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Learning in network games

Jaromír Kovářík
Departamento Fundamentos Análisis Económico I, University of the Basque Country and CERGE–EI

Friederike Mengel
Department of Economics, University of Essex

José Gabriel Romero
Departamento de Economia, Universidad de Santiago de Chile

We report the findings of experiments designed to study how people learn in network games. Network games offer new opportunities to identify learning rules, since on networks (compared to, e.g., random matching) more rules differ in terms of their information requirements. Our experimental design enables us to observe *both* which actions participants choose and which information they consult before making their choices. We use these data to estimate learning types using finite mixture models. Monitoring information requests turns out to be crucial, as estimates based on choices alone show substantial biases. We also find that learning depends on network position. Participants in more complex environments (with more network neighbors) tend to resort to simpler rules compared to those with only one network neighbor.

Keywords. Experiments, game theory, heterogeneity, learning, finite mixture models, networks.

JEL classification. C72, C90, C91, D85.

1. Introduction

In many situations of economic interest people arrive at their decisions via a process of learning. As examples, consider decisions such as how to conduct business negoti-

Jaromír Kovářík: jaromir.kovarik@ehu.es
Friederike Mengel: fr.mengel@gmail.com
José Gabriel Romero: gabriel.romero@usach.cl

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ations, which projects to dedicate effort to, and in which assets to invest our money. Economists have developed a number of different models to describe how people learn in such situations (Fudenberg and Levine (1998)). These models, however, often lead to very different predictions. In a Cournot duopoly, for example, imitation learning can lead to the Walrasian outcome (Vega Redondo (1997)), while most belief learning models converge to the Cournot–Nash outcome. In the prisoner's dilemma, some forms of aspiration-based learning can lead to cooperation (Karandikar, Mookherjee, Ray, and Vega-Redondo (1998)), while imitation and belief learning models typically lead to defection. Hence to make predictions in these situations, it seems crucial to have some understanding about how people learn.

In this paper, we conduct an experiment designed to study how people learn in games. In the experiment participants play a network game over multiple rounds. We keep track of which information participants request between rounds. We then combine our knowledge of information requests with observed action choices to estimate a distribution of learning types using mixture models. The advantage of observing both action choices and information requests is that even if different learning rules predict the same action choices, they can be distinguished as long as different information is needed to make this choice.

Network games offer new opportunities to identify different learning rules. In networks (compared to random matching or fixed pairwise matching protocols) it is more often possible to distinguish learning models via information requests. As an example, consider myopic best-response and forward-looking learning. Under random matching an agent needs to know the distribution of play in the previous period irrespective of whether she is myopic or forward-looking. In a network, though, a myopic best responder needs to know *only* the past behavior of her first-order neighbors (with whom she interacts), while a forward-looking learner may need to know the behavior of her second-order neighbors to be able to predict what her first-order neighbors will choose in the following period.[1] An additional advantage of using networks is that doing so allows us to systematically change the network topology (moving, e.g., from very homogeneous to heterogeneous situations) and see how this affects the estimated distribution of learning types. We also ask whether an agent's position *within* a network affects the way she learns. Hence our study allows us to address two issues that previous studies have found difficult to address: identifying learning rules based on information requests and studying how stable learning is across differently structured social interactions.

In our main treatments, participants interacted in a 4×4 anti-coordination game. Anti-coordination appears in many important economic situations such as congestion, pollution, oligopolistic (quantity) competition, immunization, provision of public goods, and whenever there are gains from differentiation. Compared to pure coordination games, anti-coordination games have the advantage that different learning rules predict different choices more often (making identification easier) and, compared to, for example, conflict games, they have the advantage that standard learning models do

[1]Which information she needs exactly will depend on her theory about how her first-order neighbors learn. However, it is clear that a myopic best-response learner does *not* need information beyond her first-order neighborhood.

not lead to limit cycles. Since Nash equilibria are attractors of many of the learning rules we will consider, these rules can only be distinguished using out-of-equilibrium choices. With 4×4 games we hoped that, even if there is convergence to Nash equilibrium, such convergence would not be immediate. Slow enough convergence is necessary to identify learning rules using out-of-equilibrium choices (Knoepfle, Wang, and Camerer (2009)).

Our analysis considers different learning types, where a subject's type first determines her information requests, possibly with error, and her type and information requests jointly determine her decision, again possibly with error. Learning types are drawn from a common prior distribution that we estimate using mixture models. We consider learning models from three prominent classes as possible descriptions of participants' behavior: reinforcement learning, imitation, and belief-based models, in particular myopic best response, different variants of fictitious play, and forward-looking learning. These rules differ widely in their degree of sophistication. While forward-looking agents reason strategically, reinforcement learners do not even need to know that they are playing a game at all.[2]

The experiment consists of nine main treatments. Three treatments have endogenous information requests for three different network topologies. Three intermediate treatments on the same networks have endogenous information requests about actions and payoff, but *not* about the network structure. Those treatments were added to address potential endogeneity concerns with respect to network position in the fully endogenous treatments. We also conducted three treatments with the same networks but *without* information requests. In these full-information treatments, participants were given all the information that can be requested in the other treatments by default. We use these treatments to see whether the existence of information requests per se affects action choices and whether participants in the endogenous information treatments request all the information they would naturally use in making their decisions. We find no significant pairwise differences between the distribution of action choices across these three treatment variations.[3]

We now briefly summarize our main results. First, we find that monitoring information requests is crucial. We compare our main results with simpler estimations based on action choices alone (i.e., ignoring information requests) and detect substantial biases in these estimates. Estimations based solely on observed action choices lead us to accept certain learning rules that participants could not have been using, simply because they did not consult the minimum amount of information necessary to identify the corresponding actions. Since we use a relatively large 4×4 game, which allows us to distinguish learning rules more easily on the basis of choice behavior only, this problem is likely to be more severe in smaller 2×2 games often studied in experiments.

Second, we find that network position affects how people learn. Participants with only one network neighbor resort more often to myopic best-response learning compared to others with more neighbors who tend to resort more often to reinforcement

[2]All learning rules are described in detail in Section 4.

[3]In addition to these nine treatments, we also conducted three treatments using a coordination game and find evidence for the same rules as in the anti-coordination game. We also conducted one treatment where participants play the anti-coordination game bilaterally as a benchmark.

learning. Those results suggest that people adapt the learning heuristics they employ to the complexity of the environment. In particular, people facing more complex environments (such as having more network neighbors) seem to resort to simpler learning rules.

In terms of the specific rules participants use, there is substantial heterogeneity. However, most of our participants' decisions are best described by either reinforcement learning or myopic best responses. There is very little evidence of forward-looking behavior and almost no evidence of imitation. This is true for all the networks we consider.

Since almost all our participants can be described by either reinforcement learning or (myopic) belief-based rules, our results support the assumptions of experience-weighted attraction (EWA) learning (Camerer and Ho (1998, 1999), Camerer, Ho, and Chong (2002)). EWA includes reinforcement and belief learning as special cases as well as some hybrid versions of the two. Unlike in EWA we do not restrict to those models ex ante, but our results suggest that—at least in the context considered—a researcher may not be missing out on too much by focusing on those models. However, while EWA should be a good description of behavior at the aggregate level, at the individual level fewer than 15% of our participants persistently request information consistent with *both* reinforcement learning and belief-based learning rules.

In the following discussion, we relate our paper to the experimental literature on learning and also highlight some methodological differences between the existing literature and our approach. By far the most common method to study learning in experiments has been the representative-agent approach, where one single learning model is estimated to explain the average or median behavior of participants (see, e.g., Erev and Roth (1998), Mookherjee and Sopher (1997), Apesteguia, Huck, and Oechssler (2007), Kirchkamp and Nagel (2007), or Feltovich (2000), among others). While the representative approach is simple and allows for parsimonious rules, one downside of this approach is that if there is heterogeneity in learning types, it is far from clear how robust the insights are to small changes in the distribution of types or whether comparative statics predictions based on the representative agent will be correct (e.g., Kirman (1992)). In addition, Wilcox (2006) has shown that in the presence of heterogeneity, estimating representative-agent models can produce significant biases favoring reinforcement learning relative to belief learning models (see also Cheung and Friedman (1997), Ho, Wang, and Camerer (2008), or Frechette (2009)). Overall, this research has provided mixed evidence on which learning model best describes behavior, and models that have found support in some studies have been rejected in others.[4] Our approach is conceptually different from this literature. Instead of trying to find one rule that describes the average or median behavior of a population, we try to understand the distribution of learning rules.

One way to do so is to estimate learning models individually for each subject (Cheung and Friedman (1997), Ho, Wang, and Camerer (2008)). This approach leads to

[4]Imitation learning has been shown to explain behavior well in, for example, Cournot games. See Apesteguia, Huck, and Oechssler (2007) as well as the literature cited therein. Reinforcement learning has done well in Erev and Roth (1998) and best-response learning has done well in Mookherjee and Sopher (1997). Forward-looking behavior matches experimental data well in Mengel (2014).

consistent estimates if the experiment involves "sufficient" time periods in which participants learn, that is, before the learning process has converged.[5] If both cross-sectional and longitudinal variation is exploited, fewer periods of nonconvergence are needed to avoid small-sample biases. Such studies have been conducted by Camerer and Ho (1998, 1999), who assume that agents can be categorized into two subpopulations with different parameter values, and by Camerer, Ho, and Chong (2002), who estimate a mixture of standard and sophisticated EWA learning in the population. While the latter also estimate mixture models, the class of learning rules they consider is limited to EWA with its component rules reinforcement learning and fictitious play.[6]

There are two main differences between these studies and our research. First we keep track of which information participants request between rounds. This allows us to base our estimations on more than just choice data, making it easier to detect the underlying data-generating process (Salmon (2001)). It also allows us to exploit the identification possibilities arising in network games if information requests are monitored. Second, our design allows for any kind of learning rule or heuristic ex ante, and we restrict attention to certain rules only at the estimation stage. Since most other studies restrict information feedback given to participants, they effectively rule out some types of learning ex ante. If, for example, no information about payoffs of other participants is provided, then payoff-based imitation learning is impossible.

Our paper is methodologically closely related to El-Gamal and Grether (1995), Costa-Gomes, Crawford, and Broseta (2001; CCB, henceforth), and Knoepfle, Wang, and Camerer (2009). CCB also monitor information lookups (using the software MouseLab) to study procedural models of decision-making, where a participant's type reflects his/her degree of sophistication. The main difference from our study is that they do not study learning, but static decision rules instead. Knoepfle, Wang, and Camerer (2009) study learning in different 4×4 normal form games using eye-tracking software. They find that, while eye tracking seems to suggest that participants are quite sophisticated (similar to our forward-looking types), their choices are more consistent with adaptive learning models. One of their conclusions is that, due to the large degree of noise in eye-tracking data, fundamental changes in the observational paradigm could help to differentiate genuine information lookups from noise fixations. Our paper provides a methodological contribution in this regard.

While there is a considerable amount of experimental research aimed at understanding how people learn in games, there is relatively little research on whether the same rules are used in different contexts or whether people adapt the heuristics they use in comparable environments of different complexity. Some studies ask whether learning differs across games. Camerer and Ho (1999), for example, estimate their EWA learning model on different classes of games (unique mixed equilibrium, coordination, and dominance solvable). They find that EWA fits better than the comparison models across

[5]The term "sufficient" can often mean practically infeasible in a typical experiment. Cabrales and García-Fontes (2000, footnote 17) report that the precision of estimates starts to be "reasonable" after observing around 500 periods of play.

[6]Gill and Prowse (2016) estimate mixture models to study how cognitive and emotional skills affect level k learning.

all classes, but there are some differences across games in estimated EWA parameters. Knoepfle, Wang, and Camerer (2009) study learning in different 4×4 normal form games and find largely consistent patterns across games. In this paper, we also find evidence for broad consistency across games in our anti-coordination as well as three additional coordination treatments, in that reinforcement learning and myopic best-reply learning are the most important rules in both games considered. Grimm and Mengel (2012) find that learning is affected by the complexity of the environment (number of games), but they do not compare different learning models. To the best of our knowledge our paper is the first to study how the complexity of social interactions (measured by the number of neighbors in the network) affects learning in a given game.

The paper proceeds as follows. Section 2 describes in detail the experimental design. Section 3 gives an overview of behavior using simple descriptive statistics. Section 4 introduces the learning models and the econometric framework. Section 5 contains the main results. Section 6 presents additional results and robustness checks, and Section 7 concludes. Additional analyses, figures, and tables as well as the experimental instructions can be found in the Supplemental Material, available in a supplementary file on the journal website, http://qeconomics.org/supp/688/supplement.pdf.

2. Experimental design

In this section we describe our design and provide details about the underlying two-player game, the networks, and the information structure.

2.1 *The game*

In most of our treatments, participants repeatedly played the symmetric two-player game depicted in Figure 1. We chose a 4×4 rather than a 2×2 game, because (i) we hoped that this would generate sufficiently slow convergence to equilibrium to be able to analyze learning in a meaningful way and since (ii) a larger game makes it easier to identify a larger number of different learning rules from observing agents' choices only. Hence, by choosing such a game, we hoped to give good chances to estimations based on action choices alone.

Within each session the networks were fixed, which means that each participant played with the same first-order neighbors in all 20 periods. Each player had to choose the *same* action against all her neighbors. If participants were allowed to choose different actions for their different neighbors, the network would become irrelevant for choices and many learning rules would become indistinguishable in terms of information requirements.

Payoffs in each period are given by the average payoff obtained in all the (bilateral) games against the neighbors. We chose to pay the average rather than the sum of payoffs to prevent too high inequality in earnings due to different connectivity. The game payoffs are expressed in terms of experimental currency units (ECU), which were converted into euros at the end of the experiment at exchange rate 1 euro to 75 ECU. Our main focus is on an anti-coordination game (see, e.g., Bramoulle (2007)), since, as

	A	B	C	D
A	20, 20	40, 70	10, 60	20, 30
B	70, 40	10, 10	30, 30	10, 30
C	60, 10	30, 30	10, 10	30, 40
D	30, 20	30, 10	40, 30	20, 20

Anti-Coordination Game

FIGURE 1. The bilateral anti-coordination games used in the main treatments with pure strategy Nash equilibria (A, B), (B, A), (C, D), and (D, C).

discussed above, in anti-coordination games different learning rules predict different choices more often compared to coordination games (making identification easier). In Section 6.5, we discuss results of treatments based on a coordination game.

Treatments differed along two dimensions: network topology and information. Throughout the paper we denote network architectures by numbers 1, 2, and 3 (see Figures 2–4) and information levels by capital letters N (eNdogenous), M (inter$M$ediate), and F (Full information). In Section 2.2, we present our three network topologies and in Section 2.3, we explain the information conditions.

2.2 *Network topology*

As we argued in the Introduction, network games allow us to identify learning rules more easily compared to, for example, random matching and fixed pairwise matching protocols. Additional advantages of using networks (compared to pairwise matching protocols) include the fact that participants cannot trade off different pieces of information as easily. For instance, knowing one's own action and the action of the opponent fully reveals the latter's payoff and vice versa in pairwise matching, but generally not in a network. There are also independent reasons to study learning in networks, as arguably, most real-life interactions take place via social networks, see, e.g., Jackson (2011). In our design we systematically manipulate the network topology.

To select network topologies we focus on one particular property of networks, namely the variance in degree. In networks with a low variance of the degree distribution, players tend to have a similar amount of neighbors, while in networks with a high variance in degree there will be some players who have many network neighbors and others who have few. We are interested in whether and how learning differs across these two types of players (few and many neighbors) and networks (low and high variance). The most symmetric situation we study is the circle network with zero variance in the degree distribution. Starting from the circle, we then increase the variance in degree (keeping some other network characteristics constant; see Table 1), thereby creating more asymmetric situations. Figures 2–4 show the three network architectures used

Table 1. Network characteristics.

	Network 1	Network 2	Network 3
Number of players	8	8	8
Number of links	8	8	7
Average degree	2	2	1.75
Variance degree	0	8	16.5
Characteristic path length	2.14	2.21	2.21
Clustering coefficient	0	0	0
Average betweenness	0.42	0.40	0.37
Variance betweenness	0	0.21	0.21

in the experiment and Table 1 summarizes the most standard network characteristics of these networks.[7]

We used networks of eight players, because in smaller networks, identification of learning rules is harder. For example, in a circle of three players, the sets of first-order neighbors and second-order neighbors coincide. In a circle of four (or five) players the same is true for the sets of first- (second-) and third-order neighbors, and so forth. To distinguish, for example, myopic best-response learning from forward-looking learning in terms of information requests, these sets of neighbors should not overlap too much as we indicated above and make clearer in Section 4. While many real-life networks will be even larger than eight players, choosing larger networks in our experimental setting is likely to make the environment too complex for many participants. The trade-off between these two forces motivated us to choose networks of eight players.

Network equilibria An equilibrium in a network game (in our experiment of eight players) is obtained when all players choose an action that is a best response to whatever their neighbors choose. In the following discussion, whenever we refer to equilibria we will refer to such network equilibria. Essentially there are two types of equilibria. In some equilibria all neighbors choose best responses. This means that neighbors alternate either between actions A/B or between actions C/D.[8] But there are also network equilibria where agents only choose a best response to all neighbors *on average* but not to each neighbor individually. A table describing all strict Nash equilibria in the three networks can be found in Appendix A. Coordinating a network of eight players on any one of several possible equilibria (between 9 and 12 depending on the network) is possible, but not obvious. We hoped to see mis-coordination in early periods, and learning and convergence to equilibrium afterward. The data show, that indeed, choices converge to a one-

[7]Degree measures the number of first-order neighbors of a node and the clustering coefficient measures the share of a node's first-order neighbors who are neighbors themselves. The characteristic path length is the average length of shortest paths between any two nodes in the network and the betweenness centrality of a node measures the share of shortest paths between any two nodes that pass through the node in question. For formal definitions of these network properties, see the textbook by Vega-Redondo (2007).

[8]For example, in Network 1 (see Figure 2), one network equilibrium is that players $1, \ldots, 8$ choose actions $(a_1, \ldots, a_8) = (A, B, A, B, A, B, A, B)$. All players who choose A in this equilibrium get an average payoff of 40 (because both their neighbors choose B) and all players who choose B get a payoff of 70 (because both their neighbors choose A).

