g., Goyal, 2007).

Model environment

Let $\mathbf{N} = \{1, \ldots, n\}$ be a set of agents and agents $i, j \in \mathbf{N}$ be typical members of this set with $n \geq 2$. The game lasts for two round in discrete time with $t = \{0, 1\}$. This time structure allows trying out risky alternatives in the first round and reaping the fruits of this exploration in the second round. In these two periods, the essence of strategic delay of adoption is captured without having to deal with more complex phenomena such as diffusion in networks.

In every round, agents choose simultaneously between three alternatives: one safe alternative and two risky alternatives. The safe arm S yields a safe return s. This safe alternative can be interpreted as the traditional way of doing things which yields a non-risky payoff to all agents. For the two risky alternatives R_1 and R_2 can be interpreted as the new way of doing things for which two distinct types exist, called "good" and "bad". If a risky arm is "good" it yields a payoff r with certainty which is higher than the safe arm $r > s > 0$. If a risky arm is bad it always yields a payoffof 0. It is common knowledge that exactly one of the two risky arms is of the "good" type and the other arm is of the "bad" type.

There are two possible states. In state $\overline{R}_1$ alternative R_1 is "good" and R_2 is "bad"; while in state $\overline{R}_2$ alternative R_2 is "good" and alternative R_1 is "bad". State $\overline{R}_1$ and $\overline{R}_2$ occur with probability $1/2$. . With this assumption agents are ex-ante indifferent between the two risky alternatives, i.e. the expected payoff of the first and the second risky arm is equal in the first period. In summary states determine payoffs as follows:

State	Probability of state	Payoff S	Payoff R_1	Payoff R_2
$\overline{R}_1$	$1/2$	s	r	0
$\overline{R}_2$	$1/2$	s	0	r

Agents can observe their payoffs at the end of each round and the actions and payoffs of neighbors. We denote $g_{ij} \in \{0, 1\}$ as the relationship between agent i and j with $g_{ij} = 0$ if the two agents are not linked and cannot observe each other and $g_{ij} = 1$ if they are neighbors in a social network. We denote the set of neighbors of player i as $\mathbf{N}_i = \{j \in \mathbf{N} \setminus \{i\} \mid g_{ij} = 1\}$ as a subset of all agents $\mathbf{N}_i \subseteq \mathbf{N} \setminus \{i\}$.

As agents can observe their own payoff and their neighbors $\mathbf{N}_i^d$, any information that is gathered on the risky alternatives is made public locally. Once one of the risky alternatives is chosen and a payoff is observed, the state of the world is perfectly revealed to the agent and her neighbors. If, for example, alternative R_1 yields a payoff of r, the posterior belief of being in state $\overline{R}_1$ jumps to 1, whereas the belief of being in $\overline{R}_2$ to 0. This structure allows agents to explore the space of risky alternatives in the first round and to benefit from this exploration in the second round. Additionally, this structure creates a situation of strategic interaction as choices in the first round influence the beliefs of all neighbors and their potential payoffs in the second round. In this strategic interaction, the exploration of risky alternatives involves taking risks while others might strategically delay the choice of the risky alternatives to the second round to benefit from the risky explorations of neighbors. Exploration in this context generates positive externalities by generating payoff-relevant informations about the state for other agents.

Strategies of agents

Each agents can choose in each period t between an action $\{k_{it}\}_{t \geq 0}$ such that $k_{it} \in \{S, R_1, R_2\}$. In this framework $k_{it} = S$ denotes the choice of the safe alternative, $k_{it} = R_1$ and $k_{it} = R_2$ the choice of the risky alternatives at time t. As the probability of both states is identical, expected payoffs of choosing R_1 and R_2 are identical as long as states of the world are not revealed. As a consequence, we assume that players are indifferent between R_1 and R_2 before the decision in the first period. In this framework the choice

Figure 1: First Period Game Expected Profits

$i=2$ / $i=1$	$k_{20}=R$	$k_{20}=S$
$k_{10}=R$	$E(r)+r$; $E(r)+r$	$E(r)+r$; $s+r$
$k_{10}=S$	$s+r$; $E(r)+r$	$s+\max(s,E(r))$; $s+\max(s,E(r))$

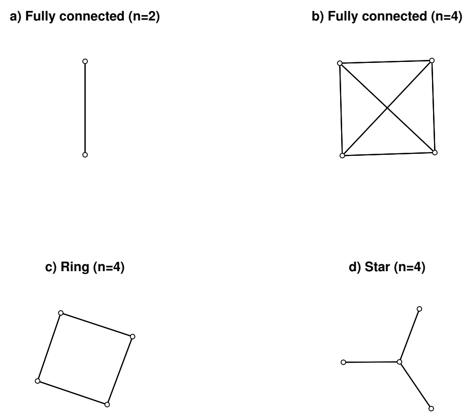
between R_1 and R_2 is trivial: risky alternatives are perfectly negatively correlated, the expected payoff in the first period is identical and states of the world are perfectly revealed after the agent or at least one neighbor has tried one of the risky alternatives. Once the agent or a neighbor has tried out one of the risky alternatives, agents strictly prefer the revealed "good" one. To simplify the choice of $k_{it} \in \{R_1, R_2\}$ as choosing alternative R. The choices of all players will be denoted as $k_t = \{k_{it}, \ldots, k_{nt}\}$ where $k_t \in \mathcal{K}$ is the set of all possible choices with $\mathcal{K} = \mathcal{K}_1 \times \ldots \times \mathcal{K}_n$.

