
Sequential Decision-Making with Group Identity

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Abstract In sequential decision-making experiments, participants often conform to the decisions of others rather than reveal private information – resulting in less information produced and potentially lower payoffs for the group. This paper asks whether experimentally induced group identity affects players’ decisions to conform, even when payoffs are only a function of individual actions. As motivation for the experiment, we show that U.S. Supreme Court Justices in preliminary hearings are more likely to conform to their same-party predecessors when the share of predecessors from their party is high. Lab players, in turn, are more likely to conform to the decisions of in-group members when their share of in-group predecessors is high. We find that exposure to information from in-group members increases the probability of reverse information cascades (herding on the wrong choice), reducing average payoffs. Therefore, alternating decision-making across members of different groups may improve welfare in sequential decision-making contexts.

Keywords Social identity · Information cascades · Herd behavior

JEL Classification C91, D82, D83, D84

1 Introduction

A large literature in the social and behavioral sciences has documented how biases in favor of one’s group and against outsiders play a substantial role in human social relations [29]. In behavioral economics, research has focused on how group identity bias affects social preferences and outcomes in public goods games [17]. This paper asks whether group identity affects individuals’ decisions to conform to the actions of others in sequential decision-making contexts, where our main evidence comes from a controlled lab experiment.

As motivation for the lab experiment, we first explore whether group identity affects real-world decision-making in a high-stakes context. We analyze the voting decisions of U.S. Supreme Court Justices in preliminary case hearings, where judges sequentially announce their votes for each case on the docket. Our empirical approach uses the political party of the appointing president as a proxy for group membership [40], and quasi-experimental variation in voting order induced by judge absences, turnover, and recusals.

We find that judges are more likely to herd when they follow more of their in-group members in the voting order, consistent with Spenkuch et al. (2018) on herding in U.S. Senate roll-call votes [42]. Arguably, U.S. Supreme Court decisions are some of the most important policy choices in the United States. The fact that voting order can induce more conformism by group in the Court’s preliminary hearings speaks to the potential relevance of group identity in these contexts.

To better understand these mechanisms in a controlled setting, we use a laboratory experiment that isolates the effect group identity on sequential decision-making when payoffs are not a function of collective actions. Our experiment builds upon Anderson and Holt’s (1997) classical information cascades experiment in which players publicly guess a random state

of the world after being shown a private informative signal. Because players act sequentially and observe the actions of their predecessors, they often ignore their private signals, conform to the actions of their predecessors, and form information cascades [5].¹ However, previous experimental studies have shown that players form cascades less often than theory would suggest [11][15][30][31][23][35][34][41][43][45]. Our contribution is to instill feelings of group identity in lab players to help explain why information cascades are more likely to occur in some settings, but not in others.^{2,3}

We find that group identity affects the probability that cascades occur in our experiment. Relative to players in control rounds (where group identities are hidden), players in treatment rounds (where group identities are revealed) are more likely to conform to the actions of in-group predecessors and less likely to conform to the actions of out-group predecessors. Social welfare is 15 percentage points lower in rounds where players observe the actions of only in-group predecessors compared to rounds where players observe the actions of only out-group predecessors. Welfare is reduced in these rounds because players are more likely to ignore their private signals, particularly on “tie-breaking” turns, and to form cascades on incorrect actions (i.e., reverse cascades).

We also find an asymmetry in how group identity affects players’ choices. On turns in which players draw signals that do not match their predecessors’ actions, players are more likely to ignore their private signals and conform

¹ Celen and Kariv (2004) distinguish between herds and information cascades. Herds form when an infinite sequence of agents choose the same action, while information cascades form when an infinite sequence of agents choose the same action *and* their signals differ from the actions that they chose [12]. Therefore, information cascades are a special case of herding. We focus on information cascades because they are more likely to have negative consequences for player welfare.

² Our strategy for instilling feelings of group identity follows the literature on group identity and social preferences [14][36].

³ Fahr and Irlenbusch (2011) take a different approach to adding groups to the information cascades experiment: they compare decisions made by small groups to decisions made by individuals and they find that small groups are more likely to choose actions according to Bayes’ Rule. [19].

to their predecessors' actions when their predecessors are members of their group. In contrast, on turns in which players draw signals that match their predecessors' actions, players are equally likely to choose actions that match their signals regardless of the group identities of their predecessors. This result suggests that in-group identity bias induces players to conform, but only when they receive contradictory information.

Our results imply a simple yet powerful policy recommendation. Committees and other sequential decision-making bodies should adopt an alternating-groups rule, where the voting sequence is deliberately ordered to alternate between groups. With this rule, individual members may be more likely to reveal their private information and therefore less likely to form information-destroying cascades. An alternating-groups rule might result in more efficient revelation of information and therefore better decision-making in courts, committees, and other collective decision-making bodies.

2 Group Identity Literature

This paper contributes to previous work on induced group identity in experimental economics. However, this literature mostly finds that in-group favoritism improves the welfare of in-group members. For example, Eckel and Grossman (2005) find that in-group bias can reduce free-riding in public goods games [17]. Charness et al. (2007) find that players play more aggressively against out-group members in Battle of the Sexes and Prisoners' Dilemma games, and the effect is strongest when group membership is rendered salient. Using a broader selection of games [13], Chen and Li (2009) produce evidence consistent with higher altruism toward in-group members relative to out-group members [14], while Masella et al. (2014) find that performance incentives can crowd out in-group altruism [36]. All of these papers describe how group iden-

tity affects players in strategic settings where players have the opportunity to help or hurt others. The equilibrium outcome, in-group favoritism in social dilemmas, can be rationalized in an evolutionary game-theoretic framework [21]. In our setting, however, there is no social dilemma, no scope for cooperation or conflict. Yet we still find that group identity affects decision-making, and we find that in-group bias can make players worse off.

Our results are consistent with a burgeoning literature on how group identity affects information processing and revelation. Le Coq et al. (2015), for example, find that players matched from different groups persist longer in centipede games because players believe that out-group members are more likely to act randomly, rather than act strategically [32]. Lee et al. (2015) find that movie-goers are more likely to herd on movie reviews following their friends' reviews compared to strangers' reviews [33]. Previous literature in social psychology has also shown that group membership affects information processing via social projection [2][3][39]. The novel result of our study is that group identity affects information processing even when players do not have incentives to consider group identities when updating their beliefs.

3 Preliminary Hearings of the U.S. Supreme Court

To motivate the importance of group identity in sequential decision-making contexts, we analyze vote data from preliminary case hearings in the U.S. Supreme Court. The preliminary hearings give the judges the opportunity to discuss matters before the court and make collective decisions. Besides administrative business before the court, the hearings have two major functions. First, the judges vote on which cases should be accepted for review on appeal. At least four judges must vote to accept a decision in order for it to be reviewed. Second, judges announce their initial vote on the outcome of the case.

This is also a binary choice, where judges vote whether to affirm or reverse the lower-court decision. These votes are not binding, and judges often change their votes by the time the final decision is voted on. Still, these hearings have a large impact on the court’s subsequent rulings, and therefore have a large impact on U.S. law and policy [38].

Judges vote sequentially in a pre-determined order in the preliminary hearings. Perry (1991, [38]) presents anecdotal evidence that judges pay attention to the votes of their predecessors and are often swayed by their votes. Judges may plausibly be swayed by colleagues’ votes at this stage because they have had limited time to review the cases since their clerks do most of the hearing prep work. It is only after these hearings, when cert is granted and when they prepare for oral arguments, that judges will likely form more concrete opinions on the cases.

The hearings are confidential, meaning that the judges believe that their individual votes will be known only to other judges and their clerks. However, the sequence of votes in these hearings was recorded by Justice Blackmun for the years 1986 through 1993. This data has recently become available with the posthumous publication of Blackmun’s papers [18].

Given the sequential decision-making context of preliminary hearings, there is the potential for bias toward the decisions of in-group predecessors. In the context of legal and political decision-making, an important group division is political party affiliation. Here we follow the political science literature in assigning judges to an affiliation based on the party of the president who appointed them [40]. In our sample, the Republican-appointed judges are Rehnquist, Blackmun, Powell, Stevens, O’Connor, Scalia, Kennedy, Souter, and Thomas. The Democrat-appointed judges are Brennan, White, Marshall, Ginsburg, and Breyer. Due to turnover, and due to absences, the panel of

participating judges varies across dockets, but nine judges typically vote in a docket.

There are some critical differences between the judge voting data and our subsequent lab experiment. First, the sequence of votes is determined by judge seniority (rather than random assignment), where the Chief Justice (Rehnquist) votes first, and then the rest of the judges vote in order from longest tenure to shortest tenure. Second, the judges know the group membership of their successors (rather than having it concealed). Third, group membership is not arbitrary; judges have different preferences over decisions which are likely to be correlated with their group membership. Fourth, there is no “correct” state of the world that the judges are trying to guess, like in an information cascades experiment. Fifth, this is a repeat game with strategic interaction across cases. For these and other reasons, the following results motivate our lab experiment, but do not necessarily corroborate its findings.