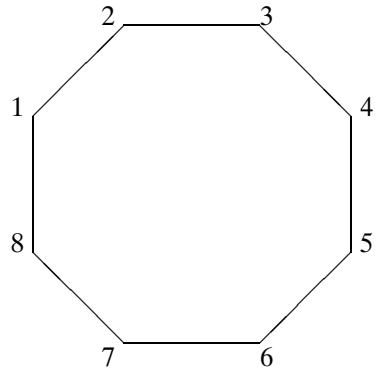


FIGURE 2. Treatments N-1, M-1, and F-1.

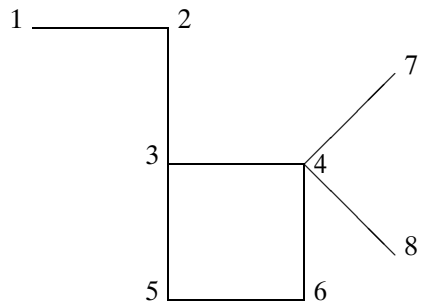


FIGURE 3. Treatments N-2, M-2, and F-2.

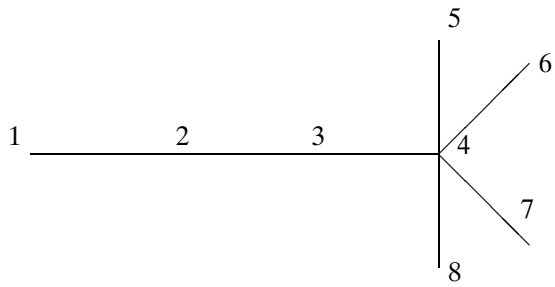


FIGURE 4. Treatments N-3, M-3, and F-3.

shot network equilibrium in several networks (see Section 3). It is important, though, to note that whether or not participants do converge to a Nash equilibrium does not matter for us per se, as long as they do learn. In fact, as highlighted above, observing some out-of-equilibrium choices helps identify learning rules.

2.3 *Information*

Our second treatment dimension varies how information about the network and histories of play is provided. We consider three variations labelled N (endogenous), M (intermediate), and F (full).

N treatments In the *endogenous information* treatments (N-1, N-2, and N-3), we did not give our participants any information either on the network or on histories by default. Instead, at the beginning of each period, participants were asked which information they would like to request. They could request three types of information: (i) the network structure, (ii) past action choices, and (iii) past payoffs. More precisely, if a participant requested the network position of her first-order neighbors, she was shown how many neighbors she has and their experimental label (which is a number between 1 and 8; see Figures 2–4). With second-order neighbors, she was shown their experimental label as well as the links between the first- and second-order neighbors, sand so forth. Regarding actions and payoffs, participants were shown the actions and/or payoffs of their first-, second-, third-, and/or fourth-order neighbors if they requested this information. Participants were also not shown their own payoff by default, but instead had to request it. This design feature allows us to have complete control over which information participants held at any time of the experiment.

We placed two natural restrictions on information requests. First, participants were only allowed to ask for the actions and/or payoffs of neighbors whose experimental label they had previously requested. Second, they were not allowed to request the experimental label of higher-order neighbors without knowing the label of lower-order neighbors. Each piece of information about actions and/or payoffs had a cost of 1 ECU. Requesting information about the network had a larger cost of 10 ECU, since, once requested, this information was permanently displayed to the participants.

Imposing a (small) cost on information requests is a crucial element of our design. Of course, even though costs are "small," this does affect incentives. We imposed costs to avoid that participants request information they are not using to make their choices. We also conducted one treatment that coincided with treatment N-2 but where there was no cost at all to obtain information. In this treatment action, choices did not differ significantly from N-2, but participants requested all the information (almost) all the time. This essentially means that without costs, monitoring information requests does not help us to identify learning rules.[9]

M treatments Data generated by our N treatments will allow consistent estimation of learning rules as long as the information collected does not affect a participant's learning type. However, we have conjectured that the complexity of social interactions, measured by the number of network neighbors, may affect learning. If this was indeed the case, then learning type would be endogenous to the information collected about the network structure, leading to model misspecification.[10] As one way to address this issue, we conducted the M treatments (M-1, M-2, and M-3). They only differ from the

[9]An alternative approach was taken by CCB. They use the computer interface MouseLab to monitor mouse movements. However, as they state, "the space of possible lookup sequences is enormous, and our participants' sequences are very noisy and highly heterogeneous" (p. 1209). Knoepfle, Wang, and Camerer (2009), who use eye-tracking software, report similar issues.

[10]Since 90% of participants request information about the network structure by period 5 (see Section 3) in the N treatments (and this information is permanently displayed once requested), this should not be too much of a problem. Still, the M treatments described here can provide evidence on how important this issue is for the N-treatment estimates. We thank a reviewer for suggesting these treatments.

N treatments in that the network structure was known since the beginning of the experiment. Afterward, participants could request information on past action choices and payoffs, as in the N treatments. While the M treatments avoid this possible endogeneity problem, the N treatments allow for better separation of learning rules. We will always show the results of both sets of treatments in parallel and discuss differences where they arise.

F treatments Finally, to see whether information requests per se affect action choices (e.g., because participants might not request "enough" information due to the costs), we conducted three treatments with full information. Those treatments F-1, F-2, and F-3 coincided with N-1, N-2, and N-3, respectively, but there was no information request stage. Instead, all the information was displayed at the end of each period to all participants.

Four more treatments were run. In a bilateral treatment, participants were matched in pairs to play the game for 20 rounds (see the last column in Table 2). Further three treatments were conducted with a coordination game (in the M condition) to see how much learning changes across game forms. Results on the coordination games are discussed in Section 6.5. Table 2 summarizes the treatment structure of the experiment.[11]

All elements of the design were clearly explained in the Instructions, which can be found in the Supplemental Material posted with the replication files. After finishing the instructions, our participants had to answer several control questions regarding their understanding of the game, network interactions, information requests, and how payoffs are computed. There was no time constraint, but participants were not allowed to proceed without correctly answering all these questions. Experiments were conducted at the BEE-Lab at Maastricht University (N and F treatments) and at the Bilbao LABEAN at the University of the Basque Country (M treatments, bilateral treatment, coordination treatments) using the software Z-tree (Fischbacher (2007)). A total of 442 students participated. The experiment lasted between 60 and 90 minutes. Each 75 ECU were worth 1 euro and participants earned between 7.70 and 16.90 euros.

TABLE 2. Treatments and number of participants (number of observations; networks/pairs).

	Network 1	Network 2	Network 3	Bilateral
Endogenous information (N)	40 (800; 5)	56 (1120; 7)	40 (800; 5)	
Intermediate information (M)	40 (800; 5)	32 (640; 4)	32 (640; 4)	
Full information (F)	24 (480; 3)	24 (480; 3)	24 (480; 3)	26 (520; 13)
Total anti-coordination	104 (2080; 13)	112 (2240; 14)	96 (1920; 12)	26 (520; 13)
Coordination (M-Co)	32 (640; 4)	32 (640; 4)	40 (800; 5)	

[11]The table does not contain the treatment N-2 without costs mentioned above. We will not discuss this treatment any further, but results are available upon request. Other than the treatments reported, we did not conduct any other treatments or sessions and we did not run any pilot studies. The number of observations reported in the table differs across treatments, because of different "show-up rates" in the different treatments.

3. Action choices and information requests

In this section, we provide a brief overview of action choices and information requests. Since our main interest is in estimating learning types, we keep this section short. Appendix A as well as the Supplemental Material contain many additional tables and details.

3.1 *Action choices and payoffs*

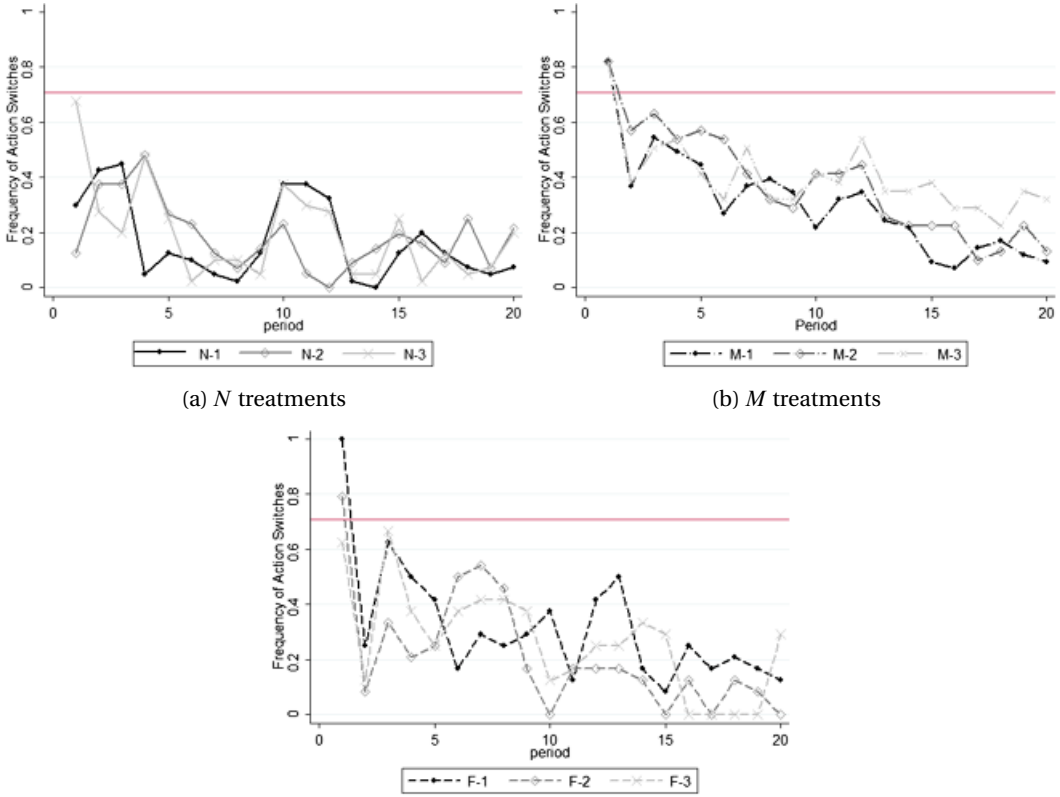
We analyze three aspects of choice behavior, all related to the question of learning: (i) the frequency of switches, (ii) the evolution of payoffs over time, and (iii) convergence to Nash equilibrium.

Switching and payoffs Since it is only meaningful to analyze learning types if there is learning, we report some evidence concerning the stability of action choices. Figure 5 illustrates that players change their action less and less often over time, indicating that some convergence took place. Across periods, switching decreases by 1.4–2.3 percentage points on average, depending on treatment. Switching is also substantially lower compared to the bilateral (pairwise matching) treatment. Participants also learned in the sense that they were able to increase their mean payoffs over time. Figure 6 shows that mean gross profits (i.e., game payoffs without taking into account the costs of information requests) are increasing over time in all treatments. Payoffs range between two benchmarks: (i) the mean payoff in bilateral Nash equilibria (C, D) and (D, C), which is 35, and (ii) the payoff implied by random play of C and D, which is 25.

Nash equilibria Players do not only switch less often and obtain higher payoffs over time, they also are more likely to play a Nash equilibrium of the network game over time. The entire network converges to an equilibrium between 0 and 46% of the time across the last five periods of play, depending on treatment.[12] Participants never reach a Nash equilibrium in Network 3 and most often in Network 2. There seems to be no systematic effect of information conditions, with most coordination being observed in the F treatments and the least observed in the M treatments (Tables 9 and 10 in Appendix A). In line with previous evidence on the conflict between risk and payoff dominance (e.g., Camerer (2003)), action choices always converge toward the "risk-dominant" actions C and D in our experiment. This also seems to be a result of learning, as the number of participants playing these actions is lower in the first half of the experiment across all three networks (see Table 11 in Appendix A). Full, intermediate, and endogenous information treatments are statistically no different in terms of the distribution of action choices across the 20 periods (two-sided rank-sum test, $p > 0.2$).

Overall the evidence collected suggests that participants did learn in the experiment. Interestingly, having full information (as in the F treatments) does not seem to improve payoffs or lead to less switching compared to the N and M treatments. This suggests that participants do request the information they need for learning in the M and N treatments and that information requests do not per se affect participants' behavior.

[12] To help interpret these numbers, note that if players did choose actions uniformly at random, the probability to coordinate on a Nash equilibrium would be 0.00018 for Network 1 and 0.00015 for Networks 2 and 3.



(a) N treatments

(b) M treatments

(c) F treatments

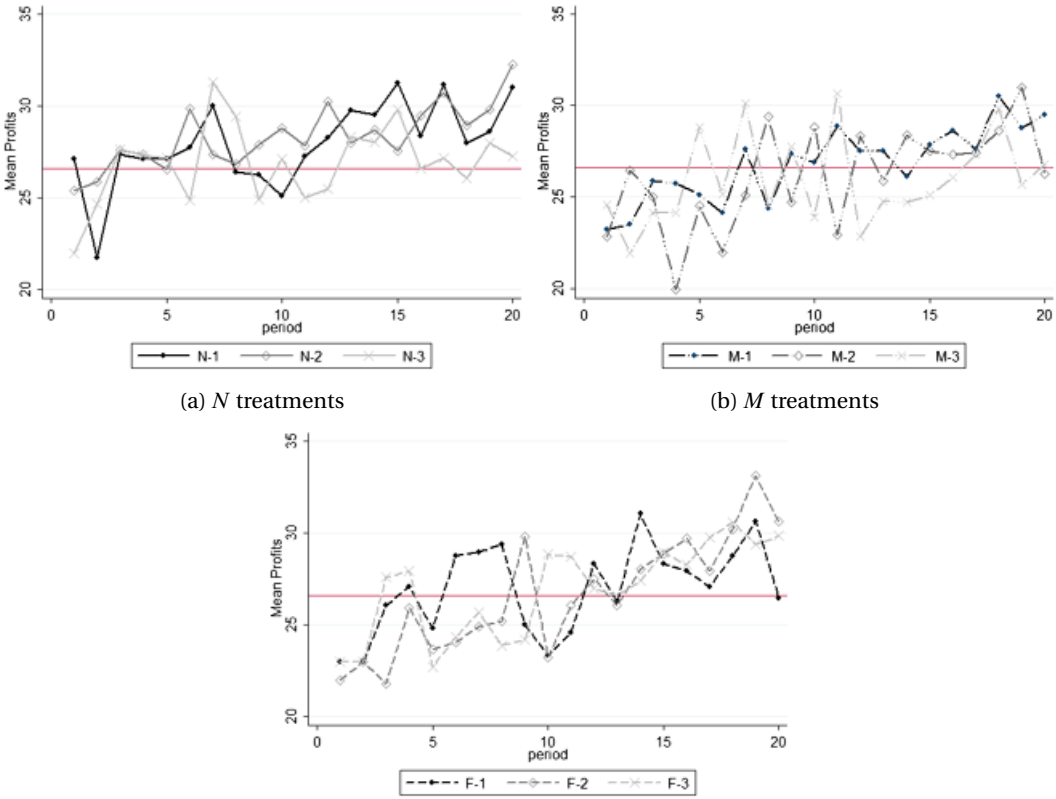
FIGURE 5. The frequency with which players change their action across rounds in different treatments. The horizontal reference line indicates the mean frequency of switches in the bilateral treatment.

3.2 *Information requests*

This subsection focuses on information requests. We focus on simple averages in this subsection. Appendix C contains several figures showing the evolution of information requests over time.

Network structure In the first period 77.5%, 76.8%, and 72.5% of participants in N-1, N-2, and N-3, respectively, requested information about the experimental label of their first-order neighbors. Roughly 90% of individuals end up requesting this information by the fifth period of the experiment. Around 45% of participants request to know the network structure up to their second-order neighbors. Only 12.5%, 23.2%, and 12.5%, respectively, request information about the entire social network. Remember that information about the network structure—once requested—is permanently displayed.

Payoffs Around 50% of participants request their own payoffs in the N treatments and around 30% do so in the M treatments. Only between 8 and 12% of the time (depending on treatment) is information about the payoffs of first-order neighbors requested



(a) N treatments

(b) M treatments

(c) F treatments

FIGURE 6. Mean *gross* payoffs across rounds in different treatments. The horizontal reference line indicates the mean payoffs in the bilateral treatment.

across all N and M treatments. For higher-order neighbors, these percentages are all below 2%.

Actions Around 50% and 40% of participants request information about past actions of their first-order neighbors in the N and M treatments, respectively. Information requests about actions decline over time, which is consistent with the decline in switching behavior observed in Figure 5 and could be attributed to convergence. Despite the strategic effect of second-order neighbors' action choices on the choices of direct opponents, the interest in their behavior is relatively small (requested ≈10%–15% of the time).

4. FRAMEWORK AND METHODS

This section discusses our selection of learning models and sets out basic issues in identifying learning rules from our data (i.e., from action choices and information requests). In our baseline specification, we consider four possible learning types. One rule is reinforcement, another rule is based on imitation, and two rules are belief-based. The criterion for the selection of these learning types is their prominent role in the theoretical

and experimental literature. In what follows, we describe each of them informally; the exact algorithms used for each learning model can be found in Appendix B.1.

C1. Under *reinforcement learning* (RL), participants in each period randomize between actions with probabilities that are proportional to the sum of past payoffs they obtained with these actions (Roth and Erev (1995), Börgers and Sarin (1997), Erev and Roth (1998), Sutton and Barto (1998), Skyrms and Pemantle (2000), Hopkins (2002)).[13]

C2. Under *payoff-based imitation* (PBI), participants choose the action with the highest average payoff in the previous period in their first-order neighborhood including themselves (Eshel, Samuelson, and Shaked (1998), Vega Redondo (1997), Schlag (1998), Skyrms and Pemantle (2000), Alós-Ferrer and Weidenholzer (2008), Fosco and Mengel (2011)).[14]

C3. Under *myopic best responses* (MBR), players choose a myopic best response to the distribution of choices of their first-order neighbors in the previous period (Ellison (1993), Jackson and Watts (2002), Goyal and Vega-Redondo (2005), Hojman and Szeidl (2006), Blume (1993)).

