Overview

Section 1: Additional theoretical analyses

In Section 1, we summarized our analyses of the deterministic and the stochastic best-response model. First, we described in detail how random deviations can trigger off a cascade and how cascades can lead to regime shifts on the macro-level. Second, we studied under which experimental conditions the two model versions make different predictions. The figures of the main paper show that the stochastic best-response model predicts for two conditions of the two studies the emergence of a descriptive norm, a collective pattern that the deterministic model is not able to explain. These figures focus on the structural conditions of the experimental settings and do not inform about whether the two model versions generate the same predictions also under alternative conditions. Therefore, we conducted several simulation experiments, testing whether model predictions depend on the amount of deviations ($\beta$), the initial color distribution in the network, and the duration of the interaction process. The following list provides an overview over the core results of the additional analyses presented in Section 1.

- Figure 2 of the main paper shows that in the experimental condition with $P = 1$ of Study 1, two deviations from the best-response model suffice to create a shift from anomic coexistence to coordination. Here we show that this holds true even when the two deviations occur at maximally distant positions in the network and at different points in time. (see Figure S1).

- Extensive simulations showed that the simulation trajectories shown in Figures 3 and 8 of the main paper illustrate typical predictions of the stochastic best-response model ($\beta = 1.5$) (see Figure S2).

- According to the stochastic best-response model, the initial distribution of colors substantially affects the simulation outcome after 150 periods only if there are many deviations (see Figure S2).

- The stochastic best-response model ($\beta = 1.5$) predicts that in the experimental condition with $P = 1$ of Study 2 oscillation is stochastically stable during the 150 periods of the experiment (see Figure S2). Simulations demonstrated, however,
that transitions from oscillation to coordination (and back) occur when longer time intervals are simulated (see Figures S4, and S5).

- Simulations showed that the predictions of the best-response model change when deviations are included also if the assumption is relaxed that actors choose the color that corresponds to their type at the outset (see Figures S6, S7 and S8). This holds in particular when $P = 1$ in Study 1, and when $P = 3$ in Study 2.

Section 2: Description of the experimental setup

In Section 2, we described in detail the experimental setup. We included the instructions and a screenshot of the main stage of the experiments. What is more, we compare the design of our experiments with designs of existing experimental studies [1–6].

Section 3: Additional analyses of the empirical data

In Section 3, we included the following analyses of the experimental data:

- We provide detailed graphical analyses for each session of the two laboratory experiments (see Figures S10 - S22).

- For each session of the experiments, we compare predictions of the two versions of the best-response model (deterministic vs. stochastic) given the initial color choices of the participants of the respective session and the amount of deviations that we observed ($\beta = 1.5$) (see Figures S10 - S22).

- Figure 4 of the main paper showed that the observed distribution of deviations supports the theoretical assumption that deviations are more likely when they imply small payoff losses. We show here that the same result obtained when we studied each condition of the two experiments separately (see Figure S24).

- Based on the decisions of the participants we could estimate the parameter of the stochastic best-response that controls the amount of deviations ($\beta = 1.5$) (see Table 1 and Figure S25).

- In the first 10 periods of the experiment, the amount of deviations does not differ significantly between the conditions of the two experiment (see Figure S26).

- In Study 1, the amount of deviations did not change significantly over time. In contrast, in Study 2 the amount of deviations decreased over time (see Figure S26).
1 Additional theoretical analyses

1.1 Effects of deviations: an example

Study 1 tested the hypothesis that very few deviations from general patterns of decision-making can have a critical impact on the properties of the whole population. Illustrating this notion for one of the conditions that we studied in the laboratory experiment \((P = 1)\), Figure 2 of the main paper shows that only two deviations are needed to change the collective pattern from anomic coexistence to coordination on a descriptive norm even though anomic coexistence is an equilibrium according to the deterministic best-response model. Figure S1 provides a second example. In contrast to the example from the main paper, however, the two deviations occur in the present example at very distant positions in the network and at different points in time. Thus, the second example illustrates that various combinations of deviations can lead to system shifts.

According to the deterministic best-response model, the state of anomic coexistence is an equilibrium when individuals have mixed neighborhoods and receive a payoff of \(P = 1\) when they choose the color that corresponds to their type (dogs: red; cats: blue). This is because actors anticipate a payoff of 3 payoff units \((= 1 \cdot P + 2 \cdot C)\) when they continue choosing the color that corresponds to their type. The opposite choice would lead to a smaller payoff of only 2 units \((= 0 \cdot P + 2 \cdot C)\).

However, already a single deviation from the best-response rule has substantive impact. To show this, we imposed that at the outset the dog at the 12 o’clock position (see Figure S1) does not follow the best-response rule and adopts color blue instead of red. In the subsequent period (see network of period 1 in Figure S1), this dog switches back to red, but her initial deviation has an impact on the decisions of the two dogs that are connected to the dog at the 12 o’clock position. As a result of the initial deviation, these two dogs have three blue contacts and, thus, switch to blue. In the subsequent periods (see periods 2 and 4), this leads to color changes of their neighbors.

In Period 4, we imposed the second deviation. This time, the dog at the 6 o’clock position, who should have chosen color red according to the best-response rule, adopts color blue. This second deviation triggers off a similar cascade as the first deviation and eventually leads to the emergence of global coordination.

In the example shown in Figure S1, agents made 180 decision. Even though there were only two deviations from the best-response rule, the system switched from a state of anomic coexistence to coordination on a descriptive norm. Without these deviations, anomic coexistence would have been stable. This illustrates that very few deviations from prevalent patterns of individual behavior can have substantial impact on collective outcomes when systems are stochastically unstable.
Figure S1: Transition from anomic coexistence to a descriptive norm resulting from only two deviations in the condition with $P = 1$. 
1.2 Predictions of the stochastic best-response model (with deviations)

Figures 3 and 8 of the main article show ideal-typical dynamics that the stochastic best-response model predicts to obtain under the conditions of the laboratory experiments. In order to test the robustness of these predictions, we conducted two simulation experiments, analyzing predicted outcomes for different amounts of deviations on the individual level.

