Ingroup bias in a social learning experiment

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Abstract
Does social learning and subsequent private information processing differ depending on whether the observer shares the same group identity as the predecessor whose action is observed? In this paper, we conduct a lab experiment to answer this question, in which subjects first observe a social signal and then receive a private signal. We find that subjects put greater weights on the social signal if they share with the predecessor the same group identity that is induced in the experimental environment. We also provide suggestive evidence that such an ingroup-outgroup difference cannot be explained by individuals' beliefs of the predecessor’s rationality. Moreover, heterogeneous effects of group identity exist in weights given to the subsequent private signal: Compared to when the predecessor is an outgroup, those who have learned from an ingroup predecessor put a greater (smaller) weight on the private signal if it contradicts (confirms) the social signal. We conjecture that such group effects are consistent with the perspective that group identity works as a framing device and brings about certain decision heuristics in the social signal phase, which no longer exist in the private signal phase.

Keywords Ingroup bias · Social learning · Belief updating · Laboratory experiment

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1 Introduction

Social learning is an important source for individuals to gather information to update their beliefs and make decisions. It has drawn growing research interest from economists since the early work pioneered by, for example, Banerjee (1992), Bikhchandani et al. (1992), Anderson and Holt (1997). In a digital era like ours, in which social network sites play important roles in information dissemination, it’s easy to think of situations where individuals observe behavior and opinions of others before they receive and process objective signals themselves, regarding various types of events and facts, such as the safety and effectiveness of Covid-19 vaccines, and the validity of investment opportunities.1

Does social learning differ whether people learn from others who share the same or have different social identities with them? For example, does a Facebook post from a fellow alumna have the same effect on shaping one’s own beliefs and choices as a Reddit post from a stranger? How about a twitter comment from someone belonging to the same or opposing political party? If an ingroup-outgroup difference exists in processing the social signal, then the next question is whether the impact persists, or perhaps the difference will be offset once the person receives objective signals herself. Answering these questions may provide novel insights for understanding phenomena such as chamber effect and polarization (see Levy and Razin 2019 for a review), which are among the major themes in the public arena of our time.2

In this paper, we investigate these research questions in a controlled lab experiment, with group identities induced in the experimental environment. We also simplify away from the numerous factors in the real world by adopting the existing paradigm in the social learning literature—asking subjects to make incentivized judgments regarding a neutral event (color of the jar) that requires no previous knowledge and invokes no prior opinions or intrinsic preferences. We conjecture that the case of such a minimal group and a neutral event probably provides us a conservative estimate of the ingroup-outgroup difference in social learning, if it ever exists. On the one hand, natural group identities might have stronger effects. On the other hand, if, for example, the belief is ego-relevant or identity-relevant, the ingroup bias might interact with a motivated belief-updating process, resulting in a larger ingroup-outgroup difference when processing the social signals. Specifically,

1 As of August 2017, two-thirds (67%) of Americans report that they get at least some of their news on social media—with a fifth doing so often (Shearer & Gottfried, 2017).
2 Levy and Razin (2019) identify two broad reasons behind echo chambers: One is the tendency for individuals to segregate with like-minded ones, which leads to the creation of chambers; The other is the echo, that is, behavioral biases including correlation neglect, selection bias, and confirmation bias that induce polarization when individuals exchange beliefs in these chambers. Here we conjecture a new mechanism that can result in polarization of beliefs and opinions even if there is no segregation—if individuals put a greater weight on social information from ingroup than outgroup, and members of the same group receive correlated signals, then in some sense, such ingroup bias in social learning creates a virtual chamber. In other words, even if you are able to force people with opposite beliefs and opinions to desegregate and listen to each other, if there exists ingroup bias in social learning, their minds might still diverge further away.
we follow the experimental procedure used by De Filippis et al. (2022): The color of an urn is either black or white—the two events are, \textit{a priori}, equally likely; subjects are asked to state their beliefs about the likelihood of the urn being white, and the belief-elicitation task is incentivized. A randomly chosen subject receives a noisy binary symmetric signal about the color of the urn, after which she is asked to state her belief. Then other subjects observe the first subject’s stated belief and make the same type of prediction themselves. Finally, each subject receives another conditionally independent signal and makes a new prediction.

As we aim to investigate whether ingroup bias exists in social learning, besides the standard social learning (SL) treatment as in De Filippis et al. (2022), we design group social learning (GSL) sessions, in which before the social learning phase we add a phase of group assignment and enhancement following the previous experimental work on group identity (Tajfel et al., 1971; Chen & Li, 2009). Depending on whether sharing the same group identity as the first subject, subjects in the GSL sessions are divided into the ingroup social learning (ING) treatment and the outgroup social learning (OUTG) treatment. We repeat the learning procedure for 30 rounds in all treatments. In the first 20 rounds of the GSL sessions, we randomly select the first subject among members of one group, and then switch to the other group for the last 10 rounds, with the order counter-balanced—In this way, we embed a within-subject design in the between-subject design. Besides, we also design an individual decision-making (IDM) treatment as De Filippis et al. (2022) did, to provide a benchmark for comparison. Instead of observing the first subject’s prediction and then a private signal, all subjects receive two independent private signals consecutively in the IDM treatment.

We hypothesize that when processing the social signal, an ingroup-outgroup difference exists. Our experimental results confirm this hypothesis, as we find that based on weights computed with the Bayesian updating structure, subjects in the OUTG treatment underweight the social signal compared to the Bayesian benchmark to a significantly greater extent than those in the ING treatment, whereas subjects in SL or IDM treatments are more close to Bayesian updating. Moreover, in round 21 of the experiment, we elicit subjects’ beliefs on the first subject’s rationality, that is, the likelihood that the first subject has reported beliefs regarding the color of the urn in the correct direction as the signal suggests. We find no statistically significant ingroup-outgroup differences in these elicited beliefs on the predecessor’s rationality; neither can these rationality beliefs explain the impact of the group identity on the weight placed on the social signal. By checking whether and how the ingroup-outgroup difference varies over the rounds, we find that it is more prominent in the first several rounds than in the later rounds. These results suggest that instead of working via a belief-updating process about the predecessor’s rationality, the ingroup-outgroup difference might reflect heuristics that prescribe caution and suspicion with others’ behavior, especially with the outgroup predecessors’, which are brought about by the group frame.

We further examine whether sharing the same group identity as the predecessor has an impact on the weights put on the subsequent private signal. We find that when the private signal contradicts (confirms) the social signal, subjects in the ING treatment put a greater (lower) weight on the private signal than those in the OUTG.
treatment. Since the weight for the private signal is calculated with the Bayesian updating structure using the stated belief after observing the social signal as the prior belief, we conjecture that these empirical patterns are, again, consistent with that group identity works as a framing device, the heuristics cued by which no longer exist in the private signal phase. In other words, because the ingroup-outgroup difference in processing the social signal no longer exists in the private signal phase when subjects process the social and private signals together, subjects behave as if they were putting a higher (lower) weight on the private signal if it contradicts (confirms) the social signal, given the way the weights are calculated in our analyses.

Finally, since our study adopts an experimental design similar to that used by De Filippis et al. (2022), we can check whether our results replicate theirs. They found that when processing the private signal, subjects weighed the signal as a Bayesian agent if the signal confirmed the social signal; subjects overweighted the signal if it contradicted the social signal. In contrast, in our SL and GSL treatments, after receiving a contradicting private signal, subjects weigh the signal similar to a Bayesian agent; subjects underweight the signal when it confirms the social signal. At first glance, the results are quite different between the two studies. However, the commonality lies in that subjects nevertheless put a higher weight on a contradicting private signal than on a confirming one. The intuition captured by the specific case of the Likelihood Ratio Test Updating (LRTU) model discussed by De Filippis et al. (2022), which reconciles the empirical patterns they found, can be used to explain our results as well, as long as we are willing to impose an ad hoc assumption that in our private signal phase, the updating benchmark is not Bayesian updating but some extent of underweighting. Intuitively, subjects hold confident prior beliefs about the predecessor’s rationality after observing the social signal. Then, a confirming private signal retains such confident beliefs; subjects update their event beliefs under a general tendency of underweighting. In contrast, a contradicting private signal makes one adjust downward her belief about the predecessor’s rationality, and thus she adjusts downward the weight she puts on the social signal. Because such an adjustment is not captured by our way of calculating the weight placed on the private signal, it will appear as if the subject puts more weight on the private signal—the greater weight then offsets the general tendency to underweight among our subjects, rendering the belief-updating consistent with Bayesian updating. We provide evidence supporting this interpretation by showing that the rationality belief we elicit in round 21 becomes significantly lower after observing a contradicting private signal than after observing a confirming one.