We apply the following analytical approach to the Supreme Court votes, where we have judge j voting in turn i at docket t . Here, “turn” means the position in the voting sequence, between 1 and 9, while “docket” refers to the case being reviewed. Our outcome variable Y_{ijt} gives the probability that vote i joins a herd, where herding is formally defined as at least three identical consecutive votes. We use “herding” rather than “information cascades” because we do not know the judges’ private signals. Then we estimate the probability that $Y_{ijt} = 1$ for vote i by judge j in docket t using a linear probability model described below:

$$Pr(Y_{ijst} = 1) = \alpha + \gamma InGroup_{ijst} + u_{ijst} \quad (1)$$

where $InGroup_{ijt}$ is the proportion of judge j 's predecessors in docket t who were nominated by the same political party. Standard errors are clustered by docket. We run separate regressions for the certiorari votes and the affirm/reverse votes. We also interact the share of in-group predecessors with the judge's political party to determine whether judges appointed by Republican vs. Democrat presidents are more likely to herd.

Our results on Supreme Court voting appear in Table 1. The top panel gives the results on certiorari votes, while the bottom panel gives the results on affirm/reverse votes. Each column represents a different model, as detailed at the bottom of the table and explained in the notes. Column 1 reports the baseline estimates, which only include a constant term and the coefficient on the share of in-group predecessors. Here we see a statistically significant relationship between herding rates and the share of in-group predecessors. The relationship holds for both the cert votes and the affirm/reverse votes. Column 2 adds turn fixed effects, which control for the judges' positions in the vote sequence. We still find that the coefficient on the share of in-group predecessors is statistically significant, which means that the effects in Column (1) are not driven by differences in the likelihood of herding for judges on different turns in the sequence. Next, Column 3 adds a dummy variable for the party of the judge. While the effect on herding in the affirm/reverse regressions is similar and still statistically significant, the herding effect in the certiorari votes is smaller and no longer statistically significant (yet still positive, so we may be under-powered). The different results for cert votes versus affirm/reverse votes may reflect the fact that the latter are more ideologically motivated, and therefore they may be more consistently correlated with group identity.

Columns 4 and 5 present results for a model that interacts the share of in-group predecessors with the covariate for party affiliation. We see that for the cert votes, Republican-appointed judges are somewhat more likely to herd than

Democrat-appointed judges, but Republican- and Democrat-appointed judges are equally likely to herd following in-group predecessors on the affirm/deny votes. Controlling for year fixed effects in Column 5 does not affect the results, nor does clustering the standard errors by judge rather than by docket (results not shown).

These Supreme Court voting results suggest that voting order can exacerbate in-group conformism among U.S. Supreme Court Judges. The possibility that the voting order of Supreme Court judges affects their probability of herding on particular outcomes is remarkable, though it is consistent with a recent paper on herding by political party in U.S. Senate roll-call votes [42]. Motivated by these quasi-experimental results, we now turn to our lab experiment to more precisely identify group identity’s effects on individual decision-making in sequential decision-making contexts.

4 Experiment Design

To isolate the effects of group identity on individual decision-making, we use a lab experiment similar to Anderson and Holt (1997), with additional experimental games designed to render group identity salient. Previous economics experiments have shown that “minimal” groups with mere labeling have little effect on social preferences, but instilling group identity through team-building games results in a stronger group effect [13][17]. Our team-building experimental games are designed to fulfill this requirement.

We run 4 sessions with a total of 60 players. Each experimental session has four parts. The first part sorts players into groups based on painting preferences. The second part asks players to answer trivia questions with their group members. The third part consists of the information cascades experi-

ment, which is described below. The fourth part assesses group salience with an allocation game.⁴

In part one (i.e., the paintings stage), players view a series of five pictures and select the picture that they like the best. Figure 1 shows an example of what a player in our experiment would see at this stage. After players make their choices, they learn that the paintings were created by the artists, Paul Klee and Wassily Kandinsky. The computer adds up the number of times players prefer Klee to Kandinsky and then ranks the players by their preferences. Then the computer sorts players into two equally-sized teams based on their ranks. The teams have either six or nine members each, so Team Klee fills up once the top six or nine players with the most Klee preferences have been assigned to the team.⁵ In the event of a tie at the margin (e.g., two players have the same number of preferences for Klee, but there is only one spot left on Team Klee), then players are randomly assigned across the two teams.

For the rest of the experiment, each player’s team membership is salient on her computer terminal with the use of a team name and a representative icon. This approach to instilling group identity is popular in previous work in this literature because painting preferences have been shown to be largely uncorrelated with observable player characteristics [14].⁶

In part two (i.e., the trivia stage), players further solidify group identity through a team trivia task. As in Masella et al. (2014), players work together to answer three multiple choice questions [36]. These questions are challenging enough that the players probably do not know the correct answers outright, but they might be able to reach the correct answers through deliberation

⁴ Please see the [Appendix A](#) for the methodological details.

⁵ The number of players per team is the same within session, but it varies across sessions. We ran some sessions with 12 players and other sessions with 18 players based on the availability of participants.

⁶ In our data, we find small but statistically insignificant differences in some player characteristics recorded by the lab. Relative to the Kandinsky team, the Klee team has 9% more women, 3% more STEM majors, and 2% more graduate students.

with their team members.⁷ Before answering the questions, players have 90 seconds to discuss the questions with their team members (Figure 2). Players communicate with each other by typing into a chat box. Besides the chatbox during this round, no communication is allowed throughout the experiment.⁸ Players from the team with the most correct answers win \$3 each, regardless of each player’s individual answers. Players from the losing team receive nothing from this part of the experiment. The outcome is not announced until the end of the session.⁹

The third and main part of the experiment is the jars game based on Anderson and Holt (1997) [5]. To ensure that players understand how to play the game, they receive comprehensive instructions, play two practice rounds, and must correctly answer a set of quiz questions on the key features of the game. As depicted in Figure 3 (an image from the instructions slide deck), the game centers around two virtual jars, one red and one blue. The red jar has two red balls and one blue ball; the blue jar has two blue balls and one red ball. The balls serve as informative signals with signal precision $p = \frac{2}{3}$. In each round, players are randomly assigned to sets of six ($N = 6$), which can have any composition of the teams. The computer randomly selects a jar for each set and players do not observe which jar the computer selected.

Players are ordered in a random sequence for play in the jars game. On their turn (Figure 4), players observe a ball drawn from the jar as well as the jar choices of the preceding players (but not subsequent players). Their drawn balls and their predecessors’ choices are informative about the color of the jar. There are 32 rounds in the jars game that are divided between

⁷ The trivia questions and answers appear in the Appendix.

⁸ While the chat box includes player number labels, those labels have no relation to other parts of the experiment.

⁹ The outcome is not announced until the end of the session because we do not want players to infer that their group members are “smarter” than the other group’s members before we play the information cascades game.

24 treatment rounds and 8 control rounds, with the treatment and control rounds randomly ordered. Control rounds and treatment rounds are identical with one exception. In treatment rounds, the team identity of predecessors is revealed (through the team icon and in parentheses in the text, as shown in Figure 4). In control rounds, that information is not revealed.

Players have up to one minute to select a jar; the game moves forward once all players in a turn select a jar. At the end of a round, the sets are reshuffled, new jars are selected, and a new round begins. Players earn \$0.50 for guessing the correct jar, and \$0.00 for incorrect guesses. We follow most of the previous literature in minimizing effects due to reinforcement learning; players receive no feedback during the task and they only learn about their earnings at the end of the session. We emphasize in the instructions that individual payoffs do not depend on what other players choose or the team membership of other players.

In the fourth and final part of the experiment, players play an allocation game based on Chen and Li (2009) [14]. The game is illustrated in Figure 5. For each of 3 rounds, players are asked to allocate \$1 between two other players, in 25-cent increments. The other players are selected randomly – their individual identities are not revealed, only their team membership. In the three respective allocation decisions, the recipient players are two members of one’s own team, two members of the other team, and one member of each team. We used the allocation game to assess whether the group identity treatment is still working at the end of the session. In our data, players favor their in-group members with an unfair allocation 65% of the time, which is consistent with other studies that have found that discrimination against out-group members is driven by favoritism toward in-group members [1][27].

After the experiment, players answer a brief questionnaire and are then paid privately in cash.