Solution concepts

For a first analysis of the solution concept we assume that players maximize expected profits, have standard preferences and do not discount profits from $t=1$. In this simple setting, the equilibrium solution of choices in $t=0$ depends only on the ratio of s and r. If $s < {}^{r}\!/_{2}$, then choosing the risky alternative is the dominant strategy for all agents in the network as this maximizes the expected earnings over the course of the game as $E(r)+r > 2s$. If $s > {}^{3r}\!/_{4}$, then choosing the safe alternative is the dominant strategy as higher payoffs from knowing the state of the world do not outweigh the expected loss of trying out a risky alternative as $E(r)+r < 2s$. In these two cases dominant strategies and a best-response unique Nash-equilibrium in pure strategies exists.

For ${}^{r}\!/_{2} \leq s \leq {}^{3r}\!/_{4}$ multiple Nash-equilibria exists as it would be sufficient for the creation of information that exactly one agent in a neighborhood tries out a risky alternative. For this range of parameters, neighborhood size and the structure of the network structure matter. To illustrate our point we present the game for $n=2$ and $g_{12}=1$ in the normal form (Figure 1). In this case, two Nash-equilibria in pure strategies exist with $k_0 = \{R, S\}$ and $k_0 = \{S, R\}$, thus only one of the two agents has to explore the space of risky alternatives in the first round and both players profit from this exploration in the second round. Furthermore a equilibrium in mixed strategies exists $k_0 = \{(\alpha R, (1-\alpha)\,S), (\beta R, (1-\beta)\,S)\}$ with α and β depending on the ratio of s and r. E.g., for the case that $r = {}^{2s}\!/_{3}$, the mixed equilibrium is $\alpha = \beta = {}^{1}\!/_{2}$ so that subjects toss a coin whether to choose R or S.

Figure 2: Examples of networks



Neighborhood size

First, we look at changes of the network size $|\mathbf{N}| = \text{n}$ in fully connected networks, i.e. all agents are able to observe each others with $g_{ij} = 1$ for every $i, j \in \mathbf{N}$. In this case the neighborhood of every agent i in the network is equal to the set of agents $\mathbf{N}_i = \mathbf{N} \setminus \{i\}$. This allows to isolate the effect of group size. For $r/2 \leq s \leq 3r/4$, a Nash-equilibrium in pure strategies exists, in which exactly one agent explores the risky alternatives in the first round. All other agents stay with the safe alternative and can achieve a higher payoff r in the second round. As players are symmetric, we should also expect that the individual propensity of i to choose R in an equilibrium of mixed strategies decreases as n grows. For example, if the fully connected network grows from $n = 2$ to $n = 4$ (see figure 2a and 2b) and $r = 2s/3$, then the individuals propensity to choose R decreases from $1 - 1/2$ to $1 - (1/2)^{1/3} \approx 0.2063$ in the mixed equilibrium. From these theoretical predictions we derive our first hypothesis about possible behavior in an experimental setup of the model:

Hypothesis 1: The average propensity to explore the risky alternatives decreases as the fully connected network grows.

The same intuition hold in the case where networks are not fully connected, but all agents are symmetric with respect to their neighborhood size $|\mathbf{N}_i| = c$ and have at least two neighbors $|\mathbf{N}_i| \geq 2$. Classical examples of these kind of network structures are the lattice or the ring (see figure 2c). In this case, for every agent i with a neighborhood of $\mathbf{N}_i \subset \mathbf{N} \setminus \{i\}$, the propensity to explore the risky alternatives in the mixed equilibrium decreases with the growing size of the neighborhood as in the case of the fully connected network. This results leads to a precision of our first hypothesis:

Hypothesis 2: The average propensity to explore the risky alternative decreases as the neighborhood grows for networks with symmetric agents.

Network structure: the star

Introducing asymmetry with respect to the number of neighbors complicates the analysis of expected equilibrium behavior. However, some examples of network structure are nevertheless tractable without further refinement. One example which has gained special attention in the literature of network formation (e.g., Bala and Goyal, 2000) is the a star network. This network, in its simplest form, consists of two types of agents: one center agent i and $n-1$ symmetric periphery agents $j \in \mathbf{N} \setminus \{i\}$. The center agent i is connected to all other agents j with $g_{ij} = 1$ while all agents in the periphery are only connected to the center agent $g_{ji} = 1$. Figure 2d depicts such a star network for $n = 4$. In a framework of costly link formation this network structure provides highest efficiency together with shortest average pathlength[2].