Our work contributes to the large and growing literature on the various aspects of group identity effects in experimental economics. Given the significant impact of group identity on lots of important outcomes such as distributive preferences, cooperation behavior, evaluations of task performances, and general attitudes (for example, Tajfel et al. 1971; Ryen and Kahn 1975; Brewer 1979; Bettencourt et al. 1992; Brown et al. 1999; Bernhard et al. 2006; Goette et al. 2006; Chen and Li 2009; Currarini and Mengel 2016; Xu et al. 2020; Li 2020,) it is reasonable to conjecture that social learning from an ingroup member could be different compared to that from an outgroup member. So far, research directly examining the impact of group identity on social learning is limited. To the best of our knowledge, only in two recent
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Experimental studies, Ash and Van Parys (2015) and Berger et al. (2018) investigated how group identity affects the formation of information cascade. They both adopted the minimal group paradigm similar to the one used in the current paper to assign subjects to two groups (Tajfel et al., 1971; Chen & Li, 2009). After the group assignment stage, subjects engaged in repeated information cascade games based on Anderson and Holt (1997) in which each of them in a sequence knew all the prior players’ choices of the true state as well as her own private signal, and the group identities of the prior players were revealed. They found that information cascades are more likely to occur when learning from ingroup members compared to when learning from outgroup individuals. There are two major differences between the present study and theirs. First, we let subjects report their beliefs about the true state instead of making a binary decision regarding on which state to bet, which allows us to compute and compare the weights they put on the signals in different situations. Second, we collect subjects’ beliefs two times, one time after they observe a predecessor’s belief and the other time after they receive their own private signal, with which we can distinguish between their belief updating upon learning the two types of information. In contrast, Ash and Van Parys (2015) and Berger et al. (2018) let subjects make a decision after knowing the social and private information at the same time, focusing on the formation of information cascades. To summarize, we investigate the effect of group identity on social learning in a more general sense that is not constrained to the context of information cascade, and we also examine the implications beyond the social learning phase per se, that is, when new private information is available.

Our results also speak to an on-going debate in the broader literature on how to explain the identity effect in shaping behavior and cognition. First, the social preferences perspective has been popular among experimental economists, who represent the impact of group identity as changes in the values of prosocial parameters (Chen & Li, 2009; Müller, 2019; Robson, 2021). Second, some other researchers have focused on the role of beliefs. For example, Ockenfels and Werner (2014) examined the effect of second-order belief of group identity on ingroup favoritism in dictator games. Tanaka and Camerer (2016) showed that differences in outgroup discrimination can be explained by beliefs about the characteristics of potential outgroups. Grimm et al. (2017) found that beliefs about the behavior of other groups’ extent of ingroup favoritism matter. Third, an alternative tradition exists, viewing group identity as a framing device (Tajfel et al., 1971; Bacharach, 2006). Recent psychological research suggests that more similarity or experiences of more aligned interests among subjects may lead to a more “trusting mindset” (Gino et al., 2009; Levine et al., 2014; Bolton et al., 2016). More recently, Guala and Filippin (2017) and Filippin and Guala (2017) provided experimental evidence supporting the heuristics interpretation, by showing that the effect of group identity on distributive choices is highly dependent on contextual factors and that it can be easily displaced by changing the framing of decisions. As argued earlier, our findings can be viewed as supporting the framing perspective.

Last, this paper relates to the broader literature on other types of cognitive bias in information processing. For example, existing experimental evidence suggests that people tend to overweight their private information and underweight the
social information (Nöth & Weber, 2003; Çelen & Kariv, 2004; Goeree et al., 2007; Weizsäcker, 2010; Ziegelmeyer et al., 2013). It is then an open question how the ingroup-outgroup difference, if existing, interacts with such a tendency to underweight social information. In our data, we do not find evidence supporting that people in general underweight social information compared to private information. Interestingly, we find that introducing the group frame makes people underweight the social signal, especially if the predecessor is an outgroup.

The remaining of the paper structures as follows: We introduce the experimental design in Sect. 2, report the results in Sect. 3, and then conclude as well as provide our discussions of the results and future research directions in Sect. 4.

2 The experiment

2.1 Design

The experiment consists of four treatments, SL, IDM, and GSL (including ING and OUTG). Our SL and IDM treatments are similar to those of De Filippis et al. (2022). In the GSL treatments, we assign subjects to two groups and they observe the choices made by either an ingroup or an outgroup predecessor before making their own decisions. Then each subject receives an independent private signal. Details of experiments are as follows.

There are two parts in all treatments. In part 1, subjects see paintings in pairs on the screen. One of the paintings is drawn by Paul Klee, and the other is drawn by Wassily Kandinsky. The artists’ names do not appear on the screen, and the positions of the paintings are randomly decided, that is, it could either be Klee on the left and Kandinsky on the right, or the opposite. Subjects are requested to indicate which one they prefer in each pair of paintings. There are 5 pairs in total. Then, according to their relative preferences over the two artists, subjects in the GSL treatments are assigned to the Klee group or the Kandinsky group. We use relative preferences instead of absolute preferences over the two artists for group assignment since we want to create two groups with the same or close number of members to control for the impact of group size within sessions. There were 14–22 participants in a GSL session. If the number of participants $n$ is even, then both group sizes are $n/2$; otherwise, one group size is $(n - 1)/2$ and the other is $(n + 1)/2$. There is no group assignment in the IDM and SL treatments, while subjects in these two treatments nevertheless make choice between the paintings.

Subjects in all treatments then perform a task of moving sliders to the middle points of slider bars. In the IDM and SL treatments a subject earns 5 points for every
slider she moves to the middle point. In the GSL treatments a subject earns 0.5 points for every slider either she or any other group member moves to the middle point. Payoffs of the first part are not revealed until the end of the experiment. We introduce such common payoffs to enhance subjects’ perception of group identity (Charness et al., 2007).\(^4\)

Part 2 lasts for 31 rounds. In the beginning of each round, the computer randomly chooses one from two (virtual) urns, a white urn and a black urn, with a 50–50 chance. The white urn contains 7 white balls and 3 black balls, while the black urn contains 3 white balls and 7 black balls. Subjects won’t know which urn has been chosen until the end of each round. In round 1 of all treatments, the computer randomly draws a ball out of the chosen urn with replacement for each subject, and subjects observe whether it is a white ball or a black ball. Then, subjects report individually the probability that they believe the chosen urn is white in this round, ranging from 0 to 100 (up to two decimal points). The first round serves as a chance for practice.

In each of rounds 2–31 in the IDM treatment, subjects first observe a ball privately drawn from the chosen urn and report individually their subjective probability beliefs about the chosen urn being white. This process repeats twice in a round. In each of rounds 2–31 in the SL and GSL treatments, the computer first randomly chooses one subject as Player A and then randomly draws a ball out of the chosen urn with replacement. Only Player A observes the drawn ball and reports her subjective probability belief about the chosen urn. After Player A’s decision, every other subject observes the subjective probability Player A reported (social signal), and reports individually his own belief about how likely the chosen urn is white. Last, each subject privately observes another randomly drawn ball (private signal) and reports his belief about the chosen urn again.

In the GSL treatments, the group identity of Player A is revealed. We introduce the ING and OUTG treatments within the same session, which means that Player A sends social signals to both groups at the same time. Such a design feature guarantees that any group identity effect we find in information processing is not because subjects expect Player A to act differently when sending social signals to ingroup versus outgroup. In particular, in a Klee-Kandinsky (Kandinsky-Klee) session, one subject is chosen randomly from the Klee (Kandinsky) group in each of rounds 2–21, and from the Kandinsky (Klee) group in each of rounds 22–31. Therefore, those in the Klee (Kandinsky) group in a Klee-Kandinsky session are in the ING (OUTG) treatment in rounds 2–21, but are in the OUTG (ING) treatment in rounds 22–31.

