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Group Identity and Belief Formation: A Decomposition of Political Polarization

Abstract

How does group identity affect belief formation? To address this question, we conduct a series of online experiments with a representative sample of individuals in the US. Using the setting of the 2020 US presidential election, we find evidence of intergroup preference across three distinct components of the belief formation cycle: a biased prior belief, avoidance of outgroup information sources, and a belief-updating process that places greater (less) weight on prior (new) information. We further find that an intervention reducing the salience of information sources decreases outgroup information avoidance by 50%. In a social learning context in wave 2, we find participants place 33% more weight on ingroup than outgroup guesses. Through two waves of interventions, we identify source utility as the mechanism driving group effects in belief formation. Our analyses indicate that our observed effects are driven by groupy participants who exhibit stable and consistent intergroup preferences in both allocation decisions and belief formation across all three waves. These results suggest that policymakers could reduce the salience of group and partisan identity associated with a policy to decrease outgroup information avoidance and increase policy uptake.

JEL-Codes: D470, C780, C920, D820.

Keywords: group identity, information demand, information processing, political polarization.

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1 Introduction

People act based on what they believe. These beliefs may affect their assessment of the correctness of stated facts (Peterson and Iyengar 2021), opinions about optimal policies (Alesina, Miano and Stantcheva 2020), moral values and norms (Andre, Boneva, Chopra and Falk 2022), or general perceptions of how the world and society function (Chinoy, Nunn, Sequeira and Stantcheva 2023). Recently, both academic and popular debates have focused on an observed increase in the polarization of beliefs across individuals (Abramowitz and Saunders 2008, Allcott, Boxell, Conway, Gentzkow, Thaler and Yang 2020). These debates reflect deep concerns about a deterioration in the constructiveness of public discourse and even a loss of the efficient functioning of a democratic society (Kingzette et al. 2021).

But how do divergent, or polarized, beliefs emerge? In this paper, we analyze the role of group identity in the formation of individual beliefs. Information is rarely represented neutrally; it is often embedded within a social context. These social contexts impact not only the presentation of information but also the beliefs that individuals carry. Both social psychologists (Brewer 1993, Turner 1985, Hewstone 1996, Turner, Hogg, Oakes, Reicher and Wetherell 1987) and more recently, behavioral and experimental economists (Akerlof and Kranton 2000, Charness and Chen 2020, Shayo 2020) have found that social contexts can have substantial group identity effects on individual behavior. We hypothesize that group identity also affects individual belief formation as individuals tend to selectively demand and process information in a way that is sensitive to the group associations of the information source.

Our study examines the impact of group identity on individual belief formation across three waves of online experiments. The first wave uses the 2020 US presidential election as our setting for examining belief formation. The 2020 election took place in a context of heightened partisanship and political identities. As such, it represents a promising setting for investigating the existence, nature, and origins of intergroup preferences in belief formation. To measure individual beliefs, we conducted an online experiment starting the week before the election. In this experiment, we incentivized a representative US sample of 1,005 participants to predict the trajectory of official public health and unemployment statistics in September 2021, conditional on which candidate became president. Our results from this wave show a partisan gap in initial beliefs in that participants systematically predict more optimistic policy-sensitive statistics conditional on their preferred candidate winning the election.

Exploring this result, we are interested in whether our documented partisan gap in participants' predictions stems from the influence of intergroup preferences on belief formation and, if yes, how. We test two possible channels of intergroup preferences in belief formation: 1) when updating their beliefs, people could be less likely to select information coming from outgroup sources (*outgroup information avoidance*) or 2) when updating their beliefs, people could attribute a lower weight to outgroup information (*ingroup bias in information processing*). We analyze these two potential building blocks of belief formation across the first two waves. In the first wave, subjects make predictions about the development of the policy statistics mentioned above. In the second wave which takes place three months later, subjects are given a simple social learning task and asked to guess whether an urn contains more green or yellow marbles after observing the guesses of others who drew marbles from the urn. We then employ a combination of measurement and treatment experiments to investigate the nature and structure of intergroup preferences in its influence on belief formation. Finally, in wave 3, we repeat the measurement of relevant variables and pay participants according to their prediction from wave 1.

Our experiments yield findings across three key areas: (i) we document the *existence* of intergroup preferences in information demand and processing in that people are willing to pay money to avoid outgroup-sourced information and to attribute lower weight to this information when updating initial beliefs, (ii) we isolate a new mechanism underlying these findings that we call "source utility" in that information impacts beliefs based on the group association of the information itself independent of its instrumental value or content valence, and (iii) we find that *heterogeneity* in intergroup preferences in individual belief formation is highly correlated with heterogeneity in intergroup allocation decisions, suggesting a common group identity foundation for these biases.

We begin by examining whether participants demand different information based on their perceived political affiliations. To test this conjecture, we provide participants in wave 1 with summaries of news articles on their respective topic before asking if they would like to update their initial predictions about the trajectory of policy-sensitive statistics. While the articles cover the same facts, they differ with respect to their attributed sources, which range from left-leaning (e.g. *The New York Times*) to neutral (e.g., *Nature*) to right-leaning (e.g. Fox News). Our results from this set of experiments show that subjects exhibit strong outgroup information avoidance. That is, almost 40% of the participants are willing to pay part of their monetary endowment to avoid reading articles from the opposing political camp, i.e., outgroup sources.

We next examine whether participants process information differently from the standard Bayesian agent. To test this conjecture, we ask participants to read two news article summaries (one left-leaning and one right-leaning) presented in random order that discuss the policy consequences of different presidential election outcomes. After reading the two articles, participants can update their predictions on their respective topic. Our results show that participants attribute 62% to 80% of the weight to their prior beliefs in determining their posterior beliefs, leading participants exposed to the same articles to diverge in their posterior beliefs.

To isolate the underlying mechanisms driving our results, we conduct a second wave of social learning experiments with the same participants three months later, where we ask them to predict whether an urn contains more green or yellow marbles. In this simple task, we induce the participants' prior beliefs to be 50/50. As before, we offer participants the possibility to learn from different information sources, this time from prior guesses made by either Democrats or Republicans. The results from this experiment reinforce the existence of ingroup bias. Specifically, we find that participants spend almost twice as much of their payment endowment to avoid guesses made by members of an out- versus ingroup. Regarding information processing, we find that participants place 33% more weight on information originating from an ingroup than outgroup source.

Having shown that individual belief formation reflects intergroup preferences, we next examine whether this bias is driven by source utility, that is, whether it is based on the group association of the information independent of its instrumental value and content valence. To study this mechanism at a more refined level, we run a treatment variation in each wave of our study. In the first wave, our treatment consists of withholding the sources of the articles (*unlabeling treatment*). Doing so, we find that participants reduce their outgroup information avoidance expenditures by 50% (from 14.9% to 7.4%). We do not find the unlabeling treatment to affect information processing. In the second wave, our treatment consists of truthfully informing half of the participants that there is no difference in the guess accuracy between Democrats and Republicans (*debiasing treatment*). Doing so, we find persistence for our main results of outgroup information avoidance and differential processing of in- versus outgroup information. In sum, the results from our treatment conditions show that participants exhibit significant intergroup preferences in information demand and processing, even when the perceived signal quality and content valence is the same. Thus, we conclude that source utility is the likely mechanism underlying our finding of intergroup preferences in individual belief formation.

Finally, we examine whether different types of participants exhibit different results. To do so, we classify participants into "groupy" and "non-groupy" types based on their behavior in a classic minimal group other-other allocation task (Tajfel et al. 1971, Chen and Li 2009, Kranton and Sanders 2017, Kranton et al. 2020). Groupy participants are defined as those who show ingroup favoritism in the task. Examining our findings by participant type, we find that groupy participants consistently display stronger outgroup information avoidance. We further find that groupy participants respond more strongly to a reduction in the salience of information sources than their non-groupy counterparts. Our participant-type results suggest that policies aiming to reduce political polarization should target groupy people by reducing source utility.

The paper proceeds as follows. Section 2 discusses the related literature. In Section 3, we detail the experimental design of our study, which comprises the three waves of the experiment across various treatments. In Section 4, we outline a theoretical framework that formalizes the role of group identity in information demand and processing. Section 5 presents the results, and Section 6 concludes.

2 Related Literature

Our study builds on three different streams of work within the social science literature: identity economics, information preferences, and political polarization.

First, we contribute to the identity economics literature pioneered by Akerlof and Kranton (2000). Research in this area has examined the various behavioral consequences of group identity, using both natural identities (Goette, Huffman and Meier 2006) and artificial ones induced in the laboratory (Eckel and Grossman 2005, Charness, Rigotti and Rustichini 2007, Chen and Li 2009). This vast and growing experimental literature on group identity primarily investigates its effects on allocation decisions in various games, redistribution, and labor market outcomes, as summarized in three recent surveys (Charness and Chen 2020, Shayo 2020, Li 2020). In our study, we extend this research by broadening the scope of group identity effects to the domain of belief formation. Drawing parallels with the minimal group paradigm observed in allocation decisions (Tajfel, Billig, Bundy and Flament 1971, Tajfel 1978, Tajfel and Turner 1979), we decompose the group effects in the formation of individual beliefs into the bias observed in prior beliefs, information demand and information processing. Furthermore, by investigating individual heterogeneity across different domains, we find support for the notion that groupiness (Kranton and Sanders 2017, Kranton et al 2020), i.e., individual sensitivity to group settings, may be a fundamental human trait (Müller 2019, Hett, Mechtel and Kröll 2020). Our approach also integrates the concept of groupiness as an individual trait into the economic literature through our use of experimental methods as behavioral measurement tools, following the method used when studying risk, time and social preferences (Camerer, Fehr et al. 2004).

We also complement recent online experiments that study various aspects of identity and belief formation. In particular, Dekel and Shayo (2023) study social learning, conformity, and differentiation within and between groups. Their experiment design is the closest to ours in that it consists of three waves of online experiments. However, the settings and timing of the waves differ across the two studies. In particular, for the first wave focusing on belief formation in a political context, we focus on 2020 just prior to the US presidential election whereas they focus on 2021 just after a contentious Israeli election. For the second wave focusing on social learning, we use the same set of participants in 2021 whereas they focus on the role of expertise in social learning with a new set of UK participants. Finally, in the third wave, both studies include state identity, but each uses a different task. Interestingly, the results of the two studies complement and strengthen each other. Both studies find that, in social learning tasks, individuals follow their ingroup significantly more than their outgroup and that there is behavioral heterogeneity among participants. Our study also extends the scope of our conclusions by using a panel design to examine the stability and persistence of groupiness across the same set of participants. We also focus on the entire cycle of belief formation across prior beliefs, information demand, and information processing.

In another recent study, Dimant, Donkor, Goette, Kurschilgen and Mueller (2023) theoretically and empirically analyze how identity affects investment decisions. In their theoretical model, they posit that identity distorts individual beliefs about uncertain outcomes and drives preferences by imposing psychic costs on identity-incongruent actions. Using soccer betting in Kenya and the

UK, they experimentally vary investment incentives for future match outcomes for soccer fans who are neutral, favorable, or unfavorable to one of the teams playing. Their result that soccer fans have overoptimistic (underconfident) beliefs about identity-congruent (incongruent) outcomes in comparison to neutral outcomes is consistent with Result 1 in wave 1 of our experiment.

Finally, Liu and Zhang (2023) use an online experiment with the issue prompt of genetically modified mosquitoes to study whether subsequent information acquisition can mitigate the impact of biased narratives (interpretations of objective facts or events) on belief formation. Their experiment design is similar to the information demand and processing part of our wave 1 design in that participants receive, in random order, narratives that cover the same facts, but with different slants. We compare their results with ours in Section 5. Together with Fryer, Harms and Jackson (2019), the findings of Liu and Zhang (2023) and our results provide robust evidence on whether and how individuals update their beliefs when signals are open to interpretation.

Second, we contribute to the literature on information acquisition and information preferences. While classic theories on the value of information have focused on its instrumental value (Stigler 1961), there is a growing body of literature exploring belief-based and non-instrumental information preferences (Golman and Loewenstein 2018, Golman, Hagmann and Loewenstein 2017). There is a large body of theoretical literature on information acquisition in mechanism design (Bergemann and Valimaki 2002), bargaining (Dang 2008), committee decision making (Persico 2004, Gerardi and Yariv 2008), and matching market (Chen and He 2022). Experimental studies include Eliaz and Schotter (2007, 2010), who evaluate agents' demand for non-instrumental information. Other experiments examine the willingness of subjects to pay for non-instrumental information in the contexts of social learning (Kübler and Weizsäcker 2004, Çelen and Hyndman 2012, Goeree and Yariv 2015) and matching (Chen and He 2021). We extend the information gap theory of Golman and Loewenstein (2018) by introducing the concept of "source utility," or a preference for information based solely on the group association of the source. Importantly, we find that this preference persists even when the information content remains unchanged.

Lastly, we contribute to the broader literature and discussion surrounding the sources, forms, determinants, and consequences of political polarization, particularly within the United States (Abramowitz and Saunders 2008, Fiorina and Abrams 2008). Classically, the discussion in this field focuses on *ideological* polarization, i.e., the increased divergence of political views and opinions of different partisan groups. However, recent research also documents the increasing prevalence of *affective* polarization – negative feelings towards people identifying with political parties other than their own (Iyengar, Sood and Lelkes 2012, Doherty, Kiley and Asheer 2019). This affective polarization has been shown to trigger detrimental behavioral responses in both social (Chen and Rohla 2018, Gimpel and Hui 2015) and economic (Michelitch 2015, McConnell, Margalit, Malhotra and Levendusky 2018, Gift and Gift 2015, Dimant forthcoming) contexts. Using social identity theory, several studies posit that affective polarization stems from partisans increasingly viewing each other as disliked outgroups (Iyengar et al. 2012, Iyengar, Lelkes, Levendusky, Malhotra and Westwood 2019). Our research complements this literature by decomposing political polarization into three distinct components of the belief formation cycle: biased prior belief, information demand, and information processing. Finally, we evaluate the efficacy of simple interventions, such as unlabeling information sources or debiasing signal quality.

3 Experimental Design

To investigate the role of group identity in belief formation, we conducted three waves of online experiments between October 2020 and November 2021. In wave 1, we recruited a representative sample of the US adult population and investigated individuals' belief formation in the context of the 2020 US presidential election. Wave 2 was implemented three months later with participants from the same sample. The objective in the second wave was to explore the same belief formation processes using simple social learning tasks. Finally, we implemented wave 3 between 23 October and 3 November 2021 after all the policy predictions from the previous waves were realized. Each of the three waves of our study was pre-registered at the AEA RCT Registry (Bauer, Chen, Hett and Kosfeld 2020, Bauer, Chen, Hett and Kosfeld 2021a, Bauer, Chen, Hett and Kosfeld 2021b). We used the online platform *Prolific.co* to implement the experiment. In what follows, we explain the design of each wave in detail.

3.1 Wave 1: Belief Formation in a Political Context

For wave 1, we deployed an online experiment with 1,005 participants the week before the 2020 US presidential election. Our sample is nationally representative of the US population in terms of gender, urban versus rural location, race, and ethnicity, but is slightly younger and better educated than the US population average (Table C.1 in Appendix C). These participants form the basis for our panel whom we re-contact in subsequent waves.

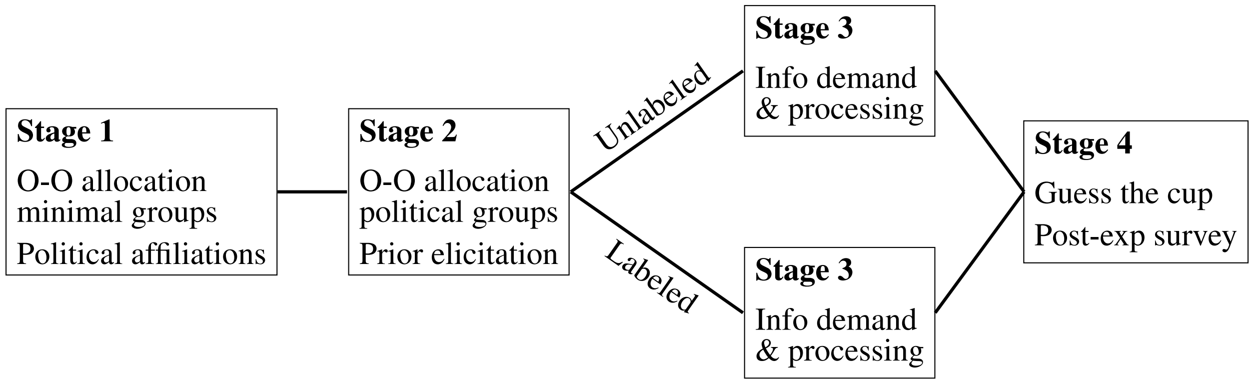

Figure 1: Wave 1 experiment (26-29 October 2020)

Figure 1 illustrates the four stages of our experiment in wave 1. As our goal is to explore the relationship between group identity and belief formation, we start by measuring participants' sensitivity to group identity. To do so, we draw on classic studies on social identity theory (Tajfel et al. 1971, Turner 1985) and use incentivized other-other allocation games with randomly assigned minimal groups (Chen and Li 2009) and political groups (Kranton, Pease, Sanders and Huettel 2020). We use the results of these games to classify participants based on their propensity to exhibit ingroup favoritism in the games.

Stage 1. We begin with minimal groups, where we randomly assign participants to either a "circle" or "triangle" group. Each participant receives $6 to allocate between two randomly-selected participants, one from each group or both from the same group. The minimum amount participants can allocate to each individual is $1. We use their choices in this game to identify a participant's tendency to differentiate between ingroup and outgroup members, favoring the former over the latter, and refer to this tendency as the participant's level of *groupiness* (Kranton and Sanders 2017, Kranton et al. 2020). Participants are classified as *minimally groupy* if they allocate at least one dollar more to an ingroup member, i.e., exhibit ingroup favoritism, in the context of minimal groups. Using minimal groupiness to measure a participant's intergroup preferences has two major advantages: (1) groups are randomly assigned and (2) the measurement is simple and portable.

Stage 2. After observing participant behavior in this minimal group setting, we ask participants to answer survey questions designed to measure their political party affiliation and degree of affiliation.[1] We use their answers to classify them as Democrat (Democrats and Independents leaning Democratic) or Republican (Republicans and Independents leaning Republican). Using these political identifications, we again implement our other-other allocation game, this time requiring participants to allocate money between a randomly-selected member of the Democrat group (henceforth Democrat) and a randomly-selected member of the Republican group (henceforth Republican), or between two participants from the same group. Participants are classified as *politically groupy* if they allocate at least one dollar more to those in their party, i.e., exhibit ingroup favoritism in the context of partisan groups.

In this stage, we also measure participants' prior beliefs in the context of the 2020 US Presidential Election. Specifically, we ask participants to predict the outcome of the election as well as the trajectory of an official public health system ranking (based on the annual rankings from *US News and World Report*) and the US unemployment rate in September 2021, conditional on which candidate becomes president, i.e., they make predictions under both possible election outcomes. We incentivize participants by paying them $10 per correct forecast in February (for their forecast of the election outcomes) and November 2021 (for their forecasts of the unemployment rate and the public health system ranking), respectively. Since public health system rankings and unemployment rates are tied to specific candidate platforms, conditional beliefs about these statistics reflect participants' prior beliefs about the efficacy of each candidate's policies (Bartels 2002). These incentivized forecasting tasks create a demand for relevant information about each candidate.

Stage 3. To examine participants' information demand and processing behavior, we next implement two respective substages where participants can update their prior predictions about the trajectory of public health and unemployment statistics based on curated news articles. We randomize the order of the two substages at the individual level.

In the *information demand* substage, participants are presented with two titles of articles that discuss the potential policy consequences for either the public health system or unemployment rates under different election outcomes. Participants can choose to read one of the two articles and

[1] Validating our classification through a set of factual statements which prior research has shown to demonstrate partisan gaps, we find that we replicate the partisan gap (Peterson and Iyengar 2021). See Table C.2 in Appendix C for our survey instruments and results.

subsequently update their predictions on the respective topic. As a default, one of the two articles is selected with 50% probability and displayed on the participant's computer screen. Participants use a slider to indicate how much of a $3 endowment they would spend to adjust the probability of receiving one article versus the other, where each 10% probability change costs $1. Participants are allowed to keep any remaining portion of their endowment.[2] In this stage, participants make two consecutive slider decisions, one of which we randomly select for implementation. In both cases, one article is from a neutral (or non-partisan) news source while the second is from either a left- or right-leaning source. We curate articles from well-known news media outlets with different political leanings and then synthesize these articles to ensure they are similar in length, format, and facts (see Appendix E.1.8).[3] After reading the article provided to them, participants answer incentivized review questions about the article, indicate its perceived leaning and quality, and decide whether to update their predictions on the corresponding topic. The share of their endowment they choose to spend to increase the probability of receiving information from the (relatively) more party-favorable source reflects their ingroup bias in information demand; e.g., the share a Democrat spends to receive a left-leaning (neutral) article versus a neutral (right-leaning) one.

In the *information processing* substage, each participant exogenously receives in random order two news articles that both discuss the potential policy consequences for the public health system or unemployment under different election outcomes. Regardless of the topic, one article is always curated from left-leaning sources and another from right-leaning news sources. The topic (public health or unemployment) of the articles in this substage differs from the topic a participant receives in the information demand substage. Again, the articles cover the same facts but with a different slant. After reading both articles, participants answer incentivized review questions about the articles and indicate their perceived leaning and quality. Importantly and similar to the demand stage, participants have the option to update their predictions on the topic chosen for this stage.

Intervention – Unlabeling of News Sources. In wave 1 of our experiment, at the beginning of stage 3, half of the participants are randomized into seeing the labels of the news sources

[2] Note that they can increase the probability of reading an article to at most 80%, if they spend their entire endowment.

[3] Our left-leaning news outlets include the *New York Times*, the *Washington Post*, and NBC or MSNBC; our neutral outlets include The Bureau of Labor Statistics (for the economy), the *Economist*, *Nature* (for health), and Reuters; our right-leaning outlets include the *Wall Street Journal*, the *Washington Examiner*, and Fox News. Our classification of the political leanings of the news media outlets is consistent with that based on a combination of machine-learning and crowdsourcing techniques (Budak, Goel and Rao 2016).

("Labeled" - control condition) in the demand and processing stage, whereas the other half of the subjects see the identical articles in the information demand and processing stage without the labels of the news sources ("Unlabeled" - treatment condition). Since labels provide a meaningful cue regarding the group association of information (Goren, Federico and Kittilson 2009), the unlabeling of this information should reduce source utility and hence intergroup preference in selecting and processing information. Figures E.13 and E.14 in Appendix E.2 illustrate how participants see articles with and without labels.

Stage 4. In the fourth stage, participants play an incentivized, neutral "guess-which-cup-is-used" game of the following structure. We first show participants a Green and a Yellow cup and explain that the Green (Yellow) cup contains two green (yellow) marbles and one yellow (green) marble. We then randomly choose one of the two cups with 50% probability without informing the participant about its color. For each participant, the computer randomly draws a marble from the chosen cup and reveals its color to the participant. Upon seeing the color of the marble, a participant guesses the cup's color, receiving $1 for a correct guess, and no payment otherwise. This game is designed to examine the participants' Bayesian inference in a neutral context. As such, it provides a control variable for participant behavior and establishes the nature of the wave 2 task for participants.

Lastly, participants complete a questionnaire containing items on their socio-demographics and their news consumption behavior (see Appendix E.1.6 for the questionnaire and survey items).

3.2 Wave 2: Belief Formation in a Neutral Context

We implemented wave 2 of our online experiments at the end of January 2021, after Joe Biden's inauguration. We conduct this wave to assess groupiness stability as well as intergroup preferences in belief formation in a neutral context where we control prior beliefs. We also pay participants for their election prediction accuracy at this time. Of the 1,005 participants from the first wave, 740 participated in this second wave, yielding a retention rate of 74%. Despite the attrition, wave 2 participants continue to be representative of the US population in terms of gender, age, race and ethnicity, and urban/rural distribution (Table C.1). Figure 2 presents a schematic diagram of wave 2.

Stage 1. As in wave 1, we again randomly assign participants to one of two minimal groups

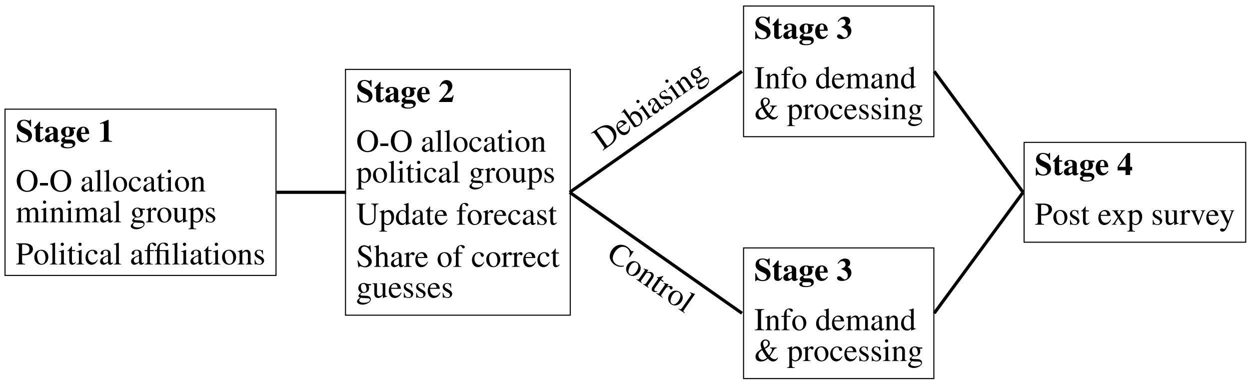

Figure 2: Wave 2 of the experiment (29 January - 8 February 2021)

(triangle or circle) and repeat the other-other allocation game with the minimal groups. Participants then answer the same survey questions designed to measure their degree of political party affiliation. By having participants answer the same questions as in wave 1, we measure the stability of groupiness and check the consistency of their party affiliation.

Stage 2. Given that Joe Biden was inaugurated as the President of the United States in January 2021, we next give participants the opportunity to update their predictions about the US public health system ranking and unemployment rate in September 2021 for the Biden-win case. To reduce noise originating from imperfect memory, we remind participants of their updated policy predictions conditional on Biden winning at the end of wave 1.[4] Subsequently, participants again play the other-other allocation game with participants of the same or different political party affiliations or leanings. This second measurement of participants' political allocation decisions enables us to analyze the stability of their previously-revealed level of intergroup behavior.

At the end of this stage, we remind participants of the "guess-which-cup-is-used" game they played in wave 1 and inform them that, across all participants, 67% guessed their cup correctly. After anchoring their belief on the guess accuracy, we ask participants to estimate the share of correct guesses among Democrats and Republicans, respectively.

Intervention – Debiasing. As in wave 1, we include a between-subject treatment variation in wave 2. Specifically, at the end of stage 2, participants in the treatment condition learn that the

[4] 70% of participants in wave 2 did not change their prediction for the health system ranking, whereas 59.3% did not change their prediction for the unemployment rate. 44.7% did not change either prediction. On average, participants' predictions became slightly more optimistic. For the health system ranking, participants' new average prediction is ranking 14.06 (compared to 14.16 before). For the unemployment rate, participants' new average prediction is a rate of 7.42% (compared to 7.75% before). Both Democrats and Republicans adopt more optimistic beliefs on average.

share of correct guesses is 67% for both Democrats and Republicans, whereas those in the control condition do not receive any information on the share of correct guesses. Put differently, treated participants learn that the observed guesses of Democrats and Republicans are equally accurate, i.e., have the same instrumental value.

Stage 3. In this stage, we explore participants' information demand and processing behavior in the neutral context of various "guess-which-cup-is-used" games. The order of the information demand and processing substages is randomized at the individual level.

The structure of the *information demand* substage in the second wave of our experiment closely mirrors that of its counterpart in wave 1. Specifically, it comprises two independent rounds of a "guess-which-cup-is-used" game, i.e., we randomly draw a new cup for each round with the composition of marbles in each cup being identical to that in wave 1. In both rounds, participants observe either a randomly-drawn marble or the wave-1 guess of another participant whose marble had been drawn from the same cup (with replacement), with a probability of 50% of either. Using a slider on a computer screen, participants have the option to change their same-party observation probability, with each 10 percentage points in either direction costing 10 of their 40-cent endowment. Participants are shown both the guess and political party affiliation of the wave-1 guess individual. In a random order, the other participant is either a Democrat or a Republican. Based on the chosen probabilities, we randomly determine whether participants observed a marble or the guess. Subjects earn $1 for a correct guess, and no payment otherwise. At the end of the experiment, we randomly select one of the two rounds for the final payment.

We next have participants observe the independent wave-1 guesses of two other participants, each of whom had observed a randomly-drawn marble from the same colored cup (with replacement). Each of three rounds includes two groups comprised of two other participants. Each participant observes the guesses from one of these two groups. The default probability of observing a given group's guesses is 50%. Again, participants observe both the guesses and the guesser political party affiliations and are able to change their observation probability, with each 10 percentage point change costing 10 cents of their 40-cent endowment. The composition of the two groups varies across the three rounds: (i) two Democrats v. two Republicans; (ii) two Democrats v. one Democrat and one Republican, and (iii) two Republicans v. one Democrat and one Republican. We randomize the order of the different scenarios. Based on the chosen probabilities, we randomly draw one of the two groups and show the corresponding guesses to the given participant. Participants earn $1 for a correct guess, and no money otherwise. At the end of the experiment, we randomly select one of the three rounds in this stage for payment.

In all of these rounds, we use the endowment share a participant spends to increase the probability of seeing the guesses of participants with the same political affiliation to indicate that participant's intergroup preferences in information demand.

