Online appendix for:
Americans Can Imagine Changing Partisan Affiliation: Evidence from Hypothetical Scenarios

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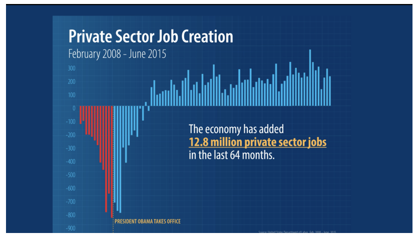
Contents

A Survey Experiments

A.1 Screenshot of ads tested in survey experiments

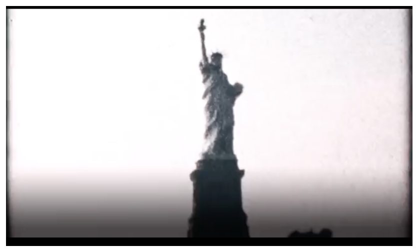
(a) Issues (Firm A)



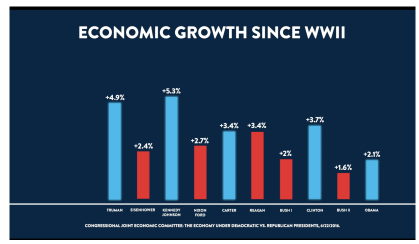
(b) Performance (Firm A)

(c) Charisma (Firm A)

(d) Social Identity (Firm A)

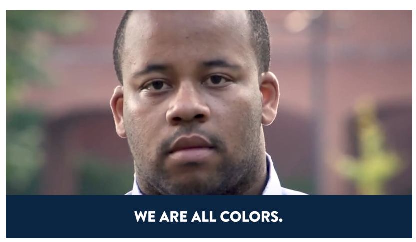


(e) Generic (DNC)



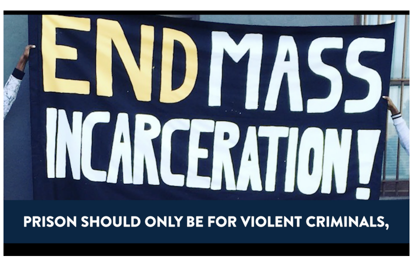
(f) Performance (Firm B)

(g) Charisma (Firm B)



(h) Identity (Firm B)

(i) Issues (Firm B, V1)



(j) Issues (Firm B, V2)

(k) Issues (Firm B, V3)

(l) Negative Partisanship (Firm B)

Figure A.1: Screen shots of the ads produced and tested.

A.2 Treatment assignment details from survey experiments

Table A.1: Assignment of Treatments to Subjects, Studies 1 & 2

	Study 1	Study 2
No video	142	256
Issues (Firm A)	155	
Performance (Firm A)	107	236
Charisma (Firm A)	118	
Social Identity (Firm A)	140	
Generic (DNC)	124	242
Performance (Firm B)	108	
Charisma (Firm B)	152	
Social Identity (Firm B)	130	
Issues (Firm B, version 1)	131	258
Issues (Firm B, version 2)	127	225
Issues (Firm B, version 3)		238

Cell entries are numbers of subjects assigned to each condition.

Table A.2: Assignment of Treatments to Subjects, Studies 3, 4, & 5

Study	Dosage	N	Charisma	Social Identity	Performance	Issues	Generic	Placebo
3	0	870	0	0	0	0	0	870
3	1	846	144	122	147	134	151	846
3	2	851	273	312	259	299	289	851
3	3	859	425	423	447	429	425	0
4	0	1550	0	0	0	0	0	1550
4	3	1581	786	789	800	800	779	0
4	6	1500	1500	1500	1500	1500	1500	0
5	0	878	0	0	0	0	0	878
5	3	891	471	427	431	450	465	0
5	6	894	894	894	894	894	894	0

Cell entries are numbers of subjects who saw each video.

A.3 Attrition analysis of the survey experiments

In the main text, we describe how our survey experiments that randomize subjects to view many (up to 6 in some cases) treatment views encountered differential attrition that confounded our treatment effect estimates. In this section, we describe this problem in more detail and offer trimming bounds estimates of the effects.

Our experiments followed a placebo-controlled, panel survey experimental design over three waves. In wave 1, we measured pre-treatment covariate information. In wave 2, we administered treatments and collected wave 2 outcomes. In wave 3 approximately 10 days later, we re-interviewed subjects and collected wave 3 outcomes. We used placebo-controlled designs throughout. Subjects in the placebo groups were assigned to see an equivalent number of product advertisements. We used a placebo-controlled designs because we anticipated that watching as many as six videos would cause some subjects to quit the survey and we wanted to maintain balance across treatment and control, though this design feature was not sufficient to address the problem.

Figure A.2 shows the response rates by save and condition. Wave 2 attrition rates are balanced across condition in studies 1 and 3. We only ever obtained "complete case" data for study 4, so we don't know the extent of the problem in that study. Wave 2 attrition is imbalanced in studies 2 and 5; Figure A.3 shows the treatment effects on response, which are significant in studies 2 and 5. The effects on wave 3 attrition are similarly sized in study 5, but are estimated with greater uncertainty.

Finally, Figure A.4 shows a trimming bounds analysis of the effects on Wave 3 party ID. Trimming bounds target the effects of treatment among "always responders" under the monotonicity assumption that if anything, treatment increases attrition for all subjects, and does not decrease it for any units. The resulting bounds are wide.

