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No imitation — on local and group interaction, learning and reciprocity in prisoners' dilemma experiments*

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Abstract

This study disentangles experimentally imitation, reinforcement, and reciprocity in repeated prisoners' dilemmas. We compare a simple situation in which players interact only with their neighbours (local interaction) with one where players interact with all members of the population (group interaction). We observe choices under different information conditions and estimate parameters of a learning model. We find that imitation, while assumed to be a driving force in many models of spatial evolution, is often a negligible factor in the experiment. Behaviour is predominantly driven by reinforcement learning.

JEL-Classification: C72, C92, D74, D83, H41, R12

Keywords: Imitation, reinforcement, learning, local interaction, experiments, prisoners' dilemma.

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1 Introduction

In this paper we study with the help of experiments a question from evolutionary game theory: if agents are in a situation where they can learn from their own experience as well as from other players' experience, how do they weight these two sources of information? Evolutionary game theory would traditionally assume that players weight information from both sources equally: When Axelrod (1984, p. 158ff) discusses the evolution of a network of cooperators and defectors in a prisoners' dilemma he naturally assumes that players choose the strategy with the highest payoff in the past, regardless whether this payoff was obtained by the learning player or by a neighbour. Nowak and May (1992), Eshel, Samuelson, and Shaked (1998) and many others[1] follow this approach. The approach is simple and reasonable if we interpret the evolutionary dynamics in a biological context where successful species displace less successful ones. Also in an economic context where successful firms invade the markets of less successful ones we may treat both sources of information equally. Neither resources nor markets have to make a distinction between the success of the incumbent species or firm and the success of the invading species or firm.

However, if the objects of evolution are learning agents we have to be careful. In contrast to resources or markets, agents have the ability to distinguish between their own success and success of other strategies. Whether they do distinguish between own and others' success should theoretically depend on the degree of homogeneity of the environment. If the agent and the neighbours are in the same environment there is no reason to value information differently. However, one can argue (see Kirchkamp (1999)) that in a heterogeneous environment agents should learn relatively more from their own experience and relatively less from the experience of other players.

In this paper we investigate with the help of laboratory experiments whether players indeed weight own and neighbours' information equally in homogeneous environments and differently in heterogeneous environments. To control the degree of homogeneity, we compare two structures: In one structure agents are located on a circle and interact in overlapping neighbourhoods. This is what we call *local interaction* or a *spatial structure*. In such a structure players' environments are not entirely identical. Players may learn from their neighbours, still, a neighbour's success might be due to an opponent that is not part of the interaction neighbourhood of the learning player. In the other structure agents operate in a group where each agent is equally likely to interact with every other agent. This is what we call *group interaction* or *spaceless structure*. In this structure all agents face the same interaction partners.

From several other experiments we know that players do learn from their own experience (for an overview see Erev and Roth (1998)). From this literature we know that reinforcement describes this learning process fairly well. Most of these experiments are based on games with mixed equilibria only and most experiments study a homogeneous environment. In our experiment we use a game with an equilibrium in pure strategies and we compare a homogeneous with a heterogeneous environment. With an equilibrium in pure strategies incentives to learn decrease less when converging to an equilbrium. A

[1] See also Nowak and May (1993), Bonhoeffer, May, and Nowak (1993), Lindgreen and Nordahl (1994), Kirchkamp (2000).

heterogeneous environment allows us to distinguish between reinforcement learning and imitation.

Related experiments have been done by Keser, Ehrhart, and Berninghaus (1998) who study selection of equilibria in coordination games in similar structures. To answer our question, however, coordination games are not ideally suited. In these games we can not distinguish between a player who chooses a strategy as a result of imitating successful neighbours, and a player who chooses a strategy as a result of myopic optimisation. Both motives call for the same action. If we want to learn more about imitation we have to look at a different game. A very simple game is a prisoners' dilemma.

This game is interesting in the context of local interaction not only because it describes the well known dilemma situation. What is useful here are two other properties: firstly, that learning and myopic optimisation may call for very different actions in this game, and, secondly, that theoretical analysis shows that interaction structure may crucially determine the behaviour of a population (see footnote 1). If players copy successful strategies from their neighbours, cooperation may be a stable outcome in prisoners' dilemma games in a locally structured population, but can not be stable in a population without such a structure.

While space is here introduced as a helpful tool to model similarity of situations and to allow studying the evolution of strategies, space is also crucial in many economic situations. Restaurants or shops along streets do not compete equally with all other restaurants or shops on that street. Strategic interaction and imitation is more important among producers of similar products. Should we, therefore, find more tacit collusion in industries where product space or geographic space is relevant for interaction?

In our experiment groups of players repeatedly play prisoners' dilemmas either within a locally structured neighbourhood (a circle with overlapping neighbourhoods) or within an unstructured (spaceless) group. Players get information about the success of the two strategies separately for their neighbourhood and for themselves. We find that players indeed learn from their own experience. Success of their neighbours, however, does not seem to play any significant role. This holds for both structures: the spatial as well as the spaceless one. As a consequence we do not find the higher levels of cooperation in the spatial structure that were predicted by the theoretical literature under the assumption of learning from neighbours (see footnote 1). Various modifications of our setup do not change this result.

In section 2, we briefly summarise a theoretical argument that is based on imitation and that suggests more cooperation in a spatial world than in a non-spatial world. We will describe the experimental setup in section 3. In section 4 we come to our experimental results. We will study stage game behaviour and learning behaviour. In section 4.2 we study a structure where the population is seeded with computerised cooperators. Section 4.3 studies the effect of introducing information not only about realised payoffs but also about the payoff matrix. Section 5 concludes.

Payoff:					
own	number of	[neighbours / group members]			choosing C
action	0	1	2	3	4
C	0	5	10	15	20
D	4	9	14	19	24

TABLE 1: Payoff Matrix

2 A simple imitation model

In this section we will sketch a simple and common evolutionary learning dynamics that is based on imitation[2] and that suggests more cooperation in a spatial environment and less in a non-spatial one. From the example in this section, it should become clear that with imitation we should expect more cooperation in the spatial structure than in the non-spatial one.

Let us assume that players play a prisoners' dilemma in a neighbourhood of five as described in table 1. Players can only use the same strategy against all four neighbours/group members. Playing C contributes 5 points to the payoff of each neighbour, playing D contributes nothing but gives always a payoff that is 4 points higher than the payoff from playing C.

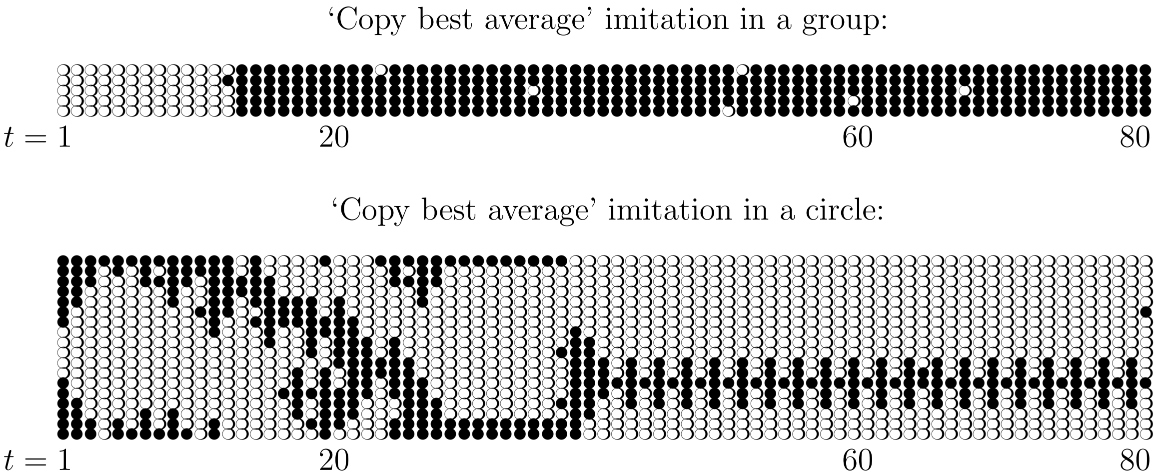
Obviously, in a non-spatial (group) setting with myopic imitation, or replicator dynamics, non-cooperation is always more successful than cooperation. Hence, in a non-spatial setting, cooperation always dies out. In the upper part of figure 1 we give an example. We simulate a group of five players who always imitate the strategy with the highest average payoff in their neighbourhood (*copy best average*). With a small probability (1% in this example) players 'mutate' and choose the other strategy. We start with 5 cooperating players who imitate cooperation until the first mutant arrives. In the example this happens in period 13 where one player mutates and plays D. Being very successful, this player is imitated by all neighbours and from period 14 on everybody plays D. Further mutants that appear in later periods do not lead the group back to cooperation[3].

In a spatial setting and with similar imitation dynamics (see footnote 1) however, cooperation is protected through space and may, hence, survive.[4] Let us assume that player 2 from table 2 knows his own payoff from playing D, which is 14, but also the payoff from his two D-playing neighbours, 9 and 4. The average payoff of playing D is, hence, 9. The two C-playing neighbours of this player have a payoff of 15 and 10, on average, hence, 12.5. If player 2 copies the strategy with the highest average payoff then

[2]Similar dynamics are used e.g. in Nowak and May (1992, 1993), Bonnhoeffer, Nowak, and May (1993), Lindgren and Nordahl (1994), Eshel, Samuelson, and Shaked (1998), Kirchkamp (2000).

[3]The only way to move a population where everybody plays D back to cooperation is a simultaneous mutation of all five players. With independent mutations this is not very likely. And even if it happens, cooperation will not last for long since the first single mutant leads the population back to D. As a result the population will spend most of the time in a state where most of them play D.

[4]With myopic optimisation (Ellison 1993) players would obviously never cooperate.



❍ $=C$, ● $=D$. Time is shown on the horizontal axis, different players are shown on the vertical axis. The first mutant D makes cooperation disappear completely in groups. Cooperation in circles, however, persists despite mutant Ds.
(The imitation rule is 'copy best average payoff', the mutation rate is 1%, the imitation and interaction radius is 2, as in the experiment. Simulations starts with 5 cooperators in the first period.)