5 Empirical Approach

Our empirical approach tests whether group identity affects individual decision-making by asking whether players choose different actions when they receive relatively more information from in-group vs. out-group predecessors.¹⁰ We focus on five outcomes. The first outcome is the probability that players choose actions (i.e., jars) that match their private signals (i.e., balls). The frequency with which players follow their own signals, as opposed to the choices of their predecessors, reveals how much they weigh their private information relative to the information they learn from their predecessors. The second outcome is the probability that players choose actions that correspond to the optimal choices according to Bayes' Rule. In instances where Bayes' Rule delivers posteriors that equal 0.5, players can choose either action and be consistent with Bayes' Rule. The third outcome is the probability that players start or join an information cascade. The fourth outcome is the probability that players start or join a reverse information cascade, meaning a cascade on the incorrect action. The fifth outcome is the probability that players choose the correct actions. Correct actions measure player welfare because players only receive compensation when they choose the correct actions.

Our first regression framework tests whether the composition of group identities within rounds affects individual decision-making. We estimate the probability that $Y_{ijst} = 1$ for player i on turn j in round s in session t using a linear probability model:¹¹

$$Pr(Y_{ijst} = 1) = \alpha + \gamma InGroup_{ijst} + u_{ijst} \quad (2)$$

¹⁰ Our empirical approach is motivated by a model of information cascades that incorporates group identity. In the model we show how agents attach different weights to the information that they receive from in-group versus out-group predecessors. We have omitted the model from the main text for the sake of brevity, but it appears in [Appendix B](#). We also estimate the parameters of our model and present those results in the appendix as well.

¹¹ We have also used a logit model and it delivers the same results.

for $Y_{ijst} \in \{\textit{Own Ball}_{ijst}, \textit{Bayesian}_{ijst}, \textit{Cascade}_{ijst}, \textit{Reverse}_{ijst}, \textit{Correct}_{ijst}\}$, where we have defined:

$$\textit{InGroup}_{ijst} = \frac{\text{Number of in-group predecessors}}{\text{Total number of predecessors}}$$

where $\textit{InGroup}_{ijst}$ is randomly assigned by the experiment design. We estimate the model using data from treatment rounds, so γ measures how the share of in-group predecessors affects player i 's choices when group identity is revealed (we turn to control rounds in the second regression framework below). We cluster standard errors at the player level unless otherwise noted in the tables.

Equation (1) is designed to see whether the group identities of predecessors have an overall effect on player actions. If players treat the actions of out-group members differently from the actions of in-group members, that will be reflected in $\gamma \neq 0$. By looking at different outcomes in these treatment rounds, we can test a range of hypotheses. For one, players may be more likely to conform to their predecessors' actions (rather than follow their own observed signal) when their predecessors are members of their group. Similarly, players may be more likely to act as Bayesian decision-makers and join information cascades as the share of in-group predecessors increases. However, Bayesian players cannot differentiate between welfare-improving cascades and reverse cascades, so the probability of reverse cascades may also increase as the share of in-group predecessors increases. Lastly, if players discard their private information to join reverse cascades formed by their in-group predecessors, then players will be less likely to choose the correct actions as the share of in-group predecessors increases.

Our second regression framework decomposes the total effect of group identity by distinguishing between cases when player i has drawn a signal that

either matches (i.e., “corroborates”) or does not match (i.e., “contradicts”) her predecessors’ actions. We further distinguish between cases in which her signal corroborates her predecessors’ actions *and* her predecessors are members of her group versus cases when her signal corroborates her predecessors’ actions and her predecessors are not members of her group. We similarly distinguish between cases where her signal contradicts her predecessors’ actions and her predecessors are members of her group or not. Therefore, for player i , we construct:

$$Share\ InGroup\ Corroborate_{ijst} = \frac{\#In\text{-}group\ predecessors\ who\ corroborate}{Total\ \# \text{ of predecessors}}$$

$$Share\ OutGroup\ Corroborate_{ijst} = \frac{\#Out\text{-}group\ predecessors\ who\ corroborate}{Total\ \# \text{ of predecessors}}$$

$$Share\ InGroup\ Contradict_{ijst} = \frac{\#In\text{-}group\ predecessors\ who\ contradict}{Total\ \# \text{ of predecessors}}$$

$$Share\ OutGroup\ Contradict_{ijst} = \frac{\#Out\text{-}group\ predecessors\ who\ contradict}{Total\ \# \text{ of predecessors}}$$

where the shares are defined for players on turn numbers 2, 3, 4, 5, and 6 and the four shares always sum to 1. Then we test whether group identity is more relevant when players draw signals that contradict (at least some of) their predecessors’ actions. To do this, we estimate:

$$\begin{aligned} Pr(Y_{ijst} = 1) = & \alpha + \beta_1 Share\ InGroup\ Contradict_{ijst} \\ & + \beta_2 Share\ InGroup\ Corroborate_{ijst} \\ & + \beta_3 Share\ OutGroup\ Corroborate_{ijst} + u_{ijst} \end{aligned} \quad (3)$$

for $Y_{ijst} \in \{\textit{Own Ball}_{ijst}, \textit{Bayesian}_{ijst}, \textit{Cascade}_{ijst}, \textit{Reverse}_{ijst}, \textit{Correct}_{ijst}\}$.

The omitted share is *Share OutGroup Contradict_{ijst}*, and so all coefficients should be interpreted relative to the case when player i has drawn a signal that contradicts all of her predecessors' actions and none of her predecessors are members of her group.

Regardless of group identity, we expect that on turns in which player i draws signals that match her predecessors' actions, she will be more likely to choose the actions that match her signals, more likely to choose actions that align with Bayes' Rule, more likely to form information cascades, and more likely to choose the correct actions compared to turns in which she draws signals that contradict (at least some of) her predecessors' actions.

The importance of group identity for players' decision-making will be summarized by the sign and statistical significance of β_1 , as well as the differences between β_2 and β_3 . The sign and statistical significance of β_1 reveals the degree to which player i takes different actions when her predecessors are members of her group on turns in which she draws a signal that contradicts her predecessors' actions. The difference between β_2 and β_3 reveals the degree to which player i takes different actions when her predecessors are members of her group on turns in which she draws a signal that corroborates her predecessors' actions. Our hypothesis is that player i will be equally likely to conform to her predecessors' actions, regardless of their group identities, when she draws signals that match her predecessors' actions (i.e., $H_O : \beta_2 = \beta_3$). However, on turns where she draws signals that do not match her predecessors' actions, we hypothesize that player i will only conform to her predecessors' actions when her predecessors are members of her group (i.e., $H_O : \beta_1 \neq 0$).

We test the robustness of our results in several ways. First, we control for turn fixed effects and player fixed effects in Equation (2). Second, we cluster our standard errors at the session-level instead of the player-level. Third, we

estimate Equation (2) on the subset of data from control rounds where group identity was not revealed. We hypothesize that $\beta_1 = 0$ and that $\beta_2 = \beta_3$ in control rounds, meaning that the relative shares of in-group and out-group predecessors have no effect on players' decision-making when players do not learn the group identities of their predecessors. Fourth, we stratify our results by the first 16 vs. the last 16 rounds in each session to determine whether players are more likely to conform at the start of the session or toward the end of the session.

In our final empirical analysis we focus on specific turns in which group identity induces players to make different choices. Specifically, we re-estimate Equation (1) on additional subsets of data: tie-breaking turns and cascade turns in treatment rounds, which we describe presently.

To qualify as a tie-breaking turn, a Bayesian player's posterior on the state must equal 0.5. We focus on players with turn numbers 2 or 4 because their actions on tie-breaking turns can trigger cascades for subsequent players. We hypothesize that players on tie-breaking turns that also feature high shares of in-group predecessors will be less likely to choose actions that match their own signals and will be more likely to follow the dominant actions of their predecessors. In the regression notation, this corresponds to the hypothesis that $\gamma < 0$ for $Pr(Own\ Ball_{ijst} = 1)$, and the hypothesis that $\gamma > 0$ for $Pr(Cascade_{ijst} = 1)$ and $Pr(Reverse_{ijst} = 1)$. It is important to empirically demonstrate what happens on tie-breaking turns because in the standard model, players will randomize on these turns. However, if players systematically conform to their predecessors' actions instead of randomizing, then they will be more likely to initiate information cascades, which provide less information to subsequent decision-makers. In this way, conformism on tie-breaking turns can inflict a negative externality on subsequent players in the round.

Cascade turns can occur for players 3, 4, 5, or 6, and refer to those turns where an information cascade has already begun for Bayesian players and where the player’s signal contradicts the cascade. Specifically, a cascade turn is any turn where at least two consecutive previous players took the same action and the next player draws a signal that contradicts those actions. For example, player 3 faces a cascade if she draws a red ball when players 1 and 2 have chosen the blue jar. In cascade turns, players break the cascade if they choose the action that matches their signal rather than the action that conforms to their predecessors’ actions. We hypothesize that players on cascade turns that feature high shares of in-group predecessors will be less likely to choose their own signals, more likely to choose actions that are consistent with Bayes’ Rule, and less likely to break cascades. To the extent that they are less likely to break reverse cascades, we predict players may also be less likely to choose the correct actions.