For $r/2 \leq s \leq 3r/4$, two Nash-equilibria in pure strategies exists, with either the center or all periphery players choosing R. Additionally, a mixed equilibrium exists with different behavior for each type of agent. The center player has to play a best-response strategy to players with only one neighbor (himself) and the periphery players have to play best-response strategies to a neighbor with $n-1$ neighbors (all periphery players). This implies that the center has a higher propensity to explore the risky alternatives in the mixed equilibrium for any $n > 2$. For example, for $n = 4$ and $r = 2s/3$, the center agent i has to play a best-response to a neighbor with just one opponent (himself), which implies that his propensity to provide the public good is $1 - 1/2$ in equilibrium; the same propensity as agents in a bilateral relationship (network of $n = 2$). The agents j, however, know that the center player has $n - 1 = 3$ neighbors, which implies that they have to choose R with a probability of $1 - (1/2)^{1/3} \approx 0.2063$. This mixed-equilibrium leads to the following hypothesis regarding possible behavior in the experimental setup:

Hypothesis 3: In a star network the central player has a higher propensity to explore the risky alternatives than the periphery players when all agents play a best-response strategy.

Note however, that this mixed equilibrium does not maximize the expected payoff of the network. A equilibrium that maximizes the payoff of the network would be a situation in which the center agent chooses R while all periphery agents choose S in the first round of

[2] I.e. the number of links (edges) that are necessary to traverse to reach any agent (node) in the network.

the game. In this case all agents can benefit from the center's exploration in the second round. If the center agent is concerned about the efficiency of the whole network, he should choose R in every instance.[3] In this case, the central agent in a star network should adopt even more than agents in a bilateral relationship (network of $n = 2$).

Hypothesis 4: If the central agent in a star network is concerned about the efficiency of the network, he should explore the risky alternative more often than agents in a bilateral relationship.

Additional to these theoretical predictions, participants in an experimental setting might deviate from equilibrium predictions because of limited and costly cognitive ressources. This leads to a simplified decision-making process in which not all information is properly processed. In a recent paper on public good games in network structures, Rosenkranz and Weitzel (2008) observe subjects failing to play equilibrium strategies in complex network structures while still reacting on changes in the network structure. Following their observation, agents may react on changes in their own neighborhood but do not account for the neighborhood of neighbors and, hence, their position in the network. To simplify decision-processing they play a best-response to neighbors that are erroneously perceived as similar to themselves. In this case, they would apply a correct strategy, but with a wrong perception of the model (DellaVigna, 2009). The results of Rosenkranz and Weitzel are comparable to a situation described by Galeotti et al. (2009) where agents are only partially informed of the network structure. This kind of ignorance about the network strucure has a couple of consequences for sparsely connected networks. E.g., in the star network, equilibrium predictions shift diametrically. In a group of four, the center player faces three neighbors and might reason like an agent in a group of four. Contrarily, the periphery players face just one neighbor and might reason like an agent in a group of two. These observations from previous experiments in similar setting lead to a completely contrary behavior:

Hypothesis 5: If agents assume that their neighbors' reasoning is similar to themselves, center agents would have a lower propensity to choose the risky alternatives than agents in the periphery.

Behavioral hypotheses on learning

Playing according to the Nash equilibrium poses high demands on the cognitive capability of agents. In order to play the Nash-strategy in the first period of the game at least three

[3] This does not mean that an equilibrium with the center choosing R is payoff-dominant.

requirements need to be fulfilled (Boyce et al., 2008): (1) Agents have to process informations regarding the profitability of alternatives and have to implement this information in actions. (2) Agents must be forward-looking which implies that they recognize the value of the information for themselves and others. (3) Agents have to be strategically rational which implies that they have to recognize that they are in a situation of strategic interaction.

Charness and Levin (2005) find in an experiment on two-armed bandit models, that agents underestimate the informational value of their own actions. If agents underestimate the informational value of choosing R, the general propensity to take risks in the first period might be lower than predicted by the mixed equilibrium. The same effect can be expected if agents are on average risk averse. Originating from the psychological literature and prominently discussed in the economic literature by Erev and Roth (1998) subjects might not learn perfectly from the feedback in their environment. Following this literature, agents might not perfectly respond to revealed information and choose sub-optimal alternatives. Agents might need more stimuli (e.g., more than one piece of information) to update their beliefs about the state of the world and choose a risky alternative. Therefore, a larger neighborhood might associated with better learning as more stimuli are possibly made available. Following these behavioral implications, deviations from a profit maximizing strategy might be observable which lead to deviations from equilibrium predictions. However, once we control for the informational environment, these decision making errors should not have an additional effect on either group size or network structure.

