Current Research Overstates American Support for Political Violence

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Political scientists, pundits, and citizens worry that America is entering a new period of violent partisan conflict. Provocative survey data show that a large share of Americans (between 8% and 40%) support politically motivated violence. Yet, despite media attention, political violence is rare, amounting to a little more than 1% of violent hate crimes in the United States. We reconcile these seemingly conflicting facts with four large survey experiments (N=4,904), demonstrating that self-reported attitudes on political violence are biased upwards because of respondent disengagement and survey questions that allow multiple interpretations of political violence. Addressing question wording and respondent disengagement, we find that the median of existing estimates of support for partisan violence is nearly 8 times larger than the median of our estimates (18.5% versus 2.4%). Critically, we show the prior estimates overstate support for political violence because of random responding by disengaged respondents. Partial identification bounds imply that, under generous assumptions, support for violence among engaged and disengaged respondents is at most 6.3%. Respondent disengagement also inflates the relationship between support for violence and previously identified correlates by a factor of 4. Finally, nearly all respondents support criminally charging suspects who commit acts of political violence. These findings suggest that although recent acts of political violence dominate the news, they do not portend a new era of violent conflict.

Political Violence | Affective Polarization | Democratic Norms

Provocative recent work (1–4)—cited in The Proceedings of the National Academy of Sciences (5, 6), The American Journal of Political Science (7), 60 other articles and books, and 40 news articles that together have garnered over 2,281,133 Twitter engagements—asserts that large segments of the American population now support politically motivated violence. These studies report that up to 44% of Americans would endorse hypothetical violence in some undetermined future event (1–4, 8). This survey work fits within a media landscape that regularly raises the spectre of political violence. Since 2016 we counted 2,863 mentions of political violence on news television, more than 630 news stories about political violence, and over 10 million Tweets on the topic of the January 6th riot alone (see Appendix Section 1 for details for all counts in this paragraphs). Political violence, however, remains exceedingly rare in the United States, amounting to 48 incidents (9) in 2019 (the most recent year for which data are available) compared to 4,526 incidents of non-political violent hate crimes (10) and 1,203,808 total violent crimes (11) documented by the Department of Justice.

In this paper, we reconcile supposedly significant public support for political violence with minimal actual instances of violent political action. To do this we use four survey experiments that assess respondents' reactions to specific acts of violence, where we experimentally manipulate whether partisanship motivated the activity and the severity of the violence. Using these studies we identify two reasons why current survey data overestimate support for political violence in the United States.

First, ambiguous survey questions cause overestimates of support for violence. Prior studies ask about general support for violence without offering context, leaving the respondent to infer what "violence" means. Using detailed treatments and precisely worded survey questions we resolve this ambiguity and reveal that support for violence varies substantially depending on the severity of the specific violent act. With our measures, assault and murder attract minimal support, while low-level property crimes gain higher (though still low) support. Moreover, even though segments of the public may support violence or report that it is justified in the abstract, nearly all respondents still believe that perpetrators of well-defined instances of severe political violence should be criminally charged.

Second, disengaged survey respondents cause an upward bias in reported support for violence. Prior survey questions force respondents to select a response without providing a neutral midpoint or a "don't know" option. This causes disengaged respondents—satisficers (12)—to select an arbitrary or random response (13). Current violence-support scales are coded such that four of five choices indicate acceptance of violence. In the presence of arbitrary responding, such a scale

Significance Statement

Recent political events show that members of extreme political groups support partisan violence and survey evidence supposedly shows widespread public support. We show, however, that after accounting for survey-based measurement error support for partisan violence is far more limited. Prior estimates overstate support for political violence because of random responding by disengaged respondents and because of a reliance on hypothetical questions about violence in general instead of questions on specific acts of political violence. These same issue also cause the magnitude of the relationship between previously identified correlates and partisan violence to be overstated. As policy makers consider interventions designed to dampen support for violence, our results provide critical information about the magnitude of the problem.

SW, designed the studies, and collected the data. SW analyzed the data. SW and JG wrote the manuscript. SW, JG, MT, and CN discussed the project and commented on the final draft

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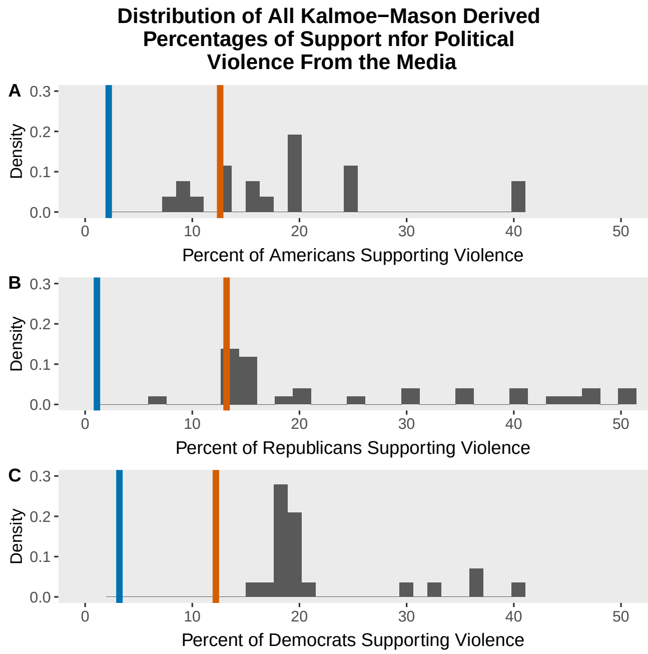

Fig. 1. This figure shows the distribution of percentages of public support for political violence from the Kalmoe-Mason measures as reported in the media. We report this in the full sample (A), for Republicans (B) and for Democrats (C). To contextualize the problems in these estimates we overlay the largest estimates (orange line) and smallest estimates (blue line) from the studies that follow. There is large variation in the reported values, but all are significantly larger than ours.

will overstate support for violence. Across all four studies we show that disengaged respondents report higher support for violence.

Accounting for these sources of error, our four studies show that American support for political violence is less intense than prior work asserts and is contingent on the severity of the violent act. Depending on how the question is asked, we show that median of existing estimates of the public's support for partisan violence are nearly 8 times larger than the median of our estimates (18.5% versus 2.4%). While recent political events show that extreme political groups are willing to engage in violence, these groups are likely to overlap with the narrow segment of the population who already support political violence. As policy makers consider interventions designed to dampen support for violence, our results demonstrate that support for violence is not a mass phenomenon, indicating that anti-violence measures should be appropriately tailored to match the scale of the problem.

Support for Partisan Violence is Lower than Previously Reported

Partisan animosity, often referred to as affective polarization (14), has increased significantly over the last 30 years. While Americans are arguably no more ideologically polarized than in the recent past, they hold more negative views toward the political opposition and more positive views toward members of their own party. This pattern has been documented across several measures of animosity and has raised alarm among scholars across disciplines about the potential consequences of growing partisan discord (e.g., 15). Numerous studies have documented the negative *interpersonal*, "apolitical" (16) consequences of affective polarization, including politically based discrimination against job applicants (17), prospective romantic partners (18), workers (19), and even scholarship recipients (for review, see 14). These findings have created substantial concerns over partisan animosity's pervasive effects on American social life (20).

Yet, evidence suggests that affective polarization is not related to and does not cause increases in support for political violence (21, 22) and is generally unrelated to political outcomes (22, 23). Moreover, partisan violence appears to be unrelated to many other political variables (3). We are therefore left with a phenomenon that is not explained by the current literature on partisan animosity, that is rarely observed in the world, but that is apparently supported by a near majority of the American population (1–4).

We show that documented support for political violence is illusory, a product of ambiguous questions and disengaged respondents. We now explain how each causes political violence to appear more popular than it is in the public.