C4. *Forward-looking* (FL) players assume that their first-order neighbors are myopic best responders and best respond to the anticipated distribution of choices in the following period (Blume (2004), Fujiwara-Greve and Krabbe-Nielsen (1999), Selten (1991), Mengel (2014)).[15]

In Section 6, we also include some variants of these rules, such as fictitious play learning with different memory lengths. In several robustness checks, we also included less well known rules such as conformist imitation, aspiration-based reinforcement learning, and several variants of payoff-based imitation (including imitation of different sets of players, e.g., higher-order neighbors). These rules only differ from the above rules in a few instances of predicted action choices and information requests. The four rules singled out above are each representative of a larger class of learning models. Including all possible variants would (a) overspecify the model considerably and (b) lead to many instances of nonidentifiability (where two, possibly quite similar, rules prescribe both the same action choice and information requests).

We exclude hybrid models, such as the experience-weighted attraction of Camerer and Ho (1999). However, we can say something about how well EWA will be able to describe behavior by looking at how well its component rules perform. The reader may also wonder why we did not include level-k learning rules. The main reason is that level-k learning—despite its name—is a model of initial responses and is not defined as an explicitly dynamic learning model. As a consequence, it is not clear how level-k types

[13]In our estimations we will assume that a participant perfectly consistent with RL chooses the most preferred action with probability 1. This approximates some exponential choice rules used in the literature, but is not the case with, for example, the linearly proportional rule.

[14]Some of these authors study, in fact, imitation of the action with the maximal payoff obtained by any single agent instead of the highest average payoff. Using this variation does not fundamentally alter any of our results.

[15]Tang (2001) experimentally tested the model of anticipatory learning by Selten (1991).

should update their beliefs about the distribution of levels k in the population upon receiving new information.[16] There is a connection, though, between our myopic best-response type and level-1, and between the forward-looking type and level-2 in that the latter reasons about how their opponents learn (choose), while the former takes opponents' choices as given.

4.1 *Identifying learning rules from data*

It is only possible to identify learning rules if different rules imply different choices and/or information requests in the experiment. The average number of periods (out of 19) in which two different learning types predict different action choices for a participant given the history of play ranges between 7 and 15 periods for our rules (Table 19 in Appendix D). The fact that the learning rules considered entail different predictions quite often is due to our design involving the 4×4 anti-coordination game and should give good chances to estimations based on action choices alone. We will see below that, despite this fact, estimates are substantially biased if only action choices are considered.

Apart from choices, we also observe participants' information requests. Figure 7 provides an example of how different learning rules imply different information requests for player 7 in Network 1. As a reinforcement learner, she does not need to know anything

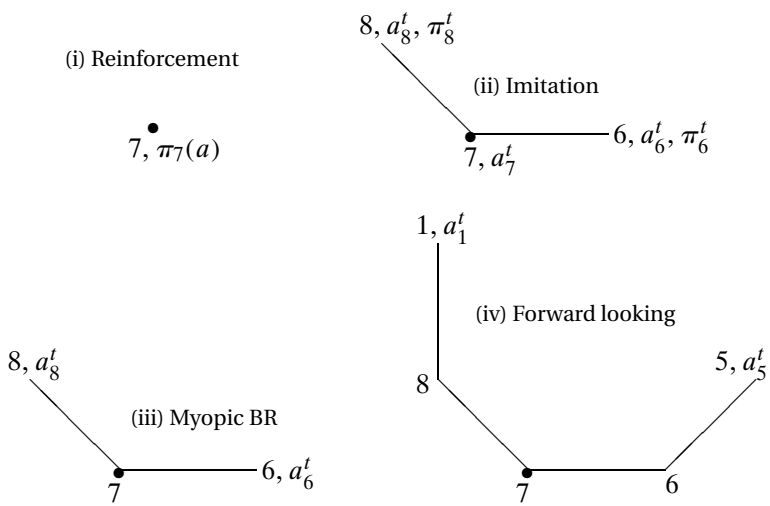


FIGURE 7. Player 7 in Network 1. Information required for rules (i) RL, (ii) PBI, (iii) MBR, and (iv) FL. The term a_i^t denotes the action taken by player i at time t, π_i^t denotes the payoffs obtained by player i at time t, and $\pi_i(a)$ denotes the vector of average payoffs obtained by player i with each of the four actions.

[16]One proposal in this vein was made by Knoepfle, Wang, and Camerer (2009), who model a sophisticated learning type (similar to our forward-looking type) that exhibits a recursive structure similar to level-k models starting from Cournot best response as the anchoring $C0$ (level-0) type. Using eye-tracking technology, they find information lookup patterns consistent with such a learning type, though choices are better explained by adaptive models. Gill and Prowse (2016) estimate a mixture model based on level-k types to analyze how cognitive ability and character skills affect equilibrium play.

about the network or the choices of others. In fact she does not even have to know the payoff matrix. She only has to know the payoffs she obtained in the past with each of the different actions. A payoff-based imitator should have information about the choices of her first-order neighbors and the payoffs they obtained in the previous period.[17] Under myopic best responses, she would need to know past choices of her first-order neighbors, and as a forward-looking learner, she would also need to know her second-order neighbors and their choices in the previous period. Table 20 in Appendix D summarizes the information requirements for each rule.

If participants always requested at least the minimal information needed for a learning type, then all rules could be identified in all of the 20 periods in the N treatments. An important question is whether participants can trade off different pieces of information. One could imagine, for example, that a participant asks for choices of her first- and second-order neighbors, and then uses this information together with the payoff matrix to compute the payoffs of her first-order neighbors. Clearly, we cannot avoid this. Our design is such, however, that in the N treatments, it is always more costly (in terms of the costs we impose on information requests) to make indirect inference about desired information rather than consulting it directly. This is, hence, an additional advantage of having small costs for information requests (in addition to those mentioned in Section 2). Because, in the M treatments, participants do not request information about labels, identification is not as good. In particular, reinforcement learners can also infer their payoffs from their neighbors' action choices without having to request their labels in addition. (The converse is not true: belief learners cannot, in general, identify choices of neighbors from their own payoffs.) Since we can exploit correlations between information requests and implied choices, identification is still reasonably good, even in the M treatments.

4.2 *Econometric framework*

In this section, we introduce the econometric framework. Our aim is to estimate population shares p_k of the different learning rules k discussed above. To do so, we will estimate mixture models to try and find the distribution $p = (p_1, p_2, \ldots, p_K)$ that can best explain our data, that is, action choices and information requests. We start with the following assumption, which links information requests to learning rules.

Occurrence Assumption. In every period, a participant requests at least the minimal information she needs to identify the action choice corresponding to her learning type.

While this assumption seems quite innocuous, it can still be too strict in some cases and we will relax it sometimes. For instance, after convergence has occurred, participants may not always ask for the minimal information. On the other hand, unlike in

[17]Note that we have not included a participant's own payoff in the minimal information set for PBI. The reason is that this information can be inferred from observing one's own and neighbor's action choices. The *minimal information set* we are looking for hence excluded this information. We have, however, also run all estimations with the larger set that requires PBI types to request their own payoffs as well. Results do not change qualitatively, and quantitative changes are minimal.

eye-tracking studies, it is unlikely that occurrence is satisfied by chance, since participants had to pay for each piece of information they requested (see Section 2).

We then proceed as follows. For each subject i and learning type $k \in \{1, 2, \ldots, K\}$, we compute the number of periods I^i_{kO} in which subject i asked at least for the minimum information required to be consistent with learning rule k. Subscript O stands for compliance with occurrence; $I^i_{kZ} = 19 - I^i_{kO}$ measures the number of periods subject i did not ask for the minimum information set corresponding to rule k, where subscript Z stands for zero compliance with occurrence. Let θ_{kj} denote the probability that a participant has compliance j with rule k in the experiment, where $j \in \{Z, O\}$ and $\theta_{kZ} + \theta_{kO} = 1$ for each k. Hence $\theta_{kZ} = 1 - \theta_{kO}$ is the probability that a participant of type k does *not* request the information required for k. We define $\theta_k = (\theta_{kO}, \theta_{kZ})$.[18]

We now turn to action choices. For a given subject in a given period, a learning type may predict more than one possible action. We assume that in this case participants choose uniformly at random among those actions. Let $c \in \{1, 2, 3, 4\}$ denote the number of action choices consistent with a given learning rule in a given period. A subject employing rule k normally makes decisions consistent with k, but in each period, given compliance j, she makes an error with probability $\varepsilon_{kj} \in [0, 1]$. We assume that error rates are independent and identically distributed (i.i.d.) across periods and participants. In the event of an error, we assume that participants play each of the four actions with probability $\frac{1}{4}$. As a result, given j and c, the probability for a decision-maker of type k to choose a given action consistent with rule k (either by mistake or as a result of employing rule k) is

$$(1 - \varepsilon_{kj})\frac{1}{c} + \frac{\varepsilon_{kj}}{4} = \left(1 - \frac{4 - c}{4}\varepsilon_{kj}\right)\frac{1}{c}. \tag{1}$$

The probability to choose a given action that is inconsistent with rule k is $\frac{\varepsilon_{kj}}{4}$.[19] We define $\varepsilon_k = (\varepsilon_{kZ}, \varepsilon_{kO})$. Under the assumptions made, (low) compliance ("errors in information requests") and action errors will be positively correlated. This is shown in Appendix B.2. In fact, for our main estimates, we will even assume that in the case of zero compliance with rule k, participants can only be consistent with k by mistake, though dropping this assumption only leads to minimal changes in estimates. Conditional on j and k, however, errors are i.i.d across periods and participants.

For each learning rule k in each period, we observe which action a player chooses and whether or not it is consistent with learning rule k. Let I^{ic}_{kj} denote the number of periods in which subject i has compliance j with learning type k and c action choices that are consistent with k. Hence $\sum_c I^{ic}_{kj} = I^i_{kj}$ $\forall i, k, j$. The term x^{ic}_{kj} denotes the number of periods in which i takes one of c possible action choices consistent with k and has compliance j with k. Define $\sum_c x^{ic}_{kj} = x^i_{kj}$ for all i, k, and j. Additionally, define $x^i_k = (x^i_{kZ}, x^i_{kO})$, $I^i_k = (I^i_{kZ}, I^i_{kO})$; $I^i = (I^i_1, \ldots, I^i_K)$, $x^i = (x^i_1, \ldots, x^i_K)$; $\Im = (I^1, \ldots, I^N)$, and $X = (x^1, \ldots, x^N)$. As a result, the probability of observing sample (I^i_k, x^i_k) when participant i

[18] In Section 6.3, we increase the number of compliance categories.

[19] Note that $c(1 - \frac{4-c}{4}\varepsilon_{kj})\frac{1}{c} + (4 - c)\frac{\varepsilon_{kj}}{4} = 1$.

is of type k is

$$L_k^i(\varepsilon_k, \theta_k | I_k^i, x_k^i) = \prod_j \prod_c \theta_{kj}^{I_{kj}^{ic}} \left[\left(1 - \frac{4-c}{4}\varepsilon_{kj}\right)\frac{1}{c} \right]^{x_{kj}^{ic}} \left(\frac{\varepsilon_{kj}}{4}\right)^{I_{kj}^{ic} - x_{kj}^{ic}}, \tag{2}$$

and the log-likelihood function for the entire sample is

$$\ln \mathrm{LF}(p, \varepsilon, \theta | \Im, X) = \sum_{i=1}^{N} \ln \left\{ \sum_{k=1}^{K} p_k \prod_j \prod_c \theta_{kj}^{I_{kj}^{ic}} \left[\left(1 - \frac{4-c}{4}\varepsilon_{kj}\right)\frac{1}{c} \right]^{x_{kj}^{ic}} \left(\frac{\varepsilon_{kj}}{4}\right)^{I_{kj}^{ic} - x_{kj}^{ic}} \right\}. \tag{3}$$

Under mild conditions satisfied by (3), the maximum-likelihood method produces consistent estimators for finite mixture models (Leroux (1992)). Our aim is to find a mixture model $p = (p_1, p_2, \ldots, p_K)$ that provides the best evidence in favor of our data set. With K learning types, we have $(4K - 1)$ free independent parameters: $(K - 1)$ independent probabilities p_k, K information request probabilities θ_{kj}, and $2K$ error rates ε_{kj}.

It is well known that testing for the number of components in finite mixture models "is an important but very difficult problem, which has not been completely resolved" (McLachlan and Peel (2000, p. 175)). Standard information criteria for model selection, such as the likelihood ratio test or the Aikaike or Bayesian information criteria, might not perform satisfactorily (Prasad, Shi, and Chih-Ling (2007), Cameron and Trivedi (2005, 2010)). In the literature there are two different approaches to deal with with model selection (i.e., selection of components). Cameron and Trivedi (2005) propose to use the "natural" interpretation of the estimated parameters to select components, while McLachlan and Peel (2000) argue that the true number of components generating the data is the smallest value of K such that the estimated likelihoods differ across components and all the p_k are nonzero. In the following discussion, we use a procedure that combines these two criteria. First note that for given k, j, and c, x_{kj}^{ic} exerts a significant positive influence on the estimated value of p_k as long as the following inequality holds:

$$\ln \left[\frac{\left(1 - \frac{4-c}{4}\varepsilon_{kj}\right)\frac{1}{c}}{\frac{\varepsilon_{kj}}{4}} \right] \geq 0. \tag{4}$$

The left hand side of (4) is decreasing in the error rate, approaching 0 as $\varepsilon_{k,j}$ tends to 1. This means that choices consistent with type k are taken as evidence of learning rule k only if the estimated error rates suggest that those choices were made on purpose rather than by error.

CCB show that, regardless of the level of compliance j, the log-likelihood function favors type k when the estimated θ_{kj} are more concentrated on compliance j. CCB use the *unrestricted* estimates of θ_{kj} as a diagnostic, giving more confidence to the estimated values of p_k for which θ_{kO} is high. High concentration at zero compliance, for example, can lead to a probability θ_{kZ} very close to 1 and to a high estimated frequency p_k. However, a high value of θ_{kZ} and, consequently, low estimated values of θ_{kO} indicate

that participants do not consult the minimum information corresponding to rule k very often and it would be hard to argue that learning rule k explains the behavior of the participants clustered in component k. In other words, if θ_{kZ} is very high, people classified as type k almost never consult the information corresponding to rule k, and this is evidence that their learning behavior was not actually generated by type k, irrespective of the estimated p_k.

With these considerations in mind, we will use the estimated values of θ_k as a tool for selecting the components of our finite mixture model. In particular, we will (i) repeatedly estimate the multiple learning rule model and (ii) eliminate after each repetition the rule l with the highest estimated θ_{lZ} whenever it is larger than an elimination threshold $\overline{\theta}_Z$. The process stops with the final estimation when either all remaining rules have an estimated $\theta_{lZ} < \overline{\theta}_Z$ or when only one rule remains. We also would have eliminated rules if estimated error rates did not increase as compliance decreased, but this never did happen in our data.

The elimination threshold $\overline{\theta}_Z$ can, in principle, be set to any level, depending on when one starts to believe that a rule fails to explain behavior. The rules we eliminate have an estimated $\theta_{lZ} > 0.9$, meaning that participants clustered in these rules only consult the information required for these rules with less than 10% probability.

Robustness checks We also artificially altered the order of elimination of types (for which $\theta_{lZ} > \overline{\theta}_Z$), and, in all cases, we converge to the same mixture composition as in the benchmark cases (see the Supplemental Material). Hence, the results are robust to the order of elimination of learning types. They are also robust to alternative assumptions on the data-generating process, to changing the number of compliance categories, and to relaxing the assumption of compliance with occurrence (Section 6). We now proceed to presenting our main results.

5. Main results

5.1 *Results based on information requests and choices*

This section contains our main results. We start by illustrating how our algorithm selects components using treatment N-1 as an example. Table 3 shows the estimated type frequencies p_k and parameters θ_{kZ}. After the first estimation with all rules, we find that $\widehat{\theta}_{\text{PBI},Z} = 1$ (in bold in Table 3), meaning that participants classified as PBI do *not* ever consult the information required by this learning rule.[20] Therefore, our selection criterion suggests that there is no evidence that participants' choice behavior was induced by PBI, so we remove PBI from the estimation. In the second iteration, we eliminate the forward-looking rule with $\widehat{\theta}_{\text{FWL},Z} = 0.99$. The algorithm stops with only two rules, RL and MBR, remaining. The selection algorithm selects the same learning rules in N-2 for all thresholds $\overline{\theta}_Z \in [0.48, 0.97]$, and in treatment N-3, only MBR survives for all $\overline{\theta}_Z \in [0.17, 0.97)$. We describe the results in more detail below.

[20]The acronyms PBI, FL, RL, and MBR stand for payoff-based imitation, forward-looking, reinforcement learning, and myopic best responses, respectively (see Section 4).

TABLE 3. Estimation results after different iterations of the selection algorithm: treatment N-1.

	Learning Types			
Parameters	RL	PBI	MBR	FL
First iteration				
p_k	0.25	0.55	0.20	0
θ_{kZ}	0.04	**1**	0.07	–
Second iteration				
p_k	0.18		0.24	0.58
θ_{kZ}	0.09		0.07	**0.99**
Final iteration				
p_k	0.57		0.43	
θ_{kZ}	0.56		0.10	

How can it be that at the first step of estimations a rule that clearly does not describe behavior well, such as PBI, obtains an estimated value of $p_{\text{PBI}} = 0.55$? Remember that the estimation procedure favors a rule k if its compliance with occurrence is more concentrated on one particular value. Hence if participants' choices explain the variation in information requests poorly, this will lead to a high concentration of zero compliance (high θ_{kZ}) and will favor the estimated value of p_k. For this reason, any estimated value of p_k can only be interpreted jointly with the vector θ_k (see also the discussion in Section 4.2).