In the first simulation experiment, we focused on the dynamics that the model predicts to obtain within 150 interaction periods, the number of interaction periods that we studied in the laboratory. Probabilistic systems, however, often make very different predictions in the long run than in the short run, an aspect that we studied in the second simulation experiment, which focused on predicted outcomes after 15,000 interaction periods.

**Experiment 1: short term predictions.** In this simulation experiment, we studied model prediction for the four conditions of the laboratory experiments, varying the composition of the neighborhoods (mixed vs. heterophilous) and the payoff parameter \( P \) (\( P = 1 \) vs. \( P = 3 \)). In addition, we varied the amount of deviations (\( \beta \)), in order to test whether model predictions depend on the amount of deviations from the best-response rule. We varied \( \beta \) between 0 and 3 in steps of 0.1. A value of zero means that agents’ decisions are random. A value of 3, on the other hand, imposes that deviations from the best-response rule are very rare (but not impossible). The simulation experiment included a condition where \( \beta = 1.5 \), the value that we estimated based on the data of our laboratory experiment (see Section 3.2). In accordance with the literature [10], we will refer to parameter \( \beta \) as the “responsiveness to rationality” in the remainder of this document. Finally, we also studied whether prediction may depend on the colors that agents adopt at the outset of the dynamics. We focused on three different initial color distributions: all agents start with the color that corresponds to their type; all agents start with the same color; and agents start with a randomly picked color. For each of the \( 2 \cdot 2 \cdot 3 \cdot 3 = 372 \) experimental conditions, we conducted 1000 independent replications.

The results of the simulation experiment are shown in Figure S2. To generate the Figure, we assessed for each simulation run the size of the biggest cluster after 150 interaction periods. Like in Figures 5 and 9 of the main paper and the remainder of this document, a cluster was defined as the set of agents with adjacent positions on the circle who adopted the same color at a given interaction period. Figure S2 informs about the distribution of this measure that we found in the 1000 independent replications for each of the conditions of the simulation experiment. The solid lines inform about the average size of the biggest cluster in the respective experimental condition. The dark blue area shows the interquartile range and the light blue area represents the complete value range that we observed in the 1000 replications per condition.

Panel A of Figure S2 shows results for those simulations where agents initially adopted
Figure S2: Results of simulation experiment 1: short-term predictions of the stochastic best-response model for the four conditions of the laboratory experiments, different amounts of deviations ($\beta$), and different initial color distributions.
the color that corresponded to their type. The top left subgraph informs about model predictions for the condition with mixed neighborhoods and \( P = 1 \). When agents are assumed to have a minimal responsiveness to rationality (\( \beta = 0 \)), color decisions are random. Accordingly, simulations generate random color distributions, which typically result in a size of the biggest cluster of 5. However, the more individual decisions were based on the best-response rule, the more simulation runs ended with a size of the biggest cluster of 20. In other words, runs ended with global coordination, replicating the prediction that we formulated in the main paper. If the responsiveness to rationality is increased further, the value range on the distribution increases again. This is because under these conditions deviations from the best-response rule are very rare. Accordingly, in some simulation runs dynamics did not reach a state of global coordination within the 150 interaction periods. This interpretation is supported by the fact that we did not find similar results in those simulation runs that started with global coordination (see top left graph in Panel B of Figure S2).

The bottom left graphs in the three panels of Figure S2 focus on the condition with mixed neighborhoods and \( P = 3 \). Replicating the prediction of the main paper, we found very low values of the outcome variable, which indicates that runs typically ended in anomic coexistence. This result obtained independent of the initial color distribution, which suggests that anomic coexistence is a very strong attractor under this condition.

It turned out that the short term model predictions for the condition with heterophilous neighborhoods and \( P = 1 \) strongly depend on the initial colors of the agents. When agents started with the color that corresponded to their type (Panel A), simulations typically ended with a very small size of the biggest cluster. Only for small values of \( \beta \), clusters of a considerable size formed. What is more, we found that in those runs where the size of the biggest cluster was very small, the majority of the agents changed their color at each interaction period (not shown in the Figure). This shows that when agents adopted the color that corresponded to their type at the outset of the dynamics, most runs ended with a collective oscillation pattern. Strikingly, a very different pattern emerged when simulations started with global coordination (see Panel B of Figure S2). With this initialization, very few runs ended with global oscillation. Instead, most populations remained in a state of global coordination. When the initial colors of the agents were randomly selected, we found that the distribution of the size of the biggest cluster was bipolar for most values of \( \beta \). To be more precise, 89.9 percent of the 20,000 runs with a responsiveness to rationality \( \beta > 1 \) ended either in global oscillation (49.2 percent) or global coordination (40.7 percent). Thus, with a random initial distribution of colors, the system reached one of the two attractors.

In sum, the simulations that generated predictions for the condition of the laboratory experiment with heterophilous neighborhoods and \( P = 1 \) showed that the system has two attractors under this condition: global oscillation and global coordination. Which attractor is reached heavily depends on the initial color distribution. As reported in the main paper, most of the participants of the laboratory experiment started with the color that corresponded to their type. For this initial setup, the model predicts the collective
Initially, agents adopt color according to their type

Initially, all agents adopt the same color

Initially, all agents adopt a random color

Figure S3: Results of simulation experiment 1: with heterophilous neighborhoods and $P = 3$, the short-term outcomes do not depend on the initial color distribution ($\beta = 1.5$).

Pattern of global oscillation (see Panel A of Figure S2).