Ambiguous Questions Create Upward Bias in Estimates of Support for Violence Even if respondents truthfully report their views on political violence, vague questions make it impossible to compare responses across individuals and render sample averages uninterpretable. For example, a measure from Kalmoe and Mason (hereafter, Kalmoe-Mason) (2–4) asks about perceived justification for partisan violence generally: "How much do you feel it is justified for [respondent's own party] to use violence in advancing their political goals these days?" But the estimand measured by this survey item is unclear, because it leaves ambiguous what "violence" refers to. Another question from Robert Pape (24), "The use of force is justified to restore Donald Trump to the presidency," offers a specific motivation, but, like the Kalmoe-Mason measures, leaves definition of "violence" to the respondent to fill in. As a simplistic example, suppose that respondents interpret the question as asking about either partisan-motivated assault or partisan-motivated murder (both acts of violence). If one individual interprets violence as "assault" while another interprets violence as "murder" then these responses are not comparable and therefore we cannot make an inference about which respondent expresses more support for political violence (25). This also affects mean expressed support for violence. The quantity $P(\text{support partisan violence})$ is an average of respondents who interpret the question as asking about assault and others interpreting the question as asking about murder. The conditional average support for partisan violence and the relative prevalence of the components of the mixture are unknown, $P(\text{support partisan violence}) = P(\text{support partisan violence}|\text{assault})P(\text{assault}) + P(\text{support partisan violence}|\text{murder})P(\text{murder})$.

It is impossible to know from existing responses to vague questions whether respondents support severe, moderate, or minor forms of violence, which could range from support for violent overthrow of the government to minor supporting assault at a local protest. We address this concern in two ways across our four survey experiments. First we use two different levels of violence for Study 1, Study 2, and Study 3: assault and murder. Second, in Study 4 we vary the underlying violent act along a taxonomy of severity.

Disengaged Respondents Cause Upwardly Bias Measures of Support for Political Violence The goal of all surveys is to capture genuine opinions from a sample. However, it is well known that not all respondents engage in the thought, consideration and reflection necessary to provide reasoned responses to all questions (26) and some may even over-report rare and negative traits/opinions to troll researchers (27). As the complexity of the work needed to answer a question increases (i.e., thinking about meaning, filling in details in ambiguous questions, forming opinions on a question a respondent has never previously considered, etc.) and motivation to deeply engage decreases respondents are more likely to satisfice (13). When satisficing, respondents may simply select a neutral midpoint (12), randomly select a response (28), or even leave a survey (26). We suspect that the vague and ambiguous nature of current survey measures of political violence are especially likely to cause respondents to satisfice.

Two features of the current survey designs cause the problem. First, existing measures of support for partisan violence collapse response categories to indicate support (1, 2). For example, one survey question asks respondents "How much do you feel it is justified for Democrats to use violence in advancing their political goals these days?" and uses a 5-point Likert-like scale with options "Not at all", "A little", "A moderate amount", "A lot", and "A great deal". (3) then recodes the responses "A little" to "A great deal" as indicating support for partisan violence and "Not at all" as opposing partisan violence. Second, such survey questions fail to offer a neutral midpoint or a "don't know" option. If these imperfect options or frustration from the ambiguous nature of the actual question cause a respondent to disengage from the survey task and satisfice (12), they are likely to arbitrarily pick from the set of imperfect options. But in this example, satisficers picking a random response would end up indicating support for violence four times out of five.

To formalize this example, the goal is to measure the true preferences for partisan violence in the population, which we will call $\mathbb{E}[Y]$. This quantity is estimated from a representative survey of the population by taking a mean of a survey question, $\mathbb{E}[Y^{\text{survey}}]$. If some disengaged respondents satisfice, then the estimated support for partisan violence will be:

$$\begin{aligned}\mathbb{E}[Y^{\text{survey}}] &= \mathbb{E}[Y \mid \text{Engaged}]P(\text{Engaged}) \\ &+ \mathbb{E}[Y^{\text{satisfice}} \mid \text{Disengaged}]P(\text{Disengaged}),\end{aligned}$$

where reported support when satisficing, $Y^{\text{satisfice}}$, might be different from the true support Y depending on the survey respondent's behavior when satisficing. If $\mathbb{E}[Y^{\text{satisfice}} \mid \text{Disengaged}] > \mathbb{E}[Y \mid \text{Disengaged}]$, then the survey-based estimate will be larger than the true level of support for violence. This condition is likely to hold under current survey-based approaches to measuring preferences for partisan violence where four of five response options indicate support for violence (80% of possible responses). If respondents choose their response at random with a uniform probability then the chance that they would appear to support partisan violence is 0.8. If true $\mathbb{E}[Y \mid \text{Disengaged}] < 0.8$ then the presence of disengaged respondents will cause an upward bias. In an extreme example, if no one actually supports partisan violence, but 31% of respondents—the proportion who fail our engagement test in Study 1—in a survey answer at random a survey would find that $0.31 \times 0.8 = 24.8\%$ of respondents support partisan violence. This is very close to the amount of inflation we see in partisan violence in our following studies.*

We take explicit steps to address disengaged respondents who satisfice. We offer satisficers response options that are less likely to upwardly bias estimates: a balanced five point scale with a neutral midpoint. This brings the measure in line with standard and methodologically robust approaches to measurement, and reduces the chances that a satisficer will randomly select a response indicating support for violence. We also report our estimates based on individuals who are engaged—passing a comprehension check—and individuals who are disengaged, or fail a comprehension check.

Assessing Partisan Differences in Who Commits Political Violence. Concern about political violence in the United States is often associated with increasing levels of affective polarization between Democrats and Republicans (15). But existing measures of support for partisan violence tend to not assess whether providing information about the partisanship of who committed the act of violence affects support or opposition for the act of violence. Providing this information is important, because there are two potential interpretations of a positive effect. If the response is sincere, it could be that co-partisans give additional leeway for acts committed by co-partisans. But if the response is insincere, it could be that partisans, in general, are merely offering support for their party–a version of partisan cheerleading. While randomizing information about partisanship alone is insufficient to distinguish between these two possibilities, if we fail to find a difference in a well-powered study provides strong evidence that neither leeway nor cheerleading occur.

To assess how partisanship affects support for violence, in our Study 1 and Study 2 we explicitly vary information about the partisanship of who committed the acts of violence. As we show below, we fail to find a consistent partisan difference–implying that there is little evidence for a general leeway or cheerleading effect.

While we find little evidence of partisan cheerleading among all partisans, we might worry that a specific subset of partisans engage in explicit partisan cheerleading. To make this assessment in Study 3 we use existing survey questions to identify partisan cheerleading (29) and find that partisan cheerleaders inflate support for violence, but those cheerleaders comprise only a small share of respondents and therefore do not appear to meaningfully affect results.

Methods

To uncover how these sources of error affect perceptions of partisan violence, we conducted four survey experiments. We fielded our first survey (which contained Study 1 and Study 4) via Qualtrics Panels in January 2021—starting two days after the violence of January 6th. This allows us to test our predictions during a period when partisan discord and violence dominated news coverage. Our second survey (Study 2) was fielded in April 2021, also on Qualtrics panels. Our final survey (Study 3) was fielded in November of 2021 on the YouGov panel. This allows us to verify that our results are not dependent on proximity to the Capitol riots or on a specific survey panel.

*We note that, while not observed here, if true support for violence were above .8, the bias would be negative. Also, if the true prevalence rate among the disengaged were 0.8, then the bias for the population parameter would be zero.

The Qualtrics data were collected from Qualtrics Panels and utilized quota sampling. Respondents were recruited from panel members by email. All surveys were restricted to Democrats and Republicans. Leaners were coded as partisans. For Qualtrics data we quota sampled on age, sex and race/ethnicity to match Census targets. The sample is generally very representative of the population (see Appendix Tables S1, S19, S30 and S39). These data were analyzed without survey weights per our pre-analysis plan. The YouGov data were sampled with the standard YouGov matching procedure. YouGov data were analyzed with provided weights[†].