FIGURE 1: Simulated learning.

Player						···	1	2	···	···			
Neighbourhood of Player 2						-	-	⇓	-	-			
Action:	···	D	C	C	C	C	C	D	D	D	D	D	···
# of other Cs in the neighbourhood	···	2	2	3	4	3	2	2	1	0	0	0	
Own payoff	···	14	10	15	20	15	10	14	9	4	4	4	
Average payoff of C		12.5	15	15	14	15	15	12.5	10	—	—	—	
payoff of D in the neighbourhood		9	11.5	14	—	14	11.5	9	7.75	7	5.25	4	

TABLE 2: Example of a neighbourhood of Cs and Ds

player 2 will choose C in the next period — thus, cooperation will grow[5].

In our example (see the bottom part of figure 1) cooperation grows from the initial configuration of only five Cs and is not much affected by mutants.

In describing the above dynamics we used the rule 'copy best average payoff' (see the literature given in footnote 2). We should note that this learning rule does not distinguish between a players' own experience and his neighbours' experience. This is expressed in the following hypothesis:

Hypothesis 1 *A player learns as much from his neighbours' experience as from his own.*

We, furthermore, assumed that players would learn from payoffs of C and D in the same way, i.e. an increase in the observed payoff of C would increase a player's inclination to play C in the same way as a similar decrease in the observed payoff of D.

Hypothesis 2 *Players learn from C and D in the same way.*

Following the argument sketched in section 2 and discussed in detail in the literature (see footnote 2), then the following should hold:

Hypothesis 3 *We find more cooperation in populations with a spatial structure than in populations without such a structure.*

It is, however, not obvious, that hypothesis 1 and 2 *should* hold. In a spatial structure players' environments are not identical. Making no distinction between own experience and one's neighbours' experience may, hence, be suboptimal.[6] We summarise this in the following hypothesis:

Hypothesis 4 *Players learn relatively more from their own experience and less from their neighbours' experience the more local their interaction structure is.*

Imitation is, as we have seen in the example above, a major driving force behind the survival of cooperation in a spatially structured population. A player who looks only at his own payoff in a prisoners' dilemma will quickly learn that defection gives a higher payoff. If hypothesis 4 holds, we might also find the following:

Hypothesis 5 *Levels of cooperation are* not *higher in a spatial structure.*

3 The experimental setup

In this paper we describe results from five different treatments which are based on 35 sessions run in Barcelona and Mannheim, involving 339 participants[7]. A list of these sessions is given in appendix A.

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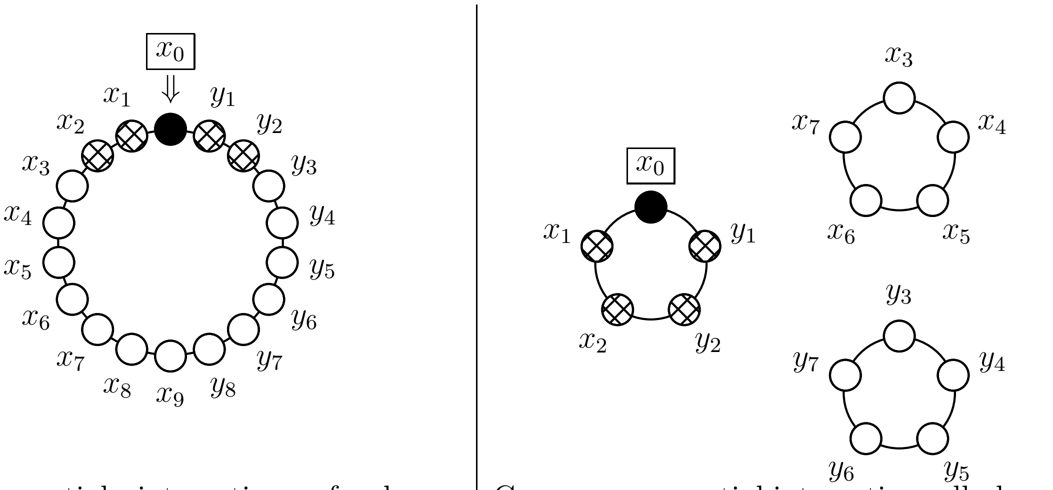
[5]Once the cluster of Ds becomes small the payoff of the remaining Ds grows and the process stops or enters a cycle. With standard imitation processes stable equilibria are often reached when clusters of successful Cs are separated by small clusters of equally successful Ds.

[6]See Kirchkamp (1999).

[7]Students of the UPF in Barcelona and Universität Mannheim respectively.



Circle: spatial interaction of players through overlapping neighbourhoods

Groups: non-spatial interaction, all players are either in the same neighbourhood, or do not interact at all.

FIGURE 2: Neighbourhoods

In the current section we will give a description of the first two treatments. One of them will be called a 'circle' treatment, the other 'group' treatment. The remaining three treatments are modifications that are described in sections 4.2 and 4.3 below.

- In each session of the circle treatment we study a spatial structure of 18 players. Participants are randomly seated in front of computer terminals that are networked to create a neighbourhood structure (see left part of figure 2). Each player interacts in each round with two neighbours to the left and two neighbours to the right. Player x_0 in the figure is in interaction with x_1, x_2, and y_1, y_2. Player x_2 is in interaction with x_3, x_4, and x_1, x_0. Players are able to observe payoffs and strategies of their four interaction neighbours. We ran five sessions of this treatment.

- In the group treatment we study groups consisting of five players each. Each member of a group interacts in every round with all members of the group (see right part of figure 2).

Thus, both in the group and in the circle treatment the number of interaction partners is four. In each session we invited 15 players that were randomly divided into groups of five. We conducted three sessions, thus involving nine independent groups.

During any session players always interact with the same neighbours. Sessions last for 80 periods. In each period participants play a prisoners' dilemma against all members of their neighbourhood/group as described in table 1.

During the course of play players observe their own payoff and action and the average payoff for their neighbours' actions C and D as shown in table 3. This takes place in circles and groups in the same way. The payoff matrix (table 1) is not known to participants. Thus, only the information required by the evolutionary learning models[8] is available to participants.

[8]See footnote 2.

History		
Round	Your action and gains are	in your neighbourhood the average payoff was with... C D
...	......	... ...
...	D 14	12.5 9
...	......	... ...

In the experiment strategies were called A and B. In some sessions A was the cooperative strategy, in others B. Payoffs of Cs are shown in a box, payoffs of Ds are shown in gray. In the experiment we use the colours red and blue.

Table 3: Representation of payoffs in the 'less-information' treatment

4 Results

4.1 Two baseline treatments

As baseline treatments we ran 4 sessions on a circle and 10 in groups, each lasting for 80 rounds. Players receive average payoff feedback as in table 3. The players' actions are shown in appendix B.1 and B.2.

We will first study stage game behaviour and find that in contrast to the simple imitation dynamics discussed in section 2 and summarised in hypothesis 3 there is not more cooperation in space (in circles) than without space (in groups). Then we relate this observation to learning. We will see that, contradicting hypothesis 1, imitation is a very weak force. Players' behaviour is much more drive by their own experience (learning through reinforcement) than by what they observe from their neighbours which is in line with hypothesis 4.

4.1.1 Stage game behaviour

In figure 3 we show the relative frequency of cooperation in circles and groups. Levels of cooperation decrease over time and are about the same in groups and in circles. In circles the average relative frequency of cooperation over all 80 periods is 0.176, in groups the level is 0.187. Neither a t-test[9] ($t = -0.47$, $P_{>|t|} = 0.646$, allowing for correlations within sessions) nor a two-sample Wilcoxon rank-sum test ($z = 0.820$, $P_{>|z|} = 0.4120$) find a significant difference between groups and circles. They are similar to what is found in other non-spatial experiments[10]. Hence, we do not find support for hypothesis

[9] When calculating levels of standard deviations and levels of significance we have to take into account that observations within any session may be correlated. We can, however, assume that covariances of observations from different sessions are zero. Covariances of observations from the same session are replaced by the appropriate product of the residuals (Rogers 1993). We will use this approach throughout the paper to calculate standard errors.

[10] Bonacich et. al. (1976) studied cooperation within groups of 3, 6, and 9 players in a game where cooperation is less attractive than in our game. They found levels of about 30% of cooperation in groups, which is close to the initial levels results in our experiment.

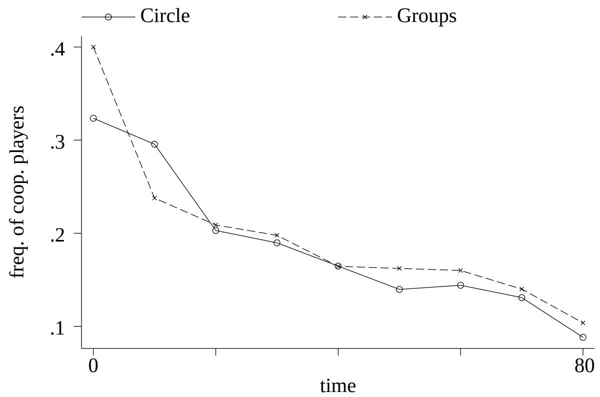


FIGURE 3: Frequency of cooperative players in circles and groups over time

3. Hypothesis 5 is, however, consistent with our observation.

4.1.2 Learning from own and others' payoff

In this section start investigating hypothesis 1 and 4 and study players' learning and imitation behaviour. Since we can not directly observe the learning process but only its outcomes, i.e. players' choices, we have to use a statistical model of the learning process. The logit model is perhaps the most common model that allows us to describe discrete choices between two alternatives, here C and D. To be consistent with the literature and the simple model from section 2 we use differences in payoffs of C and D as explanatory variables of our model. $\Delta_t^{\text{own}} := u^{c,\text{own}} - u^{d,\text{own}}$ is the difference between payoff from cooperation and payoff from non cooperation as experienced by the player in period t. $\Delta_t^{\text{other}} := u^{c,\text{other}} - u^{d,\text{other}}$ is the difference between payoff from cooperation and payoff from non cooperation as experienced by player's neighbours in period t. To allow for some inertia we include the current choice c_t which we code as 1 if the player cooperates today, and 0 otherwise. A more detailed model will follow in section 4.1.3. We estimate

$$P(c_{t+1}) = \mathcal{L}(\beta_0 + \beta_c c_t + \sum_{i \in \{\text{own},\text{other}\}} \beta^i \Delta_t^i) \tag{1}$$

where $\mathcal{L}(x) = e^x/(1+e^x)$, c_{t+1} is 1 if a player cooperates tomorrow, and 0 otherwise.[11] The factor β_{own} captures, hence, reinforcement, β_{other} measures the amount of imitation, β_c measures inertia, and β_0 a general inclination to play C.