Model predictions for the condition with heterophilous neighborhoods and $P = 3$ also depend on the initial color distribution (see the bottom right graphs in the three panels of Figure S2). Under this condition, however, this dependency was mainly found when agents were very responsive to rationality. For moderate values of $\beta$ (including the value 1.5, which we measured in the laboratory experiments) the initial color distribution does not lead to very different distributions of the size of the biggest cluster. Showing this in more detail for $\beta = 1.5$, Figure S3 depicts the exact distributions of the size of the biggest cluster for the three initial color setups. The figure shows that the distributions of the outcome measure were very similar in the three conditions of the simulation experiment.

Furthermore, Figure S3 shows that the model generates a high variation in the size of the biggest cluster. This, however, does not imply that coordination was a rare outcome under this condition. For instance, a high percentage of runs ended with a size of the biggest cluster between 9 and 13. These values obtain when a population reached a state of coordination but two individuals happen to deviate from the best-response rule. Such deviations occur frequently because they imply very small payoff losses\(^1\). Thus, Figure

\(^1\)For instance, if the population coordinated on option blue, then dogs (who prefer red) will loose only one payoff unit if they deviate from the best-response rule. Accordingly, dogs will deviate relatively frequently. Nevertheless, such a deviation fails to disrupt coordination. With heterophilous neighborhoods, dogs are connected to four cats, who will switch to red only when all four neighbors chose red in the previous period. Thus, it is very unlikely that a deviation by a dog triggers off a
S3 supports that coordination is a likely outcome under the experimental condition with heterophilous neighborhoods and $P = 3$.

Experiment 2: long term predictions. The second simulation experiment was a replication of experiment 1 but it focussed on the long-term predictions of the model. Thus, instead of stopping the simulations after 150 interaction periods, we waited 100 times longer and interrupted the dynamics after 15,000 periods. We studied the same conditions as in the first experiment, experimentally manipulating the composition of the neighborhoods, the payoff parameter $P$, agent’s responsiveness to rationality $\beta$, and the initial distribution of colors. We conducted 100 independent replications per experimental condition.

Figure S4 depicts the results of the second simulation experiment, applying the same statistics as Figure S2. Results resemble those of the short term simulations experiment. However, three main differences between Figure S2 and S4 draw attention. First, Panel A in Figure S4 shows that all runs with mixed neighborhoods, $P = 1$, and a high responsiveness to rationality ended in perfect coordination. In the short term simulations, in contrast, there were several runs that ended with a smaller size of the biggest cluster. We argued that this was the result of the very strong responsiveness to rationality under these conditions, which make deviations very unlikely. The fact that we did not find similar results when simulations were run longer, which makes the occurrence of deviations more likely, supports this explanation.

Second, in the condition with heterophilous neighborhoods, and $P = 3$ all three panels in Figure S4 show much higher variations of the outcome measure when $\beta$ had moderate values. Most importantly, under the condition where $\beta = 1.5$, it turned out that the size of the biggest cluster had a bipolar distribution when simulations were run for 15,000 periods. For instance, in the condition where agents started with the color that corresponds to their type (see Panel A), 35 percent of the runs ended with a size of the biggest cluster of 20. 55 percent of the runs ended with a size of the biggest cluster of 1. In the short term simulations, in contrast, we found the outcome measure to be highly dependent on the initial color distribution. For instance, those runs that started with global coordination also ended with the same pattern after 150 periods.

The reason why we found the bipolar distribution in the long term simulations is illustrated in Figure S5, which shows the development of the size of the biggest cluster of an ideal-typical long term simulation for each condition of the laboratory experiment. In the four simulation runs we imposed a responsiveness to rationality of $\beta = 1.5$ and that all agents adopted the color that corresponds to their type at the outset. Note that we plotted the size of the biggest cluster only for every 100th interaction period, because otherwise the plot in Panel 4 would be very cluttered and difficult to interpret. Panel
Figure S4: Results of simulation experiment 1: long-term predictions of the stochastic best-response model for the four conditions of the laboratory experiments, different amounts of deviations ($\beta$), and different initial color distributions
Figure S5: Ideal-typical long term dynamics for the four conditions of the laboratory experiments generated by the stochastic best-response model ($\beta = 1.5$)
2 of Figure S5 shows ideal-typical dynamics under the condition with mixed neighborhoods and \( P = 1 \). One can see that the model generates abrupt transitions from a state with a minimal size of the biggest cluster (oscillation) to a state with a maximal size of the biggest cluster (global coordination) and vice versa. These transitions resemble the shifts that the model generates under the condition with heterophilous neighborhoods and \( P = 3 \) (see Panel 4). However, transitions are much less frequent when \( P = 1 \). Accordingly, we did not expect to observe such transitions in the laboratory experiment.

Third, there are differences between short term and long term predictions for the condition with heterophilous neighborhoods and \( P = 3 \). To be more precise, in the simulations where agents had a high responsiveness to rationality (\( \beta > 1.5 \)), we found that the outcome after 150 periods depended very much on the initial color distribution. We argued that this was the result of the small number of deviations that occur when responsiveness to rationality is high. In the long term simulations we did not find this dependency. However, the distributions of the size of the biggest cluster of the long term simulations resemble very much those of the short term distribution when \( \alpha = 1.5 \). In other words, under this condition, there is no qualitative difference between the short term and the long term predictions of the model. Panel 4 of Figure S5 shows why. Under this condition, the transitions from one system state to the other occur very frequently.

1.3 Predictions of the deterministic best-response model (without deviations)

The predictions of the deterministic best-response model may critically depend on the assumption that all agents chose the color that corresponds to their type at the very outset of the dynamics. Therefore, we sought to test whether predictions of the deterministic best-response model resemble those of the model version that includes deviations when different assumptions about the initial colors are made. To this end, we conducted additional analyses on the predictions of the deterministic best-response model if this assumption is relaxed. First, we conducted a simulation experiment with the deterministic best-response model where the initial colors of the agents were randomly selected. We experimentally manipulated the composition of the neighborhoods (mixed vs. heterophilous), and the payoff parameter \( P \) (\( P = 1 \) vs. \( P = 3 \)); and conducted 10,000 replications for each of the four experimental conditions. For each simulation run, we assessed the size of the biggest cluster at period 150.