The survey flow was as follows: consent, attention check, demographics, covariates (including the measure from (1–3)), randomized treatment, engagement test, and then outcome questions. Our experiments were approved by IRBs at Stanford, Dartmouth and UCSB. Participants were asked to give consent after reading an information sheet.

All four experiments were preregistered. For our Qualtrics data, following our pre-analysis plan, we excluded participants who failed a pre-randomization attention check (a question asking respondents to make two specific response choices) and those who completed the survey in less than one third of the median complete time. Neither of these choices altered the demographic composition of the sample as purged respondents were not counted toward quotas and were replaced. Both of these choices work against us by removing disengaged subjects, which means that our estimates are conservative as these design choices remove respondents who are most likely to respond to all survey questions at random. Those who remain and satisfice are likely doing so because of flawed, ambiguous, or insufficiently contextualized questions and not because of general inattention.

Measuring Engagement To assess how satisficing affects responses, we group participants based on their cognitive engagement with our survey, measured as the retention of information from vignettes. Respondents who can identify the state where the event in the vignette they just read occurred (information that was repeated in the headline and up to two times in the text) are coded as engaged and those who cannot are coded as disengaged. Reading short passages is not a cognitively intense task, but committing content to memory is (30), and reveals engagement with cognitive work. Across our three studies we group our sample into "engaged" respondents—those who are sufficiently motivated to carefully read and retain information—and "disengaged" respondents—those who can follow instructions but are less likely to retain facts or carefully evaluate questions.[‡]

Outcome Questions We use three core questions for Study 1, Study 2, and Study 3 and deploy two strategies to identify satisficing's upward bias on estimates of support for violence. First, in our justification outcome question we use a dichotomous scale which should prompt disengaged respondents to randomly respond, which we can detect by observing the response distribution. Second, we offer a balanced scale with a neutral midpoint when measuring support, building on prior work that suggests disengaged respondents will respond with a "don't know" or neutral midpoint response (12). Our three questions are:

1) "Was the suspect justified or unjustified?" using a dichotomous outcome scale. This differs from (1–4) where the authors ask a hypothetical question with a unbalanced five point Likert scale that is then recoded in their analysis to a dichotomous measure.

2) "Do you support or oppose the actions of [suspect]?" This is measured with a balanced Likert with a neutral midpoint and is intended to separately capture support for a suspect when a violent act is committed.

3) "Should the suspect face criminal charges?" We capture responses with a dichotomous yes/no scale and is intended to determine if the respondent thinks that someone who commits an act of violence should or should not face charges.

Respondents Reject Extreme Violence, Whether it is Political Or Not

Study 1, Study 2, and Study 3 show that, as preregistered, respondents overwhelmingly reject both political and non-political violence, and disengaged survey respondents show higher measured support for political violence. We find no evidence of partisan effects, as partisans from both sides express similar tolerance for political violence. We also find higher (though still low) levels of support for the less violent act in Study 1 relative to the more violent act in Study 2 and Study 3.

To avoid the problem of ambiguous question wording, our design presents a detailed act of violence, which prevents respondents from substituting their own definition of "violence" when answering our outcome questions.

In Study 1 (N = 1,002) we randomly assigned participants to read one of two stories based on real acts of political violence. In the first story, a Democratic driver was charged with hitting a group of Republicans in Florida who were registering citizens to vote. In the second story, a Republican driver was charged with assault for driving his car though Democratic protesters in Oregon. Respondents were also randomized to see the original version of the story that included partisan details or a version of the story that was altered to remove any reference to partisan motivation.

In this study we focused on reporting details from real events. This means that, while comparable, the Democratic and Republican stories varied in several ways. To ensure that any effects we identify are not the result of those differences, we conducted a second version of this experiment. Study 2 (N = 1,023) used a single contrived story of violence in Iowa. To test the bounds of support for political violence, this story reported an extreme form of violence: murder. Similar to Study 1, participants were randomly assigned to see a story with a Republican or Democratic shooter engaging in politically motivated violence or an apolitical act of murder. This story was necessarily fabricated to limit the differences across treatment conditions.

Study 3 (N=1,863) is a replication of Study 2 using the YouGov panel with the following alterations: 1) we removed the apolitical condition to focus on attitudes toward partisan

[†] By necessity, weights were not used when estimating partial bounds.

[‡] Appendix Table S64 shows that removing disengaged respondents does not meaningfully change the demographics of our sample (age, gender, race, partisanship, income, education). Another concern is that we are conditioning on a post-treatment outcome. However, our goal is not to measure the causal effect of engagement (31), but to merely show that responses differ based on engagement.

violence, 2) we removed questions to measure covariates to reduce survey time, and 3) we introduced an incentivized attention manipulation (detailed below).

Disengaged Responses Lead to Higher Estimates of Support for Political Violence. At first glance, the results of this experiment appear to align with prior surveys. Across conditions where the driver's actions are presented as political violence, we find that 21.1% of respondents in Study 1 say the attack was justified. We find a similarly high level of support for the apolitical versions, where 20.1% of respondents in Study 1 say the driver's action is justified. The overall support for violence is lower in Study 2 and Study 3, reflecting the greater severity of the violence, with 10% of respondents in Study 2 describing the political homicide as justified and 10.1% describing the homicide as justified in Study 3. In Study 2 6.7% of the respondents describe the apolitical homicide as justified.

But this is biased upwards by respondents who fail the engagement test (approximately 31% of respondents in Study 1, 19% of respondents in Study 2, and 19% of weighted respondents in Study 3). For the political treatments, 37.9% of respondents who fail the engagement test say the driver's actions were justified, while only 12.1% of respondents who passed the engagement test agree that the driver's actions are justified. For the non-political treatment, we find that 44.9% of respondents who failed the engagement test say the driver's actions were justified, but only 10.9% of respondents who passed the engagement test say the driver's actions are justified. Similarly, for Study 2 in the political treatments we find that 33.8% of the respondents who fail the engagement test say the shooter's actions were justified, but only 4.3% of individuals who passed the engagement test say the action was justified. In the non-political treatments we find a similar large gap: 25.9% of respondents who fail the engagement test say the action was justified, but 2.7% of those who passed say the action was justified. The same pattern is found in Study 3 (YouGov data), with 32.6% of disengaged respondents saying the shooting was justified, while only 5.9% of engaged respondents say the shooting was justified.

Figure 2 shows that this overall pattern is found across all treatment conditions in both studies. The red circles and lines in Figure 2 show disengaged respondents, while teal circles and lines show engaged respondents. In all cases, disengaged responses indicate significantly greater justification and support for political violence relative to engaged responses.

When it comes to our third outcome question, support for charging the accused, we see a different pattern. Unlike the first two outcome questions, which are abstract moral judgments, this question is concrete: should those who commit a crime face legal consequences? Consistent with the specificity of this question, we find much higher overall agreement. Across our conditions, between 83% and 100% of respondents who passed the engagement test want the suspect in the politically motivated violent crime charged, while between 81% and 94% of disengaged respondents want the suspect in the politically motivated violent crime charged.