Figure A.2: Wave 2 and Wave 3 response rates by condition

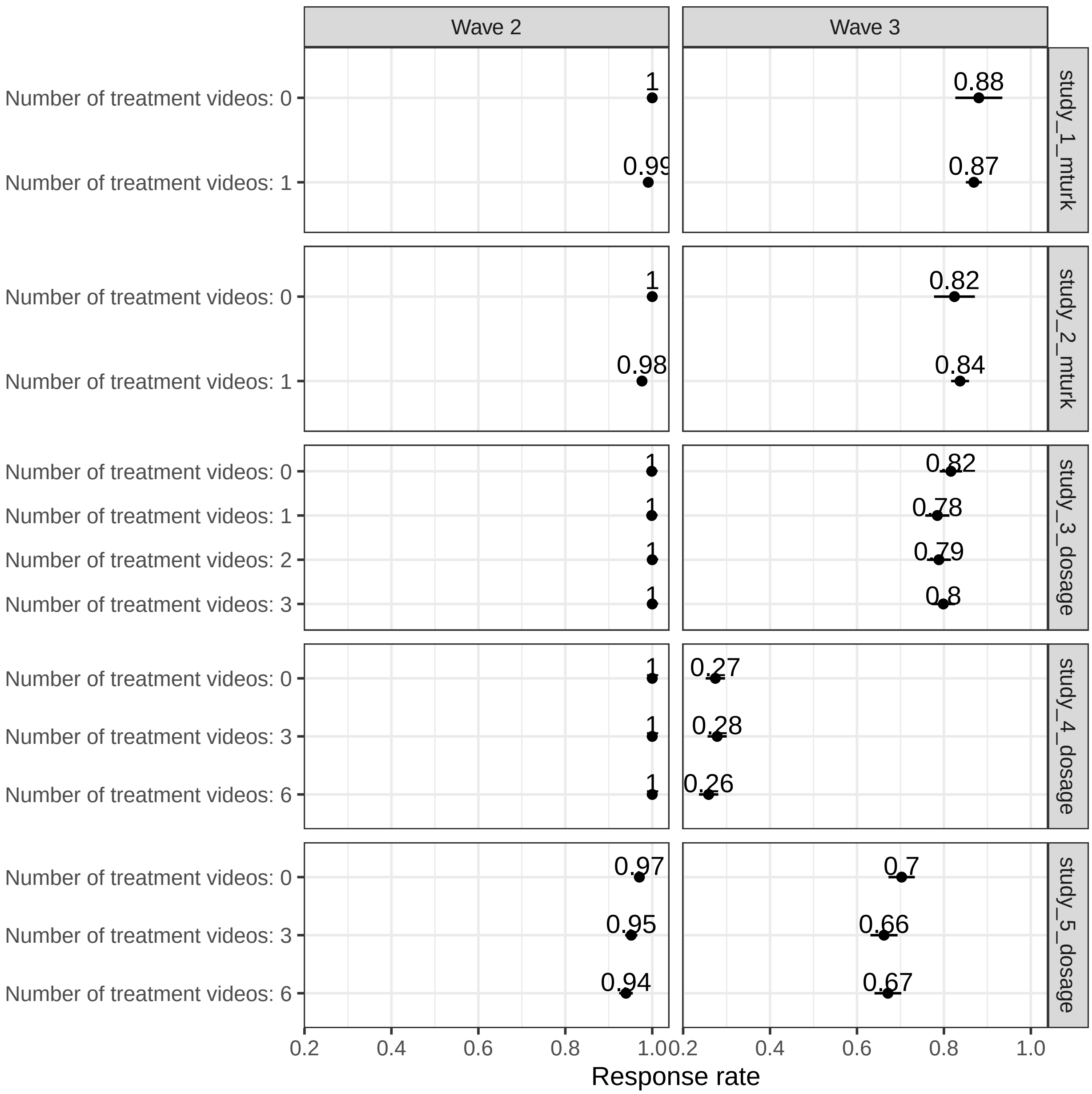


Figure A.3: Effects of treatments on Wave 2 and Wave 3 response rates

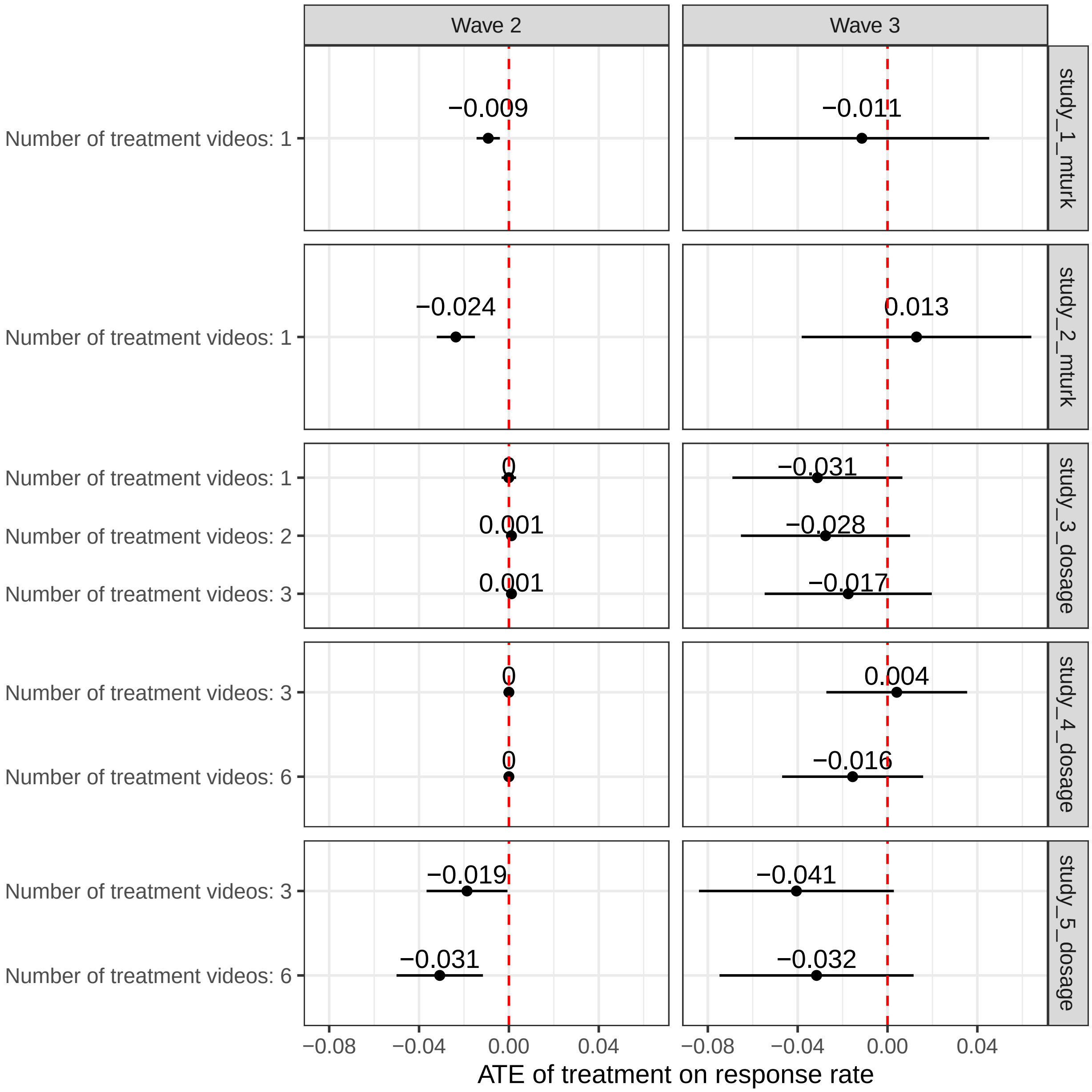
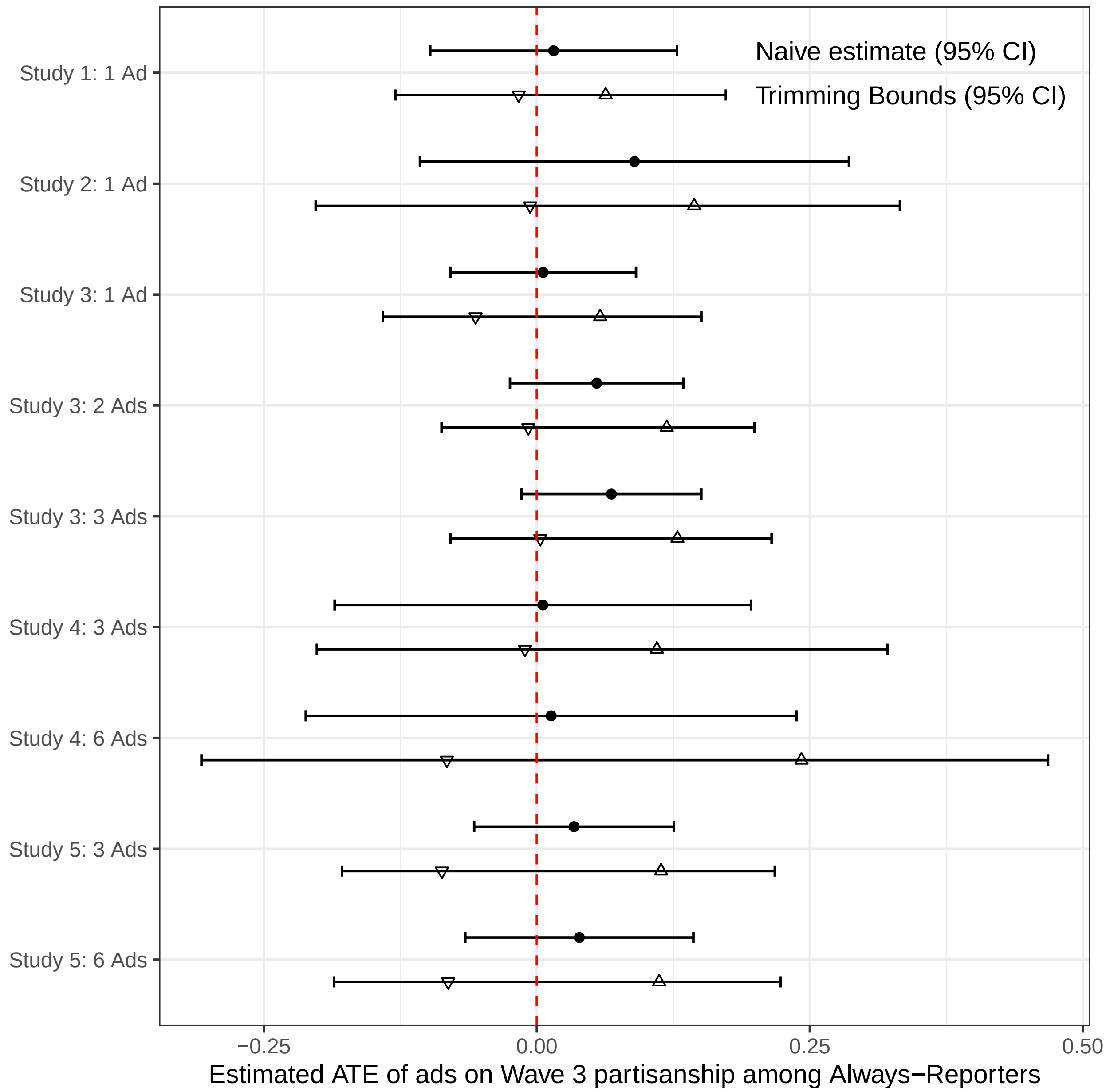


Figure A.4: Estimated effects on 7-point party ID at Wave 3 using bounds



B Field Experiment

In the fall of 2023, we collaborated with two left-leaning organizations working in Minnesota to test the effect of a phone and mail campaign aimed at moving partisanship. The design and analysis of this study was pre-registered (the preanalysis plan is included below).

The subjects of our experiment are Minnesota residents who have in the past responded to Organization 1 or Organization 2 surveys. The Organization 1 sample is comprised of 11,199 individuals living in 11,005 households and the Organization 2 sample is comprised of 19,026 individuals living in 18,424 households.

For both samples, we randomized assignment to treatment or control at the household level. For the Organization 1 sample, we created matched quartets of households based on the average answers to a pre-treatment 7 point party ID question and an indicator variable for whether the party ID information was available. We created these matched quartets within but not across state house districts, which had the effect of blocking on house district as well. For the Organization 2 sample, we had access to a few more demographic variable when blocking. For households of size 1 (that is, individuals), we blocked on race, partisanship, age, gender, and indicators for missingness in partisanship and age. As in the Organization 1 sample, we created matched quartets within house district. For households with size greater than 1, we calculated average partisanship, then created matched quartets of households based on average partisanship. Because there were too few households with size greater than one across the state, we did not conduct this matching within house district.

We treated exactly two units in all matched quartets. In the small number of cases with blocks smaller than size 4, we flipped a coin to break ties.

The treatment includes four postcards mailed to treatment group households. Two postcards focuses on education policy ("Minnesota Democrats are putting students first") and feature photos of Ron DeSantis and Mike Pence; a third focuses on abortion ("Minnesota Democrats are protecting abortion access") and features a photo of Tim Walz; the fourth features the same photo of Walz and focuses on him specifically ("Under Governor Tim Walz's leadership, Minnesota Democrats provided the tools for Minnesota to thrive").

Treated participants also received phone calls and text messages, with different messages focusing on abortion access, public education and school meals. The message for each subject varied based on their interest; the subject could indicate which topic meant the most to them.

Outcomes were assess via telephone survey. The outcomes were identical to battery described in the main text. We report here the effects on seven-point party ID, the partisan evaluation index, and the partisan identification index.

B.1 Results

Here we report average and conditional average treatment effect estimates on our three main outcomes:

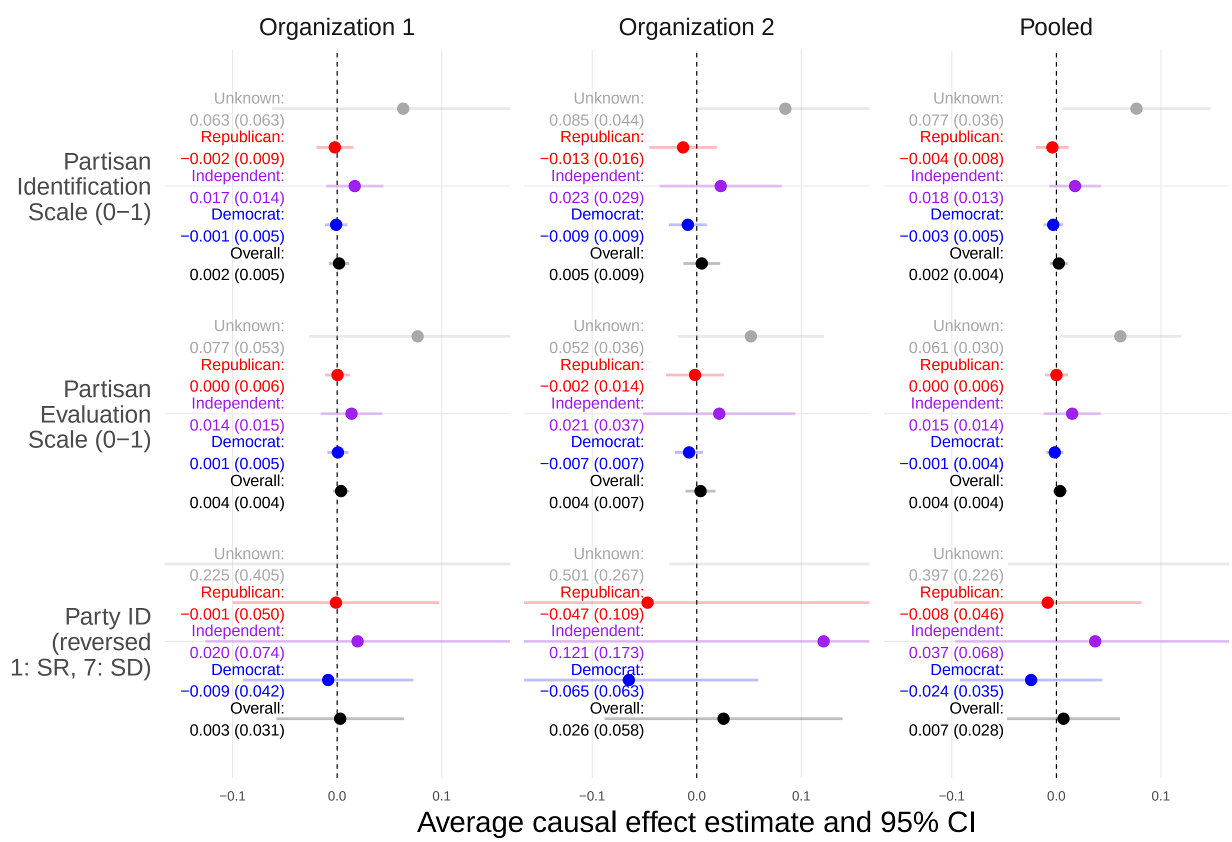
1. Seven point party ID 2. A partisan evaluation scale that varies between 0 and 1 (higher values higher

evaluations of Democrats), constructed from feeling thermometers, a vote intention outcome, and party evaluation questions 3. A partisan identification scale that varies between 0 and 1 (higher values higher identification with Democrats), constructed from the seven point party ID and a Republican self-description question.

We report here the results of regression estimates of the outcome on treatment, a four category partisanship variable with Democrat, Independent, Republican, and Unknown as the levels, and an indicator for organization. When we estimate the effects among partisan subgroup, we control only for organization; when we estimate the effects among each organization, we control only for partisan subgroup. This control strategy deviates from our preregistered "fixed effects" specification for reasons described in the "Deviations from the PAP" section.

Figure B.5 shows that the treatment had precisely estimated effects that cannot be distinguished from zero on average and within each partisan subgroup, with the exception of the "Unknown" group. We eye the small "unknown" partisan subgroup with suspicion, especially considering the possible differential attrition in that subgroup.

Figure B.5: Average and Conditional Average Treatment Effect Estimates on Main Outcomes



We also preregistered that we would directly estimate the differences-in-CATEs. As shown in Table B.3, none of the pre-registered differences are substantively large or statistically significant.