The structure of the *information processing* substage in the second wave of our experiment similarly mirrors that of its counterpart in wave 1. For each participant in each of six independent rounds, we randomly draw a new cup, and they observe a randomly drawn marble from that cup along with the independent wave-1 guesses of two other participants whose marble had been drawn from the same cup (with replacement). In three of the six rounds, both of the observed guesses contradict their private signal (the observed marble). In different rounds, the contradicting guesses come from two Democrats, two Republicans, or two participants from unknown party affiliations, in random order. In the other three rounds, only one of the observed guesses contradicts their private signal. In different rounds, the contradicting guess comes from a Democrat, a Republican, or a participant with unknown party affiliation. This structure allows us to identify when participants are willing to abandon their private signal conditional on the respective party affiliations of the two individuals whose guesses they observe. One of the six rounds is randomly selected for payment at the end of the experiment. Participants earn $1 for a correct guess and zero otherwise.

Stage 4. In the final stage of the experiment, participants complete a questionnaire designed to elicit their attitude toward the then-ongoing debates about Covid-19 vaccinations, beliefs about the legitimacy of the 2020 presidential election, and perceptions about the social status of Democrats and Republicans (see Appendix E.3.6).

3.3 Wave 3: Repeat Measurement and Final Payment

Wave 3 of the experiment was implemented between 23 October and 3 November 2021, after both policy predictions were realized. This wave consists of repeated measures of groupiness and political affiliations as well as additional items to explore the nature of groupiness. We also use this time to pay participants for correct policy predictions. Of the 1,005 participants from wave 1, 530 returned for wave 3. This subsample remains representative of the US population in its gender and rural / urban living, but not the other characteristics (Table C.1).

In addition to the other-other allocation games in the minimal and political group contexts, in wave 3, we have participants play an allocation game between a random other from their own state and one from another state. We use state identity, a natural identity shown to be not as extreme as political party identity, to calibrate our groupiness measure.[5] We also have participants complete a survey on their political identification, perceptions about the social status of Democrats and Republicans, and media consumption habits, as well as additional questions on characteristics possibly related to groupiness and biased opinion formation processes (see Appendix E.5.2).

4 Theoretical Framework and Hypotheses

In this section, we begin by outlining a theoretical framework to incorporate the role of group identity in belief formation. The main purpose of the theoretical framework is to provide a model for us to identify potential channels and develop our main hypotheses.[6] The proposed framework builds on and extends existing models of information demand (subsection 4.1) and information processing (subsection 4.2), as we consider both to be important components in the belief formation process.

4.1 Information Demand

Since Stigler (1961), classic theories on the value of information have focused on its instrumental value. However, more recent studies on information acquisition and information preferences provide evidence that people value information beyond its instrumental value (Thornton 2008, Ganguly and Tasoff 2017, Chen and He 2021, Möbius, Niederle, Niehaus and Rosenblat 2022). Contemporary models typically specify a utility function with both an instrumental and a non-instrumental component. The latter might come from anticipatory utility (Caplin and Leahy 2001), motivated beliefs (Bénabou and Tirole 2016), or valence (Golman and Loewenstein 2018).

Let $\mu \in \Omega$ be a possible state of the world and $m(\mu) \geq 0$ be the instrumental (monetary) value associated with state μ. In our experiment, an agent will receive a monetary prize $m(\mu)$, if they

[5] We thank Steve Leider for this suggestion.

[6] For a full description and derivation of our pre-registered hypotheses we refer to the Appendix (see also AEA RCT Registry trial numbers AEARCTR-0006670, AEARCTR-0007106, and AEARCTR-0008584).

correctly guess the state of the world, and will receive zero otherwise. Let $\pi(\mu)$ be the subjective belief of an agent that state μ is the true state and $\pi^0(\mu)$ denote their prior belief. Signals come from various sources. An information source, $z \in \{f, n\}$, might be favored or non-favored.[7] An agent's expected utility function has the following components:

(IN) Expected instrumental value, $\sum_\mu \pi(\mu)m(\mu)$, which motivates the formation of accurate beliefs;

(VA) Expected valence, $\sum_\mu \pi(\mu)v_z(\mu)$, where $v_z(\mu)$ is the goodness (or badness) of having a subjective belief; and

(SU) Source utility, $g_z \in \mathbb{R}$, which captures a preference for or aversion to a specific information source *per se*, i.e., independent of its content. We expect that groupy participants have source utility, i.e., $|g_z| \neq 0$, whereas non-groupy ones do not, $g_z = 0$.

Golman and Loewenstein (2018) posit that information *content* has valence. This framework has been used in the health care context to illustrate the case of why people might avoid learning their HIV status when testing is free and treatments are highly effective (Thornton 2008) as well as why people who have been tested might avoid learning their test results (Ganguly and Tasoff 2017). Content valence likely matters as well in the political sphere, where people may make choices that help them maintain the view that their preferred policy options or candidates are effective.

In our experiment, agents have the possibility to learn by acquiring information signals from one of two possible sources. We set the default probability of learning from either source at 0.5. An agent can spend resources, $x \in [0, \bar{x}]$, to change the likelihood of receiving a signal from one source versus the other. Let c be the marginal cost of changing the likelihood of observing a signal from a specific source. An agent incurs a cost of cx to increase the probability of receiving a signal from a favored source by $\Delta p(x)$, with $\Delta p(0) = 0$ and $\Delta p'(x) > 0$. If an agent invests x to increase the probability of observing a signal from a favored source, the agent's expected utility equals:

$$u(\pi, x) = (0.5 + \Delta p(x))u_f + (0.5 - \Delta p(x))u_n - cx, \tag{1}$$

[7] In wave 1, an information source might come from an ingroup, neutral or outgroup source. Therefore, we use favored versus non-favored to compare them.

where

$$u_z = \sum_{\mu} \pi(\mu|s_z)[m(\mu) + v_z(\mu)] + g_z, \tag{2}$$

for $z \in \{f, n\}$. After an agent receives a signal from an information source, z, and updates their posterior to $\pi(\mu|s_z)$.

Equations (1) and (2) suggest that an agent's desire to acquire or avoid information comes from three sources: (1) the instrumental value of that information, (2) its content valence, and (3) its source utility. We now state our first proposition.

Proposition 1 (Information Demand)**.** *Ceteris paribus, an agent's willingness to pay to change the received information source increases in the information's instrumental value, content valence, and source utility.*

Proofs are relegated to Appendix A, where we also outline how each proposition implies various hypotheses. From Proposition 1, we derive the following hypotheses. First, holding the instrumental value the same, we expect participants will be willing to pay more for information from ingroup versus outgroup sources (Hypothesis 1). The intuition here is that ingroup sources may have both higher content valence and source utility.

Second, we expect any treatment targeting either the source utility or the perceived instrumental value should reduce intergroup preferences in the demand for information. In particular, when source utility is reduced (as in our wave 1 *unlabeling* treatment), we expect a decrease in intergroup preferences in information demand (Hypothesis 2). Similarly, if participants learn that both information sources are equally accurate (as in our wave 2 *debiasing* treatment), we again expect a decrease in the willingness to pay for ingroup information (Hypothesis 3).

Third, to the extent that valence and source utility are rooted in group identity, we expect that participants who exhibit a higher general sensitivity to group identity (i.e., groupy participants) will attach higher utility to ingroup versus outgroup sources. We expect that the treatment effect of unlabeling will be stronger for groupy participants (Hypothesis 4).

4.2 Information Processing

To derive our hypotheses related to how participants process information, i.e., update their subjective beliefs after observing signals, we start by adding group identity to a simple Bayesian updating model in which signals are discrete and unambiguous (as in wave 2 of the experiment). We then consider a broader model of information processing, developed by Fryer et al. (2019), where signals are continuous and open to interpretation. Adapting this model to our setting enables us to derive additional predictions when participants receive information in the form of a summary of a set of newspaper articles (as in wave 1 of the experiment).

To begin with, suppose there are two possible states of the world, $\mu \in \{A, B\}$, as in wave 2 of our experiment. Let $P(\mu)$ denote a rational agent's prior belief. Let S be a set of signals and $P(S|\mu)$ be the likelihood of observing S in state μ. In general, Bayes' Rule prescribes how a rational agent updates their prior beliefs after observing a set of signals, S. In its posterior-odds form, the posterior odds of state A to state B are equal to the likelihood ratio times the prior odds:

$$\frac{P(A|S)}{P(B|S)} = \frac{P(S|A)P(A)}{P(S|B)P(B)}.$$

Furthermore, suppose that there are only two types of signals (as in wave 2 of our experiment) denoted by a and b. We then let $\theta_A \equiv P(a|A)$ and $\theta_B \equiv P(a|B)$. Let $\theta = \theta_A = 1 - \theta_B$ be the diagnosticity parameter indicating the informativeness of a signal. When a Bayesian decision maker observes multiple independent signals, they should pool the signals. More precisely, let N_a and N_b be the numbers of a and b signals, respectively. A Bayesian decision maker thus treats $N_a - N_b$ as the sufficient statistic for making an inference, when both states are ex ante equally likely and signals are informative ($\theta > 1/2$). We formulate this known result as an observation (Kahneman and Tversky 1972).

Observation 1. *Given a uniform prior, $P(A) = P(B)$, a Bayesian decision maker infers the state of the world to be: (1) A iff $N_a > N_b$, (2) A with probability 1/2 iff $N_a = N_b$, and (3) B otherwise.*

To allow for biases in information processing, we use $\pi(\cdot)$ to denote an agent's subjective (posterior) belief. Following Grether (1980) and subsequent research on belief updating, we use the following reduced-form representation:

$$\frac{\pi(A|S)}{\pi(B|S)} = \left[\frac{P(S|A)}{P(S|B)}\right]^{\beta} \left[\frac{P(A)}{P(B)}\right]^{\gamma},$$

where the parameter $\beta \geq 0$ measures the biased use of the signals and $\gamma \geq 0$ measures the biased use of the prior. Bayes' Rule emerges when $\beta = \gamma = 1$. In the case of a uniform prior (as in wave 2 of our experiment), $P(A) = P(B)$, the prior ratio drops out.

In our setting, an agent may receive multiple independent signals, $s_1, \cdots, s_n$, from different sources that may be treated differently. We represent this scenario as follows (see Appendix A.2 for derivations):

$$\frac{\pi(A|s_1, s_2, \cdots, s_n)}{\pi(B|s_1, s_2, \cdots, s_n)} = \left[\frac{P(s_1|A)}{P(s_1|B)}\right]^{\beta_1} \left[\frac{P(s_2|A)}{P(s_2|B)}\right]^{\beta_2} \cdots \left[\frac{P(s_n|A)}{P(s_n|B)}\right]^{\beta_n}. \tag{3}$$

Taking a logarithmic transformation of Eq. (3) yields:

$$\ln\left[\frac{\pi(A|S)}{\pi(B|S)}\right] = \beta_1 \ln\left[\frac{P(s_1|A)}{P(s_1|B)}\right] + \cdots + \beta_n \ln\left[\frac{P(s_n|A)}{P(s_n|B)}\right]. \tag{4}$$

We can then use Eq. (4) to distinguish among private signals, as well as signals from ingroup and outgroup sources. Let β_S, β_I and β_O be the weight an agent attaches to a signal from their own observation, an ingroup and an outgroup source, respectively. Multiple signals from the same source are pooled by the agent (Observation 1). This leads to the following equation that will form the basis for our estimation strategy:

$$\ln\left[\frac{\pi(A|S)}{\pi(B|S)}\right] = \beta_S(N_a^s - N_b^s) + \beta_I(N_a^i - N_b^i) + \beta_O(N_a^o - N_b^o), \tag{5}$$

where $N_a^k - N_b^k$ is the difference between the number of a and b signals that come from an agent's own observation, an ingroup source, or an outgroup source, respectively, with $k \in \{s, i, o\}$. We now state our second proposition.

Proposition 2 (Information Processing)**.** *An agent's posterior belief about the true state of the world increases in the number of supporting signals that come from their own observation, ingroup sources, and outgroup sources, respectively.*

Proposition 2 implies the following hypotheses regarding information processing when signals are discrete and unambiguous. First, we hypothesize that the information from the ingroup will resonate more with an individual, and thus the individual accords this information more weight than the corresponding outgroup information (Malmendier and Veldkamp 2022), that is, $\beta_I > \beta_O$ (Hypothesis 6).

Second, we expect that our experimental treatment that targets perceived source accuracy (*debiasing* treatment in wave 2) will reduce the level of observed ingroup bias in information processing. In other words, $\beta_I = \beta_O$ (Hypothesis 7). The reason for this expectation is that the treatment decreases the participants' differential beliefs related to the instrumental value of the signals.

Finally, we hypothesize that our treatment effects will be heterogeneous, with groupy participants reacting differently to the debiasing treatment compared to their nongroupy counterparts (Hypothesis 5).

As mentioned, we begin with a model that assumes signals are discrete and unambiguous. However, it is possible that signals may be continuous and open to interpretation, as in wave 1 of our experiment. To address this possibility, Fryer et al. (2019) extend the Bayesian updating framework and show that differences in priors can prevent agents who receive exactly the same signals from converging in their posteriors. The key feature of their belief-updating model is that agents first *interpret* the signal according to their prior, and then update their beliefs using the interpreted signal. We adapt their model to our experimental setting to be able to derive additional hypotheses for our experiment. For completeness, we summarize their model specifications below and refer the reader to the original paper for more details.

In Fryer et al. (2019), the true state is denoted by $\mu \in \mathbb{R}$. An agent's prior μ_0 is the expectation of the true mean based on a normal distribution over potential means with a variance σ_0^2. There is a sequence of signals, s_t, arriving in period t that are i.i.d. according to a normal distribution centered around the true mean μ and with variance $\sigma_s^2 \sim N(\mu, \sigma_s^2)$. Let $\hat{\mu}_t$ denote the posterior of an agent after observing t signals.

This model comprises a two-stage updating process. The first stage is the interpretation stage. Let $\hat{s}_t$ be the interpreted signal:

$$\hat{s}_t = \frac{\hat{\mu}_{t-1} + x_t s_t}{1 + x_t}, \tag{6}$$

where $x_t = \sigma_{t-1}^2 / \sigma_s^2$ is the weight an agent applies when interpreting the signal and $\sigma_{t-1}^2 = \sigma_0^2 \sigma_s^2 / (\sigma_s^2 + (t-1)\sigma_0^2)$. Proposition 5 in Fryer et al. (2019) characterizes the agent's posterior as follows:

$$\hat{\mu}_t = \left[\mu_0 \left(\frac{\sigma_s^2}{\sigma_s^2 + \sigma_0^2}\right) + \sum_{\tau=1}^{t} s_\tau \left(\frac{\sigma_0^2}{\sigma_s^2 + \tau\sigma_0^2}\right)^2 \left(\frac{\sigma_s^2 + \tau\sigma_0^2}{\sigma_s^2 + (\tau+1)\sigma_0^2}\right)\right] \left[1 + \frac{\sigma_0^2}{\sigma_s^2 + t\sigma_0^2}\right]. \tag{7}$$

Eq. (7) implies that the estimating equations should take the form of posteriors as a linear function of priors and signals.

Adapting the model to our experimental setting in wave 1, we set $t = 2$, as each participant reads two summaries of news articles (signals). For simplicity, we assume that the signals and prior are equally noisy, $\sigma_s^2 = \sigma_0^2$. After an agent receives the first signal, they interpret the article using their own prior. Applying Eq. (6) for the interpreted signal, $\hat{s}_1$, and Eq. (7) for their posterior, $\hat{\mu}_1$, we obtain:

$$\hat{s}_1 = \frac{1}{2}\mu_0 + \frac{1}{2}s_1, \text{ and } \hat{\mu}_1 = \frac{3}{4}\mu_0 + \frac{1}{4}s_1. \tag{8}$$

Thus, the interpreted signal is closer to the prior belief μ_0. In the updating stage, the agent uses the interpreted signal, $\hat{s}_1$, which effectively weights the prior belief twice. Similarly, after receiving the second signal, and interpreting it, the agent has the following posterior:

$$\hat{\mu}_2 = \frac{2}{3}\mu_0 + \frac{2}{9}s_1 + \frac{1}{9}s_2. \tag{9}$$

By contrast, a standard Bayesian agent who does not interpret any signal weights the prior and all subsequent signals equally, i.e., $\hat{\mu}_2 = \frac{1}{3}\mu_0 + \frac{1}{3}s_1 + \frac{1}{3}s_2$.

This model has two implications in our context. First, it implies that priors are sticky in that they hold greater weight in an agent's posterior than do signals (Hypothesis 8). This overweighting of priors prevents agents with heterogeneous priors from converging, even if they observe the same information. Second, it implies that there is an order effect, as an early signal, which receives less interpretation, is weighted more than a later one (Hypothesis 9).[8]

[8]Note that Hypotheses 8 and 9 are not pre-registered.

5 Results

In this section, we present our results in the following order. First, we report our results regarding participants' prior beliefs. We then provide the results of our information demand and processing experiments. Finally, we provide the results of our analysis of the role of groupiness in explaining the heterogeneity in our findings.

When presenting wave 1 results, we compare our subjects' behavior with the forecasts by 34 academic experts from the Social Science Prediction Platform (shortened as SSPP henceforth) (DellaVigna and Pope 2017). Appendix B contains our forecast survey and expert responses.

5.1 Prior Beliefs

In wave 1, participants were asked to predict the unemployment rate and the US public health system ranking in September 2021, conditional on the outcome of the presidential election.

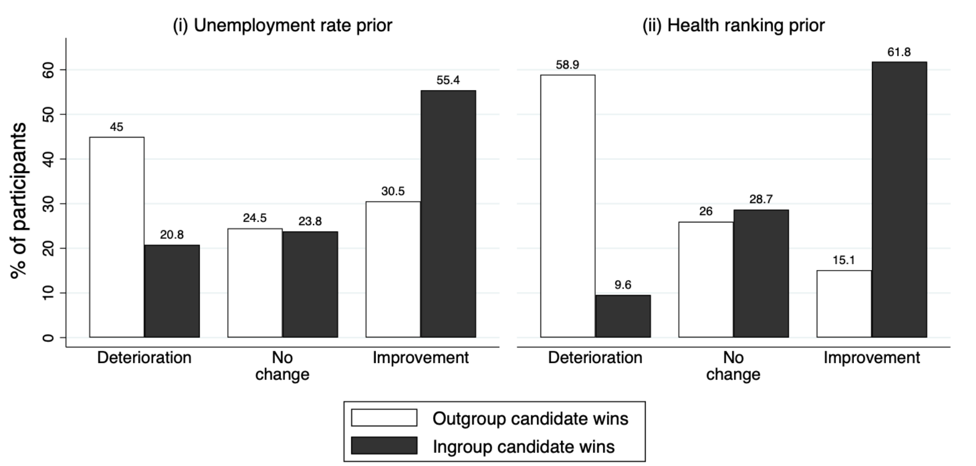

Figure 3: Distribution of prior beliefs for unemployment rate (panel i) and public health system ranking (panel ii) in wave 1: The white (black) bar indicates the proportion of guesses if the outgroup (ingroup) candidate wins the election.

Figure 3 shows a notable partisan divide among participants in their initial predictions about the unemployment rate (panel i) and the public health system ranking (panel ii). We find that 45% (20.8%) of participants anticipate an increase in unemployment if the outgroup (ingroup) candidate wins. Conversely, 30.5% (55.4%) of participants predict a decrease in the unemployment rate if the outgroup (ingroup) candidate wins. Similarly, while 58.9% (9.6%) of participants anticipate a decline in the health system ranking if their outgroup (ingroup) candidate wins, 15.1% (61.8%) believe that the health system will improve if the outgroup (ingroup) candidate wins. Individual level results are summarized below.

Result 1 (Partisan gap in prior beliefs: Wave 1)**.** *Participants' prior beliefs about the development of unemployment rate and public health system ranking display a substantial partisan gap. Specifically, 63.3% of the participants predict a higher improvement (lower decline) for both statistics should their ingroup candidate win.*

Result 1 documents the partisan gap in prior beliefs, which we take as input for their subsequent belief updating process. The mean SSPP expert forecast is 62.6% (stdev 0.256), which is remarkably accurate ($p = 0.23$).

In wave 2, we ask participants to separately predict the proportion of wave-1 Democrats and Republicans who guessed the cup correctly. Figure D.2 in Appendix D.3 presents the distribution of participants' beliefs about others' guess accuracy separately for ingroup and outgroup members. Table D.6 shows that wave-2 participants believe that ingroup members' wave-1 guesses are 5.5 percentage points (pp) more likely to be correct than outgroup members' guesses (+9.6%, $p < 0.01, F$-test). At the extensive margin, we find 35.4% of participants to believe that ingroup members are strictly better at guessing the correct cup.

Result 2 (Ingroup bias in prior beliefs: Wave 2)**.** *In wave 2, participants believe that ingroup members' wave-1 guesses are 5.5 pp more likely to be correct than outgroup members' guesses.*

Result 2 indicates that participants consider their ingroup members to be more accurate in this neutral belief updating task, where Democrats and Republicans are actually equally accurate (67%). Notably, participants' inclination to exhibit an ingroup bias in prior beliefs across waves 1 and 2, is significantly correlated, showing a consistency of this behavior across domains (Spearman's $\rho = 0.115, p < 0.01$). Next, we report our results for participants' information demand in both political and neutral contexts.

5.2 Information Demand

Wave 1. Figure 4 illustrates participants' demand for ingroup versus outgroup information relative to receiving information from a neutral information source. The white (black) bar corresponds to the choice between a neutral and an outgroup (ingroup) information source. We show separate results for the baseline (with labels) and the treatment group (without labels).

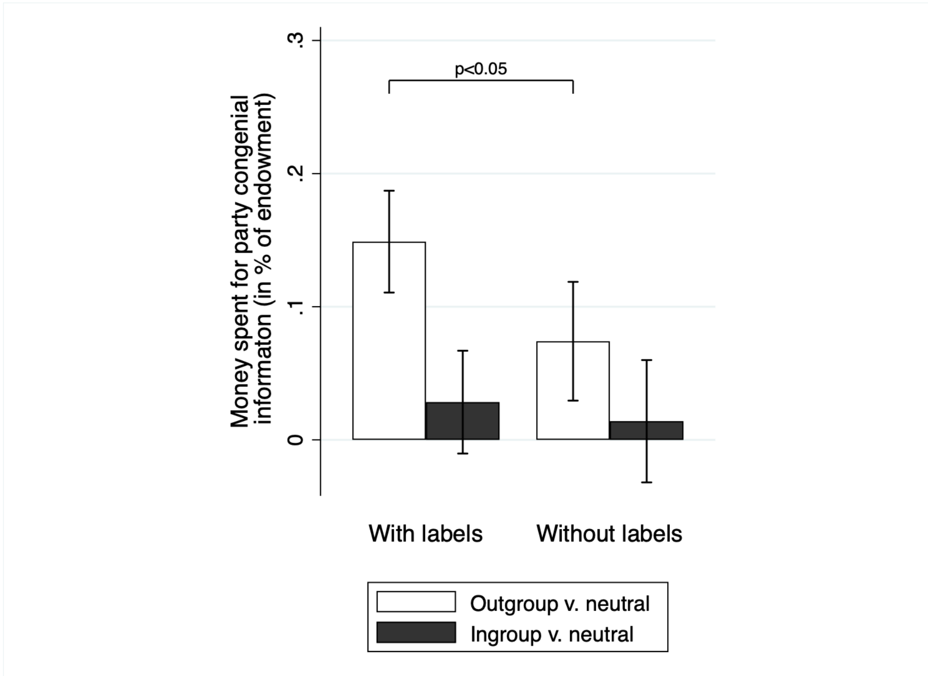

Figure 4: Treatment effects on information demand in wave 1: Participants' willingness to pay to obtain information from a neutral (ingroup) versus an outgroup (neutral) information source. Error bars represent 95% confidence intervals.

Table 1 presents results from four OLS specifications with robust standard errors reported in parentheses. The dependent variable measures the share of their endowment that participants spend to increase the likelihood of reading an article from a more-favored source. From Table 1 and Figure 4, we see that our baseline participants spend, on average, 14.9% of their endowment to avoid information from the outgroup source in favor of the neutral source ($p < 0.01$, F-test; see Table 1 column (1)). On the extensive margin, 38.2% of the individuals reveal a strictly positive preference to avoid outgroup-sourced information. On the other hand, they spend only 2.8% of their endowment to receive information from ingroup versus neutral sources, suggesting indifference between these sources ($p = 0.15$, F-test, see Table 1 column (3)).[9]

[9]Note: for the outgroup (ingroup) v. neutral decision, 16.5% (24%) of participants favored the neutral source whereas 45.3% (47.7%) are indifferent. 28.3% of individuals reveal a strictly positive preference for ingroup over neutral information sources.

Table 1: Participants' information demand (wave 1).

DV: Share of endowment spent for a more favored source	Outgroup v. neutral (1)	Outgroup v. neutral (2)	Ingroup v. neutral (3)	Ingroup v. neutral (4)
Treatment (No labels)	-0.075**	-0.066**	-0.014	0.003
	(0.030)	(0.029)	(0.031)	(0.030)
Constant	0.149***	-0.020	0.028	-0.077
	(0.019)	(0.083)	(0.020)	(0.089)
Controls	No	Yes	No	Yes
Observations	1,005	1,005	1,005	1,005
Adj. R-squared	0.005	0.055	-0.001	0.037

[a.] As controls, we include participants' minimal groupiness, political leaning, party identification, factual bias, frequency of consuming media from opposing viewpoints, gender, education level, ethnicity, area of living, age, Bayesian rationality, and the topic encountered in the demand stage.

[b.] We report robust standard errors in parentheses. We denote significance levels by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Result 3 (Outgroup Information Avoidance: News)**.** *When information sources are labeled, participants spend approximately 15% of their endowment to obtain information from a neutral versus outgroup source. They are indifferent between ingroup and neutral information sources.*

By Result 3, we reject the null in favor of Hypothesis 1. In comparison, SSPP experts expect that participants would spend 39% (44%) of their endowment to avoid outgroup (receive ingroup) versus neutral information, both of which are sizeable deviations from the actual demand ($p < 0.001$ in each case).

To what extent does this observed avoidance of outgroup information stem from source utility? Our treatment is designed to explore this question. Figure 4 shows that our treatment intervention reduces the avoidance of outgroup information by approximately 50% (from 14.9% in the baseline to 7.4% in the treatment, $p < 0.05, F$-test; Table 1 column (1)), suggesting that source utility plays an important role in outgroup information avoidance. This effect is robust to the inclusion of demographic controls (Table 1 column (2)). At the same time, we see no treatment effect on participants' demand for ingroup versus neutral sources (Table 1 columns (3) and (4)).

Result 4 (Average Treatment Effect: Unlabeling)**.** *Unlabeling information sources decreases outgroup information avoidance by 7.5 pp, or 50% relative to the control condition.*

By Result 4, we reject the null in favor of Hypothesis 2. Compared to the actual 50% reduction in outgroup information avoidance, SSPP experts predict a 100% reduction, again more extreme than the actual observation ($p < 0.001$).

While the timing of wave 1 creates a realistic demand for policy-relevant information, each news article summary varies in both its source utility and content valence. We conjecture that the remaining 50% of our observed information avoidance might be due to content valence, as participants are still able to see the title and "teaser" content even when the source is removed. By contrast, our experiment design in wave 2 removes content valence while retaining source utility, enabling us to identify the underlying mechanisms more precisely.

Wave 2. Recall that we vary the "guess-which-cup-is-used" task for participants in wave 2. In the following, we present the results from the two rounds where participants may choose between drawing a marble (a private signal) versus observing another participant's guess knowing the political party affiliation of the guesser.[10]

From Figure 5, we see that participants generally prefer to observe a signal themselves instead of observing another participant's guess. On average, they spend 11.5% of their endowment to increase their likelihood of drawing a marble.[11] Table 2 presents results from two OLS specifications with robust standard errors clustered at the individual level and reported in parentheses. In both columns, the dependent variable measures the share of their endowment that participants spend to observe a marble instead of another participant's guess. Independent variables include the treatment dummy, outgroup guess, their interaction, and a constant.

More importantly, and in line with our findings for wave 1, this preference differs according to the group membership of the guesser: if the guess comes from an outgroup (ingroup) member participants spend, on average, 14.9% (8.2%) of their endowment ($p < 0.05$, F-test; see Table 2

[10]Results from the rounds, in which participants do not themselves observe a marble but may choose between guesses from different groups, are shown in Figure D.1 and Table D.5) in Appendix D. The results of these tasks mirror the results for information demand reported in the main text, providing additional evidence of avoidance of outgroup information.

[11]This is consistent with findings by Conlon, Mani, Rao, Ridley and Schilbach (2022) in whose study participants observe signals of others, however, not guesses.

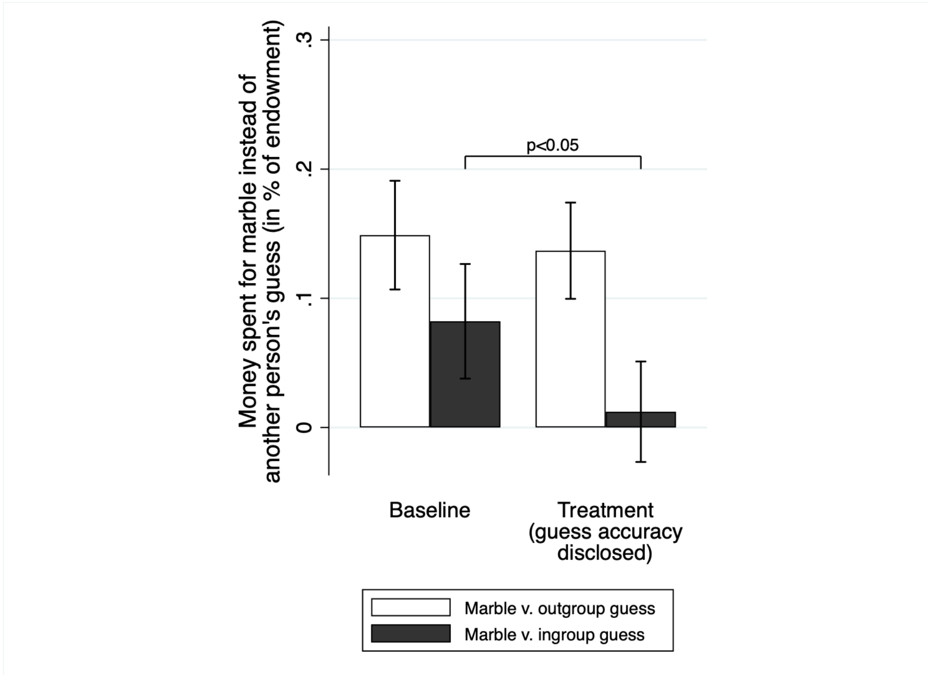

Figure 5: Information demand (wave 2): Participants' willingness to pay to observe a marble instead of the guess of another participant. Error bars represent 95% confidence intervals.

column (1)). These findings provide support for the existence of outgroup information avoidance in a domain absent of content valence. Notably, participants' inclination to exhibit an outgroup information avoidance across waves 1 and 2, is significantly correlated, showing a consistency of this behavior across domains (Spearman's $\rho = 0.135, p < 0.01$).