Abstract Questions and Disengaged Respondents Inflate Support for Violence. Respondents who fail our engagement test express much higher rates of support for the hypothetical political violence measure used in extant observational studies (which we included in all our studies pre-treatment). We show

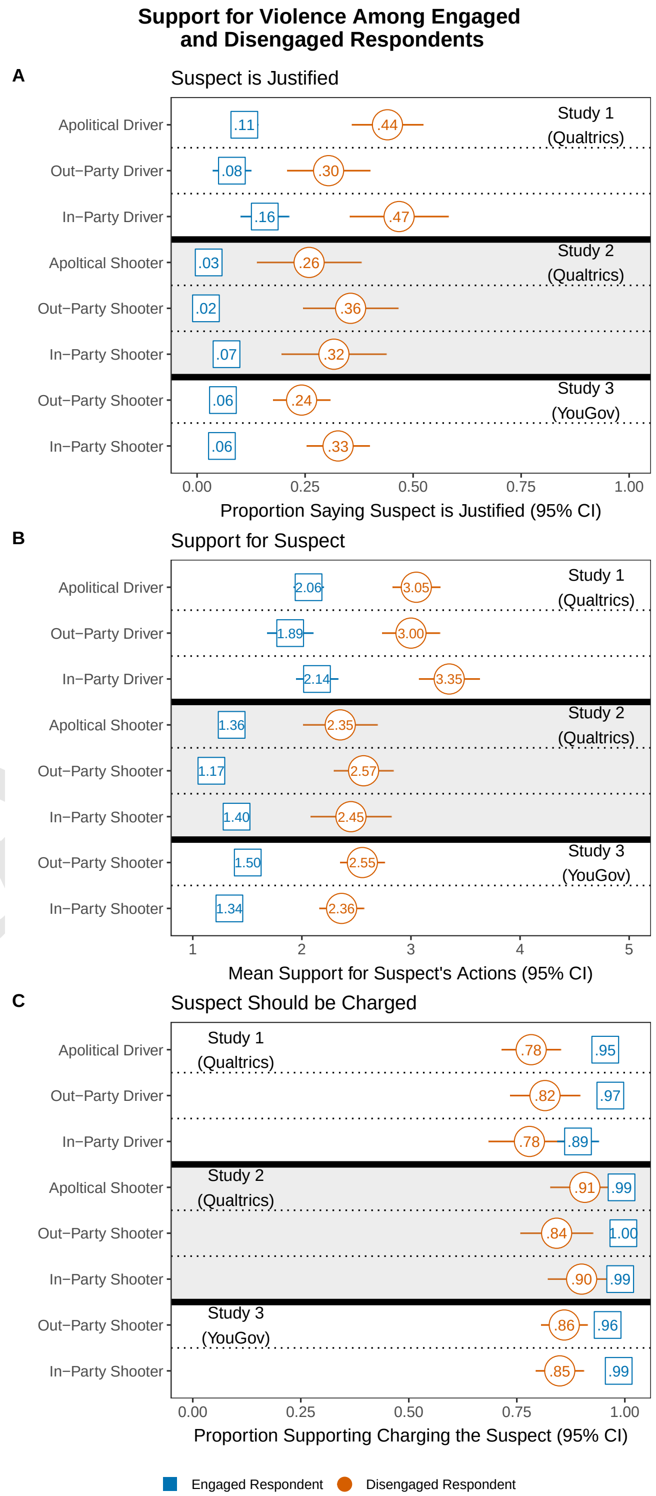

Fig. 2. This figure shows attitudes toward violence for each of our three measures: Justification (A), Support (B) and Should the subject be charged (C). We plot group means and 95% confidence intervals. For the YouGov data (study 3) we utilize survey weights. Providing partisan motivations has no effect on support for violence relative to identical, but apolitical, violence.

Table 1. Kalmoe-Mason Support for Violence Measure by Engagement

	Support for Violence Kalmoe-Mason Measure % (N)		
	Study 1	Study 2	Study 3
Disengaged Respondents	55% (312)	43% (190)	41% (354)
Engaged Respondents	21% (690)	26% (833)	19% (1,509)
Combined estimate	32% (1,002)	29% (1,023)	23% (1,863)

problems with disengaged respondents with two sets of analyses. First, we show in Table 1 that the current hypothetical question developed by (1, 2) (measured here with a balanced Likert with a neutral midpoint) generates overestimates of public support for partisan violence because of disengaged respondents. Across our three studies, we find that support for violence on this measure is nearly twice as large in the disengaged group as in the engaged group.

Second, we look for evidence of satisficing on our three outcome measures. Our preregistered expectation is that disengaged respondents provide upwardly biased responses to abstract questions. We find substantial support for this hypothesis in the data. As detailed earlier, our questions vary in the extent to which they demand a well-considered response. Questions of justification and support require reflection on the criminal act, a personal moral code and social norms, whereas asking if a person who committed a violent act should be charged requires no such introspection. Assuming respondents are cognitive misers who satisfice to escape considered thought where possible, we should then expect more satisficing on the first two questions than the third (12).

This is borne out in our data. Figure 3A shows that, when presented with a dichotomous question and no "don't know" option disengaged respondents essentially randomly split their responses between the two choices, while engaged respondents overwhelmingly report that the driver is not justified. Figure 3B shows that when disengaged respondents are presented with five choices that include a neutral midpoint, the modal response is the midpoint with the remaining respondents splitting their responses between the remaining four categories. Both response strategies are consistent with satisfying. A plurality of engaged respondents report strongly opposing violence.

Figure 3C shows that, when answering a simpler question with clear normative expectations—charging criminals for crimes—disengaged and engaged respondents are much more comparable. It is also possible that respondents deemed the information in the newspaper articles we provided insufficient to establish moral justification, but sufficient to determine a preference for criminal charges.

Results from Study 2, where the reported crime was murder, show a more dramatic difference between the engaged and the disengaged. For engaged respondents, justification peaks at 6.8%, support peaks at 2.1%, and willingness to excuse the suspect from criminal charges peaks at 1%. This compares to disengaged respondents where justification peaks at 35.5%, support peaks at 20.0%, and willingness to excuse the suspect from criminal charges peaks at 15.8%. Depending on the measure, disengaged respondents report support that is 5 to 15 times greater than engaged respondents.

Study 3, our YouGov replication of Study 2, produces very similar results. Justification is approximately 5.5 times