Table B.3: Differences-in-CATES

Outcome	Contrast	Estimate (SE)	p-value
partisan_evaluation_index_post	Independent vs Democrat	0.017 (0.014)	0.252
partisan_evaluation_index_post	Republican vs Democrat	0.002 (0.007)	0.821
partisan_evaluation_index_post	Republican vs Independent	-0.015 (0.015)	0.318
partisan_evaluation_index_post	Org 2 vs Org 2	-0.000 (0.008)	0.972
partisan_identification_index_post	Independent vs Democrat	0.021 (0.014)	0.117
partisan_identification_index_post	Republican vs Democrat	-0.001 (0.009)	0.928
partisan_identification_index_post	Republican vs Independent	-0.022 (0.015)	0.140
partisan_identification_index_post	Org 2 vs Org 2	0.003 (0.010)	0.807
pid_7_rev_post	Independent vs Democrat	0.062 (0.076)	0.418
pid_7_rev_post	Republican vs Democrat	0.016 (0.058)	0.783
pid_7_rev_post	Republican vs Independent	-0.045 (0.082)	0.584
pid_7_rev_post	Org 2 vs Org 2	0.021 (0.066)	0.747

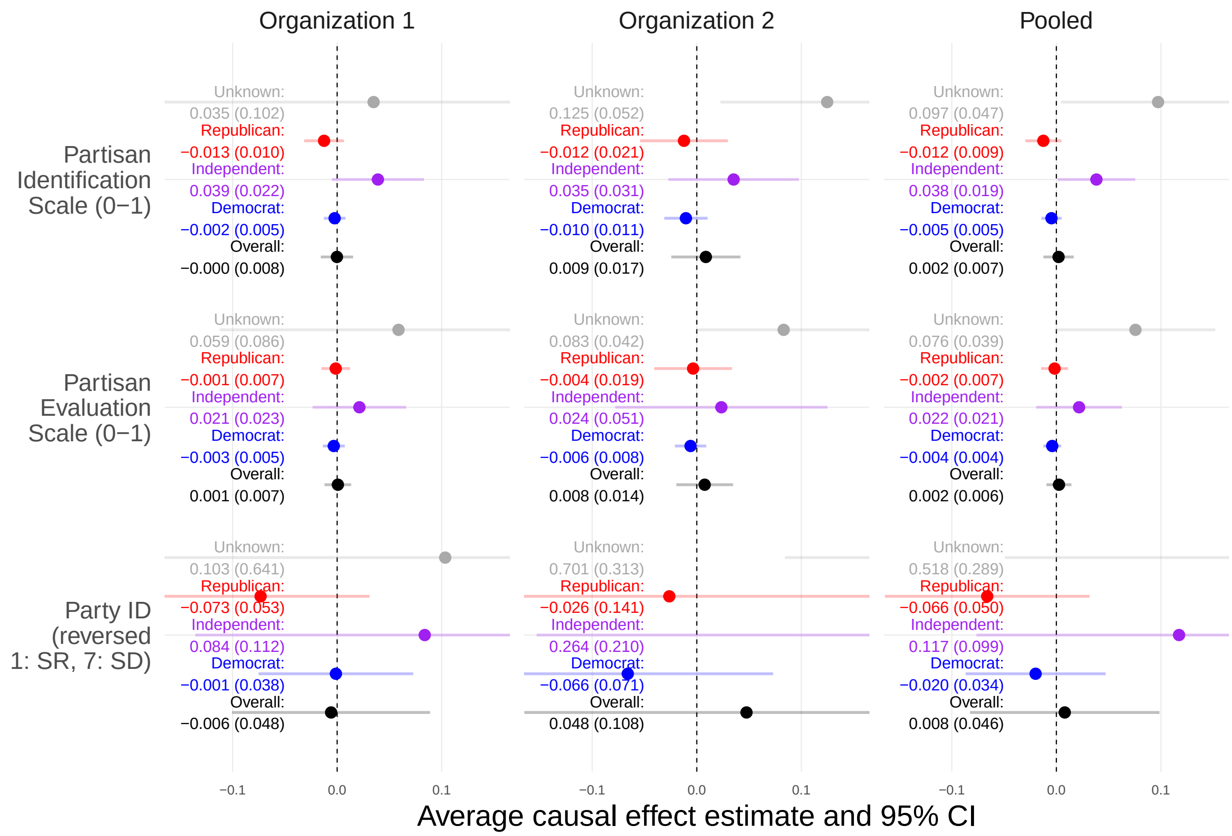
B.2 Deviations from the PAP

By and large, the preceding analysis follows our PAP faithfully, but a few issues came up that we document here

1. OLS versus Fixed Effects

In our PAP, we preregistered that we would include block fixed effects when estimating the effects of treatment. Our blocking strategy aimed to create matched quartets of units based on pre-treatment information. However, because of nonresponse, many of these blocks end up having fewer than two units per block; when we use fixed effects for block, the estimation effectively drops units in blocks of size 1. One "fix" for that problem is to group all units that are in blocks of size 1 into a composite block (separately for each organization), which we then control for in a fixed effects model. We report the results of this approach in figure B.6. We can see here that the uncertainty attending to the (modified) fixed effects estimate is higher than the OLS models above, mainly because we essentially perform no covariate adjustment for any of the units in the composite blocks. For comparison, the adjusted R-squared of the OLS model predicting the effects on seven-point partisanship is 0.76, compared with 0.48 for the fixed effects model; this difference highlights how much more predictive of outcomes the covariates are than the composite blocks.

Figure B.6: Average and Conditional Average Treatment Effect Estimates on Main Outcomes with modified fixed effects



2. We preregistered we would estimate CR2 clustered standard errors, but they are prohibitively computationally expensive. We use estimatr's "stata" default clustered standard errors instead. Since we have many clusters, this change has minimal effects on our estimated standard errors.

3. We forgot to indicate we would include the feeling thermometers for Democrats and Republicans along with the thermometers for party elites in the partisan evaluation index; we do include those outcomes in the index reported here.

4. The post-treatment survey for org 1 appears to not have asked the "Self Description Democrat" variable, so we could not include it in the partisan identification scale nor estimate effects on it as a secondary outcome.

5. We did not specify how we would handle missingness in the index creation – we average together all non-missing index components for each unit; if a unit is missing on all of the index components, they are missing on the index as well.

6. We do not have the registration information needed to split the sample by registration status as described by the pap. Since the unregistered only received two of four treatment mailers, the current estimates are presumably smaller than they would have been had the unregistered received four mailers.

B.3 Field Experiment pre-analysis plan

Pre-analysis plan for Minnesota field experiment

[redacted]

2023-11-06

This document describes a pre-analysis plan for a field experiment conducted in the Fall of 2023. We are filing this PAP after randomization has occured and treatments have been deployed, but before outcomes have been collected.

The experiment was jointly conducted by [Organization 1] and [Organization 2] with design input from the academic team.

Units

The subjects of our experiment are Minnesota residents who have in the past responded to Organization 1 or Organization 2 surveys. The Organization 1 sample is comprised of 11,199 individuals living in 11,005 households and the Organization 2 sample is comprised of 19,026 individuals living in 18,424 households.

Randomization

For both samples, we randomized assignment to treatment or control at the household level.

For the Organization 1 sample, we created matched quartets of households based on the average answers to a pre-treatment 7 point party ID question and an indicator variable for whether the party ID information was availble. We created these matched quartets within but not across state house districts, which had the effect of blocking on house district as well.

For the Organization 2 sample, we had access to a few more demographic variable when blocking. For households of size 1 (that is, individuals), we blocked on race, partisanship, age, gender, and indicators for missingness in partisanship and age. As in the Organization 1 sample, we created matched quartets within house district. For households with size greater than 1, we calculated average partisanship, then created matched quartets of households based on average partisanship. Because there were too few households with size greater than one across the state, we did not conduct this matching within house district.

We treated exactly two units in all matched quartets. In the small number of cases with blocks smaller than size 4, we flipped a coin to break ties.

Treatment

The treatment includes four postcards mailed to treatment group households. Two postcards focuses on education policy ("Minnesota Democrats are putting students first") and feature photos of Ron DeSantis and Mike Pence; a third focuses on abortion ("Minnesota Democrats are protecting abortion access") and features a photo of Tim Walz; the fourth features the same photo of Walz and focuses on him specifically ("Under Governor Tim Walz's leadership, Minnesota Democrats provided the tools for Minnesota to thrive").

Treated participants also received phone calls and text messages, with different messages focusing on abortion access, public education and school meals. The message for each subject varied based on their interest; the subject could indicate which topic meant the most to them.

Outcome measurement

We measure outcomes via survey. Our primary outcome is 7 point party ID, measured via the tradition ANES branching question.

We then measure a series of secondary outcomes:

1. feeling thermometers for these political leaders (Kamala Harris, Barack Obama, Alexandria Ocasio-Cortez, Donald Trump, Marjorie Taylor-Green, Ron DeSantis, Mitt Romney, Mike Pence, Joe Biden) and these groups (The Democratic Party, The Republican Party, The National Rifle Association, Black Lives Matter, Planned Parenthood, The American Civil Liberties Union, Moms for Liberty, Libs of TikTok)
2. A vote preference question: "If the 2024 presidential election was held today, would you want to see the Republican Party or Democratic Party win?" [The Republican Party, The Democratic Party, Neither/don't know]
3. Favorability scales: "On a scale from 1 to 7, with 1 being the least favorable and 7 being the most favorable, how would you rate the Republican party?" "On a scale from 1 to 7, with 1 being the least favorable and 7 being the most favorable, how would you rate the Democratic party?"
4. Self-descriptions: "On a scale from 1 to 10, where '10' represents a description that is perfect for you, and '1' a description that is totally wrong for you, how well do each of the following describe you?" [A Republican, A Democrat, A Midwesterner, An environmentalist, A feminist, An evangelical Christian]

We will estimate the effects on each of these outcomes separately, in their natural scales.

We will further create a partisan evaluation index that will average together the following 12 outcomes with equal weights, all rescaled from 0 to 1 with higher values indicating more pro-Democrat sentiment.

- FT Kamala Harris
- FT Barack Obama
- FT Joe Biden
- FT Alexandria Ocasio-Cortez
- FT Donald Trump (reversed)
- FT Marjorie Taylor-Green (reversed)
- FT Ron DeSantis (reversed)
- FT Mitt Romney (reversed)
- FT Mike Pence (reversed)
- vote preference (Democratic Party = 1, Republican Party = 0, Neither/ don't know = 0.5)
- favorability Democratic Party
- favorability Republican Party (reversed)

We will also create a partisan identity scale will average together the following 3 outcomes, all rescaled from 0 to 1 with higher values indicating more Democratic self-identification.

- Seven-point party ID
- Self-Description Democrat
- Self-Description Republican (reversed)

We consider the seven point party ID and the two indicies as our main outcomes, and we consider all other outcomes secondary.

Estimation and null hypothesis testing

We will estimate treatment effects with a regression of each outcome on the treatment indicator, with fixed effects for block, with CR2 clustered standard errors by household. We will do inference against the null hypothesis of no effect via t-tests using those standard errors to construct t-statistics. For tests of ATEs and CATEs against the null hypothesis of no effect, we will use one-tailed tests because we expect our treatments to have positive (i.e., pro-Democratic) effects. For tests of differences-in-CATEs against the null of no differences in average treatment response, we will use two-tailed tests.

Heterogeneity

We will estimate the effects of treatment (CATEs) separately by partisan subgroup (Republicans, Independents, Democrats, including leaners as partisans). We will also estimate the effects of treatment separately by experimental sample, Organization 1 and Organization 2. We will report three pairs of differences-in-CATEs (R v I, R v D, D v I) for partisans and a fourth for the difference-in-CATEs by sample.

Any other investigation of effect heterogeneity that occurs to the research team or reviewers will be marked as "exploratory."

Anticipated problems

We have encountered some treatment noncompliance. Our partner discovered that they removed all non-registered voters in the treatment group from the mailing list in between the second and third mailings. Registered voters in the treatment group were treated with four mailers, unregistered (potential) voters were treated with two. Since we can identify who in the control group is and isn't registered, we will conduct our analyses separately by registration status, focusing our attention mainly on the effects of the full treatment dosage on the registered voter sample.