Figure S6 informs about the main results of this simulation experiment, showing the distribution of the size of the biggest cluster in the 10,000 replications for each of the four experimental conditions. The small box of each subgraph shows the same statistic for the stochastic best-response model with a responsiveness to rationality of \( \beta = 1.5 \), the parameter value that we estimated from the empirical data. Also these results were obtained from simulations that started with random color distributions (see Panel C in
Figure S6: Predictions of the deterministic best-response model ($\beta = \infty$) for the four conditions of the laboratory experiments when initial colors are random; inserted boxes show predictions of stochastic model with random initial colors, for comparison.
Figure S2). For illustration, Figures S10 to S22 provide examples of the dynamics that the deterministic best-response model generates (see Panels C in these Figures).

The top left graph of Figure S6 informs about the distribution of the size of the biggest cluster in the condition with mixed neighborhoods and $P = 1$, showing that relatively few simulation runs with the deterministic best-response model ended in a state of global coordination. The stochastic model, in contrast, generated global coordination in the majority of the runs (see the small box). Thus, under this experimental condition the deterministic best-response model makes different predictions than the same model with deviations even when agents are assumed to adopt a randomly picked color at the outset of the simulations.

Likewise, the two versions of the best-response model imply different predictions for the condition with heterophilous neighborhoods and $P = 1$ (see top right graph in Figure S6). According to the stochastic model, the system either moves to a state of global oscillation or a state of global coordination when initial colors are random (see small box or Panel C in Figure S2). With the deterministic best-response model, both outcomes are possible but much less frequent when colors are selected randomly. Instead, the simulation experiment showed that many runs ended in a state where one cluster formed and the remaining agents oscillated, a dynamic that is illustrated in Panel C of Figure S17.

For the condition with mixed neighborhoods and $P = 3$ the predictions of the deterministic best-response model resemble very much those of the stochastic model version. Both models imply that the system adopts a state of anomic coexistence even when colors are randomly distributed at the outset. This is in line with our earlier observation that anomic coexistence is a strong attractor under the condition with mixed neighborhoods and $P = 3$.

The bottom right graph in Figure S6 suggests that the deterministic model and the model with deviations make relatively similar predictions for the condition with heterophilous neighborhoods and $P = 3$. However, the dynamics that the two theories imply are very different, which is illustrated for instance in Panels C and D of Figure S21. The deterministic model typically predicts that clusters of agents that happen to have adopted the same color initially will persist and that the remaining agents will oscillate. The stochastic model, on the other hand, generates regime shifts from a state of global coordination to global oscillation (see also Figure S8, and Panel 4 of Figure S5). These regime shifts can not be explained with the model that excludes deviations because both systems states are equilibria according to this version of the model.

The simulations which are summarized in Figure S6 departed from random color distributions. In the laboratory experiment, however, we observed that on average about 80 percent of the participants chose the color that corresponded to their type in the first interaction period. We conducted an additional simulation experiment, in order to test whether the differences and similarities between the predictions of the deterministic and the stochastic model are found also when simulations start with color distributions.
that correspond to those of the laboratory experiment. This simulation experiment was an exact replication of the previously described study. However, unlike in the previous experiment, we implemented that agents initially adopted the color that corresponds to their type with a probability of 0.8 and adopted the opposite color otherwise. Results are summarized in Figure S7. In Figure S7, the small boxes inform about the predictions of the stochastic model ($\beta = 1.5$). Also these statistics are based on simulations where on average 80 percent of the agents initially adopted the color that corresponded to their type. For each of the four experimental conditions with the two model versions we conducted 10,000 independent replications.

The results of the simulation experiment where dynamics started with similar color distributions as in the laboratory experiment (Figure S7) resemble the results from the simulations with perfectly randomized initial colors (Figure S6). There is, however, one important difference. In the condition with mixed neighborhoods and $P = 1$, the differences between the deterministic and the stochastic best-response model turned out to be more pronounced in the simulation experiment with the initial color distributions.
that resemble those of the experiment. This is due to the fact that the predictions of the deterministic model depend very much on the initial color distribution. When agents hold a randomly picked color at the outset of the simulations, it is very likely that neighbors happen to hold the same color and form a cluster. Clustering at the outset, however, is rather unlikely when on average 16 of the 20 agents tend to adopt the color that corresponds to their type. Thus, with the color initialization that mimics the pattern that we observed in the laboratory experiment, system dynamics tend to start with color configurations that are more similar to the state of anomic coexistence. The stochastic model version ($\beta = 1.5$), on the other hand, turned out to predict the emergence of coordination independent of the initial color distribution. Therefore, differences between the two model predictions are more pronounced when initial color distributions resemble those that we observed in the laboratory.

As we have discussed earlier, Figures S6 and S7 suggest that the stochastic model and its deterministic counterpart make very similar predictions for the experimental condition with heterophilous neighborhoods and $P = 3$. However, the size of the biggest cluster that formed at interaction period 150, the outcome measure which is shown in the Figures, fails to capture regime shifts. In order to demonstrate that the stochastic model implies regime shifts whereas the deterministic model generates more stable color distributions, we replicated parts of the previously described simulation experiment, measuring not only the values that the outcome measures adopt at the end of the process but also the development of the outcome measures. In this experiment, we focussed on the condition with heterophilous neighborhoods and $P = 3$. We assumed that initially each agent has an 80 percent probability of adopting the color that corresponds to his type and conducted 10,000 independent replications for both versions of the model (no deviations vs. $\beta = 1.5$). For each simulation run, we measured the average size of the biggest cluster and the standard deviation of this outcome measure in the 150 interaction periods. Figure S8 shows box plots that inform about the distribution of the two measures in the simulation experiment.

