Abstract

Can voters who know little about their representatives’ actions in office effectively hold them accountable? An influential perspective argues that voters are able to infer their representatives’ actions using heuristics—cognitive shortcuts that allow reasonably accurate inferences to be made from limited information. Interest group ratings are among the most common examples of such heuristics named in the literature and are frequently present in real-world politics. In a series of nine studies across four original samples, we show that information about interest group ratings can have surprisingly pathological effects on voters’ judgments. In our studies, voters shown interest group ratings are typically no more accurate at inferring their Member of Congress’ votes, nor do they appropriately adjust their views of their representatives. But voters do often engage in heuristic projection: voters act as if interest groups share their own views on average, and approve of their representatives more when they learn their representatives received favorable interest group ratings regardless of the groups issuing those ratings—even when their representatives earn favorable ratings by casting votes that voters disagree with.

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Democratic accountability hinges on voters’ ability to reward and punish their representatives for taking actions they approve and disapprove of (Fearon 1999). However, typical voters know little about their representatives’ actions in office (Converse 1964; Delli-Carpini and Keeter 1997). This has long left many scholars pessimistic about the potential for voters to “control” (Miller and Stokes 1963) their representatives (e.g., Achen and Bartels 2016; Tausanovitch and Warshaw 2018; Gilens 2012; Clinton 2006).

An influential claim in the study of democratic accountability is that many relatively uninformed voters are, nevertheless, able to behave as if they were informed about their representatives’ actions—and thus effectively hold their representatives accountable—by using heuristics. Heuristics are “cognitive shortcuts” that voters are thought to use to infer representatives’ actions or traits based on limited pieces of information (Popkin 1994). Perhaps the most common example of a heuristic named in the literature is inferences voters are thought to make about politicians from how special interest groups (SIGs) rate them. Arceneaux and Kolodny (2009) ably summarize this influential perspective:

...to make good decisions, low-information voters need only look to someone who has an incentive to possess accurate information about the candidate (Lupia and McCubbins 1998). Issue advocacy groups are well suited to fill this role, because they have a strong incentive to know how the candidate votes on the issues important to their group. In fact, the group need not even be aligned with the voters’ interests, because signals from opposition groups can also be informative by indicating whom the voter should not support... (p. 757)

Such SIG positions are a common feature of politics, frequently appearing in advertisements, on candidate websites, and in candidacy statements in official voter guides. For example, Druckman, Kifer and Parkin (2019) find that the average Congressional incumbent features 10 endorsements on their campaign website. In addition, SIGs often advertise their own evaluations of
politicians during campaigns, especially following *Citizens United* [Petrova, Simonov and Snyder 2019]. In line with traditional theories of heuristics, campaign finance scholars have argued seeing which SIGs support which candidates through advertising may help inform voters about candidates (for review, see Wood 2018). In light of the frequent appearance of SIG ratings in campaigns and the strong theoretical reasoning that voters should be able to make inferences about politicians based on which SIGs support and oppose them, SIG ratings may play an important role in maintaining democratic accountability (Arceneaux and Kolodny 2009).

There is, however, another possibility that existing literature has not considered to our knowledge. Based on insights from classic theories of interest groups and from research in psychology, we argue that SIG endorsements could often undermine accountability. First, classical theories predict that interest groups typically form to support policies favored by concentrated groups but opposed by many in the broader public (Olson 1971; Bawn et al. 2012; Hertel-Fernandez 2014; Hacker and Pierson 2002). Many SIGs may therefore seek to frustrate the public’s ability to use their ratings, scorecards, or endorsements of politicians as “signals...indicating whom [voters] should not support” (Arceneaux and Kolodny 2009, p. 757). To do so, SIGs may name and otherwise advertise themselves so to appear to have broad, cross-ideological appeal. And indeed, real SIGs have names such as “FreedomWorks,” “Federation for American Immigration Reform,” and the “American Energy Alliance” that voters may not only be unfamiliar with but, regardless of their own views, may interpret as indicating that these SIGs share their own interests and values. Voter psychology might assist SIGs in this aim: voters may be susceptible to false consensus, wherein they assume others share their views [Ross, Greene and House 1977; Mutz 1998; Conover and campaign website. In addition, in our own analysis of data from the 2008 Wisconsin Advertising Project data, we find that 22% of 2008 US House elections in the data feature one of the candidates noting a SIG endorsement or rating in their television advertisements, as compared with only 15% of elections where candidates feature endorsements from other politicians.]

[2] For example, reviewing conventional wisdom in the literature, Druckman, Kifer and Parkin (2019) summarize endorsements as “a common method by which voters infer [candidates’] issue positions.”

[3] Groups may create such ratings for many reasons, such as for the narrow audience of their members or contributors [Rapoport, Stone and Abramowitz 1991].
in a process of attribute substitution (Kahneman and Frederick 2002), wherein they focus on the positive or negative valence of a SIG rating when they are not familiar with a SIG. This could result in what we call heuristic projection: when voters respond to SIG ratings as if SIGs share their own preferences even when they know nothing about the SIG. Such behavior could produce perverse incentives for politicians, producing incentives for them to earn positive ratings from SIGs by taking positions SIGs support but that voters disagree with.

In this paper, we examine the standard view of heuristics as helpful and the possibility of this novel pathology. Do interest group ratings usually buttress electoral accountability in the way many scholars hope? Or can they also act more pathologically, undermining accountability because voters reward their representatives for earning positive ratings from essentially any SIG, even when their representatives earn these ratings by casting votes that voters disagree with?

Across a series of studies, we find considerable support for the pathology. Voters, we find, are rarely aware of SIG’s actual stances nor do they accurately use information about SIG ratings to infer their representatives’ actions. The exceptions only occur for the rare groups with clear names (e.g., “NARAL Pro-Choice America”) and with the National Rifle Association (NRA), where we do find evidence consistent with classic heuristics theory. However, heuristic projection is widespread when voters learn about ratings from most SIGs. Voters often assume that SIGs share their own views, and hence, when they see their representatives earn positive ratings from SIGs, think their representatives have cast more votes aligned with their own views and approve of their representatives more—even when their representatives actually earned these favorable SIG ratings by casting votes voters disagree with and from SIGs not aligned with voters’ views.

We draw this surprising conclusion from a series of nine studies from four original samples. Our studies rely on a diverse set of approaches that entail different assumptions and have com-
plementary strengths and weaknesses. Despite their differences, our studies all point toward these same findings.

In a first pair of studies, we show that voters informed of actual special interest group (SIG) ratings of their actual Members of Congress (MCs) typically do no better at inferring how their MCs voted in Congress (Studies 1 and 2). Next, we show that informing voters of SIG ratings also fails to change their approval of how their MC is representing them in the direction it should: voters who learn an interest group on the opposite side of an issue from them gave their MC a high rating do not approve of their MCs less. Instead, consistent with heuristic projection, we find that voters reward their MCs for high SIG ratings and punish them for low SIG ratings regardless of whether these ratings come from SIGs that do not align with voters’ own views (Study 3).

In our final series of studies, we show that this may be because voters engage in heuristic projection: voters have little knowledge about the policy positions (Studies 4-5) or ideology (Studies 6-7) of the vast majority of SIGs. The little knowledge voters do have about SIG ideology is offset by projection, whereby voters on average assume that SIGs share their views (Study 8). Moreover, in an experiment, upon learning that their actual representatives received a positive rating from a SIG, voters are more likely to perceive that their representatives share their own views on issues, again regardless of the SIG issuing the rating (Study 9).

These findings suggest SIG ratings only rarely act to buttress electoral accountability; MCs appear to have little reason to fear that SIG ratings will alert voters to any out-of-step positions they take. But SIG ratings do often appear to undermine electoral accountability: voters reward MCs for earning positive ratings from SIGs by casting votes voters dislike (Study 3), perhaps because they on average assume they SIGs share their own views (Study 8) and therefore that MCs that earn SIG endorsements share their own views, too (Study 9). This pattern is discouraging for electoral accountability, but is exactly what SIGs themselves may hope for.

Our work is the first we are aware of to identify this pathology. Despite widespread claims in the heuristics literature that voters can make accurate inferences from information about SIG
ratings, relatively little empirical evidence has examined how voters actually use SIG heuristics to form judgments about their representatives in practice. Scholars note that it remains “a hard question...whether most people appropriately use” heuristics such as SIG ratings (Kuklinski and Quirk 2000 p. 156) and that “what types of information facilitate” voters voting on issues “remain unsettled questions” (Boudreau, Elmendorf and MacKenzie 2015, p. 853). Some studies have identified examples where voters change their candidate choices based on SIG endorsements in a manner predicted by heuristics theory (Arceneaux and Kolodny 2009; McDermott 2006), but this finding is not universal (Boudreau, Elmendorf and MacKenzie 2019; Lau and Redlawsk 2006).

Our studies are the first we are aware of to experimentally manipulate voters’ knowledge about actual SIG ratings of their actual representatives and to measure voter perceptions of dozens of SIGs.

In the pages that follow we present our original studies that support these conclusions. Due to the number of studies and samples we present in this paper, we review our studies and the samples they rely on in Table 1. We present data on the representativeness of all four of our samples in Online Appendix B.

Can Voters Use SIG Heuristics to Infer How Their MCs Voted?

We first present two studies investigating whether voters informed of an interest group endorsement more accurately infer their Member of Congress’ (MC’s) vote on a related issue. For example, when voters learn that the League of Conservation Voters has given their MC a perfect 100/100

5Most empirical work on the use of SIG ratings as heuristics focuses on how they affect how individuals form preferences about issues, such as in referendums (Boudreau and MacKenzie 2014, 2019; Brady and Sniderman 1985; Lupia 1994). However, in the case of referendums, it is usually difficult to determine whether SIG heuristics are improving decision-making because it is often unclear how voters “should” be expected to behave if fully informed; there is rarely a clear benchmark for what a “better” decision is in such elections. Studies involving candidate choice entail less ambiguity. For example, in our studies we can measure whether voters form more accurate judgments about the votes their MCs actually cast, such as whether information about ratings from environmental groups improve voters’ accuracy in inferring MCs’ votes on environmental issues. A related body of work has also considered how voters use other heuristics, such as politicians’ party or demographics, with mixed results (e.g., Dancey and Sheagley 2013; McDermott 1998).
Table 1: Summary of Samples and Studies In This Paper

<table>
<thead>
<tr>
<th>Study</th>
<th>Research Question</th>
<th>Sample</th>
<th>N</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Can voters infer representatives’ votes from SIG ratings?</td>
<td>MTurk</td>
<td>1,220</td>
<td>March - April, 2013</td>
</tr>
<tr>
<td>2</td>
<td>Can voters infer representatives’ votes from SIG ratings?</td>
<td>Sample Strategies</td>
<td>3,958</td>
<td>February 2018</td>
</tr>
<tr>
<td>3</td>
<td>How do SIG ratings affect voters’ approval of their MC?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Do voters know which policies SIGs support?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Do voters know which policies SIGs support?</td>
<td>SSI in CA</td>
<td>4,298</td>
<td>April 2013</td>
</tr>
<tr>
<td>6</td>
<td>Do voters perceive SIG ideology accurately?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Do voters perceive SIG ideology accurately?</td>
<td>Lucid</td>
<td>3,178</td>
<td>October 2017</td>
</tr>
<tr>
<td>8</td>
<td>Do voters project their own ideology onto SIGs?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Do voters naively interpret positive SIG ratings as a signal their MC shares their issue views?</td>
<td>Same as Studies 2-4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Details on sample representativeness are provided in Online Appendix B. Abbreviations: MC stands for Member of Congress; SIG stands for Special Interest Group.

rating, how does that affect their guess about how their MC voted on bills to repeal environmental protections?