3 Experimental Design

The experiment was conducted in September 2009 in the computer laboratory of the Friedrich-Schiller-University Jena. Subjects were recruited via ORSEE (Greiner, 2004) and overall 160 undergraduate students from a wide variety of majors participated in 10 sessions. After registration, subjects were randomly seated at computers and received a outline of the experiment and detailed instruction of the game. Subjects could consult these instructions, which are provided in the appendix, during the whole course of the experiment. The experiment and the questionnaire were fully computerized with the help of z-Tree (Fischbacher, 2007).

Based on the previous section, we test our hypotheses experimentally by manipulating network size, network structure and subjects' position in three treatments. In all treatments, the game lasts for two rounds, alternative S yields a payoff s of €2, while the superior payoff r is €3. Two baseline treatments investigate the effect of group size on experimenting in fully connected networks in a network of $n = 2$ (BL2; see figure 2a) and $n = 4$ (BL4; see figure 2b). One treatment investigates the effect of network structure in a group of four players with one center agent and three periphery agents (STAR; see figure 2d). With this parameterization, we should observe the equilibrium outcomes discussed in the examples of section 2. That is, the individual's propensity to choose R should decrease from BL2 to BL4 as described in hyopthesis 1. In the STAR treatment, the center agent should behave as players in BL2 whereas the periphery agents should behave as players in BL4 following hypothesis 3. If agents erroneously ignore the network structure (hypothesis 5), central players would behave as players in BL4 whereas the periphery agents should behave as players in BL2.

At the beginning of the experiment matching groups of eight participants were randomly formed. Overall, the game was repeated 15 times with a within-subject design. Every subject participated in all three treatments and subjects were randomly rematched within matching groups at the beginning of each game while the order of treatments was randomized over matching groups. In each treatment, the game was repeated 5 times and the position in networks was randomly assigned for every game. At the beginning of each game, subjects were informed about the size of the groups, the network structure and their position within the network. Subjects were also informed that a state was randomly chosen. To account for learning and order effects, matching groups were allocated to one of two sequences. In the first sequence BL4 was played 5 times, then BL2 5 times and then STAR for 5 times. In the second sequence this order of treatments was reversed. For payment, one of the 15 games is selected for payment at the end of the experiment with a draw from a physical urn. Additionally, subjects earned a show-up fee of €3 so that average earning was € 7.10. The experiment lasted on average 45 minutes including instructions, questionnaires, registration, and payment.

This design allows to account for learning effects and fixed subject-specific unobservable factors such as risk aversion and to estimate the effect of changes in the network size, structure and network position on the propensity to explore the risky alternatives in the first period. At the end of the experiment, participants were asked a questionnaire for demographic covariates. In addition questions of trusting behavior and willingness to risk taking from the GSOEP (Wagner et al., 2007) were asked and subjects had to describe their strategy in detail.

4 Results

4.1 Risk taking

In this section, we look at the choice of R in the first period of the game. Figure 3 shows the proportion of all subjects choosing one of the risky alternatives in period $t = 0$ by treatment (Figure 3a) and repetition (Figure 3b). The results indicate that the proportion of subjects that take risks in the group of two (BL2) is on average 0.33, pooled across all repetitions of the game in this treatment. The propensity to take risk in a group of four (BL4) is consistently lower for all repetitions of the game with a pooled average of 0.26. The propensity to take risks is lower in the center of the STAR then in the periphery, with exception of period 1 and 15. We test our conjectures statistically by running a linear regressions with a dummy variable for the choice of R in the first period as the dependent variable (See table 1). In column (a) we report a random effects model with dummy variables for treatment BL4 and dummy variables for both roles in the STAR treatment with random effects for subjects and matching groups.[4] BL2 is the baseline category in this model. The dummy variable for BL4 is negative and highly significant supporting hypothesis 1.

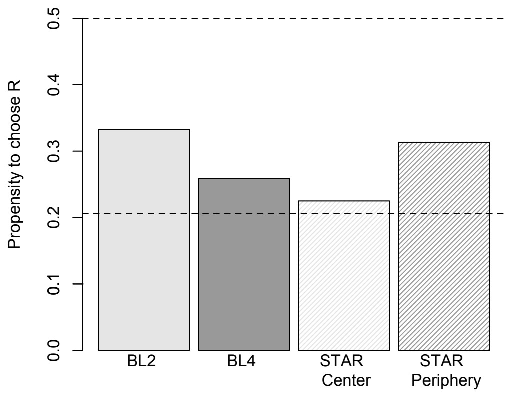
Result 1: *The propensity in a fully connected group of four is significantly lower than in a group of two. Increasing group size in fully connected networks has a negative effect on the propensity to take risks.*