There is information, though, that can be gained by studying the sequence of estimations (see the Supplemental Material). In N-3, for example, our population is overall best described by MBR. But small percentages of decisions are also very accurately described by other rules that eventually get eliminated by the algorithm. For example, 15% are very accurately described by reinforcement learning with $\widehat{\theta}_{\text{RL},O} = 0.85$ (first iteration). Hence, while our selection algorithm forces the estimation to explain *all* decisions (by the entire population) that attribute a significant share of decisions to noise or errors, studying the sequence of estimations can also give us insights into which rules are able to explain (a small) part of the data accurately and which rules can best account for the more noisy decisions.

Table 4 reports the maximum-likelihood estimates of learning type probabilities p_k, compliance probabilities θ_{kj}, compliance conditional error rates ε_{kj}, and the corresponding standard errors (s.e.) in the selected models for the N treatments. In treatment N-1, 57% of the population is best described as reinforcement learners and the remaining 43% as myopic best responders. RL has high compliance with occurrence ($\widehat{\theta}_{\text{RL},O} = 0.44$), while $\widehat{\theta}_{\text{MBR},O}$ even equals 90%. In both cases, estimated error rates increase as compliance decreases (i.e., the more frequently people classified as type k request information consistent with k, the more frequently their choices are consistent with rule k). These results suggest that the estimated type frequencies of RL and MBR are reliable. In N-2, 24% and 76% of participants are best described by RL and MBR, respectively. The estimated θs and εs are also well behaved. For thresholds below 97%,

TABLE 4. Main estimation results using *both* information requests and action choices: N treatments.

	Treatments					
	N-1		N-2		N-3	
Parameters	RL	MBR	RL	MBR	MBR	FL
p_k	0.57***	0.43***	0.24*	0.76***	0.27***	0.73***
(s.e.)	(0.10)	(0.10)	(0.16)	(0.17)	(0.08)	(0.08)
θ_Z	0.56*	0.10	0.05	0.47**	0.16***	0.97***
(s.e.)	(0.30)	(0.26)	(0.27)	(0.20)	(0.05)	(0.04)
θ_O	0.44	0.9***	0.95***	0.53***	0.84***	0.03
(s.e.)	(0.30)	(0.26)	(0.27)	(0.20)	(0.05)	(0.04)
ε_Z	1***	1***	1***	1***	1***	1***
(s.e.)	(0.06)	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)
ε_O	0.51***	0.45***	0.48***	0.43***	0.64***	0.72***
(s.e.)	(0.09)	(0.11)	(0.08)	(0.07)	(0.08)	(0.13)
ln LF	−1325		−1861		−1203	
Individuals	40		56		40	
Observations	760		1064		760	

Note: ***, significant at the 1% level; **, significant at the 5% level; *, significant at the 10% level. Standard errors are computed using a bootstrapping method with 500 replications (Efron and Tibshirani (1994)). The rule FL is eliminated in this stage in N-3 as $\theta_Z > 0.9$.

only MBR survives in N-3. In the final estimation, 73% of participants are classified as forward-looking learners, but they request information consistent with this rule (i.e., their second-neighbors' action choices) only with probability 0.03.

Table 5 shows the analogous results for the M treatments. In all three M treatments, the population is described as composed of RL and MBR. In M-1, about equally many participants are classified as RL (51%) and MBR (49%), even though the MBR estimate is very noisy. In M-2, the percentage classified as MBR increases to 69% and it even reaches 81% in M-3 (with the remainder being classified as RL). Across all treatments, RL types are identified more precisely than MBR types, suggesting that many of the more noisy learners are classified as MBR. This could possibly be due to the slightly worse identification in the M treatments discussed above. Some participants who request their neighbors' action choices may infer their own payoffs and, hence, display choices less consistent with MBR.[21] Overall the N and M estimates deliver a similar picture. Reinforcement learning and myopic best-response learning are the two rules selected in Networks 1 and 2, with a higher share of belief learning in Network 2. In those two networks, estimated shares are less than 7 percentage points apart across the two information conditions. There are seemingly more differences in Network 3. In M-3, reinforcement learning receives a share of 19%, while in N-3, all participants are classi-

[21]Because of our assumption that a participant who does *not* request information consistent with k can only choose an action consistent with rule k by chance and not as a result of employing rule k, the estimated $\widehat{\varepsilon}_{kZ} = 1$ for all networks and selected rules. If we drop this assumption, then the p_k estimates are the same in N-1, N-3, and M-3, we find slightly higher frequencies of RL in M-1 and M-2, and find more evidence of MBR in N-2. In that case, the estimated ε_{kZ} ranges between 0.51 and 1 for the selected rules.

TABLE 5. Main estimation results using *both* information requests and action choices: M treatments.

	Treatments					
	M-1		M-2		M-3	
Parameters	RL	MBR	RL	MBR	RL	MBR
p_k	0.51***	0.49***	0.31**	0.69***	0.19**	0.81***
(s.e.)	(0.00)	(0.00)	(0.13)	(1.35)	(0.07)	(0.08)
θ_Z	0.20***	0.90***	0.22	0.68***	0.09	0.68***
(s.e.)	(0.040)	(0.05)	(0.13)	(0.07)	(0.11)	(0.05)
θ_O	0.80***	0.10**	0.78***	0.14*	0.91***	0.12**
(s.e.)	(0.04)	(0.05)	(0.13)	(0.07)	(0.11)	(0.05)
ε_Z	1***	1***	1***	1***	1***	1***
(s.e.)	(0.06)	(0.00)	(0.04)	(0.04)	(0.04)	(0.04)
ε_O	0.57***	0.48***	0.6***	0.49***	0.84***	0.63***
(s.e.)	(0.00)	(0.15)	(0.11)	(0.13)	(0.11)	(0.14)
ln LF	−1316		−1082		−1060	
Individuals	40		32		32	
Observations	800		640		640	

Note: ***, significant at the 1% level; **, significant at the 5% level; *, significant at the 10% level. Standard errors are computed using bootstrapping with 500 replications (Efron and Tibshirani (1994)).

fied as belief learners. Remember, though, that in the initial step of elimination, 15% of decisions were very accurately described by reinforcement learning even in N-3 (Supplemental Material).

Since almost all our data can be described by either reinforcement learning or belief-based rules, our results support the assumptions of EWA (Camerer and Ho (1998), Camerer, Ho, and Chong (2002)), which include reinforcement and belief-based learning as special cases as well as some hybrid versions of the two. Unlike in EWA, we do not restrict to those models ex ante, but our results suggest that—at least in the context considered—a researcher may not be missing out on too much by focusing on those models. While EWA should be a good description of behavior at the aggregate level, at the individual level, fewer than 15% of our participants persistently request information consistent with both reinforcement learning and belief-based learning rules (see Figure 12 in Appendix C). There is also a connection between our findings and the idea of multidimensional iterative reasoning introduced by Arad and Rubinstein (2012). Our participants who are best described by MBR (as opposed to FL) are myopic (level 1) both in terms of assuming stationary behavior of neighbors and in terms of only reasoning about first-order neighbors, but not higher-order neighbors.

Some readers might wonder whether we are overestimating the frequency of RL, because participants might look up their own payoffs just because they want to know their payoffs and not because they use this information in their learning rule. We probably do, but only to a small extent. Note, first, that the estimation procedure identifies high correlations between information requests and "correct" choices given the learning models consistent with the information request. As a result, if a decision-maker always looks up

some information for other reasons (unrelated to the way she learns and plays), then this will *not* lead to high correlations and, hence, will *not* mislead the estimation procedure. In addition, the fact that we find no evidence for RL in N-3 indicates that this is a minor issue in our study.

The comparison of the three networks suggests that network topology affects how people learn. In both the N and M treatments, we observe an increase of belief-based models at the expense of the simpler reinforcement learning as we move from Network 1 to Network 3. One possible reason for this pattern could lie in the fact that in Network 3 there are many (five) network positions with only one network neighbor and there are some (three) in Network 2, but none in Network 1. A conjecture we will evaluate in Section 5.3 is that players in simpler environments (i.e., with fewer network neighbors) rely on more sophisticated learning rules, while players in more complex environments tend to resort to simpler rules, such as reinforcement learning.

5.2 *Results based only on action choices*

In this section, we will try to understand how much is gained by using the methodology outlined in the previous subsection compared to simpler estimations based on action choices alone. If results obtained via the latter set of estimations are "worse" than those obtained via our main estimations, then (at least in this context) collecting the additional information seems crucial and the advantage of the network approach would be highlighted. Hence, the objective is to test whether estimates are less accurate if data on information requests are ignored.

Recall that we assume that a type-k subject normally makes a decision consistent with type k, but she can make an error with probability ε_k. Let T_k^{ic} be the number of periods in which subject i has c possible action choices consistent with rule k, and let x_k^{ic} measure the number of periods in which subject i has c possible action choices and makes a decision consistent with k. Under this model specification, the probability of observing sample x_k^i can then be written as

$$L_k^i(\varepsilon_k|x_k^i) = \prod_{c=1,2,3,4}\left[\left(1-\frac{4-c}{4}\varepsilon_k\right)\frac{1}{c}\right]^{x_k^{i,c}}\left(\frac{\varepsilon_k}{4}\right)^{T_k^{i,c}-x_k^{i,c}}. \tag{5}$$

The log-likelihood function is

$$\ln \mathrm{LF}(p,\varepsilon|x) = \sum_{i=1}^{N}\ln\left\{\sum_{k=1}^{K}p_k\prod_{c=1,2,3,4}\left[\left(1-\frac{4-c}{4}\varepsilon_k\right)\frac{1}{c}\right]^{x_k^{i,c}}\left(\frac{\varepsilon}{4}{}_k\right)^{T_k^{i,c}-x_k^{i,c}}\right\}. \tag{6}$$

As in (3), the influence of x_k^{ic} on the estimated value of p_k decreases as ε_k tends to 1, meaning that learning type k's decisions are taken as evidence of rule k only to the extent that the estimated value of ε_k suggests they were made on purpose rather than in error. The parameters of equation (6) are estimated using maximum likelihood methods as before. Now we have $2K-1$ free independent parameters, $(K-1)$ corresponding to frequency types p_k, and K corresponding to the error rates.

TABLE 6. Estimation based solely on observed action choices.

	Treatment N-1				Treatment M-1			
Parameters	RL	PBI	MBR	FL	RL	PBI	MBR	FL
p_k	0.21***	0.08	0.42***	0.30***	0.46***	0.20**	0.24***	0.10*
(s.e.)	(0.08)	(0.07)	(0.12)	(0.10)	(0.09)	(0.08)	(0.09)	(0.05)
ε_k	0.08	1***	0.58***	0.42***	0.35***	0.87***	0.57***	0.09
(s.e.)	(0.16)	(0.21)	(0.16)	(0.07)	(0.06)	(0.08)	(0.08)	(0.20)
ln LF			−760				−794	
Individuals			40				40	
Observations			760				760	
	Treatment N-2				Treatment M-2			
p_k	0.49***	0.04	0.35***	0.11***	0.17*	0.53***	0.24***	0.06
(s.e.)	(0.08)	(0.04)	(0.08)	(0.06)	(0.10)	(0.16)	(0.09)	(0.13)
ε_k	0.26***	0.48**	0.47***	0.76***	0.33**	0.87***	0.41***	0.03
(s.e.)	(0.04)	(0.25)	(0.08)	(0.19)	(0.17)	(0.11)	(0.09)	(0.46)
ln LF			−1022				−709	
Individuals			56				32	
Observations			1064				608	
	Treatment N-3				Treatment M-3			
p_k	0.51***	0.23**	0.21***	0.05	0.33**	0.50***	0.08	0.09
(s.e.)	(0.09)	(0.08)	(0.08)	(0.05)	(0.15)	(0.17)	(0.13)	(0.11)
ε_k	0.34***	0.70***	0.42***	0.28	0.48***	0.88***	0.27	0.15
(s.e.)	(0.06)	(0.21)	(0.07)	(0.26)	(0.15)	(0.22)	(0.31)	(0.32)
ln LF			−772				−718	
Individuals			40				32	
Observations			760				608	

Note: ***, significant at the 1% level; **, significant at the 5% level; *, significant at the 10% level. Standard errors are computed using bootstrapping methods with 500 replications (Efron and Tibshirani (1994)).

Table 6 reports the estimated frequencies and error rates. There is evidence in favor of all four learning types. Based on these results, we could conclude that there is evidence of payoff-based imitation in N-3 (23%), M-1 (20%), M-2 (53%), and M-3 (50%) even though we have already seen above (Section 4) that action choices and information requests are inconsistent with PBI. We also obtain a significant share of FL (30% for N-1 and 11% in N-2) despite the fact that participants hardly ever requested information needed to identify the corresponding action choices. Consequently, it is very unlikely that these learning rules have generated the behavior of participants in the experiment.

How do we know that the model with information requests gives "better" and not just "different" estimates than the model without information request? Obviously estimations that take into account information requests use more information and, hence, they can rule out learning rules that are plausible when looking at decisions only, but simply not possible because the decision-maker did not have the minimal information

needed for those rules. The estimation procedure identifies high correlations between information requests and "correct" choices given the learning models consistent with the information requests. Hence, if a decision-maker always requests some information for other reasons (unrelated to the way she learns), then this will *not* lead to high correlations and, hence, will *not* mislead the procedure based on information requests. The only case in which the process with information requests could be misled is if (i) two different rules predict the same choices and (ii) information needed for one rule can be deduced from information needed for the other rule. Our experimental design renders (ii) unlikely, and (i) is only very rarely the case in our experiment (Table 19 in Appendix D). Note also that situations such as (i) will likely affect estimations that disregard information requests even more.

We conducted analogous estimations for the full-information treatments (Table 24 in Appendix D). Note that in these treatments, since all information is available, we do not know which information participants used in their decisions. Any inference, hence, has to be made purely on the basis of observed action choices. The estimates show no systematic shift of learning toward any rule when comparing these tables. This provides further evidence that the small costs imposed on information requests did not distort the way participants learn (see also Section 4).

To sum up, we have seen that straightforward maximum-likelihood estimation that disregards information requests ends up accepting learning rules for which participants would need information that we know they did not have. As our design (involving the 4×4 anti-coordination game) was chosen to give estimations using action choices alone good chances to detect learning strategies (see Section 4.1), one might expect these biases to be much more severe for smaller games or pure coordination games, where identification based on choices alone is more difficult.

5.3 *Estimates by network position*

To understand whether learning is affected by network position, we estimate our model separately for different groups of network positions. In particular, we ask whether the number of network neighbors affects how people learn. Since having more neighbors involves collecting and processing more pieces of information and, hence, higher cognitive costs, players with many neighbors might resort to rules that are less demanding in terms of information requirements.[22] Since reinforcement learning requires storing and processing one piece of information (own payoff) irrespective of the number of neighbors, it is arguably less costly in terms of cognitive resources to resort to this rule in positions with many neighbors. The number of different pieces of information a decision-maker needs to process under MBR learning, however, is linearly proportional to the number of neighbors (action choices for each neighbor).[23]

[22] In a different context, Brock and Hommes (1997) show that acknowledging agent's choice between simple and more complex learning or predictor rules can dramatically alter our understanding of equilibrium (or nonequilibrium) behavior.

[23] In particular, agents with more than one neighbor need to consider multiple past/future action choices and take weighted averages to make their choice (under the more sophisticated rules MBR and FL), while agents with only one neighbor do not need to do this. Note, though, that only *one* request is needed to receive information about choices for all neighbors.

To estimate the model separately for each position in the networks would lead to very small samples and likely to small-sample biases. Hence, we aggregate data from the heterogeneous networks (Networks 2 and 3) and categorize people into two groups according to whether they have one neighbor or more than one neighbor. To have balanced groups, we omit Network 1, but it is included in Tables 22 and 23 in Appendix D without substantially affecting results. Group 1 (with one network neighbor) contains players 1, 7, and 8 in Network 2 and players 1, 5, 6, 7, and 8 in Network 3, whereas Group 2 (multiple network neighbors) contains players 2, 3, 4, 5, and 6 in Network 2 and players 2, 3, and 4 in Network 3. Table 7 reports the estimation results.

TABLE 7. Participants with one network neighbor (players 1, 7, and 8 in M-2 and players 1, 5, 6, 7, and 8 in M-3) versus participants with multiple network neighbors (players 2, 3, 4, 5, and 6 in M-2 and players 2, 3, and 4 in M-3).

	N Treatments							
	Group 1: One Network Neighbor				Group 2: Multiple Network Neighbors			
Parameters	RL	PBI	MBR	FL	RL	PBI	MBR	FL
p_k	0.54***		0.46***		0.65***		0.35*	
(s.e.)	(0.10)		(0.10)		(0.18)		(0.18)	
θ_Z	0.87***		0.74**		0.61*		0.11	
(s.e.)	(0.26)		(0.33)		(0.37)		(0.21)	
θ_O	0.13		0.26		0.39		0.89***	
(s.e.)	(0.26)		(0.33)		(0.37)		(0.21)	
ε_Z	1***		1***		1***		1***	
(s.e.)	(0.04)		(0.04)		(0.04)		(0.04)	
ε_O	0.63***		0.7***		0.49***		0.35***	
(s.e.)	(0.12)		(0.11)		(0.16)		(0.07)	
ln LF		−1630				−1652		
Individuals		46				50		
Observations		874				950		
	M Treatments							
p_k	0.23***		0.77***		0.41***		0.59***	
(s.e.)	(0.09)		(0.09)		(0.117)		(0.117)	
θ_Z	0.21		0.86***		0.27**		0.95***	
(s.e.)	(0.149)		(0.053)		(0.118)		(0.072)	
θ_O	0.79***		0.14***		0.73***		0.05	
(s.e.)	(0.149)		(0.053)		(0.118)		(0.072)	
ε_Z	1***		1***		1***		1***	
(s.e.)	(0.045)		(0.045)		(0.065)		(0.045)	
ε_O	0.68***		0.64***		0.69***		0.49**	
(s.e.)	(0.155)		(0.115)		(0.091)		(0.203)	
ln LF		−1091				−1051		
Individuals		32				32		
Observations		640				640		

Note: ***, significant at the 1% level; **, significant at the 5% level; *, significant at the 10% level. Standard errors are computed via bootstrapping with 500 replications (Efron and Tibshirani (1994)).