Study 1

For our first study, we recruited 1,372 respondents through Amazon.com’s Mechanical Turk in March and April 2013. See Appendix B for statistics on representativeness. The experiment involved three treatment conditions and a control condition. In the control condition, we asked respondents to provide their best guess about their representative’s vote on one of seven issues, detailed in Table 2 with the following prompt: “Please give your best guess for the question be-
low: Did [respondent’s representative in the US House] vote for [policy text]?” Respondents could answer “yes”, “no”, or “abstained.” Since voters know their MC’s party when voting in real world elections—it is on the ballot—the first treatment condition exposed respondents to their representative’s party: “Did [respondent’s representative] vote for [policy text]? Before you answer this question, here’s some information you might find relevant: Your representative is a member of the [respondent’s representative’s party] Party.” The second treatment condition exposed respondents to interest group ratings (see Table 2) in place of the party cue from an interest group related to that issue. The cues varied by interest group, but generally took the form of “Representative [Rep.] received a score of [x]% from the [Interest Group],” and presented all available ratings from the previous four years. The third treatment condition presented respondents with both interest group ratings and their representative’s party. (In this experiment, we did not explain that SIG base these ratings on MC’s previous votes, but we did do so in Study 2.)

The policy summaries we provided to respondents are in the fourth column of Table 2. We determined each voter’s actual MC, and that MC’s votes, using data from Project Vote Smart (PVS). We selected interest group endorsements from those SIGs that rated the largest number of sitting MCs and who had the highest budgets. We matched 741 respondents to 278 MCs with SIG ratings and roll call votes.

If these interest group ratings helped voters form more accurate impressions of how their MCs voted, then the treatment group that received SIG rating statements should be more accurate than the control group, and the joint cue condition should be more accurate than those receiving only their MC’s party affiliation. However, this is not what we find. On average, respondents in the

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6 From the original 1,372 respondents, we lost 162 because they did not enter their nine-digit zip codes, 420 because we lacked SIG ratings for their MCs, and 49 because their MC was not in office during the votes. We assessed these prior to random assignment, except for the 49 with an MC not in office.

With half the sample, we randomly assigned which vote in the third column of Table 2 we asked about. For the other half of the sample, we assigned a vote based on respondents’ answers to a question of what “political issues would you say is most important to you personally?” This manipulation had no effect on accuracy. To simplify the presentation, we pool the results for these conditions and discuss the details after presenting the main results.

7 SIG ratings are in fact highly predictive of MC’s votes on these issues; on average a regression can predict votes on these issues correctly approximately 95% of the time.
Table 2: The issue area, interest group, House of Representatives bill identifier, survey prompt, and vote breakdowns for the six issues used in Study 1.

<table>
<thead>
<tr>
<th>Issue</th>
<th>Interest Group</th>
<th>Vote</th>
<th>Did your representative support...?</th>
<th>Dems in favor</th>
<th>Reps in favor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abortion</td>
<td>NARAL Pro-Choice America</td>
<td>HV 292 2011</td>
<td>“banning federal funding for elective abortions”</td>
<td>8.3%</td>
<td>97.5%</td>
</tr>
<tr>
<td>Energy</td>
<td>Chamber of Commerce, League of Conservation Voters</td>
<td>HV 650 2011</td>
<td>“building the new Keystone XL oil pipeline”</td>
<td>24.4%</td>
<td>96.7%</td>
</tr>
<tr>
<td>Trade</td>
<td>AFL-CIO</td>
<td>HV 283 2011</td>
<td>“the free trade agreement with Korea”</td>
<td>30.7%</td>
<td>90.5%</td>
</tr>
<tr>
<td>Environment</td>
<td>League of Conservation Voters</td>
<td>HV 249 2011</td>
<td>“preventing the Environmental Protection Agency from regulating greenhouse gases”</td>
<td>9.9%</td>
<td>97.9%</td>
</tr>
<tr>
<td>Guns</td>
<td>NRA</td>
<td>HV 842 2011</td>
<td>“allowing individuals to carry concealed firearms in all states if they have a licence in one state”</td>
<td>21.9%</td>
<td>94.6%</td>
</tr>
<tr>
<td>Healthcare</td>
<td>Chamber of Commerce</td>
<td>HV 14 2011</td>
<td>“universal healthcare”</td>
<td>1.6%</td>
<td>100%</td>
</tr>
</tbody>
</table>

control condition accurately reported their MCs’ votes 60% of the time. The top panel of Figure 1 shows the estimated effect on the proportion correct by condition, using a least squares regression and coding accuracy to 0/1. Being told MCs’ party affiliation improves accuracy by 0.10 (or 10 percentage points) over the control group ($p = 0.038$), but providing respondents with a SIG rating does not increase accuracy—if anything, it slightly decreases it relative to the control. The estimates are somewhat imprecise but when we estimate main effects for the SIG and the party conditions, with no interaction to increase precision, the point estimate for the interest group cue effect is close to zero, -0.0017, and the top of the 95% confidence interval is 0.066, implying that we can be reasonably sure the effect is smaller than a 6.6 percentage point increase.\(^8\)

An important wrinkle in this finding is that there is some heterogeneity among interest groups. Figure 1b shows change in respondents’ accuracy by treatment condition and interest group. Endorsements boost accuracy for “NARAL Pro-Choice America” and the NRA, but undermine accuracy for the League of Conservation Voters and the AFL-CIO. For the Chamber of Commerce and for the League of Conservation Voters endorsement related to the Keystone XL Pipeline, SIG ratings have effects close to zero. This mirrors findings in later studies that voters are aware of the NRA and interest groups with very clear names (e.g., “Pro-Choice”) but lack knowledge of essentially all other SIGs. This uneven pattern of accuracy even for very large and influential

\(^8\)Removing the NRA and “NARAL Pro-Choice America”, we find a 6.6 percentage point decrease in accuracy for the remaining groups, but this is only borderline significant ($p = 0.11$).
Figure 1: Study 1—Can respondents infer how their representatives vote using heuristics?

(a) Estimated Effects on Accuracy, Pooled Across SIGs

(b) Estimated Effects on Accuracy, by SIG/Issue

Notes: N=741. The top panel shows that providing respondents with special interest group ratings for their Member of Congress fails to improve respondents’ accuracy at identifying how their representative voted on key legislation (coded to 0/1). In contrast, providing them with their Member’s party affiliation does improve accuracy by about 0.10 (10 percentage points). Across the four conditions, the Ns are 191, 214, 154, and 182, respectively. The bottom panels show that this pattern varies somewhat across groups with NRA and NARAL ratings increasing accuracy but League of Conservation Voters (LCV), AFL-CIO, and Chamber of Commerce (CoC) reducing accuracy relative to the control group. Estimates are from least squares regression models with indicator variables for condition. 95% confidence intervals.

groups such as the AFL-CIO and League of Conservation Voters is consistent with our argument that voters usually have difficulty correctly using SIG ratings as heuristics and that they may even be pathological.

For most respondents, the SIG ratings sent a clear signal about how MCs voted, predicting votes with 95% accuracy. A small number of respondents did receive mixed signals. First, just over a dozen MCs had middling ratings (between 40 and 60). Second, since we showed SIG ratings from the previous four years, noticeable changes in ratings occurred, with 24 MCs experiencing ratings changes from under 50 to over 50. Finally, 31 MCs voted inconsistently with the ratings shown. To ensure that these mixed signals do not drive the findings, we discarded MCs whose average ratings were between 40 and 60, 30 and 70, 20 and 80, 10 and 90, whose ratings changed from below 50 to above 50,
Would respondents find the SIG ratings more helpful if they cared about the issue, perhaps because they are more familiar with the relevant SIGs? To explore this possibility, we asked before the experiment, “Which of the following issues would you say is most important to you personally?” Respondents could choose from a list of policies that matched the roll call votes we later asked them about, e.g., abortion, environment, guns and gun control, etc. Half of respondents were then asked about their MC’s roll call vote that corresponded to the policy they chose (for the other half, the issue was randomly assigned). Respondents shown a SIG rating were then, as before, shown a rating from a SIG relevant to that issue. If respondents can better use SIG ratings as heuristics on issues they care about, we should see the effect of providing a SIG rating on their accuracy increase. We do not find, however, any such effect. Even when respondents can choose their policy, Appendix C reports that the SIG ratings continue to slightly decrease accuracy relative to the control condition. There we also show that the results are unchanged for individuals high in political knowledge.\footnote{Finally, given the complexity of the design, we explored whether we could improve precision with random or fixed effects for Member and policy area and with probit regression, but the results remained unchanged.}

**Study 2**

Study 2 again considers whether informing voters of SIG ratings allows them to more accurately infer how their MC voted on roll call votes. Study 2 probes the generalizability of our findings from Study 1 on this question across time, additional SIGs, and in a larger and more representative sample. For Study 2, we gathered a national sample of 3,958 respondents recruited through Sample Strategies in February 2018. See Appendix B for statistics on representativeness. In this study we considered 17 issues that had been voted on in Congress and corresponding SIGs; each respondent saw questions about a random half of the issues to reduce survey fatigue. The large sample size of this study and the number of issues every respondent considered means we have 31,729 issue-and who voted out of line with their ratings. These robustness checks left the findings unchanged—the SIG-cue effect estimates remain stubbornly near zero and often negative.\footnote{Finally, given the complexity of the design, we explored whether we could improve precision with random or fixed effects for Member and policy area and with probit regression, but the results remained unchanged.}
respondent observations. The roll call votes and SIGs we used in this study are shown in Table 3. We again identified the roll call votes and SIGs using Project Vote Smart, selecting the interest groups in each issue area that rated the largest number of sitting MCs. In the study we showed respondents the title of every vote as well as short summaries we prepared, also shown in Table 3.

