Investigating the effects of out partisan media: Pre-Analysis Plan [draft]

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Abstract

Can exposure to out-partisan news on social media alleviate polarization in American voters? Despite widespread concern regarding the polarizing effects of selective exposure the experimental literature yields mixed results. We test the effects of a novel, scalable intervention in the Twitter news feed that increases respondents' exposure to out-partisan news while maintaining high ecological validity. The intervention, based on a web browser extension, allows us to directly manipulate respondents' exposure to partisan messages in the field as well as gather fine grained data describing both what respondents saw on Twitter, their web browsing behavior, and their interactions on Twitter during the treatment period. Our design eliminates confounders such as the platform feed ranking algorithm, variation in participant's existing Twitter subscriptions, and selection bias inherent to encouragement treatments. We differentiate between different forms of polarization and test for a variety of potential mechanisms.

1 Introduction

The impact of selective exposure to partisan media on political polarization has drawn considerable concern from social scientists and civil society (Benkler et al., 2018; Guess, 2021; Guess et al., 2023; Nyhan et al., 2023). Preferences for like-minded news media and aversion to outpartisan sources supposedly exacerbate ideological and social divisions between partisans (Sunstein and Sunstein, 2018). Certainly, a growing body of evidence shows both that Americans increasingly engage in selective exposure (Nyhan et al. (2023), but also see Bakshy et al. (2015)) and that partisan media has a substantial influence on political behavior and attitudes (Broockman and Kalla, 2022; DellaVigna and Kaplan, 2007; Martin and Yurukoglu, 2017).

Many commentators and members of civil society advocate for mitigating such selective exposure effects by increasing information diversity, sometimes even calling for a legal mandate for ideologically diverse news content (Helberger et al., 2018). However, experimental evidence presents a murky view of the effectiveness of such an intervention. Results range from modest (Broockman and Kalla, 2022) to minimal (Guess et al., 2021, 2023; Levy, 2021; Nyhan et al., 2023) to actually *increasing* polarization (backlash effect) (Bail et al., 2018; Levendusky and Malhotra, 2016).

We believe that there are still important questions to answer regarding the impact of increasing exposure to outpartisan content on depolarizing audiences, especially in the context of social media. Much existing experimental work (even those leveraging close collaboration with social media companies) have increased respondents' exposure to outpartisan news only indirectly (Bail et al., 2018; Guess et al., 2023; Levy, 2021; Nyhan et al., 2023). Treatment strength is diluted (or more concerningly, potentially counfounded) by the platform ranking algorithm and the naturally low levels of pre-existing outpartisan news content in respondents' social media feeds.[1] A second challenge is the common use of encouragement designs, where treated respondents are merely 'nudged' to increase exposure to outpartisan media with no additional incentive. These designs are easy to implement, allow analytical convenience, and are congruent to a high media choice environment (Casas et al., 2022; Guess et al., 2021). However, for researchers interested in disrupting selective exposure effects, participants who are less likely to volunteer exposure to outpartisan media constitute exactly the population of interest! Recent work in traditional media bucks the trend of underwhelming results: Broockman and Kalla (2022) show that incentivizing respondents to watch CNN instead of Fox News results in significant changes in political attitudes and beliefs. Importantly, this study features a treatment and incentive that is both strong and direct and a study population that already engages in selective exposure.

We present a pre-analysis plan for a field experiment on social media that

[1] Treated respondents in Bail et al. (2018) and Levy (2021)are asked to follow sources of out-party content. However, the ultimate delivery of outpartisan content is controlled by the platform ranking algorithm (Lazer et al., 2014). This algorithm driven noncompliance reduces treatment strength; Levy (2021) is able to monitor some respondents' feeds and shows that following outparty news sources results in approximately one additional outparty news post shown on Facebook per day on average for treated respondents. Algorithm driven noncompliance can also confound estimates if users who are shown more outparty content by the ranking algorithm differ systematically from users who are shown less. This is eminently plausible especially given recent evidence that feed ranking algorithms tend to favor in-party content more for stronger partisans (Guess et al., 2023). Bail et al. (2018) attempts to sidestep this concern by asking respondents to use chronological feed ranking: however, most of these issues persist even assuming perfect compliance. Under chronological feed ranking, treatment strength varies by how much content is produced by the respondents' network - respondents with large networks are less likely to see treatment tweets than respondents with smaller networks.