Our partner has also reported that, as anticipated, some treated households did not answer the phone when called with phone treatments. We will report phone compliance estimates. We will neverthless exclusively report intention-to-treat estimates of causal effects.

We also have encountered some problems with attrition, i.e., some voters are not completing the survey, as we anticipated. We will investigate whether treatment causes attrition by regressing an indicator for response on treatment assignment. We will further investigate the heterogeneity in the effects of treatment on attrition using the same heterogeneity analyses as in the estimation of treatment effects. If we find that treatment does not cause attrition, we will proceed with effect estimation, interpreting our results to be local to the "always responders" or that subset of voters who would respond to the outcome survey in either the treatment or control groups. If we find that treatment does cause attrition (in some or all cases), we will report trimming bounds around the effect for always reporters (in those cases only).

Unanticipated problems

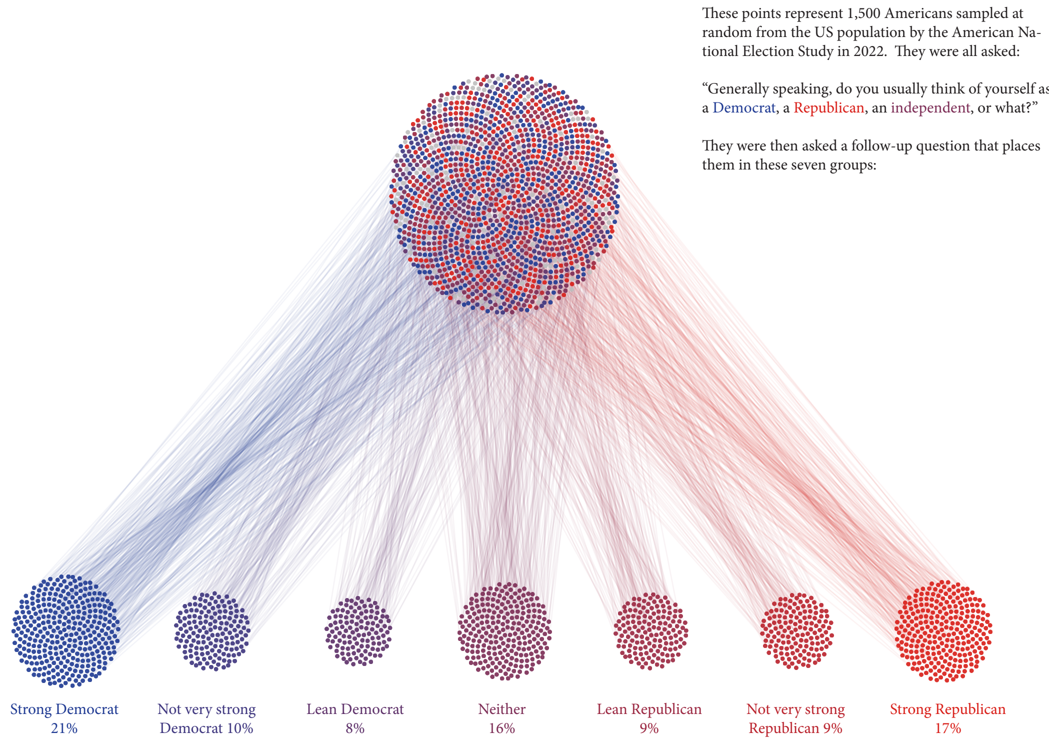
For those problems we have not anticipated here, we will follow the standard operating procedures outlined here: [redacted]

C Hypothetical Experiments

C.1 Soliciting pre-treatment party ID

In our hypothetical survey experiments, we lead subjects through the measurement of party ID in an effort to cause subjects to reflect on their partisanship explicitly as a group identity. We told subjects:

> Surveys often take a random sample of Americans and ask them the following question: "Generally speaking, do you usually think of yourself as a Democrat, a Republican, an Independent, or what?" In a 2022 survey, 31% of Americans said that they were Democrats, 32% said Independents, 27% said Republicans, 6% said that they weren't sure, and 4% said that they didn't want to give an answer at all. The survey doesn't stop there. Among people who call themselves Democrats, there are people who are stronger and weaker Democrats. Among people who call themselves Republicans, there are stronger and weaker Republicans. Some people who call themselves Independent do so because they don't feel strongly politically, but if you ask a follow-up question, they will pick a party that they lean toward. You can see how this all breaks down in the graph.



We then asked subjects: "Looking at this graph, which group do you see yourself as belonging to the most?" with these response options: Strong Democrat, Not very strong Democrat, Lean Democrat, Neither, Lean Republican, Not very strong Republican, Strong Republican.

C.2 The Office

After soliciting subjects' pre-treatment party ID using the procedure described in the previous section, we asked subjects in both Study 1 and Study 2 to guess the partisanship of five characters from the television program The Office. This warm-up was intended to induce subjects to think about what kinds of people belong to which partisan groups.

We told subjects, "Now we are going to imagine how different characters from TV programs might respond to the question of how they identify politically (e.g., Strong Democrat, Strong Republican)." We then asked subjects "Do you watch The Office or have you ever watched The Office?" If they said no, we told them, "Even though you haven't watched The Office, we're going to give you some pictures of the characters and ask you to imagine their political affiliations all the same."

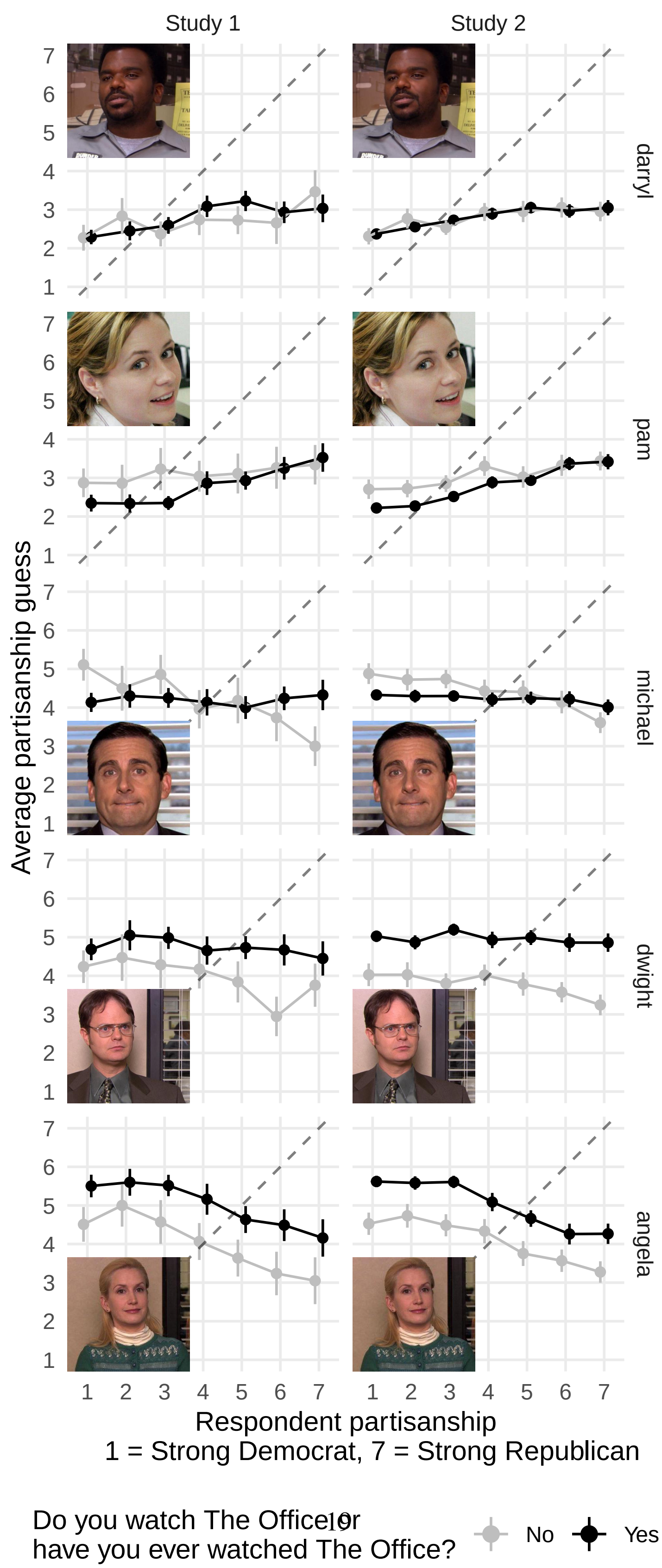
We then showed subjects pictures of five characters from the Office one after the other and asked: "How do you think that [Michael Scott/Angela Martin/Dwight Schrute/Pam Beesly/Darryl Philbin would identify politically?" with the response options being the seven points of party identification.

The results are shows in Figure C.7. We split respondents by partisanship and by whether they have seen the show; plotted estimates are simple group means with 95% confidence intervals. Among office characters, Darryl and Pam are seen as the most Democratic, and the answers are quite similar between those who have seen those show and those who have not. We see a gradient with respect to subjects' partisanship – the more Republican subjects see these two characters as (relatively) more Republican, though on average, subjects from all partisan backgrounds tend to see Darryl and Pam as Democrats.

Perceptions of Michael, Dwight, and Angela follow different patterns. Among those who have seen the show and regardless of partisanship, Michael is viewed as a pure Independent and Dwight is viewed as weakly Republican. Among those who haven't seen the show, the most Democratic subjects view Michael as weakly Republican and the most Republican view him as weakly Democratic. A similar negative gradient holds for both Dwight and Angela; those who have seen the show place Angela as the most Republican, Democratic subjects especially so.

For us the most interesting pattern is that partisans seem to imagine the sympathetic characters are more like them (positive gradients for Darryl and Pam) and that the unsympathetic characters are less like them (negative gradients for Michael, Dwight, and Angela.)

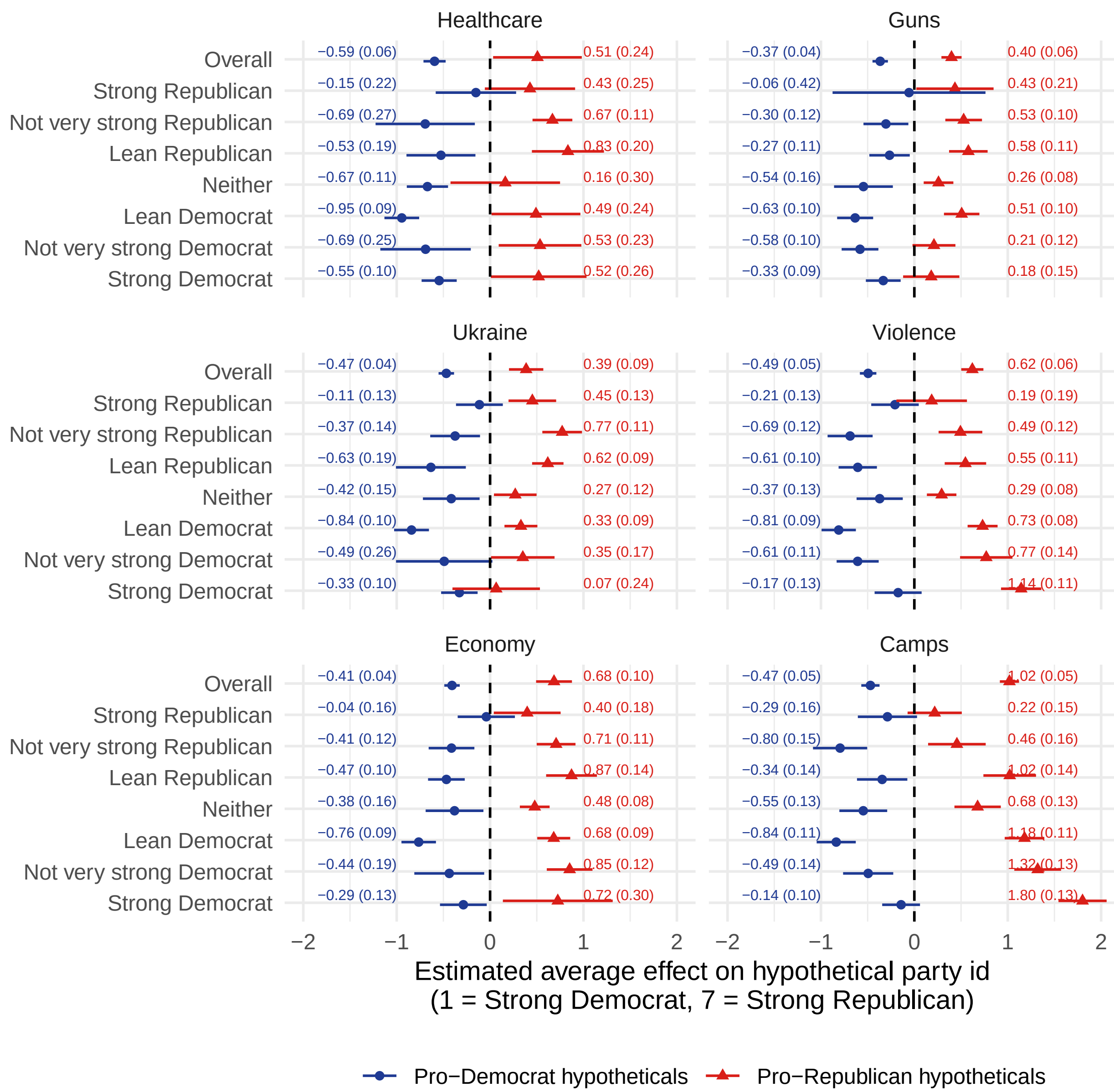
Figure C.7: Imagined partisanship of characters on The Office