Result 5 (Outgroup Information Avoidance: Guesses)**.** *When deciding between observing a marble directly or the guess of another participant, participants spend 6.7 pp, or 87% more of their endowment to observe a marble when the guess comes from an outgroup versus ingroup participant.*

Table 2: Participants' information demand behavior (wave 2).

DV: Share of endowment spent for a marble	(1)	(2)
Treatment (guess acc. disclosed) (β_1)	-0.070**	-0.068**
	(0.030)	(0.030)
Outgroup guess (β_2)	0.067***	0.067***
	(0.031)	(0.031)
Outgroup guess*Treatment (β_3)	0.058*	0.058*
	(0.041)	(0.041)
Constant (β_0)	0.082***	-0.014
	(0.023)	(0.063)
F-test: $\beta_1 + \beta_3 = 0$	0.67	0.726
F-test: $\beta_0 + \beta_1 = 0$	0.538	0.184
F-test: $\beta_0 + \beta_1 + \beta_2 + \beta_3 = 0$	0.000	0.485
Controls	No	Yes
Observations	1,480	1,480
Adj. R-squared	0.016	0.023

[a] As controls, we include participants' minimal groupiness, political leaning, party identification, factual bias, frequency of consuming media from opposing viewpoints, gender, education level, ethnicity, area of living, age, Bayesian rationality.

[b] We cluster robust standard errors at the individual level and report them in parentheses. We denote significance levels by $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

In our analysis, we consider whether our observed outgroup information avoidance reflects the instrumental value of information. Recall that baseline participants consider their ingroup members to be more accurate in the guess-the-cup game (Result 2). In our debiasing treatment, we truthfully communicated to half of the participants that the accuracy of Democrats and Republicans is identical (67%), and equal to the diagnosticity of a marble (2/3), thus removing any instrumental value for demanding information from a particular source.

The results in Figure 5 show that informing participants of the identical accuracy has no effect on their outgroup source avoidance. Compared to baseline participants (14.9%), their counterparts in the treatment condition spend on average 13.7% of their endowment to avoid information from the outgroup ($p = 0.67$, F-test). However, as the results in Table 2 indicate, the treatment significantly reduces participants' willingness to pay for observing a marble instead of an ingroup guess by 7 percentage points (8.2% v. 1.2%, $p < 0.05$, F-test).

Result 6 (Average Treatment Effect: Debiasing)**.** *The debiasing treatment decreases the demand for observing a marble rather than an ingroup guess by 7 pp, or 85% over the baseline, while it has no effect on outgroup information avoidance.*

By Result 6, we reject the null in favor of Hypothesis 3. This result suggests source utility is persistent and independent of the instrumental value or content valence of the information sources.

The information people choose to consume is an important building block in their belief formation process. In our study, we have shown that outgroup information avoidance is an important factor in explaining the observed divergence in political opinions in the US. We next examine whether people also differ in their processing of information, namely, the weight they accord to prior beliefs versus new information in their posterior beliefs, as well as to information coming from ingroup versus outgroup sources.

5.3 Information Processing

We examine how participants process information differently across wave 1 and wave 2 in our experiment. In wave 1, priors are endogenous, whereas in wave 2, they are exogenously given and perfectly uninformative (50-50). Furthermore, in wave 1, signals (news article summaries) are continuous and open to interpretation, whereas in wave 2, signals are binary and unambiguous. Lastly, predicting unemployment rates and public health system rankings in the future is arguably more difficult relative to guessing the correct cup.[12]

Wave 1. In wave 1, participants were given a left- and right-leaning news article summary, respectively, in random order. After reading the articles, they answered review questions.[13] and had the opportunity to update their predictions on the unemployment rate and the public health system ranking.

[12] As a benchmark, of the 31 experts on the US Economic Experts Panel who were asked in October 2020 to predict the December 2020 unemployment rate, 10% predict the range correctly (IGM COVID-19 Economic Outlook Survey Series). In comparison, 12% of our participants correctly predicted the September 2021 unemployment rate back in October 2020, whereas 7.5% predicted the public health system ranking. At the end of wave 1, 63% correctly predicted the outcome of the 2020 election, whereas 67% correctly guessed the cup.

[13] On average, participants answered 1.5 out of the two review questions correctly, with 64.5% answering both questions correctly. Notably, participants are 3.2 pp (+ 4.3%, $p < 0.04, \chi^2$-test) more likely to answer the review questions correctly for the article from the ingroup source (77.4% v. 74.2%).

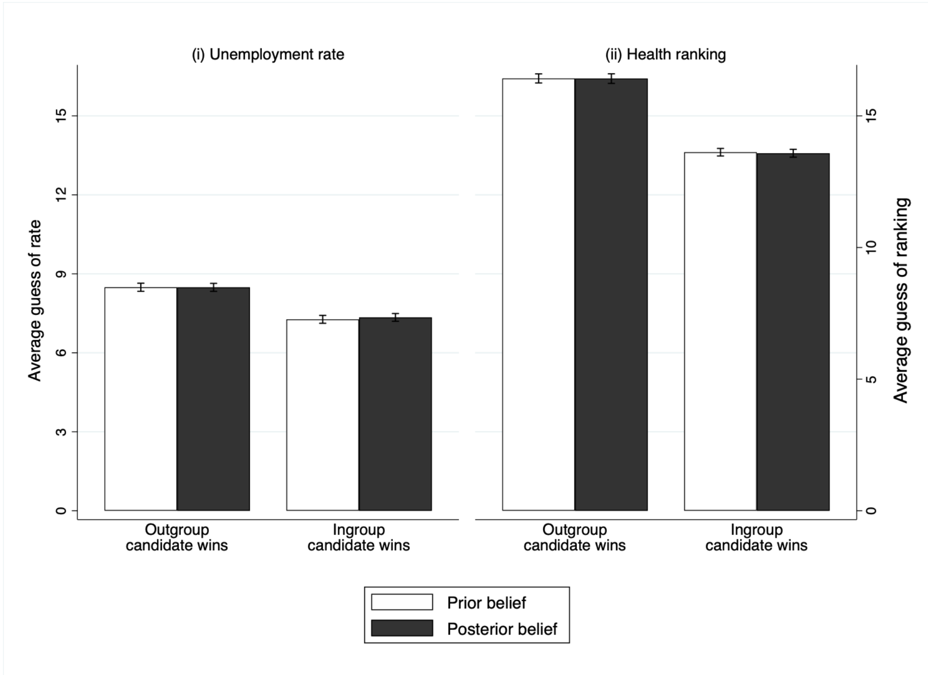

Figure 6: Prior and posterior beliefs (wave 1, baseline) about the unemployment rate (left panel) and the health system ranking (right panel) 10 months after the 2020 election. Error bars represent 95% confidence intervals.

Figure 6 presents the average prior (white bars) and posterior beliefs (black bars) of participants after reading two respective news articles from ingroup and outgroup sources in wave 1. From Figure 6, we see that our initial partisan gap in predictions persists, even in the face of diverse-source information. Specifically, 68.5% (64.1%) of participants adhere to their initial beliefs if the ingroup (outgroup) candidate wins ($p < 0.05$, F-test). Meanwhile, approximately equal percentages of participants update their beliefs in an optimistic (15.3% for ingroup win, 17.6% for outgroup win; $p = 0.25$, F-test) or pessimistic (16.2% for ingroup win, 18.2% for outgroup win; $p = 0.35$, F-test) direction. This heterogeneity in updating enables us to use linear regressions suggested by Eq. (7) to decompose participants' posterior beliefs into their prior beliefs and signals, as follows:

$$\text{(Posterior Belief)}_i = \alpha + \beta_0 \times \text{(Prior Belief)}_i + \beta_1 \times \text{(Ingroup Article First)}_i + \varepsilon_i, \tag{10}$$

where i indexes individuals, β_0 corresponds to the weight on the prior, α (β_1) corresponds to the weight on signals when the first signal comes from an outgroup (ingroup) source.

Table 3 presents the summary statistics (panel A) and five OLS specifications with robust standard errors reported in parentheses (panels B and C). The dependent variable is participants' posterior on the unemployment rate (specifications 1 and 2) and the public health system ranking (specifications 3, 4 and 5). Results in columns (1) to (3) are robust to the inclusion of individual-level controls, whereas results in column (4) slightly change when we include these controls (column 5). Independent variables include their prior beliefs in panel B, with an additional dummy variable, ingroup article first, in panel C. For each topic, we report their posterior conditional on the outgroup (columns 1 and 3) or ingroup (columns 2, 4 and 5) candidate winning.

The regression results in Table 3 suggest that participants' prior beliefs significantly influence their posteriors across the domains. Using the prior and posterior beliefs reported in panel A and the corresponding regression coefficients estimated in panel B of Table 3, we find that participants' prior beliefs account for at least 62% and up to 80% of their posterior beliefs. We summarize the results below.[14]

Result 7 (Sticky Priors)**.** *The prior beliefs of the participants accounts for between 62% and 80% of their posterior beliefs.*

Result 7 provides support for Hypothesis 8. In fact, our estimated weight on the prior is remarkably close to the theoretical prediction of 2/3. Consistent with Result 7, Liu and Zhang (2023) also find that prior beliefs are sticky and that the opportunity to read additional arguments does not prompt participants to adjust their attitudes shaped by the initial narrative. Our study extends the setting in which prior beliefs are sticky to the realm of economic and public health policy conditional on a political candidate's win, and provides additional evidence on how individuals update their beliefs when signals are open to interpretation.

[14] In column (2) of Table 3, for the posterior on the unemployment rate conditional on the ingroup candidate winning, the contribution of the prior to the posterior is computed as $\beta_0(\text{Prior})/\text{Posterior} = 0.65 \times 7.26/7.37 = 0.64$. Repeating this process for columns (1), (3) and (4) yields 0.62, 0.80 and 0.68 respectively.

Table 3: Participants' information processing in wave 1: Estimating posterior from Eq. (10)

Panel A	Summary statistics				
	Unemployment Rate		Public Health System Ranking		
	Outgr. wins	Ingr. wins	Outgr. wins	Ingr. wins	
Prior	8.39	7.26	16.32	13.67	
Posterior	8.34	7.37	16.27	13.59	
Panel B	Regression analyses				
DV: Posterior	Unemployment Rate		Public Health System Ranking		
	Outgr. wins	Ingr. wins	Outgr. wins	Ingr. wins	Ingr. wins
	(1)	(2)	(3)	(4)	(5)
Prior	0.618***	0.650***	0.802***	0.683***	0.591***
	(0.059)	(0.061)	(0.043)	(0.052)	(0.060)
Constant	3.225***	2.656***	3.199***	4.312***	5.344***
	(0.496)	(0.453)	(0.710)	(0.718)	(0.943)
Controls	No	No	No	No	Yes
Observations	594	594	606	606	606
Adj. R-squared	0.387	0.426	0.559	0.415	0.448
Panel C	(1)	(2)	(3)	(4)	(5)
Prior	0.618***	0.649***	0.801***	0.689***	0.599***
	(0.059)	(0.061)	(0.043)	(0.052)	(0.059)
Ingr article first	-0.013	0.117	-0.076	-0.313**	-0.278*
	(0.174)	(0.168)	(0.170)	(0.152)	(0.148)
Constant	3.229***	2.613***	3.253***	4.380***	5.376***
	(0.497)	(0.452)	(0.712)	(0.724)	(0.945)
Controls	No	No	No	No	Yes
Observations	594	594	606	606	606
Adj. R-squared	0.386	0.426	0.559	0.422	0.453

[a.] Controls include participants' minimal groupiness, political leaning, party identification, factual bias, frequency of consuming media from opposing viewpoints, gender, education level, ethnicity, area of living, age, Bayesian rationality, and the topic encountered in the processing stage.

[b.] We report robust standard errors in parentheses. We denote significance levels by $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

The results in panel C of Table 3 show that the dummy variable, ingroup article first, is negative and significant in the public health system ranking domain ($p < 0.05$, column (4)), indicating that reading an ingroup article first causes participants to be 0.278 ranking levels (or 2 pp) more optimistic conditional on the ingroup candidate winning ($p < 0.1$, column (5)). We further see that there is an insignificant effect for the outgroup candidate (column (3)) and no effect for the unemployment prediction (columns (1) and (2)).

Result 8 (Order Effect)**.** *When participants read the ingroup article first, they are 2 pp more optimistic about the improvement of the US public health system ranking. This effect becomes marginally significant when we control for demographics.*

Result 8 provides some support for Hypothesis 9. The analysis suggests that the influence of a signal on a participant's posterior beliefs, albeit small, depends on the order in which it is presented.

In sum, the information processing results from wave 1 of our experiment suggest that when signals (news article summaries) are open to interpretation, participants' priors carry more weight than the signals they receive in determining their posterior beliefs. We further find some evidence that signals have different weight on posteriors depending on the order in which they are presented. Specifically, when the ingroup signal arrives before the outgroup signal, participants are more optimistic in their predictions of the public health system ranking, although the magnitude of this effect is small. We conclude that our results in this section provide empirical support for the double updating model of Fryer et al. (2019).

Wave 2. Recall that, in wave 2, we measure participants' belief updating through a "guess-which-cup-is-used" game. Unlike the news article summaries in wave 1, the signals in wave 2 are not open to interpretation, nor is there any content valence. This simple setting thus enables us to estimate the effects of group identity on participants' belief updating.

In our context, Observation 1 suggests that, when each participant is presented with a private signal and two guesses, a Bayesian decision maker should follow the majority rule.[15] However, we find that only 63.3% of the decisions in our baseline condition follow this majority rule.

[15] Under the assumption that everyone follows Bayes' Rule, seeing a guess is as good as seeing another independently drawn marble.

Figure 7 presents the results when participants observe a privately-drawn marble (private signal) and the guesses of two other participants, conditional on whether the contradictory guess comes from an ingroup or an outgroup member. The vertical axis depicts participants' likelihood of abandoning their own signal. Panel (i) shows the results for the case where only one of the guesses is the same as their private signal while the other contradictory. In this case, a rational participant should not abandon their private signal. Panel (ii) shows the results for the cases where both guesses contradict their private signal. In this case, a rational agent should abandon their private signal.

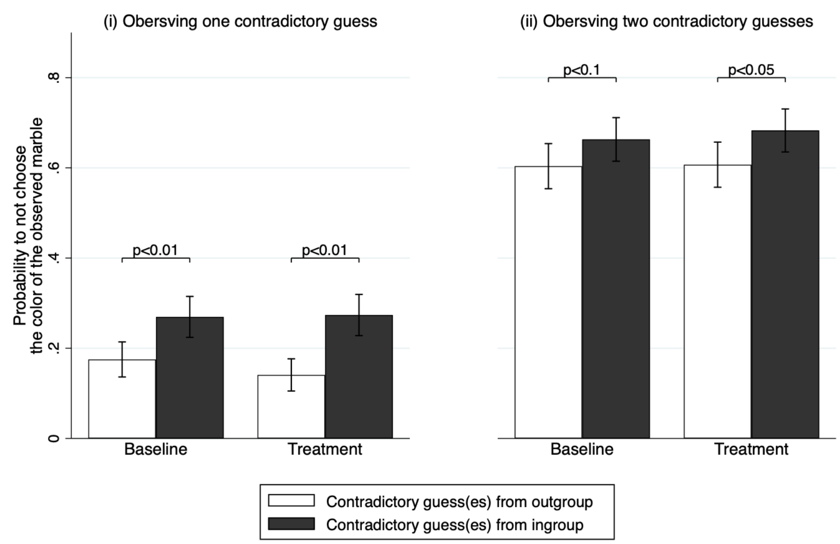

Figure 7: Probability of abandoning a private signal in favor of contradictory guess(es) when participants observe one (panel i) or two contradictory guesses (panel ii) of other participants in wave 2.

In our baseline condition, 22.3% of the participants abandon their private signal if one of the observed guesses contradicts it. From panel (i), we see that participants irrationally abandon their private signal in 27% (17.5%) of the cases when the contradictory signal comes from an ingroup (outgroup) participant. This difference is statistically significant and economically sizeable ($p < 0.01, F$-test; see column (1) in Table D.7 in the Appendix D.5). When both guesses contradict their private signal, participants follow the majority rule in 63.4% of the cases. Panel (ii) reveals that participants are more likely to follow the majority rule by abandoning their private signal when the two contradictory signals come from an ingroup as opposed to an outgroup source (66.3% v. 60.4%, $p < 0.05, F$-test; see column (4) in Table D.7). Together, these findings depict that participants place more weight on guesses from ingroup than outgroup members.

To estimate the ingroup bias in belief updating, we employ the following estimation equation based on Eq. (5):

$$\text{(Posterior)}_{igj} = \alpha + \beta_S \times \text{(Self)}_{ij} + \beta_I \times N^I_{ij} + \beta_O \times N^O_{ij} + \gamma X_{igj} + \varepsilon_{igj}, \tag{11}$$

where (Posterior)_{igj} represents individual i in group g guessing cup j, (Self)_{ij} indicates individual i's own signal is of color j, N^I_{ij} (N^O_{ij}) is the number of i's ingroup (outgroup) members guessing cup j, X_{igj} is the set of demographic controls, and ε_{igj} is an error term.

Table 4 presents the results from our six OLS specifications estimating Eq. (11), with robust standard errors clustered at the individual level. The dependent variable is whether a participant guesses the green cup. Independent variables include whether a participant observes a green marble, the number of green cup guesses from ingroup members, the number of green cup guesses from outgroup members, a debiasing treatment dummy, and interaction terms. Specification (1) includes only the baseline data, whereas specifications (2) and (3) include both baseline and treatment data. From Table 4, we see that participants put significantly more weight on their own signal than the corresponding guesses of ingroup members ($\beta_S > \beta_I$, $p < 0.01$; F-test) and more weight on the guesses of ingroup members than those of outgroup members ($\beta_I > \beta_O$, $p < 0.01$; F-test), regardless of the treatment condition ($p > 0.10$ for the Treatment dummy and its interactions). We summarize these findings below.

Result 9 (Biased Information Processing: Guesses)**.** *In a neutral context without content valence, participants place 5 pp, or 33% more weight on ingroup than outgroup guesses. They also place 8 pp, or 40% more weight on their own signal than ingroup guesses. The debiasing treatment has no significant effect, indicating that these differential weights are not associated with any perceived instrumental value of the information.*

By Result 9, we reject the null in favor of Hypothesis 6. We further reject Hypothesis 7. Notably, additional analyses reveal that participants' inclination to update beliefs in an ingroup favorable way across waves 1 and 2 are not significantly correlated (Spearman's $\rho = -0.01, p = 0.4$), which is arguably not surprising considering the remarkable stickiness of priors in wave 1.

Table 4: Information processing (Wave 2): OLS.

DV:	Baseline		Baseline and Treatment			
Guessing green cup	(1)	(2)	(3)	(4)	(5)	(6)
Self green marble (β_S)	0.282***	0.282***	0.266***	0.267***	0.282***	0.283***
	(0.025)	(0.025)	(0.018)	(0.018)	(0.025)	(0.025)
Ingroup # of green guesses (β_I)	0.202***	0.201***	0.190***	0.191***	0.202***	0.202***
	(0.018)	(0.018)	(0.013)	(0.013)	(0.018)	(0.018)
Outgroup # of green guesses (β_O)	0.150***	0.151***	0.130***	0.130***	0.150***	0.151***
	(0.018)	(0.019)	(0.013)	(0.013)	(0.018)	(0.018)
Treatment			0.006	0.007	0.044	0.044
			(0.015)	(0.015)	(0.031)	(0.031)
Treatment×Self Green marble					-0.032	-0.033
					(0.037)	(0.037)
Treatment×Ingroup # of green guesses					-0.024	-0.022
					(0.025)	(0.025)
Treatment×Outgroup # of green guesses					-0.041	-0.041
					(0.026)	(0.026)
Constant	0.237***	0.185***	0.256***	0.247***	0.237***	0.230***
	(0.021)	(0.055)	(0.017)	(0.043)	(0.021)	(0.044)
$\beta_S - \beta_I > 0$	0.080***	0.081***	0.076***	0.076***	0.080***	0.081***
$\beta_I - \beta_O > 0$	0.052***	0.050***	0.061***	0.060***	0.052***	0.051***
Controls	No	Yes	No	Yes	No	Yes
Observations	2,226	2,226	4,440	4,440	4,440	4,440
Adj. R-squared	0.085	0.082	0.074	0.073	0.074	0.073

a. As controls, we include participants' minimal groupiness, political leaning, party identification, factual bias, frequency of consuming media from opposing viewpoints, gender, education level, ethnicity, area of living, age, Bayesian rationality.

b. Robust standard errors are clustered at the individual level and reported in parentheses. We denote significance levels by $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

5.4 Heterogeneity: Groupiness

Our results so far show a pattern of intergroup preferences in belief formation that resembles a widely-recognized behavioral outcome of group identity, i.e., ingroup favoritism in allocation decisions (Tajfel et al. 1971, Tajfel and Turner 1979, Chen and Li 2009, Kranton and Sanders 2017). It is possible that some people are more susceptible to ingroup bias in both belief formation and allocation decisions. We consider this possibility in the following analysis.

Measuring groupiness. Figure 8 illustrates the participants' decisions in our wave-1 other-other allocation game with minimal groups (white bars) and political groups (black bars). For corresponding results in waves 2 and 3, refer to Figures D.3 and D.4 in the Appendix D. Recall that for wave 3 we not only observe allocation decisions in the context of minimal and political groups, but also the state participants live in. We focus on minimal groups as a key measure of participants' behavioral sensitivity to group contexts in allocation choices, as the minimal group membership is randomly assigned, stable across waves, and highly correlated with political groupiness in wave 1 ($\rho = 0.361$, $p < 0.01$), wave 2 ($\rho = 0.466$, $p < 0.01$) and wave 3 ($\rho = 0.406$, $p < 0.01$). We also find a strong correlation between minimal and state groupiness in wave 3 ($\rho = 0.388$, $p < 0.01$).[16]

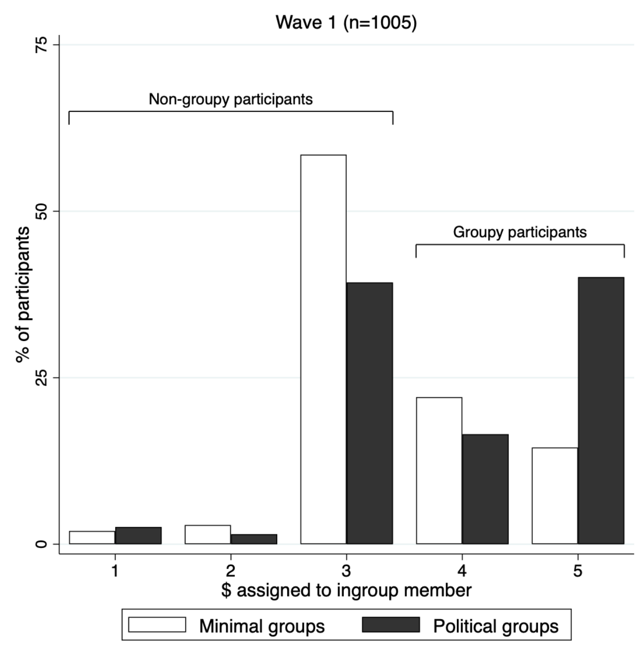

Figure 8: Distribution of allocation decisions in the minimal (white bars) and political (black bars) other-other allocation games: The horizontal axis shows the amount (in dollars) allocated to an ingroup member out of a total budget of $6. The maximum amount a participant can allocate to another participant is $5.

From Figure 8, we see that 59% of our participants split their endowment equally, 5% strictly favor outgroup participants, and 37% strictly favor ingroup participants. We refer to this latter

[16]Note that Kranton et al. (2020) define groupiness as the intersection of minimal and political groupiness. Our key results remain similar if we use political groupiness instead.

group as *(minimally) groupy* individuals, and the first two groups as *non-groupy* individuals.[17] Note that these distributions are comparable to those found in previous studies (Chen and Li 2009, Kranton et al. 2020). In particular, we do not find any difference in the distributions of the allocation choices between Democrats and Republicans ($p = 0.393$, Kolmogorov-Smirnov test).

Table 5: Stability and predictive power of (minimal) groupiness across waves.

DV: Being group	in wave 2		in wave 3			
	Minimal		Minimal		Political	State
	(1)	(2)	(3)	(4)	(5)	(6)
Min. groupy in wave 1	0.441***	0.421***	0.274***	0.277***	0.043	0.099*
	(0.035)	(0.036)	(0.050)	(0.050)	(0.048)	(0.053)
Min. groupy in wave 2			0.349***	0.348***	0.182***	0.101*
			(0.049)	(0.050)	(0.05)	(0.052)
Min. groupy in wave 3					0.337***	0.264***
					(0.048)	(0.055)
Constant	0.199***	0.226**	0.094***	0.234**	0.007	0.097
	(0.018)	(0.093)	(0.018)	(0.107)	(0.113)	(0.102)
Controls	No	Yes	No	Yes	Yes	Yes
Observations	740	740	496	496	496	496
Adj. R-squared	0.191	0.201	0.291	0.291	0.233	0.165

a. As controls, we include participants' political leaning, party identification, factual bias, frequency of consuming media from opposing viewpoints, gender, education level, ethnicity, area of living, age, Bayesian rationality, and the topic encountered in the demand stage.

b. Robust standard errors are in parentheses. We denote significance levels by $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

With multiple repeated measurements across different waves of our experiment, our panel design allows us to investigate both the consistency and stability of the distribution of groupiness: in wave 1 (2, 3), respectively, we find that 37% (35%, 30%) of our participants are minimally groupy. Table 5 presents six linear panel specifications. The dependent variable is being minimally groupy in waves 2 (columns (1) and (2)) and 3 (columns (3) and (4)), being politically groupy in wave 3 (column (5)), and being state groupy in wave 3 (column (6)). Independent variables include being minimally groupy in waves 1, 2 and 3 respectively, and a constant. Results from this anal-

[17]Using other-other allocation games across different domains of natural identities, Enke, Rodriguez-Padilla and Zimmermann (2022) define a behavioral type called *moral universalism*, which corresponds to our measure of non-groupiness.

ysis reveal a strong and significant predictive power of wave-1 groupiness for wave-2 groupiness, as well as wave-1-and-2 groupiness for wave-3 groupiness ($p < 0.01$, F-test; see colunmns (1) - (4)). Columns (5) and (6) further reveal that minimal groupiness in our different waves predicts participants' political and state groupiness in wave 3. We will leverage this relatively stable trait to examine the moderating role of groupiness on belief formation.[18]

In the following, we explore heterogeneities in our wave 1 and 2 results regarding participants' minimal groupiness as measured in wave 1 and 2, respectively.

Groupiness in prior beliefs. As seen in Table D.8 in the Appendix D.5, whereas groupy participants exhibit a strict partisan gap for both prediction tasks in 45.9% of the cases, non-groupy types do so in 40% of the cases (+14.8%; $p < 0.05$, F-test). Looking at the two topics individually, groupy types are more likely to possess a partisan gap in their guess about the development of unemployment rates (57.3% v. 51.3%; $p < 0.07$, F-test), but not in the public health system ranking (71.3% v. 71.5%; $p = 0.94$, F-test).

Looking at participants' prior beliefs about the guess accuracy of others in wave 2 (see Figures D.7 and D.8 in the Appendix D.5), we find that groupiness also exacerbates any prior partisan gap. Specifically, the regression results in Table D.9 show that groupy participants' beliefs are significantly more biased (Ingroup accuracy: 63.5% v. Outgroup accuracy: 56.2%) than those of their non-groupy counterparts (62.5% v. 58%, $p < 0.05$, F-test). As columns (3) and (4) show, this heterogeneity is driven by groupy participants' lower (higher) estimates of outgroup (ingroup) guess accuracy of outgroup guesses ($p < 0.05$ and $p < 0.01$, F-tests, respectively). We summarize the results below.

Result 10 (Groupiness in prior beliefs)**.** *Groupy participants are 6.3 pp, or 37% more likely to exhibit a partisan gap in their prior beliefs than their non-groupy counterparts in wave 1. They overestimate (underestimate) the guess accuracy of their ingroup (outgroup) members by a wider margin (7.31 pp v. 4.69 pp) compared to their non-groupy counterparts in wave 2.*

SSPP experts correctly predict the direction of Result 10. We next explore whether this systematic difference is also reflected in the two building blocks of belief formation, information demand

[18]For individuals who participate in all three waves ($n = 496$), we consistently classify 63.9% of them as either groupy (14.7%) or non-groupy (49.2%) across all three waves.

and processing.

Groupiness in information demand. Table 6 summarizes the effects of groupiness in information demand. In this analysis, the dependent variable is the proportion of their endowment participants spend to acquire information from a specific news source during wave 1 (left panel): neutral versus outgroup (columns (1) and (2)), and neutral versus ingroup (columns (3) and (4)). In wave 2 (right panel), the dependent variable is the fraction of their endowment that participants spend to have the opportunity to draw a marble rather than seeing a guess from an outgroup (columns (5) and (6)), or an ingroup participant (columns (7) and (8)).