11 Online Appendix Figure A2 shows a histogram of all the ratings we presented by interest group. The SIG ratings were again typically very highly predictive of how MCs actually voted in this study. One exception is the “National Association of Police Organizations”, which, as shown in Figure A2, gave positive ratings to essentially every sitting Member of Congress. The National Active and Retired Federal Employees Association and Center for Security Policy also scored two Congressional votes that were highly lopsided, but their ratings nevertheless very highly predict votes on other issues. As shown in Figure 2, our findings are consistent across groups and are not sensitive to the removal of these groups.
<table>
<thead>
<tr>
<th>SIG Used</th>
<th>Corresponding Bill Title</th>
<th>Corresponding Bill Description Shown to Respondent</th>
</tr>
</thead>
<tbody>
<tr>
<td>National Rifle Association</td>
<td>Sportsmen’s Heritage and Recreational Enhancement (SHARE) Act of 2015</td>
<td>Allows individuals to fish and hunt on federal lands without a license, unless the lands are closed for conservation, public safety, or national security.</td>
</tr>
<tr>
<td>Human Rights Campaign</td>
<td>Prohibits Use of Funds for Discrimination Based on Sexual Orientation or Gender Identity</td>
<td>Prohibits the government from doing business with companies that discriminate against individuals based on sexual orientation or gender identity.</td>
</tr>
<tr>
<td>NARAL America Pro-Choice</td>
<td>No Taxpayer Funding for Abortion and Abortion Insurance Full Disclosure Act of 2017</td>
<td>Prohibits the use of any federal funds for health insurance that provides abortion services.</td>
</tr>
<tr>
<td>Gun Owners of America</td>
<td>Veterans 2nd Amendment Protection Act</td>
<td>Allows any veteran deemed mentally incompetent to buy and own firearms and ammunition, unless a judge deems them dangerous.</td>
</tr>
<tr>
<td>Campaign for Working Families</td>
<td>Working Families Flexibility Act of 2017</td>
<td>Allows employers to give employees who worked overtime paid time off instead of only overtime pay.</td>
</tr>
<tr>
<td>Chamber of Commerce</td>
<td>American Health Care Act of 2017</td>
<td>Repeals “Obamacare”: 1) Allows states to allow insurance companies to charge individuals more for insurance if they have a pre-existing condition. 2) Removes the requirement that Americans must carry health insurance. 3) Reduces amount given to low-income Americans to help them purchase health insurance.</td>
</tr>
<tr>
<td>National Association of Police Organizations</td>
<td>Thin Blue Line Act</td>
<td>Allows the death penalty in the case of a murder or attempted murder of police officers, correctional officers, firefighters, or other first responders.</td>
</tr>
<tr>
<td>League of Conservation Voters</td>
<td>Reducing Regulatory Burdens Act of 2017</td>
<td>Allows pesticides to be sprayed near water sources without obtaining a permit.</td>
</tr>
<tr>
<td>Club for Growth</td>
<td>Financial CHOICE Act of 2017</td>
<td>Allows banks of sufficient size to take additional risk, and limits the power of the Consumer Financial Protection Bureau to investigate banks.</td>
</tr>
<tr>
<td>National Active and Retired Federal Employees Association</td>
<td>Department of Veterans Affairs Accountability and Whistleblower Protection Act of 2017</td>
<td>Authorizes the Secretary of Veterans Affairs to demote, suspend, or fire senior Veterans Affairs employees for performance or misconduct, but forbids retaliation against whistleblowers.</td>
</tr>
<tr>
<td>Federation for American Immigration Reform</td>
<td>Kate’s Law</td>
<td>Increases criminal penalties for unauthorized immigrants who re-enter the United States after having been deported.</td>
</tr>
<tr>
<td>National Federation of Independent Businesses</td>
<td>No Sanctuary for Criminals Act</td>
<td>Prohibits giving federal grants to cities with “sanctuary” policies, policies cities enact to limit their cooperation with federal immigration law enforcement.</td>
</tr>
<tr>
<td>National Parks Conservation Association</td>
<td>Ozone Standards Implementation Act of 2017</td>
<td>Delays the implementation of a rule that would have reduced ozone pollution, allowing previous levels of pollution until 2026.</td>
</tr>
<tr>
<td>American Energy Alliance</td>
<td>Promoting Cross Border Energy Infrastructure Act</td>
<td>Allows oil and natural gas pipelines that cross into Canada or Mexico to be built without the President’s permission.</td>
</tr>
<tr>
<td>Center for Security Policy</td>
<td>Countering America’s Adversaries Through Sanctions Act</td>
<td>Places additional sanctions on Iran, Russia, and North Korea, as well as individuals who conduct business with these countries.</td>
</tr>
<tr>
<td>Freedomworks</td>
<td>Tax Cuts and Jobs Act</td>
<td>Reduces corporate taxes from 35% to 20% permanently. Temporarily reduces individual income taxes, with larger reductions for wealthier individuals. Increases the federal budget deficit by $1 trillion.</td>
</tr>
<tr>
<td>AFL-CIO</td>
<td>Save Local Businesses Act</td>
<td>If an employee working for a company through a ‘temp’ agency is injured, only the temp agency is responsible and not the company directing the worker day-to-day.</td>
</tr>
</tbody>
</table>
There was also an important difference between the design of this study and Study 1. In this study’s treatment group, although we again randomly assigned which of multiple SIG ratings we showed, we asked respondents to guess their MC’s votes on both a directly relevant issue and a number of unrelated issues (on which we could have shown them ratings from other interest groups, but did not). This means we can make two comparisons. We first compare how accurate voters were in our control condition, which was shown no SIG ratings, to how accurate voters were in our treatment condition when guessing how their MC voted on roll call votes directly related to the SIG rating they were shown. For example, we can test whether voters informed that their MC received a 100/100% rating from the League of Conservation Voters were any more accurate at inferring how their MC voted on the roll call vote we described as “Allows pesticides to be sprayed near water sources without obtaining a permit.” Second, we can compare how accurate voters were in the control group to how accurate voters were in the treatment group on other issues not directly related to the interest group rating they were shown. This will allow us to detect whether voters are able to, for example, infer that a positive rating from the League of Conservation Voters is also informative about how a Member voted on the other issues, such as the vote that “Prohibits the use of any federal funds for health insurance that provides abortion services.” We pre-registered these comparisons and how we would conduct them in a pre-analysis plan, provided in Online Appendix E.

To implement this experiment, we first asked respondents for their nine-digit zip code to determine their actual representative in the US House. We then told respondents “Your representative in Congress is [Name] ([MC Party]).” Treated respondents then saw this statement:

Various groups often provide “ratings” or “scorecards” of how much they approve the votes every Member of Congress has taken. We have compiled the “scorecards” of many such groups and have selected one at random to show you:

---

12 We always showed MC party in Study 2 because when voters make choices in elections, MC party is always available to them on the ballot (Bullock 2011).
To confirm that any findings are not driven by innumeracy, we next asked respondents what they thought the rating meant about whether the SIG usually “agreed or disagreed” with how their MC “voted in Congress.” As shown in Appendix Figure A3, respondents overwhelmingly understood that positive ratings indicate the SIGs usually agree with MC’s votes and the opposite for negative ratings.

Finally, we next asked respondents how they thought their MC voted on approximately eight bills Congress had voted on. Comparing how their MC actually voted with respondents’ perceptions of their MC’s votes allows us to compute our dependent variable for Study 2: whether respondents accurately identified each of their MC’s actual votes. In the control group shown no SIG ratings, respondents on average correctly identified 68% of their MC’s votes, a figure similar to the figure observed in Study 1 when MC party was provided (as it always was in Study 2). As random guessing would yield a 50% correct rate, this 68% figure implies that approximately 36% of respondents actually knew their MC’s vote on the average issue.

Analyzing the data from Study 2 correctly requires the presence of fixed effects. In Study 2 and the other studies that use this sample, when voters were randomly assigned to the treatment group that was shown a SIG rating, we randomly selected which SIG’s rating of their MC we then showed. As a result, among those shown SIG ratings, the probability of assignment to ratings from different groups, or that sent different signals, varied across respondents because their MCs varied in how many SIGs rated them. In the Studies that use data from this sample (2, 3, and 9), we therefore include fixed effects to ensure that all our comparisons are conducted among individuals who had the same probability of assignment to each kind of SIG rating treatment. For Study 2, these fixed effects are simply the number of SIG ratings available for each MC.

[13] If 36% of respondents actually knew their MC’s vote and the remaining 64% guessed randomly, we would anticipate observing $36% + \frac{1}{2} \times 64% = 68\%$ of respondents selecting the correct option, which is what we observe.

[14] Online Appendix Figure A1 provides an overview of the experimental design. The regressions for Study 2 take place at the respondent-issue level. We only include respondent-issue observations for issues for which a SIG rating
Figure 2a shows our estimates for whether providing a SIG rating improved respondents’ accuracy, using ordinary least squares regressions with the above mentioned fixed effects with the dependent variable coded 1 accurate, 0 inaccurate. First, on average, voters are actually 0.3 percentage points less accurate in identifying their MC’s vote on an issue when a rating from a relevant SIG is shown, a difference statistically indistinguishable from zero (SE = 1.5 percentage points, $t = -0.21$). As shown in Figure 2b, voters are also unable to accurately infer what the SIG ratings imply about their MC’s votes on other issues, with respondents only being 0.6 percentage points more accurate on other issues when shown an unrelated interest group rating versus when shown no interest group ratings whatsoever (SE = 0.9 percentage points, $t = 0.65$). However, Figure 2a shows that there are some limited exceptions where voters are able to make inferences about particular policies: the National Parks Conservation Association and potentially the NRA (the National Rifle Association). These are the exceptions to the rule. The NRA may be relatively alone in being an interest groups Americans are consistently familiar with, and the National Parks Conservation Association appears to have named itself to clearly indicate its position given its cause enjoys general support. However, these positive examples are offset by the other groups, which on average lead respondents to be less accurate.

We find similar results for individuals high in political knowledge. Some previous work finds that individuals high in political knowledge are more likely to use SIG heuristics (e.g., Lau and Redlawsk 2001; 2006; Boudreau and MacKenzie 2019). However, we find that voters who answered all four questions correctly on a political knowledge battery are only 2.6 percentage points more accurate when guessing an MC vote related to the SIG rating shown, which is both substant...
Figure 2: Study 2—Effect of Showing Each Interest Group’s Heuristic on Accurate Perception of MC’s Vote

(a) Treatment Effect of Seeing SIG’s Rating on Accurate Perception of MC’s Vote on Relevant Issue

(b) Treatment Effect of Seeing SIG’s Rating on Accurate Perception of MC’s Vote on Other Issues
tively small and statistically insignificant (SE = 2.6 percentage points, \( p = 0.30 \)). Individuals high in knowledge also show no sign of being able to use SIG ratings to infer how their MCs voted on other issues (\( \beta = -0.7 \) percentage points, SE = 1.1 percentage points, \( t = -0.65 \)). These nulls are not driven by a ceiling effect, as knowledge of roll calls was 77% for high knowledge respondents, consistent with 54% possessing actual knowledge when correcting for guessing.

We return to this data in Study 9, where we find that there is another, more surprising way that SIG heuristics do affect how voters perceive how their MCs voted.

**Study 3: Perverse Consequences of Interest Group endorsements**

Electoral accountability ultimately manifests when voters actually decide how to vote in elections. What do our findings indicate for how voters will use interest group heuristics when making their voting decisions? One possibility is that voters may not be able to understand the implications of SIG heuristics for particular roll call votes, but still may understand the broad signal sent by a SIG rating and update their approval of their Member of Congress as an optimistic understanding of heuristics would predict. Of course, it is also possible that voters, not understanding the implications of most interest group endorsements, will simply ignore them. We find evidence consistent that a third, perverse consequence is in fact more common: heuristic projection. In particular, we find that voters in fact interpret positive interest group ratings as sending positive signals about their representatives *regardless* of whether voters actually share that interest group’s view on issues. Likewise, when voters learn about negative ratings from SIGs that support policies voters disagree with, voters approve of their MC less, even though this is a signal to voters that their MC actually agrees with them.

To measure our dependent variable in Study 3, after showing the SIG heuristic in Study 2 we also asked participants a series of three MC approval questions: an approval question, a favora-
We combine these into an index standardized to standard deviation one, consistent with a pre-registration we filed (see Online Appendix E). This \textit{MC Support Scale} is our dependent variable in Study 2.