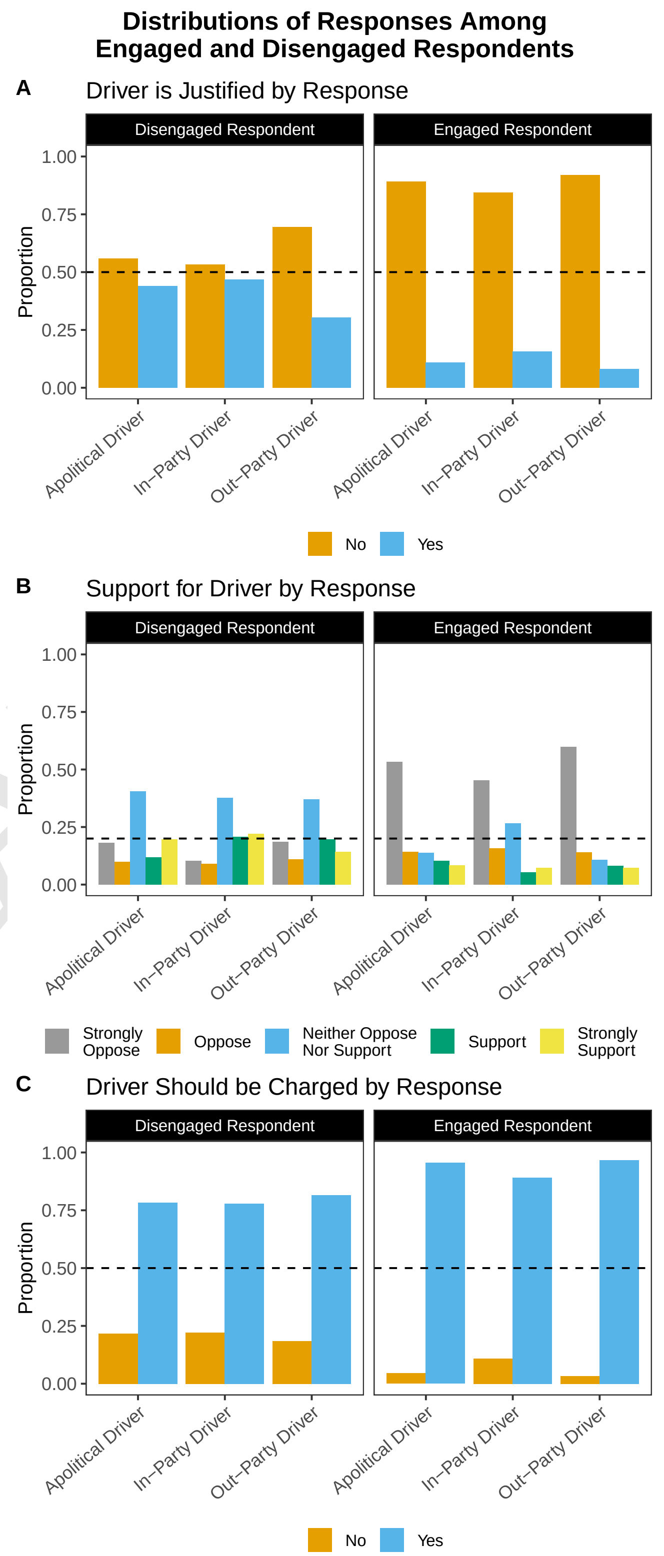

Fig. 3. The response distribution for each of our measures by engagement for Study 1. High levels of support for political violence can be partially attributed to random responding by disengaged respondents, especially when questions are vague.

larger for disengaged (30.1%) versus engaged (5.4%) respondents, support is approximately 9.7 times larger for disengaged (22.3%) versus engaged (2.3%) respondents, and willingness to excuse the suspect from criminal charges is approximately 4 times larger for disengaged (14.6%) versus engaged (3.5%) respondents.

These results suggest that overestimates of support for political violence on surveys are partially explained by satisficing and random response because of flawed questions.

Incentives improve attentiveness and reduce justification. In Study 1 and Study 2 we rely on measurement of attentiveness and not its manipulation. In Study 3 we introduced a manipulation designed to increase attentiveness to allow for causal estimation of the effect of attentiveness on attitudes toward political violence. We randomly told half the sample "We noticed that you completed the last page very quickly. It is important to us that you carefully read all parts of this survey and think carefully about the question we ask. We have developed a response quality scoring system and are using it here. We will pay $1 to everyone who completes this survey with a high quality score." The treatment was delivered regardless of prior behavior, and we merely used this as a cover story for our manipulation. [§]

This treatment significantly increased the percentage of respondents who passed the state attention check by 5.9 percentage points (95% confidence interval [0.01, 0.11]). It also significantly reduced average reported justification for political violence ($\beta = -0.040$, 95% confidence interval [-0.08, -0.00]. Our treatment did not move attitudes on the support and charged measures (see Appendix Table S31 and S32).

Support for Political Violence is Lowest for the Most Severe Crimes

We have so far demonstrated that disengaged respondents create upward bias in support for political violence and that this is a function of the amount of thought questions require of respondents. Our expectation is that offering additional information—that a suspect has been convicted of a specific crime—reduces question ambiguity enough to attenuate differences between disengaged and engaged respondents. By reporting an exact crime we are also able to bound what support for political violence exists by crime severity.

Study 4 (N = 1,009) captures support for nullifying convictions for a set of politically motivated crimes (some violent and some not) that vary in severity from protesting without a permit to murder. To administer the survey, we first asked standard demographic and covariate batteries and administered a neutral vignette that mentioned a state. We coded engagement by asking respondents to identify the state where a news event occurred in a pre-treatment and unrelated vignette (32). Each respondent then read a short prompt informing them that a man, "Jon James Fishnick", had been convicted of a crime and faces sentencing in the coming week. We then randomly selected a single crime (protesting without a permit, vandalism, petty assault, arson, assault with a deadly weapon and murder) along with details specifying that the crime was partisan and committed against a member of the opposing party. Participants were then asked to suggest a sentence for Fishnick that ranged from community service to more than 20 years in prison.

Figure 4 shows the frequency of each suggested sentence by crime and by respondent engagement. When the crime is nonviolent (protesting without a permit, vandalism) a near majority of both engaged and disengaged respondents support the minimal penalty of community service. A minimally violent crime (assault—throwing rocks leading to an injury) sees most respondents suggest a term in jail, though about 20-25% of respondents still support community service. However, a clear inflection point arrives when the crimes become violent and serious. For the remaining three crimes, respondents overwhelmingly support lengthy prison terms. Almost no engaged respondents favor community service as punishment for severe crimes: arson (3.8% of engaged respondents), assault with a deadly weapon (4.6%) and for murder (2.6%). Indeed, the majority of engaged respondents believe more than 20 years in prison is the appropriate punishment for murder.

In addition to asking about the appropriate punishment, we asked if the governor should pardon Fishnick. Appendix Figure S2 shows that, on average, respondents only support a pardon for minor crimes. Engaged respondents are, however, much more likely than disengaged respondents to oppose a pardon for serious acts of violence.

Disengaged Respondents Bias Estimates of the Correlates of Political Violence

Our primary goal thus far has been to precisely estimate the levels of support for partisan violence in the public. However, others focus on a second goal: finding the characteristics of individuals that predict support for violence (3, 33, 34). But the same issues that create bias in estimates of support for violence also cause bias in estimates of the relationship between supporting violence and other variables. This is because the usual rules of vanilla measurement error are not applicable with disengaged survey respondents, who are likely to remain disengaged across several questions and therefore cause non-random measurement error. The consequence is that disengaged survey respondents can create measurement error that causes bias in an unknown direction and in some cases can make the relationships between variables appear stronger, rather than weaker.

To get intuition for how this can occur, consider a simple example. Suppose our goal is to measure how much support for violence differs across a dichotomous attribute, X. As in our analyses above, we suppose that our respondents are divided into engaged and disengaged individuals. We will further suppose that being disengaged affects both the reported support for violence and the measured value of X, biasing both upwards. As a hypothetical example, suppose that P(Violence| Engaged, X= 1) = 0.15, P(Violence| Engaged, X= 0) = 0.05, that P(X = 1| Engaged) = P(X =0 | Engaged) = 0.5, and that P(Engaged) = 0.8. But for disengaged respondents we suppose that P(Violence| Disengaged, X= 1) = P(Violence| Disengaged, X= 0) = 0.8, and that P(X = 1| Disengaged) = 0.8. The true difference among the engaged respondents is P(Violence| Engaged, X= 1) - P(Violence| Engaged, X= 0) = 0.1. But because of the non-random measurement error among the disengaged respondents, the estimated difference using the overall data is P(Violence| X = 1) - P(Violence| X = 0) = 0.217. Non-random measurement error from disengaged

[§] We paid all subjects in the group the additional bonus, regardless of their responses.