Confirming the observations from Figures S6 and S7, the left panel of Figure S8 shows that both model versions generate similar color distributions. However, the right panel shows that the variation of the outcome measures during the simulation runs was significantly higher in the simulations with the stochastic model. In the simulations with the stochastic model, the size of the biggest cluster deviated on average by 4.8 from the run’s average. In the simulations with the deterministic model, the average standard deviation was only 1.79 ($t = 174.06$).
Figure S8: Distribution of the average and the standard deviation of the size of the biggest cluster within simulation runs (condition with heterophilous neighborhoods and $P = 3$; agents had a 80 percent chance of initially adopting the color that corresponds to their type)
2 Description of the experimental setup

2.1 Overview

The experiments were conducted in the period from February to April 2012 at the Decision Science Laboratory at ETH Zurich, Switzerland (www.descil.ethz.ch). Participants were recruited out of a common subject pool of the laboratories of ETH and University of Zurich.

Initially, we scheduled three sessions for each of the four experimental conditions. However, one session had to be excluded from the analyses because participants completed only 68 periods. In this session, two participants repeatedly waited very long before they entered their decisions and, thus, slowed down the experiment. After the experiment, we talked to the two participants, who independently from each other explained their behavior in the following way. According to the instructions, the final payoff did not depend on all decision periods but only on a random set of 3 periods. This is a standard payoff method, which motivates participants to remain focused also in later stages of the experiment. We applied this method because the experiment consisted of a large number of periods (150). The two participants had received high payoffs at the beginning of the experiment, but then received relatively small payoffs. Trying to increase their chances of being paid based on the successful periods, the two participants tried to keep the number of periods low by entering decisions very slowly.

It can not be excluded that the slow decision entries of the two participants affected the decisions of the other participants. Therefore, we decided to exclude this session and scheduled two additional sessions under the same experimental condition (heterophilious neighborhoods and $P = 3$). We conducted two additional sessions to make sure that the time between the first and final session of the experiment would not increase further if one of the additional sessions had to be excluded. Since there were no problems during the two sessions, we included both additional sessions in the analyses.

All sessions of the experiment lasted less than one hour including the instructions, and the payoff process.

2.2 Instructions

The experiments were conducted in German language. Here, we show English translations of the instructions. The original instructions will be provided by the authors upon request.

\textsuperscript{2}The experiment was anonymous, making it impossible to match participants behavior with their names or other personal information. However, during the experiment, it was possible to identify the computer of each participant. This allowed us to talk to the two participants before they left their computers to receive their payoffs.
In each period of the two experiments, participants had to decide between two options. In the main paper and the analyses in this document, we referred to these options as “red” and “blue”. In the experiment, however, we used the labels “yellow” and “blue”. We changed the labels for the documentation of the results for purely graphical reasons (yellow is more difficult to see on white paper). We refrained from using the label “red” in the experiment because the color red is associated with negative emotions [9], which might bias participants’ decisions. Our analyses support that the labels “yellow” and “blue” did not create such biases (see Table 1).

At the very beginning of each session, the experimenter (the first author of the paper) read aloud the following general instructions. The payoffs that are mentioned in the instructions depended on parameter $P$. Here, we report the instructions for $P = 1$. 
Welcome to the experiment. It’s great that you are here.
As you know, you will earn money during the experiment. How much
money you are going to earn will depend on the decisions that you will
make during the experiment.
In today’s experiment, the payment works as follows. Every partici-
pant will receive a fixed show-up fee of 10 Swiss Francs. In addition,
the experiment consist of many rounds. In each round, you will make
one decision, which will determine how many points you receive in the
respective round.
When the experiment is over, the computer will randomly pick three
rounds of the experiment. You will be paid two Francs for each point
that you received in these three rounds. You can receive up to 5 points
per round. This corresponds to 10 Francs. If the computer randomly
picks three rounds where you received 5 points, you will receive a payoff
of 30 Francs plus the 10 Francs show-up fee. Every participant has the
same chance to receive this maximal payoff. It is, thus, important that
you read carefully the instructions.
During the experiment, you do not know which rounds will determine the
final payoff. Each round can be amongst the three rounds that determine
how much money you are going to earn.
The experiment will proceed as follows.
1. You will read the instructions. Try to memorize the most impor-
tant rules. Most importantly, try to understand how you can earn
points.
2. You will answer a short quiz. In this way, we want to make you
aware of the most important instructions. After you have com-
pleted the quiz, you will read the correct answers.
3. There will be a trial round. This will show you what will happen
in each round.
4. Then, the main part of the experiment starts. Note that the most
important instructions will always be summarized on the screen.
5. When the main part of the experiment is over, we will ask you to
answer two short questions.
6. Then the experiment will be over. Please remain seated.
Please do not talk to other participants. If you have a question, please
raise your arm.

After these general instructions had been read out, we started the computer program
that executed the experiment. This program was implemented in z-tree [8]. At the first
stage of the experiment, participants read the following detailed instructions. Here, we
report the instructions for $P = 1$ and for participants who received payoff $P$ when they
chose color blue (cats).
This experiment consists of many rounds. In each round, you will make one decision. These decisions will determine how much money you will earn during the experiment.

The other participants will be confronted with the same decision problem. In each round, we will inform you about the decisions of four other participants in the previous round. We refer to these participants as your “buddies”. Your buddies will always be the same persons. Your buddies are not necessarily buddies of each other.

In each round, you will have to make a choice between two options: you choose between YELLOW and BLUE.

1. **You receive one point**, if you choose color BLUE.
2. In addition, **you receive one point for each of your buddies that chose the same color** as you did. For instance, when all of your buddies choose the same color as you, you will receive 4 points.

When the experiment is over, the computer will randomly pick three rounds of the experiment. **We will pay you two Francs for each point that you have received in these three rounds.** In addition, each participant gets a show-up fee of 10 Franks.

**Important:** The computer will pick the three rounds that determine your payoff when the experiment is over. Each round can be picked with the same probability.