While Guess et al. (2023); Nyhan et al. (2023) did not face the same algorithmically driven challenges, both studies' interventions only slightly increased the amount of out-partisan news in subjects' news feeds. Nyhan 2023's main intervention was to decrease the amount of like-minded content in respondents' news feeds. Since most respondents were not following many sources of out-party news, this caused only a marginal increase in the amount of exposures to out-party news. For similar reasons, when Guess 2023 switched participants' feeds to chronological feed ranking, their change in outparty news exposure was also minimally affected. We argue that these studies, albeit impressive in many ways, do not adequately test the question of the effects of exposure to out-partisan news on social media.

directly increases the proportion of outpartisan content in treated respondents' Twitter feeds (without coordination with the social media platform) using a browser extension. This eliminates the possibility of ranking algorithm driven differential compliance and allows us to control the treatment strength directly. We aim to mitigate attrition of respondents with a distaste for outparty news by providing an aggressive incentive structure that rewards participants for using Twitter with the extension enabled. We also take advantage of the fact that out-of-network content injections are increasingly common on Twitter, allowing the treatment to be ostensibly unrelated to the experimental surveys. We also are able to collect fine grained data on respondents' Twitter usage habits, including a behavioral measure of selective exposure post-treatment. We leverage recent work on misperceptions, partisan social identity, and the distinction between various forms of political polarization to explore both top-level effects of outpartisan media exposure on polarization as well as several potential mechanisms.

2 Theory and Hypotheses

2.1 Affective Polarization

Exposure to outpartisan media plausibly mitigates affective polarization by disrupting the 'echo chamber' effect of overly like-minded media exposure (Nyhan et al 2023). Counterarguments presented by out-partisan media could promote moderation and tolerance (Helberger et al., 2018; Levy, 2021; Mutz, 2002; Stroud, 2010). Similarly, out-partisan media exposure could correct overly negative perceptions participants may have about outpartisan voters and outpartisan media itself (Lees and Cikara, 2020; Orr and Huber, 2020; Peterson and Kagalwala, 2021). Finally, out-partisan exposure could dilute the identity-reinforcing effect of congenial content (Dias and Lelkes, 2022; Huddy et al., 2015).

H1: Exposure to outpartisan media decreases affective polarization

2.2 Ideological Polarization

Consumption of outpartisan media can also affect issue attitudes and ideological polarization directly through persuasion or backlash. While much of the existing literature on media persuasion supports a 'minimal effects' perspective, recent experimental work shows that persuasion can happen through the presentation of new information favorable to one political side (Broockman and Kalla, 2022). At the same time, a parallel branch of research documents a backlash effect, where respondents tend to become even more ideologically extreme after outpartisan media exposure (Bail 2018, Levendusky 2013). However, the nature of the backlash effect is far from settled, with some replication attempts failing to find empirical regularity and arguments that previous backlash findings could have been unduly influenced by experimenter effects in the lab, low experimental power, or a distinctive effect of out-partisan opinion leaders as opposed to out-partisan news media (Casas 2022; Levy 2021).

H2: Exposure to outpartisan media decreases ideological polarization.

2.3 Issue Priority Polarization (Agenda Setting)

One of the most durable and longest standing media theories is that of agenda-setting: the media choose to emphasize different topics, affecting audience's perceptions of which issues are more important (Broockman and Kalla, 2022; McCombs and Shaw, 1972). We expect that outpartisan media exposure causes participants to shift their issue priorities to more closely align with the outpartisan media agenda.