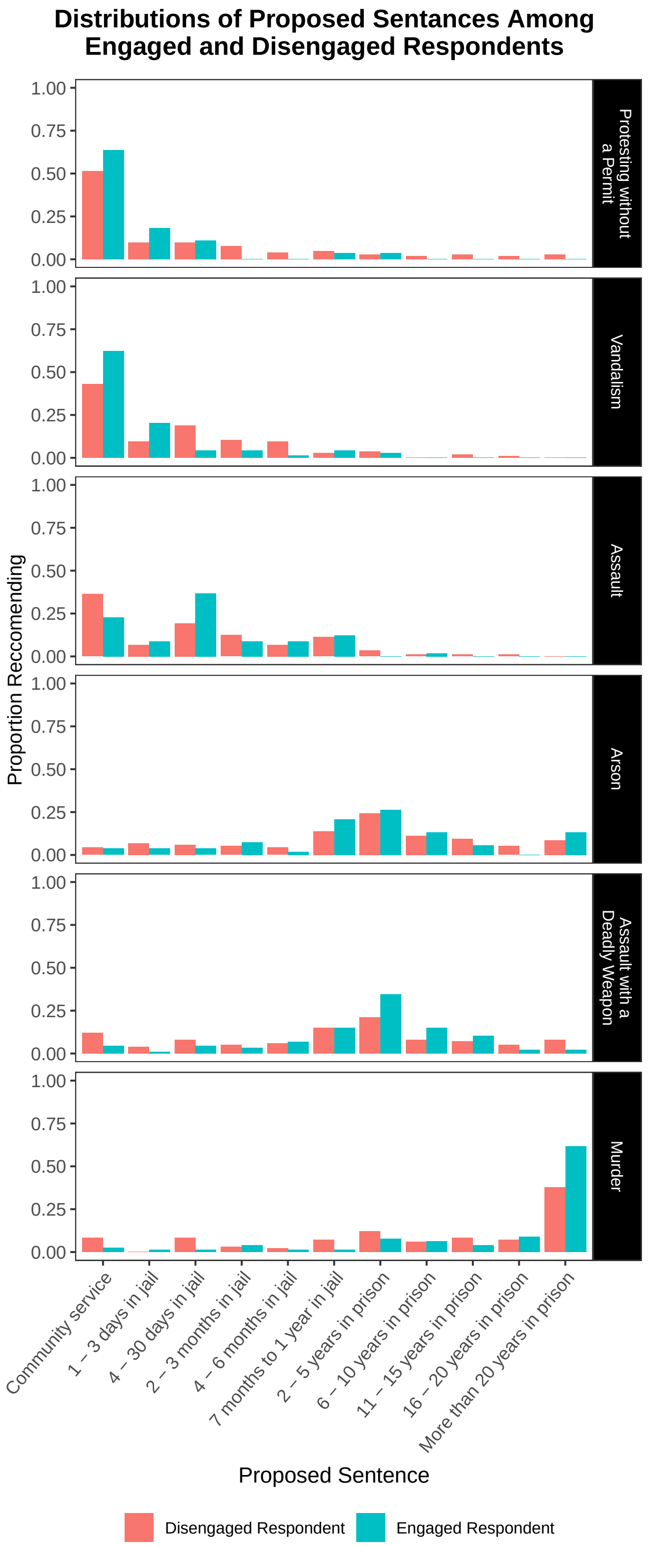

Fig. 4. In this study we remove as much ambiguity as possible by identifying a specific crime for which someone has been convicted. This additional context makes differences between engaged and disengaged respondents largely vanish. Furthermore, respondents, especially engaged ones, punish more severe violent crimes with longer prison sentences. This suggests that although support for political violence exists in the electorate, it is primarily constrained to support for minor crimes.

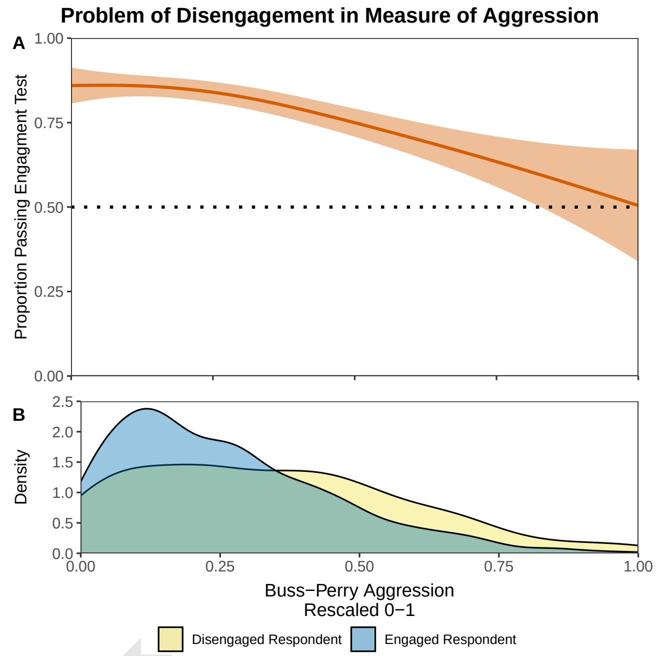

Fig. 5. This figure shows the problems with estimating correlates of support for violence when measures are biased. (A) Shows the proportion of respondents who are disengaged by scored level of aggression on the Buss-Perry scale. (B) Shows the distribution of aggression by engagement.

respondents causes the relationship between X and support for violence (measured as the difference in average support for violence at levels of X) to be more than twice as large than the true relationship.

We find evidence that this bias occurs when assessing predictors of political violence. The literature has identified three significant predictors of support for violence: partisan social identity, aggression and hostile sexism (3, 33, 34). Here we focus on the largest predictor: aggression (as measured in our work with the Buss-Perry Short Form (35) from Study 2). As we show in the top panel of Figure 5 below, the proportion of respondents who are engaged decreases rapidly at high levels of reported aggressive personality. The bottom panel shows that, as a result, disengaged respondents are disproportionately represented among those with the highest levels of reported aggressive personality.

The higher reported levels of aggressive personality are coupled with the higher levels of support for violence among disengaged respondents that we documented above, resulting in disengaged respondents creating a stronger relationship between aggressive personality and support for violence. Figure 6 shows that if we use all respondents and the original measure of violence support from (3), that moving from the least to most aggressive personalities is associated with an 82 percentage point increase in support for violence. That same shift goes down to 67 percentage points among just the engaged respondents with the original measure. But if we focus on only the engaged respondents using our more precise measure, that same large shift from least to most aggressive is associated with a 20 percentage point increase in support for violence. Taken together, using imprecise survey questions and failing to account for disengaged respondents produces a relationship between aggressive personality and support for

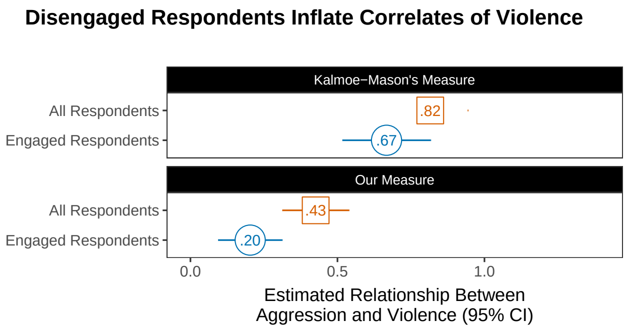

Fig. 6. This plot shows that the relationship between aggression and support for political violence—as measured as the regression coefficient from a linear regression of support for violence on aggressive personality—is biased upward by disengaged respondents. Moreover, the relationship is much smaller when using a more precise measure of support for political violence.

violence that is approximately 4 times too large.

Finally, the top panel of Figure 5 suggests that the assumption of a linear relationship obscures a non-linear relationship (36). We do so here to provide an apples-to-apples comparison to (2, 3). In Appendix Table S66 we provide binned estimates of the relationship between aggression and violence.

Recommendations

Our goal is not to argue that there is no support for political violence in America. Recent events demonstrate that groups of American extremists will violate the law and engage in violence to advance their political goals. Instead, our purpose is to show that when attempting to estimate support for political violence among the public, care and precision is required. Generic and hypothetical questions offer respondents too many degrees of freedom, require greater cognition than a sizable portion of the population will engage in, and capture support for violence in general. We suggest that future attempts to measure support for political violence: 1) utilize specific examples with sufficient details to remove the need for respondents to speculate; 2) benchmark results against general support for all violence; and 3) capture support for crimes that vary in severity.

Conclusion: Limited Support for Political Violence

Our results show support for political violence is not broad-based and is, on average, approximately 13 times lower than the average estimate previously reported by Kalmoe-Mason and 6 times lower than the estimate provided by Pape (24). To the contrary, we find the public overwhelmingly rejects acts of violence, whether they are political or not. Our evidence suggests that extant studies have reached a different conclusion because of design and measurement flaws. When disengaged respondents are not excluded from analysis, measured support for violence is biased upward. Our evidence suggests that this is because disengaged respondents are satisficing in response to ambiguous questions. Vague questions about acceptance of partisan violence demand too much interpretation from respondents, yielding incorrect inferences about support for severe political violence. Not only is support for violence low overall, but support drops considerably as political violence becomes more severe. The most serious form of political violence—murder in service of a political cause—is widely condemned.