C.3 Meta-analysis of studies 1 and 2

Here we report the meta-analytic estimates of the hypothetical effects across studies 1 and 2, as pre-registered.

Figure C.8: Meta-analysis: average effects on hypothetical partisanship



C.4 Study 2: Probability Evaluations

In study 2, after subjects completed all six hypothetical scenarios, we asked them to evaluate the probability a hypothetical scenario would occur. We did this for two reasons: first, to see if our hypotheticals seemed plausible to our subjects and two, to help subjects draw the connection between the hypothetical scenarios and possible futures before assessing their post-treatment party ID.

Table C.4 displays the complete text of this consolidation exercise for all scenarios.

Figure C.9 shows the average probability judgments of each hypothetical, by pre-treatment party ID. Respondents judge the status quo hypotheticals to be reasonably probable, with mean judgments exceeding 50% in all cases, for all partisan subgroups. The pro-Democratic and pro-Republican hypotheticals are judged to be reasonably probable by in-partisans, but nonprobable by outpartisans, with nearly perfect symmetry across treatments. The only exception to this is the "camps" hypothetical. The pro-Democrat hypothetical in which Donald Trump puts immigrants in camps follows the usual pattern, but the pro-Republican camp in which Biden inters Republicans is judged to be quite improbable by all partisans, with only a mild partisan gradient to the responses.

Scenario	Status quo	Pro-R	Pro-D
Healthcare	After you were presented with a scenario describing the healthcare situation in this country as not really changing, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that the healthcare situation in this country will not really change?	After you were presented with a scenario describing Democratic healthcare policies leading to the death of a close friend, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that Democratic healthcare policies will lead to the death of a close friend?	After you were presented with a scenario describing Republican healthcare policies leading to the death of a close friend, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that Republican healthcare policies could lead to the death of a close friend?
Guns	After you were presented with a scenario describing the gun control situation in this country as not really changing, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that the gun control situation in this country will not really change?	After you were presented with a scenario describing Republicans passing laws to dramatically reduce gun violence and school shootings, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that Republicans will pass laws that reduce gun violence and school shootings?	After you were presented with a scenario describing Democrats passing laws to dramatically reduce gun violence and school shootings, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that Democrats will pass changes to laws that reduce gun violence and mass shootings?
Violence	After you were presented with a scenario describing the prevalence of political violence in this country as not really changing, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that the political violence situation in this country will not really change?	After you were presented with a scenario describing Joe Biden supporters committing mass political violence, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that Joe Biden supporters will commit mass political violence?	After you were presented with a scenario describing Donald Trump supporters committing mass political violence, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that Donald Trump supporters will commit mass political violence?
Ukraine	After you were presented with a scenario describing the situation in Ukraine as not really changing, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that the situation in Ukraine will not really change?	After you were presented with a scenario describing Donald Trump's policy toward Ukraine saving the lives of many innocent Ukrainians, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that Donald Trump's Ukraine policies will save the lives of many Ukrainians?	After you were presented with a scenario describing Donald Trump's policy toward Ukraine leading to the death of many innocent Ukrainians, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that Donald Trump's Ukraine policies would lead to the death of many innocent Ukrainians?
Economy	After you were presented with a scenario describing the economic conditions in America as not really changing, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is the economic conditions in America will not really change?	After you were presented with a scenario describing the American economy collapsing because of Democratic policy choices, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that the American economy will collapse because of Democratic policy choices?	After you were presented with a scenario describing the American economy collapsing because of Republican policy choices, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the described scenario could become reality. How likely do you think it is that Republican policies will cause the American economy to collapse?
Camps	After you were presented with a scenario describing the winner of the 2024 election as not locking anyone up in camps, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that the winner of the 2024 election will not lock anyone up in camps?	After you were presented with a scenario describing Joe Biden putting some of his political opponents in camps, with some of them dying, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that Joe Biden will put his political opponents in camps, leading some to die?	After you were presented with a scenario describing Donald Trump putting immigrants in internment camps and killing some, you said that your party affiliation would be the following: [prior answer]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that Donald Trump will put immigrants in internment camps, leading to the death of some?

Table C.4: Consolidation exercise (Study 2 only)

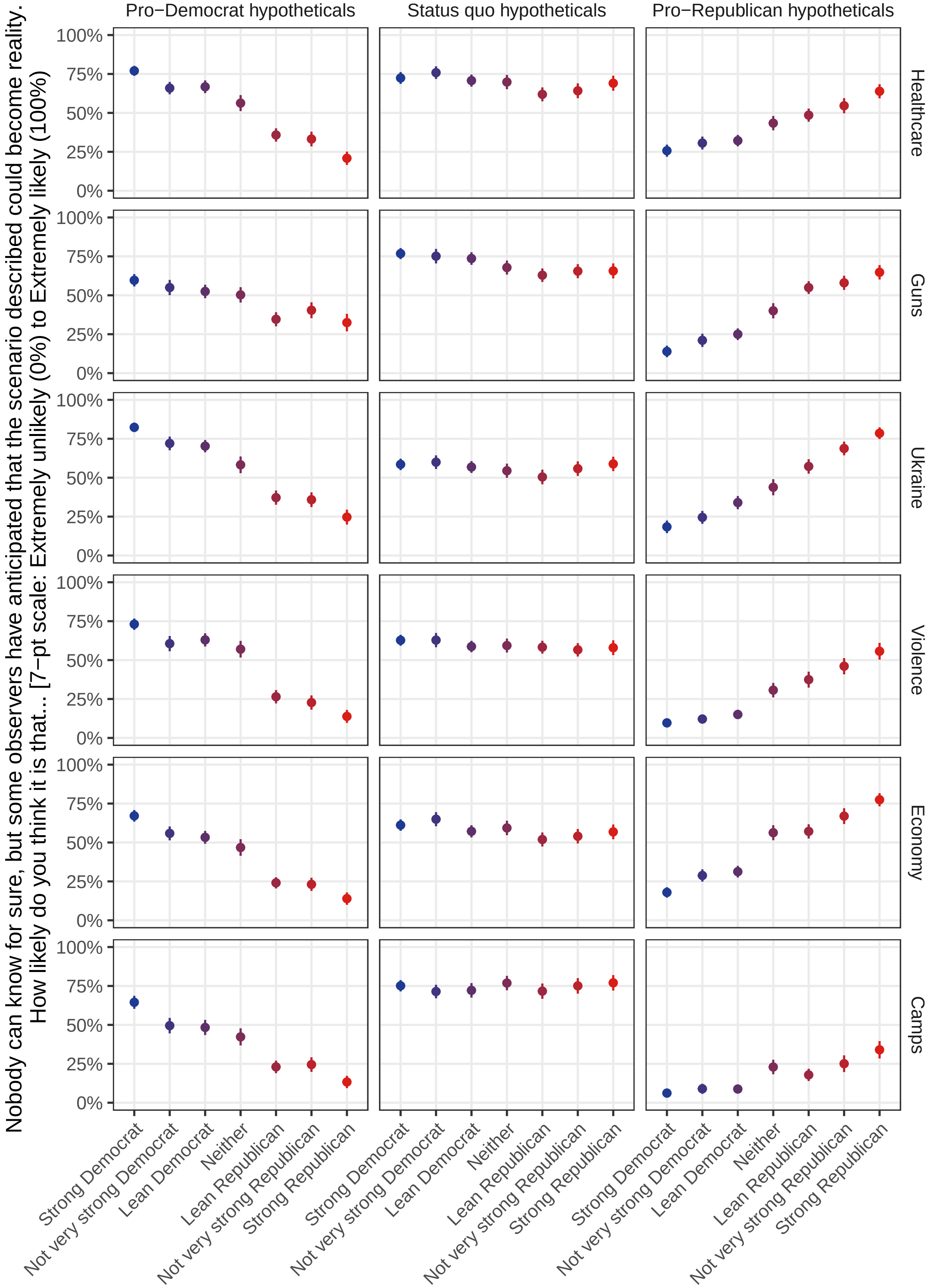


Figure C.9: Average estimates of the probability a hypothetical would occur, by partisanship

C.5 Macropartisanship analysis

Here we report the effect of the hypotheticals on "macropartisanship," operationalized as the fraction of partisans (excluding leaners) who identify as Democrats. The entries in TableC.5 report the difference in macropartisanship in pro-Democratic hypotheticals versus the status quo hypotheticals. Bootstrapped standard errors (with bootstraps clustered by respondent) are reported in parentheses. These analyses were not pre-registered.

Table C.5: Effects on Macropartisanship

Study 1		
hypothetical	Effect of pro-Dem Hypotheticals	Effect of pro-Rep Hypotheticals
Healthcare	0.24 (0.05)	-0.04 (0.06)
Guns	0.16 (0.05)	-0.05 (0.05)
Ukraine	0.17 (0.05)	-0.04 (0.05)
Violence	0.18 (0.05)	-0.14 (0.05)
Economy	0.15 (0.05)	-0.14 (0.05)
Overall	0.18 (0.05)	-0.08 (0.05)
Study 2		
hypothetical	Effect of pro-Dem Hypotheticals	Effect of pro-Rep Hypotheticals
Healthcare	0.15 (0.03)	-0.26 (0.03)
Guns	0.11 (0.03)	-0.16 (0.03)
Ukraine	0.15 (0.03)	-0.16 (0.03)
Violence	0.17 (0.03)	-0.26 (0.03)
Economy	0.14 (0.03)	-0.28 (0.03)
Camps	0.14 (0.03)	-0.38 (0.03)
Overall	0.14 (0.03)	-0.25 (0.03)

Bootstrapped standard errors are in parentheses.

C.6 Party switching analysis by hypothetical

Figures C.10 and C.11 are analogous to main text figure 5, but are broken down by hypothetical. The figure shows that the basic patten we obtained overall does hold in each hypothetical topic, i.e., approximately 10% or more of partisans would switch parties under the pro-outpartisan hypothetical. The fraction under the status quo hypotheticals is consistently in the single digits. The hypothetical that generates the largest change is the pro-Democrat healthcare hypothetical, under which 19.4% of Republicans would become Democrats; this hypothetical is also the most effective of the pro-Democrat hypotheticals measured in Study 2.

As mentioned in the main text, the analysis of party switching was not preregistered. We include it here and in the main text at the request of a reviewer and because we think it is an important experimental summary.