The coefficient for the periphery players in the STAR treatment is negative but insignificant ($p = 0.183$) while the center players have a significantly lower propensity to take risks ($p < 0.001$). A χ^2-test rejects equality of both STAR-coefficients at the 5%-significance level ($p = 0.011$). This result is in sharp contrast to hypothesis 3 and hypothesis 4. The significantly lower propensity to take risk supports hypothesis 5. Indeed, periphery players with only one neighbor do not play significantly different than players in a group of two (BL2). In analogy, subjects in a group of four (BL4) do not play significantly different from players in the center of the STAR. A χ^2-test does not reject ($p = 0.449$) the equality of coefficients for BL4 and STAR center. This indicates, that different network structures do not have a significant effect, besides varying the size of the neighborhood for agents. As the neighborhood grows, subjects decrease their risk taking propensity. This is not in line with the prediction of a theory where subjects play a best-response strategy to the neighborhood of their neighbors. Instead, subjects behave similar to a symmetric, fully

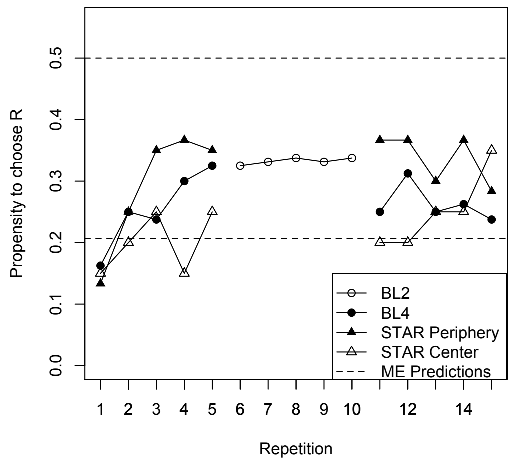
[4] As a robustness check, the model was tested against results from a fixed effects regression. The Hausman test indicated that a random effects model is uncritical in all specifications. To test the functional form, a nonlinear Probit regression yield qualitatively similar results.

Figure 3: Propensity to explore risky alternatives by treatment

(a) All repetitions pooled



(b) By repetition



Notes: Y-axis shows the choices of R as the proportion of all choices in the 1st period of the game by treatment. "BL2" stands for fully connected network of two. "BL4" stands for fully connected network of four. "STAR Center" stands for players in the center of the star network of four. "STAR Periphery" stands for players in the periphery of the star network of four. The dotted lines indicate the equilibrium predictions at 0.5 in a group of two and 0.21 in group of four in fully connected networks.

Notes: X-axis shows the number of repetition of the game and Y-axis shows the choices of R as the proportion of all choices in the 1st period of the game by treatment. White dots indicate observations in fully connected network of two. Black dots indicate observations in fully connected network of four. White triangles indicate observations for players in the center of the star network of four. Black triangles indicate observations for players in the periphery of the star network of four. The dotted lines indicate the equilibrium predictions at 0.5 in a group of two and 0.21 in group of four in fully connected networks.

Table 1: Propensity to explore risky alternative

	All Periods			Period 2-15
	(1)	(2)	(3)	(4)
Constant	0.333***	0.302***	0.261***	0.349***
	(0.027)	(0.030)	(0.033)	(0.048)
BL4	-0.074***	-0.074***	-0.063***	-0.059***
	(0.016)	(0.016)	(0.017)	(0.027)
STAR Periphery	-0.024	-0.024	-0.013	0.005
	(0.018)	(0.018)	(0.018)	(0.019)
STAR Center	-0.094***	-0.094***	-0.083**	-0.080**
	(0.026)	(0.026)	(0.027)	(0.028)
Repetition		0.004*		
		(0.003)		
ln(Repetition)			0.034***	-0.008
			(0.009)	(0.015)
Observations	2400	2400	2400	2080

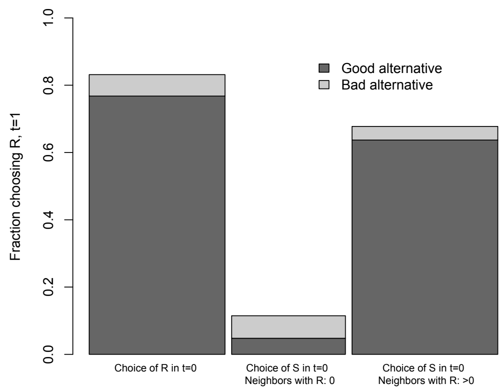
Notes: All regressions with a linear mixed effects model with random effects for subjects (160) and matching groups (20). Columns indicate regression models with choice of R in the 1st period as dependent variable. Rows indicate independent variables. "BL4" is a dummy variable for fully connected networks of four. "STAR Periphery" is a dummy variable for players in the periphery of the star network. "STAR Center" is a dummy variable for players in the center of the star. "Repetition" stands for the number of the repetition of the game. Cells indicate coefficients; standard errors in parenthesis. Stars indicate levels of significance: * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$.

connected network in which their neighbors face the same strategic situation as they do. However, agents do not completly ignore their information on the network structure but react to a change in the size of their own neighborhood. This partial ignorance about the network structure is in line with the "neighborhood heuristic" where agents misperceive the strategic situation of neighbors to be similar to their own.