H3: Exposure to outpartisan media aligns respondents' views on issue importance to be more consistent with the issue priorities of outpartisan media

2.4 Engagement

Social media is accused of exacerbating selective exposure because social media business models and content ranking algorithms reward audience engagement which causes like-minded content to be over-represented in the social media feed (Nyhan et al 2023). However, while recent innovative work has shown that the ranking algorithm in general increases engagement (Guess et al 2023), we have little conclusive tests of the effect on engagement specifically by outpartisan content exposure. Increasing outpartisan media exposure may cause users to disengage, diluting potential depolarization effects. Understanding the relationship between outpartisan media exposure, depolarization, and disengagement is critical to evaluating the feasibility of increasing outpartisan content as a policy internvetion.

H4: Exposure to outpartisan media decreases respondents' time spent on the platform.

2.5 Heterogenous Effects of Political Knowledge

Finally, we register a set of secondary hypotheses regarding differential effects of political knowledge. Many theories of persuasion (eg, (Zaller et al., 1992)) posit that pre-existing levels of political knowledge block the adoption of novel information and considerations. We therefore expect that exposure effects of outpartisan news on **issue depolarization** and **agenda setting** to be higher for respondents with lower pre-treatment levels of political knowledge.

We do not register a hypothesis on affective polarization. While informational theories of persuasion suggest that lower political knowledge respondents may moderate their views of outpartisans more than higher knowledge respondents (and thus decrease levels of affective polarization more), the misperceptions literature suggests that higher knowledge effects respondents have more misperceptions to correct, leading to potential effects in the opposite direction.

2.6 Summary of Hypotheses

Primary Hypotheses

- **H1: (Affective depolarization)** Exposure to outpartisan tweets decreases respondents' affective polarization as measured by feeling thermometer, selective exposure (more of a manipulation check), post-treatment selective exposure, partisan identity strength, perceptions of outpartisan issue position extremity, negative perceptions of outpartisan news
- **H2: (Issue Depolarization)** Exposure to outpartisan tweets moderates respondents' issue positions
- **H3: (Agenda Setting)** Exposure to outpartisan tweets aligns respondents' issue importance to be more consistent with the issue priorities of outpartisan media
- **H4: (Engagement)** Exposure to outpartisan media decreases respondents' time spent on the platform.

Secondary Hypotheses

- **Issue Depolarization**: Exposure to outpartisan media cause low political knowlege respondents to depolarize on issue positions more than respondents with higher levels.
- **Agenda Setting**: Exposure to outpartisan media cause low political knowlege respondents to adopt outpartisan agenda priorities more than respondents with higher levels.

3 Experimental Design

We plan to test our hypotheses with a randomized field experiment using a convenience sample of U.S. based Twitter (X) users. Treated participants will have popular recent tweets (posts) about politics and social issues from out-partisan news media accounts inserted into their Twitter feed; Democrat-identifying participants will see content from right-leaning news sources while Republican-identifying participants will see content from left-leaning sources. Participants assigned to the control group will have popular recent tweets from popular, non-political US-based magazines such as National Geographic inserted into their feed. We use a custom web browser extension to administer the treatment as well as to collect behavioral digital trace data to supplement survey-based outcome measures. Respondents will be additionally incentivized to use Twitter every day of the treatment period via the web browser in order to maximize treatment compliance.

Participants will be recruited using advertisements placed on Facebook and screened using a Qualtrics survey for basic eligibility. We target Facebook ads to users browsing Facebook. Ad copy will advertise the opportunity to earn