6 Lab Experiment Results

This section reports results from the empirical analysis described in [Section 5](#) using the data generated from the experiment described in [Section 4](#). First, we test whether the overall share of in-group predecessors affects decision-making in treatment rounds where group identity is revealed. Second, we test whether the share of in-group predecessors is more likely to affect decision-making on turns where players have drawn private signals that contradict (at least some) of their predecessors’ actions. Third, we explore how the share of in-group predecessors affects the probability that players conform to the actions of their in-group predecessors on tie-breaking turns and cascade turns.

Table 2 shows how players respond to receiving more information from in-group predecessors compared to out-group predecessors. The table reports

estimates for γ , which capture how higher shares of in-group predecessors affect the probabilities that players choose actions that match their signals, choose actions that are consistent with Bayes' Rule, conform to form information cascades, conform to form reverse cascades, and choose the correct actions. We find that on turns with all in-group predecessors (relative to turns with all out-group predecessors), players are 9.6 percentage points less likely to choose actions that match their signals (Column 1), 7.7 percentage points more likely to form information cascades (Column 3), and 12.5 percentage points more likely to form reverse cascades (Column 4). We also find that players are less likely to choose the correct actions, meaning that their payoffs are 15 percentage points lower when all of their information comes from in-group predecessors compared to out-group predecessors (Column 5).

Expanding on the results in Table 2, Figure 6 shows how the probability of choosing the correct action varies across turns in treatment rounds. The red line plots the probability that players choose the correct action when the share of in-group predecessors is less than or equal to 0.5. The blue line plots the probability that players choose the correct action when the share of their in-group predecessors is greater than 0.5. The figure shows that, across all turns in the game, players are 7-15 percentage points less likely to choose the correct actions when they receive more information from in-group vs. out-group predecessors.

Next we consider whether the effect of predecessors' group identities is driven by turns in which players draw signals that contradict their predecessors' actions. The results from estimating Equation (3) are reported in Table 3. In the first row, we show whether in-group identity affects player i 's action when her predecessors have chosen actions that contradict her signal (i.e., $\beta_1 \neq 0$). The estimates imply that in rounds where player i has drawn a signal that contradicts all of her predecessors' actions and all of her predecessors are

members of her group, she is 22 percentage points less likely to choose the action that matches her signal, 20 percentage points more likely to start or join a cascade, 16 percentage points more likely to start or join a reverse cascade, and 21 percentage points less likely to choose the correct action, compared to turns in which she has drawn a signal that contradicts all of her predecessors' actions and all of her predecessors are *not* members of her group.

Next we ask whether the share of in-group predecessors affects player i 's actions when she draws signals that match her predecessors' actions. Unsurprisingly, as shown in the second and third rows of Table 3, players make different choices on turns where their signals match their predecessors' actions compared to turns where their signals contradict their predecessors' actions (i.e., $\beta_2 \neq 0$ and $\beta_3 \neq 0$). With greater agreement, players are more likely to choose actions that match their signals (Column 1), more likely to choose actions that align with Bayes' Rule (Column 2), more likely to form or join information cascades (Column 3), and more likely to choose the correct actions (Column 5).¹² To look at the importance of group identity, we test for differences in the coefficients between in-group and out-group predecessor agreement ($\beta_2 \neq \beta_3$). The F -test is reported at the bottom of Table 2 and it shows that players do not differentiate between information that comes from in-group versus out-group predecessors when that information corroborates their private signals.¹³

Table 4 provides a range of robustness checks. First, we control for turn fixed effects because players' choices and outcomes can depend on their turn

¹² Interestingly though, on net, reverse cascades are no more likely to result from these types of turns. Reverse cascades predominantly originate on turns in which there is contradictory information and where players are members of the same group.

¹³ Players are somewhat more likely to start or join reverse cascades when their signals match their predecessors actions and their predecessors are members of their group (as opposed to their predecessors being members of the other group) since the p -value = 0.03 in Column 4. However, β_2 is not statistically significantly different from zero (the case where players draw signals that contradict their predecessors' actions and their predecessors are not members of their group), and so we do not place too much emphasis on this result.

numbers. However, since the share of in-group predecessors is randomly assigned across rounds, we find that including turn fixed effects does not affect our estimates. Second, we control for player fixed effects to see if the same players make different decisions when they have conflicting information and higher shares of in-group predecessors, and we find that they do. Third, we cluster the standard errors at the session-level to allow for correlation in the error terms across players within sessions, but we find that this adjustment makes little difference in terms of inference.

Table 5 provides an additional robustness check by re-estimating the results for players in control rounds. In these rounds, group identities are not revealed to the players. As expected, group identity has no effect on player actions in control rounds.

Next, we take advantage of the temporal dimension of our data to determine when players are more likely to conform to the actions of their predecessors. Table 6 reports regression results like those reported in Table 3, but estimated separately for the first 16 rounds of each session (top panel) compared to the last 16 rounds of each session (bottom panel). The sample is limited to treatment rounds where group identities are revealed. Players are more likely to disregard their own signals and to join cascades in the earlier rounds of the session, suggesting that players default to conformity when they are less familiar with the game. However, players may learn over the course of the session that group identity information is irrelevant, and so they are somewhat less likely to conform toward the end of the session. These results may showcase a “reverse expectations adjustment effect” [6], where players have to learn that conformity is unhelpful in our manufactured environment.

We now turn to investigate why higher shares of in-group predecessors decrease the probability that players choose the correct actions. Recall from the estimates in Table 3 that more contradictory information from in-group prede-

cessors reduces payoffs ($\hat{\beta}_1$ in Column 5) but does *not* reduce the probability that players choose actions that are consistent with Bayes' Rule ($\hat{\beta}_1$ in Column 2). In other words, we find that group identity bias induces players to receive systematically lower payoffs while still behaving rationally. One potential explanation is that these two results are driven by tie-breaking turns where it is consistent with Bayes' rule for players to choose either action – follow their predecessors or follow their signals. In tie-breaking turns, conforming (rather than following one's own signal) will trigger a cascade, which reduces information revelation and potentially reduces payoffs for subsequent players in the round. Therefore, in-group bias that increases conformity on tie-breaking turns can reduce payoffs by inflicting a negative externality on subsequent players in the round.

Moreover, there is a second reason that pro-in-group bias increases the frequency of reverse cascades. In turns where an information cascade has already begun (“cascade turns”), players are less likely to break the cascade when their predecessors are members of their group. We demonstrate both of these phenomena presently.

Table 7 reports the regression results from estimating Equation (1) for tie-breaking turns and cascade turns. The top panel shows results for tie-breaking turns. Tie-breaking turns occur when Bayesian players ought to be indifferent between choosing the red or blue jar. However, Column 1 shows that as the share of in-group predecessors increases from 0 to 1, players are 11.3 percentage points less likely to choose actions that match their signals and they are correspondingly more likely to form information cascades. They are also 8.4 percentage points more likely to form reverse cascades. The consequences of conforming to their predecessors' actions are highlighted in Column 4. As the share of in-group predecessors increases from 0 to 1, the probability that players choose the correct action decreases by 22.1 percentage points. This

highlights one reason why payoffs declined when players received more information from in-group predecessors: they were more likely to conform on tie-breaking turns that featured in-group predecessors.

The bottom panel of Table 7 reports regression results for cascade turns. Cascade turns occur when an information cascade has already formed, and players decide whether to join the cascade or to break it. As the share of in-group predecessors increases from 0 to 1, players are 16.7 percentage points less likely to choose actions that match their signals and they are correspondingly more likely to join information cascades. They are also 31.3 percentage points more likely to join reverse cascades. The consequences of joining reverse cascades appear in Column 4, which shows that as the share of in-group predecessors increases from 0 to 1, players are 25.9 percentage points less likely to choose the correct actions.

These results show that in-group bias can trigger conforming behavior on tie-breaking turns, which can increase the frequency of reverse cascades. In-group bias can then perpetuate reverse cascades because players are less likely to deviate from their own group members' actions. These pivotal effects can result in lower payoffs for all players. Nevertheless, we acknowledge that statistical noise could be another reason why payoffs are so much lower in our setting; even perfectly Bayesian players will sometimes guess incorrectly depending on the noisiness of the signal. Therefore, since the probability of guessing incorrectly exceeds the probability of forming a cascade, it's likely that we overestimated the negative consequences of in-group conformism on player welfare, and if we had more sessions of data, the effects would have been smaller.