The results in Table 6 show that groupy participants spend significantly more resources to avoid outgroup information than do non-groupy participants in the wave-1 baseline condition (19.6% versus 12.2% of their endowment, $p < 0.05$, columns (1) and (2)). In wave 2, we see that non-groupy participants in the baseline spend 11.6% of their endowment to avoid the guess of an outgroup participant, compared to 21.3% for groupy participants ($p < 0.05$, columns (5) and (6)). Thus, our results show that outgroup information avoidance is consistently greater for groupy participants in the baseline of both waves. From a policy perspective, it is interesting to observe that both groupy and non-groupy participants are indifferent between ingroup and neutral news sources in wave 1.

The results from our treatment conditions show a similar picture. From Table 6, we see that reducing source utility by unlabeling in wave 1 decreases outgroup information avoidance (cf. Result 4). We further see that this effect is larger for groupy types (a decrease from 19.6% to 8.3%) compared to non-groupy types (a decrease from 12.2% to 6.9%). We also find that the treatment effect is statistically significant only for our groupy participants ($p < 0.05$, F-test, column (2)). In other words, the treatment effect in wave 1 is driven by groupy participants.

Turning to our wave 2 treatment results, we find that the only effect of our debiasing treatment is a reduction in the amount spent on drawing a marble oneself versus seeing an ingroup guess (cf. Figure 5). Again, the results in column (7) of Table 6 show heterogeneity in our effect, with our observed reduction significant for only non-groupy participants (a decrease from 9.5% to 0.2% compared to a decrease from 5.7% to 3% for our groupy participants). We summarize the results below.

Table 6: Groupiness in information demand: Waves 1 and 2

Share of endowment spent for	Source of news articles (wave 1)				A marble instead of a guess (wave 2)			
	Neutral v. outgroup		Neutral v. ingroup		Marble v. outgroup guess		Marble v. ingroup guess	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (β_1)	-0.054	-0.041	-0.065*	-0.038	-0.023	-0.022	-0.093***	-0.091***
	(0.036)	(0.035)	(0.036)	(0.036)	(0.034)	(0.034)	(0.034)	(0.035)
Min groupy (β_2)	0.074*	0.102**	-0.032	-0.006	0.097**	0.104**	-0.038	-0.025
	(0.043)	(0.042)	(0.043)	(0.044)	(0.045)	(0.046)	(0.050)	(0.051)
Treat.*Min groupy (β_3)	-0.059	-0.069	0.136**	0.108	0.026	0.024	0.066	0.077
	(0.064)	(0.063)	(0.066)	(0.066)	(0.061)	(0.061)	(0.067)	(0.067)
Constant	0.122***	-0.038	0.040*	-0.049	0.116***	0.087	0.095***	-0.032
	(0.022)	(0.083)	(0.023)	(0.090)	(0.026)	(0.085)	(0.026)	(0.087)
F-test ($\beta_1 + \beta_3 = 0$)	0.04	0.04	0.19	0.20	0.95	0.96	0.64	0.80
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,005	1,005	1,005	1,005	740	740	740	740
Adj. R-squared	0.007	0.055	0.002	0.039	0.015	0.006	0.005	0.014

[a] We depict results from OLS regression models. As controls, we include participants' political leaning, party identification, factual bias, frequency of consuming media from opposing viewpoints, gender, education level, ethnicity, area of living, age, Bayesian rationality. Additionally, for waves 1 and 2 respectively, we include controls the topic encountered in the demand stage, and participants' prior beliefs about guess accuracies.

[b] We report robust standard errors in parentheses and denote significance levels by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Result 11 (Groupiness in information demand)**.** *Groupy participants reveal a 7.2 pp (9.7 pp) larger outgroup information avoidance, compared to non-groupy participants in the baseline of wave 1 (wave 2). Groupy types respond significantly to a reduction in source utility (unlabeling treatment, wave 1) by reducing their outgroup information avoidance (-11.3 pp). Non-groupy types' treatment response is insignificant. Removing differences in beliefs about the instrumental value of information sources (debiasing treatment, wave 2) only reduces non-groupy types' preference for drawing a marble instead of seeing an ingroup guess (-9.3 pp). Groupy types do not respond significantly.*

By Result 11, we reject the null in favor of Hypotheses 4 and 5. Result 11 indicates that groupy participants respond more strongly to a reduction in source utility, which is correctly predicted by 85% of the SSPP experts.

Groupiness in information processing. Recall that we do not find any treatment effect on information processing in wave 1, as participants' prior beliefs carry more weight than the signals in determining their posterior beliefs (Result 7). Therefore, it is not surprising that we find a similar lack of heterogeneous treatment effects with respect to groupiness in this wave (see Table D.10 in the Appendix D.5).

When considering heterogeneities in participants' information processing in wave 2, we also do not find significant differences between groupy and non-groupy individuals (see Tables D.11 and D.12 in Appendix D). Similarly, there is no heterogeneous treatment effect between groupy and non-groupy participants in their response to the debiasing treatment in wave 2 (see columns (3) and (4))

In sum, we find that groupy participants have more biased prior beliefs and exhibit stronger outgroup information avoidance compared to their non-groupy counterparts. They also respond more strongly to the unlabeling treatment. By contrast, they do not respond to the debiasing treatment. Their differential reactions to the two treatments suggest that they are motivated by source utility.

6 Conclusion

In a series of online experiments, we examine how group identity influences the formation of individual beliefs. Our 3-wave panel study is situated in the context of the 2020 US presidential election, asking participants to predict the trajectory of the US unemployment rate and public health system ranking ten months post election. Taking into account the full cycle of belief formation, from prior beliefs to the demand for and processing of new information, we document robust intergroup preferences in individual belief formation in three sets of results:

Existence of intergroup preferences in information demand and processing. First, our analyses show that participants are willing to pay to avoid outgroup information in favor of neutral information sources, and that they weight outgroup-sourced information less when forming their posterior beliefs.

Mechanism. Second, through two waves of interventions, we identify 'source utility' as the mechanism driving group effects in belief formation. Intergroup preferences in belief formation remain even when eliminating differences in the (i) content valence of different information sources as well as the (ii) perceived instrumental value of different information sources. Specifically, we find that outgroup information avoidance decreases when the difference in the source utility of different information sources decreases, suggesting that differences in source utility are the main driver of our finding of intergroup preferences in belief formation.

Heterogeneity. Finally, investigating individual heterogeneity, we find systematic differences across our analysis according to participants' groupiness. Specifically, we find that groupy individuals: (i) hold more pronounced biases in their prior beliefs, (ii) exhibit increased outgroup information avoidance in both waves, and (iii) react more strongly to a reduction of source utility (unlabeling treatment), but not to a removal of the differential instrumental values of information sources (debiasing treatment) in information demand.

Our study has important implications for those seeking to understand the phenomenon of political polarization. In particular, our results suggest that political polarization is founded, at least partly, in group identity rather than merely reflecting differences in underlying political views.

That is, our study points to a deeply-ingrained social, affective component that further refines differences in political views by biasing how individuals demand and process information. From this perspective, marked differences in political views may be only the starting point in explaining an ideological divide based on partisan group identity and its impact on ingroup biases in belief formation (Iyengar et al. 2012, Iyengar et al. 2019).

Our study also lends insight to foundational research on group identity by illustrating the relevance of individual-level differences in understanding the consequences of perceived group membership as well as outlining how group identity can bias opinion formation. We consistently find that identity-related behavior occurs in allocation choices as well as belief updating. These findings suggest that the tendency to understand the world through ingroup-outgroup distinctions is a deeply-rooted aspect of personality and constitutes a fundamental individual trait (Kranton and Sanders 2017). Our methodology could inspire future work delving into the nature of this trait, both empirically and theoretically.

On a broader level, our results provide guidance for designing policies to alleviate political polarization documented across the world, by suggesting that such policies take into account the group-identity roots of belief formation. For example, policymakers could reduce the salience of group and partisan identity associated with a policy to decrease outgroup information avoidance and increase policy uptake. Indeed, a recent field experiment in the US on the Affordable Care Act shows that emphasizing the private versus government-based aspect of the policy substantially increases insurance uptake by Republicans (Lerman, Sadin and Tratchman 2017). This particular intervention reduces the source utility of ACA. Policymakers might also reduce political group salience by providing opportunities for individuals to humanize those outside of their group through social interaction (Bruneau, Cikara and Saxe 2015). Overall, emphasizing a common identity while reducing source utility may serve as a pivotal building block in reducing political polarization.

Lastly, an unexpected finding of our experiment is that participants do not favor ingroup over non-partisan information sources. People from both ends of the political spectrum treat non-partisan information sources, such as *Nature* and *The Economist*, the same as their ingroup information sources. This underscores the value that people place on objective news reporting even within a landscape of partisan coverage.

Online Appendices for

Group Identity and Belief Formation

Kevin Bauer Yan Chen Florian Hett Michael Kosfeld

December 19, 2023

List of Appendices

Appendix A Theoretical Framework and Hypotheses

A.1 Information Demand

In this section, we outline the proof of Proposition 1 and its connections with our pre-registered hypotheses on information demand.

Proof of Proposition 1: Applying Theorem 1 of Golman, Loewenstein, Molnar and Saccardo (2022) to our environment (Equations (1) and (2)), we can decompose an individual's demand for information into the following three components:

$$D = D^{\text{IN}} + D^{\text{VA}} + D^{\text{SU}}, \tag{12}$$

where each component represents the individual's demand for the instrumental value, the content and source utility of the information, respectively.

From Eq. (12), it is straightforward to see that *ceteris paribus*, an individual's demand for an information source increases in its instrumental value, content valence, and source utility. ∎

In wave 1, as ingroup information source is perceived to have higher intrumental value, content and source utility, Proposition 1 implies the following pre-registered hypothesis.

Hypothesis 1 (Ingroup Bias in Information Demand)**.** *Participants will be willing to pay more for ingroup information sources than outgroup ones.*

In wave 1, the unlabeling treatment removes the information sources of news articles, thus removing the differential source utility, whereas in wave 2, participants in the debiasing treatment are told that Democrats and Republicans are equally accurate in their guesses, thus removing the differential instrumental values. Both interventions should lead to a reduction in outgroup information avoidance.

Corollary 1. *Both the unlabeling treatment in wave 1 and the debiasing treatment in wave 2 reduce outgroup information avoidance.*

Corollary 1 implies the following pre-registered hypotheses.

Hypothesis 2 (Treatment effect of unlabeling: Wave 1)**.** *When information sources are unlabelled, outgroup information avoidance is reduced compared to the control condition.*

Hypothesis 3 (Treatment effect of debiasing: Wave 2)**.** *The ingroup bias in information demand is smaller in the treatment group (where participants are informed that Democrats and Republicans are equally accurate in guessing the right cup) than in the control group (where participants do not learn this).*

As groupy (non-groupy) participants have positive (zero) source utility and the unlabeling treatment removes differential source utility, we expect a stronger treatment effect from groupy participants.

Hypothesis 4 (Heterogeneous treatment effects: Unlabling)**.** *The treatment effect of unlabeling is stronger for groupy participants.*

Similarly, since the debiasing treatment removes the differential instrumental values of information sources, we expect a stronger treatment effect from non-groupy participants.

Hypothesis 5 (Heterogeneous treatment effects: Debiasing)**.** *The treatment effect of debiasing is stronger for non-groupy participants.*

A.2 Information Processing.

We provide proofs of stated theoretical results and their connections to the hypotheses on information processing.

Proof of Observation 1: Let N_a and N_b be the numbers of a and b signals, respectively. In our study as well as in many other experiments, $\theta > 1/2$, and $P(A) = P(B)$. A Bayesian would treat $N_a - N_b$ as the sufficient statistic for making an inference:

$$\frac{p(A|S)}{p(B|S)} = \frac{\binom{N}{N_a}\theta^{N_a}(1-\theta)^{N_b}}{\binom{N}{N_a}(1-\theta)^{N_a}\theta^{N_b}}\left[\frac{p(A)}{p(B)}\right] = \left(\frac{\theta}{1-\theta}\right)^{(N_a-N_b)}. \tag{13}$$

Therefore, a Bayesian decision maker infers the state of the world to be: (1) A iff $N_a > N_b$, (2) A with probability 1/2 iff $N_a = N_b$, and (3) B otherwise. ∎

Derivation of Eq. (3): The following derivations follow Benjamin (2019), which are included here for completeness. In our experiment, participants see multiple signals and guesses. With two independent signals presented sequentially (own signal followed by other's signal), s_1 and s_2, a Bayesian should pool the signals together. After observing the first signal, she updates as follows:

$$\frac{p(A|s_1)}{p(B|s_1)} = \frac{p(s_1|A)}{p(s_1|B)}\frac{p(A)}{p(B)}; \tag{14}$$

after observing the second signal, her posterior odds become:

$$\frac{p(A|s_1,s_2)}{p(B|s_1,s_2)} = \frac{p(s_2|A)}{p(s_2|B)}\frac{p(A|s_1)}{p(B|s_1)} = \frac{p(s_2|A)}{p(s_2|B)}\left(\frac{p(s_1|A)}{p(s_1|B)}\frac{p(A)}{p(B)}\right) = \frac{p(s_1,s_2|A)}{p(s_1,s_2|B)}\frac{p(A)}{p(B)}. \tag{15}$$

For people with biased updating, grouping matters (Cripps 2018). After observing the first signal, equation (14) becomes:

$$\frac{\pi(A|s_1)}{\pi(B|s_1)} = \left[\frac{p(s_1|A)}{p(s_1|B)}\right]^{c_1}\left[\frac{p(A)}{p(B)}\right]^{d}. \tag{16}$$

For a person who pools the signals, her posterior odds become:

$$
\begin{aligned}
\frac{\pi(A|s_1,s_2)}{\pi(B|s_1,s_2)} &= \left[\frac{p(s_1,s_2|A)}{p(s_1,s_2|B)}\right]^{c_2}\left[\frac{p(A)}{p(B)}\right]^{d} \\
&= \left[\left(\frac{p(s_2|A)}{p(s_2|B)}\right)\left(\frac{p(s_1|A)}{p(s_1|B)}\right)\right]^{c_2}\left[\frac{p(A)}{p(B)}\right]^{d} \\
&= \left[\frac{p(s_2|A)}{p(s_2|B)}\right]^{c_2}\left[\frac{p(s_1|A)}{p(s_1|B)}\right]^{c_2}\left[\frac{p(A)}{p(B)}\right]^{d}
\end{aligned}
\tag{17}
$$

Equation (17) indicates that each signal is given the same weight.

By contrast, for a biased person who does not pool the signals, after the second signal, her posterior odds become:

$$
\begin{aligned}
\frac{\pi(A|s_1,s_2)}{\pi(B|s_1,s_2)} &= \left[\frac{p(s_2|A)}{p(s_2|B)}\right]^{c_1}\left[\frac{p(A|s_1)}{p(B|s_1)}\right]^{d} \\
&= \left[\frac{p(s_2|A)}{p(s_2|B)}\right]^{c_1}\left[\left[\frac{p(s_1|A)}{p(s_1|B)}\right]^{c_1}\left[\frac{p(A)}{p(B)}\right]^{d}\right]^{d} \\
&= \left[\frac{p(s_2|A)}{p(s_2|B)}\right]^{c_1}\left[\frac{p(s_1|A)}{p(s_1|B)}\right]^{c_1 d}\left[\frac{p(A)}{p(B)}\right]^{d^2}
\end{aligned}
\tag{18}
$$

More generally, when a person treats signals from different sources differently, we can use the representation by Equation (3) in the main text. ∎

We now state our hypotheses regarding information processing:

Hypothesis 6 (Group-contingent Information Processing)**.** *Participants will put more weight on the guesses of ingroup members than those of outgroup members when updating in the "guessing the cup game." In other words,* $\beta_I > \beta_O$*.*

Hypothesis 7 (Treatment Effects of Debiasing)**.** *Participants in the debiasing treatment will put equal weights on the guesses of ingroup and outgroup members when updating in the "guessing the cup" game. In other words,* $\beta_I = \beta_O$*.*

We can further test the hypothesis that an agent differentiates between one's own signals and those of ingroup others, i.e., $\beta_S \neq \beta_I$, which was not pre-registered. We now state two more hypotheses in information processing which were not pre-registered.

Hypothesis 8 (Sticky priors)**.** *An agent's prior holds more weight in their posterior than do the signals.*

As noted by Fryer et al. (2019), this "double updating" can prevent participants who observe the same information, i.e., read the same news article summaries as they do in our information processing stage, from converging if they have different priors. The model also implies an order effect.

Hypothesis 9 (Order effect)**.** *An earlier signal receives more weight than a later one.*

Appendix B Expert Forecasts

After running Wave 1 of our study, we participated in a community forecast on the Social Science Prediction Platform taking place in the context of the Stanford Institute for Theoretical Economics (SITE) conference 2021 (Session 5: Experimental Economics). Participation in the forecast was possible until Oct. 31, 2021.

B.1 Forecast Survey

Introduction Political polarization is commonly considered to be a threat to the efficient functioning of democracy. Political polarization typically refers to the increased divergence of political views and opinions of different partisan groups. However, recent research documents the increasing prevalence of *affective polarization* – negative feelings towards people identifying with political parties other than their own. To assess the relation between affective and political polarization, we designed and deployed a survey experiment with a representative sample of the US population (n=1,005) the week before the 2020 US presidential election. We will ask you to predict six sets of outcomes (8 effects) from this study.

Forecast Questions Participants in our experiment provided incentivized forecasts (they received a payment of $10 per correct forecast) about the development of official public health and unemployment statistics a year after the election, conditional on the election results. Initially, these predictions were made using prior knowledge and opinion.

The unemployment question asks: "According to the Bureau of Labor Statistics, the unemployment rate in September 2020 was 7.9 %. What will the unemployment rate be in September 2021 if Joe Biden wins the election in November 2020?" which respondents answered on a 5-point scale from "Strong increase (10 % or higher)" to "Strong decrease (6 % or lower)". They were then asked the same question substituting "Joe Biden" for "Donald Trump". The healthcare question is structured similarly but asks where the U.S. would rank in a global ranking of health systems (conditional on each president winning).

Question 1. *We would like to predict the* ***percent of participants' whose prior belief will exhibit ingroup bias****, in that both unemployment and health system ranking will improve (deteriorate) if the own-party (opposing-party) candidate wins.*

Note that in order for a participant to be classified as "bias", they must (a) predict that their candidate will perform better in at least one of the two domains, and (b) must not predict that the opposing candidate will perform better in at least one of the two domains.

In the next "information demand" stage of the experiment, participants see the titles of two articles and the outlets they are assembled from. As a default, one of the two articles is selected with equal probability and displayed on screen. Participants receive an endowment of $3 which they can spend to adjust the probabilities for a specific article to be selected in steps of 10%, where each step costs $1. They make two decisions, one of which is randomly selected for implementation. In both cases there is always an article from neutral news sources; in one case, the second article is curated from right- leaning news sources and in the other case, the second article stems from left-leaning news sources. After reading the respective article, participants can update their incentivized predictions (from the first question).

Question 2. *We would like you to predict what* ***percent of participants will update beliefs in the party-congenial direction*** *such that their posterior beliefs are more polarized than their prior beliefs.*

We use the monetary amount a participant spends to increase the likelihood of receiving information from the relatively more party congenial source in these two decisions as a measure of **partisan bias in information demand.** For instance, if democratic participants spend part of their endowment to receive the left-leaning (neutral) article instead of the neutral (right-leaning) one, it means that she spent money to obtain the relatively more party-congenial information.

Question 3. *How much less or more of the $3 endowment are participants willing to pay to increase the probability of receiving an article curated* ***from their political ingroup rather than one from neutral new sources****?*

Question 4. *How much less or more of the $3 endowment are participants willing to pay to increase the probability of receiving an article curated* ***from neutral news sources rather than one from outgroup new sources****?*

We also employ measures from psychology to understand participants' predispositions to make sense of the environment through intergroup distinctions, which we refer to as "groupiness". Prior to any prediction tasks, participants had to allocate $6 between two other participants – a randomly selected Democrat and a randomly selected Republican. As decision makers cannot keep any money from this allocation decision for themselves, and the two other participants are paid according to the chosen allocation, this decision constitutes an intuitive individual-level measure capturing people's party-contingent social preferences towards others. We interpret an allocation which gives people from their own partisan group a higher payment than those from the other partisan group as 'politically groupy' and hence as individually susceptible for affective polarization.

Question 5. *Overall, do you think partisan biases are stronger or weaker (based on three preceding predictions) for "groupy"participants, compared to their non-groupy counterparty?*

In the "information demand" part of the experiment (described previously), we display summaries of news articles. In the "Labels" treatment, the names of the news sources are labelled. In the treatment with "No Labels," the names of the news sources are replaced by "A news source" the first time we mention it, and "the news sources" the last time we mention it.

Here are the labels of the articles about unemployment:

- **Right-leaning news source**: New Jobs, Unemployment Numbers Point to 'V'-Shaped Recovery – Only a Biden Lockdown Could End It

- **Neutral news source**: The Good and Bad of Trumponomics, and an Overview of the Labor Market
- **Left-leaning news source**: 'Staggeringly High': U.S. Jobless Claims Remained Elevated Last Week

Here are the titles of the articles about healthcare:

- **Right-leaning news source**: Trump's Healthcare Plan Puts the Patient Where Obamacare Didn't: First
- **Neutral news source**: What the United States Might Look Like After the Election for Key Health Issues
- **Left-leaning news source**: Bidencare Would Be a Big Deal

Question 6. *How much more or less (of their $3 endowment) are participants who are randomly assigned to see labels of news sources willing to spend to increase the probability of receiving an article curated from ingroup (neutral) rather than neutral (outgroup) news sources, compared to those who do not see the labels?*

Next, we are interested in your prediction of the treatment effects of the *Label* treatment, which exposes participants to the labels of news sources. Specifically, we measure the percent of participants who update in an ingroup-congenial direction for those exposed in the label condition, versus those in the unlabeled condition.

Question 7. *How many percentage points more or less likely are participants in the label condition to update in the ingroup-congenial direction?*

Note that *negative values* imply a *decrease* in updating in the ingroup-congenial direction, and *positive* values imply an *increase* in updating in the ingroup-congenial direction.

Compared to participants who are randomly assigned *not to see news sources*, **what percent of participants** will update beliefs in the party-congenial direction, such that their posterior beliefs are more polarized than their prior beliefs?

Question 8. *Overall, do you think the label treatment effects for both information demand and processing are stronger for "groupy" participants, compared to their non-groupy counterparts?*

B.2 Forecasts versus Actual Results

In total, 34 experts participated in the survey. When applicable, we report the average and standard deviation of the individual forecasts for each question and compare it with the actual result.

Q1. Ingroup Bias in Prior Beliefs. Share of participants that have an ingroup bias in prior beliefs:

- Actual Result: 63.3% (stdev: 48.23)
- Average prediction: 62.59% (stdev: 25.6)
- $p = 0.23$

Q2. Ingroup Bias in Updating. Share of participants with party congenial updating:

- Actual Result: 22.2% (stdev: 41.57)
- Average prediction: 38.86% (stdev: 23.93)
- $p < 0.001$

Q3. Ingroup Bias in Information Demand. How much less or more of the $3 endowment are participants willing to pay to increase the probability of receiving an article curated from their political ingroup rather than one from neutral news sources:

- Actual Result: $0.08 (stdev: 1.44); or 3% of endowment
- Average prediction: $1.31 (stdev: 0.86); or 44% of endowment
- $p < 0.001$

Q4. Outgroup Information Avoidance. How much less or more of the $3 endowment are participants willing to pay to increase the probability of receiving an article curated from neutral news sources rather than one from outgroup news sources?

- Actual Result: $0.45 (stdev: 1.43); or 15% of endowment
- Average prediction: $1.17 (stdev: 0.98); or 39% of endowment
- $p < 0.001$

Q5. Partisan Bias and Groupiness. Overall, do you think partisan biases are stronger or weaker (based on three preceding predictions) for "groupy" participants, compared to their non-groupy counterparts:

- Actual Result: yes, whenever there is an effect, it systematically varies wrt groupiness
- Average prediction: yes
- Standard Deviation: no variation in answers

Q6. Effect of unlabeling on information demand How much more or less (of their \$3 endowment) are participants who are randomly assigned to see labels of news sources willing to spend to increase the probability of receiving an article curated from ingroup (neutral) rather than neutral (outgroup) news sources, compared to those who do not see the labels:

- Actual Result: 0.23\$ (se: 0.03) (for outgroup information avoidance)
- Average prediction: 1.38\$ (stdev: 0.96)
- $p < 0.001$

Q7. Effect of unlabeling on information processing. How many percentage points more or less likely are participants in the label condition to update in the ingroup-congenial direction:

- Actual Result: 0.93 pp (se: 0.03)
- Average prediction: 17.81 pp (stdev: 22.35)
- $p < 0.001$

Q8. Groupiness and unlabeling treatment. Overall, do you think the label treatment effects for both information demand and processing are stronger for "groupy" participants, compared to their non-groupy counterparts:

- Actual Result: yes, they are
- Average prediction: 85.3% of respondents say yes (stdev: 0.36)

Appendix C Summary statistics

C.1 Summary statistics on participants' socio-demographic characteristics across waves

Table C.1: Summary statistics on participants' socio-demographic characteristics.

Variable	US Average	Wave 1 (N=1005)		Wave 2 (N=740)		Wave 3 (N=496)	
		Mean	P-value	Mean	P-value	Mean	P-value
Gender							
Male	0.49	0.48	0.57	0.47	0.20	0.47	0.40
Female	0.51	0.51	0.95	0.53	0.35	0.52	0.56
Non-binary	-	0.01	-				
Age	47.8	45.7	0.00	48.35	0.35	50.96	0.00
Area of living							
Rural	0.19	0.17	0.07	0.19	0.88	0.2	0.42
Urban and suburban	0.81	0.83	0.95	0.81	0.88	0.8	0.42
Ethnicity							
Caucasian	0.72	0.74	0.19	0.75	0.09	0.77	0.01
African American	0.13	0.13	0.61	0.11	0.20	0.10	0.04
Asian American	0.06	0.07	0.26	0.07	0.18	0.06	0.85
Other	0.10	0.06	0.00	0.06	0.00	0.06	0.00
Academic Degree							
No degree	0.10	0.01	0.00	0.12	0.00	0.01	0.00
High School	0.55	0.30	0.00	0.33	0.00	0.34	0.00
Bachelor	0.22	0.44	0.00	0.46	0.00	0.45	0.00
Master	0.11	0.22	0.00	0.17	0.00	0.17	0.0003
PhD	0.02	0.03	0.07	0.03	0.12	0.03	0.12
Democrats							
Overall	0.29	0.48	0.00	0.52	0.00	0.5	0.00
Moderate		0.26		0.24		0.21	0.00
Strong		0.22		0.28		0.29	0.00
Republicans							
Overall	0.30	0.26	0.00	0.23	0.00	0.24	0.00
Moderate		0.16		0.14		0.16	
Strong		0.10		0.09		0.08	
Independents							
Overall	0.38	0.22	0.00	0.25	0.00	0.26	0.00
Leaning Democrat		0.14		0.15		0.17	
Leaning Republican		0.08		0.1		0.09	
Groupiness							
Min. groupy		0.37		0.35		0.30	
Pol. groupy		0.57		0.57		0.56	

[a.] US statistics are based on the 2019 American Community Survey for gender, age, and ethnicity, the 2020 Census data for Area of living, and the Current Population Survey, 2020 Annual Social and Economic supplement, for academic degree. P-values are from proportion of t-tests.

Table C.1 presents information about the demographic representation of our participants across gender, age, education level, residential areas, and ethnicity. When we compare our sample with the U.S. population data derived from the 2020 US Census and the 2019 American Community Survey, we observe a close resemblance in terms of gender, residential areas, and ethnicities. However, our participants tend to be slightly younger and possess higher educational qualifications. A notable difference emerges in the participants' self-reported political leanings. Participants who identify as "Leaning" Democrats or Republicans claim independence but express a preference for one of the parties. Notably, our sample has a higher proportion of Democrats and independents.

C.2 Wave 1: Factual questions with partisan valence (Peterson and Iyengar 2021)

Table C.2: Responses to factual questions

Factual question	Correct Response	Party Valence	Share of corrects answers (Democrats)	Share of corrects answers (Republicans)	Partisan Divide
Illegal immigrants commit violent crime at a significantly higher rate than legal American citizens.	False	Rep	89.5	57.3	32.2
Millions of illegal votes were cast in the 2016 presidential election.	False	Rep	80.9	71.3	9.6
Former President Obama ordered wire taps on Donald Trump's phones.	False	Rep	92.3	51.7	40.6
40% of firearm sales in the US occur without a background check.	False	Dem	23.4	43.3	19.9
The vast majority (over 90%) of climate scientists believe that global warming is an established fact and that it is most likely caused by man-made emissions.	True	Rep	96.5	75.6	20.9
Michael Cohen, Donald Trump's personal lawyer pleaded guilty to fraud and illegal campaign finance charges in August 2018.	True	Rep	91.4	76.7	14.4

[a.] Summary statistics on participants' partisan divide in correctly answering factual questions. Shares of participants, conditional on their partisanship, who provide a correct answer to factual questions with a given valence. We pool observations for both label and no-label conditions.

Table C.2 presents participants' responses to factual questions sourced from (Peterson and Iyengar 2021). We detail the percentages of Democrats and Republicans who correctly answered factual questions that present a particular party in a less favorable light. Take, for instance, the statement: "Millions of illegal votes were cast in the 2016 presidential election." The accurate response to this is 'false'. This response casts the Republicans in a negative light, given their repeated assertions to the contrary, making the statement lean Republican in its valence. The table indicates the percentage of respondents who answered each question correctly. We combine observations from both our label and no-labels conditions. Additionally, the table measures the partisan divide for each question, defined as the absolute difference in the percentages of Democrats and Republicans answering correctly. The answers to these factual questions closely align with findings by (Peterson and Iyengar 2021). On average, there's a partisan disparity of 22.9 percentage points in the propensity to correctly answer a factual question. This suggests that participants are significantly less inclined to answer correctly if the truthful response casts their affiliated party in an unfavorable light.