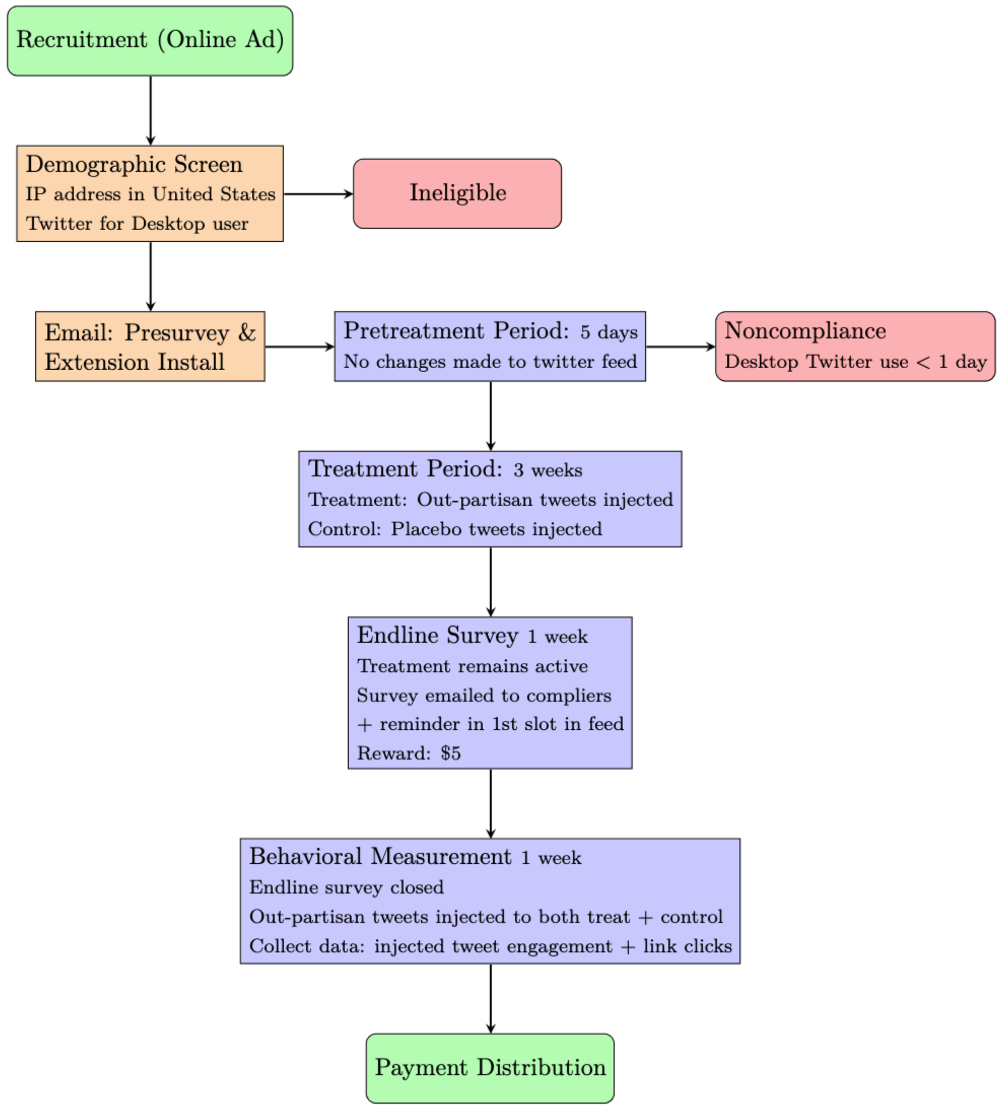

Figure 1: Overview of experimental design

money for participation in a study on Twitter. The ad will link directly to a pre-screening survey asking (1) whether the respondent has a Twitter account, (2) how frequently the respondent uses a desktop computer, (3) whether the respondent identifies as a Democrat, Republican, or Independent, and (4) their vote choice in 2020. We will also collect respondent email addresses. Eligible respondents must use a desktop computer multiple times per week and and have a Twitter account. Ineligible respondents will be screened out. Once enough eligible respondents have completed the prescreener (see section 4 for details on power analysis and sample size) eligible users will be emailed a link to the pre-treatment survey and extension installation instructions. They will be informed that they need access to their primary desktop computer in order to complete the pre-treatment survey.

The pre-treatment survey will provide more complete details about the experiment, collect demographic information and pre-treatment outcome measures, and provide instructions on how to install the Chrome web browser extension. Respondents will be awarded 50 cents per day browsing Twitter for at least 2 minutes up to $10 total, and awarded $5 for completing the post-treatment survey. The extension monitors respondents' Twitter usage in real-time, providing both them and the research team with information about their accrued rewards. We choose this incentive design in order to increase compliance with treatment delivery.