Subjects’ reported beliefs are incentivized with a quadratic scoring rule, that is, \(\text{payoff} = 150 - 0.015 \times (V - \text{reported belief})^2\). We adopt the quadratic scoring rule

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\(^4\) Subjects’ responses to the predecessor’s decision may depend on their judgment about the predecessor’s rationality or intelligence. Online chat, which is a popular group enhancing device used in the literature, may provide information for them to make inferences about the the predecessor’s rationality or intelligence. Hence, we instead use common payoff to enhance group identity.
following De Filippis et al. (2022).\footnote{It is worth noting that the quadratic scoring rule is not incentive compatible under risk aversion, which might be the reason why subjects’ beliefs often peak at 50\% in our results. There exist other methods that are incentive compatible for risk-averse agents in a theoretical sense such as the binarized scoring rule (Hossain & Okui, 2013). However, in state-of-the-art methodological discussions of belief elicitation, researchers emphasize the importance of so-called behavioral incentive compatibility and demonstrate that both the binarized scoring rule and the quadratic scoring rule violate some weak conditions for behavioral incentive compatibility (Danz et al., 2022). As a result, Danz et al. (2022) advocate for less-precise measurements with simpler and starker incentives for truthful reporting. In our elicitation procedure, after introducing the quadratic scoring rule, we explain to the subjects that it is in their best interest to state their true belief, to maximize the amount of money they could expect to gain. Such a descriptive representation of the scoring rule to some extent resonates with the advocate of Danz et al. (2022)’s.} If the chosen urn is white, $V = 100$; otherwise, $V = 0$. In rounds 2–31, the computer randomly draws one out of two reported beliefs to generate the payoff of the corresponding round. After round 31 ends, the computer randomly selects one round from rounds 1–10, 11–21, and 22–31 respectively. The sum of subjects’ earnings of the three selected rounds makes up the main part of their payoffs in the second part.

Moreover, we design two questions to elicit subjects’ beliefs about Player A’s rationality in round 21 of the SL and GSL treatments. Since beliefs about Player A’s rationality serve our secondary research objectives, we elicit them only in round 21, leaving the other rounds succinct. We ask subjects to report the probability they believe that Player A saw a white ball in the current round. The reported numbers also range from 0 to 100. They are asked twice, once after observing Player A’s action, and the other time after receiving the private signal. The answer is incentivized; the second-time question is phrased as a chance to modify the answer reported for the first time. Payoff $= 50 - 0.005 \times (C - \text{reported number})^2$. If Player A did see a white ball, $C = 100$; otherwise, $C = 0$. Subjects’ final earnings include the payoff from this extra question in round 21. Together with Player A’s action, such probability beliefs provide us with a measure of probability beliefs regarding Player A’s rationality. Specifically, if Player A’s action is larger than 50, which suggests a white ball, then the reported probability belief in round 21 that Player A has seen a white ball is equivalent to the probability belief that Player A has not made a mistake, or, that Player A is rational. If, instead, Player A’s action is smaller than 50, the probability that a subject thinks Player A has observed a white ball is the same as her probability belief that Player A has made a mistake. We use this simple and neutral belief question instead of directly asking about how likely subjects think Player A is or is not rational, or how likely that Player A has or has not made a mistake, to avoid potential confusion and minimize the influence of language connotation.

### 2.2 Hypotheses

First, we aim at testing whether there is a direct impact of group identity on subjects’ social learning. We focus on $\alpha_1$, the weight that individuals put on a social signal calculated from the following formula:
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where $a_1$ is the first belief, $a_A$ denotes Player A’s action, and $q$ is the signal precision, which equals 0.7 in our experiment. If $a_1 = 1$, it means that the subject updates his belief in a Bayesian way; if $a_1$ is larger (smaller) than 1, it means that he updates his belief as if a Bayesian belief updater has observed the signal more (fewer) than once.

In the existing experimental studies, Ash and Van Parys (2015) and Berger et al. (2018) found that information cascades were more likely to occur when learning from ingroup members than learning from outgroup members. Here, we provide our belief-based reasoning of an ingroup-outgroup difference in social learning under the Likelihood Ratio Test Updating (LRTU) rule model, a non-Bayesian updating model developed and empirically verified by De Filippis et al. (2022). Below, we describe the intuition; interested readers can find more formal analyses in Online Appendix C.1.

According to the LRTU model, when an individual observes Player A’s action, she is initially ambiguous about Player A’s rationality, that is, whether Player A correctly takes an action $a_A > 50$ ($a_A < 50$) if she observes a white (black) ball. She first selects her prior belief for Player A’s rationality, and then she updates her evaluation regarding the color of the urn. Specifically, she sets a critical value $c$ and compares it to the likelihood ratio of observing a (set of) signal(s) conditional on the predecessor being rational. If the likelihood ratio is greater than or equal to $c$, then the individual will select the prior belief that is most confident about the predecessor’s rationality within the possible belief range. Otherwise, she will select the least confident prior belief. The value of $c$ indicates how strong (or weak) the evidence needs to be to support the confidence in the predecessor’s rationality. When only one social signal is available, as in the first phase in each round of our experiment, the likelihood ratio of observing any given signal, conditional on the predecessor being rational, equals one. Let us discuss how group identity can make a difference in the three representative cases as follows.

1. Suppose that (a) the value of $c$ differs depending on whether the predecessor is an ingroup or an outgroup; for the ingroup $c < 1$, whereas for the outgroup $c > 1$; (b) the range of the rationality belief is identical for an ingroup and an outgroup. This means that it requires weaker evidence for the individual to have confidence about an ingroup’s rationality than about an outgroup’s rationality. Then, with the likelihood ratio equal one, the individual will select the most confident prior belief for the ingroup’s rationality while she will select the least confident prior belief for the outgroup’s rationality. Therefore, the individual will have a more confident belief about the ingroup’s rationality than the outgroup’s, and as a result, the weight calculated with the Bayesian updating structure, $a_1$, will be higher if the predecessor is an ingroup than if he is an outgroup.

2. Suppose that (a) $c$ has no ingroup-outgroup difference; $c \leq 1$; (b) the most confident prior belief within the belief range is more confident for the ingroup than for the outgroup. In this case, the individual will select the most confident ration-
ality belief within the respective range for both the ingroup and the outgroup. Because of the difference in the range, the same conclusion can be drawn as in the first case—\(\alpha_1\) would be higher if the predecessor is an ingroup than if he is an outgroup.

3. Suppose that (a) \(c\) has no ingroup-outgroup differences; \(c > 1\); (b) the least confident prior belief within the belief range is more confident for the ingroup than for the outgroup. In this case, the individual will select the least confident rationality belief within the respective range for both the ingroup and the outgroup. Again, because of the difference in the range, the same conclusion can be drawn as in the first case—\(\alpha_1\) would be higher if the predecessor is an ingroup than if he is an outgroup.

In these cases above, the assumption that weaker evidence is required to have confidence in an ingroup’s rationality than that of an outgroup, as well as the assumption that either the most confident or least confident belief about the predecessor’s rationality is higher for an ingroup than for an outgroup, can find support in a broad sense in the existing literature. For example, Cacault and Grieder (2019) found that people are overconfident in their fellow group members’ intelligence. Summing it up, we propose the following hypotheses:

\[ H_1 \quad \text{Subjects in the same group as Player A put a greater weight on the social signal than those in the other group do, that is,} \]
\[ \alpha_{1,\text{ING}} > \alpha_{1,\text{OUTG}}. \]

\[ H_2 \quad \text{Subjects in the same group as Player A have a higher belief regarding Player A being rational than those in the other group do. Once controlling for the rationality beliefs, the ingroup-outgroup differences in } \alpha_1, \text{ if any, disappears, or at least, diminishes.} \]

Moreover, we are interested in whether group identity has any impact on subsequent processing of private information after the social learning phase. We compute \(\alpha_2\), the weight that an individual puts on his private signal using the following formula:

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6 The social preference perspective might also predict an ingroup-outgroup difference when processing the social signal. Specifically, if people are more inequality averse toward an ingroup member than an outgroup individual, they will place a higher weight on the social signal to better align one’s own belief with the predecessor’s, reducing inequality in the monetary payoff from the belief-elicitation task. Alternatively, people might have an intrinsic preference to comply with (contradict) the behavior of an ingroup (outgroup). Either case, the social preference perspective predicts our \(H_1\) but not \(H_2\) or \(H_3\). While our results support \(H_1\) but not \(H_2\) or \(H_3\), there are other patterns in the private signal phase that are difficult to be reconciled from the social preference perspective. In general, we do not put much emphasis on this perspective in the current study, as we find it a bit stretchy while lacking specific support in the existing literature.
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where \( a_2 \) is the second belief, and \( s = 1 (0) \) means that a white (black) ball was drawn. Similar to \( a_1 \), when \( a_2 = 1 \), it means that the subject updates his belief in a Bayesian way; \( a_2 \) deviating from 1 indicates over- or under-updating in comparison to Bayesian updating.