Importantly, our results are not conditional on partisanship (see Appendix Tables S2, S20 and S33). Our results are robust to several other predicted causes of political violence. We find that several standard political measures (i.e., affective polarization and political engagement) are less predictive of support for political violence than are general measures of aggression (measured using the Buss-Perry scale (35); see Appendix Tables S10 and S26), suggesting that tolerance for violence is a general human preference and not a specifically political preference.[¶] We also find that social desirability (measured with the Marlowe Crowne scale (37)) does not temper support for political violence on surveys, suggesting that social desirability is not responsible for our lower estimates of support.

In study 3 we address two alternative mechanisms: partisan cheerleading and respondent trolling. We find that both significantly inflate support for violence, but do so for both engaged and disengaged respondents, suggesting that these mechanisms offer additional reasons to be skeptical of prior estimates. To test for partisan cheerleading (38) we use the design from (29). Partisan cheerleaders are significantly more likely to support partisan violence across all three of our measures (see Appendix Table S34), but this is unlikely to drive our results as this represents 3.6% of the sample and cheerleaders are nearly evenly split between disengaged respondents (n=33) and engaged respondents (n=38). Secondly, we test for trolling using a shark bite question (27) as deployed on the ANES (the expectation is that responses above the known rate indicate trolling behavior). Trolling respondents inflate support for violence on two of our three measures (see Appendix Table S33), but again they represent a small portion of the sample (2.7%) and are split between engaged (n=17) and disengaged respondents (n=34). Removing cheerleaders and trolls decreases mean support for political violence from 1.42 to 1.39 (a change of .03 points).

Another concern is that focusing on engaged respondents is misleading because *true* support for violence might be correlated (positively or negatively) with disengaged survey responding. To address this, (39) derives partial identification bounds assuming that the true support for violence among disengaged respondents is not observable from the survey question (see Appendix Section S9 for details on the methods used below). For example, in the Study 3 outcomes asking about murder, if we assume that true support for violence among disengaged respondents is anywhere between 0% and 100%, then the 95% confidence interval expands from [1.3%, 3.4%] to [0.5%, 24%]. However, if we cap true support among the disengaged at a more plausible yet still alarming number, such as 20% (approximately the median value reported in prior work), then the partial identification confidence intervals shrinks considerably to [0.5%, 6.3%].[‖] We note that 6.3% support is less than the minimum support for violence reported in Figure 1. Overall, these bounds suggest that, unless disengaged respondents are orders of magnitude more pro-violence than engaged respondents, the population average support for violence is still much lower than previous estimates have implied.

[¶] We do, however, find that Strong partisans are more likely to support violence.

[‖] For completeness, we note the other outcomes from Study 3. For the justification outcome, engaged respondents: [3.3%, 6.4%], 0-100 disengaged support: [2.0%, 26%], 0-20 disengaged support: [2.0%, 9.4%]. For charging the attacker: engaged respondents: [98%, 99%], 0-100 disengaged charging: [76%, 100%], 80-100 disengaged charging: [94%, 100%]. Note that all of these estimates are for respondents assigned to the in-party shooter condition, and no survey weights were used.

Of course, it is important to understand that while we show that support for political violence is lower than expected it is not precisely measured as zero. An important next step is identifying why remaining support exists and where, specifically, violent political action is likely to emerge. Future work could randomize attention and identify what crimes people default to when asked generic violence questions.

Our results offer critical context to stakeholders, citizens and politicians on the nation's response to political protests in Portland and the events following the 2020 presidential election. A small share of Americans support political violence, but most of this support comes from a troubling segment of the public who support violence in general. Even among this group, support is further contingent on the severity of the violent act and is generally limited to relatively minor crimes. Political violence is a problem in every public, but as our results show, it is important to carefully and accurately measure such support before raising alarm that might not be warranted. This is especially true when these alarms direct attention, funding and concern away from other critical policy debates (40).

Violence of the sort seen on January 6 is, at most, concentrated at the extremes of the parties, and despite the massive news coverage of political violence the underlying acts are very rare by comparison to general crime trends. Nevertheless, any amount of support for political violence is troubling and worthy of exploration. Researchers should set their sights on these pockets of extremism and organized violent activity—not the casual and frequently under-considered opinions of everyday voters. Mainstream Americans of both parties have little appetite for violence—political or not.

ACKNOWLEDGMENTS. For helpful discussions we thank Andrew Hall, Shanto Iyengar and Jonathan Mummolo.

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Supporting Material for "Current Research Overstates American Support for Political Violence"

Contents

S1 Context

S1.1 Engagement with Current Estimates

S1.1.1 Google Scholar

We searched for citations to Kalmoe, Nathan P and Lilliana Mason. 2019. Lethal mass partisanship: Prevalence, correlates, and electoralcontingencies. In *NCAPSA American Politics Meeting*.

S1.1.2 News Coverage

To count news coverage we used a basic search on Lexis Nexis:

Language: English
Terms: “Kalmoe” and “Mason”

We also used the same search terms on Google News.

The resulting articles were then manually cleaned to remove duplicates and unrelated articles.

S1.1.3 Social Media

Twitter
We used the Twitter Academic API to obtain all tweets with a link to an article on Kalmoe and Mason results. We then summed likes, quotes, retweets and total tweets. NOTE: This is a dramatic under-count of engagement as it does not count exposure to these tweets or the number of users who clicked on the links.

URLs:

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https://www.nytimes.com/2019/03/13/opinion/hate-politics.html
www.politico.com/news/magazine/2020/10/01/political-violence-424157
https://politi.co/3cJtVHQ
https://politi.co/2SeWmnv
https://www.dannyhayes.org/uploads/6/9/8/5/69858539/kalmoe___mason_ncapsa_2019_-_lethal_partisanship_-
_final_lmedit.pdf
https://www.washingtonpost.com/politics/2021/01/11/what-you-need-know-about-how-many-americans-
condone-political-violence-why/
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violence
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danger-dehumanizing-language-ncna1254530
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right
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those-in-opposing-political-party-behave-like-animals-study.html
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79997
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https://www.washingtonpost.com/politics/fear-of-election-violence/2020/10/30/5b4f5314-17a3-11eb-befb-8864259bd2d8_story.html
https://www.nytimes.com/2021/01/18/us/supporters-of-donald-trump.html
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https://www.washingtonpost.com/opinions/americans-are-at-each-others-throats-heres-one-way-out/2019/12/20/c8de01ca-2292-11ea-a153-dce4b94e4249_story.html
https://www.timesrecordnews.com/story/life/2021/01/16/mattingly-christians-and-conspiracies-dont-mix/6654273002/
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https://www.niskanencenter.org/the-niskanen-centers-science-of-politics-podcast/
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https://www.usatoday.com/story/opinion/2019/04/12/record-breaking-national-deficit-partisanship-threaten-us-future-leadership-column/3438887002/
https://reason.com/2020/08/05/the-looming-illegitimate-election-of-2020/
https://reason.com/2019/10/01/in-todays-america-everybody-who-disagrees-with-you-is-a-traitor/

S1.2 Political Violence News Coverage

S1.2.1 Print/Online

To count print and online news coverage we used a basic search on Lexis Nexis:

Language: English
Period: 1/1/2016 - 8/31/2021
Terms: "political violence" and ("Democrat" or "Republican")

The resulting articles were then manually cleaned to remove duplicates and non-news sources.

This is a simplistic search, yet it establishes a conservative baseline of coverage of American political violence.

We plot results by Month and Year.