Please click the continue button, when you understood these rules. In the following step, we will ask you to fill in a short quiz. In this way, we want to make you aware of the most important instructions.

After all participants had finished reading the instructions, everybody filled in a quiz with eight multiple-choice question. All questions concerned the payoff rules. For instance, we asked the following question: "Assume that you chose color YELLOW. Two of your buddies chose Yellow and two chose BLUE. How many points will you receive in this round?" Subsequently, participants read the correct answers to the eight questions.

The final stage of the instructions part was a trail round. Each participant made one decision, which had no impact on the payoffs. Subsequently, participants saw the decisions of their neighbors (buddies) in the trail round and were informed about how many points they would have earned. These decisions of the four buddies in trial round were also displayed in the very first period of the actual experiment.

### 2.3 Decision entry

Figure S9 shows a screen-shot of the main stage of the experiment. This screen consisted of three parts. On the top of the screen, we included a box with a summary of the payoff rules. Below this box, five colored rectangles informed participants about their own choice and the choices of their buddies in the previous round. Participants could also
read how many points they had earned in the previous period (see information below each rectangle). On the bottom of the screen, participants entered their choice in the current period by clicking the button in the respective rectangle.

The information that was displayed on the center of the screen provided participants with the information that they needed to apply the best-response decision rule [13]. We deliberately withheld any additional information that was needed to apply alternative decision rules. In particular, we did not inform participants about the types of their network neighbors and the structure of the network. This made it difficult to apply decision rules that are based on expectations about the future behavior of interaction partners [14, 15]. Likewise, we did not inform participants about the payoffs of their interaction partners, in order to exclude that participants imitated the behavior of successful others [16, 17].

2.4 Comparison with existing designs

Our experiments resembles earlier empirical work on coordination and graph coloring in networks [1–6]. However, crucial features of our design deviated from each of these earlier approaches. This created a setting where the emergence of coordination is particularly surprising.
First, our participants were not instructed to reach certain collective pattern and did not receive extra payoff when a collective pattern occurred or not [4–6]. In contrast, our participants received a payoff only for choosing one of the two behavioral options and for coordinating with their local network neighbors.

Second, we informed participants only about the behavior of their local network neighbors and did not provide information about the global distribution of behavior [4–7]. Thus, participants did not know whether the population had reached a state of coordination or not.

Third, each participant took part in only one series of 150 periods. This excluded that participants could learn how to reach or avoid certain collective patterns [5].

Fourth, the non-zero values of parameter $P$ imposed that cats and dogs had opposing preferences concerning the two possible forms of global coordination (all red or all blue) [1–3]. What is more, the two forms of global coordination were equally focal in the sense that they had the same Pareto rank and did not differ in the risks they implied [1–3].

Finally, we exclusively studied perfectly symmetric networks where all nodes faced the same decision problem and no participant adopted a network position that provided him with more or less influence on the collective pattern [4,5]. Likewise, there were as many dog as cats in all population [7].

In a nutshell, in the setup of our experiments coordination on a descriptive norm is an unintended consequence of individuals decisions. Unlike existing designs, our experimental setup does not create incentives for participants to reach a specific collective pattern. What is more, even if participants wanted to reach a collective pattern, our design makes it very difficult to do so, because participants are not informed about the structure of the network, the types of their neighbors, and the distribution of colors in the population. Likewise, in our design the two behavioral options are always equally focal and participants have opposing preferences for the two behavioral options. Therefore, it can be excluded that participants coordinated on the same behavioral option because they independently from each other reacted to the same stimulus.
3 Additional analyses of the empirical data

3.1 Description of the experimental sessions

Figures S10 to S22 provide detailed information about each of the 13 sessions of the two laboratory experiments. Each figure consists of 4 panels. Panel A informs about the micro dynamics that we observed in the respective session of the laboratory experiments. Each individual decision is represented by a colored symbol. The color of the symbol shows whether the participant chose red or blue (yellow or blue). Squares indicate that the decision was in line with the best-response rule. That is, the participant chose the color option that would maximize her payoff in this period if her network neighbors made the same decision as in the previous period. Circles, on the other hand, indicate that the respective decision deviated from the best-response rule. Furthermore, the size of a circle indicates the magnitude of the difference between the payoff that would have been expected based on the best-response rule and the payoff that one would have expected from deviating.

Panel B describes the development of four macro-outcome measures that we observed during the respective experimental session. First, we counted the number of clusters in the population. A cluster was defined as a set of participants with adjacent positions on the circle (e.g. 1 and 2; not 1 and 3 ) who chose the same color. This measure adopts a value of 1 when all participants chose the same color at a given period (descriptive norm). It adopts its maximal value of 20 when all agents chose the color that corresponds to their type (cat or dog), or when everybody made the opposite decision. Second, we report how many participants belonged to the biggest cluster in the population, a measure that informs about whether a clustered population consists of one big plus several small clusters; or several clusters of equal size. Third, Panel B shows the development of the number of participants who chose color blue. Fourth, Panel B shows how many participants changed their decision compared to the previous period. This measure allows distinguishing a state of anomic coexistence (no changes) from a state of coupled offset oscillation (many changes).

Panel C shows dynamics that follow from the deterministic best-response model and the initial decisions of the participants of the respective experimental session. To generate this, we implemented in our simulation model that computer agents initially made the same decision as the participant who was assigned the same position on the circle. Presuming that agents applied the deterministic best-response rule, we simulated the color decisions in the subsequent periods. We included these analyses because the color dynamics that follow from the best-response rule without deviations can depend on the initial color choices (see Section 1.3). It is, thus, possible that the decision of the participants in the first period in tandem with the deterministic best-response rule imply dynamics that are similar to those of the stochastic best response model. The panels inform about whether this was the case or not, showing whether deviations played a critical role in the emergence of the collective patterns that we observed during the
Likewise, we conducted additional computer simulations with the stochastic model. To be more precise, we implemented in the simulation model the initial decisions of the participants of the respective experimental session and simulated subsequent decisions based on the stochastic best-response model. We assigned the value 1.5 to the responsiveness-to-rationality parameter $\beta$. This value corresponds to the parameter value that was estimated based on the observed decisions in all experimental sessions.