To understand how SIG ratings affect voters’ approval of their MCs, we define two treatment variables.

Our first treatment variable, \textit{SIG Rating Signals MC Matches Voter Issue Preference}, is coded 1 if a SIG rating was shown that sends a signal that a voter’s MC has cast a vote that matches the voter’s issue preference, which was asked at the beginning of the survey prior to treatment. A SIG rating is coded as sending a positive signal if an \textit{aligned} SIG issues a positive rating or a \textit{misaligned} SIG issues a negative rating, where a SIG is defined as aligned if it shares a voter’s issue preference. This treatment variable is instead set to 0 if the voter was shown a rating from another SIG that would send a signal that the voter’s MC cast a vote incongruent with the voter’s issue preference. A negative rating from an aligned SIG or a positive rating from a misaligned MC would send such a signal\footnote{Consistent with our pre-analysis plan (see Online Appendix E), we code all ratings 50 and below as negative and ratings 51 and above as positive. As shown in Figure A2, the ratings are largely bimodal. Only 0.5\% of ratings are exactly 50.}

Our second treatment variable, \textit{SIG Rating Supportive}, is simply coded as 1 if the rating is 51 or above and 0 if the rating is 50 or below, regardless of whether the SIG’s issue preferences are aligned with voters’ own or not.

Our design generates random variation in both of these treatment variables. For example, suppose a voter gave a liberal answer to a question about gun control and a conservative answer to a question about taxes. If this voter had a Republican MC, this MC would likely have cast conservative votes on both issues and had high ratings from both the NRA and FreedomWorks. If we randomly decided to show the NRA rating, this means the heuristic should send a negative signal about whether the MC matches the voter issue preference (corresponding with a value of 0).\footnote{Participants in the control condition were then exposed to material for another project, so we were unable to include control participants in this comparison. See Figure A1 for an overview of the design.}
the *SIG Rating Signals MC Matches Voter Issue Preference* treatment of 0). If we instead selected FreedomWorks, this MCs’ high rating should be interpreted as a positive signal about whether the MC matches the voter issue preference (corresponding with a value of the *SIG Rating Signals MC Matches Voter Issue Preference* treatment of 1). However, the positive ratings from the NRA and FreedomWorks would both count as positive ratings, meaning the *SIG Rating Supportive* treatment variable would be set to 1 in either case.

Table 4 summarizes these two treatment variables. Because most respondents have a mix of liberal and conservative views across issues, our random assignment of which SIG rating to show produces random variation at the respondent level in whether we showed respondents a SIG rating of the four possible types shown in Table 4. This is what allows us to test whether, for example, “signals from opposition groups can also be informative by indicating whom the voter should not support” (Arceneaux and Kolodny 2009); we can compare how voters behave when they are shown positive ratings from misaligned groups to how they behave when they see positive ratings from aligned groups.

**Table 4: Treatments in Study 3**

<table>
<thead>
<tr>
<th>SIG Rating Signals MC Matches Voter Issue Preference</th>
<th>SIG Rating Supportive</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Negative rating from aligned SIG (N = 223)</td>
</tr>
<tr>
<td></td>
<td>Negative rating from misaligned SIG (N = 210)</td>
</tr>
<tr>
<td>1</td>
<td>Positive rating from aligned SIG (N = 303)</td>
</tr>
<tr>
<td></td>
<td>Positive rating from misaligned SIG (N = 244)</td>
</tr>
</tbody>
</table>

Notes: A SIG is coded as aligned if that SIG’s issue preference matches the voter’s own issue preference as measured at the beginning of the survey. For example, an individual who favors gun control would be coded as misaligned with the NRA. Ns record the number of respondents actually shown heuristics of each type as a result of the random assignment in Study 3. Ns differ because the probabilities of receiving each treatment differs by respondent and MC, which our analysis takes into account using fixed effects for the probability of treatment.
To estimate the impact of SIG ratings on MC approval, we use regression to compare individuals randomly assigned to be shown ratings that send different signals and which are supportive and unsupportive. In our regressions we also include fixed effects for the average of these variables across all the comparisons that could have been shown; these have no interpretation but capture the endogenous relationship between the average value of treatments that could have been shown and the outcome.\footnote{Our causal identification comes from the random assignment of which SIG’s rating we showed, which produces variation in the signal sent by the rating shown. For example, conditional on an MC having three positive SIG ratings and four negative SIG ratings, our treatment variable is what signal the one randomly shown heuristic actually sent. However, this is only random conditional on the number of positive and negative ratings that could be shown, and so we include a control for this—e.g., in the previous example, the fact that only three of seven total possible heuristics were positive.}

To increase precision, we also include party identification as a control, coded such that the traditional 7-point scale is oriented so that more positive values correspond with greater identification with their MCs’ party.\footnote{We also pre-registered our specification and use of this control variable in our pre-analysis plan, provided in Online Appendix E. However, the pre-analysis plan did not specify that we would test whether the rating’s valence would have its own direct effect, as we find. As the $p$-value on this comparison is approximately 0.005, it would only be rendered insignificant under a Bonferroni correction if this were at least the tenth non-pre-registered comparison we ran. Our other deviation from the pre-analysis plan was to control for possible treatments using fixed effects, instead of a linear term, as we thought this would be less sensitive to functional form; the results are essentially identical when using a linear term.}

Table 5 presents the results. Column 1 shows that showing a rating that should send a positive instead of negative signal about issue alignment between the voter and their MC has no detectable effect on their support for their MC. Column 2, however, shows that seeing supportive instead of unsupportive ratings from interest groups in fact does boost voters’ support. Columns 3 and 4 shows that this finding survives when both coefficients are present in the same regression and in the presence of MC fixed effects.\footnote{For a separate project, we showed the control group how their Members of Congress actually voted on these issues. That project finds very large effects on the Member support scale of providing this information, indicating that our null results here are not due to voters being indifferent to the position information these interest group ratings imply.}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
Column & Result \\
\hline
1 & No detectable effect \\
2 & Positive ratings boost support \\
3 & Both positive and negative ratings have significant effects \\
4 & Positive ratings boost support in the presence of MC fixed effects \\
\hline
\end{tabular}
\caption{Results of regression analysis.}
\end{table}

We do not include the group shown no SIG endorsement at all in these comparisons because they were exposed to material from other project instead of asking them an MC approval question. They were assigned to this other project with $\frac{3}{4}$ probability, which is why the sample size in Table 5 is one fourth the size of the overall sample size. See Figure A1 for an overview of the design.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figureA1.png}
\caption{Overview of the design.}
\end{figure}

\footnote{Running the regression in Model 2 separately for aligned and misaligned interest groups yields similar estimates—that is, positive ratings from both aligned and misaligned groups yield similar increases in the MC approval scale. Although these coefficients are more imprecisely estimated than the omnibus regression, the coefficient for misaligned
Table 5: Study 3–Effect of SIG Rating Information on Support for Member of Congress

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Randomized Treatments</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shown SIG Rating Signals MC Matches Voter</td>
<td>-0.04</td>
<td>-0.06</td>
<td>-0.09</td>
<td></td>
</tr>
<tr>
<td>Issue Preference (0 = Signals MC Does Not Match / 1 = Signals MC Does Match)</td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.07)</td>
<td></td>
</tr>
<tr>
<td>Shown SIG Rating Supportive (0 = Unsupportive / 1 = Supportive)</td>
<td>0.12**</td>
<td>0.13**</td>
<td>0.17**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Control Variables for Precision</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Party ID Match (1-7)</td>
<td>0.29**</td>
<td>0.31**</td>
<td>0.29**</td>
<td>0.29**</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Fixed Effects for Possible Treatments?</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>MC Fixed Effects?</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>980</td>
<td>980</td>
<td>980</td>
<td>980</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.54</td>
<td>0.52</td>
<td>0.55</td>
<td>0.73</td>
</tr>
</tbody>
</table>

Notes: The dependent variable in all regressions is the pre-registered MC Approval Scale, rescaled to have standard deviation one. Standard errors in parentheses. * indicates significance at $p < 0.05$, ** indicates significance at $p < 0.01$.

We see similar results across the spectrum of political knowledge. Although the standard errors are larger, the positive point estimates for the main effect of a supportive rating are similar for the highest knowledge respondents who answered all four political knowledge questions correctly ($\beta = 0.13$ (0.10), as compared with $\beta = 0.13$ (0.05) for the entire sample), as are the null results for the effect of showing a rating that signals a voter–MC issue position match ($\beta = -0.01$ (0.11), as compared with $\beta = -0.06$ (0.05) for the entire sample). Appendix Figure A4 also re-runs these regressions by SIG. The only clear exception to the results in Table 5 is that respondents do groups is actually slightly larger.
appear to accurately use the rating from the National Parks Conservation Association as a signal, consistent with the finding from Figure 2 that respondents are able to use this group as a heuristic.

These results indicate that voters rarely use heuristics in the way many scholars hope, but do often use them in the way interest groups might hope: instead of reacting negatively to positive ratings from SIGs who disagree with them, voters respond positively to positive ratings regardless of the ideological or policy position of the group issuing those ratings.

Studies 4-7: Voters Do Not Know What Policies SIGs Support

Studies 1-3 found that voters usually fail to use SIG ratings as signals of how their MCs voted or to hold them accountable, but do appear to naively reward them for receiving positive SIG ratings. Our remaining studies seek to explain these patterns. First, Studies 4-7 examine why voters fail to use SIG ratings as a signal. This next set of studies finds, for a wide range of interest groups, that voters simply do not know what policies nearly any SIGs support.\(^\text{22}\) Studies 4 and 5 consider individual policies, and Studies 6 and 7 consider whether voters are able to perceive the overall ideology of SIGs.

Study 4: Policy Support Perceptions

First, in our 2018 study, we asked respondents to identify which of two interest groups, both active in the same policy space, would be more likely to support a specific policy. For example, we asked some respondents to identify whether the Brady Campaign to Prevent Gun Violence or the National Rifle Association support requiring background checks before purchasing a firearm. We randomly assigned which of the interest groups appeared first to avoid order effects.

\(^{22}\)Few previous studies to our knowledge systematically study how voters perceive the issue preferences or ideologies of SIGs. One rare exception is an unpublished paper by Leeper (2013), who, in studying how SIGs affect issue attitudes on immigration, finds many instances of clear misperceptions of SIG ideology (e.g., the National Council of La Raza as conservative and the Minuteman Project as liberal) and, in general, relatively low levels of familiarity with interest groups even among a relatively high knowledge sample.
Table 6 shows the exact language used in the study and the results. In most cases voters are not much better than chance, picking the correct group only about 50% of the time. We only see evidence of greater accuracy from the NRA and the “National Committee to Preserve Social Security and Medicare”—an example of a rare group that names itself to send a clear signal about what policies it supports.

We also show the results among individuals who identified themselves as in a relevant issue public. We might expect members of an issue public to more accurately guess which of two groups holds a given policy, but we do not find that to be the case. In fact, if anything, the issue publics are less accurate.

Study 5: Policy Support Perceptions

We next examine respondents’ perceptions in a separate survey of 1,180 respondents in California recruited by Survey Sampling International. We asked these voters to guess which side of major legislation that prominent interest groups would be likely to support. We used the interest groups and bills from Study 1, but added a tax issue tied to a debt ceiling vote paired with the Club for Growth.