C.3 Wave 2: Additional survey questions.

Table C.3: Survey questions wave 2.

Question	Possible answers	Average answer
Which state do you live in?	50 possible states	-
Who did you vote for in the 2020 Presidential Election?	Biden, Trump, Other	-
Have you received a vaccine shot?	Yes (1), No (0)	0.08
Do you intend to get vaccinated when the opportunity arrives?	Yes (1), No (0)	0.77
Do you think close to 300 million Americans will have their shots by September 1, 2021?	Yes (1), No (0)	0.53
Where would you place Democrats on this ladder? (value from 1-10, where rung 10 represents the top of the ladder and rung 1 the bottom)	1 to 10	5.64
Where would you place Republicans on this ladder? (value from 1-10, where rung 10 represents the top of the ladder and rung 1 the bottom)	1 to 10	5.77
Do you think that the 2020 Presidential Election was rigged?	Yes (1), No (0)	0.22

[a] Survey questions and average answers in wave 2.

Appendix D Additional analyses

D.1 Wave 1: Prediction performance.

Table D.4: Overview of participants' prior prediction performance.

	Correct prediction			
	Electoral outcome of election	Popular vote of election	Unemployment numbers	US health ranking
Overall	0.63	0.75	0.12	0.07
	(0.483)	(0.434)	(0.325)	(0.263)
Democrats	0.84	0.93	0.14	0.02
	(0.367)	(0.254)	(0.344)	(0.14)
Republicans	0.25	0.42	0.09	0.17
	(0.432)	(0.494)	(0.286)	(0.38)
Politically groupy individuals	0.62	0.72	0.13	0.09
	(0.485)	(0.447)	(0.337)	(0.281)
Politically non-groupy individuals	0.64	0.78	0.1	0.06
	(0.481)	(0.415)	(0.31)	(0.237)

[a] We depict the prediction accuracy of participants for the different guessing tasks they encounter in the experiment. Reported measures represent participant shares. We report standard deviations ins parentheses. We pool observations for both label and no-label conditions.

Table D.4 depicts the share of participants who correctly predicted (i) the electoral outcome of the 2020 presidential election, (ii) the popular vote of the 2020 presidential election, (iii) the US unemployment rate in November 2021, and (iv) the US' position in the global health ranking in November 2021. The table pools observations for both label and no-label conditions.

Election predictions. We find that most participants make party-congenial election outcome predictions. Given that Joe Biden won both the electoral outcome and the majority of the popular vote, the forecast accuracy in the election domain is higher for Democrats than Republicans. Specifically, 84% (25%) and 93% (42%) of Democrats (Republicans) correctly predict Joe Biden to win the presidential election and the majority of the popular vote, respectively ($p < 0.01$ for both predictions, χ^2-test).

Policy sensitive statistics. According to official statistics from the Bureau of Labor Statistics, the unemployment rate in September 2021 equaled 4.8%, i.e., a decline by 3.1 percentage points from September 2020 when the unemployment rate equaled 7.9%. Hence, the correct prediction on our predefined 5-point scale is a "strong decline". According to the US News and World Report, the health ranking of the US in September 2021 was the 22nd place, i.e., a deterioration by 7 spots in comparison to rank 15 in September 2020. Hence, the correct prediction on our predefined 5-point scale is a "strong decline".

When examining the accuracy of predictions for the development of the two policy sensitive statistics, we use participants' final forecasts, i.e., after the possibility to adjust priors, as a basis. Table D.4 shows that 12% of participants correctly anticipate the strong decrease in the unemployment rate (given Joe Biden being the president), while 7.5% of participants' predict the outcome in the US health ranking correctly. These numbers are remarkably similar to the share of US economic experts who in October 2020 predicted the unemployment rate in December 2020 correctly (10%); see IGM COVID-19 Economic Outlook Survey Series[19].

The strong decrease of the unemployment rate over the last year under Joe Biden's presidency – which, in the context of our experiment, can be seen as reflecting positively on the Democratic Government – was more frequently correctly predicted by Democrats than Republicans ($p < 0.01$, χ^2-test). By contrast, the strong deterioration of the US health system's ranking under Joe Biden – which can be seen as reflecting negatively on the Democratic Government – was more frequently correctly predicted by Republicans than Democrats ($p < 0.01$, χ^2-test).

Notably, there is no significant difference in the likelihood of making a correct final prediction across the label and no-label treatment conditions (p = 0.664, χ^2-test). On the aggregate level, there is also no significant difference in forecast accuracy for participants conditional on whether they can update the unemployment rate or health ranking prediction in the information demand or processing stage ($p = 0.731$, χ^2-test).

[19] https://www.igmchicago.org/economic-outlook-survey/

D.2 Wave 2: Demand stage; guess v. guess

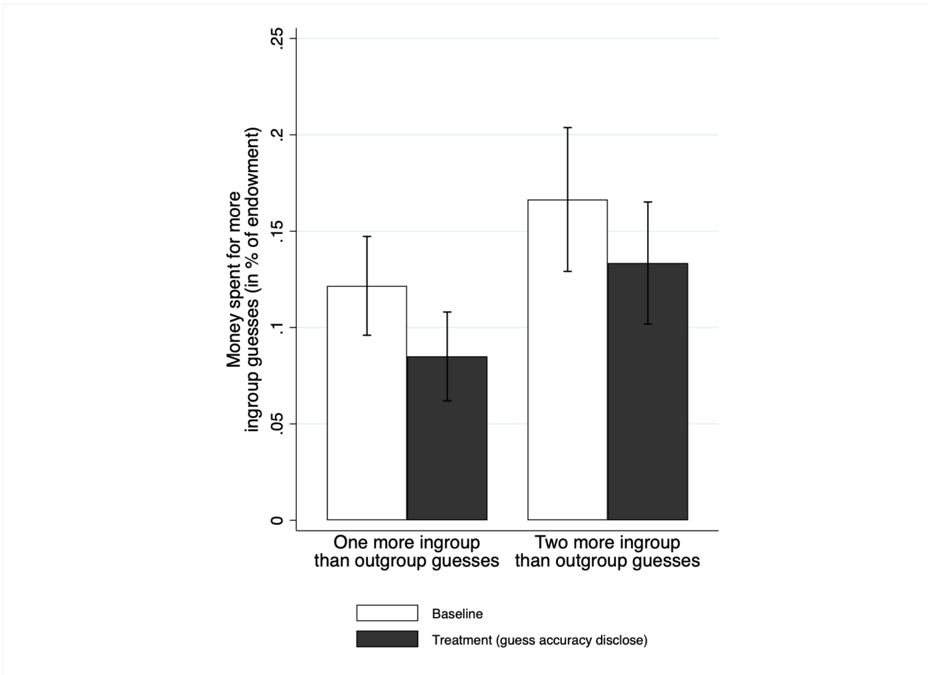

Figure D.1: Information demand (wave 2).

Notes: We depict participants' willingness to pay to observe the guesses from the group with more ingroup members. The white (black) bars depict results for the baseline (treatment) condition. Error bars represent 95% confidence intervals.

Figure D.1 shows participants' information demand behavior in Wave 2 where they had to choose from which of two different groups they would observe guesses. Each group comprised two other participants from the experiment. The groups differed in their composition regarding the participants political affiliations. One of the groups comprised one or two more individuals with whom the decision maker shares their political affiliation. For these two scenarios, Figure D.1 depicts the average share of their endowment that participants are willing to spend in order to see the guesses from the group comprising more members with a shared political affiliation (ingroup members).

Depicted results reveal that participants prefer to observe information from the group comprising more ingroup members. Participants spend 12.2% (16.7%) of their endowment to observe the guesses of the group that comprises 1 (2) more ingroup members. Difference between these two scenarios is significant ($p < 0.05$, F-test; see Table **??**), indicating that their demand for information from the ingroup is responsive at the intensive margin.

Importantly, we find that our treatment intervention of informing participants about the equal guess accuracy of Democrats and Republicans reduces participants' demand for information from the ingroup by about 4 percentage points in both the condition with one more ingrpoup member (-33.6%) and two more ingroup members (-19.9%). Both decreases are statistically significant

($p < 0.05$, F-test; see Table D.5).

These insights are in line with our findings for the case where participants had to choose between drawing a marble themselves or observing a guess from another participant with a particular political affiliation.

Table D.5: Participants' information demand behavior in the guess v. guess task (Wave 2).

DV: Share of endowment spent for more ingroup guesses	(1)	(2)	(3)	(4)
2 more ingr. guesses	0.045**	0.045**	0.045**	0.045**
	(0.019)	(0.019)	(0.019)	(0.019)
Treatment			-0.037*	-0.039**
			(0.019)	(0.019)
Treatment*2 more ingr. guesses			0.004	0.004
			(0.024)	(0.024)
Constant	0.122***	0.155**	0.122***	0.157***
	(0.015)	(0.074)	(0.015)	(0.053)
Controls	No	Yes	No	Yes
Observations	1,113	1,113	2,220	2,220
Adj. R-squared	0.003	0.041	0.006	0.049

[a.] We depict results from OLS regression models with robust standard errors reported in parentheses. In both columns, the dependent variable is a dummy that is equal to one in case a participant preferred to observe the guesses of the group of other participants that contains more ingroup members. As additional individual level controls we include but do not explicitly report participants' gender, age, level of education, ethnicity, whether they engage in bayesian updating, and whether they line in an urban region. We denote significance levels by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.3 Wave 2: Accuracy guesses

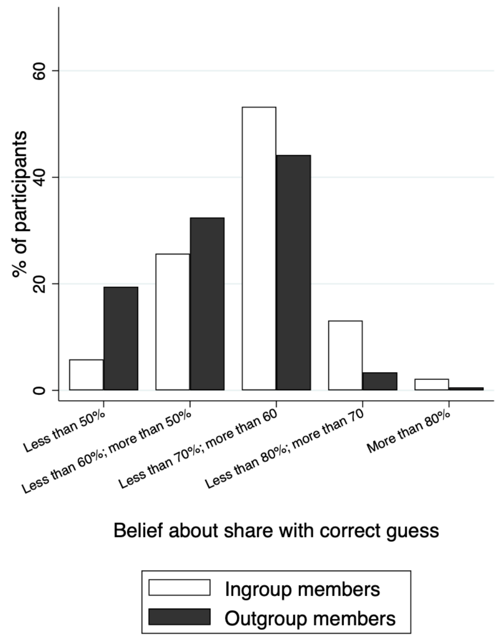

Figure D.2: Belief about others' guess accuracy (wave 2).

Notes: We depict the distribution of participants' beliefs about other participants' guess accuracy separately for ingroup and outgroup members.

Figure D.2 shows the distribution of Wave 2 participants' beliefs of others' guess accuracy. We show results separately for participants' guesses concerning ingroup and outgroup members (as defined by shared political affiliations). Overall, our results show that participants believe that guesses of ingroup members are significantly more likely to be correct than outgroup ones (62.8% versus 57.4%, $p < 0.01$, F-test; see Table D.6 column (1)). Looking at the extensive margin, we find that 35.4% believe that the ingroup members are strictly better at guessing the correct cup.

Table D.6: Beliefs about others' guess accuracy (wave 2).

DV:	Estimated accuracy of others' guess	
	(1)	(2)
Ingr. guess	5.466***	5.466***
	(0.437)	(0.439)
Constant	57.365***	62.759***
	(0.373)	(0.275)
Controls	No	Yes
Observations	1,480	1,480
Adj. R-squared	0.074	0.639

[a.] We depict results from OLS regression models with robust standard errors reported in parentheses. As controls we include participants' minimal groupiness, party identification, factual bias, their party affiliation, their regular consumption of outgroup media sources, gender, education level, ethnicity, area of living, age, and Bayesian rationality. The dependent variable measures participants' estimates of others' guess accuracy. We denote significance levels by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.4 Wave 2: Information processing

In our regression in Table D.7 reported below, we effectively estimate $\beta_I - \beta_O$ separately for the cases where participants observe one and two guesses that oppose the color of the observed marble. In our context where each participant receives three signals, a private one and two guesses, a Bayesian decision maker should follow the majority rule, i.e., guess the color that showed up more often. In contrast, we find that only 63.3% of the decisions in our baseline condition do so. Investigating whether this deviation from the Bayesian benchmark is subject to ingroup bias,

Table D.7: Information processing (Wave 2).

DV: Not choosing color of observed marble	One opposing and one aligned guesses (violation of majority rule)			Two opposing guesses (adherence to majority rule)		
	(1)	(2)	(3)	(4)	(5)	(6)
Opposing guess(es) from ingroup (β_1)	0.094***	0.094***	0.094***	0.059**	0.059**	0.059**
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Treatment (β_2)		-0.034	-0.041		0.003	0.003
		(0.027)	(0.027)		(0.036)	(0.036)
Treatment*Opposing guess(es) from ingroup (β_3)		0.038	0.038		0.017	0.017
		(0.037)	(0.038)		(0.037)	(0.037)
Constant	0.175***	0.175***	0.222***	0.604***	0.604***	0.499***
	(0.020)	(0.020)	(0.063)	(0.025)	(0.025)	(0.086)
F-test ($\beta_1 + \beta_3 = 0$)		0.001	0.001	0.103	0.103	0.104
Ind. controls	No	No	Yes	No	Yes	Yes
Observations	742	1,480	1,480	742	1,480	1,480
Adj. R-squared	0.012	0.018	0.040	0.002	0.003	0.018

[a] We depict results from OLS regression models with robust standard errors reported in parentheses. The dependent variable measures participants' likelihood of not choosing the color of observed marble. As controls we include participants' minimal groupiness, party identification, factual bias, their party affiliation, their regular consumption of outgroup media sources, gender, education level, ethnicity, area of living, age, Bayesian rationality, and their belief about guess accuracies. We cluster robust standard error on the individual level and denote them in parentheses. We denote significance levels by $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

D.5 Heterogeneity with respect to minimal groupiness

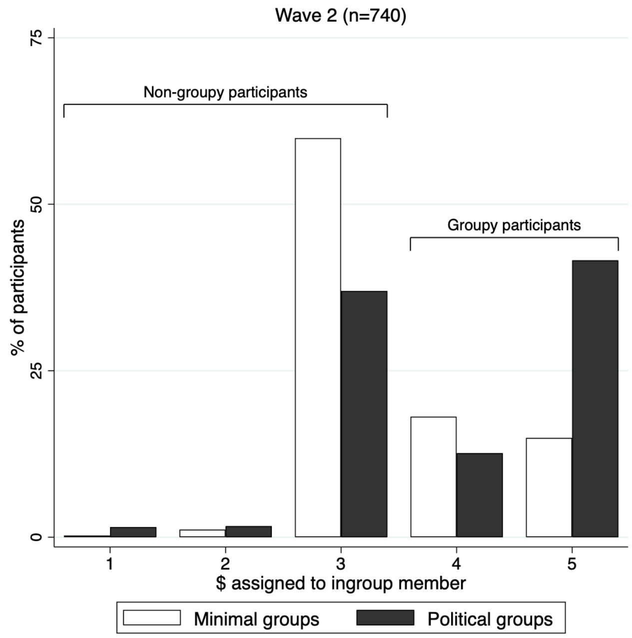

Figure D.3: Distribution of Allocation Decisions in the Minimal (White Bars) and Political (Black Bars) Other-Other Allocation Games: The horizontal axis shows the amount (in dollars) allocated to an ingroup member out of a total budget of $6. The maximum amount a participant can allocate to another participant is $5.

Relation between different groupiness measures

Heterogeneity in prior beliefs Wave 1. Figures D.5 and D.6 show the distribution of participants' prior beliefs about how policy-sensitive statistics develop 11 months after the 2020 presidential election. We show results separately for the two topics (unemployment rate and public health system ranking) and and the event that the ingroup or outgroup candidate becomes president. Figures D.5 and D.6 depict prior beliefs in Wave 1 for non-groupy and groupy types, respectively.

Results in these two figures reveal that both non-groupy and groupy types hold more optimistic beliefs about the trajectory of policy relevant statistics. This is true for concerning the development of the unemployment rate and the US health system ranking.

Regression analyses reported in Table D.8 suggests that on an individual level, groupy types are significantly more likely to exhibit a partisan gap in their prior beliefs. In all three columns, the dependent variable is a dummy that is equal to one in case a participant holds more optimistic beliefs about the development of policy sensitive statistics when the ingroup candidate wins the election. In columns (1) and (2), we pool the two topics, i.e., the dummy is equal to one if participants hold more positive beliefs for both topics. In columns (3) and (4), and (5) and (6), we respectively consider the topics of the unemployment rate and health systems ranking development. We report robust standard errors in parentheses.

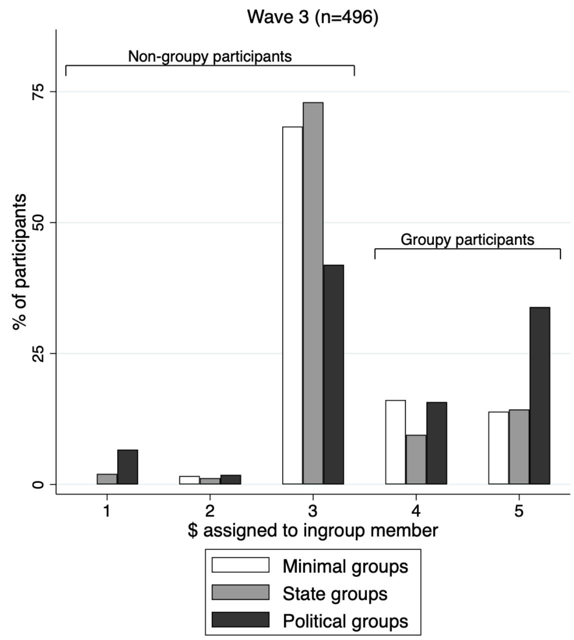

Figure D.4: Distribution of Allocation Decisions in the Minimal (White Bars), State (Light Grey), and Political (Black Bars) Other-Other Allocation Games: The horizontal axis shows the amount (in dollars) allocated to an ingroup member out of a total budget of $6. The maximum amount a participant can allocate to another participant is $5.

The results indicate that groupiness is a strong and significant predictor for the existence of a strict partisan gap in prior beliefs across both topics and for the belief about the trajectory of the unemployment rate. Specifically, whereas groupy participants exhibit a strict partisan gap for both prediction tasks in 45.9% of the cases, non-groupy types do so in 40% of the cases (+14.8%; $p < 0.07$, F-test, Table D.8). Looking at the two topics individually, groupy types are only more likely to possess a partisan gap in their guess about the development of unemployment rates (57.3% v. 51.3%; $p < 0.07$, F-test), but not the public health system ranking (71.3% v. 71.5%; $p = 0.94$, F-test). Our the results are robust to the inclusion of additional controls (see Table D.8 in the Appendix).

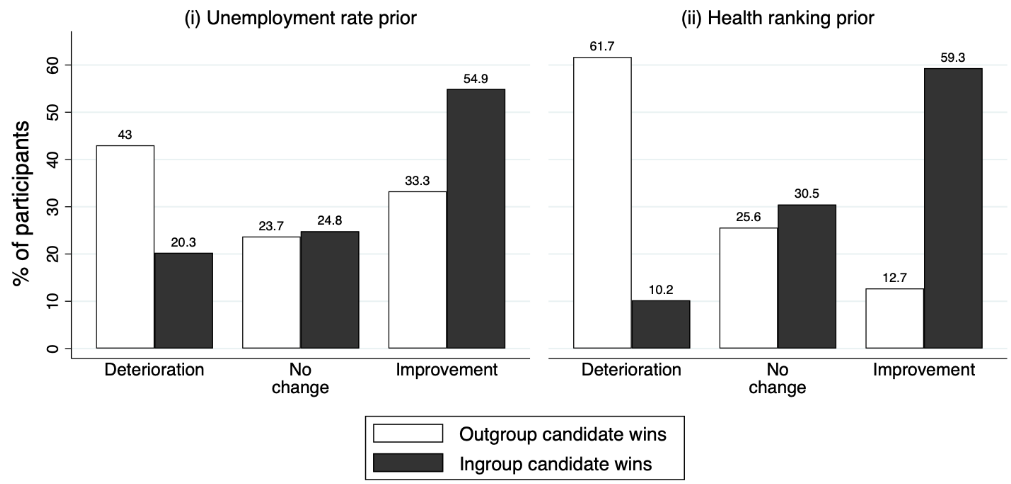

Figure D.5: Prior partisan beliefs (wave 1) – Non-groupy types. We depict the share of participants that reported specific beliefs about the trajectory of policy relevant statistics (unemployment rate and public health system ranking). The white (black) bar indicates the proportion of guesses if the ingroup (outgroup) candidate wins the election.

Table D.8: Groupiness in prior beliefs (wave 1).

DV: Strict partisan	Both topics		Unempl. rate		Health ranking	
gap in prior beliefs	(1)	(2)	(3)	(4)	(5)	(6)
Min. groupy	0.059*	0.063**	0.060*	0.060*	0.002	0.009
	(0.032)	(0.032)	(0.033)	(0.033)	(0.030)	(0.027)
Constant	0.400***	0.171**	0.513***	0.320***	0.713***	0.575***
	(0.019)	(0.086)	(0.020)	(0.088)	(0.018)	(0.074)
Ind. controls	No	Yes	No	Yes	No	Yes
Observations	1,005	1,005	1,005	1,005	1,005	1,005
Adj. R-squared	0.002	0.063	0.002	0.027	-0.001	0.185

[a] We depict results from panel OLS regression models with robust standard errors reported in parentheses. The dependent variable measures participants' likelihood to exhibit a strict partisan gap in priors. As controls we include participants' minimal groupiness, party identification, factual bias, their party affiliation, their regular consumption of outgroup media sources, gender, education level, ethnicity, area of living, age, and Bayesian rationality as measured in wave 1. We denote significance levels by $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

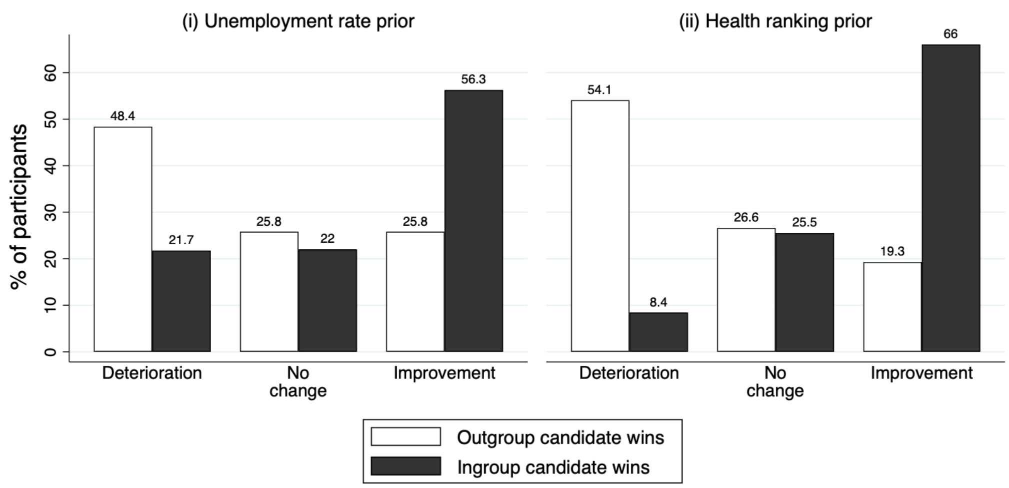

Figure D.6: Prior partisan beliefs (wave 1) – Groupy types. We depict the share of participants that reported specific beliefs about the trajectory of policy relevant statistics (unemployment rate and public health system ranking). The white (black) bar indicates the proportion of guesses if the ingroup (outgroup) candidate wins the election.

Heterogeneity in accuracy beliefs Wave 2. Figures D.7 and D.8 show the distribution of Wave 2 participants' beliefs of others' guess accuracy for non-groupy and groupy types, respectively. We show results separately for participants' guesses concerning ingroup and outgroup members (as defined by shared political affiliations). Overall, our results show that both tyoes if participants believe that guesses of ingroup members are significantly more likely to be correct than outgroup ones. Additional regression analyses reported in Table D.9 further reveal that groupy types hold more ingroup favorable beliefs than non-groupy ones.

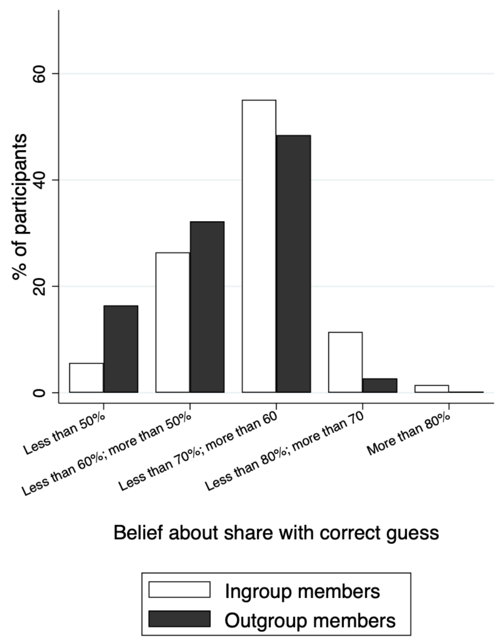

Figure D.7: Belief about others' guess accuracy (wave 2) – Non-groupy types. We depict the distribution of non-groupy participants' beliefs about other participants' guess accuracy separately for ingroup and outgroup members.

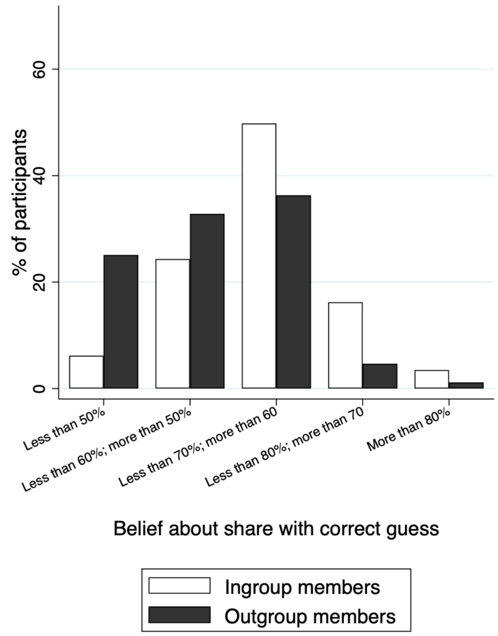

Figure D.8: Belief about others' guess accuracy (wave 2) – Groupy types. We depict the distribution of non-groupy participants' beliefs about other participants' guess accuracy separately for ingroup and outgroup members.

Table D.9: Beliefs about others' guess accuracy (wave 2).

DV:	Estimated accuracy of others' guess			
	(1)	(2)	(3)	(4)
Ingr. guess	5.466***	5.466***	4.470***	4.470***
	(0.437)	(0.439)	(0.480)	(0.483)
Min. groupy			-1.797**	-2.010**
			(0.817)	(0.832)
Ingr. guess*Min. groupy			2.847***	2.847***
			(0.987)	(0.993)
Constant	57.365***	57.766***	57.994***	58.383***
	(0.373)	(1.641)	(0.433)	(1.654)
Controls	No	Yes	No	Yes
Observations	1,480	1,480	1,480	1,480
Adj. R-squared	0.074	0.099	0.077	0.103

[a] We depict results from OLS regression models with robust standard errors reported in parentheses. As controls we include participants' minimal groupiness, party identification, factual bias, their party affiliation, their regular consumption of outgroup media sources, gender, education level, ethnicity, area of living, age, and Bayesian rationality. The dependent variable measures participants' estimates of others' guess accuracy. We denote significance levels by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Heterogeneity in information demand Wave 2 (guess v. guess). Figures D.9 and D.10 show participants' information demand behavior in Wave 2 where they had to choose between observing a marble themselves or a guess of another person for non-groupy and groupy individuals, respectively.

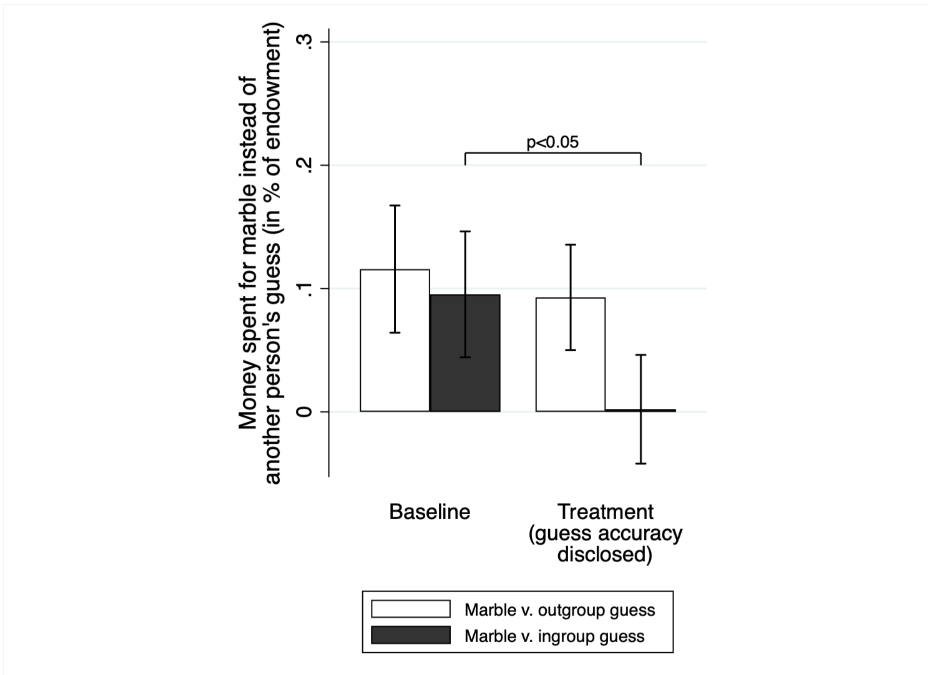

Figure D.9: Information demand (wave 2) – Non-groupy types. We depict non-groupy participants' willingness to pay to observe the guesses from the group with more ingroup members. The white (black) bars depict results for the baseline (treatment) condition. Error bars represent 95% confidence intervals.