7 Discussion

Previous lab experiments have shown that individuals often discard their private information and conform to the decisions of others in sequential decision-making games [5][43]. This paper extends the literature by showing that group identity can affect decisions to conform in laboratory environments, even when players lack incentives to take strategic actions. Our results show that in-group identity fosters conformism when players draw signals that contradict their predecessors' actions. We further find that in-group conformism can trigger information cascades on the wrong actions and reduce player welfare.

Why would players conform to the decisions of in-group members when they have no incentive to do so? Bernheim and Exley (2015) carefully tackle how conformity can arise in individual decision-making contexts [6]. Conformity can arise due to beliefs (an “expectations-adjustment effect”), where “behavior evolves when experience proves that pertinent beliefs are incorrect and in need of revision.” In this case, people abandon their contradictory beliefs due to social sanctions or some other mechanism that makes holding such beliefs costly. Alternatively, conformity can arise due to a “preference mechanism” (a “gravity effect”), where “repeated exposure to others’ choices can pull deviant group members closer to a prevalent mode of behavior even when beliefs are accurate.” In this case, people have preference disutility from continuing to disagree with their group members. In our experiment, we find greater conformity at the beginning of our experiment sessions compared to the end, suggesting that in our context, players default to conformity when they are less familiar with the game. Then players may learn over the course of the session to conform less and discard the irrelevant group identity information. We are not the first to show that players incorrectly weigh irrelevant information [24], but we are the first to show that players default to confor-

mity and then experience a “reverse” expectations-adjustment effect, where they learn that conformity does not help them in our lab environment.

If we extrapolate our results to the world outside the lab environment, then we might expect to find more information cascades occurring within groups than across groups in the real world. Therefore, our results have implications for the political economy literature on committee decision-making, which has emphasized the importance of truthful reporting and efficient aggregation of information for beneficial social decision-making [22]. Our results suggest that committees should alternate the sequence of votes cast by members of different groups; then individual members may be more likely to reveal their private information and less likely to form reverse cascades. An alternating votes rule may help committees reach more efficient decisions, and this rule could also be applied to judge and jury verdict voting [4].

Future work in this area might do more to isolate the social and psychological mechanisms underlying the differences in information processing that occur in settings with group identity. We have emphasized mechanisms related to conformity, where people are socialized to agree with in-group members and to disagree with out-group members [10][16][28]; however, beliefs about the competence of in-group or out-group members could also explain our empirical results [25][32][37][44]. More targeted experimental treatments may be able to reveal these mechanisms.

Appendix A: Experiment Details

We administered the experiment sessions at the Columbia Experimental Lab for the Social Sciences (CELSS). Players were recruited in the weeks leading up to the experiment sessions using the ORSEE recruitment platform [26]. Volunteers were required to register with the ORSEE system in order to participate. Volunteers were only allowed to participate in our experiment once; we did not accept volunteers who had already participated. Because we have $N = 6$ (six turns in a round), we recruited either 12 or 18 players, depending on the availability of recruits. Volunteers were notified that they would receive a \$5 show-up fee and up to \$22 if they participated in the experiment. If more volunteers arrived than needed, then the excess volunteers received \$5 cash and they did not participate in the experiment.

Players were randomly assigned to computer terminals upon arrival. Visual barriers were used to prevent players from seeing the screens of their neighbors. The instructions for all stages of the experiment (included below) were recited from a script and presented in a slide presentation.

At the beginning of each session, players were instructed not to use cell phones and not to talk to other players. They were told that the experiment would last for up to 75 minutes and that they would earn between \$5 and \$27. They were told that there would be four parts to the experiment.

The experiment was administered using the z-Tree economics experiment platform [20]. The terminals are Dell desktops with 16:9 displays running Windows Vista. In between parts of the experiment, players were given a numerical pass code to proceed to the next part. The jars game and the questionnaire programs for the experiment are available upon request. The instructions script, slides, and trivia questions are attached.

Besides the four sessions included in the present analysis, we attempted to administer two additional sessions with a different set of Klee and Kandinsky pictures. However there were technical issues with the experiment software, and we were unable to produce usable data.

This research has been reviewed and approved by the Human Subjects division of Columbia University’s Institutional Review Board under Protocol #AAAL5692.

Appendix B: An Information Cascades Model with Group Identity

The Bikhchandani et al. (1992) information cascades model describes a world with a finite set of identical agents, indexed by their sequence of play (i.e., their “turn”), $i \in \{1, \dots, N\}$ [7]. There is a binary, true state of the world $\theta = \{0, 1\}$ where agents share the accurate prior $\Pr(\theta = 1) = \delta = \frac{1}{2}$. Each agent takes a binary action $a_i = \{0, 1\}$ where the agent only cares about whether the action matches the state of the world (i.e., the agent’s utility equals 1 if $a_i = \theta$ and zero otherwise). Before choosing a_i , each agent observes a binary, independent, and noisy signal about the state of the world $s_i = \{h, l\}$. We assume that $\Pr(s_i = h | \theta = 1) = \Pr(s_i = l | \theta = 0) = p > \frac{1}{2}$, meaning that the signal is informative about the state.

Agents move sequentially in choosing a_i . When an agent moves, she has observed her own signal as well as the actions of her predecessors, which we represent by $a_{\sim i}$. Agents can use this information to form posteriors on θ . Let $\mu_i(s_i, a_{\sim i}) = P(\theta = 1 | s_i, a_{\sim i})$ be agent i ’s posterior belief that $\theta = 1$. We follow the previous literature in restricting analysis to Perfect Bayesian Equilibria.

To begin the equilibrium analysis, consider the best response of the first agent ($i = 1$). By Bayes' Rule, if she receives a high signal, then her posterior is:

$$\begin{aligned}\mu_1(h, \emptyset) &= \frac{\Pr(s_1 = h \mid \theta = 1) P(\theta = 1)}{\Pr(s_1 = h \mid \theta = 1) \Pr(\theta = 1) + \Pr(s_1 = h \mid \theta = 0) \Pr(\theta = 0)} \\ &= \frac{p(\frac{1}{2})}{p(\frac{1}{2}) + (1-p)(\frac{1}{2})} \\ &= p > 1/2.\end{aligned}$$

Similarly, if she receives a low signal,

$$\mu_1(l, \emptyset) = 1 - p < 1/2.$$

The first agent's best response is to choose $a_1 = 1$ if she receives a high signal and $a_1 = 0$ if she receives a low signal. If subsequent agents believe that Agent 1 is rational, then Agent 1's action reveals her signal and Agent 1's signal becomes common knowledge. As subsequent agents move in sequence, an information cascade is increasingly likely to occur. An information cascade occurs when $\exists n$ such that $\forall m > n$ all agents take the same action.¹⁴ Bikchandani et al. (1992) show that as N increases, the probability that an information cascade occurs converges to 1.¹⁵

¹⁴ We assume for simplicity, and in line with the previous literature, that when an agent is indifferent between her choices she randomizes across them with equal probability. Our key theoretical results do not depend on this assumption, although empirically, information cascades are more likely to occur when agents conform to the actions of their immediate predecessors in "tie-breaking" turns.

¹⁵ Since an imbalance of two consecutive, identical actions can trigger a cascade, the only turns in which cascades will not occur are turns in which actions alternate for every player (e.g., for player 6 the probability that a cascade has not formed is the probability that player 6 observes action sequences $\{0, 1, 0, 1, 0\}$ or $\{1, 0, 1, 0, 1\}$). Moreover, if players are updating their beliefs according to Bayes' Rule, then the only way for the action sequence to alternate for every player is if every player receives alternating signals. Therefore, it can be shown that for player n , the probability of not being in a cascade is $[(1-p)p]^{\frac{n}{2}}$.

Next we explore the idea that agents update their beliefs differently depending on whether they receive information from in-group vs. out-group members. We index agents by i as well as by $g \in \{V, W\}$, where g indexes agent i 's membership in group V or W . In addition to observing her own private signal and the actions of predecessors, agent i now observes her group identity and the group identities of her predecessors. She then guesses the state of the world. Group identity has no relevance for payoffs in this setup; it is just a label.