When estimating the above model we have to take into account correlations within variables. The dependent variable c_{t+1} influences payoffs in the next period and, hence, the explanatory variables $\Delta_{t+1}^{\text{own}}$ and $\Delta_{t+1}^{\text{other}}$. The AR(1) process can be estimated with the help

Fox and Guyer (1977) used a non-linear payoff scheme where sometimes cooperation was more attractive than in our game. They found more cooperation (around 50%) in a game with groups of 3 and 12 players.

[11] If a player does not cooperate in a given period t the value of $u_t^{c,\text{own}}$ can not directly be determined. In this case we recursively use $u_t^{c,\text{own}} := u_{t-1}^{c,\text{own}}$ until we reach a period where the player actually cooperated. Generally we define recursively $u_t^{s,i} := u_{t-1}^{s,i}$ for $s \in \{C, D\}$ and $i \in \{\text{own}, \text{other}\}$.

coeff. from eq. (1)	Learning own and others' payoff in circles					
	β	σ	t	$P_{>\vert t\vert}$	95% conf. interval	
β_c	−.1527977	.1097514	−1.39	0.164	−.3679064	.062311
β^{own}	.0893514	.0089972	9.93	0.000	.0717171	.1069857
β^{other}	.0302698	.0121571	2.49	0.013	.0064423	.0540972
β_0	−1.079484	.067418	−16.01	0.000	−1.211621	−.9473476
coeff. from eq. (1)	Learning from own and others' payoff in groups					
	β	σ	t	$P_{>\vert t\vert}$	95% conf. interval	
β_c	2.585381	.1193796	21.66	0.000	2.351402	2.819361
β^{own}	.0442708	.0097167	4.56	0.000	.0252265	.0633152
β^{other}	.0664513	.0192851	3.45	0.001	.0286532	.1042494
β_0	−1.622957	.1131753	−14.34	0.000	−1.844777	−1.401138

TABLE 4: GEE population-averaged estimation of equation (1)

of a GEE population-averaged model.[12] Results are shown in table 4. We find that in circles $\beta_{\text{own}} > \beta_{\text{other}}$ while in groups $\beta_{\text{own}} < \beta_{\text{other}}$. Players living in a spatial structure are less sensitive to their neighbour's payoffs than one in a non-spatial one. This is consistent with hypothesis 4. In a spatial structure a neighbour's success with a strategy may be due to this neighbour's neighbourhood and might not apply to the learning players. In circles β_{own} is significantly larger than β_{other} ($\chi^2(1) = 10.49$, $P_{>\chi^2} = 0.0012$). In groups the difference is not significant ($\chi^2(1) = 0.82$, $P_{>\chi^2} = 0.3663$). We can, hence, reject hypothesis 1 in the spatial structure (in circles) but not in groups.

Remember that in section 2 we explained that survival of cooperation crucially depends on imitation of neighbours. Finding only a small amount of cooperation in circles in section 4.1.1 should, hence, not come as a surprise, given that imitation plays only a limited role.

4.1.3 Differences in learning from C and D

When we estimated equation 1 we made the simplifying assumption that players are equally sensitive to payoffs from the two strategies C and D. Equation 2 describes an approach which allows for different sensitivities.

$$P(c_{t+1}) = \mathcal{L}(\beta_0 + \beta_c c_t + \sum_{\substack{s\in\{C,D\}\\ i\in\{\text{own},\text{other}\}}} \beta^{s,i} u_t^{s,i}) \tag{2}$$

Results are shown in table 5 and are again in line with hypothesis 4.

We first test the simplifying assumption that we made above in section 4.1.2. When we estimated equation (1) we implicitly assumed that players are equally sensitive to payoffs from the two strategies C and D. If this were the case we should expect in equation (2) that coefficients $\forall i \in \{\text{own},\text{other}\} : \beta^{c,i} = -\beta^{d,i}$. While, indeed, $\beta^{c,i}$ are positive for $i \in \{\text{own},\text{other}\}$and most $\beta^{d,i}$ are negative, sensitivities to payoffs from D as measured by

[12]See Liang and Zeger (1986). We use as a link function the logistic function and specify c_{t+1} to be binomially distributed.

coeff. from eq. (2)	Learning from C and D in circles					
	β	σ	t	$P_{>\|t\|}$	95% conf. interval	
β_c	$-.3078639$	.16064	-1.92	0.055	$-.6227125$	.0069846
$\beta^{c,\text{own}}$	.0909994	.0108732	8.37	0.000	.0696884	.1123104
$\beta^{d,\text{own}}$	$-.0849679$	.015454	-5.50	0.000	$-.1152572$	$-.0546786$
$\beta^{c,\text{other}}$	.0462106	.0139529	3.31	0.001	.0188635	.0735577
$\beta^{d,\text{other}}$	$-.0134582$	.0192408	-0.70	0.484	$-.0511695$	.024253
β_0	-1.257075	.0987834	-12.73	0.000	-1.450687	-1.063463
coeff. from eq. (2)	Learning from C and D in groups					
	β	σ	t	$P_{>\|t\|}$	95% conf. interval	
β_c	2.657546	.1513503	17.56	0.000	2.360905	2.954187
$\beta^{c,\text{own}}$	.0725666	.0131783	5.51	0.000	.0467377	.0983955
$\beta^{d,\text{own}}$	.0152466	.0168734	0.90	0.366	$-.0178246$	.0483179
$\beta^{c,\text{other}}$	.1177859	.022863	5.15	0.000	.0729753	.1625966
$\beta^{d,\text{other}}$	$-.1191031$	.024038	-4.95	0.000	$-.1662168$	$-.0719894$
β_0	-1.822549	.1188607	-15.33	0.000	-2.055512	-1.589586

TABLE 5: GEE population-averaged estimation of equation (2)

$\beta^{d,i}$ for $i \in \{\text{own}, \text{other}\}$ are smaller in absolute terms. We use a Wald test to jointly test $\forall i \in \{\text{own}, \text{other}\} : \beta^{c,i} = -\beta^{d,i}$ and find for circles ($\chi^2(2) = 6.01$, $P_{>\chi^2} = 0.0496$) and for groups ($\chi^2(2) = 27.82$, $P_{>\chi^2} = 0.0000$) different absolute sensitivities. So, while the simplifying approach from section 4.1.2 may help us gain a first insight, it seems justified to abandon hypothesis 2 and to attribute different strengths to learning from C and D.

Let us next come back to comparing hypotheses 1 and 4. Do players learn equally from their own and their neighbours' experience (as assumed in hypothesis 1) or is own experience more influential (as in hypothesis 4). We use a Wald test to jointly test $\forall s \in \{C, D\} : \beta^{s,\text{own}} = \beta^{s,\text{other}}$. Again we find in circles that players are more sensitive with respect to their own payoffs and less sensitive with respect to their neighbours' payoff. This difference is significant ($\chi^2(2) = 8.91$, $P_{>\chi^2} = 0.0116$). In groups we find the opposite (when one has to learn in groups it is, indeed, rational to put more weight on the average neighbours' payoff than on a player's own payoff since there is more than a single neighbour). With this more general approach differences are also significant in groups ($\chi^2(2) = 12.97$, $P_{>\chi^2} = 0.0015$).

4.1.4 Learning and reciprocity

We will explore the different sensitivities in learning from C and from D in more detail in section 4.3. In this section we attempt to find some structure in the different sensitivities $\beta^{c,\text{own}}$, $\beta^{d,\text{own}}$, $\beta^{c,\text{other}}$, $\beta^{d,\text{other}}$ and relate them to two, sometimes diverging, effects: learning and reciprocity.

If a player's behaviour would learn as assumed in hypothesis 2 then higher payoffs for C should increase, and higher payoffs for D should decrease his probability to cooperate by the same rate. We should expect $0 < \beta^{c,i} = -\beta^{d,i}$ for $i \in \{\text{own}, \text{other}\}$ (this was the implicit assumption when we estimated equation (1)). If, however, a player's behaviour

coeff. from eq. (2)	Learning and reciprocity in circles					
	β	σ	z	$P_{>\|z\|}$	95% conf. interval	
λ^{own}	.1759673	.018847	9.34	0.000	.1390278	.2129068
ρ^{own}	.0060315	.0189445	0.32	0.750	−.031099	.0431621
λ^{other}	.0596688	.026113	2.29	0.022	.0084883	.1108494
ρ^{other}	.0327524	.0211634	1.55	0.122	−.0087272	.0742319
coeff. from eq. (2)	Learning and reciprocity in groups					
	β	σ	z	$P_{>\|z\|}$	95% conf. interval	
λ^{own}	.05732	.0199049	2.88	0.004	.0183071	.0963329
ρ^{own}	.0878133	.0228156	3.85	0.000	.0430956	.132531
λ^{other}	.2368891	.042429	5.58	0.000	.1537298	.3200483
ρ^{other}	−.0013172	.0200217	−0.07	0.948	−.0405591	.0379247

TABLE 6: Learning λ and reciprocity ρ as estimated in the GEE estimation of equation (2)

was only characterised by reciprocity then higher payoffs for C and D would both indicate the presence of cooperative neighbours. We should then expect $0 < \beta^{c,i} = \beta^{d,i}$.