De Filippis et al. (2022) found an asymmetry of belief updating upon receiving a private signal after a social signal, that is, people overweighted their private signal when it contradicted the social signal while they updated their belief in a Bayesian way when their private signal confirmed the social signal. The authors reconcile such patterns in their results with the Likelihood Ratio Test Updating (LRTU) rule model assuming that the parameter values satisfy certain conditions. Suppose that when receiving the social signal, the individual’s value of \( c \) is smaller than one, and thus the individual selects the most confident prior belief regarding the predecessor’s rationality. Then, a private signal confirming the social signal makes the individual stick to the same prior belief on the predecessor’s rationality, because a confirming private signal only increases the likelihood ratio. In contrast, a contradicting private signal will result in a much lower likelihood ratio, which can be smaller than \( c \), making the individual select the least confident prior belief of the predecessor being rational within the range. As a result, the belief-updating of the events in both phases will look as if the individual overweights the private signal, because it is in the opposite direction of the social signal, the weight placed on which is now adjusted down because of lowered beliefs in the predecessor’s rationality.

Following the LRTU model while assuming that \( c < 1 \) regardless of the group identity of Player A, we generate hypotheses about the effect of group identity on the weight subjects put on their private signal in exemplary cases as follows. In general, when the private signal is confirming, the likelihood ratio becomes even larger—the belief about Player A’s rationality does not shift; it is then unlikely that the group identity exhibits any effect on the processing of the private signal. When the private signal contradicts the social signal, we discuss two cases below.

1. Suppose that (a) \( c \) is smaller for the ingroup than for the outgroup; (b) the range of the rationality belief is identical for an ingroup and an outgroup. In this case, it is possible that receiving the private signal induces a downward adjustment in beliefs of Player A’s rationality for the outgroup but not for the ingroup, if the updated likelihood ratio lies inbetween the two values of \( c \). Thus, we expect to observe an ingroup-outgroup difference in \( a_2 \) after observing a contradicting private signal, since a more dramatic downward adjustment of Player A’s rationality will demonstrate itself in the form of a greater weight placed on the contradicting private signal, calculated with the Bayesian structure.

2. Suppose that (a) \( c \) and the most confident prior belief within the belief range are both the same; (b) the least confident prior belief is more confident for the ingroup than for the outgroup. In this case, it is possible that both for the ingroup and the
outgroup, after observing a contradicting private signal, an adjustment of Player A’s rationality takes place and the individual adjusts the prior belief to the least confident one. As an ingroup-outgroup difference exists in the least confident prior belief, a group effect on $\alpha_2$ as described in the first case will also be observed here.

**H3** Subjects in the same group as Player A put less (the same) weight on their private signal when it contradicts (confirms) Player A’s action than those in the other group do, that is,

$$
\begin{align*}
\alpha_{2,\text{ING}} &< \alpha_{2,\text{OUTG}} \text{ if } s = 1(a_A < 50) \& a_A \neq 50 \\
\alpha_{2,\text{ING}} & = \alpha_{2,\text{OUTG}} \text{ if } s = 1(a_A > 50) \& a_A \neq 50
\end{align*}
$$

### 2.3 Procedures

The experiment was conducted in October and November, 2018 at Nankai University, at the China Centre for Experimental Social Sciences (CESS), which is a collaborative laboratory between Nankai University and the Nuffield College at University of Oxford. The subject pool of CESS China consists of undergraduate and graduate students in all disciplines at Nankai University. Experimental sessions were advertised within the subject pool of CESS China, and participants were recruited through a Wechat recruiting system (ancademy.org). Upon arrival, subjects were assigned to computers by randomly choosing one card from a pile of numbered cards. After subjects were seated in the lab, instructions of part 1 were distributed. The experimenter read instructions aloud in front of all subjects and then subjects answered understanding questions. After they answered all understanding questions correctly, the experiment started. Instructions of part 2 were distributed after part 1 ended. When the experiment was completed, subjects saw their final earnings on the screen privately and got paid on site. The experiment was computerized using oTree (Chen et al., 2016).

In total, 14 sessions were organized and 258 subjects participated in the experiment. On average each session lasted for one hour. Subjects earned 59.4 RMB yuan on average. The numbers of subjects and sessions as well as the means and standard deviations (in parentheses) of subjects’ characteristics are displayed by treatment in Table 1.

### 3 Results

#### 3.1 Descriptive analysis and data preparation

Figure 1 shows that the distribution of Player A’s action after observing a white (black) ball has a peak around 70 (30), which is consistent with predictions of
Bayes’ theorem. Also, a few Player As choose to report 50, which may be because of strong risk aversion.7

Figure 2 displays other players’ beliefs conditional on Player A’s action. If Player A’s action is larger (smaller) than 50, other players should consider that a white (black) ball was drawn. We do find that the distribution of first beliefs has a peak around 70 (30) when Player A’s action is larger (smaller) than 50. Compared to Fig. 1, a slightly higher percentage of subjects report 50.

Figure 3 presents the distributions of players’ second beliefs, that is after observing a private signal, conditional on that the private signal confirms Player A’s action \(a_A > 50\) (a white ball was drawn) and contradicts \(a_A > 50\) (a black ball was drawn) respectively.8 Given that most subjects report 70 as their first beliefs for \(a_A > 50\), if a majority of subjects update their second beliefs in a Bayesian way, we would observe that the distribution of their second beliefs for a confirming (contradicting) private signal had a peak around 84.5 (50). The left panel shows that quite a few beliefs deviate saliently from 84.5 and the mean of the second beliefs is a bit lower

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7 Subjects’ first beliefs in the IDM treatment have similar distributions to Fig. 1 except that a higher percentage of subjects report 50.

8 The distributions of players’ second beliefs for \(a_A < 50\) conditional on confirming and contradicting private signals are very similar to the case of \(a_A > 50\).
than 80, which does not seem to support Bayesian belief updating. The right panel confirms that most people report 50 for a contradicting private signal, which is different from a very asymmetric distribution around 50 shown by De Filippis et al. (2022).

In Table 2, we present the three quantiles of $\tilde{u}_1$ computed using Eq. (1) by treatment. Note that when $a_1 = 0$ or 100, the equation generates positive or negative infinity for $\tilde{u}_1$ respectively. We compute $\tilde{u}_1$ by approximating $a_1 = 0$ with 0.01 and $a_1 = 100$ with $100 - 0.01$. Table 2 shows that subjects display heterogeneity in belief updating upon observing the first signal. For example, some do not update at all ($\tilde{u}_1 = 0$) while others update the same as a Bayesian agent would do ($\tilde{u}_1 = 1$). We can see that median subjects in the SL and GSL treatments tend to underweight Player A’s action (the social signal) compared to a Bayesian agent ($\alpha_1 < 1$). Additionally, subjects in the OUTG treatment attach a lower weight to the social signal compared to the ING treatment.9

Table 3 displays the quantiles of $\tilde{u}_2$ computed using Eq. (2), upon observing confirming and contradicting signals respectively, and by treatment. When $a_2 = 0$ or 100, or $a_1 = 0$ or 100, the equation generates positive or negative infinity for

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9 The three quantiles of $\tilde{u}_1$ are not saliently different between the IDM and the SL treatment. In other words, subjects do not put more weight on the (first) private signal than on the (first) social signal, which indicates that people process the (first) social and private information in similar ways.
Ingroup bias in a social learning experiment

We compute \( \alpha_2 \) by approximating \( a_2 (a_1) = 0 \) with 0.01 and \( a_2 (a_1) = 100 \) with 100 − 0.01.