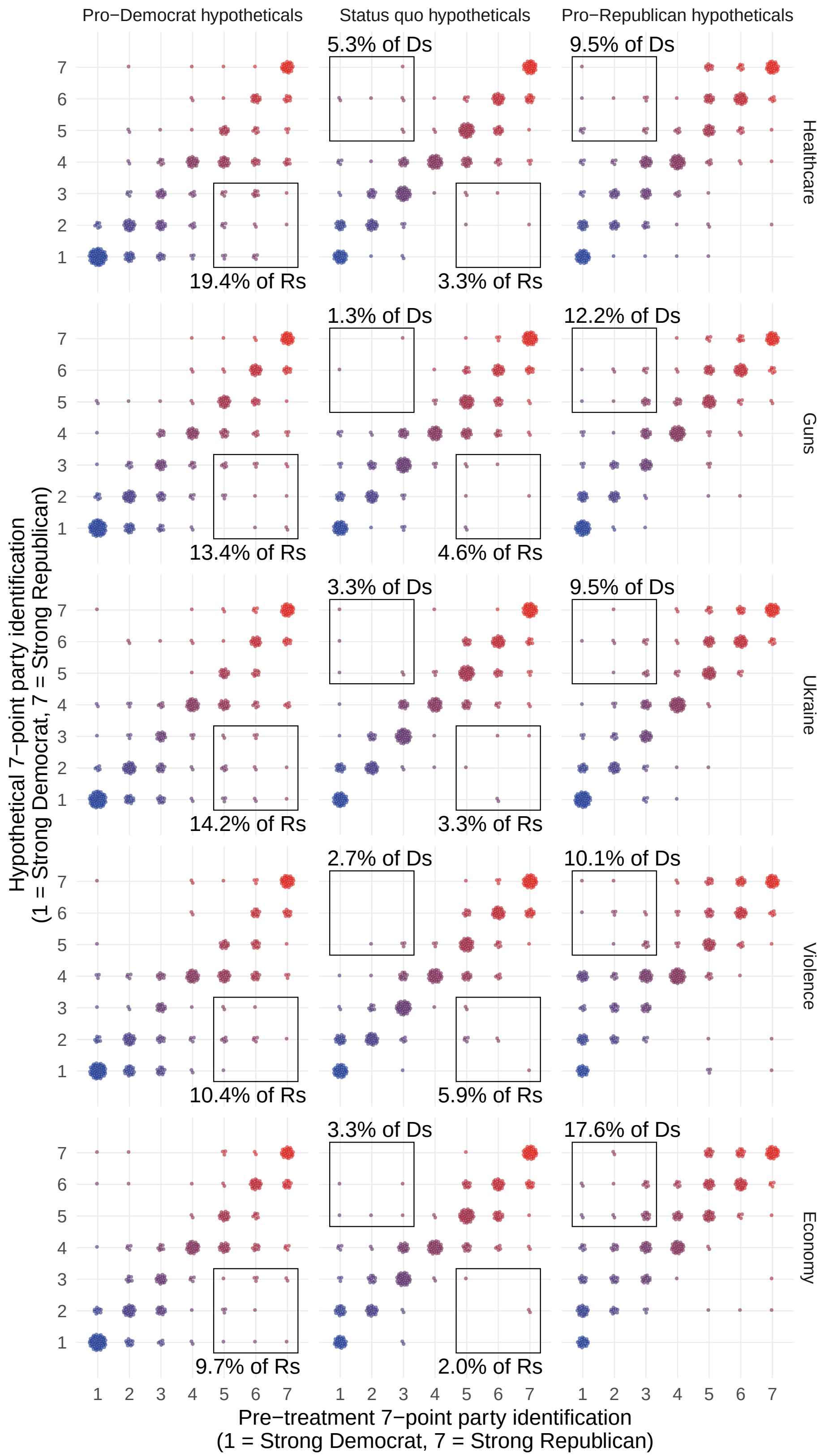


Figure C.10: Study 1 Hypotheticals Responses

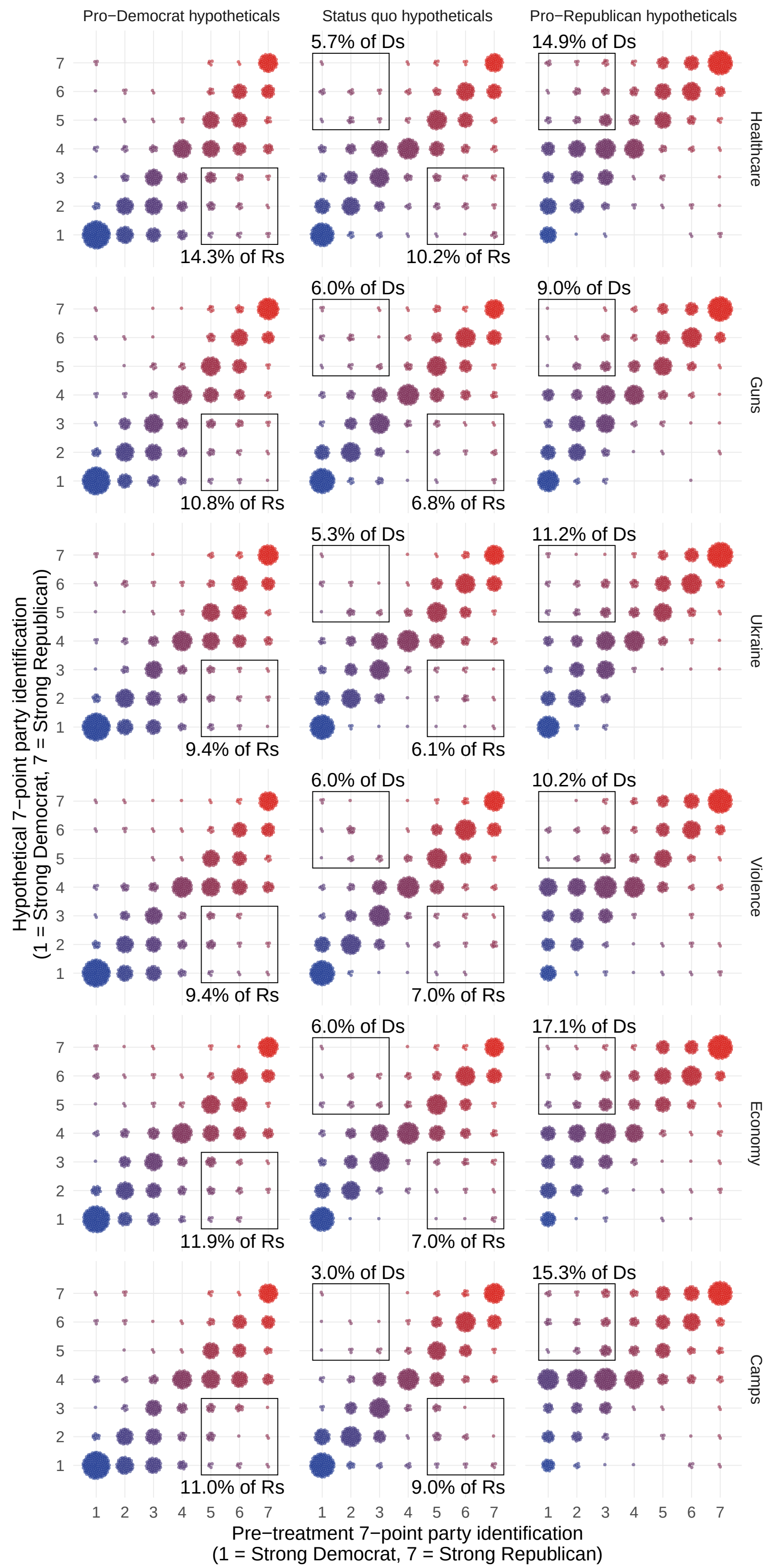


Figure C.11: Study 2 Hypotheticals Responses

C.7 Preanalysis plan

Preanalysis plan for "The Scope of Partisan Change" Study 2

[redacted]

February 5, 2024

This document describes a pre-analysis plan for a replication of an original, unregistered experiment we have already conducted. Study 1 (already completed) was conducted among 988 respondents recruited via Cloudresearch. Study 2 (to be conducted among 3,000 respondents recruited via Cloudresearch follows a nearly identical design. This document will describe both designs, noting the small differences between study 1 and study 2. The analysis of study 2 will follow exactly the same procedures as the analysis of study 1, which we present here as our pre-registered analysis of study 2.

Design of Study 1

Subjects were recruited via the Connect CloudResearch survey platform. Relying on CloudResearch's targeting capability and their existing data on party identification, we launched three identical surveys at once, each one targeting a different partisan group: Democrats, Republicans and Independents.

After obtaining informed consent, we introduced subjects to the concept of the ANES seven-point branching party ID question. We asked subjects to tell us their party ID using the ANES question. We then asked them to guess the partisanship of fictional characters from the US television show "The Office."

After these warmups, we asked subjects to consider some hypothetical scenarios:

"Next, we are going to ask you to consider several hypothetical situations. They don't describe real events, but these are events that could happen. We'd like you to read them and answer the questions that follow."

> Imagine that the following occurs:
> [Scenario]
> If this really happened, how do you think you would describe your political affiliation?
> [Strong Republican, Republican, Lean Republican, Undecided/Independent/Other, Lean Democrat, Democrat, Strong Democrat]

We randomized subjects to see only the status quo hypotheticals, the pro-Democratic hypotheticals, or the pro-Republican hypotheticals. In some cases (healthcare, guns, economy) we randomize status quo subjects to see one of two versions of the status quo hypothetical. The full set of scenarios is presented in Table 1

Table 1: Hypothetical Scenarios

SQ healthcare	Political leaders from both parties try to come together to improve our healthcare system, but they fail to pass any legislation. The costs of prescription drugs, the number of people without health insurance and the cost of insurance–they all remain the same. OR Political leaders from both parties pass a bill to change the U.S. healthcare system. But after the bill is signed into law, nothing changes. The costs of prescription drugs, the number of people without health insurance and the cost of insurance–they all remain the same.
SQ guns	Republicans and Democrats try to pass a new gun law that both parties can agree to. But they don't successfully pass any new bills into law. School shootings occur at the same rate they do now, and the number of violent crimes does not go up or down. OR Republicans and Democrats team up to pass a new gun law that both parties can agree to. But after the bill is signed into law, nothing changes. School shootings occur at the same rate they do now, and the number of violent crimes does not go up or down.
SQ Violence	On Election Day 2024, Governors around the country call up the National Guard because they are afraid of violence at the polls. Their fears are not realized, however, and voters cast their ballots peacefully, without any notable acts of violence.
SQ Ukraine	For the next few years, the Russia-Ukraine war remains at a stalemate. Neither side advances far beyond where they are today. The fighting is constant but does not escalate.
SQ Economy	Republicans and Democrats attempt to pass a comprehensive economic bill to deal with taxing and spending. Their efforts do not bear fruit, and their attempt has no impact on the economy or on your family's financial well-being. OR Republicans and Democrats pass a comprehensive economic bill to deal with taxing and spending. However, the new law doesn't actually do much, and has no impact on the economy or on your family's financial well-being.
Pro-D healthcare	Republicans in Congress have long tried to repeal government-funded medical care. Now, imagine that they succeed, and that you are diagnosed with an aggressive form of stomach cancer. Because Republicans repealed government-funded medical care, you can't afford the medical treatment that you need.
Pro-D guns	Over intense Republican objections, Democrats in Congress pass a ban on assault weapons. After the ban, school shootings decline to 1% of what they had been before. The number of violent crimes also decreases dramatically
Pro-D Ukraine	Donald Trump wins the 2024 election and immediately withdraws all U.S. support for Ukraine. Putin easily conquers Ukraine, slaughtering hundreds of thousands of people in the process. He then invades Poland, again killing many innocent people in his quest for domination.
Pro-D violence	On Election Day 2024, armed supporters of Donald Trump march into Democratic areas to intimidate Democratic voters. Some of Trump's supporters shoot at and kill unarmed Biden supporters.
Pro-D economy	Republicans have long resisted Democrats' efforts to regulate Wall Street. Now, because Republicans have limited regulation on Wall Street, the stock market crashes. The U.S. economy collapses, with widening unemployment. You have trouble meeting your monthly expenses. Your friends and family members suffer the same fate.
Pro-R healthcare	Democrats in Congress have long tried to force people to use government-run health insurance. Now, imagine that they succeed, and that you are diagnosed with an aggressive form of brain cancer. Because of the Democratic health care law, you don't get to choose your provider and must be treated by the government-selected doctor.
Pro-R guns	Over intense Democratic objections, Republicans in Congress pass legislation that provides more guns to police officers and school teachers. Afterwards, school shootings decline to 1% of what they had been before. The number of violent crimes also decreases dramatically.
Pro-R Ukraine	Donald Trump wins the 2024 election and immediately negotiates a ceasefire between Russia and Ukraine. Russia withdraws from most of Ukraine, and hundreds of thousands of lives are spared because of Trump.
Pro-R violence	On Election Day 2024, armed supporters of Joe Biden march into Republican areas to intimidate Republican voters. Some of Biden's supporters shoot at and kill unarmed Trump supporters.
Pro-R economy	Democrats have long tried to raise taxes, over Republican objections. Now, because of Democratic tax increases, the amount of money you owe in taxes increases dramatically. You have trouble meeting your monthly expenses. Your friends and family members suffer the same fate.