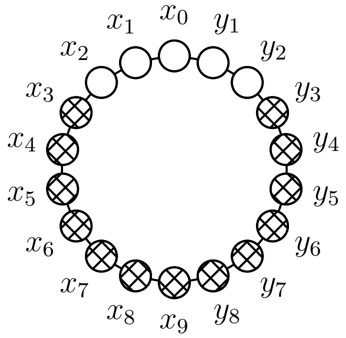
To disentangle these two effects we study two measures. As a measure for learning we take $\lambda^i := \beta^{c,i} - \beta^{d,i}$. This expression should be positive for a player who only learns and should be zero for a player who only reciprocates. Similarly we take as a measure for reciprocity $\rho^i := \beta^{c,i} + \beta^{d,i}$. This expression should be zero for a player who only learns and should be positive for a player who only reciprocates. Characteristics of these expressions are shown in table 6. Jointly testing $\lambda^i = \rho^i$ for $i \in \{\text{own}, \text{other}\}$ we find that in this treatment learning is significantly stronger than the reciprocity (in circles $\chi^2(2) = 75.60$, $P_{>\chi^2} = 0.0000$, in groups $\chi^2(2) = 35.51$, $P_{>\chi^2} = 0.0000$).

Following hypothesis 4 we should expect that players learn relatively less from their neighbours in a spatial structure and relatively more in a spaceless structure. Our data confirms this hypothesis. In circles we find $\lambda^{\text{own}} > \lambda^{\text{other}}$ ($\chi^2(2) = 8.60$, $P_{>\chi^2} = 0.0034$) while in groups $\lambda^{\text{own}} < \lambda^{\text{other}}$ ($\chi^2(2) = 10.86$, $P_{>\chi^2} = 0.0010$).

To summarise this section, we can reject hypothesis 1 and 2. Neither do players learn equally from their own and from their neighbours' experience nor treat their C and D experiences equally. We also do not find support for hypothesis 3, i.e. we do not find more cooperation in circles. Supported by our data are, however, hypotheses 4 and 5. Players put relatively more weight on their own experience the more spatial a structure becomes. As a result the mechanism that would otherwise support growth of cooperation in a spatial structure ceases to work.

4.2 Cooperation in seeded circles

In section 2 we explained how imitation of successful neighbours supports cooperation in a spatial environment. This argument relies on the assumption of an initial cluster of cooperators of sufficient size — with our payoffs we need at least five neighbouring cooperators. But how does such a cluster appear? An evolutionary game theorist might argue that we only have to wait long enough until such a cluster appears with a mutation.



The five white dots indicate the position of computerised players that always play C. The remaining dots indicate the position of the human players.

FIGURE 4: The structure of seeded circles

Sessions in our experiment, however, last only for a limited number of periods, and if the cooperative cluster does not appear during this time cooperation might never get started.

To give cooperation in circles the best possible conditions we therefore seeded a circle with a cluster of five computerised players. In figure 4 players x_2, x_1, x_0, y_1, y_2 (the 'seeds') are played by the computer and cooperate in every period.[13] The remaining players are human which obtain the same information as in the above treatment (section 3). Players x_3, x_4, y_3, y_4 do not know that their neighbours are computers. The detailed behaviour of the human players is shown in appendix B.3.

4.2.1 Stage game behaviour in seeded circles

Figure 5 shows the frequency of cooperation depending on the distance to the seeding cooperative cluster. Players with a smaller distance to the seeding cluster cooperate significantly more, (A Cuzick-Altman test finds $z = 2.55$, $P_{>|z|} = 0.01$). The four players which are closest to the seed and who obtain information about the seeding cluster (x_3, x_4, y_3, y_4 in figure 4) cooperate more frequently (a t-test finds $t = -2.68$, $P_{>|t|} = 0.044$, a one sample Wilcoxon signed-rank test finds $z = 2.201$, $P_{>|z|} = 0.0277$). The average frequency of cooperation in the whole seeded circle is slightly, but not significantly, higher then in the unseeded circle (a t-test finds $t = 1.06$, $P_{>|t|} = 0.303$, a two-sample Wilcoxon rank-sum test finds $z = 0.702$, $P_{>|z|} = 0.4829$). If we drop players x_3, x_4, y_3, y_4 the average frequency of cooperation in seeded circles is even slightly (but not significantly) lower than in unseeded circles.

Figure 6 shows the development of cooperation in this treatment. The dotted line shows, as a reference, the relative frequency of cooperative players in groups. The other lines show the development in circles. For the seeded circle we show two lines. The upper one shows all participants, including those that have immediate neighbours in the seeding

[13]Participants were told that they would play a game with 18 players sitting round a circle. They could see that only 13 players were present in the laboratory but in our experiment no participant missed the other five.

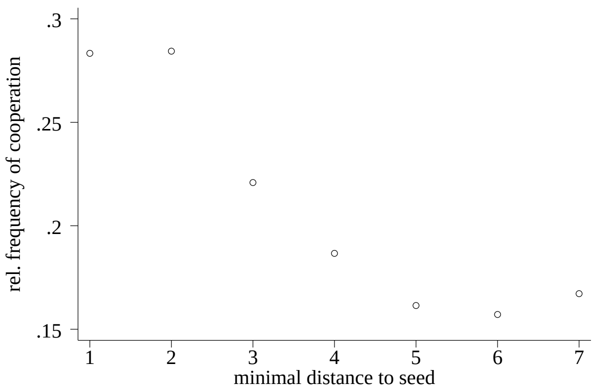
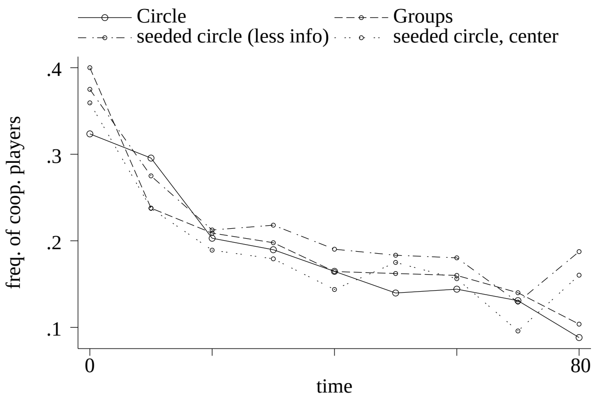


Figure 5: Cooperation in seeded circles depending on the distance to the seeding cluster



The line "seeded circle (less info)" shows the relative frequency of all human players, the line "seeded circle, center" excludes players x_3, x_4, y_3, y_4.

Figure 6: Cooperation in seeded circles

coeff. from eq. (2)	Learning in seeded circles					
	β	σ	z	$P_{>\|z\|}$	95% conf. interval	
β_c	−.2013955	.0923885	−2.18	0.029	−.3824737	−.0203173
β^{own}	.1071798	.0089123	12.03	0.000	.0897119	.1246476
β^{other}	.0679119	.0080964	8.39	0.000	.0520432	.0837806
β_0	−.7267049	.0546413	−13.30	0.000	−.8337999	−.6196098

TABLE 7: GEE population-averaged estimation of equation (1) for seeded circles

coeff. from eq. (2)	Learning from C and D in seeded circles					
	β	σ	z	$P_{>\|z\|}$	95% conf. interval	
β_c	−.6312252	.128256	−4.92	0.000	−.8826023	−.379848
$\beta^{c,\text{own}}$	.1071357	.0111059	9.65	0.000	.0853685	.1289029
$\beta^{d,\text{own}}$	−.1061983	.0124075	−8.56	0.000	−.1305165	−.0818801
$\beta^{c,\text{other}}$	.0844496	.0114302	7.39	0.000	.0620468	.1068523
$\beta^{d,\text{other}}$	−.0336295	.0134328	−2.50	0.012	−.0599573	−.0073016
β_0	−1.074731	.1057231	−10.17	0.000	−1.281945	−.8675178

TABLE 8: GEE population-averaged estimation of equation (2) for seeded circles

cluster. The latter cooperate more than those who are farther away from the cluster of cooperators. When we exclude them, we obtain the lower line. If we compare the average frequency of cooperation in seeded circles with the one in unseeded groups we find no significant difference (a t-test finds $t = 0.68$, $P_{>|t|} = 0.507$, a two-sample Wilcoxon rank-sum test finds $z = 0.589$, $P_{>|z|} = 0.5557$).

To summarise: even when we give players in circles the best possible starting conditions we do not find support for hypothesis 3 — players still do not cooperate more in circles than in groups.

4.2.2 Learning in seeded circles

Theoretically we do not see any reason why learning behaviour in the seeded treatment should differ from learning in the unseeded treatment. This is confirmed by our estimations. Tables 7, 8, 9 show GEE estimates for seeded circles similar to tables 4, 5, 6 for unseeded circles. Also in seeded circles we find $\lambda^{\text{own}} > \lambda^{\text{other}}$ ($\chi^2(2) = 11.82$, $P_{>\chi^2} = 0.0006$).

4.3 Learning and reciprocity

The treatments described in sections 4.1 and 4.2 where designed to study learning. Indeed, in the estimations of equation (2) learning was the predominant effect. Still, we have found in the discussion of tables 6 and 9 that reciprocity might be another factor which was small in circles but of more significance in groups. One reason for this difference might be that in groups participants of the experiment understand the prisoners' dilemma nature of the game more easily. Having understood that a game is a prisoners' dilemma allows players to analyse the game strategically and to rely less on imitation or reinforcement.

coeff. from eq. (2)	Learning and reciprocity in seeded circles					
	β	σ	z	$P_{>\|z\|}$	95% conf. interval	
λ^{own}	.213334	.0178997	11.92	0.000	.1782511	.2484168
ρ^{own}	.0009374	.0153027	0.06	0.951	−.0290554	.0309302
λ^{other}	.118079	.0163523	7.22	0.000	.086029	.150129
ρ^{other}	.0508201	.0188356	2.70	0.007	.013903	.0877373

TABLE 9: Learning λ and reciprocity ρ as estimated in the GEE estimation of equation (2) for seeded circles

History						
Round	Your strategy and gains are		your neighbours received			
...	...	...	...	...	...	...
...	C	10	20	15	14	9

The table shows payoff information as seen by player 1 from table 2

TABLE 10: Example of payoff representation in the detailed information treatment

In the current section we want to control this parameter. We study a treatment where players know all payoffs of the game, i.e. they are able to see that they are playing a prisoners' dilemma. Bosch-Domènech and Vriend (2001) show in a Cournot game that the amount of imitation is not affected by the available information. We will see below that in our setup the available information affects the degree of imitation considerably.