We asked respondents to identify the position each interest group took on the relating item of legislation for three issue-group pairs. We asked “Did [group] support [policy text]?” For example, “Did the League of Conservation Voters (LCV) support building the Keystone XL oil pipeline? (see Appendix D for wording). Respondents could answer “yes,” “no”, “did not take a position” or “don’t know.” Table 7 shows that only 10-36% of respondents correctly answer the questions across the seven issue-group pairs, usually because they say they do not know what the group’s position is. Even those who do say they know identify the positions correctly only 49% of the time on average (chance would be 33% because there is one right answer out of three). Again

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23 We asked “How important to you personally are each of the issues below?” and count an individual as in the issue public if they name an issue as “Extremely important” (Bizer and Krosnick 2001).
<table>
<thead>
<tr>
<th>Groups Shown</th>
<th>Issue</th>
<th>% Correct, All Respondents</th>
<th>% Correct, Issue Public Members</th>
<th>% Correct, High Political Knowledge Respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>J Street PAC vs. Security PAC</td>
<td>“a Palestinian state in the Middle East”</td>
<td>50%</td>
<td>-</td>
<td>52%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2%)</td>
<td></td>
<td>(4%)</td>
</tr>
<tr>
<td>Jobs, Opportunities, and Education PAC (Joe PAC) vs. Prosperity PAC</td>
<td>“expanding access to charter schools”</td>
<td>24%</td>
<td>-</td>
<td>26%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2%)</td>
<td></td>
<td>(4%)</td>
</tr>
<tr>
<td>League of Conservation Voters vs. the Committee for the Preservation of Capitalism</td>
<td>“reducing regulations on greenhouse gas emissions”</td>
<td>55%</td>
<td>36%</td>
<td>50%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2%)</td>
<td>(11%)</td>
<td>(4%)</td>
</tr>
<tr>
<td>NARAL Pro-Choice America vs. Susan B Anthony List</td>
<td>“requiring parental permission for underage women to have abortions”</td>
<td>54%</td>
<td>29%</td>
<td>63%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2%)</td>
<td>(18%)</td>
<td>(4%)</td>
</tr>
<tr>
<td>National Committee to Preserve Social Security &amp; Medicare PAC vs. FreedomWorks for America</td>
<td>“cutting taxes on corporations”</td>
<td>72%</td>
<td>67%</td>
<td>81%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2%)</td>
<td>(33%)</td>
<td>(3%)</td>
</tr>
<tr>
<td>Progressive Change Campaign vs. the Campaign for Working Families</td>
<td>“repealing the Affordable Care Act, also known as ‘Obama-care’”</td>
<td>55%</td>
<td>53%</td>
<td>55%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2%)</td>
<td>(9%)</td>
<td>(5%)</td>
</tr>
<tr>
<td>San Franciscans for Good Government vs. Conservative Victory Fund</td>
<td>“reducing the influence of money on politics”</td>
<td>57%</td>
<td>-</td>
<td>58%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2%)</td>
<td></td>
<td>(4%)</td>
</tr>
<tr>
<td>The Brady Campaign to Prevent Gun Violence vs. The National Rifle Association</td>
<td>“requiring background checks before purchasing firearms”</td>
<td>76%</td>
<td>52%</td>
<td>81%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2%)</td>
<td>(5%)</td>
<td>(4%)</td>
</tr>
</tbody>
</table>

Notes: SEs shown in parentheses.
we only see noticeable respondent knowledge about the NRA and “NARAL Pro-Choice America.”

**Table 7:** Study 5—Can voters guess the positions SIGs take on key bills?

<table>
<thead>
<tr>
<th></th>
<th>AFL-CIO</th>
<th>Club for Growth</th>
<th>Chamber of Commerce</th>
<th>LCV (EPA)</th>
<th>LCV (Pipeline)</th>
<th>NARAL Pro-Choice America</th>
<th>NRA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct %</td>
<td>10</td>
<td>10</td>
<td>18</td>
<td>11</td>
<td>14</td>
<td>21</td>
<td>36</td>
</tr>
<tr>
<td>DK %</td>
<td>71</td>
<td>73</td>
<td>63</td>
<td>72</td>
<td>66</td>
<td>65</td>
<td>45</td>
</tr>
<tr>
<td>Correct % exclud. DK</td>
<td>35</td>
<td>36</td>
<td>49</td>
<td>40</td>
<td>41</td>
<td>59</td>
<td>66</td>
</tr>
<tr>
<td>N</td>
<td>522</td>
<td>470</td>
<td>502</td>
<td>512</td>
<td>527</td>
<td>507</td>
<td>488</td>
</tr>
</tbody>
</table>

*Notes: LCV = League of Conservation Voters.*

**Study 6: Ideological Perceptions**

It is plausible that respondents are confused by issue questions but would be capable of identifying an interest group’s rough ideological position. To test this hypothesis, we first asked a different set of respondents from the California sample in Study 5 to rate interest groups on a seven-point ideology scale. We presented three interest groups each and prompted “We would like you to rate the following special interest groups from liberal to conservative. Where would you place [interest group] on this scale?” We did not provide a “don’t know” option but respondents could skip the question and many did.

We show the results in Figure 3. NARAL Pro-Choice America and the NRA are the only groups voters are consistently able to place. For example, many respondents guess that the League of Conservation Voters is a conservative SIG. The extremely conservative Club for Growth also receives more liberal ratings than conservative ratings, and the modal respondent guesses that the Club is moderate.
Figure 3: Study 6–Interest Group Ideological Placements

(a) Liberal SIGs

(b) Conservative SIGs

Study 7: Ideological Perceptions of 45 SIGs

Thus far, we have only studied 17 interest groups. Although we suspected these would be the most likely for voters to know, many more interest groups are active in US politics and voters may have greater knowledge about others. To expand the number of groups, we selected the top 45 Political Action Committees in terms of 2016 political contributions (data from opensecrets.org). Consistent with the heuristics literature more broadly, campaign finance scholars have speculated that campaign spending from groups such as PACs could serve as particularly strong heuristics (for a review, see Wood 2018). To see whether the public knows about this broader set of active SIGs, we conducted a demographically representative survey of US residents with Lucid in October 2017. We asked 3,178 Americans, “How liberal or conservative is [interest group]?” and gave them seven response options, from “extremely liberal” to “extremely conservative,” and a “don’t
know” option. We asked each respondent about two randomly chosen groups.

To measure these SIG’s actual ideology, we use Adam Bonica’s Campaign Finance (CF) scores (Bonica 2014). For ease of interpretation we trichotomize the SIG CF scores into conservative, moderate, and liberal.

Consistent with our earlier studies, we found low levels of knowledge about this larger set of SIGs.

First, as Figure 4a shows, the vast majority of these SIGs are either conservative or liberal. However, Figure 4b shows that respondents place under half of SIGs as either conservative or liberal, with respondents indicating many of these SIGs are moderate and, most often, simply skipping the questions (despite a request for a response).

Second, respondents are barely more likely to identify conservative groups as conservative and liberal groups as liberal. Figures 4c and 4d show respondent’s placements of liberal and conservative SIGs, respectively. Respondents are less than 10 percentage points more likely to rate liberal groups as liberal than conservative groups as liberal. About 44% skipped the question and another 15% gave midpoint responses, sometimes a sign of ignorance.

To address concerns about respondents using ideological scales idiosyncratically, we can also conduct analysis within respondent, since we had each respondent rate two groups. We check whether respondents placed the more liberal group to the left of the more conservative group. If

---

24 We drop an additional 87 respondents who dropped out of the survey prior to answering this question and an additional 2 respondents who did not provide an ideological self-placement.

25 We code the middle 1 unit of the range of CF scores as moderate; i.e., the range from -0.5 to 0.5. This codes six PACs as moderate: the Blue Dog Democrats (a PAC supporting moderate Democrats), the Tuesday Group (a PAC supporting moderate Republicans), and several explicitly bipartisan Israeli PACs: the Heartland PAC, NAC-PAC, the Desert Caucus, and the Washington PAC. The most moderate SIG we code as conservative is the Texas Freedom Fund, which describes itself as “acting in defense of private property, privacy, and the 2nd amendment” (see texasfreedom.org). The most moderate SIG we code as liberal is JoePAC, the leadership PAC of former Democratic Member of Congress Joe Crowley.

26 Although many access-seeking PACs are coded as moderate in the Bonica (2014) data, we use the largest PACs, the vast majority of which are more ideologically oriented. Consistent with this, Bonica (2014) notes that “labor and single-issue PACs tend to locate towards the extremes” (p. 301). Online Appendix Figure A5 names all the groups we used. Investigating the particular groups we code as liberal and conservative reliably shows that they are clearly affiliated with one side.
respondents know something about the ideology of these groups, they should do so more often than chance. We calculate chance here as \( \frac{21}{32} \times \frac{4}{32} = 33\% \)—the odds of placing the liberal group anywhere to the left of where they placed the more conservative group with a skip choice counted as incorrect. Using CF-scores as the benchmark, we find that respondents do worse than chance, with only 16% placing the groups on the correct side of each other. If we limit the analysis to those asked about groups on opposite sides of the spectrum (either side of zero on CF-scores),
this rises to only 17%.

Online Appendix Figure A5 gives all 45 SIGs and shows the relationship between each SIG’s CFScore and its average ideological placement by respondents. As groups become more conservative, the figure shows that respondent perceptions become slightly more conservative as well, but the relationship is weak. (Unlike in previous studies, we did not label NARAL as “NARAL Pro-Choice America” but just as “NARAL.” Consistent with the presence of “pro-choice” in the SIG’s name producing respondent knowledge and correct heuristic use, the evidence of respondent knowledge about this group in earlier studies vanishes in this study where “pro-choice” was absent from the name.) Among liberal groups and among conservative groups, the relationship is even weaker.

**Heuristic Projection**

It may not be surprising that voters know little about most SIGs, as we found in Studies 4-7 and that, as we found in Studies 1-2, voters are therefore almost never able to make more accurate inferences about their MC’s voting behavior based on SIG ratings. However, our finding from Study 3 that despite this ignorance voters nevertheless reward MCs for earning positive ratings from any SIG suggests SIG ratings may be far from innocuous. How is this possible? In this section we present two pieces of evidence consistent with a novel process that may contribute to this pathology: *heuristic projection*, whereby voters who are unfamiliar with a SIG often assume the SIG shares their own views.

**Study 8: Projection and Ideological Perceptions of 45 SIGs**

First, we examine whether respondents project their own ideologies on to interest groups, using the same data as Study 7. Figure 5 tests for this projection. Figure 5a shows how respondents placed SIGs, broken down by respondents’ own ideologies. Respondents all rated the same SIGs regard-
less of their own ideology. However, among liberal respondents, the most common placement given for SIGs was liberal. Among moderate respondents, the most common placement given for SIGs was moderate. Among conservative respondents, the most common placement given for SIGs was conservative. All three of these patterns are consistent with widespread projection (Conover and Feldman 1982).

To break down these perceptions by the actual ideology of the SIGs, Figures 5b and 5c shows how respondents perceived SIGs that were actually conservative and actually liberal, respectively. When liberals perceive conservative SIGs or when conservatives perceive liberal SIGs, they barely do better than chance at determining whether these SIGs are on their side or not. Likewise, moderates are most likely to perceive SIGs as moderate regardless of the SIG’s actual ideology.