The estimates seem to support our conjecture. More complex situations (more network neighbors) trigger the use of less sophisticated rules. In the N treatments (reported in Table 7), reinforcement learning gets attributed somewhat more and belief learning somewhat less than 50% in Group 1. In Group 2, by contrast, the shares attributed to reinforcement learning (65%) are almost double those of MBR (35%). The difference between Group 1 and Group 2 estimates is statistically highly significant ($z = 5.058$, $p < 0.001$).[24] In the M treatments, somewhat more participants are classified as MBR in both groups. But again, the estimated population share of RL is higher in the more complex environment, with 41% being classified as RL in Group 2 and only 23% in Group 1 ($z = 22.220$, $p < 0.001$).

To sum up, these results suggest that learning depends on network position. In particular, the complexity of the environment measured by the number of network neighbors seems to affect the learning rules to which participants resort.

6. Additional results

In this section, we report several robustness checks. First, using simulated data, we evaluate the extent to which our econometric model is capable of identifying the learning rules present in the population. Second, we discuss specifications with alternative learning rules. Third, we study alternative assumptions on compliance with occurrence. Fourth, we discuss alternative assumptions on the data-generating process. Last, we report results on our coordination game treatments. For reasons of space, all robustness checks in Sections 6.1–6.3 are reported only for the N treatments, but they all extend to the M treatments.

6.1 *Recovering the data-generating process from simulated data*

We test how well our estimation procedure can recover the type distribution from simulated data. We use two different type compositions for this purpose. We first ask whether we can recover the underlying data-generating process if the true composition is similar to the estimated shares from Section 5.1 with two rules, RL and MBR. To this aim, we assume that 57% of participants are RL and 43% are MBR in all simulations (Exercise 1) mimicking the population composition estimated in the case of treatment N-1. As a second exercise (Exercise 2), we ask how well our procedure performs with three rules in the population. Including three rules also provides a test for whether there is a general tendency for our procedure to favor RL and MBR, selected in most of our models. To this aim, we simulate the behavior of three different learning types: RL (15% of the population), MBR (40%), and FL (45% of the population). The specific frequencies for Exercise 2 were picked in an ad hoc manner with the idea in mind, however, to have a low frequency of RL and a higher frequency of FL types than what we find in our main estimates.

[24]The bootstrapped estimates return a covariance between the estimated p_{RL} across the groups of <0.0007. Hence, we treat them as independent and test the null hypothesis of equality of coefficients across Groups 1 and 2 using a z-statistic, which accounts for degrees of freedom across the groups.

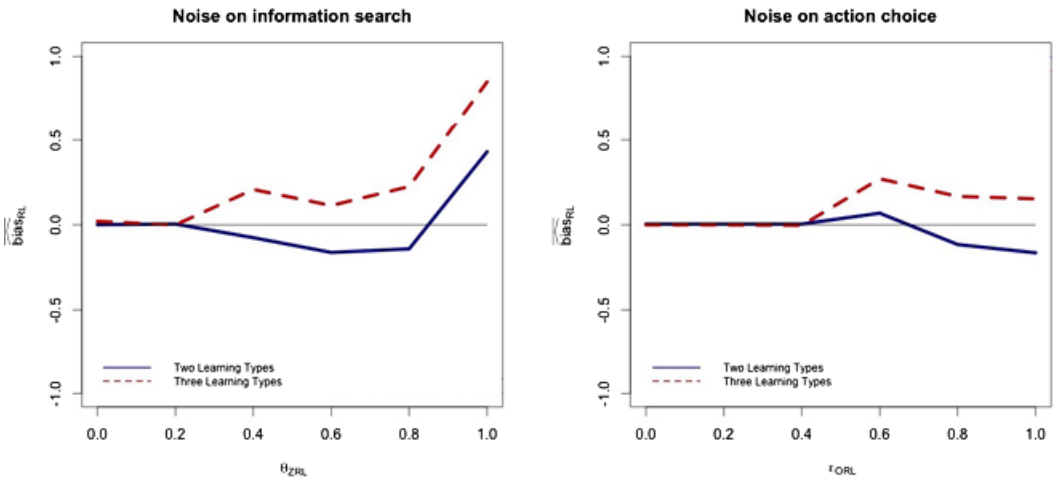


FIGURE 8. Difference between estimated parameters $\widehat{p}_{\mathrm{RL}}$ and the true value depending on (dashed line) the extent of error in information requests $\theta_{Z;\mathrm{RL}}$ (left panel) and the extent of error in action choices (right panel).

To mimic our experiment, we simulate data for five groups of eight players (40 computer-simulated participants in total) and randomly distribute learning types across computer-simulated participants. For each case, we have 500 computer-generated samples with these characteristics. We then conduct two different types of simulations. In this section, we report on simulations where we vary noise in one dimension only, that is, either in information requests or in action choices, assuming very little noise in the other dimension. Noise parameters θ and ε are separately varied between 0 and 1 in steps of 0.2 (keeping the other parameter fixed at 0.05). In all cases, our selection algorithm correctly identifies the rules present in the population.

Figure 8 shows the extent of bias (the difference between estimated and true parameter p_k) as a function of noise in information requests (left panel) and action choices (right panel). The solid line refers to Exercise 1 (two types) and the dashed line refers to Exercise 2 (three types). With noise only in information requests, the bias is near zero for $\theta_Z \lessapprox 0.2$; estimates are moderately biased for $0.2 < \theta_Z \lessapprox 0.8$ and severely biased for $\theta_Z \gtrapprox 0.8$. In our main estimates (Tables 4 and 5), values of θ_Z are generally in the accurate range $\theta_Z \lessapprox 0.2$ with the exception of N-1, where the estimated value is 0.56, suggesting that p_{RL} may be somewhat underestimated in that network. With noise only in action choices, we find that estimates are accurate until values of $\varepsilon \approx 0.4$ and imply moderate biases afterward. If information requests are not very noisy ($\theta_Z = 0.05$), then action requests can be pure noise ($\varepsilon = 1$) and the biases will still only be around 10 percentage points. In Appendix B.6, we report on simulations where we simultaneously vary noise in action choices and information requests. Those simulations show that even if we vary noise along both dimensions, biases are small as long as noise levels are not too high. Overall these results make us confident that our estimation procedure works well.

By comparing the left and right panels of Figure 8, we can also say something about how detrimental noise in information requests is as opposed to noise in action choices

for recovering the true parameters. This comparison shows that noise in information requests is more likely to lead to biased estimates. In fact, action choices can be complete noise ($\varepsilon = 1$), but as long as information requests are accurate, the bias will remain below 15 percentage points. By contrast, if information requests are pure noise ($\theta_Z = 1$), then the fact that there is little noise in action choices does not help to contain the bias. In this case, the frequency of reinforcement learning is severely overestimated, a problem pointed out by Wilcox (2006). These results highlight the importance of incorporating good quality data on information requests in the analysis.

6.2 *Alternative learning rules*

In this section, we report results from estimating our model (3) with different variations of belief learning. Under all these variations, participants form beliefs based on a fixed number of past periods. We consider six alternative specifications, where players form beliefs based on choices of their opponents in the last 3, 6, 9, 12, 15, and 20 past periods to construct their beliefs. Note that the last variation corresponds to standard fictitious play learning in our context, since our game lasts only 20 periods. Myopic best responders, by contrast, base their decisions on the last period only. Denote by FP_s the variation under which participants form beliefs based on the last s periods. Hence, under this terminology, the myopic best-response rule is denoted by FP_1, and fictitious play corresponds to FP_{20}. We compare these alternatives with the benchmark model and rank them according to their log-likelihood values.

In all treatments, the best-performing model is the benchmark from Section 5.1 with MBR (i.e., FP_1). However, the increment in the log-likelihood value in the benchmark model with respect to the second best-performing model is very small (lower than 1% in all cases). In N-1 there is virtually no difference between the benchmark model and the model with FP_3, and the estimated parameters are remarkably similar. In the other two treatments, the model including FP_6 outperforms the other alternative models and the estimated frequency types are again very similar to the benchmark model containing MBR. In all cases FP_{20} is among the last in the ranking. These results show that including fictitious play (or variants of it) instead of myopic best-response learning does not significantly alter any of the results. They also show that belief-based models focused on few past periods tend to explain data better than those based on many periods.

6.3 *Compliance with occurrence*

In this section, we discuss three variations on our assumption of compliance with occurrence.

Easier compliance Our first variation is more permissive on how often participants should request the minimal information required by each rule so as to classify as compliant. This could be important, if participants consult information less frequently, for example, after convergence (Section 3). Under the first variation, we then assume that a participant has the information she needs to identify the action choice corresponding to her type if she requested the minimal information set *at least once in the preceding four periods*. The estimates are in line with the main results reported in Section 4.2. In N-1

and N-2, we have evidence in favor of RL and MBR; their estimated population shares are about the same as in the benchmark model in N-1, while in N-2, $\widehat{p}_{\mathrm{RL}}$ is higher compared to our benchmark model. In N-3, we now have evidence in favor of MBR and FL. In all cases the estimated θs and εs are well behaved (Table 15 in Appendix B.5).

Knowledge about network structure The second variation focuses on observations where a participant has not yet requested information about the network structure and, hence, cannot (by design) request information about action choices and payoffs of these neighbors. This is the case for less than 10% of our observations. To evaluate extent to which this affects the results, we then classify all observations where this is the case as compliant with all rules. The estimated frequencies are unchanged for N-1 and N-2 (compared to Table 4). The same is true for N-3, where all participants end up classified as MBR learners. The rule surviving prior to the last step of elimination is now reinforcement learning rather than forward-looking learning as in Table 4 (Table 17 in Appendix B.5).

Number of compliance categories Third, we analyze how our findings are to the number of compliance categories. Instead of two, we consider three compliance categories under this variation. For each subject i and learning type $k \in \{1, 2, \ldots, K\}$, we compute the percentage of times subject i asked for the minimum information required to learn rule k and sort these percentages into three categories: (i) Z, 0 compliance with occurrence; (ii) M, 1%–49% compliance with occurrence; (iii) H, 50%–100% compliance with occurrence. We then estimate a model similar to (3) with $\theta_{kZ} + \theta_{kM} + \theta_{kH} = 1$ for each k.

The results generally confirm our estimates in Section 4.2: RL and MBR are selected in treatments N-1 and N-2, and only MBR is selected in N-3 (Table 16 in Appendix B.5). Why do we prefer the two-level compliance model (3) in Section 4.2 to this one? Notice that in all treatments and for all learning types in Table 16, at least one compliance level (θ_{kj}) is estimated as exactly 0. This indicates that the true number of compliance levels is lower than 3 and estimating the three-compliance variation may result in identification problems, since (if $\theta_{kM} = 0$) it is possible to find a set of parameters Ω such that all $(p, \theta, \varepsilon) \in \Omega$ generate the same distribution $(\widehat{p}, \widehat{\theta}, \widehat{\varepsilon})$ as in Table 16.

6.4 *Alternative assumptions on the data-generating process*

Poisson distribution In this subsection, we evaluate some alternative assumptions on the data-generating process. First, we reestimate the model assuming that the data-generating process (information requests and choices) follows a Poisson distribution. Let I_k^i denote the number of periods in which subject i searches information consistent with learning type k during the experiment and let x_k^i denote the number of periods in which subject i makes a decision consistent with learning rule k. We assume that the variables I_k^i and x_k^i follow a Poisson distribution with means μ_k and λ_k, respectively. Note that we again assume type-dependent parameters, which take into account that the difficulty in processing information may vary across learning rules. Again, in N-1 and N-2, the population is best described by a mix of reinforcement and myopic best-response learners, while in N-3, myopic best-response and forward-looking learning describe the population best (Table 14 in Appendix B.4).

Autocorrelation It is well known that it can be important to explicitly account for the panel structure of data when estimating learning models Frechette (2009). We hence study an alternative process where we allow for autocorrelation of information requests. We model autocorrelation as a one unit recall Markov process and show that there is some evidence for autocorrelation, especially in early periods (1–5) and for own payoff requests, but not for requests in later periods and for information associated with best-response learning. Despite there being some evidence for autocorrelation (especially for RL and early periods), the estimates are roughly similar to those reported in Tables 4 and 5. In fact, for N-1, the estimates are exactly identical and they are nearly identical for M-1 (compared to the case without autocorrelation). For N-2, N-3, and M-3, the share attributed to reinforcement learning is higher with autocorrelation, and for M-2, it is lower compared to Tables 4 and 5. In all cases, the two rules selected are reinforcement and myopic best-response learning as in the case without autocorrelation (Tables 12 and 13 in Appendix B.3).

6.5 *Coordination game*

So far all of our results were based on anti-coordination games. This raises the question regarding the extent to which the results could be game-specific. One might conjecture, for instance, that imitation learning might be more prominent in coordination games where neighbors have incentives to choose the same rather than different actions. Our last result in this section refers to treatments conducted using a coordination rather than an anti-coordination game to get a better sense of the extent to which the results are game-specific. In three treatments, participants played the coordination game shown in Figure 9 on our networks with intermediate information, that is, as M treatments. The bilateral one-shot game has four pure strategy Nash equilibria on the diagonal (i.e., (A, A), (B, B), (C, C), and (D, D)). Strategy (A, A) is efficient. Choosing action D has no risk since it guarantees a payoff of 20. As such, D is also the maxmin choice. Action B, however, maximizes payoffs against a uniform opponent and is in that sense risk-dominant.

	A	B	C	D
A	60, 60	10, 40	0, 20	0, 20
B	40, 10	40, 40	10, 10	10, 20
C	20, 0	10, 10	30, 30	20, 20
D	20, 20	20, 20	20, 20	20, 20

Coordination Game

FIGURE 9. The (bilateral) coordination game used in the experiment.

In all networks, reinforcement learning and myopic best-response learning are the two surviving rules. Despite the fact that imitation seems much more intuitive in the coordination game, there is again no evidence of imitation learning. In contrast to the anti-coordination treatments, in the last stage of the algorithm, MBR is now very imprecisely estimated with a high θ_Z. One possible reason could be that participants converge faster to equilibrium in the coordination game and request little information afterward. Indeed, we do see this in the data. The percentage of successful coordination is 90% in M-Co-1, 87% in M-Co-2, and 88% in M-Co-3 across all periods. Since many participants will stop requesting information after the network has been coordinated for a few periods, identification will be harder after convergence. If we estimate the coordination game for the first 10 periods only, where there is still somewhat more miscoordination, we find evidence for only reinforcement learning in M-Co-1, evidence for 49% of RL ($\theta_Z = 0.21$) and 51% of MBR ($\theta_Z = 0.78$) in M-Co-2, and 45% of RL ($\theta_Z = 0.14$) and 55% of MBR ($\theta_Z = 0.84$) in M-Co-3 (Table 25 in Appendix D). Hence, even in this case estimates are still quite imprecise. In sum, these results suggest that our findings are not specific to anti-coordination games. They further underline the importance of choosing a setting where enough off equilibrium choices can be observed, as too quick convergence can lead to imprecise estimates.

7. Concluding remarks

We use maximum-likelihood methods to estimate learning types in network games. Our estimates are based on knowledge about both which actions participants choose and which information they request so as to make their choice. The latter turns out to be crucial, as estimates that disregard information requests display substantial biases. We also find that network position affects how people learn. In particular, those people with fewer network neighbors tend to resort to more complex rules. Finally, we find that, while there is substantial heterogeneity in the way people learn in our data, most can be classified as either reinforcement learners or belief learners. Future research is needed to explore the question of heterogeneity and context stability across other dimensions, and within rather than between subjects. Finally, it would be interesting to see how personality characteristics lead people to adopt one or the other learning type as in Gill and Prowse (2016).

Appendix A: Detailed analysis Nash equilibrium

Table 8 below lists the strict Nash equilibria of the one-shot network game. The entries are vectors $(a_1, \ldots, a_8)$ that show the action choices of players $1, \ldots, 8$ as labelled in Section 2.2. The Nash equilibria marked in bold type are also Nash equilibria in every pairwise interaction between first-order neighbors viewed in isolation. This is not true for the other Nash equilibria.

There are also many nonstrict and, in particular, also mixed equilibria in these games, even though the game with only one neighbor (the bilateral game) has only pure strategy equilibria. We focus predominantly on strict Nash equilibria, since the set of

TABLE 8. Strict Nash equilibria.

Nash Equilibria		
Network 1	Network 2	Network 3
$(\boldsymbol{A},\boldsymbol{B},A,\boldsymbol{B},A,\boldsymbol{B},A,\boldsymbol{B})$	$(\boldsymbol{A},\boldsymbol{B},A,\boldsymbol{B},\boldsymbol{B},A,A,A)$	$(\boldsymbol{A},\boldsymbol{B},A,\boldsymbol{B},A,A,A,A)$
$(\boldsymbol{B},A,\boldsymbol{B},A,\boldsymbol{B},A,\boldsymbol{B},A)$	$(\boldsymbol{B},A,\boldsymbol{B},A,A,\boldsymbol{B},\boldsymbol{B},\boldsymbol{B})$	$(\boldsymbol{B},A,\boldsymbol{B},A,\boldsymbol{B},\boldsymbol{B},\boldsymbol{B},\boldsymbol{B})$
$(\boldsymbol{C},\boldsymbol{D},\boldsymbol{C},\boldsymbol{D},\boldsymbol{C},\boldsymbol{D},\boldsymbol{C},\boldsymbol{D})$	$(\boldsymbol{C},\boldsymbol{D},\boldsymbol{C},\boldsymbol{D},\boldsymbol{D},\boldsymbol{C},\boldsymbol{C},\boldsymbol{C})$	$(\boldsymbol{C},\boldsymbol{D},\boldsymbol{C},\boldsymbol{D},\boldsymbol{C},\boldsymbol{C},\boldsymbol{C},\boldsymbol{C})$
$(\boldsymbol{D},\boldsymbol{C},\boldsymbol{D},\boldsymbol{C},\boldsymbol{D},\boldsymbol{C},\boldsymbol{D},\boldsymbol{C})$	$(\boldsymbol{D},\boldsymbol{C},\boldsymbol{D},\boldsymbol{C},\boldsymbol{C},\boldsymbol{D},\boldsymbol{D},\boldsymbol{D})$	$(\boldsymbol{D},\boldsymbol{C},\boldsymbol{D},\boldsymbol{C},\boldsymbol{D},\boldsymbol{D},\boldsymbol{D},\boldsymbol{D})$
(D,D,C,D,C,D,D,C)	(C,D,D,D,C,D,C,C)	(D,C,D,D,C,C,C,C)
(D,C,D,C,D,D,C,D)	(D,C,D,D,C,D,C,C)	(C,D,D,C,D,D,D,D)
(C,D,C,D,D,C,D,D)	(D,C,D,D,D,C,C,C)	(A,B,C,A,B,B,B,B)
(D,C,D,D,C,D,D,C)	(C,D,D,C,C,D,D,D)	(D,C,D,B,A,A,A,A)
(C,D,D,C,D,D,C,D)	(A,B,C,D,D,C,C,C)	(C,D,C,A,B,B,B,B)
(D,D,C,D,D,C,D,C)		(B,A,B,C,D,D,D,D)
(D,C,D,D,C,D,C,D)		
(C,D,D,C,D,C,D,D)		

Note: The format is $(a_1,\ldots,a_8)$, where a_i, $i=1,\ldots,8$ is the action of player i.

strict Nash equilibria coincides with the set of asymptotically stable outcomes under the multipopulation replicator dynamics. The replicator dynamics in turn has been shown to approximate many well known learning models, including reinforcement, fictitious play, and variants of imitation learning (see, e.g., Hopkins (2002)).