We will call the treatment the *treatment with detailed information.* Participants see the payoff matrix on their screen as shown in table 1. To ease comparison with this table we present the information during the course of the session as shown in table 10. Players do not see average payoffs, as in sections 4.1 and 4.2 but payoffs of each individual player. Consider player 1 from table 2 who has two neighbours with action C and two other neighbours with D. Information about payoffs in this round is presented as shown in table 10. Player 1's own payoff is shown as 10, and displayed next to the player's own action C. The player has two neighbours with action C and payoffs 20 and 15 respectively. The two other neighbours choose action D and receive payoffs 14 and 9. Payoffs obtained with either C or D are displayed in different colours in the experiment. The payoffs are shown in the rightmost column and ordered from highest to lowest. Thus, it is not obvious to the player *which* of the player's neighbours has chosen a certain action and received a certain payoff.

4.3.1 Stage game behaviour in the detailed information treatment

In figure 7 we show the relative frequency of cooperation in the detailed information treatment as a solid line for circles and as a dotted line for groups. For comparison the figure also shows results for the less information treatment with dashed lines.

With detailed information we find more cooperation than without detailed information

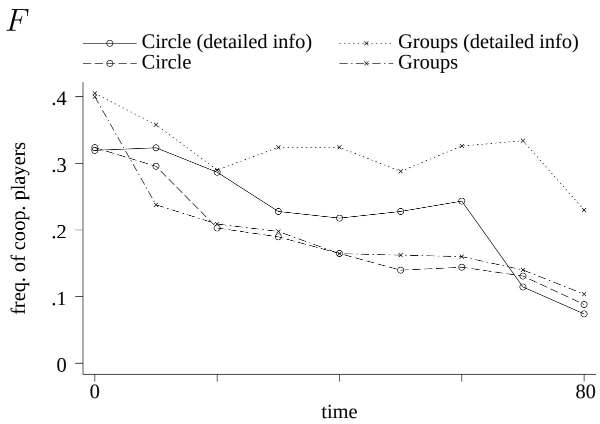


FIGURE 7: Frequency of cooperative players over time in the detailed information and in the less information treatment

in circles and also in groups.[14] However, the increase in the frequency of cooperation is not the same in the two structures. While without detailed information in section 4.1.1 we did not find a significant difference between circles and groups we find with detailed information more cooperation in groups than in circles[15], i.e. an even stronger contradiction of hypothesis 3 than what we found above. We will discuss a possible explanation in the next paragraph.

4.3.2 Learning in the detailed information treatment

Similar to the estimations in sections 4.1.2 and 4.2.2 we estimate again equations (1) and (2). Results are shown in tables 11, 12, and 13. We will concentrate on learning and reciprocity as shown in table 13. Players still learn more from their own experience in circles (testing $\lambda^{\text{own}} > \lambda^{\text{other}}$ yields a $\chi^2 = 18.45$, $P_{>\chi^2} = 0.0000$) and now even in groups ($\chi^2 = 27.80$, $P_{>\chi^2} = 0.0000$ in groups).[16]

Above, in the treatment without detailed information, most reciprocity terms ρ where not significantly different from zero. Now, in the treatment with detailed information, they are. We also see that learning plays a larger role in circles than in groups while reciprocity plays a larger role in groups. Since reciprocity helps achieving cooperation we should not be surprised if players cooperate more in groups than in circles. Similarly, since learning does not play a large role in this treatment, hypothesis 3, which is based

[14]For circles we find in a t-test $t = 2.95$, $P_{>|t|} = 0.018$, in two-sample Wilcoxon rank-sum test we find $z = -1.960$, $P_{>|z|} = 0.0500$. For groups we find in a t-test $t = 3.65$, $P_{>|t|} = 0.002$, in two-sample Wilcoxon rank-sum test we find $z = -2.694$, $P_{>|z|} = 0.0071$.

[15]In a t-test we find $t = 2.89$, $P_{>t} = 0.006$, in two-sample Wilcoxon rank-sum test we find $z = 1.715$, $P_{>z} = 0.0432$.

[16]The negative estimation for λ_{other} in groups is difficult to interpret. Technically this results from a large value of $\beta^{d,\text{other}}$, i.e. players cooperate more when average payoffs of Ds are large. Stronger reciprocity might be a reason, which should, a priori, affect $\beta^{c,\text{other}}$ in the same way. However, since there are more Ds than Cs in a neighbourhood, Ds average payoffs might be considered more reliable information and, therefore, $\beta^{d,\text{other}}$ might be larger.

coeff. from eq. (2)	Learning own and others' payoff in circles					
	β	σ	z	$P_{>\|z\|}$	95% conf. interval	
β_c	3.019047	.0658539	45.84	0.000	2.889976	3.148119
β^{own}	.0497975	.0061767	8.06	0.000	.0376913	.0619036
β^{other}	.0139596	.0079059	1.77	0.077	−.0015357	.0294549
β_0	−1.888248	.0564207	−33.47	0.000	−1.99883	−1.777665
coeff. from eq. (2)	Learning from own and others' payoff in groups					
	β	σ	z	$P_{>\|z\|}$	95% conf. interval	
β_c	2.560402	.0862198	29.70	0.000	2.391414	2.72939
β^{own}	.0294385	.0065031	4.53	0.000	.0166926	.0421844
β^{other}	−.0839884	.015045	−5.58	0.000	−.113476	−.0545007
β_0	−2.239785	.1129711	−19.83	0.000	−2.461205	−2.018366

TABLE 11: GEE population-averaged estimation of equation (1) when detailed information is given

coeff. from eq. (2)	Learning from C and D in circles with detailed information					
	β	σ	z	$P_{>\|z\|}$	95% conf. interval	
β_c	2.558246	.0968281	26.42	0.000	2.368467	2.748026
$\beta^{c,\text{own}}$	.0854751	.0079583	10.74	0.000	.0698772	.1010731
$\beta^{d,\text{own}}$	−.0135855	.0085466	−1.59	0.112	−.0303365	.0031655
$\beta^{c,\text{other}}$	.0158278	.0090937	1.74	0.082	−.0019956	.0336512
$\beta^{d,\text{other}}$	.0125569	.0130059	0.97	0.334	−.0129342	.0380479
β_0	−2.465581	.0916312	−26.91	0.000	−2.645175	−2.285987
coeff. from eq. (2)	Learning from C and D in groups with detailed information					
	β	σ	z	$P_{>\|z\|}$	95% conf. interval	
β_c	1.662233	.1150202	14.45	0.000	1.436797	1.887668
$\beta^{c,\text{own}}$	.009631	.0094656	1.02	0.309	−.0089213	.0281833
$\beta^{d,\text{own}}$	−.061498	.0111853	−5.50	0.000	−.0834207	−.0395752
$\beta^{c,\text{other}}$	−.0039144	.0175425	−0.22	0.823	−.038297	.0304682
$\beta^{d,\text{other}}$	.1197077	.0173654	6.89	0.000	.0856721	.1537434
β_0	−2.278528	.1198936	−19.00	0.000	−2.513516	−2.043541

TABLE 12: GEE population-averaged estimation of equation (2) with detailed information

coeff. from eq. (2)	Learning and reciprocity in circles with detailed information					
	β	σ	z	$P_{>\|z\|}$	95% conf. interval	
λ^{own}	.0990606	.0123706	8.01	0.000	.0748148	.1233065
ρ^{own}	.0718897	.0109419	6.57	0.000	.0504439	.0933355
λ^{other}	.003271	.0168562	0.19	0.846	−.0297666	.0363085
ρ^{other}	.0283847	.0148177	1.92	0.055	−.0006576	.0574269
coeff. from eq. (2)	Learning and reciprocity in groups with detailed information					
	β	σ	z	$P_{>\|z\|}$	95% conf. interval	
λ^{own}	.071129	.013689	5.20	0.000	.044299	.0979589
ρ^{own}	−.051867	.0155572	−3.33	0.001	−.0823585	−.0213754
λ^{other}	−.1236221	.0312888	−3.95	0.000	−.184947	−.0622973
ρ^{other}	.1157934	.0154792	7.48	0.000	.0854546	.1461321

TABLE 13: Learning λ and reciprocity ρ as estimated in the GEE estimation of equation (2) with detailed information

on learning, does not hold in this context.

4.4 Learning how to learn

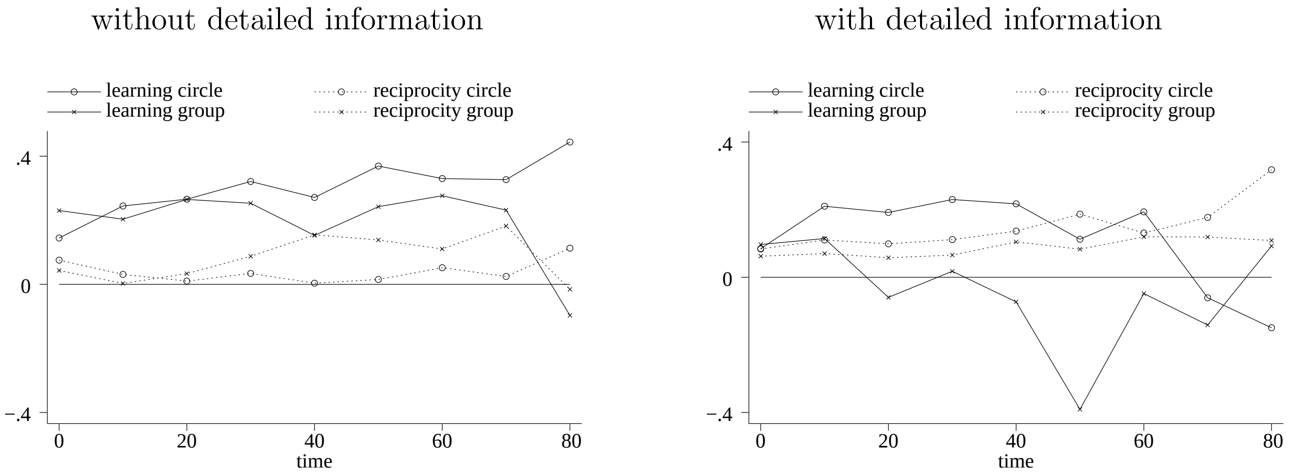
In the discussion in the previous sections we always assumed that learning and reciprocity were constant over time. A more detailed analysis shows that, indeed, they are. In figure 8 we show results of estimating the GEE population-averaged model of equation (2) for subsets of length 10 of all experiments without detailed information. To simplify the figure we show $\sum_{i\in\{\text{own,other}\}} \lambda^i$ as an indicator for learning and $\sum_{i\in\{\text{own,other}\}} \rho^i$. All major results that we found above seem to hold during the whole experiment. Trends, if they can be found at all, are weak and not significant.