As shown in Table 3, in the SL treatment, the three quantiles of \( \alpha_2 \) are all smaller upon observing a confirming signal than upon observing a contradicting signal. The median subject updates beliefs in a Bayesian way upon receiving a contradicting signal (\( \alpha_2 = 1 \)), while she attaches less weight to the second signal compared to a Bayesian agent when observing a confirming signal (\( \alpha_2 = 0.64 \)). The asymmetry of belief updating also holds for the ING and OUTG treatments, with even lower values of \( \alpha_2 \) for observing a confirming private signal. We also compute \( \alpha_2 \) for the IDM treatment, where confirming signals mean that two white or two black balls were drawn and contradicting signals mean that a white and a black ball were drawn. We find an asymmetry of belief updating upon receiving

\[
\begin{array}{cccc}
\alpha_1 & SL & IDM & ING & OUTG \\
1st quantile & 0.24 & 0 & 0.20 & 0 \\
Median & 0.93 & 1 & 0.84 & 0.73 \\
3rd quantile & 1 & 1 & 1 & 1 \\
\end{array}
\]

Fig. 2 Distribution of other players’ beliefs after observing Player A’s action. *Notes: The figures are based on other players’ actions upon observing either Player A’s action > 50 or < 50 in the SL and GSL treatments over rounds 2-31. The left panel includes 2913 observations and the right panel includes 2648 observations.*
two signals in the IDM treatment but in the opposite direction, that is, subjects put more weight on the confirming signal than on the contradicting signal.

### 3.2 Group identity and belief updating

The focus of the present study is to investigate whether group identity has an impact on social learning and subsequent private belief updating. First, we look at whether group identity has an impact on $\alpha_1$. Figure 4 displays the cumulative probability
distributions of $\alpha_1$ for ingroup and outgroup. There exists a mild but significant difference between the two distributions with the Kolmogorov-Smirnov test ($p$-value = 0.03). Table 2 also shows that the median value of $\alpha_1$ is lower in the OUTG treatment than in the ING treatment.

We then include the observations from 2-31 rounds in all treatments and run random effects regressions of $\alpha_1$ on exogenous variables $\text{Ingroup}$, $\text{SL}$, and $\text{IDM}$, controlling for round dummies, the first-round weight on a drawn ball, and subjects’ characteristics, excluding the extreme observations reporting $\alpha_1 = 0$ or 100. Table 4 displays the outcomes. We find that the coefficients of $\text{Ingroup}$ are statistically significant, which support our $H1$.10

Result 1: Subjects put more weight on Player A’s action if they are in the same group than in different groups, that is, $\alpha_{1,\text{ING}} > \alpha_{1,\text{OUTG}}$.

It should be noted that the group impact on $\alpha_1$ becomes insignificant when including extreme values with $\alpha_1 = 0$ or 100 in the linear random effects regressions ($p$-value = 0.272). Figure 5 shows that the frequency of $\alpha_1 = 100$ ($\alpha_1 = 0$) in the OUTG treatment is roughly double that in the ING treatment, given that Player A’s action is larger (smaller) than 50. An extreme value of $\alpha_1$ consistent with Player A’s action generates $\alpha_1 = 10.87$ with the approximation

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10 We also have within-subject and between-subject analyses over the impact of group identity on $\alpha_1$. Both analyses produce significantly positive results, which are displayed in Table A1 in Online Appendix A.
Table 4 Random effects regressions of $\alpha_1$

|                  | (1)       | (2)       | (3)       |
|------------------|-----------|-----------|-----------|
|                  | $\alpha_1$| $\alpha_1$| $\alpha_1$|
| Ingroup          | 0.0641*** | 0.0650*** | 0.0646*** |
|                  | (0.0206)  | (0.0209)  | (0.0210)  |
| SL               | 0.0838    | 0.0877    | 0.0900    |
|                  | (0.115)   | (0.115)   | (0.113)   |
| IDM              | 0.0553    | 0.0832*   | 0.0569    |
|                  | (0.0611)  | (0.0464)  | (0.0481)  |
| Round dummies    | Yes       | Yes       | Yes       |
| Round-1 weight   | No        | No        | Yes       |
| Controls         | No        | Yes       | Yes       |
| $N$              | 6278      | 6278      | 6278      |

Clustered standard error by session are in parentheses. Control contains age, gender, undergraduate or graduate students, having participated in any economics or psychology experiment, Han or minority, and having learned probability theory or not. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Fig. 5 Distributions of other players’ beliefs after observing Player A’s action in the ING and OUTG treatments. Notes: The figures are based on other players’ actions upon observing either Player A’s action > 50 or < 50 in the ING and OUTG treatments over rounds 2-31. The left panel includes 874 observations for ING and 983 observations for OUTG; while the right panel includes 895 observations for ING and 988 observations for OUTG.


\[ \alpha_1 = 100 - 0.01 (\alpha_1 = 0.01). \] The third quantile of \( \alpha_1 \) in either ING or OUTG is 1, which is substantially smaller than 10.87. Therefore, there are saliently more observations with a high value of \( \alpha_1 = 10.87 \) in the OUTG treatment than in the ING treatment, which reduces the group impact on \( \alpha_1 \) to nil.

As the median estimates are less sensitive to the approximate weight for extreme observations reporting \( \alpha_1 = 0 \) or 100, we run a quantile (median) regression of \( \alpha_1 \) on the same independent variables as in Table 4, with standard error clustered at the session level, including extreme values. Column (1) in Table A2 presents the results. The coefficient of INgroup is still positive and significant \((p\text{-value} = 0.012)\), indicating that there exists ingroup bias in social learning.

Finally, we investigate whether the identity effect in \( \alpha_1 \) differs between the early and later rounds. With different values of \( n \) (e.g., \( n = 4, 7 \)), we find that the identity effect in the first \( n \) rounds is significantly larger than in the later rounds (see Table A4).

Then we try to examine whether group identity has an impact on \( \alpha_2 \). Figure 6 presents the cumulative probability distributions of \( \alpha_2 \) of ingroup and outgroup, for confirming and contradicting private signals respectively. There are mild differences in their distributions, especially for the case with a contradicting signal. The Kolmogorov-Smirnov test results show that for confirming signals (left panel), the two distributions are not significantly different \((p\text{-value} = 0.649)\); while for contradicting signals (right panel), the difference between the two distributions is marginally significant \((p\text{-value} = 0.071)\). According to Table 3, the difference in \( \alpha_2 \) between the contradicting and confirming cases is the greatest in

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**Fig. 6** CDFs of \( \alpha_2 \) with groups. *Notes:* Observations satisfying \(-1 \leq \alpha_2 \leq 3\) are included.
the ING treatment, which implies that group identity increases the asymmetry in belief updating.

We also run random effects regressions of $a_2$ on exogenous variables $Ingroup$, $SL$, $IDM$, and their interaction terms with $Confirm$, controlling for round dummies, the first-round weight on a drawn ball, and subjects’ characteristics, excluding extreme observations reporting $a_2 (a_1) = 0$ or 100. Table 5 displays the results. First, the coefficients of $Confirm$ are significantly negative. The coefficients of $Confirm + SL \times Confirm$ ($p$-value = 0.075) and $Confirm + Ingroup \times Confirm$ ($p$-value < 0.001) are also significantly negative. These outcomes together suggest that there exists an asymmetry of belief updating that subjects put less weight on the private signal when it confirms the social signal than when it contradicts the social signal, regardless of group identity. In addition, the coefficients of $Confirm + IDM \times Confirm$ are not significant ($p$-value $\approx 0.5$), that is, the asymmetry in the belief updating pattern upon receiving two signals is unique to the contexts involving social learning.