Result 2: *The propensity to take risks is significantly lower in the center of the STAR then in the periphery. Increasing number of neighbors has a negative effect on the propensity to take risks.*

Learning or order effects might possibly confound the results. Therefore, we test for order effects by comparing the propensity to take risk in BL2 in both sequences. The results of a χ^2-test indicate that order effects are negligeble with an average difference of 0.005 between the two sequences which is not significantly different from zero (p = 0.881). To control for learning effects we include different specifications for learning trends in the regression (column (2) and (3) in table 1). Both, a linear learning trend (p = 0.014) and a logarithmic learning trend (p = 0.023) points towards significant learning effects in the first repetitions of the game (See also figure 3b). However, all treatment effects are

Figure 4: Propensity to adopt R



Notes: Y-axis shows the choices of R as the proportion of all choices in the 2nd period. Left bar indicates that the same subject chose R in 1st period. Middle bar indicates that the subject and all of her neighbors chose S in the 1st period. Right bar indicates that the subject chose S in the 1st period but at least one neighbor chose R. Width of bars represents relative frequency of situations. "Good alternative" stands for R-alternative, which yields a payoff of three. "Bad alternative" stands for R-alternative, which yields a payoff of zero.

qualitatively robust with respect to this learning effect. Indeed, if the first two repetitions are dropped (column (4) in table 1), the logarithmic learning trend becomes non-existent (p = 0.586). Again, all treatment effects remain significant at the 1%-level.

4.2 Learning

In this section we analyze whether subjects managed to update their beliefs about the state of the world correctly. Subjects' ability to update beliefs might influence their decision in the first round as the perception of the profitability of risky alternatives is affected. Estimates on the effect of group size or network structure on risk taking might be biased if decision making errors in the second period of the game are correlated with either group size or network structure. Overall, 23 subjects (14.3%) stayed with the safe alternative in all rounds and all repetitions of the game.[5] We will discard these subjects for further analysis in this subsection. Note that all results from the previous section hold qualitatively with the cleaned set of experimental subjects where subjects choose R at least once.

[5] This is a strategy that yields a reasonable payoff while spending minimal cognitive effort.

Table 2: Adoption of risky alternatives in the second round

Dependent variable	Choice of good R			Choice of bad R		
	(1)	(2)	(3)	(4)	(5)	(6)
States revealed	0.637***		0.636***	-0.044†		-0.046†
	(0.029)		(0.030)	(0.025)		(0.026)
> 1 choice	0.135**		0.109*	-0.033†		-0.040†
	(0.051)		(0.048)	(0.019)		(0.022)
Own choice	0.083		0.101	0.049†		0.058
	(0.055)		(0.064)	(0.029)		(0.037)
Neg feedback	-0.067*		-0.066*	0.034*		0.034*
	(0.029)		(0.029)	(0.016)		(0.016)
Pos & Neg feedback	-0.116**		-0.102*	0.049		0.057
	(0.043)		(0.049)	(0.045)		(0.052)
BL4		0.031	-0.035		-0.014	-0.011
		(0.036)	(0.049)		(0.015)	(0.016)
STAR Periphery		-0.125***	-0.061		-0.001	-0.016
		(0.038)	(0.054)		(0.008)	(0.009)
STAR Center		0.082†	-0.003		0.002	0.003
		(0.045)	(0.050)		(0.017)	(0.020)
Observations	2055	2055	2055	2055	2055	2055

Notes: All regressions with a probit model and cluster robust standard errors (20 matching groups). Columns indicate regression models with choice of the good or bad R-alternative in the second period as dependent variable. Rows indicate independent variables. "States revealed" is a dummy variable indicating that R was at least tried once in 1st period. ">1 choice" is a dummy variable indicating that R was at least tried twice in the 1st period. "Own choice" is a dummy variable indicating that R was tried out by the subject in the 1st period. "Neg feedback" is a dummy variable that R yielded only a payoff of zero in the 1st period. "Pos & Neg feedback" is a dummy variable that R yielded a payoff of zero and three in the first period. The other variables are described in table 2. Cells indicate marginal effects; standard errors in parenthesis. Stars indicate levels of significance: † $p < 0.1$, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.005$