We suppose that agent i now weighs information differently depending on whether her predecessors are part of her group or not; specifically, λ_I is the “in-group” weight and λ_O is the “out-group” weight on her predecessors’ signals. Her posterior belief on θ is now a function of her signal, her group, her predecessors’ actions, and her predecessors’ group membership. We illustrate the weighted reformulation of Bayes’ Rule by computing the posterior probabilities for Agent 2. First we assume that Agent 1 chooses $x_1 = 1$, without loss of generality. Agent 2 can infer Agent 1’s signal from her action, so $s_1 = h$. The new ingredient is that Agent 2 will over-weight or under-weight Agent 1’s signal depending on whether Agent 1 is a member of Agent 2’s group or not. We have the following four hypothetical scenarios,

1. Same group, same signal:

$$\begin{aligned}\mu_{2g} &= \Pr(\theta = 1 \mid g_1 = g_2, s_1 = s_2) \\ &= \frac{p(\lambda_I p)}{p(\lambda_I p) + (1 - p)(1 - \lambda_I p)}\end{aligned}$$

2. Same group, different signal:

$$\begin{aligned}\mu_{2g} &= \Pr(\theta = 1 \mid g_1 = g_2, s_1 \neq s_2) \\ &= \frac{p(1 - \lambda_I p)}{p(1 - \lambda_I p) + (1 - p)(\lambda_I p)}\end{aligned}$$

3. Different group, same signal:

$$\begin{aligned}\mu_{2g} &= \Pr(\theta = 1 | g_1 \neq g_2, s_1 = s_2) \\ &= \frac{p(\lambda_O p)}{p(\lambda_O p) + (1 - p)(1 - \lambda_O p)}\end{aligned}$$

4. Different group, different signal:

$$\begin{aligned}\mu_{2g} &= \Pr(\theta = 1 | g_1 \neq g_2, s_1 \neq s_2) \\ &= \frac{p(1 - \lambda_O p)}{p(1 - \lambda_O p) + (1 - p)(\lambda_O p)}\end{aligned}$$

We compare these expressions to the expression for μ_2 in the absence of group identity. The expressions are equal when $\lambda_I = \lambda_O = 1$. If the weighting parameters diverge from 1, the model with group identity will generate different posteriors for Agent 2, and potentially different best responses. This example for Agent 2 demonstrates why our model is useful for guiding our empirical work. In the lab data, a simple way to determine whether $\lambda_O \neq 1$ or $\lambda_I \neq 1$ is by observing agent actions under these different scenarios and seeing whether revealing the group identity of predecessors causes deviations in one way or the other.

In an information cascade model with N agents, Anderson and Holt (1997) show that the posterior for any agent is a function of the number of relevant signals. Relevant signals include the set of actions before a cascade starts, the two decisions that start a cascade, and non-Bayesian deviations from a cascade. If x_i is the number of relevant h signals, y_i is the number of relevant l signals, and $p = \frac{2}{3}$, then agent i 's posterior is,

$$\mu_i = \Pr(\theta = 1 | x_i, y_i) = \frac{2^{x_i}}{2^{x_i} + 2^{y_i}}$$

We modify this formula to incorporate group identity. We let j_i be the number of relevant h signals from in-group members and let $(x - j)_i$ be the number of relevant h signals from out-group members. We let k_i be the number of relevant l signals from in-group members and let $(y - k)_i$ be the number of relevant l signals from out-group members. If agent i receives signal h , without loss of generality, her posterior is,

$$\begin{aligned} \mu_{ig} &= \Pr(\theta = 1 | j_i, (x - j)_i, k_i, (y - k)_i) \\ &= \frac{\lambda_I^{j_i} \lambda_O^{(x-j)_i} p^{(x+1)_i} (1 - \lambda_I p)^{k_i} (1 - \lambda_O p)^{(y-k)_i}}{\lambda_I^{j_i} \lambda_O^{(x-j)_i} p^{(x+1)_i} (1 - \lambda_I p)^{k_i} (1 - \lambda_O p)^{(y-k)_i} + \lambda_I^{k_i} \lambda_O^{(y-k)_i} p^{y_i} (1 - p)^{(1 - \lambda_I p)^{j_i} (1 - \lambda_O p)^{(x-j)_i}}} \end{aligned}$$

This expression clarifies the role of λ_O and λ_I in our framework. If $\lambda_O = \lambda_I = 1$, the expression is equal to Anderson and Holt's (1997) formulation. If either weight does not equal one, then revealing group identities might result in players taking different actions.

In particular, there are three predictions that emerge from the information cascades model with group identity. For a given set of high and low signals $\{x_i, y_i\}$:

1. When $\lambda_I = \lambda_O = 1$, then $\mu_{ig} = \mu_i$. When the in-group and out-group weights equal 1, then there is no effect of group identity on the Bayesian posterior and no effect of group identity on individual actions.

2. $\frac{\partial \mu_{ig}}{\partial j_i} > \frac{\partial \mu_i}{\partial x_i} > \frac{\partial \mu_{ig}}{\partial (x-j)_i}$ for all $\lambda_I \in (1, \frac{3}{2}]$ and $\lambda_O \in [\frac{3}{4}, 1)$.¹⁶ As the number of h signals from in-group members increases (j_i), then agent i 's posterior increases more than it would have if the same number of h signals were observed from out-group members $(x - j)_i$ or from agents in a setup without group identity (x_i). Since agent i 's posterior increases relative to the case without

¹⁶ λ_I must be less than or equal to $\frac{3}{2}$ because probabilities cannot be negative. λ_O must be greater than or equal to $\frac{3}{4}$ because an out-group member's action must still be more informative than the prior. These are the bounds when $p = \frac{2}{3}$.

group identity, agent i is more likely to choose $\theta = 1$ when her predecessors choose $\theta = 1$ and when they are members of her group.

3. $\frac{\partial \mu_{ig}}{\partial k_i} < \frac{\partial \mu_i}{\partial y_i} < \frac{\partial \mu_{ig}}{\partial (y-k)_i}$ for all $\lambda_I \in (1, \frac{3}{2}]$ and $\lambda_O \in [\frac{3}{4}, 1)$. As the number of l signals from in-group members increases (k_i), then agent i 's posterior decreases more than it would have if the same number of l signals were observed from out-group members $(y - k)_i$ or from agents in a setup without group identity (y_i). Since agent i 's posterior decreases relative to the case without group identity, agent i is less likely to choose $\theta = 1$ when her predecessors choose $\theta = 0$ and when they are members of her group.

These predictions have implications for the probability that information cascades form in any given turn. By prediction (1), if agents do not over-weigh or under-weigh their predecessors' signals, then the probability that cascades form should be the same across rounds with all in-group members or all out-group members, and it should equal the probability that cascades form in rounds without group identity. By prediction (2), as the relative number of in-group predecessors increases, Agent i 's posterior increases relative to the model without group identity. Holding constant the number of relevant signals, the probability of observing a cascade increases in rounds with high shares of in-group predecessors. Prediction 3 is the same as prediction (2), but with the signals reversed. Therefore, as the share of in-group predecessors increases (decreases), cascades should be more (less) likely to occur, which is what we find in our experimental data.

Model Estimation

We used the experimental data to structurally estimate the λ_I and λ_O parameters from our model. The above formula for each player's Bayesian poste-

rior μ_{ig} was operationalized in Python. The objective function minimized the squared error, in this case equivalent to the number of errors, or mis-predicted decisions, based on μ_{ig} for each player. Formally, we minimized the following objective function: $\min(\text{choice} \neq \hat{\text{choice}})$, where $\hat{\text{choice}} = 1$ if the player's posterior $\mu_{ig} > 0.5$ and equals zero otherwise. The function was minimized using the Nelder-Mead algorithm, and the function was minimized separately for treatment vs. control rounds.

Our estimated parameters λ_I and λ_O appear below. We found that $\hat{\lambda}_I = 1.17$ and $\hat{\lambda}_O = 0.89$ in treatment rounds where group identity was revealed to players. We expected to find that $\hat{\lambda}_I > \hat{\lambda}_O$ because then players overweigh in-group actions relative to out-group actions. We expected to observe $\hat{\lambda}_I > 1$ because then players weigh in-group actions more than their private signals, consistent with our reduced form results. We also expected to observe $\hat{\lambda}_O \leq 1$ because then players weigh out-group actions less than their private signals, also consistent with our reduced form results.

In control rounds, we find that $\hat{\lambda}_O = 0.97$, which is very close to 1, meaning that players do not discount their out-group predecessors' actions when they do not know their predecessors' group membership. We find that $\hat{\lambda}_I = 0.78$ in control rounds, which is not as close to 1 as we expected, although we structurally estimated the model with only 432 observations, so we believe this parameter estimate is quite noisy (though it is qualitatively consistent with row 1 in Table 5 of our reduced form estimates).