However, the more detailed patterns we find are different from those of De Filippis et al. (2022). Table 3 shows that subjects in the SL and GSL treatments saliently underweight their private signal when it confirms Player A’s action compared to the

Table 5  Regressions of $a_2$ with groups

|                   | (1)     | (2)     | (3)     |
|-------------------|---------|---------|---------|
| $Ingroup$         | 0.108***| 0.109***| 0.109***|
|                   | (0.0345)| (0.0343)| (0.0342)|
| $Confirm$         | −0.362***| −0.363***| −0.363***|
|                   | (0.0916)| (0.0913)| (0.0914)|
| $Ingroup \times Confirm$ | −0.224***| −0.224***| −0.224***|
|                   | (0.0633)| (0.0637)| (0.0636)|
| $SL$              | 0.182   | 0.189   | 0.189   |
|                   | (0.167) | (0.167) | (0.167) |
| $SL \times Confirm$ | 0.0543  | 0.0524  | 0.0525  |
|                   | (0.197) | (0.196) | (0.196) |
| $IDM$             | −0.109  | −0.0997 | −0.104  |
|                   | (0.107) | (0.0967)| (0.0943)|
| $IDM \times Confirm$ | 0.447***| 0.451***| 0.451***|
|                   | (0.150) | (0.151) | (0.151) |
| Round dummies     | Yes     | Yes     | Yes     |
| Round-1 weight    | No      | No      | Yes     |
| Controls          | No      | Yes     | Yes     |
| $N$               | 5525    | 5525    | 5525    |

Random effects models are applied. Clustered standard error by session are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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11 In Online Appendix B, we analyse these extreme values separately.
Bayesian belief updating, while they update their beliefs upon their private signal when it contradicts Player A’s action in a more or less Bayesian way. In other words, the asymmetry in our experiment comes from the fact that subjects underweight the private signal when it confirms the social signal instead of the fact found by De Filippis et al. (2022) that subjects overweight the private signal when it contradicts the social signal.\(^\text{12}\)

Second, the coefficients of Ingroup × Confirm are negative and significant. Given that the coefficients of Confirm are negative, it shows that subjects in the same group as Player A exhibit a greater asymmetry in belief updating than those in the other group do. More specifically, the coefficients of Ingroup are positive and significant, indicating that subjects in the same group as Player A put more weight on the private signal when it contradicts the social signal than those in the other group do. We also test the coefficients of Ingroup + Ingroup × Confirm and obtain significantly negative results (\(p\)-value < 0.005). It means that group identity decreases the weight on the private signal when it confirms the social signal. As a consequence, the asymmetry in the belief updating pattern increases with group identity as mentioned above. \(H3\) is not supported.

Result 2a: Subjects in the same group as Player A put more weight on the private signal when it contradicts Player A’s action than those in the other group do, that is, \(\alpha_{2,\text{ING}} > \alpha_{2,\text{OUTG}} \text{ if } s = 1 (a_A < 50) \& a_A \neq 50\).

Result 2b: Subjects in the same group as Player A put less weight on the private signal when it confirms Player A’s action than those in the other group do, that is, \(\alpha_{2,\text{ING}} < \alpha_{2,\text{OUTG}} \text{ if } s = 1 (a_A > 50) \& a_A \neq 50\).

We also run a quantile (median) regression on the same independent variables as in Table 5. Column (2) in Table A2 displays the results. The signs and significance of the estimated coefficients are the same as in Table 5, except for the coefficient of Ingroup × Confirm which is negative but not significant. Therefore, we still find an asymmetric pattern of belief updating. We also find some evidence for confirmation bias in the IDM treatment since the coefficient of Confirm + IDM × Confirm is positive and marginally significant (\(p\)-value = 0.089). We do not reproduce the group effect on the asymmetry of belief updating, but the significantly positive coefficient of Ingroup supports Result 2a.

Last, we are interested in whether group identity affects learning efficiency. In particular, we examine whether a player’s payoffs of her two beliefs differ between learning from and an outgroup Player A. We conduct regressions of the payoffs of the first belief and second belief respectively. Table 6 displays the results—we do not find any salient effect of group identity on learning efficiency.\(^\text{13}\)

\(^{12}\) In fact, De Filippis et al. (2022) also show that subjects underweight their private signal when it confirms the social signal, but they do not discuss this outcome.

\(^{13}\) We also run regressions with interaction terms between treatment dummy variables and Confirm and find no significant impacts of group identity on learning efficiency either.
3.3 Group identity and the beliefs about Player A’s rationality

With the documented ingroup bias in forming the two beliefs, we further explore whether the impact of group identity is due to that subjects perceive a higher rationality of Player A in the same group than in the other group, or it is a result of an intrinsic heuristic to follow ingroup members.

Based on subjects’ answers to the questions in round 21, we generate new variables $B_{\text{error},1}$ and $B_{\text{error},2}$ to capture their belief that A made a mistake after observing the first and second signal respectively. As explained in Sect. 2.1, in the experiment, making a mistake means that Player A reported $a_A > 50$ upon observing a black ball or $a_A < 50$ upon observing a white ball. And for the questions in round 21, subjects are requested to report the probability that they think Player A observed a white ball. Therefore, if $a_A > 50$, the number a subject reported actually means the probability that she thinks Player A did not make a mistake, that is, $B_{\text{error}} = 100 -$ reported number. On the other hand, if $a_A < 50$, the probability that a subject thinks Player A observed a white ball is the same as the probability that she thinks Player A made a mistake, that is, $B_{\text{error}} = $ reported number. For example, a subject reported that the probability that she thought Player A observed a white ball is 80% ($20\%$) when she saw $a_A > 50$ ($a_A < 50$). It means that her belief that Player A made a mistake is 20% ($20\%$), that is $B_{\text{error}} = 20$. We use $B_{\text{error},1}$ and $B_{\text{error},2}$ as the proxies for subjects’ beliefs about Player A’s rationality, which are relevant and not confusing.

Figure 7 displays the means and confidence intervals (at 95% level) of $B_{\text{error},1}$ (left panel) and $B_{\text{error},2}$ (right panel) for ingroup and outgroup. We can see that subjects’ beliefs that Player A made a mistake are even a bit higher when Player A is an ingroup than when she is an outgroup, but the differences are not significant.

We run OLS regressions of $\pi_1$ in round 21 on $B_{\text{error},1}$ as well as $\text{Ingroup}$ and $\text{SL}$. Table 7 shows the result. First of all, the impact of group identity on $\pi_1$ is confirmed. Also, the coefficients of $B_{\text{error},1}$ are significantly negative, that is, a subject puts less weight on Player A’s action if her belief that A has made a mistake is stronger. But

|                  | (1)   | (2)   | (3)   | (4)   |
|------------------|-------|-------|-------|-------|
| $\pi_1$          | $-0.543$ | $-0.588$ | $-0.602$ | $-0.652$ |
|                  | $(0.459)$ | $(0.444)$ | $(0.472)$ | $(0.490)$ |
| $\pi_2$          | $-1.093$ | $-1.157$ | $-2.068^*$ | $-1.920$ |
|                  | $(1.367)$ | $(1.399)$ | $(1.066)$ | $(1.190)$ |
| $\text{SL}$      | $-0.287$ | $-0.422$ | $1.852$ | $1.859$ |
|                  | $(0.996)$ | $(1.018)$ | $(1.231)$ | $(1.207)$ |
| $\text{Round}$   | Yes   | Yes   | Yes   | Yes   |
| $\text{Controls}$| No    | Yes   | No    | Yes   |
| $N$              | 7380  | 7380  | 7380  | 7380  |

Clustered standard error by session are in parentheses. $\pi_1$ ($\pi_2$) stands for the payoffs of the first (second) belief. $^* p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.01$
Ingroup bias in a social learning experiment

Controlling for $B_{\text{error},1}$ does not decrease the ingroup bias in $\alpha_1$. These results imply that the impact of group identity on processing the first social signal is probably not driven by the beliefs that ingroup members have higher information-processing abilities or make more rational decisions than outgroup members, rejecting $H2$. In other words, even though we find that subjects put more weight on Player A’s action if they are in the same group than in different groups, there is little evidence to suggest that this observed ingroup bias in social learning is driven by people’s different beliefs about the predecessor’s rationality, that is, the belief-based channel.