The Chrome extension handles treatment administration, and behavioral and usage data collection for the duration of the experiment. On installation, the extension produces a unique registration code that respondents submit as part of the pre-treatment survey. This allows us to link survey answers, including the respondents' self reported partisanship, to the extension without the use of personal identifiers. The extension is able to collect fine grained data on what posts respondents view on Twitter and what actions they take (like, share, link click) while browsing Twitter with the extension installed. The extension will monitor Twitter usage for five days during which time no changes are made to the Twitter timeline.

Before the treatment begins, we plan to block-randomize all participants who successfully completed all previous steps and for whom we have at least one day of behavioral data. We use Moore and Moore (2013)'s multivariate blocking method and block based on party ID, pretreatment time spent on Twitter, and pretreatment Twitter news exposure.

In the treatment phase, Democrat (Republican) respondents in the treatment group will have 20% of Twitter feed posts, including the top post, be transformed into a recent tweet about politics or social issues issued by a popular conservative (liberal) news media accounts. Respondents in the control group will have the same proportion of their feed transformed into popular non political content. This treatment maintains ecological validity while prioritizing content that is likely to be depolarizing given our hypotheses. We select accounts which have over 300,000 followers on Twitter and post multiple times per day. We use a network-based homophily measure (Eady et al, forthcoming) to select left and right leaning accounts that are decidedly partisan, but avoid the most

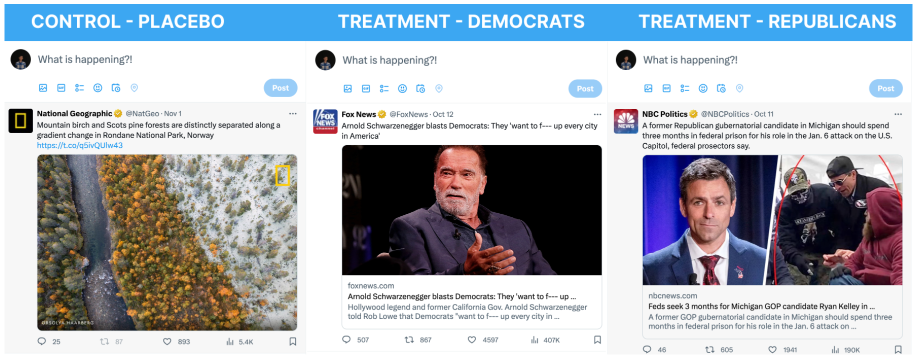

Figure 2: Overview of treatment arms

extreme accounts that might trigger a backlash effect. We collect tweets from each of the selected accounts daily during the treatment period using the Twitter Basic API and store them in a secure online database. Additionally, we use a keyword based approach to filter out tweets from our treatment that are not related to politics or social issues. When a respondent logs into Twitter, the extension requests tweets from this database which returns either left-leaning, right-leaning, or placebo tweets based on the treatment group and party ID of the respondent. See the appendix for additional details.

We choose a placebo control in order to guard against nonspecific effects inherent to the delivery of treatment. The replacement of tweets by the Chrome extension may have unanticipated effects such as reducing time spent on Twitter as participants see less of the content they are used to. The placebo arm makes exactly the same changes as the treatment arm but with explicitly nonpolitical content that we assume does not affect our primary outcome measures. One plausible problem with this design choice is that participants with highly political news feeds assigned to the placebo condition will have their political news exposure reduced. Our prior is that most respondents will not have significant levels of political content in their Twitter feeds as described by Nyhan et al. (2023); Wojcieszak et al. (2021). However, the extension also records the displaced Tweets, allowing us to accurately describe the level of displaced political content.

Finally, it is important to note that our treatment delivery mechanism allows for a significantly larger treatment dosage compared to existing studies using online media. For example, Levy (2021) and Guess (2020) estimate treatment dosages of approximately one additional outpartisan news Facebook post exposure or partisan news site visit per day on average. By contrast, we guarantee at least one Twitter post view per Twitter visit and 20% of all twitter post views. Pilot data from previous experiments suggests we can expect a median treatment dosage of 6 posts per day.