Panel D shows ideal-typical dynamics that follow from the stochastic best-response rule and the initial decisions of the participants in the respective session. For the majority of the experimental sessions, we found that the model with deviations generated very similar collective patterns. However, for three sessions, we found that two qualitatively dissimilar patterns emerged. Therefore, we included in Panel D two typical runs when the simulations showed that the model generates different patterns.

In addition, Panel E summarizes the results of a simulation study where we conducted 100 independent replications with the initial color distribution of the respective experimental session and $\beta = 1.5$. To be more precise, we assessed the values of the four outcome measures after 150 iterations and show the distribution of the four measures in the 100 replications.
Figure S10: Study 1, Session 1a (mixed neighborhoods; \( P = 1 \))
Figure S11: Study 1, Session 1b (mixed neighborhoods; $P = 1$)
Figure S12: Study 1, Session 1c (mixed neighborhoods; $P = 1$)
Figure S13: Study 1, Session 2a (mixed neighborhoods; P = 3)
Figure S14: Study 1, Session 2b (mixed neighborhoods; $P = 3$)
Figure S15: Study 1, Session 2c (mixed neighborhoods; \( P = 3 \))
A observed decisions

B observed development of macro outcome measures

C prediction of a deterministic model, given the initial decisions of participants

D two typical predictions of a noisy model, given the initial decisions of participants

E distribution of outcome measures in 100 simulation runs

Figure S16: Study 2, Session 1a (heterophilous neighborhoods; $P = 1$)
Figure S17: Study 2, Session 1b (heterophilous neighborhoods; \( P = 1 \))
Figure S18: Study 2, Session 1c (heterophilous neighborhoods; \( P = 1 \))
Figure S19: Study 2, Session 2a (heterophilous neighborhoods; $P = 3$)
Figure S20: Study 2, Session 2b (heterophilous neighborhoods; $P = 3$)
Figure S21: Study 2, Session 2c (heterophilous neighborhoods; $P = 3$)
Figure S22: Study 2, Session 2d (heterophilous neighborhoods; $P = 3$)
3.2 Estimating participants’ responsiveness to rationality

The design of our experiments and the studied values of parameter $P$ made it possible to determine for each individual decision (period > 1) of the participants whether it was in line with the deterministic best-response rule or not. It turned out that 95.95 percent of all decisions were the best response to the choices of the participant’s neighbors in the previous period. In absolute terms, out of the 38,740 observed decisions, only 1570 decisions turned out to be deviations. 35.77 percent of the participants always chose the best-response option and 18.08 percent deviated only once. Other experiments found similar amounts of deviations from the best-response model [7]. These are impressive numbers, which show that in the setting of our experiment the best-response model can very accurately predict the decision of the individuals. Nevertheless, we have shown in the main paper and Section 1 of this document that the macro-level predictions of the best-response model can critically depend on whether deviations from the best-response rule are taken into account, even if deviations are very rare.

Figure S23 provides more detailed information about how often we could observe deviations in each of the four experimental conditions. We counted for each participant the number of deviations during the experiment and show in the figure the distribution of this count. In all four conditions, the majority of the participants deviated only once or never. In particular, in Study 1’s condition with $P = 3$, more than half of the participants never deviated. Under all conditions, very few participants deviated more than 15 times from the best-response rule. There were, however, three participants in the condition with heterophilous neighborhoods and $P = 3$ who deviated more than 120 times. Strikingly, these three participants took part in the same session of the experiment (see participants who were assigned to positions 1, 17, and 19 in Figure S22) and were assigned close positions on the circle. However, the three participants were not linked to each other and, thus, were never informed about each others’ decisions. Thus, it seems to be a coincidence that these three participants happened to take part in the same session.

Figure S23 shows that there were more deviations in the condition with heterophilous neighborhoods and $P = 3$ than in the other conditions. However, this does not imply that our experimental manipulation had a psychological effect in the sense that participants had a lower responsiveness to rationality under this condition. In contrast, this difference between the conditions results from the structural implications of our experimental manipulation. In all sessions of the experiments, we found that the populations very quickly reached a collective pattern (coordination or anomic coexistence). These patterns implied for three of the four conditions that deviations implied relatively high payoff losses. Only in the condition with heterophilous neighborhoods and $P = 3$, deviations implied only small losses (see also Figure S24). Accordingly, deviations were expected to be more likely under this condition (ceteris paribus).

The model which we used to integrate deviations into the best-response decision rule makes the assumption that deviations are more likely when the expected payoff differ-
Figure S23: Distribution of the number of deviations per participant in the four conditions of the experiment.
Figure S24: Effect of payoff difference on color choices in the four conditions of the laboratory experiment.

Differences between red and blue are small (see equation 1). This is a standard assumption of economic models [10–12]. However, one can show that the predictions of the model differ critically when e.g. deviations are assumed to occur independent of the expected payoff losses that they imply. Therefore, it is important to test this assumption.

\[ p_i^{blue} = \frac{1}{1 + e^{-(\beta(U_i(blue) - U_i(red)))}} \]  

Figure S24 shows the same graphical analyses as Panel B of Figure 2 in the main paper. However, we show here separate figures for each condition of the experiments. The stacked bars show the proportion of red and blue color choices in the experiment. Had all participants applied the best-response rule without deviations, one would observe completely red (blue) bars for the decisions where the payoff differences \( U_i(blue, x_{t-1}^{t-1}) - U_i(red, x_{t-1}^{t-1}) \) were negative (positive). Obviously, this was not the case in our experiment.

What is more, the figure shows that under all four experimental conditions deviations were more likely when the expected payoff loss that they implied was small. This clearly
supports our implementation of deviations.