One pattern evident in Figures 5b and 5c is that respondents are more accurate when perceiving groups on their side. This accuracy could also result from projection, however: for example, when conservative respondents perceive a conservative SIG as conservative, this could be because they truly know the SIG is conservative or because they are projecting onto the SIG. To better appreciate the relative magnitudes of projection and reality in informing respondent’s perceptions of SIGs, Table 8 reports a regression of respondents’ perceptions of SIGs on both the SIG’s actual ideology and respondent’s own ideological self-placements, in all cases trichotomized to liberal, moderate, and conservative. The results show that respondent’s own self-placement is essentially just as strongly related to how they perceive SIGs as is the reality of the SIG’s actual ideology. This suggests that projection essentially offsets any knowledge respondents might have about SIG ideology, leading respondents to be more likely to perceive SIGs as on their side on average.

Online Appendix Figure A6 visually shows this projection across the full range of respondents’ self-placement on the 7-point ideological scale.
**Figure 5:** Study 8—Projecting One’s Own Ideology onto SIGs

(a) SIG Placement by Respondent Ideology–All SIGs

(b) SIG Placement by Respondent Ideology–Conservative SIGs

(c) SIG Placement by Respondent Ideology–Liberal SIGs
Table 8: Study 8–Predicting Respondents’ Placements of SIGs Based on Their Own Ideology and Reality

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual SIG CFScore</td>
<td>0.192</td>
<td>0.189</td>
<td></td>
</tr>
<tr>
<td>Recoded (-1, 0, 1)</td>
<td>(0.015)</td>
<td>(0.015)</td>
<td></td>
</tr>
<tr>
<td>Respondent Self-Placement</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recoded (-1, 0, 1)</td>
<td>0.181</td>
<td>0.177</td>
<td></td>
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<tr>
<td>Interception</td>
<td>0.007</td>
<td>-0.002</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>N</td>
<td>3541</td>
<td>3541</td>
<td>3541</td>
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<tr>
<td>$R^2$</td>
<td>0.05</td>
<td>0.03</td>
<td>0.07</td>
</tr>
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</table>

Notes: Dependent variable in all regressions is respondents’ ideological placements of the SIGs. Each observation corresponds with one respondent-placement. Missing placements are dropped. Respondent interest group placements, self-placements, and the SIG CFscores are recoded such that -1 corresponds with liberal, 0 with moderate, and 1 with conservative. Standard errors are given in parentheses. † significant at $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Study 9: Experimental Test

Study 9 demonstrates this projection experimentally and that it affects how voters perceive their MCs as well, returning to the data from Study 2. Recall that in Study 2, we randomly assigned whether voters were shown a SIG rating and, if one was shown, which was shown. Study 2 reported the effects of showing a SIG rating on whether voters accurately perceived their MC’s roll call votes and found little evidence that it did. Here, we revisit this data and uncover a more surprising effect is present, consistent with projection: voters on average act as if all SIGs are aligned with their own issue preferences, inferring that their MC agrees with their own views on more issues more when they see a positive rating from any SIG, and inferring that their MC disagrees with their own views on more issues when they see a negative rating from any SIG.

To demonstrate this effect, Table 9 presents regressions where the outcome is defined as the number of issues where voters perceived that their Member of Congress cast a vote that accorded
with their own issue preference (as measured pre-treatment). The treatment variable in the regression is whether the SIG rating that we showed to the respondent was positive (i.e., >50), negative (i.e., ≤50), or whether no rating was shown. We also include controls for voter-MC party match and fixed effects for the number of positive or negative ratings a voter’s MC received. These fixed effects ensure that all our comparisons are conducted among individuals who had the same probability of being shown positive SIG ratings. Since we asked some respondents about seven issues and others about eight, we include fixed effects for this as well.

Model 1 in Table 9 shows that the average causal effect of being shown a positive instead of negative SIG rating is an approximately 0.35 vote increase in the perception of the number of votes that one’s MC cast that agreed with one’s own views ($p < 0.01$). This is equivalent to what we would observe if more than one in three respondents changed their perceptions of their MC’s votes on an issue. Model 2 splits this by negative and positive SIG ratings, making the control group shown no ratings the omitted baseline category; individuals react to both negative and positive ratings in the predicted directions. Finally, Models 3 and 4 show a version of Model 1 that is estimated separately by whether the voter and the MC are of the same party; we find the effects are if anything larger in cases when voters are forming perception of outparty MCs, suggesting that our findings are not driven by simple motivated reasoning in favor of copartisan MCs. The point estimate for perceptions of outparty MCs is equivalent to what we would observe if nearly half of respondents expected to agree with their outparty MC on an additional issue as a result of seeing a positive rather than negative SIG rating. Surprisingly, these effects are almost as large as the descriptive relationship between the number of issues where voters and MCs actually agree.

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27 See Figure A1 for an overview of the design. Our dependent variable in this study is computed by comparing respondents’ own issue preferences asked pre-treatment with their perception of MC votes collected after the SIG rating was (if respondents were in the treatment group) shown.

28 This test was not pre-registered, but under a conservative Bonferroni correction the $p$-value of 0.0038 would only be rendered insignificant at the 0.05 level if we had first conducted 13 other uncorrelated tests.

29 Defining the outcome as whether voters have accurate perceptions of their MC’s vote, as in Study 2, we find that when voters see a misaligned SIG rating they are less accurate by 1.9 percentage points on the typical vote, although this is only borderline significant with MC fixed effects $p = 0.08$. 

33
Table 9: Study 9—Effect of SIG Rating on Perception that Member of Congress Cast Congruent Votes

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3 (Same Party MC)</th>
<th>Model 4 (Different Party MC)</th>
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</thead>
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<td><strong>Randomized Treatments</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rating Treatment (0 = SIG Rating ≤ 50, 0.5 = No SIG Rating Shown, 1 = SIG Rating &gt; 50)</td>
<td>0.349**</td>
<td>0.301**</td>
<td>0.447*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.120)</td>
<td>(0.154)</td>
<td>(0.222)</td>
<td></td>
</tr>
<tr>
<td>Rating ≤ 50 Shown (0/1)</td>
<td></td>
<td>-0.196*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.096)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rating &gt; 50 Shown (0/1)</td>
<td></td>
<td>0.157†</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.086)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Control Variables for Precision</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Issues Where Voter Actually Shares MC Issue Preference</td>
<td>0.474**</td>
<td>0.474**</td>
<td>0.364***</td>
<td>0.610 **</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.017)</td>
<td>(0.022)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Voter–MC Party Match (1-7)</td>
<td>0.394**</td>
<td>0.394**</td>
<td>0.306**</td>
<td>0.137†</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.048)</td>
<td>(0.069)</td>
</tr>
<tr>
<td><strong>Fixed Effects</strong></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Fixed Effects for Possible Treatments?</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Fixed Effect for Seven vs. Eight Issues?</td>
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<td>✓</td>
</tr>
<tr>
<td>N</td>
<td>3940</td>
<td>3940</td>
<td>2041</td>
<td>1348</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.297</td>
<td>0.297</td>
<td>0.049</td>
<td>0.096</td>
</tr>
</tbody>
</table>

**Notes:** The dependent variable in all regressions is the number of issues on which respondents indicated they thought their Member of Congress cast a vote that matched their own issue preference, which was measured pre-treatment. Standard errors in parentheses. † indicates significance at $p < 0.10$, * indicates significance at $p < 0.05$, ** indicates significance at $p < 0.01$.

**Discussion**

How can voters who know little about their representatives’ actions in office effectively hold them accountable? An influential perspective has long argued that many uninformed voters are able to use heuristics to do so (e.g., [Popkin 1994]). Endorsements from special interest groups (SIGs) are one of the foremost examples of such heuristics in the literature, and are present in campaign
advertisements, candidacy statements, and in advertisements placed by SIGs themselves. Heuristics theory thus gives reason to be optimistic that the ubiquitous presence of interest group endorsements in politics significantly enhances electoral accountability. However, only a small number of studies have evaluated how voters actually use the information in SIG endorsements to form impressions of their representatives. Moreover, little literature has considered how SIGs might strategically respond to the possibility that voters might use their ratings as signals of who to support.

With a series of studies considering how voters perceive dozens of SIGs and their ratings, we showed that voters know little about the vast majority of major interest groups’ stances, frustrating their ability to use interest group ratings as effective heuristics. They are typically unable to determine which side of an issue an interest group sits on, are unable to infer what a rating from them means about what their representatives have done in office on either closely related or other issues, and therefore do not appropriately adjust their evaluations of their representatives upon receiving these cues. There are exceptions to this pattern in the case of interest groups with names that clearly signal their positions, such as in the case of “NARAL Pro-Choice America”. However, voter ignorance was the norm for the vast majority of SIGs.

Surprisingly, we find that voters do not disregard information about SIG ratings despite usually lacking the knowledge of how to interpret them. Instead, we found evidence for a novel dynamic we call heurisitic projection: voters on average behave as if all SIGs share their views, even though many SIGs do not. We found evidence of heuristic projection in three conceptually and methodologically distinct ways: voters on average expect SIGs to share their broad left-right ideology (Study 8); in an experiment, voters interpret positive SIG ratings as indicating their MCs agrees with them on issues, regardless of whether the SIG is aligned with them (Study 9); and, perhaps as a result, voters more highly approve of MCs when they earn positive SIG ratings, regardless of

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30Instructively, when we removed “Pro-Choice” from the name of NARAL in Study 7, we found that respondents were then unable to place it ideologically.
whether the SIG shares their views (Study 3).

In summary, our findings indicate that voters are psychologically capable of using SIG heuristics correctly when the SIG’s positions are clear, but that their behavior in the far more common instance that they are unfamiliar with the SIG means that SIG ratings may easily generate perverse incentives on net. Our findings thus add to long-standing pessimism toward voters’ abilities to hold their representatives accountable (Druckman 2001; Oliver and Ha 2007; Gilens and Page 2014). Heuristics have long been held up as a key strategy voters may use to produce meaningful accountability, but we find that a common form of this strategy is itself susceptible to elite manipulation. In an ideal world for voters, voters would be able to infer how their MCs voted based on knowledge of SIGs’ ratings of their legislators. However, it appears voters act in a way that is much more ideal for SIGs: voters appear to incentivize their representatives to earn positive ratings from SIGs even when voters disagree with what SIGs want. This may be exactly why SIGs so often give themselves names that imply they support consensus causes with broad, cross-ideological appeal. It appears many voters believe them.