After the treatment period ends we make the endline survey available to eligible participants for a seven-day period. Eligible participants are defined as

Name	Slant
New York Times	Left
Huffington Post	Left
Salon	Left
Mother Jones	Left
The Nation	Left
Wall St. Journal	Right
Fox News	Right
National Review	Right
The Daily Wire	Right
The Federalist	Right
LIFE	Placebo
Sports Illustrated	Placebo
National Geographic	Placebo
Food Network	Placebo
Entertainment Weekly	Placebo

Table 1: List of treatment and placebo accounts

having browsed Twitter for more than two minutes on four separate days during the treatment period. A link to the endline survey will appear embedded at the top of the Twitter feed as well as emailed to eligible participants.

Finally, we collect a behavioral measure of selective exposure in a last seven day window. During this time both treatment and control groups will have the same outpartisan tweet injected into the first slot of their feed. The outpartisan tweet will be accompanied by an unobtrusive button with the text "Don't show more content from <account name>". We collect user clicks on this button in addition to clicks on the tweet link itself to form a basis for a behavioral measure of partisan media preference.

4 Empirical Strategy

4.1 Outcome Variable Construction

We operationalize affective polarization using a number of survey items and behavioral outcomes. Our main measure of affective polarization is a normalized index combining measures of outpartisan feeling, selective exposure, partisan identity strength, and misperceptions of outparty issue positions.

All indices are formed by standardizing individual items to have mean 0 and standard deviation 1 before forming an additive index of these rescaled items following Broockman and Kalla (2022).

Issue polarization is measured using a battery of issue position survey questions with 5-point Likert scale Agree/Disagree responses. We code responses such that higher values represent extreme partisan views and lower values represent views more commonly associated with the opposing party. We interpret negative movement on this scale between pre and post treatment as issue depolarization. An alternative specification sets the centrist position at zero and simply measures the change in absolute issue distance. The set of issues includes both domestic and foreign issues as well as questions specifically related to current events. These items were adapted from Bail et al. (2018); Broockman and Kalla (2022); Dimock (2014); Guess et al. (2021). The full list of survey questions is in the Appendix.

To measure agenda setting we follow Broockman and Kalla (2022) and compare the respondents' ratings of issue importance with the topics that were discussed most by the set of accounts in treatment. We use an LDA topic model to estimate the top 5 most talked about issues produced by all of the left and right-leaning accounts during the treatment period. Respondents will then be asked during the endline survey to rate each issue's importance using a 5-point likert scale from 'not very important' to 'very important.' We scale responses such that positive values correspond to survey responses more congruent with the outpartisan media agenda and construct an index of all 10 items to estimate the average agenda setting effect.

Finally, engagement is measured by using an index combining time spent on Twitter during the treatment period with link clicks.

4.2 Estimation

We plan to use OLS with pre-treatment covariates to estimate the ITT effect of the treatment for each of the main outcome variables. We also plan to estimate complier effects by filtering out respondents who did not use Twitter with the extension enabled during the treatment period. Finally, we estimate dosage-mediated complier effects using an instrumental variables approach using treatment assignment as an instrument for number of outparty tweets seen.

Sample plots and data will be provided after the conclusion of the upcoming pilot study.

4.3 Power Analysis

A preliminary power analysis suggests a participant pool size of N=1800 is sufficient to test our main hypotheses using ITT estimates. However, this analysis will be updated with additional data (specifically, estimates of outcome variance under treatment) after an upcoming pilot study.

We assume a noncompliance rate of 25%, co-variate strength $R^2 = 0.4$, and effect size $d = 0.1$. These values are drawn from the measure of ideological polarization from Bail (2018). In that study, d=0.1 translates to about a 0.1 point movement on a seven point scale, or 1.4 percentage points. Under these assumptions, N=1800 participants satisfies the traditional power requirement $\beta = 0.8, \alpha = 0.05$.