Figure S24 seems to suggest that there were some differences in the responsiveness to rationality $\beta$ between the conditions. However, the experimental condition had a critical impact on how often participants faced decisions with certain payoff differences. Therefore, we report above the bars in Figure S24 how many decisions with the respective payoff difference have been made under the respective condition. This shows, for instance, that in the condition with mixed neighborhoods and $P = 1$, only in 34 out of 8,940 (8,940 = 3sessions $\cdot$ 149periods $\cdot$ 20participants) cases, a participant expected to gain three payoff units more for choosing color red than for choosing blue. Accordingly, the difference between the probability of deviations under this condition and the condition with mixed neighborhoods and $P = 3$ may not be significant (see our analyses below).³

Parameter $\beta$ of the stochastic best-response model specifies the degree to which decision makers follow the best-response rule and to which degree deviations occur (see equation 1). The value of parameter $\beta$ can be estimated based on the observed decisions of the participants using logistic regression models. Table 1 shows the estimated coefficients of the logit estimation based on 149 observations per participant. Two results draw attention. First, the estimated constant is very small and not significantly different from zero. This shows that in a situation where both color options (red and blue) would have lead to the same expected payoff, the probabilities of choosing blue or red would not have differed significantly. When designing the experiment we deliberately excluded that participants could be indifferent between two choices. Thus, the participants never faced such a situation. Nevertheless, the insignificant regression coefficient indicates that participants were indifferent between the two colors.

Second, the estimate of the expected payoff differences between blue and red, which corresponds to the term $U_i(blue, x_{t-i}^{t-1}) - U_i(red, x_{t-i}^{t-1})$ in Equation 1, is positive and significant. To be more precise, the logarithmic odds of choosing blue rise on average by 1.50 if the expected difference between blue and red increases by one payoff unit (in the sense that the payoff of choosing blue increases). This regression coefficient corresponds to an odds ratio of 4.47, which means that if option blue became one payoff unit more valuable compared to option red, respondents were more than 4 times more likely to choose blue.

For illustration, Figure S25 plots the predicted probability $P_{i,t}^{blue}$ of choosing color blue as

³The frequency of the decision tasks that participants faced illustrates another aspect of our experiment. One can see that under both conditions of Study 1 and under the condition with $P = 1$ of Study 2 relatively few decisions implied payoff differences of only one unit. Under the condition with $P = 3$ of Study 2, however, the majority of decision tasks implied small payoff differences. This was an intended consequence of our experimental design. Under all conditions, populations relatively quickly reached a state of anomic coexistence or coordination on a descriptive norm. These are stochastically stable states in the conditions of Study 1 and the condition with $P = 1$ of Study 2, because deviations imply high payoff losses and should remain rare events. Under the condition with $P = 3$ of Study 2, in contrast, coordination was expected to be stochastically less stable because deviations implied only small losses.
Table 1: Logit regression model estimating participants’ responsiveness to rationality $\beta$; dependent variable adopted value one if participant chose blue and zero otherwise

|                | Coefficient | Std. Error |
|----------------|-------------|------------|
| constant       | 0.01        | (0.03)     |
| payoff blue - payoff red | 1.50*** | (0.02)     |

N 38,740

McFadden Pseudo $R^2$ 0.80

Standard errors in parentheses

*** significantly different from 0 at the 1 percent level

The estimated responsiveness to rationality $\beta$ of 1.5 is aggregated over all four experimental conditions, all sessions, all participants, and all interaction periods. However, visual inspection of the decision trajectories in the experiments (see Figures S10 - S22) suggests that there might have been differences in the responsiveness to rationality between the experimental conditions and over time. Figure S26 provides at least partly support for this observation. To generate the figure, we split the experimental data into chunks of 15 subsequent periods and estimated for each chunk and each condition of the experiments the responsiveness to rationality $\beta$. In Figure S26 we show the estimated values of $\beta$ (see the markers) and the 95-percent confidence intervals of each estimate. Three findings draw attention. First, in the first chunk of periods (period 2 thru 15) the estimated responsiveness to rationality hardly varied between conditions. In fact, the confidence intervals of the four estimates overlap, showing that at the beginning of the experimental sessions the responsiveness to rationality in the four conditions did not differ significantly. Second, in both conditions with mixed neighborhoods, responsiveness to rationality appears to remain relatively constant over time. Third, in the two conditions with heterophilous neighborhoods, responsiveness to rationality increases significantly over time, showing that participants who were assigned to these conditions decided more in line with the best-response rule at later stages of the experiment. Actually, in the condition with heterophilous neighborhoods and $P = 1$, there were too few deviations to allow a statistical estimation the responsiveness to rationality.
Figure S25: Estimated probabilities that a participant deviated from the best-response rule ($\beta = 1.5$).

We also sought to explore the degree to which participants differed in their responsiveness to rationality. These analyses, however, turned out to be impossible because there were too few deviations during the experiment. To be more precise, 35.77 percent of the participants always decided according to the best-response rule, a behavior that is very much in line with our model predictions. For instance, Figures 3 and 8 of the main paper shows that in the ideal-typical simulation runs numerous agents never deviated from the best-response model even though all simulated agents were assumed to have the same responsiveness to rationality of $\beta = 1.5$. The limited duration of the experiment (150 periods) and the selected experimental conditions made it very likely that some participants never deviated from the best-response model. This is not a problem for the estimation of the responsiveness to rationality under the assumption that all participants have the same parameter value. However, it makes it impossible to estimate an individual parameter value for each participant. Future experimental research should focus on experimental conditions where all participants face decision tasks with varying payoff implications. This will make it possible to measure the distribution of the responsiveness to rationality amongst participants of the experiment. We expect that integrating this information into the formal model and studying model implications is an important step for future research as it will relax the assumption that all individuals have the same responsiveness to rationality.
Figure S26: Development of responsiveness to rationality $\beta$ in the four conditions or the laboratory experiment.
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