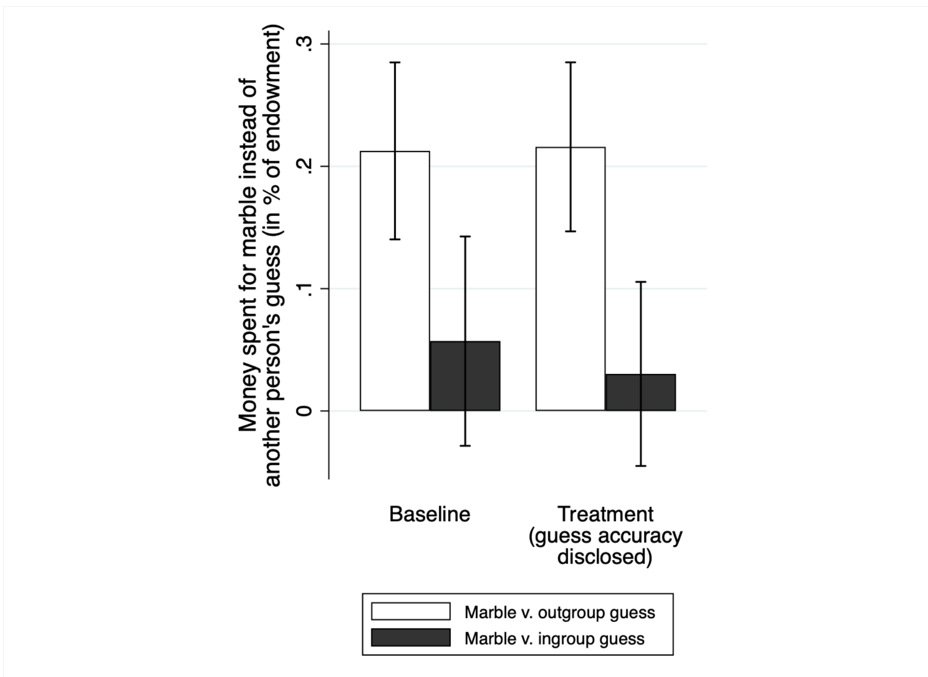

Figure D.10: Information demand (wave 2) – Groupy types. We depict groupy participants' willingness to pay to observe the guesses from the group with more ingroup members. The white (black) bars depict results for the baseline (treatment) condition. Error bars represent 95% confidence intervals.

Heterogeneity in information processing Wave 1. Figures D.11 and D.12 presents the average prior and posterior beliefs after participants have read two news articles from ingroup and outgroup sources in wave 1. We see that average predictions barely move for either type, supporting our aggregate level evidence reported in the main text.

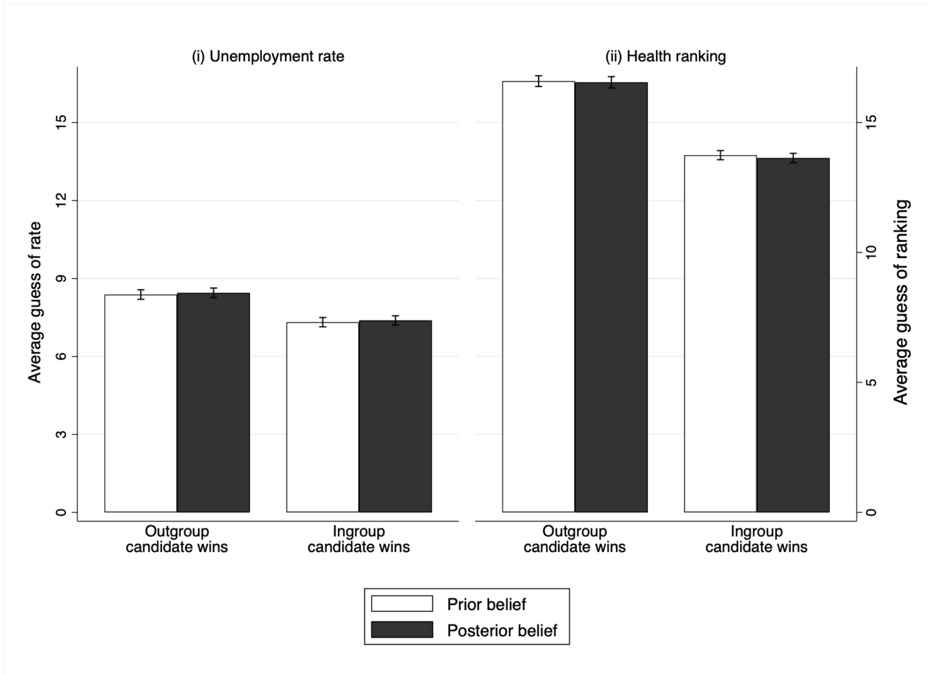

Figure D.11: Information demand (wave 2): Participants' willingness to pay to observe a marble instead of the guess of another participant for non-groupy types.

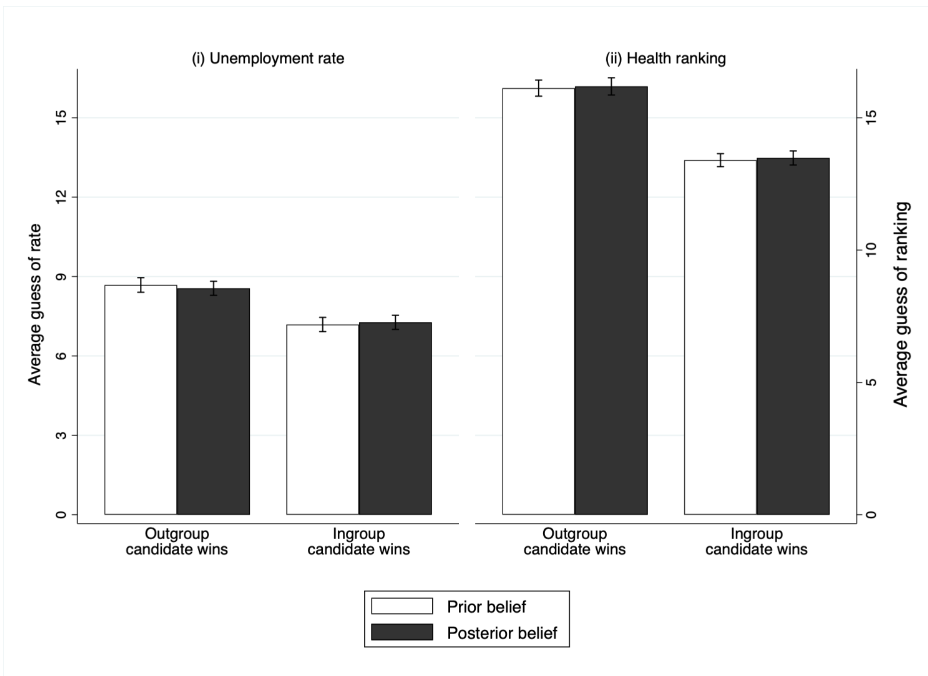

Figure D.12: Information demand (wave 2): Participants' willingness to pay to observe a marble instead of the guess of another participant for groupy types.

Table D.10: Groupiness in information processing (wave 1).

DV: Posterior	Unemployment rate		Health ranking	
Posterior belief	(1)	(2)	(3)	(4)
Min. groupy	0.361	0.489	-0.155	-0.191
	(0.869)	(0.720)	(0.963)	(0.985)
Prior	0.595***	0.668***	0.820***	0.733***
	(0.060)	(0.062)	(0.039)	(0.051)
Treatment (No label)	-0.312*	0.130	0.086	-0.097
	(0.175)	(0.148)	(0.157)	(0.135)
Min. groupy*Prior	-0.058	-0.048	0.011	0.016
	(0.103)	(0.093)	(0.058)	(0.072)
Min. groupy*Treatment	0.281	-0.507*	-0.142	0.103
	(0.328)	(0.282)	(0.252)	(0.219)
Constant	3.466***	2.477***	2.906***	3.622***
	(0.527)	(0.439)	(0.641)	(0.715)
Controls	No	No	No	No
Observations	980	980	1,030	1,030
Adj. R-squared	0.330	0.420	0.610	0.503

[a.] We depict results from OLS regression models with robust standard errors reported in parentheses. The dependent variable measures participants' likelihood of not choosing the color of observed marble. As controls we include participants' minimal groupiness, party identification, factual bias, their party affiliation, their regular consumption of outgroup media sources, gender, education level, ethnicity, area of living, age, Bayesian rationality, and the topic encountered in the processing stage. We denote significance levels by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Heterogeneity in information processing Wave 2. Figures D.11 and D.12 presents regression analyses on participants information processing in wave 2, respectively for non-groupy and groupy individuals.

Table D.11: Information processing (Wave 2): OLS, non-groupy individuals.

DV: Guessing green cup	(1)	(2)	(3)	(4)
Green marble (β_S)	0.265***	0.264***	0.272***	0.271***
	(0.022)	(0.023)	(0.032)	(0.033)
N green signals ingroup (β_I)	0.185***	0.186***	0.186***	0.188***
	(0.016)	(0.016)	(0.022)	(0.022)
N green signals outgroup (β_O)	0.143***	0.143***	0.140***	0.142***
	(0.016)	(0.016)	(0.022)	(0.022)
Treatment	-0.009	-0.005	-0.002	0.003
	(0.018)	(0.018)	(0.037)	(0.037)
Treatment*Green marble			-0.015	-0.015
			(0.045)	(0.045)
Treatment*N green signals ingroup			-0.002	-0.004
			(0.031)	(0.031)
Treatment*N green signals outgroup			0.004	0.002
			(0.031)	(0.031)
Constant	0.252***	0.228***	0.248***	0.224***
	(0.020)	(0.054)	(0.026)	(0.056)
$\beta_S - \beta_I > 0$	0.079	0.078	0.086	0.084
	(0.002)	(0.002)	(0.019)	(0.022)
$\beta_I - \beta_O > 0$	0.043	0.043	0.046	0.045
	(0.004)	(0.004)	(0.032)	(0.034)
Controls	No	Yes	No	Yes
Observations	2,886	2,886	2,886	2,886
Adj. R-squared	0.073	0.073	0.072	0.072

[a] As controls, we include participants' political leaning, party identification, factual bias, frequency of consuming media from opposing viewpoints, gender, education level, ethnicity, area of living, age, Bayesian rationality.
[b] Robust standard errors are clustered at the individual level and reported in parentheses. We denote significance levels by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D.12: Information processing (Wave 2): OLS, groupy individuals.

DV: Guessing green cup	(1)	(2)	(3)	(4)
Green marble (β_S)	0.269***	0.275***	0.301***	0.306***
	(0.031)	(0.031)	(0.039)	(0.039)
N green signals ingroup (β_I)	0.198***	0.198***	0.230***	0.228***
	(0.021)	(0.022)	(0.030)	(0.030)
N green signals outgroup (β_O)	0.105***	0.107***	0.168***	0.169***
	(0.023)	(0.023)	(0.033)	(0.033)
Treatment	0.032	0.031	0.128**	0.123**
	(0.025)	(0.026)	(0.055)	(0.055)
Treatment*Green marble			-0.064	-0.062
			(0.062)	(0.061)
Treatment*N green signals ingroup			-0.064	-0.058
			(0.043)	(0.043)
Treatment*N green signals outgroup			-0.126***	-0.123***
			(0.046)	(0.046)
Constant	0.264***	0.278***	0.217***	0.236***
	(0.030)	(0.070)	(0.035)	(0.071)
$\beta_S - \beta_I > 0$	0.071	0.077	0.070	0.078
	(0.042)	(0.026)	(0.135)	(0.092)
$\beta_I - \beta_O > 0$	0.093	0.091	0.062	0.059
	(0.000)	(0.000)	(0.057)	(0.075)
Controls	No	Yes	No	Yes
Observations	1,554	1,554	1,554	1,554
Adj. R-squared	0.078	0.080	0.081	0.082

[a.] As controls, we include participants' political leaning, party identification, factual bias, frequency of consuming media from opposing viewpoints, gender, education level, ethnicity, area of living, age, Bayesian rationality.

[b.] Robust standard errors are clustered at the individual level and reported in parentheses. We denote significance levels by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix E Details on experimental design

E.1 Instructions Wave 1

E.1.1 Consent Form

Consent to Participate in Research Study

Title of the Project: Decision-making experiment
Principal Investigators: Kevin Bauer, Yan Chen, Florian Hett and Michael Kosfeld

Invitation to Participate in a Research Study: Researchers from Goethe University Frankfurt, Johannes Gutenberg University Mainz, Leibniz Research Institute SAFE, and the University of Michigan invite you to be part of an online research study to better understand how different types of information affects our judgment and decisions. The study is funded by the three universities and SAFE.

Description of Your Involvement: If you agree to be part of the research study, you will be prompted to participate in a short demographic survey and a sequence of research games, and respond to a short questionnaire. The total time taken today will be about 30 minutes. In addition, we will send you a follow-up survey in about three months time if you agree.

Benefits of Participation: During the experiment, you will have the opportunity to earn an income that will be paid to you after the experiment. The amount of income you earn depends on your decisions and the decisions of other participants in the experiment. In addition to you directly benefit from being in this study, others may benefit because the results from the study may inform public policy.

Risks and Discomforts of Participation: Some of the survey questions may touch on sensitive topics and cause you discomfort. However, we stress that your participation is entirely voluntary. You may choose at any time to abandon the study or to skip a particular question.

Confidentiality: The results of this study will be published. We will not include any information that would identify you. Your privacy will be protected and your research records will be confidential.

It is possible that other people may need to see the information you give us as part of the study, such as organizations responsible for making sure the research is done safely and properly like the University of Michigan.

Storage and Future Use of Data We will store your answers for possible use in future research studies, for a period of up to ten years. Your study answers will be secured and stored at the University of Michigan School of Information.

Only the researchers involved in this study will have access to your research files and data. Research data may be shared with other investigators but will never contain any information that could identify you.

Voluntary Nature of the Study Participating in this study is completely voluntary. Even if you decide to participate now, you may change your mind and stop at any time. You can also skip any question you do not want to answer. Your data will not be used if you abandon the survey before reaching the end.

Contact Information for the Study Team If you have any questions about this study, click this link to be taken to a question form. A member of the research team will see your question and reply within two days. With the answer, you will receive a new link allowing you to participate in the study if you are interested.

The University of Michigan Health Sciences and Behavioral Sciences Institutional Review Board (IRB) has determined that this research is exempt from IRB oversight.

Consent By checking the box, I agree to participate in the study. I understand that if I complete it, I will be re-contacted for a follow-up in about three months. I also understand that my responses will be saved after the expiration of the study, for a period of up to ten years.

- (radio button) I agree to participate.
- (radio button) I agree to be re-contacted in January 2021.
- (radio button) I agree to be re-contacted in October 2021.

E.1.2 Stage 1. Group Assignment and Other-Other Allocation Games

Thank you for participating in this experiment. The objective of this experiment is to study how people make decisions. There is no deception in this experiment - and we want you to understand everything about the procedures. The amount of money you earn will depend upon the decisions you make and on the decisions other people make. This experiment has three parts. Your total earnings will be the sum of your payoffs in each part.

1. An other-other allocation game based on minimal groups

Choice task in part 1. Before the experiment starts, every participant is randomly assigned to one of two groups, Triangle or Circle. Half of the participants are assigned to the Triangle group, while the other half to the Circle group.

You are a member of the Circle group. [Display of a green circle.]

Instructions part 1. In Part 1 of the experiment, you will be asked to make decisions in three scenarios. For each scenario, you will have $6. You will be asked to allocate these $6 between two other participants under three scenarios:

1. if both are from your own group (Circle group)
2. if both are from the other group (Triangle group)
3. if one is from your own group (Circle group), and one is from the other group (Triangle group).

For each scenario, you must allocate all dollars between the two participants. Allocations have to be integers. You can not allocate any dollars to yourself. Your answers will be used to determine other participants' payoffs. Similarly, your payoff will be determined by others' allocations.

[Decision Screen: Each participant makes three decisions, each involving splitting $6 between two other participants in the amount of ($1, $5), . . ., ($5, $1).]

2. A Political Identity Survey:

Part 1. Please answer the following question:

1. Do you consider yourself a(n):
   (a) Democrat
   (b) Republican
   (c) Independent
   (d) None of the above
2. (Conditional on choosing option a or b) Are you a strong or moderate Democrat/Republican?
   (a) Strong
   (b) Moderate
3. (Conditional on choosing option c or d) Do you consider yourself closer to the:
   (a) Democratic party
   (b) Republican party

4. A Political Quiz:

Part 1. Please check true or false for each statement. [Statements appear in randomized order.]

1. The vast majority (over 90%) of climate scientists believe that global warming is an established fact and that it is most likely caused by man-made emissions.
2. Michael Cohen, Donald Trump's personal lawyer, pleaded guilty to fraud and illegal campaign finance charges in August 2018.
3. 40% of firearm sales in the US occur without a background check.
4. Illegal immigrants commit violent crime at a significantly higher rate than legal American citizens.
5. Former President Obama ordered wire taps on Donald Trump's phones.
6. Millions of illegal votes were cast in the 2016 presidential election.

4. Prior elicitation.

Part 1. Information Now we will ask you to make a number of predictions regarding the 2020 Presidential Election and some of its consequences 12 months from now.

Please answer the following questions: We will check the official results of the election at the end of January 2021 and inform you whether your predictions were correct. For every correct prediction we will pay you $3 in January 2021.

- By January 20, 2021, who will win the 2020 presidential election? [Candidate names appear in randomized order.]
  - (radio button) Donald Trump
  - (radio button) Joe Biden
- By January 20, 2021, who will win the majority of the popular votes in the 2020 presidential election? [Candidate names appear in randomized order.]
  - (radio button) Joe Biden
  - (radio button) Donald Trump

Next, we ask you questions about the consequences of the election outcomes. In 12 months we will check the official statistics and inform you whether your predictions were correct. For each correct prediction, we will pay you $10.

Note: in subsequent parts of the experiment, you will be given opportunities to update your initial predictions on the consequences of the election, after we provide you information that might help you make a correct prediction.

- **According to the Bureau of Labor Statistics, the unemployment rate in September 2020 was 7.9%.**

  What will the unemployment rate be in September 2021 if Joe Biden (Donald Trump) wins the election in November 2020?

  - Strong increase (10 % or higher)
  - Moderate increase (Higher than or equal to 8.5 %, but less than 10 %.)
  - Stable (Higher than or equal to 7.5 %, but less than 8.5 %.)
  - Moderate decrease (Higher than or equal to 6 %, but less than 7.5%.)
  - Strong decrease (6 % or lower)

- **According to US News and World Report, Canada ranks 1st among countries with the most developed public health care systems in 2020, while the United States ranks 15th.**

  What will be the ranking of the United States in September 2021 if Joe Biden (Donald Trump) wins the election in November 2020?

  - Strong improvement (Rank 12 or better)
  - Moderate improvement (Rank 13 or 14)
  - No change (Rank 15)
  - Moderate decline (Rank 16 or 17)
  - Strong decline (Rank 18 or worse)

5. An other-other allocation game based on political groups. In this part of the experiment, you will be asked to make decisions in three scenarios. For each scenario, you will have $6. You will again be asked to allocate these $6 between two other participants under three scenarios.

- if both are Democrats;
- if both are Republicans;
- if one is a Democrat, and the other a Republican.

Whether someone is labeled as Democrat or Republican depends on her/his responses in the previous questionnaire:

Democrats and those closer to the Democratic party are labeled Democrats. Similarly, Republicans and those closer to the Republican party are labeled Republicans.

[Decision Screen: Each participant makes three decisions, each involving splitting $6 between two other participants in the amount of ($1, $5), . . ., ($5, $1).]

E.1.3 Information Processing Stage

In part 2 (3) of this experiment, you will be given two articles, each of which summarizes current events from three different news sources. You will [will not] see the names of the news sources.

The two articles contain information that might help you improve your predictions about the United States unemployment rates 12 months from now. You will be given the chance to change your initial predictions after you have read both articles.

Additionally, you will be asked to answer two multiple-choice questions, one for each article. You will earn 50 cents for each correct answer. You will also be asked to evaluate the political leaning and reliability of the articles.

- Display screen for Article A;
- Display screen for Article B;
- Updating screen:

  Now you have the option to change your initial predictions about the unemployment rates in the United States 12 months from now. Your initial predictions will be overwritten. You will not have the chance to change your predictions about the unemployment rates again. In 12 month we will check the official statistics and inform you whether your predictions were correct. For a correct prediction, we will pay you $10.

  Your initial prediction for the unemployment rate in September 2021 if Joe Biden wins the 2020 presidential election: __

  Your initial prediction for the unemployment rate in September 2021 if Donald Trump wins the 2020 presidential election: __

  Please answer the following questions: [Display the same unemployment questions again.]

- Evaluation screen: Please answer the following questions about the articles you have just read.
  - On a scale of -3 to +3, with negative numbers representing left leaning or liberal skew, positive numbers representing right leaning or conservative skew, and 0 representing true neutral, how would you rate article A [Title]?
  - On a scale of 1 to 7, 1 being not reliable at all and 7 being very reliable, how would you rate the information in article A [Title]?
  - On a scale of -3 to +3, with negative numbers representing left leaning or liberal skew, positive numbers representing right leaning or conservative skew, and 0 representing true neutral, how would you rate article B [Title]?
  - On a scale of 1 to 7, 1 being not reliable at all and 7 being very reliable, how would you rate the information in article B [Title]?

- Multiple-choice question screen: Please answer the following MC questions about the articles you have just read. There is one question for each article. For a correct answer, you receive $0.5 paid out at the end of the experiment.. [See Appendix A8 for the articles and their corresponding multiple-choice questions.]

E.1.4 Information Demand

You will see the titles of two pairs of articles. Each article summarizes current events from three different news sources.

Under each pair of articles, a slider indicates the likelihood that you will be randomly given one of the articles to read. The default probability is 0.5. That is, each article is equally likely to be selected. You have a $3 budget which you can use to change the probabilities. Moving the slider to the left increases the likelihood that the article on the left is chosen, and vice verse. It costs $1 to change the probability by 10 percentage points. The amount of budget you do not spend will be paid out to you at the end of the experiment.

One of the two decisions you make will be randomly drawn and implemented and an article will be drawn with your chosen probabilities. You will then be able to read that article.

After you finish reading the article, you will be given the opportunity to change your initial predictions.

Additionally, you will be asked to answer a multiple-choice question. You will earn $0.5 for each correct answer. You will also be asked to evaluate the political leaning and reliability of the articles.

- Decision screen: Display titles of article pairs in random order: left and neutral; right and neutral; display sources if in treatment; slider
- Reading screen
- Updating screen (if the chosen article is about the economy):

  Now you have the option to change your initial predictions about the unemployment rates in the United States 12 months from now. Your initial predictions will be overwritten. You will not have the chance to change your predictions about the unemployment rates again. In 12 month we will check the official statistics and inform you whether your predictions were correct. For a correct prediction, we will pay you $10.

  Your initial prediction for the unemployment rate in September 2021 if Joe Biden wins the 2020 presidential election: __

  Your initial prediction for the unemployment rate in September 2021 if Donald Trump wins the 2020 presidential election: __

  Please answer the following questions: [Display the same unemployment questions again.]
- Evaluation screen: Please answer the following questions about the articles you have just read.

- On a scale of -3 to +3, with negative numbers representing left leaning or liberal skew, positive numbers representing right leaning or conservative skew, and 0 representing true neutral, how would you rate this article?
- On a scale of 1 to 7, 1 being not reliable at all and 7 being very reliable, how would you rate the information in this article?

- Multiple-choice question screen: Now we ask you to answer a question about the article you have just read. For a correct answer, you receive $0.5 paid out at the end of the experiment. [See Appendix A8 for the articles and their corresponding multiple-choice questions.]

E.1.5 The last game

At the beginning of this round, we will use the computer to simulate the draw of a marble from a "cup." There are two cups, with different mixes of colored marbles, and you will be asked to guess the cup that is being used.

First, we draw a computer-generated random number which will be either 1, 2, ... 6. Think of this as the throw of a die with 6 sides, with each side being equally likely.

- If the roll of the die yields 1 - 3, then the draw will be from the Green cup, which contains 2 green marbles and 1 yellow marble.
- If the roll of the die yields 4 - 6, then the draw will be from the Yellow cup, which contains 2 yellow marbles and 1 green marble.

You will not be told in advance the result of the die throw, so you will not know which cup is being used. Once the computerized die throw determines the cup to be used, you will be shown a randomly selected marble from that cup.

You will get a chance to indicate the cup that you think is being used. Your money payoff will depend on whether your prediction turns out to be correct. You will earn $0.5 for a correct prediction, and zero for an incorrect prediction.

E.1.6 Closing survey

Thank you! You have completed all the tasks in the experiment. Before we show you your generated income, we kindly ask you to answer the following questions about yourself.

[Demographics:]

- How old are you?
- What is your gender?
- What is your highest academic degree achieved/in progress?
- What is your ethnic background?

[News consumption:]

- Which do you think are your main sources of news?
  - ABC, NBC, or CBS
  - CNN
  - Fox News
  - Local TV or radio
  - MSNBC
  - NPR (National Public Radio) or PBS
  - Newspapers, magazines, online or in paper
  - Facebook
  - Twitter
  - Other
- (Conditional on 'Newspapers, magazines, online or in paper' being mentioned in prior question) Which of the following newspapers and magazines do you read on a regular basis (at least once a week)?
  - Economist
  - New York Times
  - Wall Street Journal
  - Washington Examiner
  - Washington Post
  - Nature
  - Science
  - Other:

E.1.7 Payoff Screen

On this screen, subjects will see his or her payoffs from each part of the experiment tabulated and summarized.

In the next couple of days, you may receive an additional bonus payment, based on the decision of other players in the first stage of the experiment. We will use the computer to randomly divide all participants in two halves.

You also receive the minimum of $1 from the allocation decision in stage 1. Within the one week (once the study is finished), you may receive an additional bonus payment, based on the allocation decision of another participant, i.e., if someone allocated more than $1 to you. We will use the computer to randomly divide all participants in two halves. For one half of participants, the allocation based on their group membership in the experiment (Triangle group or Circle group) will be payoff relevant. For the other half, the allocation based on political leaning (Democrat or Republican) will be payoff relevant. In both cases, payoffs will be determined as follows: the computer will generate a random sequence of the ID numbers. The first number in the sequence will be the ID number of the person who allocates to the second and third IDs. The second ID drawn will allocate to the third and fourth IDs, ... and so on. The last ID will allocate to the first and second IDs. Therefore, your payoff will be the sum of dollars allocated to you by the two participants preceding you.

We will contact you again in late January 2021 to pay you for your predictions of the presidential election, and in late October 2021 to pay you for your predictions on unemployment and health ranking. Thank you very much for participating in our experiment!

E.1.8 Articles used in experiment

In this section, we display the articles used in the Information Demand and Processing stages. We display summaries of news articles in the "Labels" treatment, where the names of the news sources are labelled. In the treatment with "No Labels," the names of the news sources are replaced by "A news source" the first time we mention it, and "the news sources" the last time we mention it.

The Economy - Left-leaning news sources

Title: 'Staggeringly High': U.S. Jobless Claims Remained Elevated Last Week

Both candidates have shown different predictions for how the economy will recover. MSNBC states, "Donald Trump has clearly settled on his preferred letter, telling supporters at a campaign rally in North Carolina last night, 'Our economy is doing phenomenally well. Not only is it a 'V,' it's a 'super V.' In other words, the president believes the economy fell sharply as a result of the pandemic, and it's now bouncing back with equal speed." The article continues, "This is, of course, highly dubious, especially as job gains appeared to lose momentum over the summer." Beyond just disagreeing on shape, they state, "It's a problem that Trump sees – or at least claims to see – a 'super V' recovery, but it's a bigger problem that his assessment has led to passivity when it comes to doing real work on the economy. On Labor Day, of all days, the president said he wouldn't even negotiate with congressional Democrats on a possible economic aid package. In other words, despite high unemployment and widespread economic distress, many on Team Trump are prepared to do very little to improve the status quo – and that's even more alarming than the White House's misguided choice in letters used to represent the state of the 'recovery."' (MSNBC, 9/9/2020)

Trump recently stopped talks for a stimulus package before the election. This action came as a surprise to many, and according to the Washington Post, there is fear the President's action will "stall the U.S. economic recovery – or even trigger a backslide." The article continues, "Many economists and business leaders were quick to dub the move disheartening and irresponsible... 'Corporations were holding off on laying off employees in the hopes of further stimulus. With this afternoon's news, I expect that we will see businesses capitulate and begin to announce large scale layoffs,' said Peter Atwater, an adjunct lecturer in economics at the College of William & Mary," hinting that more unemployment is coming. With his decision to shut down stimulus talks, "Trump risks the nation backsliding economically, putting more jobs and business in danger of going away. He wanted a V-shaped recovery, but a W is looking more likely." (Washington Post, 10/6/2020).

The job market is at the forefront of everyone's mind. According to the New York Times, "Monthly jobs data released last week showed that job growth slowed sharply in September, and that last spring's temporary furloughs are increasingly turning into permanent job losses. Major corporations like Disney and Allstate have announced thousands of new job cuts. And with winter approaching, restaurants and other businesses that were able to shift operations outdoors during warmer weather could be forced to pull back anew." This is worrisome for future prospects and the report states, "The net result is that potentially millions of workers could see their benefits expire this winter. Epidemiologists warn that cases of the coronavirus are likely to rise as temperatures drop, and winter weather could reduce job opportunities." (New York Times, 10/8/2020).