Table 9 shows the percentage of successfully coordinated networks in the last five periods (on any one-shot Nash equilibrium). Note that coordinating a network of eight players is difficult and the probability that a network would be coordinated by chance if all players choose actions uniformly at random is ≈0.00018 for Network 1 and ≈0.00015 for Networks 2 and 3. The table shows that across all information conditions, coordination is best in Network 2 and worst in Network 3, where participants never manage to coordinate fully.

Is there more coordination to Nash equilibrium over time? Table 10 shows the results of a logit regression of a binary variable that indicates whether a network was in Nash equilibrium (NE) regressed on period $1,\ldots,20$ as well as a square polynomial of period in odd columns. For each network, we pool data across the three information conditions in this table (though the results look similar if we disaggregate). There is no regression for Network 3 because it is never coordinated in any of the treatments. The regression shows that there is more coordination over time in both networks. In Network 1, the

TABLE 9. Percentage of successful coordination on a strict Nash equilibrium in the last five rounds.

	Network 1	Network 2	Network 3
N treatments	0.12	0.17	0.00
M treatments	0.04	0.12	0.00
F treatments	0.13	0.46	0.00

TABLE 10. Convergence to Nash equilibrium: logit regressions of binary variable indicating whether network was in NE on period and square term.

	Network 1		Network 2	
Variables	(1)	(2)	(3)	(4)
Period	1.393***	0.227***	0.154	0.213***
	(0.463)	(0.037)	(0.113)	(0.047)
Period × period	−0.040**		0.002	
	(0.017)		(0.005)	
Constant	−14.09***	−6.18***	−5.05***	−5.38***
	(2.86)	(0.97)	(0.55)	(1.01)
Observations	2080	2080	2240	2240

Note: Robust standard are given in errors in parentheses. ***, $p < 0.01$; **, $p < 0.05$; *, $p < 0.1$.

square term is negative and statistically significant, indicating that learning slows down in later periods, while in Network 2, the square term is close to zero and not statistically significant.

Table 11 shows the distribution of choices in the last 10 periods. Actions C and D are most frequently chosen, indicating that players in all networks and treatments attempt to coordinate on equilibria involving these actions.

APPENDIX B: ADDITIONAL BACKGROUND AND RESULTS

In this appendix, we collect additional results. Appendix B.1 describes the algorithms behind each learning rule. In Appendix B.2, we compute the correlation coefficient between compliance and action errors. In Appendix B.3, we study a process with autocorrelation. In Appendix B.4, we study a Poisson process. Appendix B.5 collects a variety of robustness checks on the estimates from the N treatments. Finally, in Appendix B.6, we discuss the simulation results in more detail.

TABLE 11. Distribution of choices in the last 10 periods.

	N Treatments			M Treatments		
	Network 1	Network 2	Network 3	Network 1	Network 2	Network 3
A	0.04	0.05	0.06	0.06	0.07	0.09
B	0.08	0.06	0.07	0.10	0.18	0.13
C	0.36	0.43	0.35	0.32	0.26	0.36
D	0.52	0.46	0.52	0.53	0.49	0.41

	F Treatments			
	Network 1	Network 2	Network 3	Bilateral
A	0.05	0.00	0.06	0.09
B	0.13	0.03	0.06	0.25
C	0.33	0.46	0.37	0.25
D	0.49	0.51	0.51	0.38

B.1 *Algorithms learning rules*

We present the algorithms that correspond to each learning rule. In each period, participants play a 4×4 game against their neighbors and the set of actions is $\{a, b, c, d\}$ for all players.

Under reinforcement learning, participants choose strategies that have performed well in the past with larger probabilities. More precisely, at period t each participant i has a propensity to play each of her four actions. Let $q_i(z, t)$ represent participant i's propensity at time t of playing action z for $z \in \{a, b, c, d\}$. These propensities are updated using the updating rule: $q_i(z, t+1) = q_i(z, t) + \phi$ if i played z in t and $q_i(z, t+1) = q_i(z, t)$ when i chose an action different from z in period t. Thus actions that achieved higher returns are reinforced and player i chooses action z at period $t+1$ if

$$q_i(z, t) \in \max\{q_i(a, t), q_i(b, t), q_i(c, t), q_i(d, t)\}. \tag{7}$$

In the theoretical literature, the choice rule is usually "less deterministic." Typically players are assumed to choose actions with a probability that is linearly proportional to propensities. The latter assumption means that a larger share of choices can be attributed to reinforcement learning because of the randomization. The second class of learning model we consider is imitation learning. Let N_i^R denote the set of Rth order neighbors of i, with $R \in \{1, 2, 3, 4\}$. Under payoff based imitation of order R, learners copy the most successful strategy among their Rth order neighbors. Let $\Delta_i^R(z, t)$ represent the average payoff of those players who played action z in period t within participant's i Rth order neighborhood. Then player i at time $t+1$ chooses action z if

$$\Delta_i^R(z, t) \in \max\{\Delta_i^R(a, t), \Delta_i^R(b, t), \Delta_i^R(c, t), \Delta_i^R(d, t)\}. \tag{8}$$

Under belief learning models, participants form beliefs on their opponents' strategies and choose an action that best responds to those beliefs. Let v_i be a vector whose elements $v_i(z, t)$ represent the weight participant i gives to her opponents playing each pure strategy z in period t. Therefore, player i believes her opponents in period t play action z with probability $p_i(z) = \frac{v_i(z,t)}{\sum_{s\in\{a,b,c,d\}} v_i(s,t)}$. Player i then chooses a pure strategy that is a best response to that probability distribution. Under fictitious play, agents consider the whole history of the game to compute these probability distributions. Let $Z_i(z, t)$ represent the set of player i's first-order neighbors who played pure strategy z at period t with cardinality $n_i(z, t)$. In the first period, fictitious players choose randomly. For all subsequent periods, players update their belief vector as $v_i(z, t) = v_i(z, t-1) + n_i(z, t)$. A myopic best responder only uses the most recent period to form her beliefs. Therefore, the updating rule for a myopic best responder is $v_i(z, t) = n_i(z, t)$.

Our last learning model is forward-looking learning in which players assume their first-order neighbors are myopic best responders and, consequently, choose a best response to their first-order neighbors' myopic best response. Let $q(i, t)$ be a vector containing a number of elements equal to the number of player i's first-order neighbors. Each element of $q(i, t)$ represents player i's first-order neighbors' myopic best response at period t. Thus player i chooses a pure strategy that is a best response to $q(i, t)$. For all learning rules, in case of tie, the player is assumed to choose randomly between the options that tie.

B.2 *Correlation between compliance and action errors*

We ask how errors are correlated. If we define by $\mathbf{I}_{kO}^{it}$ a random variable that equals 1 if participant i searches information consistent with k at period t and define by $\mathbf{X}_{kO}^{it}$ a random variable that equals 1 if participant i chooses an action consistent with k at period t (conditional on compliance O), then we can derive the following correlation coefficient.

From now on we consider a given learning rule k, a given subject i, and c possible action choices. Hereafter, we omit subscript k and superscripts i and t. We compute the correlation between $\mathbf{I}_{O(t)}$ and $\mathbf{X}_{O(t)}$.

The conditional probability of taking one of the decisions consistent with k at t is equal to

$$P(\mathbf{X}_{O(t)}=1|\mathbf{I}_{O(t)}=1)=\left(1-\frac{4-c}{4}\varepsilon_O\right)\frac{1}{c}, \tag{9}$$

and the probability of choosing a given action that is inconsistent with k is $P(\mathbf{X}_{O(t)}=0|\mathbf{I}_{O(t)}=1)=\frac{\varepsilon_O}{4}$.[25] The expected value and the variance of $\mathbf{I}_{O(t)}$ are hence equal to

$$E[\mathbf{I}_{O(t)}]=1-\theta_Z, \tag{10}$$

$$V[\mathbf{I}_{O(t)}]=\theta_Z(1-\theta_Z). \tag{11}$$

We now compute the conditional expectation of $\mathbf{X}_{O(t)}$,

$$\begin{aligned}E[\mathbf{X}_{O(t)}|\mathbf{I}_{O(t)}=s]&=\sum_{r=0}^{1} r\times P(\mathbf{X}_{O(t)}=r|\mathbf{I}_{O(t)}=s)\\&=P(\mathbf{X}_{O(t)}=1|\mathbf{I}_{O(t)}=s),\quad \text{with } s=\{0,1\},\end{aligned} \tag{12}$$

and the expected value of $\mathbf{X}_{O(t)}$ is

$$E[\mathbf{X}_{O(t)}]=\left(\left(1-\frac{4-c}{4}\varepsilon_O\right)\frac{1}{c}\right)(1-\theta_Z). \tag{13}$$

To abbreviate notation, let $\alpha_O=(1-\frac{4-c}{4}\varepsilon_O)\frac{1}{c}$. The unconditional variance of $\mathbf{X}_{O(t)}$ is equal to

$$\begin{aligned}V[\mathbf{X}_{O(t)}]&=E_{\mathbf{I}_{O(t)}}\big[V[\mathbf{X}_{O(t)}|\mathbf{I}_{O(t)}=s]\big]+V_{\mathbf{I}_{O(t)}}\big[E[\mathbf{X}_{O(t)}|\mathbf{I}_{O(t)}]\big]\\&=\alpha_O(1-\theta_Z)\left(\alpha_O\frac{\varepsilon_O}{4}+(1-\alpha_O)^2+\alpha_O\theta_Z\right).\end{aligned} \tag{14}$$

Note that if $\theta_Z=1$, then $V[\mathbf{X}_{O(t)}]=0$ since $\mathbf{X}_{O(t)}$ is always equal to 0; individuals cannot identify the corresponding action choices simply because they do not have the necessary information to do so.

We now compute the covariance between $\mathbf{I}_{O(t)}$ and $\mathbf{X}_{O(t)}$,

$$\mathrm{Cov}(\mathbf{I}_{O(t)},\mathbf{X}_{O(t)})=E[\mathbf{I}_{O(t)}\mathbf{X}_{O(t)}]-E[\mathbf{I}_{O(t)}]E[\mathbf{X}_{O(t)}]=\theta_Z(1-\theta_Z)\alpha_O>0, \tag{15}$$

[25] This is similar to CCB; see p. 1223.

and the correlation coefficient between information acquisition and action choices is equal to

$$\rho = \frac{\theta_Z(1-\theta_Z)\alpha_O}{\sqrt{V[\mathbf{I}_{O(t)}]}\sqrt{V[\mathbf{X}_{O(t)}]}} > 0. \tag{16}$$

This coefficient depends on the parameters θ_Z (probability of making a mistake when searching information consistent with rule k) and ε_O (the conditional probability of making a mistake with compliance O).

B.3 *Autocorrelation information requests*

We use a Markov chain over two states as a way to model the binary time series $\mathbf{I}_{kj}^{it}$ with $j \in \{Z, O\}$, $k \in \{1, 2, \ldots, K\}$, and for $t = \{1, 2, \ldots, T\}$. In particular, we assume that the probability that $\mathbf{I}_{kO}^{i;t+1}$ takes value 0 or 1 depends only on the value of the previous outcome $\mathbf{I}_{kO}^{it}$. The process starts at $t = 1$ with the probabilities[26]

$$\Pr\big(\mathbf{I}_{kZ}^{i1} = 0\big) = \Pr\big(\mathbf{I}_{kO}^{it} = 1\big) = 1 - \theta_{kZ},$$
$$\Pr\big(\mathbf{I}_{kZ}^{i1} = 1\big) = \Pr\big(\mathbf{I}_{kO}^{it} = 0\big) = \theta_{kZ}.$$

The transition matrix is equal to

$$\begin{bmatrix} \pi_{00}^k & 1-\pi_{00}^k \\ 1-\pi_{11}^k & \pi_{11}^k \end{bmatrix},$$

where $\pi_{00}^k = P(\mathbf{I}_{kO}^{i;t+1} = 0 | \mathbf{I}_{kO}^{it} = 0)$ and $\pi_{11}^k = P(\mathbf{I}_{kO}^{i;t+1} = 1 | \mathbf{I}_{kO}^{it} = 1)$.

The Markov structure implies that the probability of deviating from information search consistent with k at time $(t+1)$ equals

$$\theta_{kZ(t+1)} = (1-\theta_{kZ(t)})\big(1-\pi_{11}^k\big) + \theta_{kZ(t)}\pi_{00}^k.$$

After rearranging terms, we have

$$\theta_{kZ(t+1)} = \big(1-\pi_{11}^k\big)\frac{1-\Delta^t}{1-\Delta} + \Delta^t\theta_{kZ}, \tag{17}$$

with $\Delta = (\pi_{00}^k + \pi_{11}^k - 1)$.

The probability of requesting information consistent with k at $(t+1)$ is then

$$\theta_{kO(t+1)} = \pi_{11}^k\frac{1-\Delta^t}{1-\Delta^t} - \frac{\Delta^t\big(1-\Delta^{t-1}\big)}{1-\Delta^t} - \Delta^t\theta_{kZ}. \tag{18}$$

The log-likelihood function is

$$\log L(\Psi) = \sum_{i=1}^{N}\ln\left(\sum_{k=1}^{K}p_k\left(\prod_{j\in\{Z,O\}}\left(\prod_{t=1}^{T}\theta_{kjt}^{I_{kjt}^i}\right)\left(\frac{\varepsilon_{jk}}{4}\right)^{(I_{kj}^i - X_{kj}^i)}\prod_{c=1}^{4}\left(\left(1-\frac{4-c}{4}\varepsilon_{jk}\right)\frac{1}{c}\right)^{X_{kj}^{ic}}\right)\right),$$

[26] Recall that $\mathbf{I}_{kZ}^{it} = 1 - \mathbf{I}_{kO}^{it}$.

where now $\theta_{kj(t=1)} = \theta_{kZ}$ for $j = Z$ and $\theta_{kj(t=1)} = 1 - \theta_{kZ}$ for $j = O$; and $\theta_{kZ(t)}$ and $\theta_{kO(t)}$, for $t = \{2, 3, \ldots, T\}$ are given by expressions (17) and (18), respectively. The term Ψ is a vector with the parameters of interest: $(p_k, \theta_{kZ}, \pi^k_{00}, \pi^k_{11}, \varepsilon_{kZ}, \varepsilon_{kO})$ for $k = \{1, 2, \ldots, K\}$. We estimate $logL(\Psi)$ by applying the expectation maximization algorithm (see McLachlan and Peel (2000)).

If there is no autocorrelation in the binary time series $D^{it}_{kj}(I)$, then we should observe that the probability θ_{kj} remains constant through time. Figure 10 illustrates the evolution of the estimated parameter $\theta_{kZ(t)}$ for $k = \{\text{RL}, \text{MBR}\}$ during the experiment.

For reinforcement learning, the figure shows that estimated $\theta_{\text{RL};Z}$ are monotonically increasing in N-1 and N-2 (less compliance over time), though by a small amount. In N-3 they are increasing until about period 10, after which there is near zero compliance.

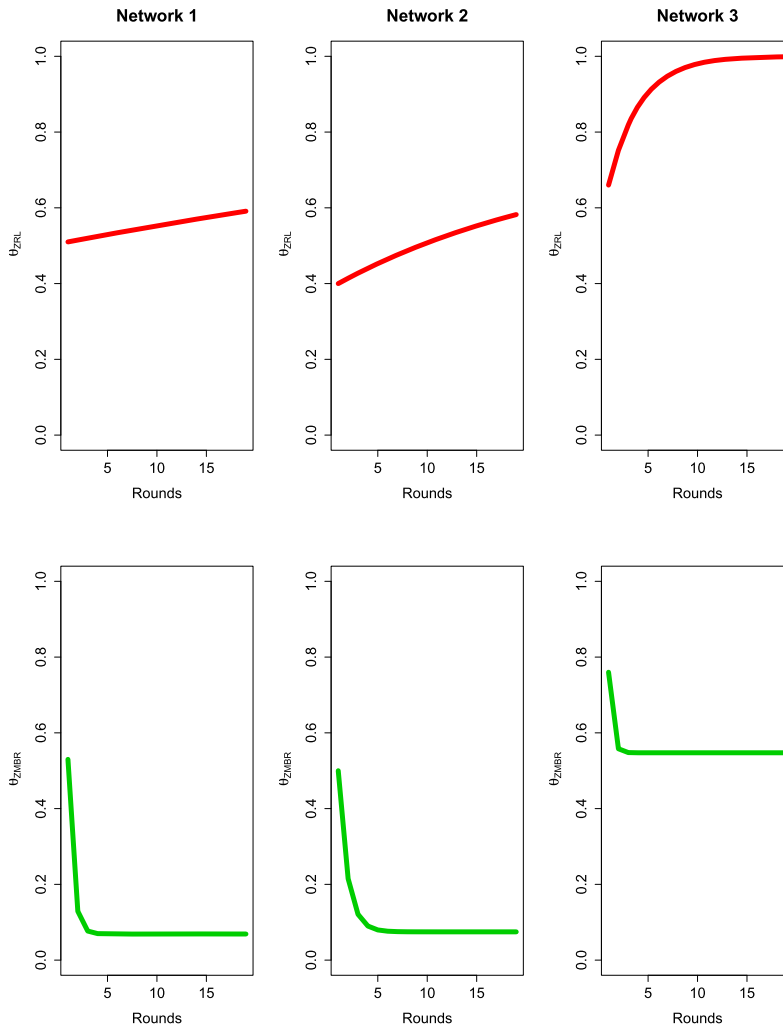


FIGURE 10. Estimated zero compliance probability θ_{kZ}. Top panels, reinforcement learning; bottom panels, myopic best-response learning (N treatments).