5 Conclusion

In this paper we have tried to find out whether players imitate, i.e. learn from the experience of other players. The answer is — yes, players do imitate sometimes. However, two other factors, learning from own experience and reciprocity, also influence players' behaviour considerably. We studied two parameters that influence the relative strength of imitation: Homogeneity of players' environment and presentation of information.

When players are in a homogeneous environment (as they are in our group treatment) then imitation plays a relatively larger role as compared to a heterogeneous environment (as in our circle treatment). This is interesting for the literature that builds upon imitation in local interaction models to explain cooperation. This literature explains very elegantly how local interaction supports cooperation in an evolutionary model. The argument, however, depends substantially on imitation. If, as we find in our experiments, players imitate less in situations with local interaction, the overall effect becomes ambiguous — in our experiments sometimes even negative.

Also the available information affects the amount of imitation in an intuitive way. The



The figure show $\sum_{i\in\{\text{own,other}\}} \lambda^i$ as a measure for learning and $\sum_{i\in\{\text{own,other}\}} \rho^i$ as a measure for reciprocity.

FIGURE 8: Learning and reciprocity over time

more information is available the less players rely on imitation. Given that in other games information is not affected by information (Bosch-Domènech and Vriend 2001) complexity of the game might be a moderating factor. In the fairly complex game of Bosch and Vriend players might disregard information altogether, always relying on imitation. In simpler games, like the prisoners' dilemma, information, if available, may be helpful and displaces imitation.

There are other questions that we had to leave aside. The development of learning over time (see figure 8) should be further explored. Also, disentangling of the parameters of our regression into learning and reciprocity effects was helpful in the analysis but lead to sometimes unexpected coefficients. Given the sheer number of coefficients that we estimate this may be hardly surprising, still, we feel that more effects than learning through reinforcement, imitation and reciprocity might be at work here.

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A List of Sessions

Overview:

Number of sessions in different treatments			
	information...		
	detailed	less	
			5 computerised cooperators
group	9	10	
circle	5	5	6

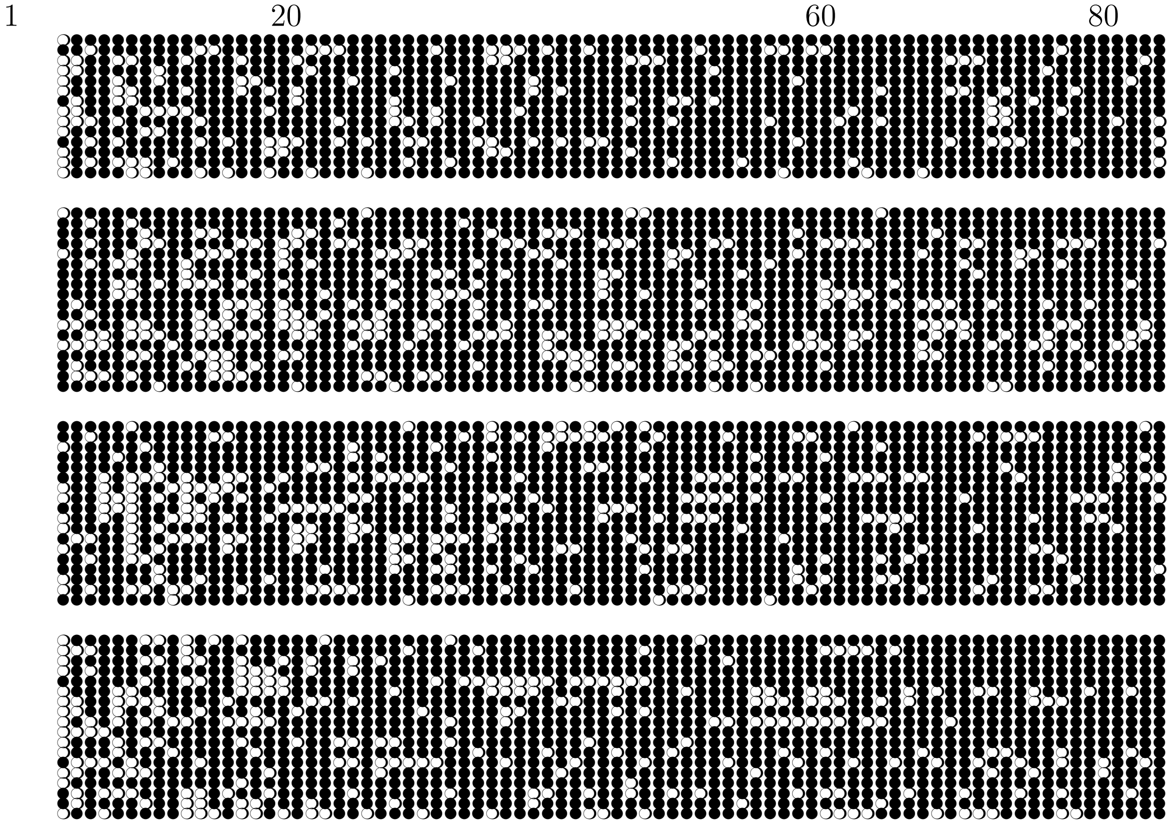
Parameters of each session:

	structure	information	computerised cooperators	number of players
1.	Group	less info	0	5
2.	Group	less info	0	5
3.	Group	less info	0	5
4.	Group	less info	0	5
5.	Group	less info	0	5
6.	Group	less info	0	5
7.	Group	less info	0	5
8.	Group	less info	0	5
9.	Group	less info	0	5
10.	Group	detailed info	0	5
11.	Group	detailed info	0	5
12.	Group	detailed info	0	5
13.	Group	detailed info	0	5
14.	Group	detailed info	0	5
15.	Group	detailed info	0	5
16.	Group	detailed info	0	5
17.	Group	detailed info	0	5
18.	Group	detailed info	0	5
19.	Group	detailed info	0	5
20.	Circle	less info	0	14
21.	Circle	less info	0	18
22.	Circle	less info	0	18
23.	Circle	less info	0	18
24.	Circle	less info	5	13
25.	Circle	less info	5	10
26.	Circle	less info	5	13
27.	Circle	less info	5	10
28.	Circle	less info	5	13
29.	Circle	less info	5	13
30.	Circle	detailed info	0	18
31.	Circle	detailed info	0	18
32.	Circle	detailed info	0	18
33.	Circle	detailed info	0	18
34.	Circle	detailed info	0	18

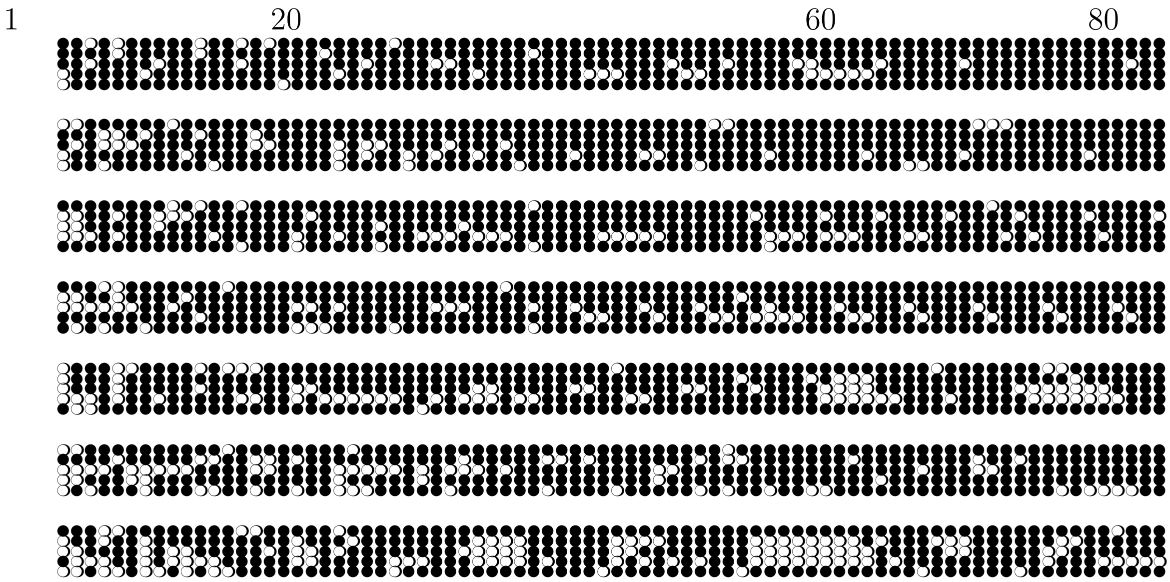
B Raw data

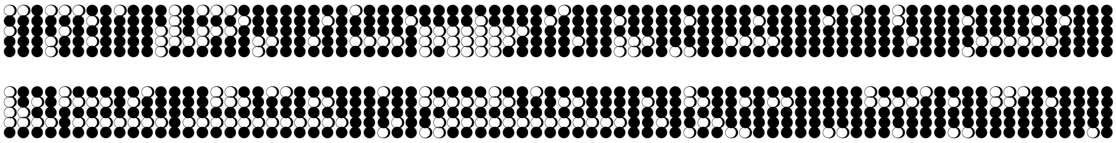
In the following graphs each line represents the actions of a player from period 1 to period 80. Cooperation is shown as ❍, non cooperation as ●. Neighbouring lines correspond to neighbouring players in the experiment. In all treatments without computerised cooperators (sections B.4 to B.2) the last line of each block of lines is in circles always a neighbour of the first line of the same block. In these sections the display of circles is always rotated such that least cooperative players are found in the first and the last lines.