After responding to these hypotheticals, the subjects then proceeded to answer a series of post-treatment outcome aimed at measuring their partisan identification and their evalution of the parties.

These outcomes are:

- Feeling thermometers for these political leaders (Kamala Harris, Barack Obama, Alexandria Ocasio-Cortez, Donald Trump, Marjorie Taylor-Green, Ron DeSantis, Mitt Romney, Mike Pence, Joe Biden) and these groups (The Democratic Party, The Republican Party, The National Rifle Association, Black Lives Matter, Planned Parenthood, The American Civil Liberties Union)

- A vote preference question: "If the 2024 presidential election was held today, would you want to see the Republican Party or Democratic Party win?" [The Republican Party, The Democratic Party, Neither/don't know]

- Favorability scales: "On a scale from 1 to 7, with 1 being the least favorable and 7 being the most favorable, how would you rate the Republican party?" "On a scale from 1 to 7, with 1 being the least favorable and 7 being the most favorable, how would you rate the Democratic party?"

- "On a scale from 1 to 10, where '10' represents a description that is perfect for you, and '1' a description that is totally wrong for you, how well do each of the following describe you?" [A Republican, A Democrat, A Midwesterner, An environmentalist, A feminist, An evangelical Christian]

From these measurements, we will focus on three main outcomes:

- A partisan evaluation index that will average together the following 12 outcomes with equal weights, all rescaled from 0 to 1 with higher values indicating more pro-Democrat sentiment: FT Kamala Harris, FT Barack Obama, FT Joe Biden, FT Alexandria Ocasio-Cortez, FT Donald Trump (reversed), FT Marjorie Taylor-Green (reversed), FT Ron DeSantis (reversed), FT Mitt Romney (reversed), FT Mike Pence (reversed), vote preference (Democratic Party = 1, Republican Party = 0, Neither/ don't know = 0.5), favorability Democratic Party, favorability Republican Party (reversed).

- A partisan identity scale that will average together the following 3 outcomes, all rescaled from 0 to 1 with higher values indicating more Democratic self-identification: Seven-point party ID (reversed), Self-Description Democrat, Self-Description Republican (reversed).

- Seven point party ID

We estimate the effects of the random assignment to pro-Democratic or pro-Republican hypotheticals (relative to status quo hypotheticals) on subjects' hypothetical partisanship and on the three main outcomes using the same procedures. Our estimator is an OLS regression of the outcome on the treatment, and indicators for each level pre-treatment party identification and indicators for recruitment batch. We assess uncertainty with HC2 robust standard errors. When conducting hypothesis tests, we employ two-sided tests using an $\alpha = 0.05$ threshold for significance. We choose not to report the unadjusted difference-in-means estimate because it has much lower precision than the OLS estimator. In study 1, the standard error of the unadjusted difference-in-means estimator was 0.17 scale points compared with 0.04 scale points for the adjusted OLS estimator. This very large improvement in precision comes from the extremely high correlation of our pre-treatment and post-treatment measures – the R2 of the adjusted regression is estimated to be 0.93.

Study 1 Results

Figure 1 shows the average effects of the pro-Democrat and pro-Republican hypothetical scenarios, relative to a status quo hypothetical on how subjects imagine they would respond to the party identification question. Here we see clear differences in the range of a third to two-thirds of a scale point, in the expected direction, depending on the hypothetical considered. We see some heterogeneity by pre-treatment partisan attachment, but not large amounts.

Figure 1: Average effects on hypothetical partisanship

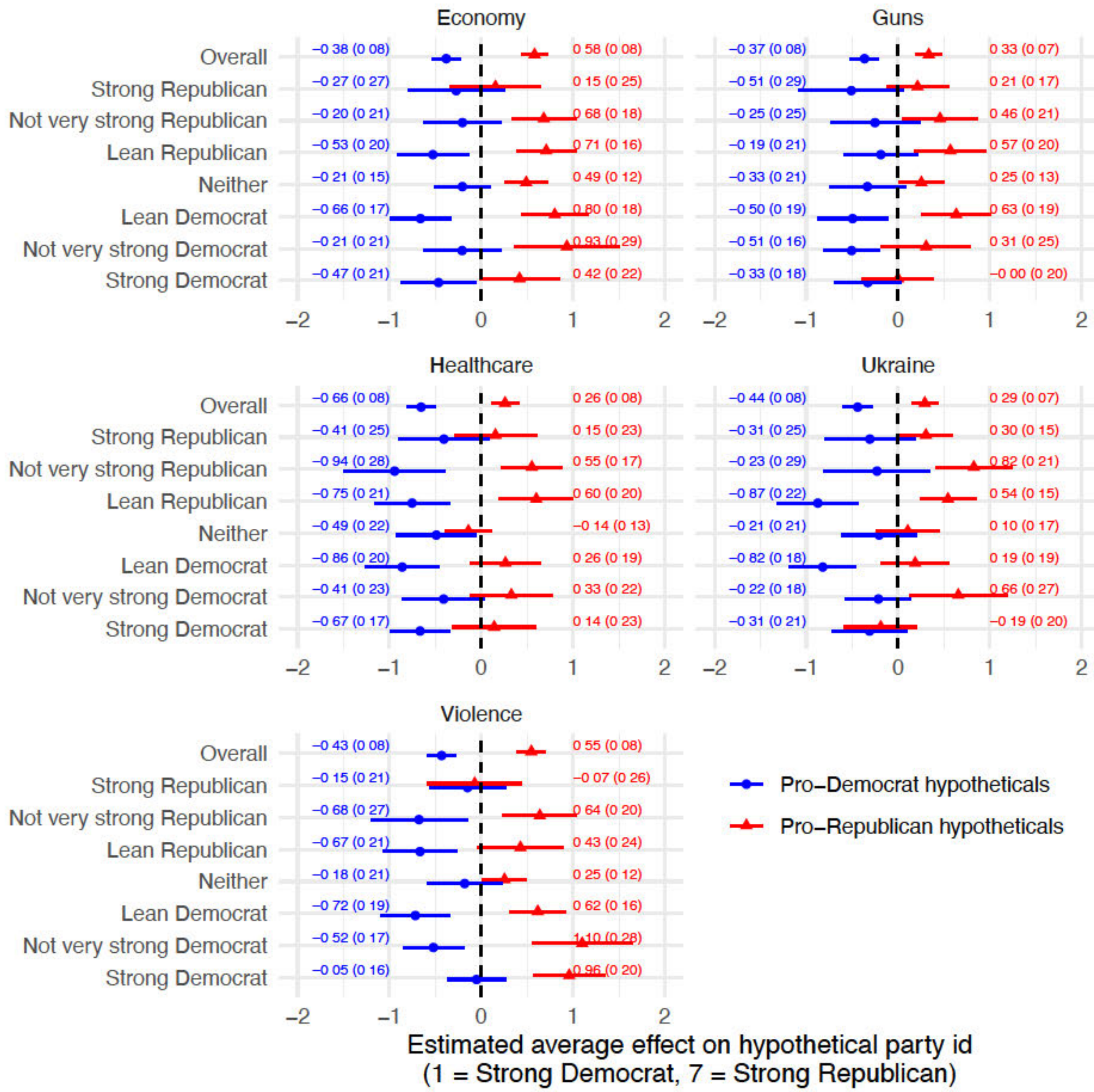
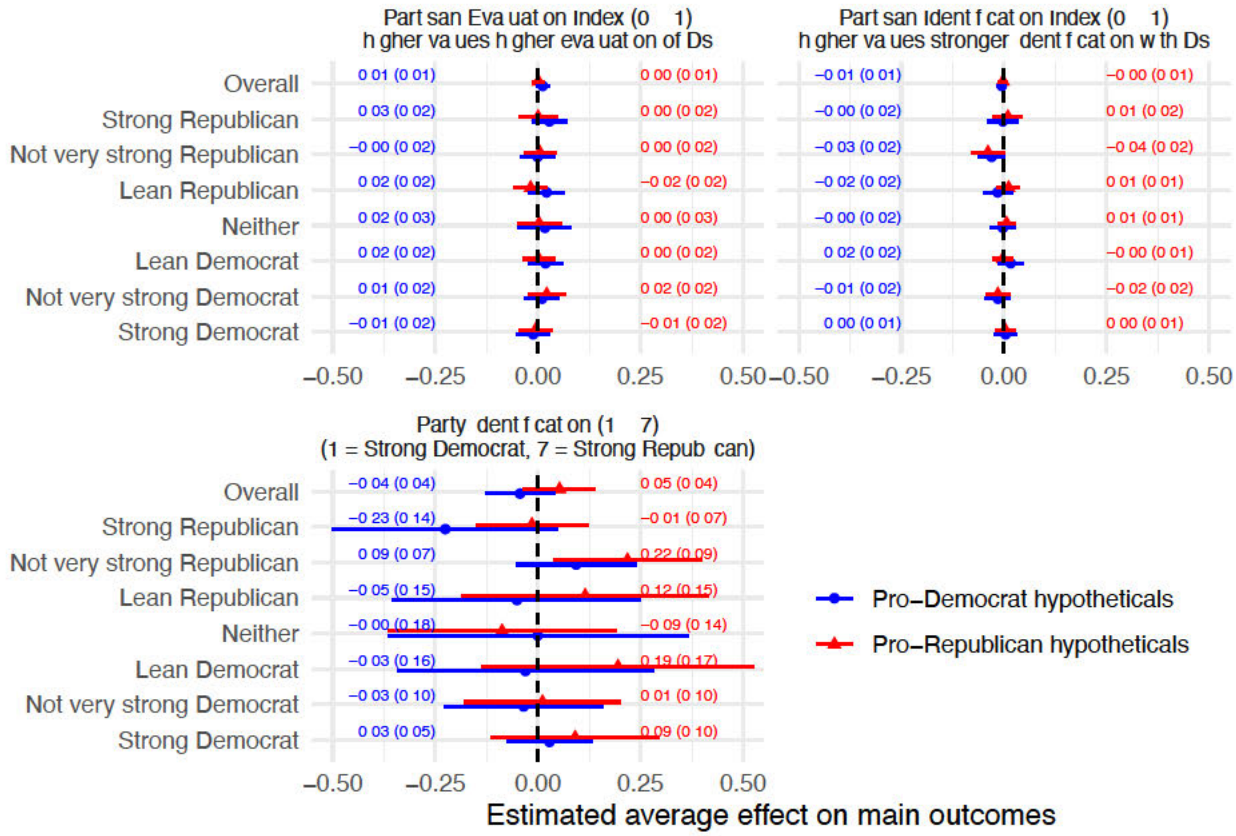


Figure 2 shows the effects on our three main outcomes.