Parameter Estimates from Structural Model

Sample	<i>Estimated Weights</i>	
	In-Group (λ_I)	Out-Group (λ_O)
Treatment Rounds (1296 turns)	1.166	0.889
Control Rounds (432 turns)	0.784	0.97

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Fig. 1: One of Five Painting Pairs Observed During Paintings Stage

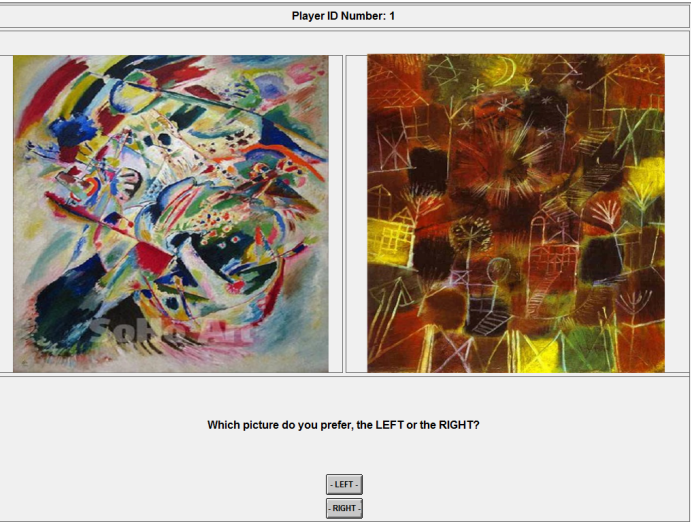


Fig. 2: Chat Interface for Trivia Stage

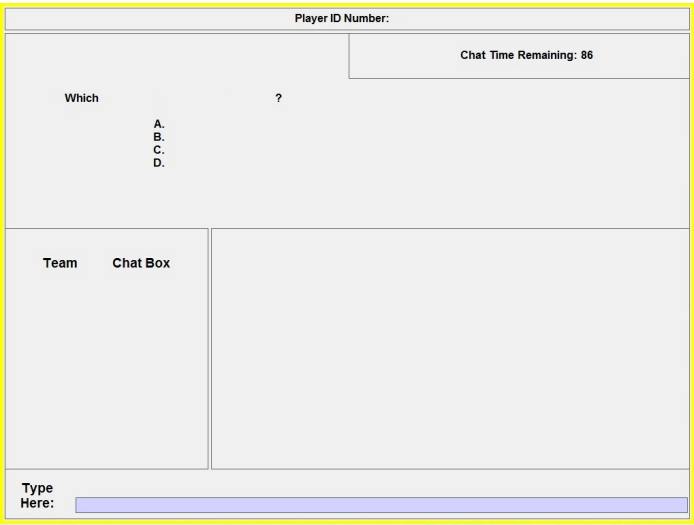


Fig. 3: Virtual Jars



Fig. 4: Example Screenshot from Jars Game

Player ID Number: _____			
Your Turn: 4. Current Turn: 4 of 6.		Your team: _____	Current Round: 2 of 2.
1 2 3 4			First Player (Team KANDINSKY) guessed the RED jar.
			Second Player (Team KLEE) guessed the BLUE jar.
			Third Player (Team KANDINSKY) guessed the RED jar.
			You have drawn a BLUE marble.
Guess a jar:		BLUE RED	

Fig. 5: Example Screenshot from Donation Game

Player ID Number:

You are on Team KLEE.

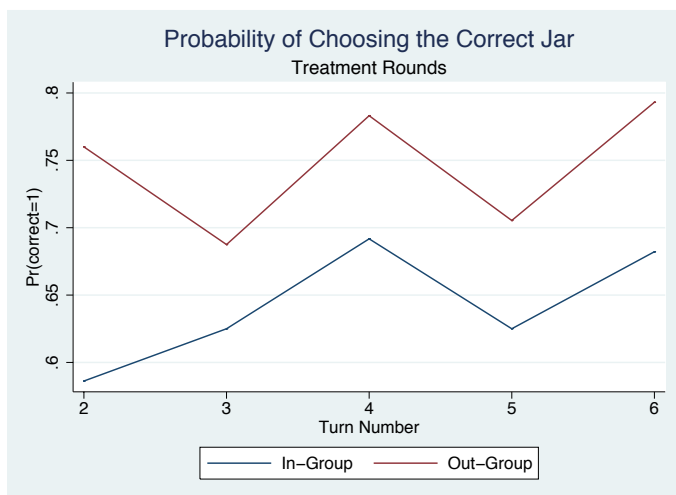


Person 1 is on team KLEE. 	Person 2 is on team KANDINSKY. 
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How do you want to distribute the \$1?

☐ \$1.00 for Person 1, \$0.00 for Person 2
☐ \$0.75 for Person 1, \$0.25 for Person 2
☐ \$0.50 for Person 1, \$0.50 for Person 2
☐ \$0.25 for Person 1, \$0.75 for Person 2
☐ \$0.00 for Person 1, \$1.00 for Person 2

Fig. 6: Probability of Choosing the Correct Jar by Turn Number



Notes: This figure plots the share of correct choices made by players on different turns in treatment rounds. The red line represents players who make decisions in rounds where the share of in-group predecessors is less than or equal to 0.5. The blue line represents players who make decisions in rounds where the share of in-group predecessors is greater than 0.5. For example, players on Turn #2 are represented by the blue line if their predecessors (players on Turn #1) were members of their group and they are represented on the red line if their predecessors were not members of their group.

Table 1: Predecessor Party Share and U.S. Supreme Court Voting

<i>Effect on Probability of Herding in Certiorari Votes</i>					
	(1)	(2)	(3)	(4)	(5)
<i>Share of Predecessors from Same-Party</i>	0.077** (0.04)	0.075* (0.04)	0.05 (0.04)		
<i>x Democrat</i>				0.030 (0.046)	0.046 (0.045)
<i>x Republican</i>				0.072* (0.038)	0.085** (0.035)
R ²	0.001	0.015	0.016	0.015	0.027
N	4,614	4,614	4,614	4,614	4,614
<i>Effect on Probability of Herding in Initial Affirm/Reverse Votes</i>					
	(1)	(2)	(3)	(4)	(5)
<i>Share of Predecessors from Same-Party</i>	0.180** (0.042)	0.130** (0.045)	0.125** (0.043)		
<i>x Democrat</i>				0.129** (0.043)	0.123** (0.042)
<i>x Republican</i>				0.130** (0.045)	0.080* (0.048)
R ²	0.006	0.017	0.017	0.017	0.020
N	5,725	5,725	5,725	5,725	5,725
Turn Fixed Effects		Yes	Yes	Yes	Yes
Party Indicator			Yes		
Year Fixed Effects					Yes

Notes: Each column presents an estimate from a separate regression. Standard errors clustered by docket and appear in parentheses. * $p < 0.10$, ** $p < 0.05$. The outcome variable is a binary variable for whether the judge's vote starts or joins a herd, as defined in the text. *Share of Predecessors From Same-Party* equals the number predecessor judges who were appointed under the same political party divided by the total number of predecessors. Columns 4 and 5 report the coefficients on the interaction terms between the share of same-party predecessors and binary variables for Democrat and Republican judges, respectively.

Table 2: Overall Effects of Group Identity on Player Actions and Outcomes

Treatment Rounds	(1) <i>Pr(Own Ball=1)</i>	(2) <i>Pr(Bayesian=1)</i>	(3) <i>Pr(Cascade=1)</i>	(4) <i>Pr(Reverse=1)</i>	(5) <i>Pr(Correct=1)</i>
<i>Share In-Group</i>	-0.096** (0.028)	0.005 (0.023)	0.077* (0.046)	0.125** (0.033)	-0.150** (0.034)
Dependent Variable Mean	0.82	0.90	0.60	0.14	0.68
R ²	0.007	0.00001	0.003	0.016	0.014
N	1,080	1,080	1,080	1,080	1,080

Notes: Each column presents an estimate from a separate regression. The sample includes players with turn numbers 2, 3, 4, 5, or 6 in treatment rounds, where players learn the group identities of their predecessors. *Share In-Group* is the number of player i 's predecessors who belong to her group divided by the total number of predecessors. $Pr(OwnBall = 1)$ is the probability that player i chooses the action that matches her private signal, $Pr(Bayesian = 1)$ is the probability that player i chooses an action that is consistent with Bayes' Rule, $Pr(Cascade = 1)$ is the probability that player i chooses the action that starts or joins an information cascade, $Pr(Reverse = 1)$ is the probability that player i chooses the action that starts or joins a reverse information cascade, and $Pr(Correct = 1)$ is the probability that player i chooses the action that is correct (i.e., matches the state of the world). Standard errors are clustered at the player-level and appear in parentheses. * $p < 0.10$, ** $p < 0.05$.