B.1 Circle treatment



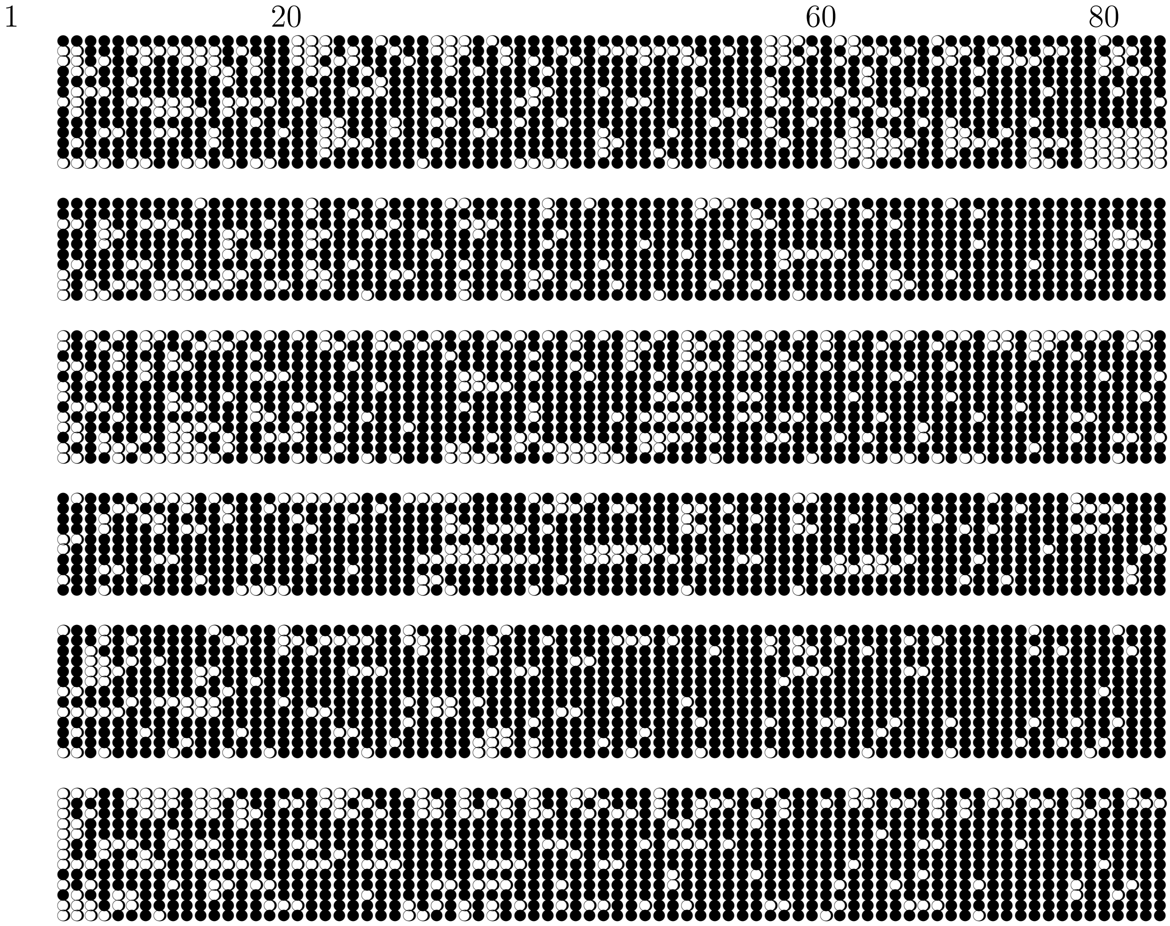
B.2 Group treatment



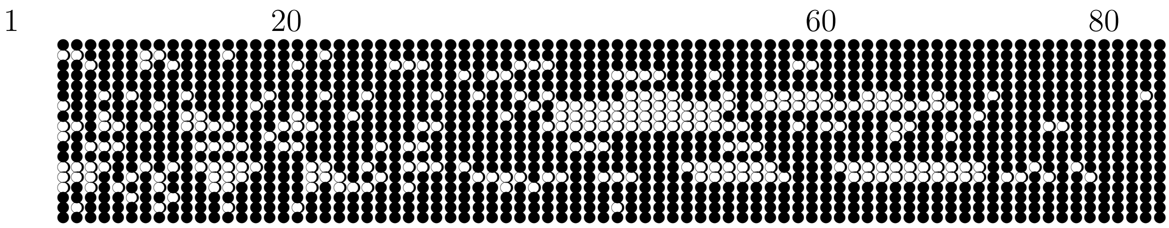


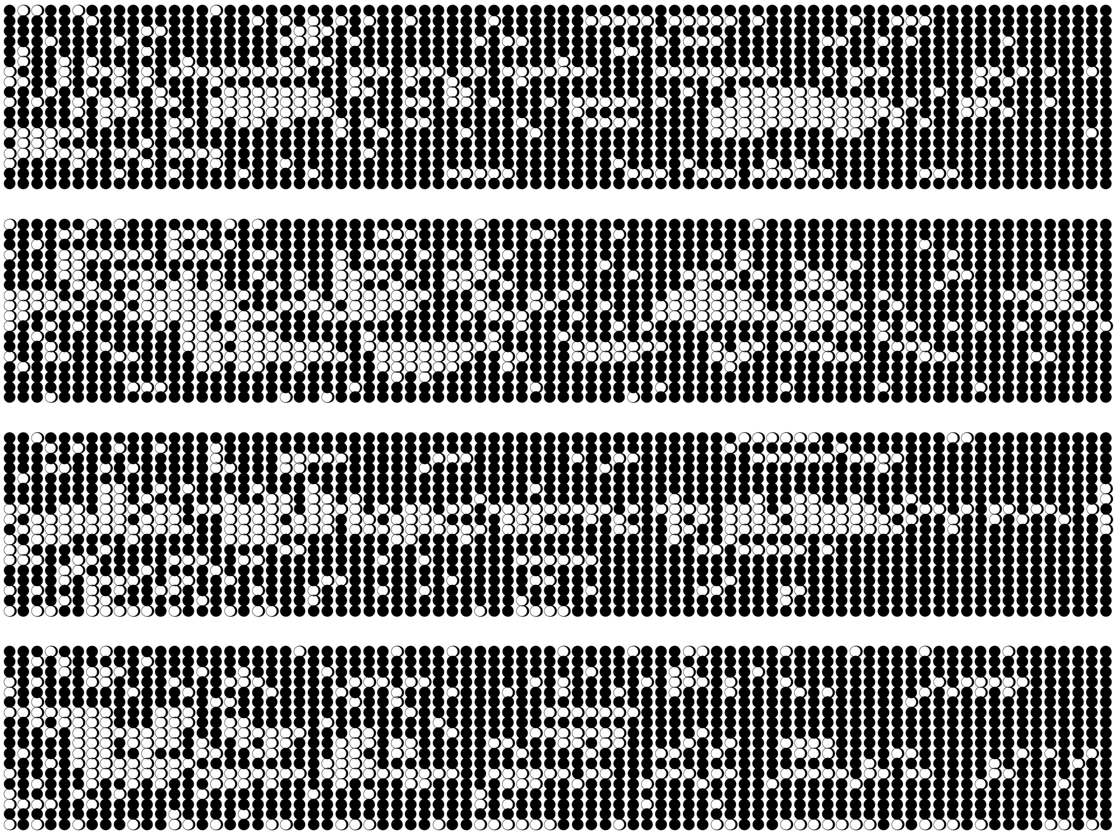
B.3 Seeded circle with less information

In the display of the circles the five computerised cooperators are not displayed. Their location is on top of the first line and below the last line of each block. The two top lines and the two bottom lines of each block are, hence, immediate neighbours of computerised cooperators.