TABLE 12. The N treatments with autocorrelation of order 1 in information requests.

	N Treatments					
	Network 1		Network 2		Network 3	
	RL	MB	RL	MB	RL	MB
Pr. learning type	0.57***	0.43***	0.66***	0.34**	0.48***	0.52***
s.e.	(0.092)	(0.092)	(0.158)	(0.158)	(0.109)	(0.109)
θ_Z	0.51***	0.53***	0.4*	0.5***	0.66***	0.76***
s.e.	(0.179)	(0.167)	(0.205)	(0.174)	(0.127)	(0.117)
π_{00}	1***	0.19	0.99***	0.38	1***	0.57***
s.e.	(0.282)	(0.312)	(0.306)	(0.31)	(0.088)	(0.22)
π_{11}	0.99***	0.94***	0.97***	0.95***	0.73**	0.48*
s.e.	(0.316)	(0.183)	(0.31)	(0.179)	(0.289)	(0.282)
ε_Z	1***	1***	1***	1***	1***	1***
s.e.	(0.057)	(0.086)	(0.057)	(0.037)	(0.077)	(0.077)
ε_O	0.51***	0.45***	0.51***	0.4***	0.79***	0.58***
s.e.	(0.101)	(0.068)	(0.096)	(0.044)	(0.259)	(0.089)
$\overline{\theta}_Z$ (average)	0.55	0.1	0.51	0.1	0.93	0.56
$\overline{\theta}_O$ (average)	0.45	0.9	0.49	0.9	0.07	0.44
Observations	760		1064		760	
ln LF	−1313.48		−1854.79		−1383.45	

Note: ***, significant at the 1% level; **, significant at the 5% level; *, significant at the 10% level.

For myopic best-response learning, the estimated $\theta_{\text{MBR};Z}$ are quickly decreasing during the first 2–3 rounds and are constant afterward. Overall, the evidence seems to suggest weak autocorrelation. The patterns are very similar across networks, though the levels differ somewhat.

Tables 12 and 13 show results when allowing for autocorrelation for both the N and the M treatments. It can be seen that despite there being some evidence for autocorrelation (especially for RL and early periods), the estimates are roughly similar to those reported in Tables 4 and 5. In fact, for N-1, the estimates are exactly identical and they are nearly identical for M-1 (compared to the case without autocorrelation). For N-2, N-3, and M-3, the share attributed to reinforcement learning is higher with autocorrelation and for M-2 it is lower compared to Tables 4 and 5.

B.4 *Poisson process*

To assess the extent to which our results depend on the distributional assumptions behind the likelihood function, in this section we reestimate the model assuming that the data-generating process (information requests and choices) follows a Poisson distribution.

Let I_k^i denote the number of periods in which subject i searches information consistent with learning type k during the experiment and let x_k^i denotes the number of periods in which subject i makes a decision consistent with learning rule k. We assume that the variables I_k^i and x_k^i follow a Poisson distribution with means μ_k and λ_k, respectively. Note that we again assume type-dependent parameters, which takes into account that the difficulty in processing information varies across learning rules.

TABLE 13. The M treatments with autocorrelation of order 1 in information requests.

	M Treatments					
	Network 1		Network 2		Network 3	
	RL	MBR	RL	MBR	RL	MBR
p_k	0.5***	0.5***	0.28***	0.72***	0.22***	0.78***
s.e.	(0.073)	(0.074)	(0.08)	(0.09)	(0.062)	(0.08)
θ_Z	0.05	0.67***	0.1	0.58***	0	0.73***
s.e.	(0.106)	(0.164)	(0.136)	(0.141)	(0.128)	(0.126)
π_{00}	1***	0.99***	0	1***	0.81***	1***
s.e.	(0.316)	(0.084)	(0.33)	(0.085)	(0.300)	(0.080)
π_{11}	0.98***	0.76**	0.72***	0.85***	0.96***	0.88***
s.e.	(0.104)	(0.306)	(0.133)	(0.318)	(0.123)	(0.306)
ε_Z	1***	1***	1***	1***	1***	1***
s.e.	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
ε_O	0.58***	0.49***	0.58***	0.51***	0.8***	0.61***
s.e.	(0.072)	(0.136)	(0.121)	(0.116)	(0.109)	(0.118)
$\overline{\theta}_Z$	0.2	0.9	0.21	0.86	0.15	0.89
$\overline{\theta}_O$	0.8	0.1	0.79	0.14	0.85	0.11
Observations	760		608		608	
ln LF	−1295.69		−1060.22		−1047.2	

Note: ***, significant at the 1% level; **, significant at the 5% level; *, significant at the 10% level.

The probability of observing sample (I_k^i, x_k^i) is

$$L_k^i(\mu_k, \lambda_k | I_k^i, x_k^i) = \frac{e^{-\mu_k} \mu_k^{I_k^i}}{I_k^i!} \frac{e^{-\lambda_k} \lambda_k^{x_k^i}}{x_k^i!},$$

and the log-likelihood function is

$$\ln \mathrm{LF}(p, \mu, \lambda | I, x) = \sum_{i=1}^{N} \ln \left(\sum_{k=1}^{K} p_k \frac{e^{-\mu_k} \mu_k^{I_k^i}}{I_k^i!} \frac{e^{-\lambda_k} \lambda_k^{x_k^i}}{x_k^i!} \right). \tag{19}$$

We apply a selection algorithm similar to that of Section 5. If a learning rule has an estimated μ_k higher than a threshold $\overline{\mu}$, we remove it from the set of rules considered. Table 14 shows the estimation results.

B.5 *Robustness estimates N treatments*

This subsection collects a number of tables with robustness estimates for the N treatments. Tables 15 and 16 show estimates under alternative assumptions on occurrence. Specifically in Table 15, we assume that a subject has the information she needs to identify the action choice corresponding to her type if she has asked for the minimal information set at least once in the preceding four periods (see Section 6.3). For the estimates reported in Table 16, we allow for three rather than two compliance levels (see Section 6.3).

TABLE 14. Poisson distribution: estimation based on information request and observed behavior.

	Endogenous Information Treatments					
	N-1		N-2		N-3	
	RL	MBR	RL	MBR	MBR	FL
p_k	0.58***	0.42***	0.52***	0.48***	0.30***	0.70***
(s.e.)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)
μ_k	1.92	7***	2.15	6.34***	12.76***	0.21
(s.e.)	(3.09)	(2.95)	(2.48)	(2.24)	(2.18)	(0.27)
λ_k	1.02	4.41***	1.15	3.99***	5.68***	0
(s.e.)	(1.83)	(1.95)	(1.54)	(1.58)	(1.85)	(0.14)
ln LF	−255		−339		−114	
Individuals	40		56		40	
Observations	760		1064		760	

Note: ***, significant at the 1% level; **, significant at the 5% level; *, significant at the 10% level. Standard errors are computed by bootstrapping methods with 500 replications (Efron and Tibshirani (1994)).

We also conduct a robustness check to deal with participants in the N treatments who do not request information about labels of first-order neighbors (and, hence, cannot by design request information about their actions or payoffs). Remember that those are relatively few observations. In period 1 already more than 70% of participants request information about first-order neighbors and ≈90% do so at some point during the experiment.

Table 17 shows estimates where these observations are classified automatically as compliant for all rules. The estimated frequencies are unchanged for N-1 and N-2 (com-

TABLE 15. Estimation results under relaxed assumptions on occurrence.

	Treatments					
	N-1		N-2		N-3	
Parameters	RL	MBR	RL	MBR	MBR	FL
p_k	0.5***	0.5***	0.49***	0.51***	0.43***	0.57***
(s.e.)	(0.087)	(0.087)	(0.076)	(0.076)	(0.091)	(0.090)
θ_Z	0.04*	0.11**	0.11***	0.02	0.21***	0.04
(s.e.)	(0.023)	(0.049)	(0.014)	(0.045)	(0.009)	(0.045)
θ_O	0.96***	0.89***	0.89***	0.98***	0.79***	0.96***
(s.e.)	(0.023)	(0.049)	(0.014)	(0.045)	(0.009)	(0.045)
ε_Z	1***	1***	1***	1***	1***	1***
(s.e.)	(0.045)	(0.045)	(0.045)	(0.045)	(0.051)	(0.045)
ε_O	0.63***	0.44	0.44***	0.51*	0.41***	0.73**
(s.e.)	(0.068)	(0.31)	(0.046)	(0.287)	(0.018)	(0.297)
ln LF	−1071		−1407		−1173	
Individuals	40		56		40	
Observations	760		1064		760	

TABLE 16. Estimation results with three compliance levels.

	Treatments					
	N-1		N-2		N-3	
Parameters	RL	MBR	RL	MBR	RL	MBR
p_k	0.57***	0.43***	0.59***	0.41***	0.68***	0.32**
(s.e.)	(0.109)	(0.109)	(0.12)	(0.12)	(0.139)	(0.139)
θ_{kZ}	0.55*	0.1	0.48	0.14	**0.9****	0.65***
(s.e.)	(0.307)	(0.260)	(0.292)	(0.253)	(0.142)	(0.225)
θ_{kM}	0.06	0	0.09*	0	0.1*	0.11*
(s.e.)	(0.039)	(0.032)	(0.048)	(0.059)	(0.052)	(0.061)
θ_{kH}	0.39	0.9***	0.43	0.85*	0	0.23
(s.e.)	(0.373)	(0.316)	(0.329)	(0.306)	(0.1967)	(0.313)
ε_{kZ}	1***	1***	1***	1***	1***	1***
(s.e.)	(0.046)	(0.045)	(0.045)	(0.045)	(0.045)	(0.064)
ε_{kM}	0.52**	0.9***	0.5***	0.87***	0.58***	0.74***
(s.e.)	(0.202)	(0.263)	(0.171)	(0.248)	(0.178)	(0.229)
ε_{kH}	0.51***	0.46***	0.5***	0.41***	0.47*	0.57***
(s.e.)	(0.123)	(0.136)	(0.118)	(0.134)	(0.240)	(0.15007)
ln LF	−1406		−2019		−1474	
Individuals	40		56		40	
Observations	760		1064		760	

Note: ***, significant at the 1% level; **, significant at the 5% level; *, significance at the 10% level. Standard errors computed by bootstrapping method with 500 replications (Efron and Tibshirani (1994)).

TABLE 17. Main estimation results using *both* information requests and action choices: N treatments.

	Treatments					
	M-1		M-2		M-3	
Parameters	RL	MBR	RL	MBR	RL	MBR
p_k	0.57***	0.43***	0.24	0.76***	0.47***	0.53***
(s.e.)	(0.100)	(0.100)	(0.167)	(0.167)	(0.118)	(0.118)
θ_Z	0.56*	0.10	0.05	0.47**	0.93***	0.60**
(s.e.)	(0.307)	(0.267)	(0.283)	(0.208)	(0.200)	(0.298)
θ_O	0.44	0.90**	0.95***	0.53**	0.07	0.40
(s.e.)	(0.307)	(0.267)	(0.283)	(0.208)	(0.200)	(0.298)
ε_Z	1***	1***	1***	1***	1***	1***
(s.e.)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
ε_O	0.51***	0.45***	0.48***	0.43***	0.49***	0.59***
(s.e.)	(0.088)	(0.113)	(0.07)	(0.068)	(0.186)	(0.148)
ln LF	−1325		−1861		−1398	
Individuals	40		56		40	
Observations	800		1120		800	

Note: All observations where a participant does not know anything about the network structure are automatically classified as compliant. ***, significant at the 1% level; **, significant at the 5% level; *, significant at the 10% level. Standard errors are computed using a bootstrapping method with 500 replications (Efron and Tibshirani (1994)).

pared to Table 4). The same is true for N-3, where all participants end up classified as MBR learners. The rule surviving prior to the last step of elimination is now reinforcement learning rather than forward-looking learning as in Table 4.

B.6 *Simulations*

This subsection contains additional information, tables, and results regarding the simulations reported on in Section 6.1. In addition to the simulations described in the main text, we also ran simulations where we simultaneously increase noise in information requests and noise in action choices. We use the same type distributions as in Exercise 1 in Section 6.1. For each parameter combination, we ran 500 replications. We first consider three different parameter constellations as follows:

1. *Full Compliance* (FC). Participants search their respective information set with probability 1 and make no mistake in choosing the corresponding action choice.

2. *High Compliance* (HC). Participants search their corresponding information request with high probability and make mistakes with low probability.

3. *Low Compliance* (LC). Participants have low compliance with occurrence and make mistakes with high probability.

Table 18 reports the results. Our selection algorithm always correctly identifies the learning rules present in the population. The shares of PBI and FL are virtually zero in the two-type case; the same holds for PBI in Exercise 2. Moreover, we find only small biases (less than 1%) in the estimated frequencies in both FC and HC. Hence, if people are relatively precise both making their choices and looking up the information, our estimation procedure succeeds in recovering the population composition in all cases. As participants become less precise in their information requests and decisions (LC), we still recover which types are present in the population, but there are biases in the estimated values. In the two-type case, the mechanism overestimates the presence of MBR by 11% and underestimates the share of RL by 16% (4% and 1% of the biases correspond to PBI and FL, respectively, though they are not significantly different from zero). Similar conclusions hold for Exercise 2.

We then increase noise simultaneously in steps of 0.1. Figure 11 shows the distribution of estimated parameters $\widehat{p}_{\mathrm{RL}}$ across the 500 runs for Exercise 1. The leftmost panel shows the case where $(\theta_Z, \varepsilon_O) = (0.15, 0.1)$. Estimated parameters are concentrated around the true value of 0.575, the standard deviation is 0.01, and the mean bias is 0. Estimates at these noise levels are, hence, extremely accurate. As we increase noise, estimates tend toward uniform distribution, which means that since the "true" value of p_{RL} is above 0.5, the estimates will be downward biased. The middle panel shows the case $(\theta_Z, \varepsilon_O) = (0.55, 0.55)$, where the mean bias is -0.17, that is, most simulations converge to a case where the parameter is underestimated. Only around 5% of simulations converge to the true value. Further increasing the amount of noise does not substantially worsen the bias as the rightmost panel illustrates, which shows the case $(\theta_Z, \varepsilon_O) = (0.75, 0.70)$.

TABLE 18. Monte Carlo simulations.

	Exercise 1				Exercise 2			
	RL	PBI	MBR	FL	RL	PBI	MBR	FL
True p_k	0.57	0.00	0.43	0.00	0.15	0.00	0.40	0.45
FC								
$\widehat{p}_k$	0.562	0.014	0.423	0.001	0.150	0.000	0.400	0.450
(s.e.)	(0.09)	(0.04)	(0.09)	(0.004)	(0.001)	(0.000)	(0.002)	(0.001)
Bias	−0.0077	0.014	−0.007	0.0008	−0.001	0.000	0.000	0.000
HC								
$\widehat{p}_k$	0.57	0	0.425	0	0.1500	0.0000	0.4000	0.4500
(s.e.)	(0.0049)	(0)	(0)	(0)	(0.0000)	(0.0000)	(0.0005)	(0.0004)
Bias	0.005	0	−0.005	0	0.0001	0.0000	0.0000	0.0000
LC								
$\widehat{p}_k$	0.404	0.042	0.542	0.012	0.271	0.05	0.323	0.355
(s.e.)	(0.203)	(0.205)	(0.183)	(0.109)	(0.376)	(0.224)	(0.248)	(0.213)
Bias	−0.165	0.041	0.111	0.0119	0.121	0.050	−0.077	−0.095
Assumptions								
θ_{kZ}	0	0.15	0.55		0	0.15	0.55	
θ_{kO}	1	0.85	0.45		1	0.85	0.45	
ε_{kZ}	1	1	1		1	1	1	
ε_{kO}	0	0.1	0.55		0	0.1	0.55	