Figure 4 depicts the choices of subjects in the second round, depending on their own choices in the first round and the information that is available about the state of world. In the second round, subject could again choose between the safe alternative, the good R-alternative yielding a payoff of three and the bad R-alternative yielding a payoffof zero. If subjects chose R in the first round, they opted for the good alternative in 76,7% of second rounds. In 6.4% of all choices they picked the bad risky alternative which yields a payoff of zero. The bad alternative is chosen somewhat more often (9.0% of choices) if the feedback from the first round is a payoff of zero. In the situation where the states were revealed only by neighbors, the choice of the good alternative drops to 63.7% of all choices. However, the choice of the bad risky alternative drops as well to 4% of all choices. In those cases where neighbors took R_1 and R_2 in the first round, not a single subject chose to try the bad alternative in the second round. If the states were not revealed by own choice or a neighbors choice, about 11.5% decide to take a risky alternative.

We test the influence of information about the state of the world on individuals' decisions by running regressions on a dummy variable for the choice of the good alternative or the choice of the bad alternative as dependent variables. Results of the regressions are reported in table 2. A probit model with adjusted standard errors for correlations within matching groups was used in all specifications.[6] Column (1) analyzes the effect of different pieces of information about the state of the world on subjects' adoption of the good risky alternative, column (2) and (3) adds treatment and role dummies. A dummy variable for revealed states indicates that the subject or one of her neighbors tried out a risky alternative in the first period. The size of the coefficient, around 0.6, reveals that adoption of the good alternative is not perfect.

Other dummy variables indicate whether at least two subjects in the neighborhood (including the subject herself) chose a risky alternative (">1 choice"), whether the same subject chose R in the first period ("own choice"), whether only a payoff of zwero was available as information about the states of the world ("neg feedback") or whether both R_1 and R_2 were chosen in the first period ("pos & neg feedback").

First, we look at the case where at least two subjects in the neighborhood chose a risky alternative (">1 choice"). In line with reinforcement learning, this additional feedback increases learning (p = 0.007). The dummy variable "own choice" turns out to be insignificant (p = 0.132). The increased propensity to choose a good alternative after the choice of R shown in figure 4 might therefore originate from changes in the other covariates (e.g., ">1 choice") or subject specific fixed effects. E.g, if. the subject is a risk taker and takes R more often in the first period, then this is correlated with choices in the second round. The dummy "neg feedback" should not have an effect on the adoption of the good alternative if learning is perfect. This negative feedback has the same informational value about the states of the world. However, subjects find it significantly harder to learn from this negative feedback. This observation is in line with reinforcement learning which predicts that positive rewards make learning easier. In the case that both R_1 and R_2 were chosen, the dummy variable "pos & neg feedback" takes a value of one. This additional feedback does not enhance performance but makes learning less effective.

Column (2) of table 2 uses the dummy variables for treatments and roles as regressors on the choice of the good alternative in the second period. Column (3) adds these covariates to the previously discussed model of column (1). Playing in the periphery of the star is significantly associated with fewer choices of the good alternative in the second round without controlling for the information that is available about the state of the world. This coefficient is reduced and turns insignificant (p = 0.261) once the available information is added in column (3). This is an indication that periphery players suffer in their ability

[6] A linear fixed effects model yields qualitatively similar results.

to adopt the superior risky alternative which can be explained by the low propensity to choose a risky alternative by the central star players in the first period. Additionally, column (3) shows that decision making errors in the second round are not associated with either group size or network structure. Once the informational environment resulting from choices in the first period is added as a control, coefficients are no longer significant.

Result 3: *Subjects on average react on the information that is provided to them and learn about the state of the world. However, learning is not perfect and decision making errors persist. Decision making errors are not significantly associated with different group sizes or network structures once the information on the state of the world is included as a covariate.*

Columns (4) to (6) use the choice of the bad alternative as the dependent variable. This severe decision making error is neither associated with network size or structure nor with the information on the states of the world. Only negative feedback from choices in the first round intensifies this decision making error significantly. In analogy to the finding from adopting the good alternative subjects find it harder to learn from negative feedback. Additionally, subjects find make slightly less errors if states are revealed or additional feedback is available. Similar to the findings of Charness and Levin (2005), subjects stay with the wrong alternative in the second round after choosing it in the first period. Although this effect is a the verge of conventional significance levels (p = 0.089).

Result 4: *Subjects find it significantly harder to learn from negative feedback. They make more mistakes when confronted with negative feedback.*

Overall, the majority of subjects reacted on the information that was made available by the trials of themselves and others. Admittedly, learning in this game is far from perfect and subjects make errors. Players react consistent with the theory of reinforcement learning and ignore information that is available to them. Decision making errors, however, are not associated with different network structures and group sizes.