Table 7 OLS regressions of $\alpha_1$ in round 21

|       | (1)      | (2)      | (3)      | (4)      |
|-------|----------|----------|----------|----------|
|       | $\alpha_1$ | $\alpha_1$ | $\alpha_1$ | $\alpha_1$ |
| Ingroup | 0.272∗ | 0.295∗ | 0.299∗∗ | 0.338∗∗ |
|        | (0.130) | (0.153) | (0.117) | (0.130) |
| SL     | 0.102 | 0.0995 | 0.0991 | 0.104 |
|        | (0.147) | (0.156) | (0.128) | (0.135) |
| $B_{\text{error},1}$ | −0.0106∗∗ | −0.0110∗∗ | (0.00391) | (0.00287) |
| Controls | No | Yes | No | Yes |
| N      | 153 | 153 | 153 | 153 |

Clustered standard error by session are in parentheses. ∗ $p < 0.1$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$

Fig. 7 The means and confidence intervals of $B_{\text{error},1}$ and $B_{\text{error},2}$ with groups
Combining the outcomes displayed in Table A4 that the group identity effects on \( \alpha_1 \) in the first 4 and 7 rounds is significantly stronger than in the later rounds, we conjecture that our findings are more consistent with the perspective that group identity works as a framing device and its effect can be easily displaced by changing the framing of decisions.

**Result 3:** The group identity effect on \( \alpha_1 \) can not be explained by different beliefs between ingroup and outgroup Player A’s rationality.

We also run OLS regressions of \( \beta_{A_{error},2} \). Table A3 in Online Appendix A shows that \( \beta_{A_{error},2} \) has no significant effects on \( \beta_{A_{error},2} \) for round 21. And it does not exhibit the group identity effects on \( \alpha_2 \) as summarized in Result 2a and Result 2b either. Therefore, it is infeasible for us to conclude that the group effects on \( \beta_{A_{error},2} \) are driven by the ingroup-outgroup differences in \( \beta_{A_{error},2} \) or not. However, we do find that a contradicting private signal results in a significantly higher \( \beta_{A_{error},2} \) than a confirming private signal. The \( p \)-values from either the Mann-Whitney \( U \) test or the t-test are smaller than 0.001; results are the same if we use the difference between \( \beta_{A_{error},2} \) and \( \beta_{A_{error},1} \) instead.

### 4 Conclusion and discussion

In this paper, we investigate whether and how group identity influences the way people process social information as well as subsequent private information. We adopt the design paradigm of De Filippis et al. (2022) and conjecture how group identity may have an impact via the belief and the belief-updating process regarding the predecessor’s rationality under the theoretical framework of the LRTU model, which is also developed by De Filippis et al. (2022).

Our results show that there exist ingroup-outgroup differences, not only in the processing of the social signal, but also seem to be in that of the subsequent private signal. That the weight on the social signal is higher if it is from an ingroup predecessor compared to if it is from an outgroup predecessor, is broadly in line with the finding of ingroup favoritism in the experimental literature. In contrast, the patterns of \( \alpha_2 \) imply that the effect of such ingroup favoritism on posterior beliefs is at least partly offset by the ingroup-outgroup differences in the private signal phase. Specifically, when the private signal accords (contradicts) the social signal of an ingroup predecessor, people appear to place a lower (higher) weight on the private signal compared to when the predecessor is an outgroup.

As to the underlying mechanism, we do not find evidence supporting the belief-based channel we have conjectured under the framework of the LRTU model, because the ingroup-outgroup difference in the social signal phase can not be explained by the elicited beliefs in the predecessor’s rationality, and no identity effects exist for the rationality beliefs. This result seems to be at odds with results from other studies in the literature; for example, Cacault and Grieder (2019) documented an ingroup bias in beliefs about others’ intelligence. We conjecture that the diverging findings might be driven by how challenging the cognitive task is. In our experimental context, the rational response is very obvious given the signal valence. In contrast, the intelligence test questions studied by Cacault and Grieder (2019)
were quite challenging. Better understanding the circumstances in which group identification distorts people’s beliefs about the ability of their peers is an interesting question for future research. On a separate note, it is also unlikely that social preferences drive the results. If individuals’ reported event beliefs were shaped by their preference to have similar monetary payoffs from the belief-elicitation task as their ingroup members, such a preference should remain in the private signal phase, which is at odds with the fact that the effect of the group identity on posterior event beliefs is partly offset after the private signal phase.

We consider our results as supporting the alternative perspective in the literature that group identity works as a framing device (Tajfel et al., 1971; Bacharach, 2006; Guala & Filippin, 2017; Filippin & Guala, 2017), as this perspective can reconcile the observed patterns in both the two phases. In the first phase, information about the group identity of the predecessor may work as a cue of the group frame that triggers certain heuristics. Specifically, since subjects observing an outgroup predecessor place lower weights on the social signal than subjects observing an ingroup, whose weights are in turn lower than those in the SL treatment, we conjecture that the heuristics triggered by the group frame prescribe caution and suspicion with others’ actions and opinions, especially with those of the outgroup. The fact that such an ingroup-outgroup difference becomes less prominent in later rounds is consistent with the decaying nature of group identity as a framing device. In the second phase, the group frame can be considered removed since the subjects now receive their own private signal. Subjects then process the social signal and private signal together, without the influence of the heuristics as in the first phase. Since we calculate the weight subjects put on the private signal based on the beliefs before and after observing the private signal with the Bayesian structure, it just appears as if the subjects put a higher (lower) weight on a confirming (contradicting) private signal if the predecessor is an outgroup than if the predecessor is an ingroup.

To better illustrate our reasoning, we provide the following examples. Suppose that Player A reports 30 after observing a black ball. Then as affected by the heuristic in the social signal phase, a Bayesian subject reports \( a_1 = 30 \) after observing Player A’s action when she is in the same group as Player A and reports \( a_1 = 40 \) when she is in the other group.\(^\text{14}\) In other words, the subject underweights Player A’s action if they are not in the same group. In the private signal phase, if the subject is NOT affected by the group framing any more, she will update her belief upon \( a_A = 30 \) and \( s = 1 \) after observing a white ball which contradicts Player A’s action, that is, the subject will report the stated belief \( a_2 = 50 \) regardless of group identity. But the calculation of \( a_2 \) will be based on \( a_1 = 40 \) when the subject is not in the same group as Player A. Then for the subject we obtain \( a_{2,\text{contradict,ING}} = 1 > a_{2,\text{contradict,OUTG}} \approx 0.47 \), which is consistent with Result 2a.

Again, suppose that Player A reports 70 after observing a white ball. Then as a consequence of ingroup bias, a Bayesian subject reports \( a_1 = 70 \) after observing Player A’s action when she is in the same group as Player A and reports \( a_1 = 60 \)

\(^{14}\) Here we take a Bayesian subject as an example for the simplicity of expression. The reasoning also works for non-Bayesian subjects.
when she is in the other group. In the private signal phase, if the subject is NOT affected by the group framing, she will update her belief upon $a_A = 70$ and $s = 1$ after observing a white ball which confirms Player A’s action, that is, the subject will report $a_2 = 84.5$ regardless of the predecessor’s group identity. But the calculation of $a_2$ will be based on $a_1 = 60$ when the subject is not in the same group as Player A. Then for the subject we obtain $\alpha_{2,\text{confirm}_\text{ING}} = 1 < \alpha_{2,\text{confirm}_\text{OUTG}} \approx 1.52$, which is consistent with Result 2b.

Comparing our results to those from De Filippis et al. (2022), we replicate an asymmetric pattern in the private signal phase in the sense that a private signal contradicting the social signal is given a much higher weight than a confirming private signal. The difference between results from the two studies is how the weights compare to the Bayesian benchmark. If we are willing to assume that our subjects have a general tendency to underweight in comparison to the Bayesian benchmark in the private signal phase, then the specific case of the LRTU model discussed by De Filippis et al. (2022) can explain the asymmetric pattern in our data as well. We provide evidence supporting such an interpretation by showing that beliefs about the predecessor’s rationality significantly differ upon receiving a contradicting and a confirming private signal. In other words, the cognitive process captured by the LRTU model probably exists among our subjects; however, the effect of the group identity does not seem to work via shifting parameters in this process.