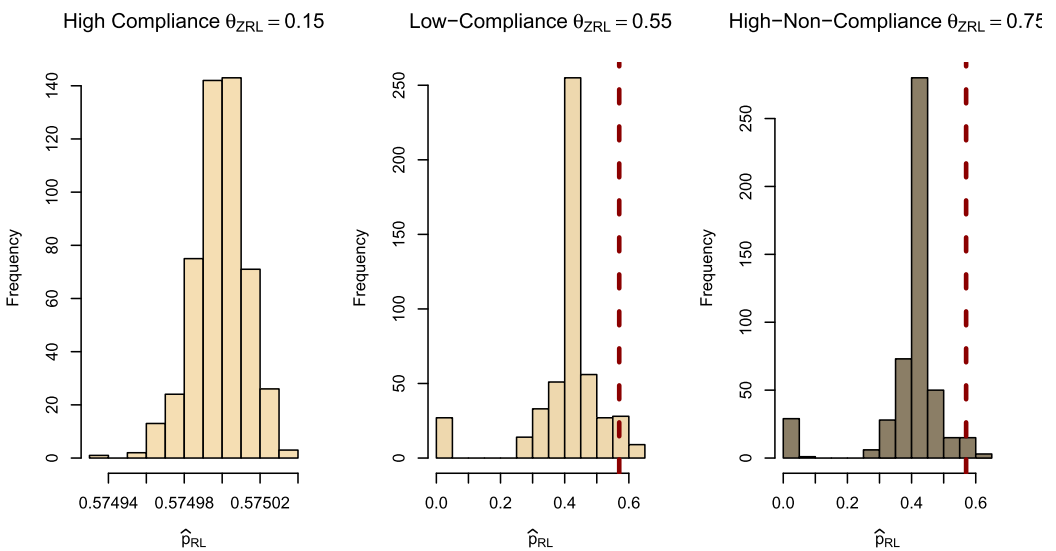
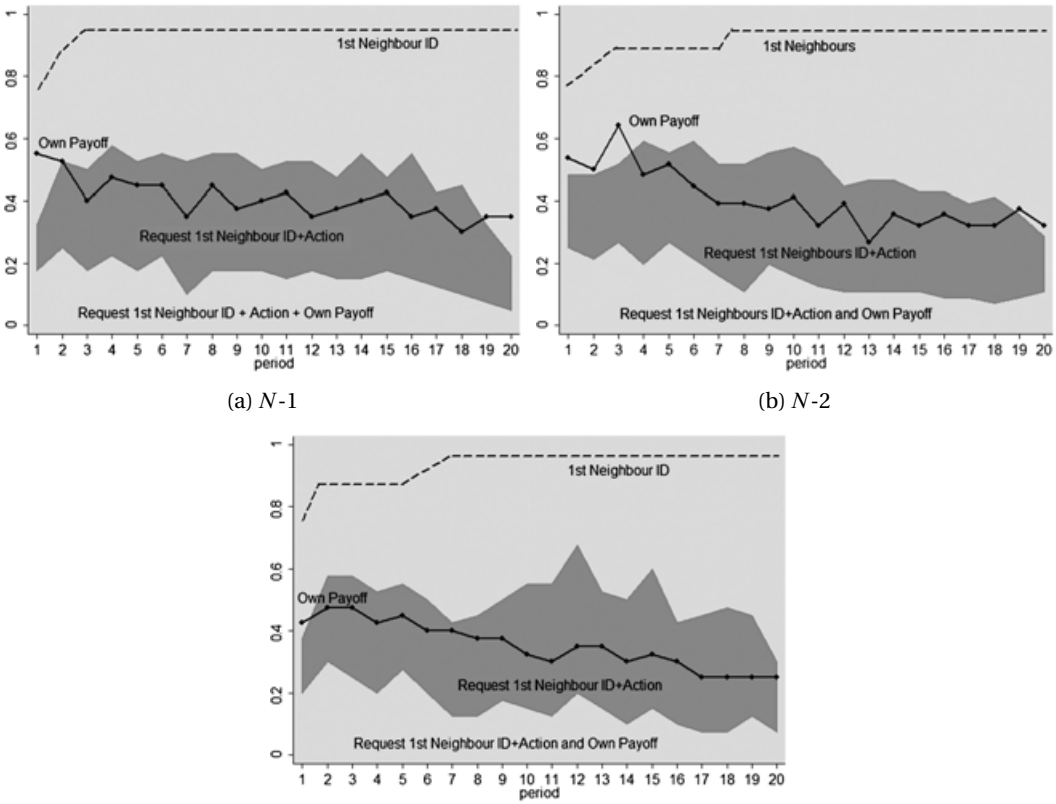


FIGURE 11. Distribution of estimated parameters $\widehat{p}_{\mathrm{RL}}$ across 500 runs of simulations of Exercise 1 (note the different scale on the x axis across panels).

Appendix C: Additional figures

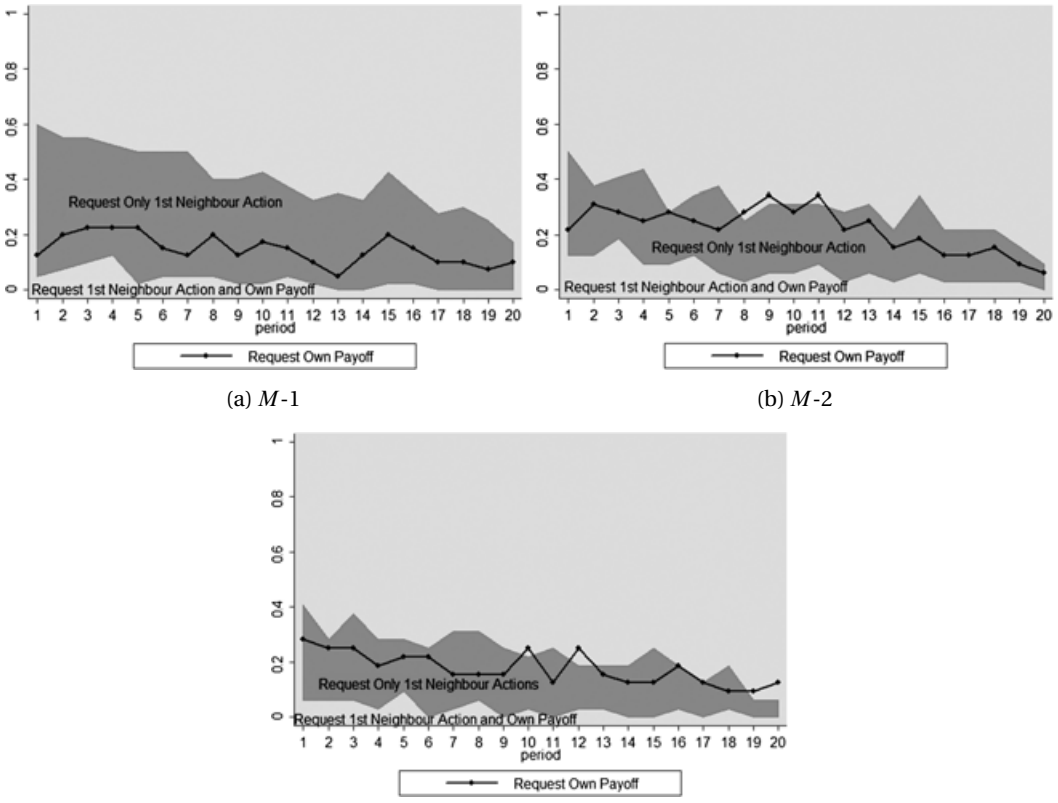
Figure 12 provides an overview of information requests over time in the N treatments. Figure 13 shows the analogous information for the M treatment. Figure 14 shows the fractions of participants who *both* request the minimal necessary information corresponding to a rule and choose as prescribed by that rule.



(a) N-1 (b) N-2

(c) N-3

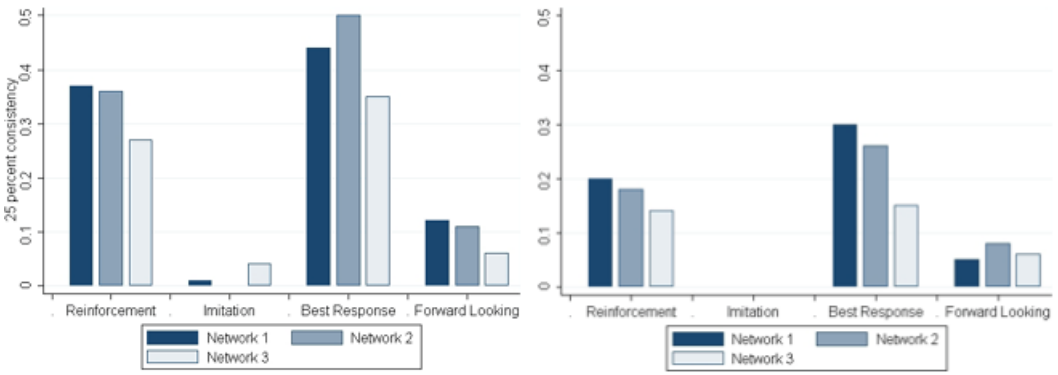
Figure 12. Share of participants (i) requesting information about all three: first-order neighbors identification (experimental label) + actions as well as own payoffs (bottom area), (ii) requesting only first-order neighbors identification and actions, but not payoffs (dark area), (iii) requesting own payoffs (black solid line), and (iv) requesting only own payoff (area between lower bound of dark area and black line). N treatments.



(a) M-1 (b) M-2

(c) M-3

FIGURE 13. Share of participants requesting information about all three: first-order neighbors actions as well as own payoffs (bottom area), requesting only first-order neighbors actions, but not payoffs (dark area), requesting own payoffs (black curve), and requesting only own payoff (area between lower bound of dark area and black curve). M treatments.



(a) At least 25% consistency (b) At least 50% consistency

FIGURE 14. Fraction of participants who request the minimal information set *and* play the action prescribed by the corresponding learning type more than 25% (panel (a)) or 50% (panel (b)) of periods.

TABLE 19. Separation between learning types on the basis of action choices.

	Treatments					
	N-1			F-1		
Learning Rules	RL	PBI	MBR	RL	PBI	MBR
PBI	11			11		
MBR	9	14		10	13	
FL	7	11	9	8	11	10
	N-2			F-2		
PBI	11			15		
MBR	9	14		8	16	
FL	8	13	8	7	14	7
	N-3			F-3		
PBI	11			11		
MBR	11	15		9	15	
FL	8	11	11	8	12	10

Note: Each cell contains the average number of periods in which the two corresponding learning types predict different choices for a participant (given the history of play in the experiment).

APPENDIX D: ADDITIONAL TABLES

Table 19 shows how often different rules predict different choices conditional on the histories in our experiment and Table 20 shows the minimal information required for each rule.

Table 21 shows the results separately for periods 1–10 and 11–20 for the N treatments. Results seem overall robust. The two surviving rules are always reinforcement learning and/or myopic best responses. In N-1, reinforcement learning has a share of 59% across periods 1–10 and 63% across periods 11–20, with the remainder being attributed to MBR. In N-2, reinforcement learning receives a share of 55% across periods 1–10 and 73% across periods 11–20, and in N-3, MBR is the unique surviving rule in both cases. Hence, in N-1 and N-3, estimates are very

TABLE 20. Minimal information required for each rule.

		Learning Type			
Info	Neighbor	RL	PBI	MBR	FL
Label	1		x	x	x
	2				x
Action	1		x	x	
	2				x
Payoff	Own	x			
	1		x		

Note: x indicates that a piece of information is required for the corresponding learning rule.

TABLE 21. Estimations separately for periods 1–10 and 11–20: N treatments.

	Treatment N-1				Treatment N-2				Treatment N-3			
	Periods 1 to 10		Periods 11 to 20		Periods 1 to 10		Periods 11 to 20		Periods 1 to 10		Periods 11 to 20	
	RL	MBR	RL	MBR	RL	MBR	RL	MBR	RL	MBR	RL	MBR
p_k	0.59***	0.41***	0.63***	0.37***	0.55***	0.45***	0.73***	0.27**	0.31***	0.69***	0.65***	0.35***
(s.e.)	(0.109)	(0.109)	(0.116)	(0.115)	(0.117)	(0.117)	(0.193)	(0.193)	(0.148)	(0.148)	(0.101)	(0.101)
θ_Z	0.48*	0.07	0.57*	0.04	0.41	0.11	0.62*	0.02	0.99***	0.55***	0.96***	0.62**
(s.e.)	(0.256)	(0.338)	(0.291)	(0.268)	(0.190)	(0.159)	(0.303)	(0.281)	(0.216)	(0.223)	(0.232)	(0.263)
θ_O	0.52**	0.93*	0.43*	0.96***	0.59***	0.89***	0.38	0.98***	0.01	0.45*	0.04	0.38
(s.e.)	(0.256)	(0.338)	(0.291)	(0.268)	(0.190)	(0.159)	(0.303)	(0.281)	(0.216)	(0.223)	(0.232)	(0.263)
ε_Z	1***	1***	1***	1***	1***	1***	1***	1***	1***	1***	1***	1***
(s.e.)	(0.045)	(0.044)	(0.071)	(0.059)	(0.045)	(0.045)	(0.063)	(0.057)	(0.045)	(0.045)	(0.045)	(0.045)
ε_O	0.69***	0.58***	0.3*	0.35***	0.61***	0.49***	0.32*	0.32***	1	0.68***	0	0.51***
(s.e.)	(0.125)	(0.154)	(0.141)	(0.119)	(0.062)	(0.069)	(0.138)	(0.093)	(0.296)	(0.174)	(0.157)	(0.218)
ln LF	−663.36		−581.75		−903.09		−833.1		−686.96		−617.02	
Individuals	40		40		56		56		40		40	
Observations	360		360		504		504		360		360	

TABLE 22. Participants with one network neighbor (1, 7, and 8 in N-2 and 1, 5, 6, 7, and 8 in N-3) versus participants with multiple network neighbors (1–8 in N-1, 2–6 in N-2, and 2, 3, and 4 in N-3).

	Group 1: One Network Neighbor				Group 2: Multiple Network Neighbors			
Parameters	RL	PBI	MBR	FL	RL	PBI	MBR	FL
p_k	0.54***		0.46***		0.61***		0.39***	
(s.e.)	(0.10)		(0.10)		(0.147)		(0.147)	
θ_Z	0.87***		0.74*		0.58*		0.11	
(s.e.)	(0.26)		(0.33)		(0.327)		(0.203)	
θ_O	0.13		0.26		0.42		0.89***	
(s.e.)	(0.26)		(0.33)		(0.327)		(0.203)	
ε_Z	1***		1***		1***		1***	
(s.e.)	(0.04)		(0.04)		(0.045)		(0.045)	
ε_O	0.63***		0.7***		0.5***		0.41***	
(s.e.)	(0.12)		(0.11)		(0.063)		(0.063)	
ln LF		−163				−2981		
Individuals		46				90		
Observations		874				1710		

Note: ***, significant at the 1% level; **, significant at rhe 5% level; *, significant at the 10% level. Standard errors are computed by bootstrapping methods with 500 replications (Efron and Tibshirani (1994)).

TABLE 23. Participants with one network neighbor (1, 7, and 8 in M-2 and 1, 5, 6, 7, and 8 in M-3) versus participants with multiple network neighbors (all players M-1, players 2, 3, 4, 5, 6 in M-2 and 2, 3, 4 in M-3).

	Group 1: One Network Neighbor				Group 2: Multiple Network Neighbors			
Parameters	RL	PBI	MBR	FL	RL	PBI	MBR	FL
p_k	0.23***		0.77***		0.44***		0.56***	
(s.e.)	(0.09)		(0.09)		(0.068)		(0.07)	
θ_Z	0.21		0.86***		0.21***		0.91***	
(s.e.)	(0.149)		(0.053)		(0.04)		(0.051)	
θ_O	0.79***		0.14***		0.79***		0.09*	
(s.e.)	(0.149)		(0.053)		(0.04)		(0.051)	
ε_Z	1***		1***		1***		1***	
(s.e.)	(0.045)		(0.045)		(0.045)		(0.045)	
ε_O	0.68***		0.64***		0.61***		0.44***	
(s.e.)	(0.155)		(0.115)		(0.058)		(0.101)	
ln LF		−1091				−2374		
Individuals		32				72		
Observations		640				1440		

Note: ***, significant at the 1% level; **, significant at the 5% level; *, significant at the 10% level. Standard errors are computed by bootstrapping methods with 500 replications (Efron and Tibshirani (1994)).

TABLE 24. Estimations based solely on observed behavior in F treaments.

	Treatment F-1			
	RL	PBI	MBR	FL
p_k	0.52**	0.10	0.34***	0.04
(s.e.)	(0.168)	(0.094)	(0.123)	(0.123)
ε_k	0.53**	1	0.37***	0
(s.e.)	(0.224)	(0.193)	(0.095)	(0.255)
ln LL		−489		
Individuals		24		
Observations		456		
	Treatment F-2			
p_k	0.12	0.21**	0.58***	0.08
(s.e.)	(0.093)	(0.093)	(0.117)	(0.065)
ε_k	0.58	0.68***	0.26***	0
(s.e.)	(0.304)	(0.095)	(0.062)	(0.286)
ln LL		−400		
Individuals		24		
Observations		456		
	Treatment F-3			
p_k	0.32**	0.04	0.34**	0.30**
(s.e.)	(0.124)	(0.062)	(0.144)	(0.118)
ε_k	0.34**	0	0.48***	0.57***
(s.e.)	(0.163)	(0.367)	(0.108)	(0.057)
ln LF		−467		
Individuals		24		
Observations		456		

Note: ***, significant at the 1% level; **, significant at the 5% level; *, significant at the 10% level. Standard errors are computed by bootstrapping methods with 500 replications (Efron and Tibshirani (1994)).

similar across the two blocks and also very similar to the estimates based on all 20 periods. In N-2, the estimates based on subperiods differ somewhat from the estimates using all periods attributing a higher share to RL. One possible reason for this difference seems to be that lots of noisy decisions are attributed to RL in this network, as indicated by relatively high values of $\theta_{\mathrm{RL};Z}$ in the estimations based on subperiods.

Table 22 shows results for splitting the N treatment data by whether participants have one or more than one network neighbor. The difference from the results reported in Table 7 in the main text is that for the estimates here, network N-1 data are included (in Group 2). Table 23 reports the same results for the M treatments. Table 24 shows estimates using only choice behavior in the F treatments. Table 25 reports the estimates from our coordination game treatments.

TABLE 25. Main estimation results using *both* information requests and action choices: M treatments and coordination game.

	Treatments					
	M-Co-1		M-Co-2		M-Co-3	
Parameters	RL	MBR	RL	MBR	RL	MBR
p_k	0.54***	0.46***	0.48***	0.52***	0.68***	0.32**
(s.e.)	(0.105)	(0.105)	(0.095)	(0.095)	(0.139)	(0.139)
θ_Z	0.31***	0.95***	0.27***	0.9***	0.34***	0.92***
(s.e.)	(0.069)	(0.052)	(0.072)	(0.049)	(0.109)	(0.081)
θ_O	0.69***	0.05	0.73***	0.1**	0.66***	0.08
(s.e.)	(0.069)	(0.052)	(0.072)	(0.049)	(0.109)	(0.081)
ε_Z	1***	1***	1***	1***	1***	1***
(s.e.)	(0.06)	(0.00)	(0.04)	(0.04)	(0.04)	(0.04)
ε_O	0.37***	1***	0.38***	1***	0.43***	1***
(s.e.)	(0.072)	(0.116)	(0.098)	(0.05)	(0.057)	(0.059)
ln LF	−1015		−1039		−1335	
Individuals	32		32		40	
Observations	640		640		800	

Note: ***, significant at the 1% level; **, significant at the 5% level; *, significant at the 10% level. Standard errors are computed using bootstrapping with 500 replications (Efron and Tibshirani (1994)).

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