Figure 2: Average effects on post-treatment partisanship outcomes



Design of Study 2

Subjects for study 2 will be recruited from Cloudresearch, with a target sample size of 3,000 respondents. We will aim to recruit 1,000 each of Democrats, Republicans, and Independents, excluding any subject who participated in Study 1. If we don't make our targets after recruitment window passes, we will make up the difference to 3,000 total subjects without any targeting (except excluding those who participated in study 1).

All other features of the design will remain the same as Study 1, with three changes.

First, we added one additional hypothetical to the set considered in study 1:

Status quo: Imagine that the following occurs:

The 2024 election occurs. The winner does not lock up his opponents in camps and does not create camps for undocumented immigrants.

Pro-Democratic: Imagine that the following occurs:

After winning the 2024 election, Donald Trump oversees the construction of internment camps for undocumented immigrants. It is later revealed that some of the undocumented immigrants in the camps were executed. Many people, including women and children, are killed.

Pro-Republican: Imagine that the following occurs:

After winning the 2024 election, Joe Biden oversees the construction of internment camps for Trump campaign officials and their families. It is later revealed that many of the people in the camps were killed, including women and children.

Second, after the hypotheticals but before assessing the post- treatment outcomes, we asked subjects to reflect on their answers to the hypotheticals and how likely they think they are to come to pass.

For example, regarding the pro-Democratic Ukraine hypothetical, we ask:

> After you were presented with a scenario describing Donald Trump's policy toward Ukraine leading to the death of many innocent Ukrainians, you said that your party affiliation would be the following: [piped party ID provided in response to this hypothetical]. Nobody can know for sure, but some observers have anticipated that the scenario described could become reality. How likely do you think it is that Donald Trump's Ukraine policies would lead to the death of many innocent Ukrainians?

[Extremely unlikely/Unlikely/Somewhat unlikely/Neither likely nor unlikely/Somewhat likely/Likely/Extremely likely]

After considering each of these hypotheticals again and thinking about how probable each is, we then asses post-treatment outcomes.

Thirdly and finally, we will use a significance cutoff of $\alpha = 0.025$ for one-sided tests of the effects of the Pro-Democrat hypotheticals versus status quo hypotheticals (in the pro-Democratic direction) and of the effects of the Pro-Republican hypothetics versus status quo hypotheticals (in the pro-Republican direction). We use one sided tests because we have weak evidence for our directional hypotheses from study 1, but we use $\alpha = 0.025$ for a cutoff because we don't want a skeptic to think we're using a lower standard of evidence. All other tests (including differences-in-CATEs and comparisons of the Pro-Democrat hypotheticals versus the Pro-Republican hypotheticals) will be two-sided with $\alpha = 0.05$. Estimation of treatment effects and standard errors in study 2 will follow exactly the same procedures as those described for study 1.

Study 2 Design Diagnosis

Here we document a design diagnosis procedure we used to arrive at our design for study 2. We conducted our simulations for study 2 in `DeclareDesign` (Blair, Coppock and Humphreys, 2023), using this code:

```
rm(list = ls())
```

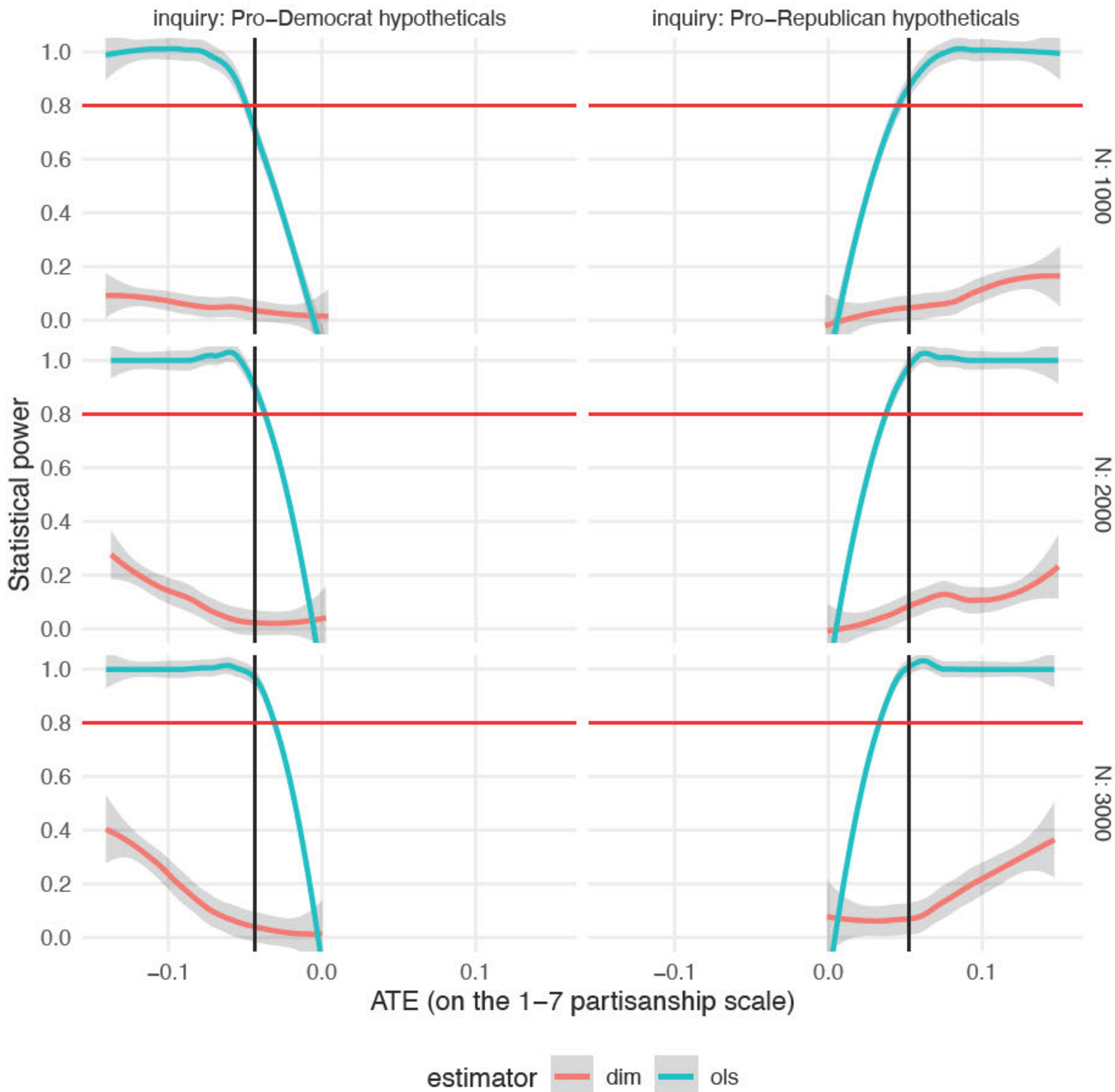
```
library(tidyverse)
library(DeclareDesign)

dat <- read_rds("data/clean_hypotheticals.rds")

likert_probs <-
  function(p = 0.95,
           d = 0.00,
           r = 0.00) {
    probs <- rbind(
      c(p, r, 0, 0, 0, 0, 0),
      c(d, p, r, 0, 0, 0, 0),
      c(0, d, p, r, 0, 0, 0),
      c(0, 0, d, p , r, 0, 0),
      c(0, 0, 0, d, p, r, 0),
      c(0, 0, 0, 0, d, p, r),
      c(0, 0, 0, 0, 0, d, p)
    )
    probs / rowSums(probs)
  }


design <-
  declare_model(handler = resample_data, data = dat, N = N) +
  declare_model(
    Y_Z_SQ = block_ra(
      pid_7_pre,
      block_prob_each = likert_probs(d = 0.02, r = 0.02),
      conditions = 1:7
    ),
    Y_Z_R = block_ra(
      pid_7_pre,
      block_prob_each = likert_probs(d = 0.02, r = runif(1, 0.02, 0.22)),
      conditions = 1:7
    ),
    Y_Z_D = block_ra(
      pid_7_pre,
```

```
      block_prob_each = likert_probs(d = runif(1, 0.02, 0.22), r = 0.02),
      conditions = 1:7
    )
  ) +
  declare_inquiry(ATE_R = mean(Y_Z_R - Y_Z_SQ),
                  ATE_D = mean(Y_Z_D - Y_Z_SQ)) +
  declare_assignment(Z = complete_ra(N, conditions = c("SQ", "R", "D"))) +
  declare_measurement(Y = reveal_outcomes(Y ~ Z)) +
  declare_estimator(
    Y ~ Z,
    term = c("ZR", "ZD"),
    label = "dim",
    inquiry = c("ATE_R", "ATE_D")
  ) +
  declare_estimator(
    Y ~ Z + pid_7_factor_pre + batch_pre,
    term = c("ZR", "ZD"),
    label = "ols",
    inquiry = c("ATE_R", "ATE_D")
  )

simulations <-
  design |>
  redesign(N = c(1000, 2000, 3000)) |>
  simulate_designs()

simulations <-
  simulations |>
    mutate(p.value_alt =
             case_when(inquiry == "Pro-Democrat hypotheticals" ~
                         pt(q = statistic, df = df, lower.tail = TRUE),
                         inquiry == "Pro-Republican hypotheticals" ~
                           pt(q = statistic, df = df, lower.tail = FALSE)
                         ),
           significance = as.numeric(p.value_alt <= 0.025)
             )
```

This simulation bootstraps a synthetic dataset of size N from our study 1 data. We then randomly generate three potential outcomes from each row using the `block_ra` function using probabilities defined by `likert_probs` function, which allows us to generate potential outcomes that are correlated with baseline party identification. The `r` and `d` arguments to that function determine the effect size of the pro-Republican and pro-Democratic hypotheticals. The design assigns units to the three conditions at random, then estimates both inquiries using both difference-in-means and ordinary least squares.

Figure 3 shows the statistical power of the design over a range of effect sizes and at three sample sizes. The study 1 effect estimates (about a twentieth of a scale point on the 1 to 7 partisanship scale) are overlaid with black vertical lines. The conventional 80% power target is shows with a red horizontal line. The difference-in-means estimates are never precise enough, and for this reason, we do not plan to report them. The OLS estimates have much higher precision (and thus higher statistical power), so we will use them. Our original study had approximately 1,000 subjects, and so was decently well-powered to detect a 0.05 scale point average treatment effect, about 80%. However, we want to power our study so well that if the effect truly is 0.05 scale points, we are approximately 100% sure to detect it, which is why we opted for a 3,000 unit study.

Figure 3: Study 2 power analysis



Meta-analysis

We will formally meta-analyze study 1 and study 2 quantities using random-effects meta-analysis. An example of this procedure for the effects of the hypotheticals on post-treatment partisanship is as follows:

```
    library(metafor)
library(broom)

set.seed(343)

study_2_simulated_estimates <-
  design |>
  redesign(N = 3000) |>
  draw_estimates() |>
  filter(estimator == "ols")

study_1_estimates <-
  fit |> tidy() |> filter(
    term %in% c(
      "treatmentPro-Democrat hypotheticals",
      "treatmentPro-Republican hypotheticals"
    )
  )

meta_df <-
  bind_rows(study_2 = study_2_simulated_estimates,
            study_1 = study_1_estimates) |>
  mutate(term = case_match(term,
                           "treatmentPro-Democrat hypotheticals" ~ "ZD",
                           "ZD" ~ "ZD",
                           "treatmentPro-Republican hypotheticals" ~ "ZR",
                           "ZR" ~ "ZR"))

meta_df |>
  group_by(term) |>
  reframe(tidy(rma.uni(estimate ~ 1, sei = std.error, data = pick(everything())), conf.int = T
```

Unanticipated problems

For those problems we have not anticipated here, we will follow the standard operating procedures outlined here: [redacted]

References

Blair, Graeme, Alexander Coppock and Macartan Humphreys. 2023. *Research Design in the Social Sciences: Declaration, Diagnosis, and Redesign.* Princeton, NJ: Princeton University Press.