Our findings raise a number of interesting questions for future research. First, given the presence of SIG ratings in many campaigns, to what extent do SIGs help create an “electorate blind spot” (Bawn et al. 2012) that helps officeholders avoid accountability for casting unpopular votes? How often do MCs cast votes out of step with public opinion expecting that a positive rating from a sympathetic SIG will help offset any electoral costs? Second, although there are clear theoretical reasons to expect SIGs to strategically contribute to heuristic projection and for voters to be susceptible to it, future research could help understand to what extent each of these potential forces contributes. For example, one possible mechanism, consistent with the mere exposure effect (Panagopoulos and Green 2008) and the likeability heuristic (Brady and Sniderman 1985; Sniderman, Tetlock and Brody 1993), would be that voters have positive affect towards unknown groups. Consistent with this, Weber, Dunaway and Johnson (2012) find that completely unknown SIGs are actually seen as the most credible messengers in campaign advertisements. On the other
hand, SIGs may also actively name themselves vaguely enough to allow voters to engage in this projection instead of clearly signaling their viewpoints. Better understanding the exact strategic and psychological underpinnings of heuristic projection would help identify remedies and scope conditions. Such research could also benefit from tracing the impacts of SIG ratings to behavior, as one clear limitation of our research is its focus on survey-based outcomes (Bullock et al. 2015, although see Berinsky (2018)). Finally, our findings may have implications for transparency measures such as the DISCLOSE Act, which seeks to force campaigns to disclose their major donors as part of their advertisements. The underlying assumption behind these efforts is that voters will be able to use these donations as negative cues about politicians’ stances when appropriate. Our findings suggest that voters may need additional information to use SIG ratings as effective cues, but that when this information is present voters may be able to do so. As it stands, however, voters are unlikely to be able to make accurate inferences from SIG ratings in many cases. Indeed, there may be a perverse consequence of such regulations: they may simply increase politicians’ incentives to secure support from special interest groups and electorally advantage the politicians that do so.

References


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Online Appendix

A Appendix Figures and Tables

Figure A1: Design of Sample Strategies Survey Used for Studies 2, 3, and 9
Figure A2: SIG ratings used in Study 2
**Figure A3:** Studies 2 and 3–Do Respondents Understand High Ratings Indicate MC Usually Votes In Ways SIG Usually Agrees With?

Notes: After showing the SIG ratings for Studies 2 and 3, we asked respondents “To make sure you understand what this rating means, do you think it means that [SIG Name] usually agrees or disagrees with how [name of respondent’s MC] has voted in Congress?” Respondents had three response options: usually agrees, neither, and usually disagrees. This Figure plots the proportion that selected the “usually agrees” and “usually disagrees” options as a function of the value of the rating they were just shown. Note that the vast majority of SIG ratings fall from 0 to 10 or 90 to 100, as shown in Figure A2.
Figure A4: Study 3—Effects of SIG Rating Information on Support for Member of Congress, by SIG

(a) Effect on MC Approval Scale of Showing Positive SIG Rating (0/1)

(b) Effect on MC Approval Scale of Showing SIG Rating that Signals Voter–MC Issue Position Match (0/1)

Notes: This Figure shows the results of Model 3 in Table 5 when this regression is run separately by SIG. The MC Approval Scale is rescaled to mean zero standard deviation one.
Figure A5: Respondent Perceptions of SIGs in Study 7 by SIG CF Score

(a) All SIGs

(b) Conservative SIGs Only

(c) Liberal SIGs Only

Note: CCLife (Citizens Concerned for Life), CGS (Citizens for Global Solutions), CUPVF (Citizens United Political Victory Fund), CWF (Campaign for Working Families), CenterPAC (Center for Coastal Conservation Political Action Committee), Ferris (Friends of Ferris), Fipac (Friends of Israel Political Action Committee Fipac), FriendsEarth (Friends of the Earth), GunOwners (Gun Owners of America), HumaneUSA (Humane USA Political Action Committee), JACPA (Joint Action Committee for Political Affairs), JoePAC (Jobs, Opportunities and Education PAC (Joe PAC)), LCV (League of Conservation Voters), NAUS (National Association for Uniformed Services), NCEC (National Committee for an Effective Congress), NOW (National Organization for Women), NPLA (National Pro Life Alliance), NRA (National Rifle Association), NRL (National Right to Life), Nacpac (National Action Committee), PACe (National Association of Social Workers Incorporated Political Action for Candidate Election), PAPAC (Peace Action PAC), PAWVF (Peace Action West Voter Fund), FCCC (Progressive Change Campaign Committee), PCPAC (Progressive Choices PAC), RL (Right to Life), SBAL (Susan B Anthony List), TDC (The Desert Caucus), TFF (Texas Freedom Fund), TG (Tuesday Group), VN (Victory Now), WAND (Womens Action for New Directions Incorporated), WOF (Winning Our Future), WPAC (Washington Political Action Committee). Forward Together and Environment America Action Fund are not shown because they are extreme outliers on the left.
Figure A6: Study 8–Respondent Perceptions of SIG Ideology, by Respondent Own Ideology

Notes: Each point corresponds with how respondents of a given ideology rated a given interest group. Points are scaled by the number of respondents with each ideology rating each SIG. Respondents’ own ideology is jittered to improve readability.
B Representativeness

Table A1 provides demographic statistics for the four samples we use in this paper in the middle four columns. The last column displays the same statistics in the 2017 American Community Survey (ACS) from the US Census Bureau, a benchmark. Unsurprisingly the MTurk sample from Study 1 is fairly unrepresentative on gender, income, and education. However, our remaining samples are broadly representative, with the main differences with the ACS being that some of our samples are slightly whiter, underrepresent individuals without high school degrees, and underrepresent individuals with incomes over $80,000 per year. Note that the ‘SSI in CA’ sample would not be expected to match the 2017 ACS exactly, as the SSI in CA sample was conducted only in California whereas the 2017 ACS is nationwide.
### Table A1: Representativeness of Four Samples Used in Paper

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<thead>
<tr>
<th>Sample</th>
<th>Study 1</th>
<th>Studies 2-4, 9</th>
<th>Studies 5-6</th>
<th>Studies 7-8</th>
<th>Benchmark: 2017 ACS</th>
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<td>17</td>
<td>9</td>
<td>7</td>
<td>12</td>
</tr>
<tr>
<td>$80k+</td>
<td>9</td>
<td>28</td>
<td>24</td>
<td>11</td>
<td>36</td>
</tr>
<tr>
<td>Unknown</td>
<td>0</td>
<td>0</td>
<td>13</td>
<td>3</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: All cell entries provide the percentage of each sample present in each demographic category. In rare cases age and income categories were inconsistent across surveys and were either combined or averaged across other categories.
C Study 1

C.1 Study 1 Robustness—Political Knowledge

It is possible that SIG ratings may be more useful for certain voters. For example, Lau and Redlawsk (2001) find that only respondents with a high level of political sophistication can effectively use heuristics, while they may be detrimental to politically uninformed respondents. If this is the case, we would expect to find a substantial positive effect of endorsement cues on high-knowledge voters partially counteracted by a negative effect on low-knowledge voters. In fact, we find very little evidence to support that hypothesis. As Figure A7, the various treatment conditions have no effect on high-knowledge voters at all. One explanation might be a ceiling effect: high-knowledge voters are already so knowledgeable about their representatives’ behavior that the treatment has no impact. However, their accuracy in the control condition is barely three-quarters, indicating room for improvement. Low-knowledge, on the other hand, voters use the party identification heuristic quite effectively, boosting accuracy from 52% to 65%. The effect for the endorsement condition is statistically insignificant, though in the opposite direction as expected.

C.2 Study 1 Robustness—Issue Publics

According to the issue publics literature, many voters have a small handful of issues which dictate their vote. One voter, for example, might be a 2nd Amendment voter and always favor the candidate who espouses more lax gun regulation. We may be underestimating our respondents’ abilities to guess votes if they simply lack interest in the issue.

Perhaps only voters who are themselves members of an interest group and are accustomed to receiving information from them can use such cues. If so, we would expect to find an effect of the endorsement condition on those respondents who self-identified as belonging to such a group. Figure A8 show this analysis. We again find that the endorsement condition has no effect:
Members and non-members in the endorsement group have similar but statistically insignificant
differences from those in the control group. Furthermore, the party identification cue only has an
effect on non-members. This is not an artifact of a correlation between membership and political
sophistication: the two have a correlation coefficient of 0.087.
Figure A7: Study 1—Can high political knowledge respondents infer how their representatives vote using heuristics? Treatment effects by number of correct responses on a five point scale.

Figure A8: Study 1—Can respondents who are members of an issue public infer how their representatives vote using heuristics?
C.3 Study 1 Means—by condition, by policy, by political knowledge, and by issue publics.

Figure A9: Study 1—Means by condition and by policy
**Figure A10:** Study 1—Means by number of correct political knowledge responses

*By Number of Correct General Knowledge Items*

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**Figure A11:** Study 1—Means by whether respondents chose policy

*Randomly Chosen Policy vs. Respondent Chooses Policy*
D Study 5

Question wording:

- Did NARAL Pro-Choice America support banning federal funding for elective abortions?

- Did the League of Conservation Voters (LCV) support preventing the Environmental Protection Agency from regulating greenhouse gases?

- Did the National Rifle Association (NRA) support allowing individuals to carry concealed firearms in all states if they have a license in one state?

- Did the Club for Growth support a tax increase on individuals with $400,000 or more in income to avert the fiscal cliff?

- Did the American Federation of Labor and Congress of Industrial Organizations (AFL-CIO) support a free trade agreement with South Korea?

- Did the League of Conservation Voters (LCV) support building the Keystone XL oil pipeline?

- Did the Chamber of Commerce support universal healthcare?

Response options:

- Yes

- No

- Did not take a position

- Don’t know
E Pre-Analysis Plan for Studies 2-4

We made the following deviations from the pre-analysis plan:

- In Studies 2-3, as described in Footnote 19 in the main text, we originally pre-specified that we would control for possible treatments using a linear term. We now use fixed effects for every level of this variable, as we thought this would be less sensitive to functional form. The results are nevertheless essentially identical when using a linear term.

- As also noted in Footnote 19 in Study 3, we did not originally anticipate that respondents would naively react to whether the rating was positive or negative regardless of the SIG issuing the rating. However, the \( p \)-value on this comparison is 0.005, it would only be rendered insignificant under a Bonferroni correction if this were at least the tenth non-pre-registered comparison we ran.

- In Study 4, Table 6, the PAP verbally indicated that we would perform a guessing correction procedure, but the code we provided did not actually implement a guessing correction procedure. In Table 6 we report raw means that are not guess-corrected, consistent with the code, instead providing guess-corrected percentages.
Pre-Analysis Plan for Interest Group Heuristics Survey Experiment

BLINDED

Background

This experiment replicates and extends work by [BLINDED] in 2013:

- That earlier work examined the extent to which interest group endorsements of Members of Congress provide useful information in helping constituents guess their representatives’ votes on key issues, finding that they largely do not. In this experiment, we will replicate previous findings using additional interest groups and additional key votes.
- As well, it attempts to identify reasons for the unhelpfulness of interest group cues by testing whether respondents can identify which of two interest groups on opposing sides of an issue is the liberal organization.
- Finally, we address a follow-up question related to approval, and ask whether learning of interest group alignment increases support for one’s member of congress.

Experimental Design

We plan to recruit a nationally representative sample to complete our online survey.

This experiment involves the following steps:

1. Identify a respondent’s Member of Congress using their 9-digit zip code.
2. Gather respondent’s preferences on about 10 policy issues.
3. If respondent is in the control group, show no treatment. If respondent is in the treatment group, show a randomly selected interest group rating for her MoC. These are the real interest group ratings for respondents’ real MoCs.
4. Gather respondent’s guesses about her MoC’s preferences on the same policy issues.
5. If a respondent is in the treatment group, gather respondent’s approval of her MoC.
6. Ask all respondents to identify which of two related interest groups supports a given policy.