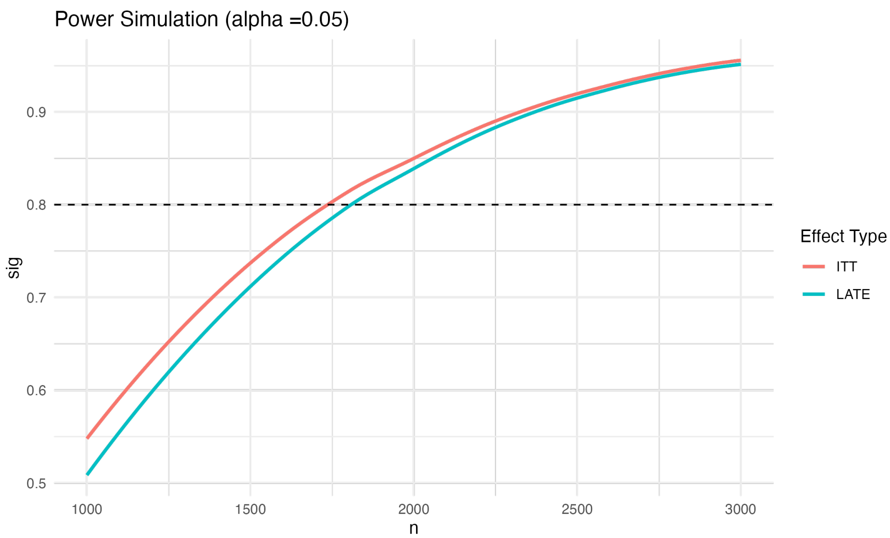

Figure 3: Preliminary Power Analysis

5 Appendix

5.1 Defining Partisan News: Treatment Media Account Selection

Partisan media outlets used for the treatment were selected using a mix of automated and manual methods to balance ecological validity and depolarization potential. We aimed to select news accounts that were active, popular, and decidedly partisan but not overly so. We began with a list of major media accounts and network-based ideology measures collected by Eady et al. (2019). We removed accounts with fewer than 300,000 follower and that had an ideology score with a magnitude greater than 2SD (eg, One America News, Breitbart) or less than 0.75SD from the mean (CNN, AP, Reuters). The remaining accounts were inspected manually and excluded if they had not posted at least twice within the last 3 days about politics or social issues. Finally, we limited the number of accounts to 10 in order to simplify the treatment and satisfy Twitter/X API rate limits by discarding accounts with fewer followers.

In order to select the placebo accounts we began with a list of the most popular US magazines collected by YouGov. For each magazine we manually collected the associated Twitter account and removed those with under 300,000 followers as well as those that *did* post about politics or social issues within the last 3 days. From tehse we selected 5 accounts that covered a wide range of nonpolitical topics (sports, wellness, entertainment, culture, and nature).

5.2 Politics and Social Issues Keywords

In order to reduce the amount of non-political news that is included as part of the treatment we exclude any tweet that contains a black-listed word in its link URL.

The following words are blacklisted: podcast, world, obituaries, movies, cooking, food, wirecutter, sports, business, travel, wellbeing, game, puzzle, style, fashion, arts, dining, theater, dance, music, lifestyle, entertainment.

5.3 Survey Questions

5.3.1 Demographics and Controls

1. How often do you look at Twitter/X? (CSIP 2022) [Several times a day, About once a day, 3 to 6 days a week, 1 to 2 days a week, Every few weeks, Less often/Never]
2. Generally speaking, do you usually think of yourself as a Republican, a Democrat, or Independent/Neither? (ANES 2018) [Republican, Democrat, Independent/Neither]
3. Who did you vote for in the 2020 presidential election? (Joe Biden, Donald Trump, Other candidate, I did not vote)
4. Age
5. Education
6. Gender
7. Employment
8. Ideology: How would you describe your political views? [very conservative, conservative, moderate, liberal, very liberal]
9. Political Knowledge: Who is the current Senate Majority Leader? [Kevin McCarthy, Chuck Schumer, Nancy Pelosi, Mitch McConnell, Not Sure]
10. Political Knowledge: For how many years is a United States Senator elected – that is, how many years are there in one full term of office for a US Senator? [2, 4, 6, 8, Not Sure]

5.3.2 Main Outcome Measures

1. **Affective Polarization:**

   (a) We would like to get your feelings toward the following groups using something we call the feeling thermometer. Ratings between 50 and 100 mean that you feel favorable and warm toward the group. Ratings between 0 and 50 mean that you don't feel favorable toward the group. You would rate the group at the 50-degree mark if you don't feel particularly warm nor cold toward the group. (Levy 2021; ANES 2018; Petersen and Kawagla 2019)