5 Conclusions

This paper has analyzed theoretically and experimentally how strategic experimentation by risk taking interacts with the size of the neighborhood and the network structure. In the presence of information externalities a strategic interaction arises with an incentive to free-ride. Our results show that subjects indeed act strategically and react to the size of their neighborhood by reducing risk taking. However, in a star network with asymmetric players, behavior is diametrically opposed to equilibrium predictions. Instead of playing a best-response to the neighborhood of neighbors, subjects behave as if they ignore their position within the network. Although the network structure is common knowledge, agents treat their neighborhood in the same way as in fully connected networks. This observation can be explained by assuming that subjects erroneously treat neighbors as similar to themselves and fail to put themselves in the shoes of others. Our results suggest that assuming that agents are only partially informed about the network structure as in Galeotti et al. (2009) might be a good description of individual behavior. This boundedly rational play results in under-efficient risk taking and less adoption in the periphery of network because central players fail to recognize the implications of their position in the network.

This experiment has shown that individual's risk taking depends crucially on the structure of their neighborhood. Also second round adoption of technologies depends on the structure of the neighborhood. This finding yields implications for the field as strategic consideration seem to be very relevant for risk taking. Central players, which are so crucial for the adoption of new technologies, may face incentives that are detrimental for whole communities. However, in field settings this incentive effect of an individuals' degree might be confined by the fact that more risk taking and cooperative individuals find it easier to become central players, or "opinion leaders" (Rogers, 2003). Nevertheless, these experimental findings call for actions to make risk taking more attractive to central players or reduce the risk associated with new technologies.

Appendix B: Instructions

B.1 Printed instructions (English translation)

Welcome to this experiment and thank you for your participation!

In this experiment – financed by the German Research Foundation (DFG) – you can earn money, depending on your own performance and decisions. Therefore, it is important that you read these instructions carefully. If you have any questions during the experiment, please raise your hand. We will then come to you and answer your question. Please pose your question quietly. All participants of this experiment receive the same printed instructions. The information on the screen, however, is only intended for the respective participant. Please do not look at the screens of other participants and do not talk to each other. If you offend against these rules, we are unfortunately required to expel you from the experiment. Please switch off your mobiles now.

General schedule:

- This experiment consists of **15 repetitions** of the game and a questionnaire

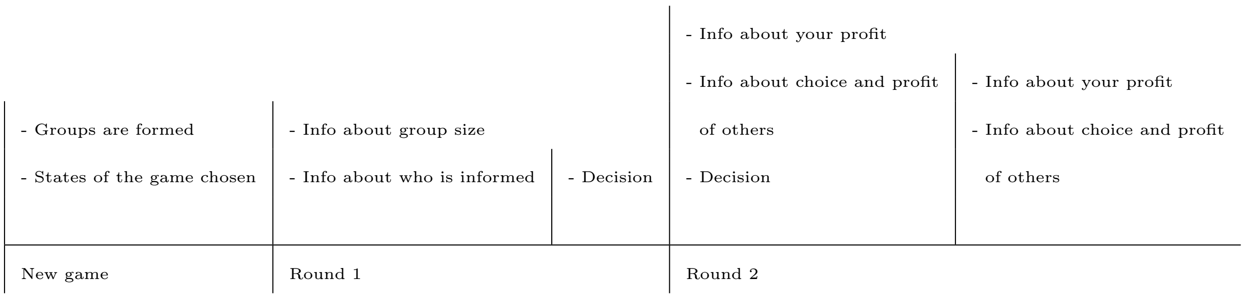
The game:

- The game consists of **2 rounds**.
- At the beginning of each game you will form a group of **2 or 4 randomly chosen participants**. You will be informed **before each game on your screen** how many participants form a group.
- After every round you will be informed about the decisions and profits of some group members. You will be informed **before each game on your screen** who is informed about whom.
- There a **2 possible states** for the game.
- One of the states is **chosen randomly at the beginning of each game**. Both states are equally likely to be chosen.
- The chosen state is valid for the **whole game** (both rounds) and the **whole group**. No group member will be informed about the chosen state.

- At the beginning of each round you and all other group members can choose 1 out of **3 alternatives: S, X and Y**. The profit of the alternatives depends on the chosen state for the game.
- In **each round** alternatives yield the following profits:

	Alternative S	Alternative X	Alternative Y
State 1	2€	3€	0€
State 2	2€	0€	3€

- Alternative S always yields a profit of 2€
  Alternative X yields a profit of 3€ in state 1 and 0€ in state 2
  Alternative Y yields a profit of 0€ in state 1 and 3€ in state 2
- You will be informed about the profit after each round.



Payment:

- After the last game, **one of the 15** repetitions is randomly selected for payments.
- One volunteer will choose a ball with the number from an urn. The chosen number determines the game for payment.
- Your payment will be payed after the questionnaire in a way that no other participant will be informed how much you earned.
- You will earn additional 3€ for your participation.

Further Schedule: After you have read the instructions carefully, please wait for the other participants and then start with the computer program on your screen.

Good luck!

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