Outcomes

We collect three outcomes.

Outcomes in Experiment

- \( mc\text{ratingscale} \) measures R’s support for her Member of Congress
- \( \text{position\_correct} \) indicates whether R correctly guessed her MoC’s position on the policy

Descriptive Statistics

- \( \text{org\_correct} \) indicates whether R successfully identified which interest groups supports a given policy; each R is shown two
This diagram shows how respondents will flow through the survey and when each outcome is collected.

Data In This PAP

This pre-analysis plan using a limited pilot of this design ran in November 2017. Given the limited sample size, we cannot use it to draw inferences about the results of the experiment to be completed.

```r
dat <- read.csv('heuristics_cleaned.csv', stringsAsFactors = FALSE)

# Our control respondents were given a different experiment. The project identifier 'heuristics' distinguishes our pure control from our two endorsement-receiving groups.
dat$ratingsshown <- dat$project == 'heuristics'
```

30 respondents completed this pilot pre-survey. To write this PAP, we use this real pre-survey data. We will not use this pre-survey data for the paper.

Experiment: Effect of heuristics on correct perception of MC votes and MC approval
Effect of heuristics on correct perception of MC votes

Does showing the heuristic make people guess the MC’s position more accurately on that or other issues?

To answer this question we reshape the dataset to the respondent by issue level. All respondents made guesses about their Member of Congress’ position across approximately ten issues each. A randomly selected subset of respondents (the treatment group) were shown heuristics relevant to one randomly selected issue. There are therefore three groups we can compare:

1. How accurate were respondents in the treatment group about the issue on which they were shown a relevant heuristic?
2. How accurate were respondents in the treatment group about the issues on which they were not shown relevant heuristics?
3. How accurate were respondents in the control group about all the issues?

Comparing groups 1 and 3 reveal the ‘direct effect’ of heuristics. Comparing groups 2 and 3 reveal any ‘spillover’ effect of heuristics. Therefore, we will run a regression with a) an indicator for whether a respondent was shown a heuristic on this issue (i.e., group 1 above), identifying the direct effect of a heuristic; and b) an indicator for whether a respondent was shown a heuristic on a different issue (i.e., group 2 above), identifying the indirect effect on other issues. The control group will be the base category. We will also use issue fixed effects to increase precision.
# Reshape the data frame so the unit of analysis is the respondent * issue area
# To perform this reshape, I use two melt() calls then merge the two.

# A helper function to extract issue area from a variable name
substrRight <- function(x, n){
  substr(x, nchar(x)-n+1, nchar(x))
}

# This first melt call produces a respondent * issue area data frame with the respondent t’s guess regarding their Congressmember’s vote.
dat_t1 = reshape2::melt(dat[,c(19:35, 47)], id = "workerId"
dat_t1$variable = as.character(dat_t1$variable)
dat_t1$issue = sapply(dat_t1$variable, FUN=function(x) substrRight(x, 5))
dat_t1 = dat_t1[,c(1,3,4)]
colnames(dat_t1) = c("workerId", "guess", "issue")

# This second melt call produces a respondent * issue area data frame with their Congressmember’s actual vote.
dat_t2 = reshape2::melt(dat[,c(67:83, 47)], id = "workerId"
dat_t2$variable = as.character(dat_t2$variable)
dat_t2$issue = sapply(dat_t2$variable, FUN=function(x) substrRight(x, 5))
dat_t2 = dat_t2[,c(1,3,4)]
colnames(dat_t2) = c("workerId", "truth", "issue")

# Then we merge the two data frames together along with an identifier for which issue area the respondent received a SIG rating for
dat_t = merge(dat_t1, dat_t2)
dat_t = merge(dat_t, dat[,c("randomrating_house_vote_id", "workerId",
"project", "num_eligible_ratings", "survey_version")])

# Calculate the dependent variable: whether the respondent guessed the MoC’s vote correctly on each issue.
dat_t$correct = dat_t$guess == dat_t$truth

dat_t = dat_t[!is.na(dat_t$correct),] # There should be no NAs here in the real data.

# Create variables indicating which treatment group each observation alls in
dat_t$indirect = dat_t$project == "heuristics" & dat_t$issue != as.character(dat_t$randomrating_house_vote_id)
dat_t$direct = dat_t$project == "heuristics" & dat_t$issue == as.character(dat_t$randomrating_house_vote_id)
dat_t$control = dat_t$project != "heuristics"

# Regress whether the respondent guessed correctly on whether they were cued, with issue area fixed effects and respondent-level clustered SEs.
# Respondents in the treatment group are only randomly assigned to one rating among the ratings that it makes sense to show them for their MoC (because the MC has both the rating and the corresponding vote). Some MCs are missing different numbers than others, meaning that respondent’s probability of assignment to each issue depends on how many other issues there. E.g., if you got issue A and your MC has 3 other issues, your prob of assignment is 1/4, but if your MC has 7 other issues, your prob of assignment is 1/8. So we need fixed effects for the number of issues to which you were assigned.
summary(miceadds::lm.cluster(data = dat_t,
formula = correct ~ indirect + direct +
          factor(issue) + factor(num_eligible_ratings),
cluster = 'workerId')


<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.61518611</td>
<td>0.14897133</td>
<td>4.1295605</td>
</tr>
<tr>
<td>indirectTRUE</td>
<td>0.03507197</td>
<td>0.08724910</td>
<td>0.4019752</td>
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<tr>
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</tr>
</tbody>
</table>

## R^2 = 0.18537
We will test whether there is a positive coefficient on direct, our main effect, or in direct, our spillover effect.

We also calculate a variable which indicates whether respondents understand that a MoC receiving a low grade from an interest group means that interest group’s policy preferences do not align with the MoC’s. This serves as a manipulation check: if we find that respondents do not adequately consider SIG endorsements when guessing their MoC’s votes, we can use this mediating variable to rule out the possibility that they do not understand the meaning of an SIG endorsement.

# First, we calculate the mediating variable -- whether respondents understand what an interest group endorsement means regarding their Member of Congress.

dat$understandsrating_correct <- ifelse((dat$randomrating_sig_rating > 50 & dat$understandrating == 1) | (dat$randomrating_sig_rating < 50 & dat$understandrating == 3)), 1, 0)

Effect of heuristics on MC approval

Here we address our second question: when people see a heuristic that suggests an MC agrees with them on an issue, do they like the MC more?

# Note: for this analysis, can’t use respondents in the other project as a control group, since for the other project other information was shown before the MC approval question was asked. So we are just going to use within-subject variation among our treatment group.

dat <- filter(dat, project == 'heuristics')

# Our dependent variable: the respondents' favorability toward their Member of Congress

dat$mcratingscale

## [1] 1.19682466 -0.43407833 0.01572741 -0.81655608 2.02910815
## [6] 0.78068291 0.81434691 0.78068291 0.22123354 -0.81655608
## [11] -0.62531721 -0.81655608 0.01572741 0.39820516 -0.81655608
# Preliminary step: identify the issues where the liberal position is support and the is
sues where the liberal position is oppose

```r
temp <- data.frame(randomrating_sig_name = unique(dat$randomrating_sig_name))
temp$randomrating_sig_libcon = c(-1, -1, 1, 1, -1, 1, -1, 1)
dat = merge(dat, temp)
rm(temp)
```

# Identify how the respondent voted on the issue relating to the heuristic
# This variable is stored as bill_pref, and is coded as either -1 (liberal) or +1 (conservative)

```r
ownview_heuristic_var = paste0("ownview", dat$randomrating_house_vote_id)
idx = sapply(ownview_heuristic_var, FUN= function(x) which(colnames(dat)==x))
temp0 = c()
for(i in 1:length(idx)){
  temp0[i] = dat[i, idx[i]]
}
temp0[temp0==0] = -1
dat$bill_pref = temp0 * dat$randomrating_sig_libcon
rm(temp0)
rm(idx)
rm(vec)
```

```r
dat$randomrating_sig_rating[dat$randomrating_sig_rating < 50] = -1
dat$randomrating_sig_rating[dat$randomrating_sig_rating >= 50] = 1
dat$heuristic_candpref = dat$randomrating_sig_rating * dat$randomrating_sig_libcon
dat$heuristic_candpref_binary = dat$heuristic_candpref > 0
```

# Define heuristicagree as whether the respondent's preference on an issue matches the c
andidate's preferences as indicated by an endorsement
# Note that the endorsement may be misleading! A candidate with a 90% grade from a SIG s
till votes against them 10% of the time.
```
```
```
```
```
```
```
```
```r
dat$heuristicagree = dat$bill_pref == dat$heuristic_candpref
by(dat$heuristicagree, dat$mcratingscale, mean)
```
Calculate the proportion of votes in which the respondent agrees with the member of Congress's votes

```
dat$rep_agree_proportion = sapply(1:nrow(dat), FUN=function(x) mean(dat[x,3:19]==dat[x,20:36], na.rm=T))
```

Regress respondents' support for their member of Congress on the proportion of votes on which they agree, and whether the SIG heuristic suggests policy preference congruence

```
summary(lm(mcratingscale ~ rep_agree_proportion + heuristicagree, dat))
```
Call: lm(formula = mcratingscale ~ rep_agree_proportion + heuristicagree, data = dat)

Residuals:

      Min       1Q   Median       3Q      Max
-0.73533 -0.30369  0.09695  0.26610  0.58738

Coefficients:

                  Estimate Std. Error t value Pr(>|t|)
(Intercept)        -0.9315     0.1964  -4.742 0.000478 ***
rep_agree_proportion 2.4655     0.4002   6.161 4.86e-05 ***
heuristicagreeTRUE   -0.3746     0.2854  -1.312 0.213949

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4355 on 12 degrees of freedom
Multiple R-squared:  0.7861, Adjusted R-squared:  0.7505
F-statistic: 22.05 on 2 and 12 DF,  p-value: 9.578e-05

If people are learning adequately, there will be a positive coefficient on heuristicagree independent of allagree

Secondary hypothesis: recent research (Russell 2017, "US Senators on Twitter: Asymmetric Party Rhetoric in 140 Characters") suggests that Democrats care more about policy alignment than Republicans.

Test this hypothesis by adding PID to the above regression by(INDICES = list(dat$heuristicagree, dat$pid), data=dat$mcratingscale, FUN = function(x) mean(x, na.rm=T))
```r
summary(lm(mcratingscale ~ rep_agree_proportion + heuristicagree + pid, dat))
```
Do people correctly perceive PACs and SIGs?

Here we produce a table indicating the interest groups for which respondents most often correctly guess their positions on a related policy. We showed respondents pairs of interest groups and PACs on different sides of a policy issue and asked them to guess which was on which side.

```r
# Reread the original dataset since we subsetted it above
dat$orgs <- with(dat, paste0(org1, ' and ', org2))
by(dat$org_correct, dat$orgs, mean)
```
Guess Correction

Many of our outcomes are whether R correctly guessed her MoC’s policy preferences. This is subject to measurement error, since an uninformed respondent may correctly guess without knowing any real information. Therefore we perform statistical guess correction on our outcomes to estimate the treatment effect; otherwise we will underestimate it. Our guess correction formula is $S = R - W / (k-1)$: corrected score is equal to the number of correct answers minus the number of incorrect answers, divided by the number of choices for each question minus one.