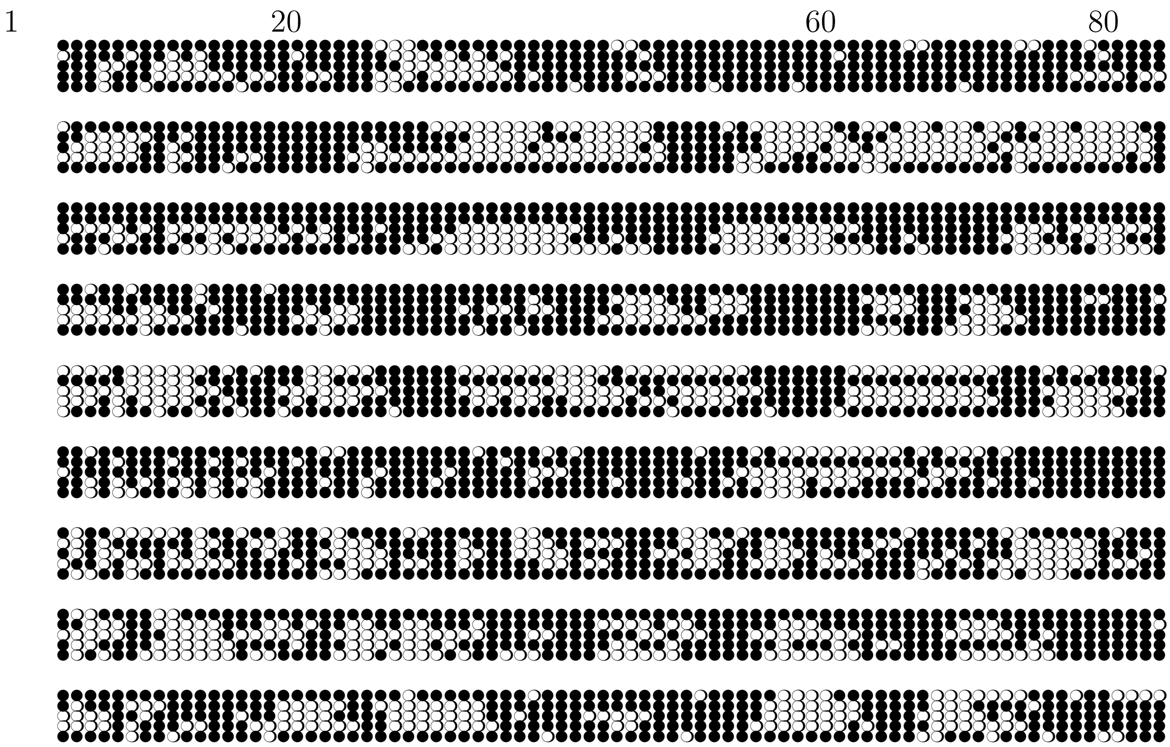


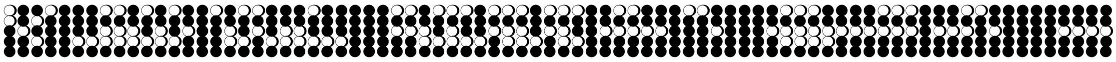
B.4 Circle treatment with detailed information





B.5 Group treatment with detailed information





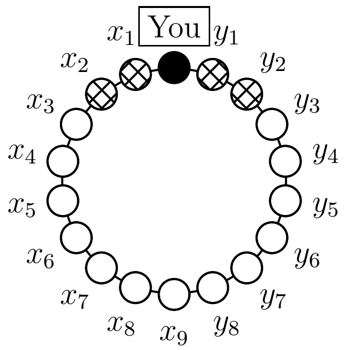
C Instructions of the Experiment

Please sit down and read the following instructions. It is important that you read them attentively. A good understanding of the game is a prerequisite of your success.

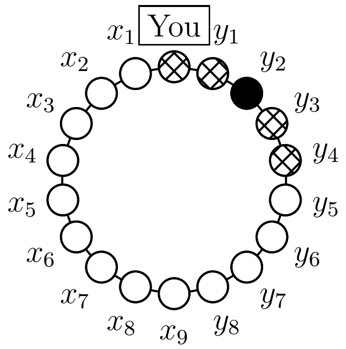
After having read the instructions you will continue with a little quiz on the computer screen. There you will be asked questions that will be easy to answer once you have read the instructions.

You may take notes but you may not talk to each other.

C.1 The structure of the neighbourhood



Your gain depends on your decision and on the decision of your two neighbours to the left and your two neighbours to the right. These four neighbours remain the same during the course of the experiment. You are connected through the computer with these neighbours. We will not tell who these neighbours are. Similarly your neighbours will not be told who you are.
In the diagram on the right side your four neighbours are shown cross-hatched.



Also your neighbours have neighbours. E.g. the neighbours of y_2 are players y_4, y_3, y_1 and you.

C.2 Rounds

In this experiment you play several rounds. In each round you take a decision. Depending on your decision and on the decision of your neighbours you receive points that will be converted to € at the end of the experiment.

C.3 Decision

In each round you choose among two decisions. You choose A or B. Your gain depends on what you have chosen and on how many of your neighbours have chosen A or B.

This relation between choices and gains is the same for all participants.

It will be shown on the screen in the form of a table.

	Your neighbours play...
You play A You play B	...Your gain ...

All players choose simultaneously, without knowing the decision of the others.

When all players have made their decision we continue with the next round.

C.4 Information after each round

In each round your receive information about your gain. Additionally you receive information about the decision of your neighbours and their gain.

Round	Your Decision	Your Gain	Decisions and gain in your neigbourhood, ordered by gain
...	...	...	...

In each row you obtain information about one round. You find your decision and your gain the second and the third column.

On the right side we show for each of your neighbours the decision of the neighbour and the obtained gain. The ordering of neighbours in this column depends on the gain in this period. First comes the neighbour with the highest gain, then the one whose gain was second, etc.. This implies that in each period a different person can be the first in the right column.

C.5 Quiz

Please answer now the questions from the quiz on the computer screen. If you are unsure how to answer a question, please consult your instructions.

Nr.	Author	Title
03-04	Oliver Kirchkamp Rosemarie Nagel	No imitation - on local and group interaction, learning and reciprocity in prisonersd́ilemma experiments
03-03	Michele Bernasconi Oliver Kirchkamp Paolo Paruolo	Expectations and perceived causality in fiscal policy: an experimental analysis using real world data
03-02	Peter Albrecht	Risk Based Capital Allocation
03-01	Peter Albrecht	Risk Measures
02-51	Peter Albrecht Ivica Dus Raimond Maurer Ulla Ruckpaul	Cost Average-Effekt: Fakt oder Mythos?
02-50	Thomas Langer Niels Nauhauser	Zur Bedeutung von Cost-Average-Effekten bei Einzahlungsplänen und Portefeuilleumschichtungen
02-49	Alexander Klos Thomas Langer Martin Weber	Über kurz oder lang - Welche Rolle spielt der Anlagehorizont bei Investitionsentscheidungen?
02-48	Isabel Schnabel	The German Twin Crisis of 1931
02-47	Axel Börsch-Supan Annamaria Lusardi	Saving Viewed from a Cross-National Perspective
02-46	Isabel Schnabel Hyun Song Shin	Foreshadowing LTCM: The Crisis of 1763
02-45	Ulrich Koch	Inkrementaler Wandel und adaptive Dynamik in Regelsystemen
02-44	Alexander Klos	Die Risikoprämie am deutschen Kapitalmarkt
02-43	Markus Glaser Martin Weber	Momentum and Turnover: Evidence from the German Stock Market
02-42	Mohammed Abdellaoui Frank Voßmann Martin Weber	An Experimental Analysis of Decision Weights in Cumulative Prospect Theory under Uncertainty

Nr.	Author	Title
02-41	Carlo Kraemer Martin Weber	To buy or not to buy: Why do people buy too much information?
02-40	Nikolaus Beck	Kumulation und Verweildauerabhängigkeit von Regeländerungen
02-39	Eric Igou	The Role of Lay Theories of Affect Progressions in Affective Forecasting
02-38	Eric Igou Herbert Bless	My future emotions versus your future emotions: The self-other effect in affective forecasting
02-37	Stefan Schwarz Dagmar Stahlberg Sabine Sczesny	Denying the foreseeability of an event as a means of self-protection. The impact of self-threatening outcome information on the strength of the hindsight bias
02-36	Susanne Abele Herbert Bless Karl-Martin Ehrhart	Social Information Processing in Strategic Decision Making: Why Timing Matters
02-35	Joachim Winter	Bracketing effects in categorized survey questions and the measurement of economic quantities
02-34	Joachim Winter	Design effects in survey-based measures of household consumption
02-33	Stefan Schwarz Dagmar Stahlberg	Motivational influences on the strength of the hindsight bias
02-32	Stefan Schwarz Dagmar Stahlberg	Strength of hindsight bias as a consequence of meta-cognitions
02-31	Roman Grunwald	Inter-Organisationales Lernen und die Integration spezialisierten Wissens in Kooperationen - Eine empirische Untersuchung anhand von kooperativen Entwicklungsprojekten
02-30	Martin Hellwig	The Relation Between Real Wage Rates and Employment: An Intertemporal General-Equilibrium Analysis

Nr.	Author	Title
02-29	Moshe Ben-Akiva Daniel McFadden Kenneth Train Axel Börsch-Supan	Hybrid Choice Models: Progress and Challenges
02-28	Angelika Eymann Axel Börsch-Supan Rob Euwals	Risk Attitude, Impatience, and Asset Choice
02-27	Axel Börsch-Supan Alexander Ludwig Joachim Winter	Aging and International Capital Flows
02-26	Rüdiger F. Pohl Stefan Schwarz Sabine Sczesny Dagmar Stahlberg	Gustatory hindsight bias
02-25	Axel Börsch-Supan	What We Know and What We Do NOT Know About the Willingness to Provide Self-Financed Old-Age Insurance
02-24	Florian Heiss	Specification(s) of Nested Logit Models
02-23	Axel Börsch-Supan	Kann die Finanz- und Sozialpolitik die Auswirkungen der Bevölkerungsalterung auf den Arbeitsmarkt lindern?
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02-21	Axel Börsch-Supan Florian Heiss Miki Seko	Housing Demand in Germany and Japan - Paper in memoriam of Stephen Mayo
02-20	Siegfried K. Berninghaus Karl-Martin Ehrhart	The power of ESS: An experimental study
02-19	Douglas Gale Martin Hellwig	Competitive Insurance Markets with Asymmetric Information: A Cournot-Arrow-Debreu Approach*

Nr.	Author	Title
02-18	Michele Bernasconi Oliver Kirchkamp	The Expectations view on fiscal policy - An experiment using real world data
02-17	Oliver Kirchkamp Rosemarie Nagel	Reinforcement, repeated games, and local interaction
02-16	Volker Stocké	Die Vorhersage von Fragenreihenfolgeeffekten durch Antwortlatenzen: Eine Validierungsstudie
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02-11	Christian Ewerhart Karsten Fieseler	Procurement Auctions and Unit-Price Contracts
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02-01	Geschäftsstelle	Jahresbericht 2001
02-09	Volker Stocké	Soziale Erwünschtheit bei der Erfassung von Einstellungen gegenüber Ausländern. Theoretische Prognosen und deren empirische Überprüfung
02-08	Benny Moldovanu Moritz Meyer-ter-Vehn	Ex-post Implementation with Interdependent Valuations
02-07	Benny Moldovanu Christian Ewerhart	A Stylized Model of the German UMTS Auction
02-06	Benny Moldovanu Aner Sela	Contest Architecture