- Republican voters
- Democratic voters
- President Biden
- Donald Trump
- The New York Times
- Fox News

(b) "I find it difficult to see things from Democrats'/Republicans' point of view" [Strongly agree, somewhat agree, neither agree or disagree, somewhat disagree, strongly disagree] (Levy, 2021)

(c) "I think it is important to consider the perspective of Democrats/Republicans" [Strongly agree, somewhat agree, neither agree or disagree, somewhat disagree, strongly disagree] (Levy, 2021)

(d) "Suppose a son or daughter of yours was getting married. How would you feel if he or she was marrying a 2020 Trump or Biden supporter? Would you be pleased, displeased, or would it make no difference?" [Very pleased, somewhat pleased, it would make no difference, somewhat displeased, very displeased] (Iyengar, 2012)

2. **Partisan Identity Strength (Huddy 2015)**

   (a) "How important is being a [Democrat/ Republican] to you?" [Extremely important, Very important, Not very important, Not important at all]

   (b) "How well does the term [Democrat/ Republican] describe you?" [Extremely well, Very well, Not very well, Not well at all]

   (c) "When talking about [Democrats/Republicans], how often do you use "we" instead of "they"?" [All of the time, Most of the time, Some of the time, Rarely, Never]

   (d) "To what extent do you think of yourself as being a [Democrat/Republican]?" [A great deal, Somewhat, Very little, Not at all]

3. **Issue Positions** How much do you agree or disagree with the following statements? [Strongly agree, somewhat agree, neither agree or disagree, somewhat disagree, strongly disagree]

   (a) Government is almost always wasteful and inefficient (Pew, 2019)

   (b) Gun control laws in the United States should be stricter (Guess 2020)

   (c) Free trade agreements like NAFTA have helped the U.S. economy (Guess 2020)

   (d) Immigrants today strengthen our country because of their hard work and talents (Pew, 2019)

(e) I approve of the 2022 Supreme Court decision that the U.S. Constitution does not guarantee a right to abortion and that abortion laws should be set by the states. (Pew, 2022)

(f) Irish, Italians, Jewish and many other minorities overcame prejudice and worked their way up. Blacks should do the same without any special favors. (ANES, 2018)

(g) It should be the responsibility of the federal government to make sure all Americans have healthcare coverage. (Gallup, 2023)

(h) I support laws or policies that protect transgender from discrimination in jobs, housing, and public spaces (Pew, 2022)

(i) Government regulation of business is necessary to protect the public interest (Guess, 2020)

(j) Poor people today have it easy because they can get government benefits (Guess, 2020)

(k) The federal government should redistribute wealth by levying higher taxes on the rich (Gallup, 2023)

(l) Global climate change poses a major threat to the country (Pew, 2023)

(m) The US should support Ukraine in reclaiming territory Russia has captured, even if it results in a more prolonged conflict between the two nations (Gallup, 2023)

(n) It is more important get tougher than build a strong relationship with China on economic issues (Gallup, 2021)

4. **Issue Importance** Please indicate how important each of the following issues is to you [Extremely important, Very important, Not very important, Not important at all]

   (a) Rising prices of consumer goods and gas

   (b) The environment and climate change

   (c) Situation with Russia

   (d) Crime and Public Safety

   (e) Gun Control

   (f) Immigration and border policy

   (g) Abortion rights

   (h) Poverty/hunger/homelessness

   (i) Race relations/racism

   (j) Healthcare

   (k) War in the Middle East

   (l) Situation with China

(m) Protection of Free Speech

(n) Criminal investigation of Donald Trump

These issues were chosen from the top 10 most common responses to Gallup 2023's Most Important Problem survey. In addition, a handful of issues (k, l, m, n) were added following a topic analysis of news from the right and left leaning accounts during fall 2023.

5. **Perceptions of Outpartisan Issue Positions** How much do you think a typical Republican/Democrat agrees with the following statements? (Lees and Cikara 2019)

   (a) <same statements as issue position questions>

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