Looking forward, it would be interesting for future researchers to further explore the relationship between social learning and group identity, viewing the case of a neutral event (the color of the jar) and an artefactual minimal group studied in the current paper as a first step. In the real world, there are many interesting cases in which certain beliefs are non-neutral in the sense that people have intrinsic preferences over the beliefs, and the identity of certain natural groups often plays a role in determining such intrinsic values. For example, believing that vaccines are ineffective in protecting us from viruses may directly bring the person utility by enhancing her sense of belonging to the social group she identifies herself with. The existence of such group identity-related utility has been proven by Hett et al. (2020) as they showed that individuals were willing to pay significant amounts of money to belong to certain groups. Another example is the belief about others’ prosocial or antisocial behavior. People probably prefer to believe that those within her social group are more prosocial than those outside the group. In general, such intrinsic preferences of beliefs can lead to motivated beliefs and bias the belief-updating process (see Gino et al. 2016 for a review of the broad literature on motivated reasoning.) Taking into consideration the social learning aspect thereof, there could be richer patterns to explore both theoretically and empirically. For instance, observing social signals that are against the predecessor’s identity-relevant utilities might be especially powerful in shifting beliefs, and if so, it can be utilized by policy-makers to bring about socially desirable changes. Another example is when the choice of information source is endogenous. While Duffy et al. (2019) documented distinct private and social information choosers but an overall tendency for choosing social information, how the inclusion of group identity may reshape such choices will be something interesting for future research.
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References

Anderson, L. R., & Holt, C. A. (1997). Information cascades in the laboratory. American Economic Review, 87(5), 847–862.
Ash, E., & Van Parys, J. (2015). Group identity bias and information cascades.
Bacharach, M. (2006). Beyond Individual Choice: Teams and Frames in Game Theory. Princeton University Press.
Banerjee, A. V. (1992). A simple model of herd behavior. The Quarterly Journal of Economics, 107(3), 797–817.
Berger, S., Feldhaus, C., & Ockenfels, A. (2018). A shared identity promotes herding in an information cascade game. Journal of the Economic Science Association, 4, 63–72.
Bernhard, H., Fehr, E., & Fischbacher, U. (2006). Group affiliation and altruistic norm enforcement. American Economic Review, 96(2), 217–221.
Bettencourt, A., Brewer, M., Croak, M., & Miller, N. (1992). Cooperation and the reduction of intergroup bias: the role of reward structure and social orientation. Journal of Experimental Social Psychology, 28(4), 301–319.
Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy, 100(5), 992–1026.
Bolton, G. E., Feldhaus, C., & Ockenfels, A. (2016). Social interaction promotes risk taking in a stag hunt game. German Economic Review, 17(3), 409–423.
Brewer, M. (1979). In-group bias in the minimal intergroup situation: A cognitive-motivational analysis. Psychological Bulletin, 86(2), 307.
Brown, R., Vivian, J., & Hewstone, M. (1999). Changing attitudes through intergroup contact: The effects of group membership salience. European Journal of Social Psychology, 29(5–6), 741–764.
Cacault, M. P., & Grieder, M. (2019). How group identification distorts beliefs. Journal of Behavioral and Experimental Finance, 164, 63–76.
Çelen, B., & Kariv, S. (2004). Distinguishing informational cascades from herd behavior in the laboratory. American Economic Review, 94(3), 484–498.
Charness, G., Rigotti, L., & Rustichini, A. (2007). Individual behavior and group membership. American Economic Review, 97(4), 1340–1352.
Chen, D. L., Schonger, M., & Wickens, C. (2016). otree–an open-source platform for laboratory, online, and field experiments. Journal of Behavioral and Experimental Finance, 9, 88–97.
Chen, Y., & Li, S. (2009). Group identity and social preferences. American Economic Review, 99(1), 431–57.
Currarini, S., & Mengel, F. (2016). Identity, homophily and in-group bias. European Economic Review, 90, 40–55.
Danz, D., Vesterlund, L., & Wilson, A. J. (2022). Belief elicitation and behavioral incentive compatibility. American Economic Review, 112(9), 2851–2883.
De Filippis, R., Guarino, A., Jehiel, P., & Kitagawa, T. (2022). Non-Bayesian updating in a social learning experiment. Journal of Economic Theory, 199, 105188.
Duffy, J., Hopkins, E., Kornienko, T., & Ma, M. (2019). Information choice in a social learning experiment. Games and Economic Behavior, 118, 295–315.
Filippin, A., & Guala, F. (2017). Group identity as a social heuristic: An experiment with reaction times. Journal of Neuroscience, Psychology, and Economics, 10(4), 153.
Gino, F., Norton, M. I., & Weber, R. A. (2016). Motivated bayesians: Feeling moral while acting egoistically. Journal of Economic Perspectives, 30(3), 189–212.
Gino, F., Shang, J., & Croson, R. (2009). The impact of information from similar or different advisors on judgment. *Organizational Behavior and Human Decision Processes, 108*(2), 287–302.

Goeree, J. K., Palfrey, T. R., Rogers, B. W., & McKelvey, R. D. (2007). Self-correcting information cascades. *The Review of Economic Studies, 74*(3), 733–762.

Goette, L., Huffman, D., & Meier, S. (2006). The impact of group membership on cooperation and norm enforcement: Evidence using random assignment to real social groups. *American Economic Review (Papers & Proceedings), 96*(2), 212–216.

Grimm, V., Utikal, V., & Valmasini, L. (2017). In-group favoritism and discrimination among multiple out-groups. *Journal of Economic Behavior & Organization, 143*, 254–271.

Guala, F., & Filippin, A. (2017). The effect of group identity on distributive choice: Social preference or heuristic? *The Economic Journal, 127*(602), 1047–1068.

Hett, F., Mechtel, M., & Kröll, M. (2020). The structure and behavioral effects of revealed social identity preferences. *The Economic Journal, 130*(632), 2569–2595.

Hossain, T., & Okui, R. (2013). The binarized scoring rule. *Review of Economic Studies, 80*(3), 984–1001.

Levine, S. S., Apfelbaum, E. P., Bernard, M., Bartelt, V. L., Zajac, E. J., & Stark, D. (2014). Ethnic diversity deflates price bubbles. *Proceedings of the National Academy of Sciences, 111*(52), 18524–18529.

Levy, G., & Razin, R. (2019). Echo chambers and their effects on economic and political outcomes. *Annual Review of Economics, 11*, 303–328.

Li, S. (2020). Group identity, ingroup favoritism, and discrimination. In K. Zimmermann (Ed.), *Handbook of Labor, Human Resources and Population Economics*. Cham, Switz.: Springer. https://doi.org/10.1007/978-3-319-57365-6_123-1

Müller, D. (2019). The anatomy of distributional preferences with group identity. *Journal of Economic Behavior & Organization, 166*, 785–807.

Nöth, M., & Weber, M. (2003). Information aggregation with random ordering: Cascades and overconfidence. *The Economic Journal, 113*(484), 166–189.

Ockenfels, A., & Werner, P. (2014). Beliefs and ingroup favoritism. *Journal of Economic Behavior & Organization, 108*, 453–462.

Ortoleva, P. (2012). Modeling the change of paradigm: Non-Bayesian reactions to unexpected news. *American Economic Review, 102*(6), 2410–36.

Robson, M. (2021). Inequality aversion, self-interest and social connectedness. *Journal of Economic Behavior & Organization, 183*, 744–772.

Ryen, A. H., & Kahn, A. (1975). Effects of intergroup orientation on group attitudes and proxemic behavior. *Journal of Personality and Social Psychology, 31*(2), 302.

Shearer, E., & Gottfried, J. (2017). *News use across social media platforms 2017*. Journalism and Media: Pew Research Center.

Tajfel, H., Billig, M., Bundy, R., & Flament, C. (1971). Social categorization and intergroup behaviour. *European Journal of Social Psychology, 1*(2), 149–178.

Tanaka, T., & Camerer, C. F. (2016). Trait perceptions influence economic out-group bias: lab and field evidence from Vietnam. *Experimental Economics, 19*(3), 513–534.

Weizsäcker, G. (2010). Do we follow others when we should? a simple test of rational expectations. *American Economic Review, 100*(5), 2340–60.

Xu, X., Potters, J., & Suetens, S. (2020). Cooperative versus competitive interactions and in-group bias. *Journal of Economic Behavior and Organization, 179*, 69–79.

Ziegelmeyer, A., March, C., & Krügel, S. (2013). Do we follow others when we should? a simple test of rational expectations: Comment. *American Economic Review, 103*(6), 2633–42.

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