The Economy - Right-leaning news sources

Title: New Jobs, Unemployment Numbers Point to 'V'-Shaped Recovery – Only a Biden Lockdown Could End It

Both candidates have shown different predictions for how the economy will recover. According to Fox News, "We increasingly appear to be experiencing a "V"-shaped recovery, with four straight months of the most robust job creation ever recorded – 10.6 million new jobs in just one-third of a calendar year and nearly half of the jobs lost in the shutdown." Continuing, they predict "a full and lasting recovery, a return to the prosperity and historically strong job market we enjoyed throughout the vast majority of the president's first term ... While the market has its ups and downs, it has basically recovered its pre-pandemic valuations and was recently again setting all-time records." However, they warn, "The only thing that could mess things up now is if – heaven forbid – politicians plunge the country into another lockdown for political reasons. Unfortunately, that's exactly what one of America's great parties is willing to do. 'I would shut it down. I would listen to the scientists,' Democratic presidential nominee Joe Biden said [on] whether he would subject the American economy to another devastating trip through the 'total lockdown' ringer that's still fresh in our minds." (Fox News, 9/4/2020).

Trump recently stopped talks for a stimulus package before the election. According to the Wall Street Journal, "President Trump halted talks with Democrats about a Covid-19 stimulus package earlier this week, instead pushing for individual relief bills, including aid for airlines and another round of direct checks to many U.S. households." Trump is still thinking of a stimulus package: "'I shut down talks two days ago because they weren't working out. Now they're starting to work out...We're talking about airlines, and we're talking about a bigger deal than airlines,' he said, mentioning the $1,200 stimulus checks to taxpayers that both parties have said they support." Further, there were other reasons for stopping talks for a stimulus package, including "Disagreements over state and local aid in the package . . .. Republicans have criticized the Democratic approach for being too sprawling and expensive, while Democrats say that the GOP plan is insufficient for the scale of the crisis." (Wall Street Journal, 10/8/2020).

The job market is at the forefront of everyone's mind. According to the Washington Examiner, Biden's job projection is questionable, stating "Here's the reality check. Despite Biden predicting 4% economic growth under Barack Obama, the economy barely averaged 2% – rather pathetic for a 'recovery.' The people who made these preposterous bullish predictions are the ones who now say the Biden economic plan will gain millions of jobs." They back this with public opinion data, stating "Throughout nearly all of the Biden-Obama presidency, roughly 1 out of 3 people in the United States rated the economy as good or great...That number surged to about 65% rating the economy as good or great within a year of Trump's presidency." Further, the path is clear: "Now, the question is which game plan gets the economy and employment back to normal as quickly as possible. Biden promises a $4 trillion tax hike almost all on U.S. businesses and investors. That's roughly 5% of everything we produce that gets snatched away in higher taxes. If you believe that this will get America back on the fast track, you probably believe Obama got us 4% growth." (Washington Examiner, 10/8/2020).

The Economy - Neutral news sources

Title: The Good and Bad of Trumponomics, and an Overview of the Labor Market

Both candidates have shown different predictions for how the economy will recover. Trump has been adamant in the greatness of Trumponomics. According to the Economist, "President Donald Trump says Americans should re-elect him because of his record on the economy. Before Covid-19, America enjoyed its lowest unemployment rate in 50 years, fast annual wage growth of almost 5% among the lowest-paid workers and a buoyant stock market. Mr Trump attributes all this to his three-pronged strategy of tax cuts, deregulation and confrontational trade policy, and says more of the same will revive the economy after the pandemic." The article states this is one of his strong suits: "Many voters agree. The economy is one issue where Mr Trump does not face a big deficit in the polls." (Economist, 10/17/2020).

Speaking to the overall picture of Trumponomics, the Economist states, "his administration's economic record from before the pandemic is mixed. It got one thing right: when Mr Trump took office the economy was still in need of stimulus, which tax cuts and more spending helped provide. But that success has also helped conceal the damage done by his protectionism." Evaluating his trade war with China and other countries, they state, "Recent research suggests that Mr Trump's tariffs destroyed more American manufacturing jobs than they created, by making imported parts more expensive and prompting other countries to retaliate by targeting American goods. Manufacturing employment barely grew in 2019. At the same time tariffs are pushing up consumer prices by perhaps 0.5%, enough to reduce average real household income by nearly $1,300." In conclusion, there are both positives and negatives: "In 2019 Mr Trump presided over the best labour-market conditions America had seen in several decades. He deserves some of the credit. Despite that, he is overselling Trumponomics. It was both a help and a hindrance." (Economist, 10/17/2020)

The job market is at the forefront of everyone's mind, given that the U.S. economy contracted at "31.4% annualized rate in the second quarter, the deepest drop in output since the government started keeping records in 1947" (Reuters, 9/30/2020). According to the U.S. Bureau of Labor Statistics, employment is going up, but more slowly than before. Breaking down the 661,000 new jobs in September 2020, they state, "In September 2020, almost two-thirds of the gain in leisure and hospitality employment occurred in food services and drinking places (+200,000). Despite job growth totaling 3.8 million over the last 5 months, employment in food services and drinking places is down by 2.3 million since February. Amusements, gambling, and recreation (+69,000) and accommodation (+51,000) also added jobs in September." Further, layoffs have been hardest on smaller establishments: "The layoffs and discharges rate in private nonfarm establishments reached a historical high of 8.8 percent in March 2020 as the Covid-19 pandemic began. The rate remained high in April at 6.9 percent. Layoffs and discharges rates in May, June, July, and

August were similar to those before the pandemic. Establishments with 10 to 49 employees had the highest layoffs and discharges rates in March and April, followed by establishments with 50 to 249 employees." (U.S. Bureau of Labor Statistics, 10/6/2020 and 10/14/2020).

Health - Left-leaning news sources

Title: Bidencare Would Be a Big Deal

Both candidates have shown very different approaches to healthcare. The New York Times states, "[Trump] is definitely lying when he claims to have a plan that's better and cheaper than Obamacare. No such plan exists, and he has to know that." In contrast, "Independent estimates suggest that under Biden's plan, 15 million to 20 million Americans would gain health insurance. And premiums would fall sharply, especially for middle-class families." Further, they state, "The plan would also provide significant aid for long-term care, rural health, and mental health. None of this amounts to revolutionary change – in contrast to Trump's efforts to kill Obamacare, which would drastically change American health care, for the worse." (New York Times, 10/5/2020).

With the upcoming case against the Affordable Care Act (ACA), NBC news reports that "Democrats have warned that Barrett's record shows that she would be just as conservative as her mentor, Justice Antonin Scalia. They have argued Barrett could vote to dismantle the Affordable Care Act, with the Supreme Court set to hear oral arguments in a case challenging the health care law Nov. 10. Democratic lawmakers also say they fear her confirmation could lead to a reversal of the landmark 1973 Roe v. Wade decision that protects a woman's right to abortion." Further, they say "one of the main reasons President Donald Trump and the Republicans are trying to ram Barrett's nomination through the Senate ahead of the election is because Trump wants her installed on the bench in case there's a dispute over the election results that rises to the Supreme Court, as it did in the 2000 Bush v. Gore case." Nonetheless, "despite Democrats' fierce opposition to her nomination, Senate Republicans are poised to confirm Barrett, filling the vacancy left by the late Justice Ruth Bader Ginsburg, as Democrats don't have the votes to block her nomination." (NBC news, 10/15/2020).

The Covid-19 vaccine has also been a hot topic, with many questioning its effectiveness and safety. The Washington Post notes, "To receive authorization, a vaccine or drug should seem effective, but its efficacy doesn't definitively need to be proved. For example, a vaccine could generate an immune response, but it might not prevent infection or serious illness. This is a much lower bar. Rather than going through the usual process of consulting panels of experts, the FDA chief alone is able to make this determination – and Commissioner Stephen Hahn has already signaled that he is willing to do so as soon as Oct. 22." Adding to the uncertainty, "Despite studies showing that hydroxychloroquine does not work, Trump has continued to insist that it is safe and effective, citing his own preventive use as evidence." Further, there are concerns about deadlines. The Washington Post continues, "medical research does not operate well on politically imposed deadlines. If this effort is going to be successful, it will need to be done in a way that builds on public trust in science and government, rather than falling into existing partisan divisions. " (Washington Post, 9/4/2020).

Health - Right-leaning news sources

Title: Trump's Healthcare Plan Puts the Patient Where Obamacare Didn't: First

Both candidates have shown very different approaches to healthcare. According to the Washington Examiner, "President Trump unveiled his own health system overhaul, the America First Healthcare Plan. Trump's healthcare plan is exceedingly specific in its diagnosis of all the damage Obamacare has wreaked upon the country and the solutions to reverse it." Further, they state, "It's the patient whom Trump had in mind, not the insurance companies or federal regulators, when he outlined the plan. It focuses on reforms that specifically address what patients want: lower costs, more options, and better care." while contrasting Biden, who "instead promises to double down on the failures of Obamacare and make them worse with his own Medicare-for-all scheme thrown in." (Washington Examiner, 10/1/2020).

With the upcoming case against the Affordable Care Act, "Former Vice President Biden has repeatedly and falsely alleged that President Trump plans to 'destroy the Affordable Care Act, and with it the protections for preexisting conditions."' However, according to Fox News, "President Trump signed an executive order that stated, in part, 'It has been and will continue to be the policy of the United States to give Americans seeking healthcare more choice, lower costs, and better care and to ensure that Americans with pre-existing conditions can obtain the insurance of their choice at affordable rates."' Although "The Trump administration has argued in court that the Affordable Care Act is no longer legal and should thus be struck down," however, "Trump and congressional Republicans have already promised to pass new legislation to protect people with preexisting conditions should the court strike the entire law down." (Fox News, 9/29/2020).

The Covid-19 vaccine has also been a hot topic, with many questioning its effectiveness and safety. As a result, according to the Wall Street Journal, "Several drug makers developing Covid-19 vaccines plan to issue a public pledge not to seek government approval until the shots have proven to be safe and effective, an unusual joint move among rivals that comes as they work to address concerns over a rush to mass vaccination." Further, "The statement would join a growing number of public assurances by industry executives that they aren't cutting corners in their rapid testing and manufacturing of the vaccines." The draft says, "We believe this pledge will help ensure public confidence in the Covid-19 vaccines that may ultimately be approved and adherence to the rigorous scientific and regulatory process by which they are evaluated." However, there have been events adding to the uncertainty. They state, "The emergency-use authorization of hydroxychloroquine, an antimalarial touted by Mr. Trump, which was rescinded over concerns of safety and efficacy, also drew criticism." Despite that, they continue, "Pfizer's CEO said the company would never submit any vaccine for authorization or approval before 'we feel it is safe and effective.' He also said Pfizer hasn't felt any political pressure to rush a vaccine out. 'We will not cut corners,' Mr. Bourla said." (Wall Street Journal, 9/4/2020).

Health - Neutral news sources

Title: What the United States Might Look Like After the Election for Key Health Issues

Both candidates have shown very different approaches to public health. Nature states, "Despite public-health agencies counting more than 200,000 Covid-19 deaths in the country, some Trump supporters feel that the impact of the virus has been exaggerated in an effort to control the populace." Further, "the Biden campaign has stated that his administration would direct the CDC to issue transparent, evidence-based guidance around the public-health risks of reopening restaurants, schools and public spaces. This could also go a long way towards restoring morale within the CDC and the FDA." Further, Biden will support the World Health Organization (WHO), "providing badly needed funds to the WHO to fight the coronavirus, polio and other diseases globally[;] reinstating the United States' commitment to the organization would pave the way for joining its international COVAX facility, which aims to accelerate the search for and manufacture of coronavirus vaccines." Beyond commitment to the WHO, "Biden has committed to continue supporting coronavirus-vaccine research, and has pledged that an eventual vaccine will be priced fairly by the federal government." (Nature, 10/1/2020).

With the upcoming case against the Affordable Care Act, according to the Economist, "each Democrat probed Ms Barrett on whether she would vote to scrap it–and strip coverage from some 23m Americans–days after taking Ms Ginsburg's seat. The interrogation was accompanied by stories and photos of sick constituents with pre-existing conditions who could be left without affordable coverage should the high court toss the law." The article follows, "The line of attack is not without footing. In 2017, Ms Barrett criticised NFIB v Sebelius, the 2012 Supreme Court decision upholding the constitutionality of the law's requirement that most Americans buy health insurance. When Chief Justice John Roberts anchored a 5-4 majority interpreting the mandate as a tax within Congress's revenue-raising power, she wrote, he 'pushed the Affordable Care Act beyond its plausible meaning to save the statute'. Juxtaposing Chief Justice Roberts with 'staunch textualists' such as her mentor, Antonin Scalia, Ms Barrett then used a footnote to detail several other cases in which the chief 'depart[ed] from ostensibly clear text' in order to achieve his 'preferable result'. She also favourably quoted Mr Scalia's condemnation of Chief Justice Roberts in Sebelius and in King v Burwell, as having turned the ACA into 'scotuscare'." (The Economist, 10/17/2020).

The Covid-19 vaccine has also been a hot topic, with many questioning its effectiveness and safety. As stated on CDC's website, "In the United States, there is currently no authorized or approved vaccine to prevent coronavirus disease 2019 (Covid-19). Operation Warp Speed has been working since the pandemic started to make a Covid-19 vaccine(s) available as soon as possible. CDC is focused on vaccine planning, working closely with health departments and partners to get ready for when a vaccine is available. CDC does not have a role in developing Covid-19 vaccines." On the website, CDC states 8 things to know about Covid-19 vaccine plans since they may become available before the end of the year, including that "The U.S. vaccine safety system ensures that all vaccines are as safe as possible." (Center for Disease Control, 10/14/2020).

E.2 Screenshots Wave 1

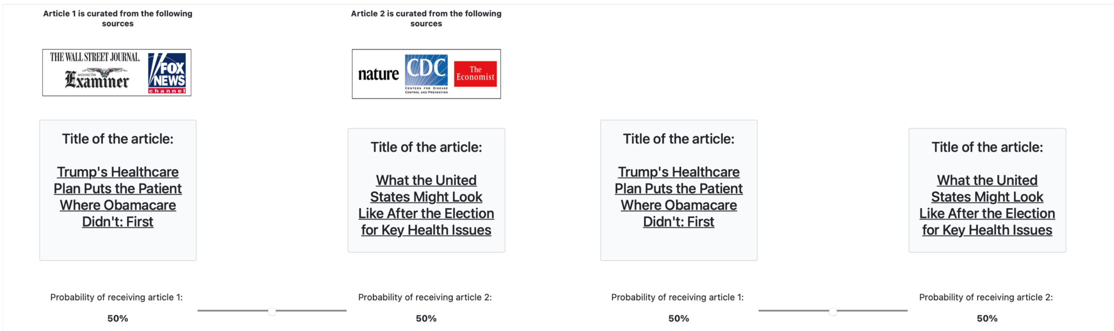

Figure E.13: Interface demand stage (wave 1).

Notes: We depict the interfaces baseline and treatment participants in wave 1 encountered in the demand stage. The left panel depicts the demand task with source labels; the right panel depicts the demand task without source labels.

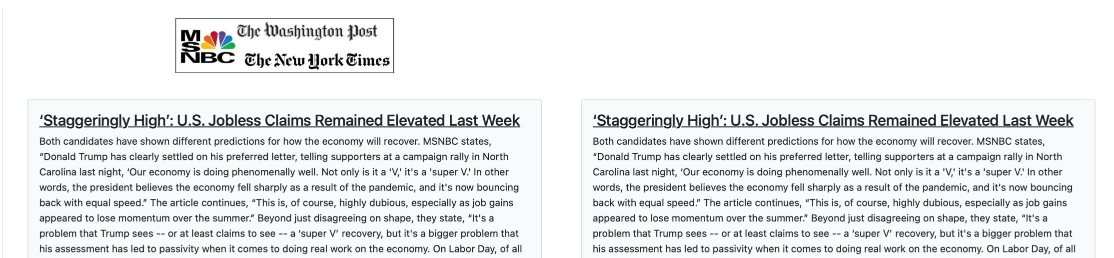

Figure E.14: Interface processing stage (wave 1).

Notes: We depict the interfaces baseline and treatment participants in wave 1 encountered in the processing stage. The left panel depicts the demand task with source labels; the right panel depicts the demand task without source labels.

E.3 Instructions Wave 2

E.3.1 Preamble

Welcome back!

Second part of research study from October, 2020

Invitation to participate in part 2 of the research study: Researchers from Goethe University Frankfurt, Johannes Gutenberg University Mainz, Leibniz Research Institute SAFE, and the University of Michigan invite you to be part of the second part of an online research study. **You already participated in the first part of this study at the end of October 2020.** The overall study's objective is to better understand how different types of information affects our judgment and decisions. The study is funded by the three universities and SAFE.

Content of second part of study: In this second part of the study, we will pay out income that you generated in the first part of the study in October 2020 from making guesses about the outcome of the 2020 Presidential Election. Additionally, we ask you to (i) repeat some of the tasks from the first part that are relevant for payment in fall 2021, and (ii) do a few new tasks with which you can generate additional income that we will pay you at the end of this part. The total time taken today will be about 15 minutes.

Benefits of participation: We pay out income that you generated in the first part of the study in October 2020 where you made guesses about the outcome of the 2020 Presidential Election. During the experiment, you will have the opportunity to earn an income that will be paid to you after the experiment. The amount of income you earn depends on your decisions and the decisions of other participants in the experiment. **Note: You can only be paid if you complete the entire experiment.** In addition to you directly benefiting from being in this study, others may benefit from public policy that is informed by the results of this study.

Confidentiality: The results of this study will be published. We will not include any information that would identify you. Your privacy will be protected and your research records will be confidential. It is possible that other people may need to see the information you give us as part of the study, such as organizations responsible for making sure the research is done safely and properly like the University of Michigan.

Storage and Future Use of Data. Participating in this study is completely voluntary. Even if you decide to participate now, you may change your mind and stop at any time. Your data will not be used if you abandon the survey before reaching the end. We will store your responses for possible use in future research studies, for a period of up to ten years. Your responses will be secured and stored at the University of Michigan School of Information. Only the researchers involved in this study will have access to your research files and data. Research data may be shared with other investigators but will never contain any information that could identify you.

The Institutional Review Board (IRB) of the Goethe University Frankfurt and Johannes Gutenberg University Mainz has determined that this research is exempt from IRB oversight.

If you have any questions about this study, please contact the research team via the chat provided by Prolific. A member of the research team will see your question and reply. If you have questions about this research after completing the study, including questions about your compensation for participating, you may contact the research team via Prolific.

E.3.2 Stage 1. Other-Other allocation games, prediction updating

Structure of the experiment. There is no deception in this experiment - and we want you to understand everything about the procedures. The amount of money you earn will depend upon the decisions you make and the decisions other people make. This experiment consists of four stages and your total earnings will be the sum of your payoffs in each stage.

1. An other-other allocation game based on minimal groups

Choice task in stage 1. Before the experiment starts, every participant is randomly assigned to one of two groups, Triangle or Circle. Half of the participants are assigned to the Triangle group, while the other half to the Circle group.

You are a member of the Circle group. [Display of a green circle.]

Instructions: In stage 1 of the experiment, you will be asked to make decisions in three scenarios. For each scenario, you will have $6. You will be asked to allocate these $6 between two other participants under three scenarios:

- if both are from your own group (Circle group)
- if both are from the other group (Triangle group)
- if one is from your own group (Circle group), and one is from the other group (Triangle group).

For each scenario, you must allocate all dollars between the two participants. Allocations have to be integers. You can not allocate any dollars to yourself. Your answers will be used to determine other participants' payoffs. Similarly, your payoff will be determined by others' allocations.

[Decision Screen: Each participant makes three decisions, each involving splitting $6 between two other participants in the amount of ($1, $5), . . ., ($5, $1).]

2. A political identity survey.

Please answer the following question:

- Do you consider yourself a(n):
  - Democrat
  - Republican
  - Independent
  - None of the above
- (Conditional on choosing option a or b) Are you a strong or moderate Democrat/Republican?
  - Strong
  - Moderate
- (Conditional on choosing option c or d) Do you consider yourself closer to the:
  - Democratic party
  - Republican party
- Since your participation in our experiment in early November, your political party affiliation, leaning, or strength of affiliation:
  - remains the same
  - has changed

3. Prediction updating

Instructions. In the first part of this study in October 2020, we asked you to make a number of predictions regarding the consequences of the 2020 presidential election in October 2021. Now that Joe Biden has become the President of the United States, we will give you the opportunity to change your predictions. Remember that for each correct prediction, we will pay you $10 in October 2021, after the official statistics come out.

We will show you your previous predictions. If you do not want to change your answers, please select the option 'I do not want to change my previous prediction.'

Please answer the following questions: You can now change your previous predictions about the consequences of the election outcomes. In October 2021, we will check the official statistics and inform you whether your predictions were correct. For each correct prediction, we will pay you $10.

Note: if you decide to change your answer, your previous guess will be overwritten and we will compare your new prediction to official statistics to determine your payoffs.

If you do not want to change your answers, please select the option 'I do not want to change my previous prediction'.

- **According to the Bureau of Labor Statistics, the unemployment rate in September 2020 was 7.9%.**

  What will the unemployment rate be in September 2021, now that **Joe Biden** is the president of the United States?

  Your previous prediction: [Copy previous prediction here.]

  - Strong increase (10 % or higher)
  - Moderate increase (Higher than or equal to 8.5 %, but less than 10 %.)
  - Stable (Higher than or equal to 7.5 %, but less than 8.5 %.)
  - Moderate decrease (Higher than or equal to 6 %, but less than 7.5%.)
  - Strong decrease (6 % or lower)
  - I do not want to change my previous prediction

- **According to US News and World Report, Canada ranks 1st among countries with the most developed public health care systems in 2020, while the United States ranks 15th.**

  What will be the ranking of the United States in September 2021, now that **Joe Biden** is the president of the United States?

  Your previous prediction: [Copy previous prediction here.]

  - Strong improvement (Rank 12 or better)
  - Moderate improvement (Rank 13 or 14)
  - No change (Rank 15)
  - Moderate decline (Rank 16 or 17)
  - Strong decline (Rank 18 or worse)
  - I do not want to change my previous prediction

4. An other-other allocation game based on political groups In this part of the experiment, you will be asked to make decisions in three scenarios. For each scenario, you will have $6. You will again be asked to allocate these $6 between two other participants under three scenarios.

- if both are Democrats;
- if both are Republicans;
- if one is a Democrat, and the other a Republican.

Whether someone is labeled as Democrat or Republican depends on her/his responses to the previous questions in the current part of the study:

Democrats and those closer to the Democratic party are labeled Democrats. Similarly, Republicans and those closer to the Republican party are labeled Republicans.

[Decision Screen: Each participant makes three decisions, each involving splitting $6 between two other participants in the amount of ($1, $5), . . ., ($5, $1).]

5. Belief elicitation, anchoring and treatment.

Instructions. Recall that, in late October, everyone participated in a "Guessing which cup is used" task. The task is described below to help refresh your memory.

In that task, we used the computer to simulate the draw of a marble from a "cup". There were two cups, with different mixes of colored marbles, and you were asked to guess the cup that was being used.

First, for every participant individually, we drew a computer-generated random number which would be either 1, 2, ... 6. Think of this as the throw of a die with 6 sides, with each side being equally likely.

- If the roll of the die yielded 1 - 3, then the draw would be from the Green cup, which contained 2 green marbles and 1 yellow marble.
- If the roll of the die yielded 4 - 6, then the draw would be from the Yellow cup, which contained 2 yellow marbles and 1 green marble.

We did not reveal the result of the die throw in advance. Once the computerized die throw determined the cup to be used, each participant was shown a randomly selected marble from his or her personal cup. Each participant was then asked to guess which cup was used.

You are now asked to estimate the proportion of Republicans and Democrats who guessed their cup correctly. You will earn 50 cents for each correct estimate.

Note: across all participants in October 2020, 67% guessed their cup correctly.

Please answer the following questions.

Among the Democrats, what is the share of participants who correctly guessed the cup?

- More than 80%
- More than 70% but less than or equal to 80%
- Between 60% and 70%, inclusive
- Less than 60%, but more than or equal to 50%
- Less than 50%

Among the Republicans, what is the share of participants who correctly guessed the cup?

- More than 80%
- More than 70% but less than or equal to 80%
- Between 60% and 70%, inclusive
- Less than 60%, but more than or equal to 50%
- Less than 50%

Results. [*Note this screen is shown to participants in the treatment group only.*]

The answers to the previous questions about the share of Democrats and Republicans who guessed the cup correctly are as follows:

Democrats: 67%

Republicans: 67%

Put differently: There is no difference in the share of Democrats and Republicans who guessed the cup correctly.

E.3.3 Stage 2. Information Demand

Instructions. This stage consists of three rounds of the task "Guessing which cup is used" that resembles the task from October 2020.

At the beginning of each round, we draw a computer-generated random number which will be either 1, 2, ... 6. Think of this as the throw of a die with 6 sides, with each side being equally likely.

- If the roll of the die yields 1 - 3, then the Green cup will be used, which contains 2 green marbles and 1 yellow marble.
- If the roll of the die yields 4 - 6, then the Yellow cup will be used, which contains 2 yellow marbles and 1 green marble.

You will not be told in advance the result of the die throw, so you will not know which cup is being used. In every round your task is to guess which cup is used. **A new die throw occurs in each round, which determines the cup used for that round.**

Details: Before you make your guess, **you will see the guesses of a group comprised of two other participants from October 2020 who were both shown a randomly selected marble from the cup being used.**

Please note that **(i) after showing a randomly selected marble to a participant, the marble is put back into the cup, before the computer randomly selects and shows a marble to another participant, and (ii) the other two participants did not see each other's guesses.** You yourself will not be shown a marble.

In each round, there are two groups that comprise two other participants. You will see the guesses of one of the two groups. Under each group, a slider indicates the likelihood that you will see their guesses. The default probability is 0.5. That is, each group is equally likely to be selected. You have a 40-cent budget which you can use to change the probabilities. Moving the slider to the left increases the probability that the group on the left is chosen, and vice versa. It costs 10 cents to change the probability by 10 percentage points. The remaining budget will be paid out to you at the end of the experiment.

Based on your choice of probabilities, the computer will randomly draw a group of two participants and show you their guesses. Based on the information, you will get a chance to indicate the cup that you think is being used. Your money payoff will depend on whether your guess turns out to be correct. You will earn $1 for a correct guess, and zero for an incorrect guess. At the end of the experiment, one of the rounds in this stage will be randomly selected for payment.

Please make a decision [Decision screen: remaining budget, group composition with partisan labels, slider,]

Guesses of other people whose marble has been drawn from your cup

Person 1, party affiliation and party image [donkey or elephant]

Person 1 guesses that the cup's color is [green or yellow].

Person 2, party affiliation and party image [donkey or elephant]

Person 2 guesses that the cup's color is [green or yellow].

Considering the guesses of the other people, which cup do you think was used in the current round?

- Yellow cup
- Green cup

E.3.4 Stage 3: Information Processing

Instructions. This stage consists of six rounds of the task "Guessing which cup is used" that resembles the task in stage 2.

At the beginning of each round, we will again use the computer to simulate the random selection of a "cup". As before, there are two cups, with different mixes of colored marbles, and you will be asked to guess the cup that is being used. You will not be told in advance which cup is being used. A new die throw occurs in each round, which determines the cup used for that round.

Details: Once the computerized die throw determines the cup to be used, you will be shown a randomly selected marble from that cup.

Furthermore, you will be shown the guesses of two other participants from October 2020 whose marble has been drawn from the same cup as yours. Note that (i) after showing a randomly selected marble to a participant, the marble is put back into the cup, before the computer randomly selects and shows a marble to the next person, i.e., you and the other two participants may have seen the same or different marble(s), and (ii) the other two participants did not see each other's guesses.

You will then get a chance to indicate the cup that you think is being used. Your monetary payoff will depend on whether your guess turns out to be correct. You will earn $1 for a correct guess, and zero otherwise. At the end of the experiment, one of the six rounds in this stage will be randomly selected for payment.

Round 1 of 4

Guesses of other people whose marble has been drawn from the same cup as yours

Person 1, party affiliation and party image [donkey or elephant]

Person 1 guesses that the cup's color is [green or yellow].

Person 2, party affiliation and party image [donkey or elephant]

Person 2 guesses that the cup's color is [green or yellow].

Your own marble The color of the marble that has been randomly drawn for you is [green or yellow].

Considering the guesses of the other participants and the marble shown to you, which cup do you think was used in the current round?

- Yellow cup
- Green cup

Please answer the following question: How have you come up with your decisions in the previous 4 rounds?

Next we ask you to make 2 more decisions in a similar fashion as before.

Round 1 of 2

Guesses of other people whose marble has been drawn from the same cup as yours

Person 1

Person 1 guesses that the cup's color is [green or yellow].

Person 2

Person 2 guesses that the cup's color is [green or yellow].

Your own marble The color of the marble that has been randomly drawn for you is [green or yellow].

Considering the guesses of the other participants and the marble shown to you, which cup do you think was used in the current round?

- Yellow cup
- Green cup

E.3.5 Stage 4: Information Demand - Signal vs. Guess

Instructions This stage consists of two more rounds of the task "Guessing which cup is used" that resembles previous tasks.

At the beginning of each round, we will again use the computer to simulate the random selection of a "cup". As before, there are two cups, with different mixes of colored marbles, and you will be asked to guess the cup that is being used. You will not be told in advance which cup is being used. A new die throw occurs in each round, which determines the cup used for that round.

Details: At the beginning of each round, you will get to choose the likelihood that you see a randomly drawn marble from that cup, or another participant's guess who saw a randomly selected marble from the same cup as yours.

A slider indicates the likelihood that you will see a marble from your cup or another person's guess whose marble has been drawn from the same cup as yours. The default probability is 0.5. That is, each is equally likely to be selected. You have a 40-cent budget which you can use to change the probabilities. Moving the slider to the left increases the probability that you see a marble drawn from the cup, whereas moving the slider to the right increases the likelihood that you see another person's guess. It costs 10 cents to change the probability by 10 percentage points. The remaining budget will be paid out to you at the end of the experiment.

Based on the probability you choose, the computerized die throw determines whether you will be shown a randomly selected marble from that cup or another person's guess.