Table 3: Effects of Group Identity on Responses to Contradictory vs. Corroborating Information

Treatment Rounds	(1) <i>Pr(Own Ball=1)</i>	(2) <i>Pr(Bayesian=1)</i>	(3) <i>Pr(Cascade=1)</i>	(4) <i>Pr(Reverse=1)</i>	(5) <i>Pr(Correct=1)</i>
β_1 : <i>Share In-Group Contradict</i>	-0.222** (0.052)	-0.016 (0.040)	0.199** (0.048)	0.160** (0.048)	-0.210** (0.057)
β_2 : <i>Share In-Group Corroborate</i>	0.384** (0.050)	0.104** (0.038)	0.636** (0.045)	0.067 (0.041)	0.161** (0.044)
β_3 : <i>Share Out-Group Corroborate</i>	0.357** (0.052)	0.078** (0.033)	0.657** (0.049)	-0.025 (0.043)	0.250** (0.054)
Constant	0.640** (0.039)	0.869** (0.037)	0.196** (0.043)	0.087** (0.028)	0.638** (0.035)
F-test: $\beta_2 = \beta_3$	p = 0.20	p = 0.25	p = 0.60	p = 0.03	p = 0.10
R ²	0.248	0.022	0.184	0.022	0.089
N	1,080	1,080	1,080	1,080	1,080

Notes: Each column presents an estimate from a separate regression. The sample includes players with turn numbers 2, 3, 4, 5, or 6 in treatment rounds, where players learn the group identities of their predecessors. *Share In-Group Contradict* is the number of in-group predecessors who chose actions that contradict player i 's signal divided the total number of predecessors. *Share In-Group Corroborate* is the number of in-group predecessors who chose actions that corroborate player i 's signal divided by the total number of predecessors. *Share Out-Group Corroborate* is the number of out-group predecessors who chose actions that corroborate player i 's signal divided by the total number of predecessors. The omitted share is the number of out-group predecessors who chose actions that contradict player i 's signal divided by the total number of predecessors. Standard errors are clustered at the player-level and appear in parentheses. * $p < 0.10$, ** $p < 0.05$.

Table 4: Robustness Tests for the Effects of Group Identity in Turns with Contradictory Information

Treatment Rounds	(1) <i>Pr(Own Ball=1)</i>	(2) <i>Pr(Own Ball=1)</i>	(3) <i>Pr(Own Ball=1)</i>	(4) <i>Pr(Own Ball=1)</i>
β_1 : Share In-Group Contradict	-0.222** (0.052)	-0.189** (0.046)	-0.194** (0.046)	-0.194** (0.058)
	<i>Pr(Bayesian=1)</i>	<i>Pr(Bayesian=1)</i>	<i>Pr(Bayesian=1)</i>	<i>Pr(Bayesian=1)</i>
β_1 : Share In-Group Contradict	-0.016 (0.040)	-0.004 (0.040)	-0.006 (0.035)	-0.006 (0.028)
	<i>Pr(Cascade=1)</i>	<i>Pr(Cascade=1)</i>	<i>Pr(Cascade=1)</i>	<i>Pr(Cascade=1)</i>
β_1 : Share In-Group Contradict	0.199** (0.048)	0.192** (0.050)	0.182** (0.050)	0.182** (0.067)
	<i>Pr(Reverse=1)</i>	<i>Pr(Reverse=1)</i>	<i>Pr(Reverse=1)</i>	<i>Pr(Reverse=1)</i>
β_1 : Share In-Group Contradict	0.160** (0.048)	0.158** (0.049)	0.164** (0.054)	0.164* (0.087)
	<i>Pr(Correct=1)</i>	<i>Pr(Correct=1)</i>	<i>Pr(Correct=1)</i>	<i>Pr(Correct=1)</i>
β_1 : Share In-Group Contradict	-0.210** (0.057)	-0.215** (0.059)	-0.235** (0.059)	-0.235** (0.084)
β_2 : Share In-Group Corroborates	Yes	Yes	Yes	Yes
β_3 : Share Out-Group Corroborates	Yes	Yes	Yes	Yes
Turn Fixed Effects		Yes	Yes	Yes
Player Fixed Effects			Yes	Yes
Clustered Errors by Session				Yes

Notes: Each cell presents an estimate from a separate regression. The sample includes players with turn numbers 2, 3, 4, 5, or 6 in treatment rounds where group identities are revealed. Each regression controls for the share of predecessors who chose actions that corroborate player i 's signal and are members of player i 's group as well as the share of predecessors who chose actions that corroborate player i 's signal and are not members of player i 's group. Column (2) adds controls for turn fixed effects, Column (3) adds controls for player fixed effects, and Column (4) clusters standard errors at the session-level. Except for Column (4), standard errors are clustered at the player-level and appear in parentheses. * $p < 0.10$, ** $p < 0.05$.

Table 5: Robustness Tests for the Effects of Group Identity in Control Rounds

Control Rounds	(1) <i>Pr(Own Ball=1)</i>	(2) <i>Pr(Bayesian=1)</i>	(3) <i>Pr(Cascade=1)</i>	(4) <i>Pr(Reverse=1)</i>	(5) <i>Pr(Correct=1)</i>
β_1 : Share In-Group Contradict	0.212 (0.138)	-0.143 (0.086)	-0.104 (0.130)	-0.085 (0.088)	-0.096 (0.128)
β_2 : Share In-Group Corroborate	0.563** (0.108)	0.170** (0.066)	0.603** (0.112)	-0.093 (0.088)	0.354** (0.109)
β_3 : Share Out-Group Corroborate	0.580** (0.099)	0.098 (0.066)	0.502** (0.111)	-0.088 (0.091)	0.266** (0.107)
Constant	0.383** (0.085)	0.849** (0.059)	0.347** (0.094)	0.150** (0.073)	0.690** (0.097)
F-test: $\beta_2 = \beta_3$	p = 0.78	p = 0.19	p = 0.50	p = 0.97	p = 0.59
Turn Fixed Effects	Yes	Yes	Yes	Yes	Yes
Player Fixed Effects	Yes	Yes	Yes	Yes	Yes
R ²	0.415	0.351	0.431	0.214	0.245
N	360	360	360	360	360

Notes: Each column presents an estimate from a separate regression. The sample includes players with turn numbers 2, 3, 4, 5, or 6 in control rounds where group identities are not revealed. The omitted share is the number of out-group predecessors who chose actions that contradict player i 's signal divided by the total number of predecessors. Standard errors are clustered at the player-level and appear in parentheses. * $p < 0.10$, ** $p < 0.05$.

Table 6: Robustness Tests for the Effects of Group Identity in First 16 vs. Last 16 Rounds

First 16 Rounds	(1) <i>Pr(Own Ball=1)</i>	(2) <i>Pr(Bayesian=1)</i>	(3) <i>Pr(Cascade=1)</i>	(4) <i>Pr(Reverse=1)</i>	(5) <i>Pr(Correct=1)</i>
β_1 : Share In-Group Contradict	-0.222** (0.074)	-0.009 (0.054)	0.208** (0.082)	0.222** (0.068)	-0.270** (0.079)
R ²	0.355	0.247	0.315	0.142	0.194
N	600	600	600	600	600
Last 16 Rounds					
β_1 : Share In-Group Contradict	-0.141* (0.085)	-0.024 (0.066)	0.140 (0.091)	0.073 (0.072)	-0.213* (0.110)
R ²	0.447	0.316	0.350	0.128	0.195
N	480	480	480	480	480
β_2 : Share In-Group Corroborates	Yes	Yes	Yes	Yes	Yes
β_3 : Share Out-Group Corroborates	Yes	Yes	Yes	Yes	Yes
Turn Fixed Effects	Yes	Yes	Yes	Yes	Yes
Player Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: Each cell presents an estimate from a separate regression. The top panel includes players with turn numbers 2, 3, 4, 5, or 6 in the first 16 rounds in each session where group identities are revealed. The bottom panel includes players with turn numbers 2, 3, 4, 5, or 6 in the last 16 rounds in each session where group identities are revealed. The omitted share is the number of out-group predecessors who chose actions that contradict player i 's signal divided by the total number of predecessors. Standard errors are clustered at the player-level and appear in parentheses. * $p < 0.10$, ** $p < 0.05$.

Table 7: Effects of Group Identity in Tie-Breaking and Cascade Turns

Treatment Rounds	(1)	(2)	(3)	(4)
Tie-Breaking Turns (N=155)	<i>Pr(Own Ball=1)</i>	<i>Pr(Cascade=1)</i>	<i>Pr(Reverse=1)</i>	<i>Pr(Correct=1)</i>
Share In-Group	-0.113** (0.049)	0.113** (0.049)	0.084** (0.039)	-0.221** (0.088)
Mean Dependent Variable	0.88	0.12	0.07	0.53
Treatment Rounds				
Cascade Turns (N=192)	<i>Pr(Own Ball=1)</i>	<i>Pr(Cascade=1)</i>	<i>Pr(Reverse=1)</i>	<i>Pr(Correct=1)</i>
Share In-Group	-0.167* (0.091)	0.167* (0.091)	0.313** (0.099)	-0.259** (0.106)
Mean Dependent Variable	0.24	0.76	0.30	0.50

Notes: Each cell presents an estimate from a separate regression. The sample in the top panel includes players in “tie-breaking turns” where the Bayes’ Rule posterior equals 0.5. The sample in the bottom panel includes players in “cascade turns” where an information cascade has already formed and players draw signals that contradict the cascade. Robust standard errors appear in parentheses. * $p < 0.10$, ** $p < 0.05$.