You will then get a chance to indicate the cup that you think is being used. Your monetary payoff will depend on whether your guess turns out to be correct. You will earn $1 for a correct guess, and zero otherwise. At the end of the experiment, one of the two rounds in this stage will be randomly selected for payment.

E.3.6 A final questionnaire

The final part of the experiment consists of a questionnaire. Please read each question carefully and answer it truthfully.

Once you have answered all questions, please press the "Next" button on your screen.

Please answer the following questions.

- Which state do you live in? (drop-down menu)
- Who did you vote for in the 2020 presidential election?
  - Joe Biden
  - Donald Trump
  - Other
- Do you think that the 2020 presidential election was rigged? (yes/no)
- Think of a ladder as representing where people from different groups stand in our society. At the top of the ladder are the people who have the highest standing in society. At the bottom are the people who have the lowest standing in society.
  - Where would you place Democrats on this ladder? (value from 1-10, where 10 represents the top of the ladder and 1 the bottom)
  - Where would you place Republicans on this ladder? (value from 1-10, where 10 represents the top of the ladder and 1 the bottom)
- On January 26, 2021, President Biden said that his administration was nearing a deal with two manufacturers that would enable 300 million Americans to have their shots by the end of the summer.
- Have you received a vaccine shot? (yes/no)
- If not, do you intend to get vaccinated when the opportunity arrives? (yes/no)

- Do you think close to 300 million Americans will have their shots by September 1, 2021? (yes/no)

E.4 Screenshots Wave 2

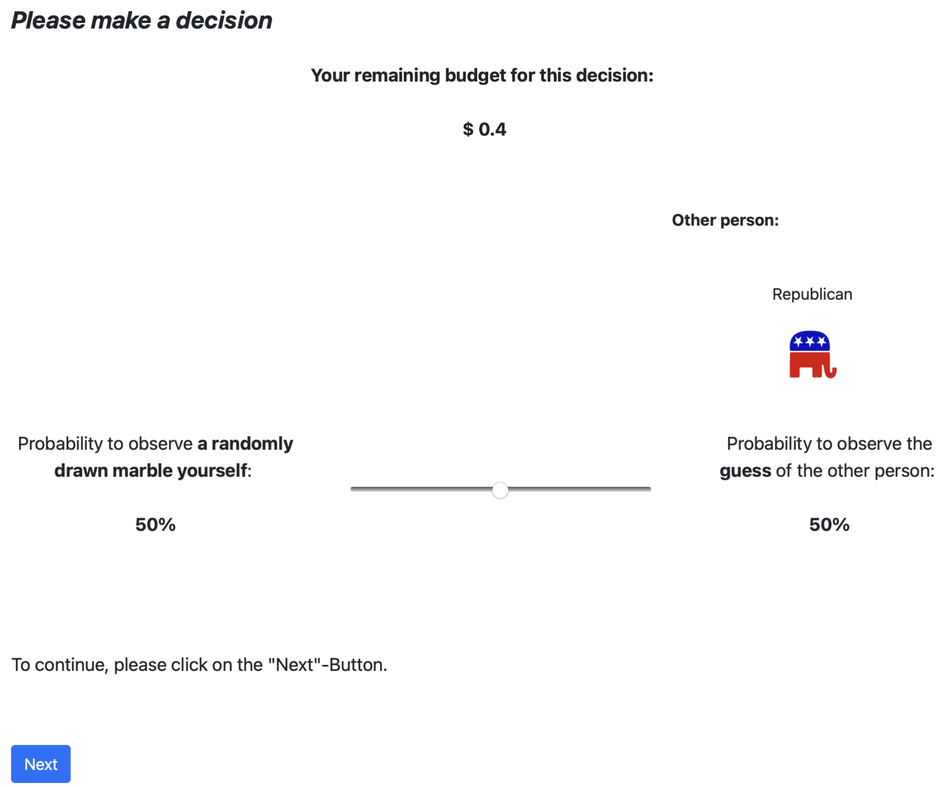

Figure E.15: Interface demand stage; marble v. guess (wave 2).

Notes: We depict the interfaces baseline and treatment participants encountered in wave 2 in the demand stage, when they had to choose between observing a marble themselves or the guess of another participant.

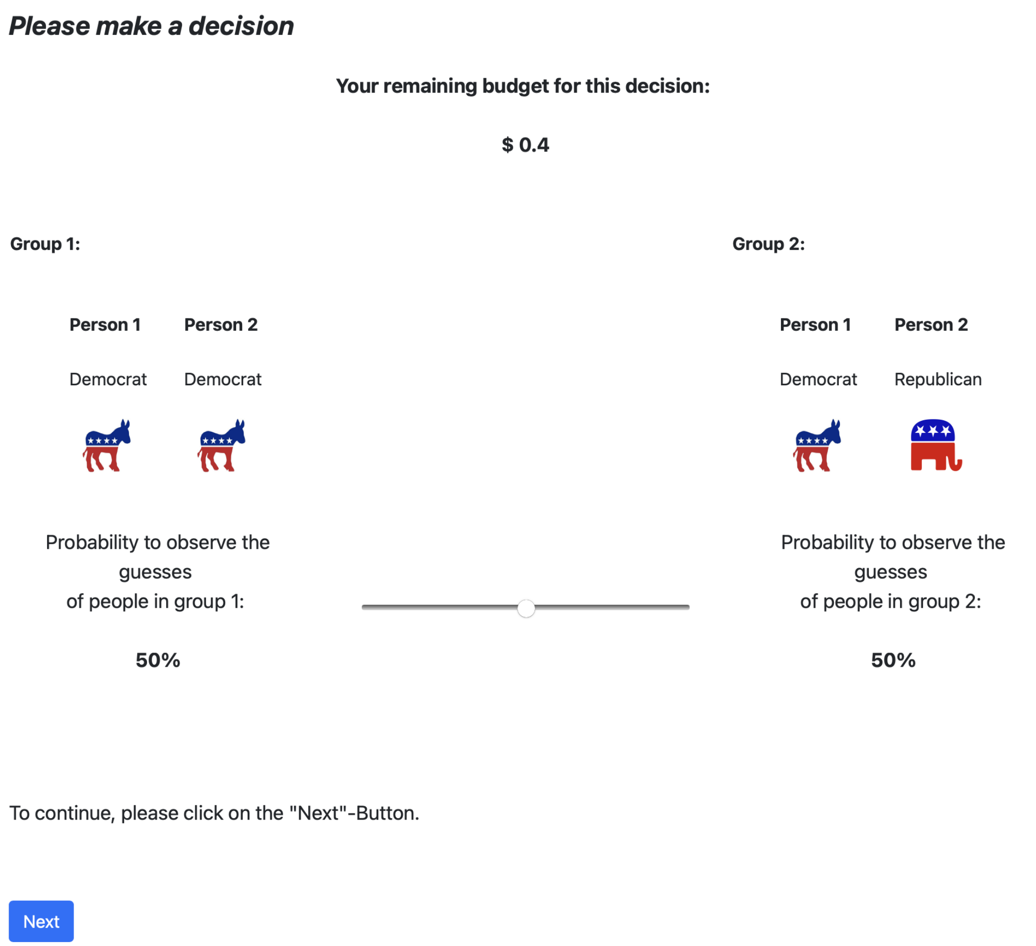

Figure E.16: Interface demand stage; guess v. guess (wave 2).

Notes: We depict the interfaces baseline and treatment participants encountered in wave 2 in the demand stage, when they had to choose between observing guesses from different participants.

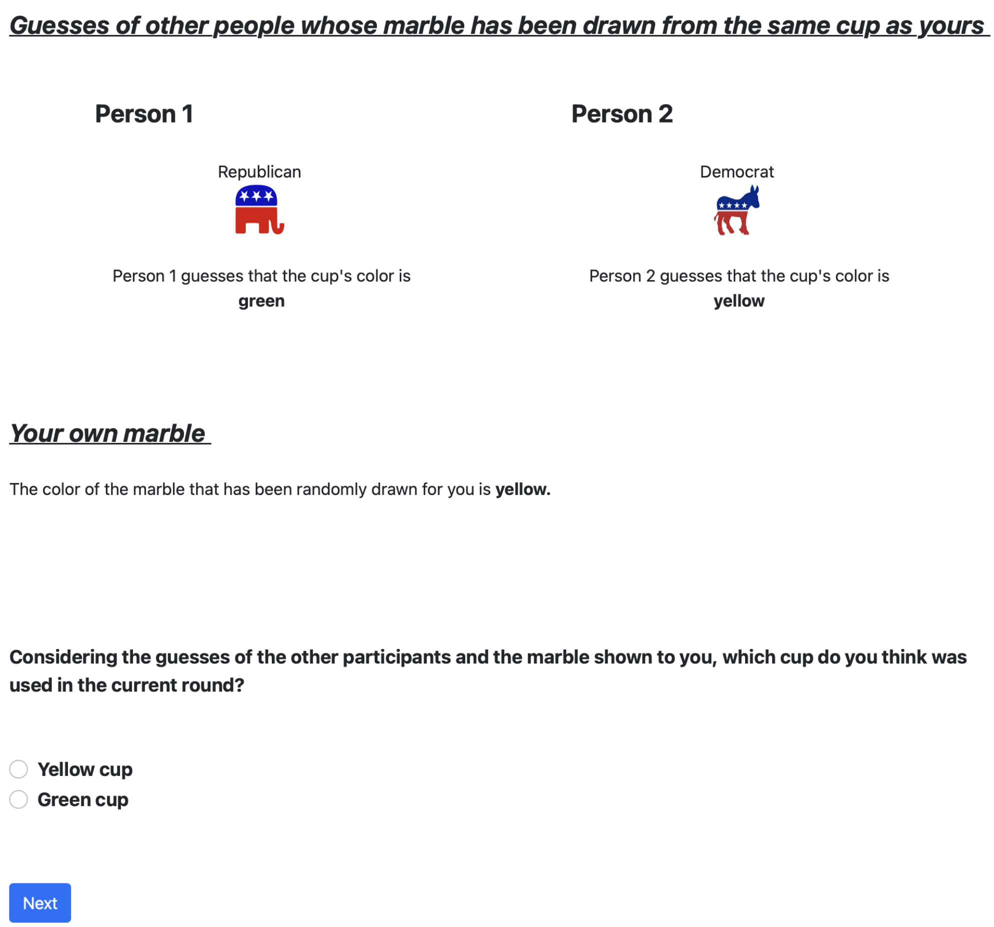

Figure E.17: Interface processing stage (wave 2).

Notes: We depict the interfaces baseline and treatment participants encountered in wave 2 in the processing stage.

E.5 Instructions Wave 3

E.5.1 Preamble

Welcome back!

Third part of research study from October, 2020

Invitation to participate in part 3 of the research study: Researchers from Goethe University Frankfurt, Johannes Gutenberg University Mainz, Leibniz Research Institute SAFE, and the University of Michigan invite you to be part of the third part of an online research study. You already participated in the first and second part of this study at the end of October 2020, and January 2021, respectively. As a reminder: The study's overall objective is to better understand how different types of information affect our judgment and decisions. The study is funded by the three universities and SAFE.

Content of third part of study: In this third part of the study, we will pay out income that you generated in the first part of the study in October 2020 when you made predictions about the development of unemployment numbers in the US and the ranking of the US health system.. We will inform you about this income at the end of the experiment. Additionally, we ask you to answer several questions that will help us better understand how different types of information affect our judgment and decisions. The total time taken today is estimated to be about 20 minutes.

Benefits of participation: We pay out income that you generated in a previous part of this study. During this part, you will also have the opportunity to earn an income that will be paid to you after the experiment. The amount of income you earn depends on your decisions and the decisions of other participants in the experiment. Note: You can only be paid if you complete the entire experiment. In addition to you directly benefiting from being in this study, others may benefit from public policy that is informed by the results of this study.

Confidentiality: The results of this study will be published in a scientific journal. We will not include any information that would identify you. Your privacy will be protected and your research records will be confidential. It is possible that other people may need to see the information you give us as part of the study, such as organizations responsible for making sure the research is done safely and properly like the University of Michigan.

Storage and Future Use of Data. Participating in this study is completely voluntary. Even if you decide to participate now, you may change your mind and stop at any time. Your data will not be used if you abandon the survey before reaching the end. We will store your responses for possible use in future research studies, for a period of up to ten years. Your responses will be secured and stored at the University of Michigan School of Information. Only the researchers involved in this study will have access to your research files and data. Research data may be shared with other investigators but will never contain any information that could identify you.

The Institutional Review Board (IRB) of the Goethe University Frankfurt and Johannes Gutenberg University Mainz has determined that this research is exempt from IRB oversight.

If you have any questions about this study, please contact the research team via the chat provided by Prolific. A member of the research team will see your question and reply. If you have questions about this research after completing the study, including questions about your compensation for participating, you may contact the research team via Prolific.

E.5.2 Stage 1. Other-Other allocation games, questionnaire, prediction updating

Structure of the experiment. There is no deception in this experiment - and we want you to understand everything about the procedures. The amount of money you earn will depend upon the decisions you make and the decisions other people make. This experiment consists of four stages and your total earnings will be the sum of your payoffs in each stage.

1. An other-other allocation game based on minimal groups

Choice task in stage 1. Before the experiment starts, every participant is randomly assigned to one of two groups, Triangle or Circle. Half of the participants are assigned to the Triangle group, while the other half to the Circle group.

You are a member of the Circle group. [Display of a green circle.]

Instructions: In stage 1 of the experiment, you will be asked to make decisions in three scenarios. For each scenario, you will have $6. You will be asked to allocate these $6 between two other participants under three scenarios:

- if both are from your own group (Circle group)
- if both are from the other group (Triangle group)
- if one is from your own group (Circle group), and one is from the other group (Triangle group).

For each scenario, you must allocate all dollars between the two participants. Allocations have to be integers. You can not allocate any dollars to yourself. Your answers will be used to determine other participants' payoffs. Similarly, your payoff will be determined by others' allocations.

[Decision Screen: Each participant makes three decisions, each involving splitting $6 between two other participants in the amount of ($1, $5), . . ., ($5, $1).]

2. A political identity survey.

Please answer the following question:

- Since your participation in our experiment in January 2021, your political party affiliation, leaning, or strength of affiliation:
  - remains the same
  - has changed
- Do you consider yourself a(n):
  - Democrat
  - Republican
  - Independent
  - None of the above
- (Conditional on choosing option a or b) Are you a strong or moderate Democrat/Republican?
  - Strong
  - Moderate
- (Conditional on choosing option c or d) Do you consider yourself closer to the:
  - Democratic party
  - Republican party
- Since your participation in our experiment in early November, your political party affiliation, leaning, or strength of affiliation:
  - remains the same
  - has changed
- What is your vaccination status?
  - I am fully vaccinated (2 shots BionTech-Pfizer/Moderna, 1 shot Johnson&Johnson)
  - I have received my first out of two vaccine shots (1 shot with BionTech-Pfizer/Moderna)
  - I have not gotten vaccinated, but plan to receive one in the foreseeable future
  - I have not gotten vaccinated, and I do not plan to receive one in the foreseeable future
  - I cannot get vaccinated.
- (Open text conditional on choosing option d) Please explain briefly, why you do not intend to get vaccinated in the foreseeable future.

3. Affective polarization measures

- How comfortable are you having close personal friends who are Democrats/Republicans? (opposing party, conditional on personal party affiliation)
  - Not at all comfortable
  - Not too comfortable
  - I feel neutral about it
  - Somewhat comfortable
  - Extremely comfortable
- How comfortable are you having neighbors on your street who are Democrats? (opposing party, conditional on personal party affiliation)
  - Not at all comfortable
  - Not too comfortable
  - I feel neutral about it
  - Somewhat comfortable
  - Extremely comfortable
- Suppose a daughter or son of yours was getting married. How would you feel if she/ he married a supporter of the Democratic party? (opposing party, conditional on personal party affiliation)
  - Not at all comfortable
  - Not too comfortable
  - I feel neutral about it
  - Somewhat comfortable
  - Extremely comfortable

Instructions: We would like you to rate how you feel toward Republican and Democratic voters, Republican and Democratic candidates and elected officials, and the Republican and Democratic parties in general on a scale of 0 to 100, which we call a 'feeling thermometer'.

On this 'feelings thermometer' scale, ratings between 0 and 49 degrees mean that you feel unfavorable and cold (with 0 being the most unfavorable/coldest). Ratings between 51 and 100 degrees mean that you feel favorable and warm (with 100 being the most favorable/ warmest). A rating of 50 means you have no feelings one way or the other.

Using the 'feeling thermometer', how would you rate your feeling toward Republican voters, Republican candidates and elected officials, and the Republican party in general?
(Slider from 0-100)

Using the 'feeling thermometer', how would you rate your feeling toward Democratic voters, Democratic candidates and elected officials, and the Democratic party in general?
(Slider from 0-100)

Now we would like to know more about what you think about Democratic (Republican) voters, Democratic (Republican) candidates and elected officials, and the Democratic (Republican) party in general. Below we have given a list of words that some people might use to describe them.
For each word, please indicate how well you think it applies to Democratic (Republican) voters, Democratic (Republican) candidates and elected officials, and the Democratic (Republican) party in general. (Participants have to answer questions for both, Democrats and Republicans)

- Patriotic:
  - Not at all well
  - Not too well
  - Somewhat well
  - Very well
  - Extremely well
- Intelligent:
  - Not at all well
  - Not too well
  - Somewhat well
  - Very well
  - Extremely well
- Honest:
  - Not at all well
  - Not too well
  - Somewhat well
  - Very well
  - Extremely well
- Open-minded:

- Not at all well
- Not too well
- Somewhat well
- Very well
- Extremely well

- Generous:
  - Not at all well
  - Not too well
  - Somewhat well
  - Very well
  - Extremely well
- Hypocritical:
  - Not at all well
  - Not too well
  - Somewhat well
  - Very well
  - Extremely well
- Selfish:
  - Not at all well
  - Not too well
  - Somewhat well
  - Very well
  - Extremely well
- Mean:
  - Not at all well
  - Not too well
  - Somewhat well
  - Very well
  - Extremely well

- How much of the time do you think you can trust Democratic voters, Democratic candidates and elected officials, and the Democratic party in general to do what is right for the country?
  - Almost never
  - Once in a while
  - About half the time
  - Most of the time
  - Almost Always

The following questions either say Republican or Democrat, conditional on participants own stated partisanship.

- How important is being a Republican (Democrat) to you?
  - Not at all important
  - Not very important
  - Somewhat important
  - Very important
  - Extremely important
- How well does the term Republican (Democrat) describe you?
  - Not at all well
  - Not too well
  - Somewhat well
  - Very well
  - Extremely well
- When talking about the Republican (Democratic) party, how often do you use ’we’ instead of ’they’?
  - Never
  - Rarely
  - Sometimes
  - Most of the times
  - All of the times
- To what extent do you think of yourself as a Republican (Democrat)?

- Not at all
- Not too much
- Somewhat
- A good deal
- Completely

- You are a Republican because you are more:
  - For what the Republican party represents
  - Against what the Democratic party represents

4. An other-other allocation game based on political groups In this part of the experiment, you will be asked to make decisions in three scenarios. For each scenario, you will have $6. You will again be asked to allocate these $6 between two other participants under three scenarios.

- if both are Democrats;
- if both are Republicans;
- if one is a Democrat, and the other a Republican.

Whether someone is labeled as Democrat or Republican depends on her/his responses to the previous questions in the current part of the study:

Democrats and those closer to the Democratic party are labeled Democrats. Similarly, Republicans and those closer to the Republican party are labeled Republicans.

[Decision Screen: Each participant makes three decisions, each involving splitting $6 between two other participants in the amount of ($1, $5), . . ., ($5, $1).]

5a. Social identity questions

- How important do you consider your political identity as part of who you are?
  - Not at all important
  - Not very important
  - Somewhat important
  - Very important
  - Extremely important
- How important do you consider your gender identity as part of who you are?
  - Not at all important

  - Not very important
  - Somewhat important
  - Very important
  - Extremely important

- How important do you consider your race identity as part of who you are?
  - Not at all important
  - Not very important
  - Somewhat important
  - Very important
  - Extremely important

- How important do you consider your American identity as part of who you are?
  - Not at all important
  - Not very important
  - Somewhat important
  - Very important
  - Extremely important

- How much do you identify with the state in which you currently live?
  - Not at all
  - Weakly
  - Moderately
  - Strongly

5b. Rosenberg self-esteem scale.

- At times I think I am no good at all.
  - Strongly Disagree
  - Disagree
  - Agree
  - Strongly Agree

- I wish I could have more respect for myself.

  - Strongly Disagree
  - Disagree
  - Agree
  - Strongly Agree

- On the whole, I am satisfied with myself.
  - Strongly Disagree
  - Disagree
  - Agree
  - Strongly Agree

- I am able to do things as well as most other people.
  - Strongly Disagree
  - Disagree
  - Agree
  - Strongly Agree

- I feel that I have a number of good qualities.
  - Strongly Disagree
  - Disagree
  - Agree
  - Strongly Agree

- I take a positive attitude toward myself.
  - Strongly Disagree
  - Disagree
  - Agree
  - Strongly Agree

- I feel that I'm a person of worth, at least on an equal plane with others.
  - Strongly Disagree
  - Disagree
  - Agree
  - Strongly Agree

- All in all, I am inclined to feel that I am a failure.
  - Strongly Disagree
  - Disagree
  - Agree
  - Strongly Agree
- I certainly feel useless at times.
  - Strongly Disagree
  - Disagree
  - Agree
  - Strongly Agree
- I feel I do not have much to be proud of.
  - Strongly Disagree
  - Disagree
  - Agree
  - Strongly Agree

6. Demographics.

- Please tell us your zip-code:
- Where would you place Democrats on this ladder? (value from 1-10, where 10 represents the top of the ladder and 1 the bottom)
- Where would you place Republicans on this ladder? (value from 1-10, where 10 represents the top of the ladder and 1 the bottom)
- Which do you think are your main sources of news?
  - ABC, NBC, or CBS
  - CNN
  - Local TV or radio
  - MSNBC
  - NPR (National Public Radio) or PBS
  - Newspapers, magazines, online or in paper
  - Facebook
  - Twitter
  - Other

7. Belief updating task

- What is your stand on mask wearing?
  - Strongly supportive
  - Supportive
  - Neutral
  - Against
  - Strongly against

Below, you find an article that we curated from the depicted news sources. The article contains information about the consequences of mask wearing. (Participants either read neutral, left- or right-leaning article)

Please take your time and read the article carefully. Afterwards, we will ask you to answer a multiple-choice question about the content. If you provide a correct answer to the question, we will pay you $1.

This article is curated from the following sources (Right-leaning: Washington Examiner, Fox News; Left-leaning: Washington Post, NBC News; Neutral:The Economist, Nature)

Right-leaning article: Surgical masks reduce COVID-19 spread: study

A new randomized controlled trial involving more than 340,000 people in Bangladesh assesses the effectiveness of wearing masks on reducing the spread of COVID-19. According to the Washington Examiner, "The researchers randomly assigned 600 villages in Bangladesh to two groups, with households in half of the villages receiving free masks, as well as education and training on proper mask use. The other half of the villages, the control group, did not receive any mask education. Researchers monitored the villages for mask use in the following weeks. The study found that the rate of mask-wearing was about 42% in the treatment villages, but only 13% in the control villages." (Washington Examiner, 9/1/2021). The article further states that blood tests confirmed a 9% reduction in the COVID-19 positivity rate for villages in the treatment group versus those in the control group.

Speaking of the same study, Fox News stated that those living in villages with mask interventions were less likely to contract COVID-19 and that, "The effectiveness increased to [a reduction of] nearly 35% for people over 60 years old." Their article further details that, "The study also looked at the effect of using cloth instead of surgical masks: Cloth masks did reduce the overall likelihood of experiencing symptoms of respiratory illness, but it was not as effective as using a surgical mask." (Fox News, 9/2/2021)

The Washington Examiner further mentions, "The study has several limitations. Because researchers did not take blood samples from those who did not report symptoms, the study was unable to determine if mild or asymptomatic infections were higher among villages with lower rates of mask use. Nor could the study rule out the possibility that those who consented to blood tests were in some important way different between the treatment and control groups, thereby biasing the results." (Washington Examiner)

Left-leaning article: Largest study of masks yet details their importance in fighting Covid-19

A new randomized controlled trial involving more than 340,000 people in Bangladesh assesses the effectiveness of wearing masks on reducing the spread of COVID-19. According to the Washington Post, "the researchers estimate that among a group of Bangladeshi adults in the study that were encouraged to wear masks, mask-wearing increased by 28.8 percentage points after the intervention. When tracked, this group saw a 9.3% reduction in symptomatic covid-19 seroprevalence, meaning that the virus was confirmed by bloodwork, as well as a further 11.9 percent reduction in covid-19 symptoms." The article stated that, "About 178,000 Bangladeshi villagers were in an intervention group and encouraged to wear masks. An additional 163,000 were in a control group, where no interventions were made," and the project "assessed the levels of mask-wearing and physical distancing through direct observations from plain-clothed staff in the community at mosques, markets and other gathering places." The article went on to quote one of the study's authors as saying that if masking were universal, the reduction would likely be much higher than 9.3%. (Washington Post, 9/1/2021).

According to NBC News, the authors of the study (which is under peer-review), said that "masks significantly reduced symptomatic infections among older adults" and found that "surgical masks were more effective than cloth versions." The article continues, "Kwong [one of the authors] said those findings may be especially important for countries such as the U. S. where people spend much more time indoors compared to those in rural Bangladesh." (NBC news, 9/1/2021).

Neutral article: Real-world evidence shows face masks reduce covid-19's spread

A new randomized controlled trial involving more than 340,000 people in Bangladesh assesses the effectiveness of wearing masks on reducing the spread of COVID-19. The Economist states, "Laboratory studies have shown that face coverings made of various materials block large amounts of the SARS-CoV-2 virus. But there is a dearth of data on how effective masks are in preventing actual covid-19 cases in real-life conditions, where masks are worn sporadically and, all too often, incorrectly. A large study published last month by a consortium of researchers from several think-tanks and American universities provides some useful evidence on the matter. It was conducted in Bangladesh, an unusually densely populated country, at a time when SARS-CoV-2 was circulating widely." The article further states, "Over the course of eight weeks observers stationed in public places around the villages recorded the frequency of mask-wearing. In those villages selected to receive masks and training, proper mask wearing increased to 42% of people counted. In those that didn't the rate was only 13% of people counted." (The Economist, 9/3/2021).

According to Nature, "The team found that the number of symptomatic cases was lower in treatment villages than in control villages. The decrease was a modest 9%, but the researchers suggest that the true risk reduction is probably much greater, in part because they did no SARS-CoV-2 testing of people without symptoms or whose symptoms did not meet the World Health Organization's definition of the disease." (Nature, 9/9/21).

According to The Economist, "The results were most striking among older people, who are the most likely to die of covid-19. The distribution resulted in a striking 35% reduction in confirmed symptomatic cases among people aged 60 or older." (The Economist)

- On a scale of -3 to +3, with negative numbers representing left leaning or liberal skew, positive numbers representing right leaning or conservative skew, and 0 representing neutral, how would you rate the article you just read?
- On a scale of 1 to 7, 1 being not reliable at all and 7 being very reliable, how would you rate the information in the article you just read?
- The reduction in symptomatic covid-19 infections after the mask intervention was greater for older adults than for other age groups.
  - False
  - True
- What is your stand on mask wearing?
  - Strongly supportive
  - Supportive
  - Neutral
  - Against
  - Strongly against

8. Digital Footprint

- What is the domain of your personal email, i.e., the part of an email address that comes after the @ symbol?
  - gmail.com/ googlemail.com
  - yahoo.com
  - hotmail.com

  - outlook.com
  - msn.com
  - inbox.com
  - aol.com
  - iCloud.com
  - Other

- Who is your Internet Service Provider?
  - AT&T
  - Xfinity
  - CenturyLink
  - Verizon
  - Charter Spectrum
  - Frontier Communications
  - Other

- What is the brand of the electronic device you use to participate in this study?
  - Apple
  - Samsung
  - Microsoft
  - Google
  - Huaweii
  - LG
  - Lenovo
  - Other

- How do you typically access news websites?
  - Via search engines such as Google or Yahoo
  - Directly by entering the web address in my browser
  - Via links from social media
  - Other

- What operating system has the electronic device you use to participate in this study?

- macOS/iOS
- Microsoft Windows
- Linux
- Android
- Chrome OS
- Ubuntu
- Other

- What is your preferred web browser?
  - Opera
  - Safari
  - Chrome
  - Edge
  - Samsung Internet
  - Firefox
  - Other

9. An other-other allocation game based on states In this part of the experiment, you will be asked to make decisions in three scenarios. For each scenario, you will have $6. You will again be asked to allocate these $6 between two other participants under three scenarios.

- if both participants live in the same state as you;
- if both live in a different state as you do (they live in the same state though);
- if one lives in the same state as you, and the other in a different state.

[Decision Screen: Each participant makes three decisions, each involving splitting $6 between two other participants in the amount of ($1, $5), . . ., ($5, $1).]

10. Payment information about predictions: In the previous part of this study, you made the following prediction about the development of the unemployment numbers in the US (example answers and outcomes for illustration):

Question: What will the unemployment rate be in September 2021 if Joe Biden wins the election in November 2020?

Your prediction: Stable (Higher than or equal to 7.5%, but less than 8.5%).

The correct answer: The unemployment rate in September 2021 was equal to 4.8%. Hence, the correct answer is ”strong decline”.

Hence, your prediction is incorrect

In the previous part of this study, you made the following prediction about the development of the US healthcare system in the ranking of the US News and World Report:

Question: What will be the ranking of the United States in September 2021 if Joe Biden wins the election in November 2020?

Your prediction: Moderate improvement (Rank 13 or 14).

The correct answer: The U.S. ranked No. 22 in September 2021, falling seven spots on the list compared to October 2020. Hence, the correct answer is ”strong decline”

Hence, your prediction is incorrect

For every correct prediction, we will pay you $10 in addition to the income you that you earned in the current part of the study. Given your predictions, you receive an income of $0.

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