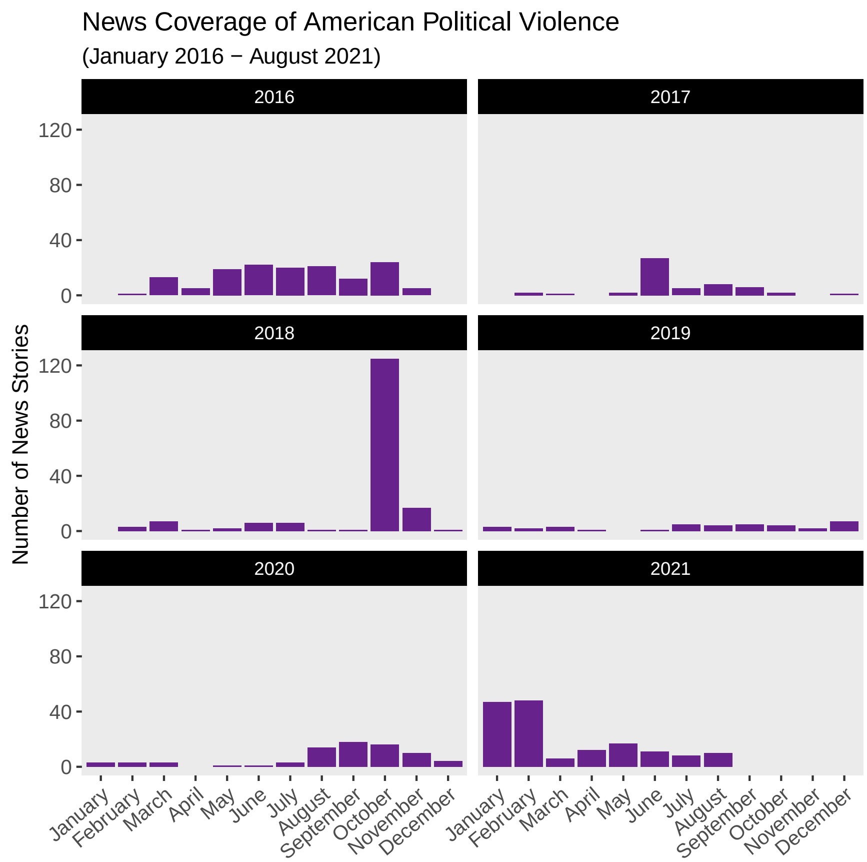

Figure S1: This plot shows counts of news coverage of American political violence by Month and Year.

S1.2.2 TV News

To count television engagement we used the same query and the Internet Archive's television news archive (see Figure S1).

S1.2.3 Twitter

To count Twitter engagement we counted references to January 6th, 2021. We did this to set a floor for discussion of political violence in America and because tweets lack the length and formal language of newspaper articles.

S1.3 Previously reported estimates

We conducted an exhaustive search of news articles reporting an estimate of public support for political violence. We recorded all aggregated estimates, and all estimates split by party. We first manually searched for estimates of support within the text using the following keywords: percent, per cent, %, "one in" (such as "one in three"), and "one-in". We then verified whether these were estimates of support for violence or other types of statistics (e.g., statistics such as "30% of Republicans say Democrats are evil" are not included). In particular, we identified which political violence survey question and wave from prior studies each estimate was based on. In a minority of cases, the survey question was clear but the survey wave was unclear. For instance, the estimate was from 2020, but we do not know if the estimate was derived from a September or October survey. We include these reported estimates despite the source ambiguity. On a few occasions, the reported support was given as a range (e.g., 15-20 percent). In each case, we converted this to the midpoint of the range (e.g., 18 for 15-20). Finally, we record each reported political violence support estimate within each story since some stories report multiple estimates of support for violence. These data are at the story-level.

S2 Study 1

S2.1 Sample Demographics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
age	1002	47.01	17.07	18	32	62	97
gender	1002						
... Female	520	52%					
... Male	482	48%					
race	1002						
... African American	132	13%					
... Asian	15	1%					
... Native American	16	2%					
... Other	57	6%					
... Pacific Islander	4	0%					
... White/Caucasian	778	78%					
pid	1002						
... Democrat	547	55%					
... Republican	455	45%					

Table S1: Summary Statistics for Study 1

S2.2 Treatment Text

S2.2.1 Oregon - Democratic Version

Suspect Drives Into Group of Republicans in Jacksonville

Republican volunteers in Jacksonville, Fla., were registering people to vote in a shopping center Saturday afternoon when a man drove a van through their red tent, then fled, according to law enforcement officials. The incident has drawn condemnation from prominent Florida lawmakers and President Trump.

Stan Gimm, 27, was charged with two counts of aggravated assault on a person 65 years old or older, plus criminal mischief and driving with a suspended license, jail records show.

A Spokeswoman said the statements made by Gimm "makes it clear that Saturday was a deliberate attack that was completely reprehensible and unacceptable."

S2.2.2 Oregon - Apolitical Version

Suspect Drives Into Group in Jacksonville

Volunteers in Jacksonville, Fla., were working in a shopping center Saturday afternoon when a man drove a van through their red tent, then fled, according to law enforcement officials. The incident has drawn condemnation from prominent Florida lawmakers and President Trump.

Stan Gimm, 27, was charged with two counts of aggravated assault on a person 65 years old or older, plus criminal mischief and driving with a suspended license, jail records show.

A Volunteer Spokeswoman said the statements made by Gimm "makes it clear that Saturday was a deliberate attack that was completely reprehensible and unacceptable."

S2.2.3 Florida - Republican Version

Republican Arrested After Assaulting Democratic Protesters

Republicans gathered in a Portland, Oregon suburb and formed a caravan and proceeded to assault Democratic protesters by pepper-spraying people and shooting paintballs. They also physically intimidated protesters by driving their trucks at unsafe speeds through crowded streets.

Thomas Kelly, a 31-year-old Portland Republican, was among the drivers arrested following the caravan. He was charged with Disorderly Conduct II and Interfering with a Peace Officer.

Portland Mayor Ted Wheeler, a Democrat, denounced the caravan. "All of us must take a stance against violence. It doesn't matter who you are or what your politics are. We have to all stop the violence," he said at a press conference.

S2.2.4 Florida - Apolitical Version

Man Arrested After Assaulting Pedestrians

A group gathered in a Portland, Oregon suburb and formed a caravan and proceeded to assault pedestrians by pepper-spraying people and shooting paintballs. They also physically intimidated people by driving their trucks at unsafe speeds through crowded streets.

Thomas Kelly, a 31-year-old Portland man was among the drivers arrested following the caravan. He was charged with Disorderly Conduct II and Interfering with a Peace Officer.

Portland Mayor Ted Wheeler denounced the caravan. “All of us must take a stance against violence. It doesn’t matter who you are, we have to all stop the violence,” he said at a press conference.

S2.3 Engagement Question

S2.3.1 Democratic Story

In what state did the event covered by the article you just read occur?

- Florida
- Nevada
- Georgia
- Alabama
- Texas
- South Carolina
- Kentucky

S2.3.2 Republican Story

In what state did the event covered by the article you just read occur?

- Oregon
- Nevada
- Washington
- California
- Idaho
- New Mexico
- Arizona

S2.4 Outcome Questions

Do you support or oppose the actions of [Stan Gimm/Thomas Kelly]?

- Strongly Support
- Support
- Neither support nor oppose
- Oppose
- Strongly Oppose

Was the driver justified or unjustified?

- Justified

- Unjustified

Should the driver face criminal charges?

- Yes
- No

S2.5 Heterogeneity by Copartisanship

While support for violence is low overall, we find that individuals are more willing to excuse the actions of co-partisans, which we present in Table S2. However, we find no consistent evidence that individuals are more permissive toward political violence than apolitical violence. Among those who were engaged in Study 1, we find that support for violence is higher when the assailant is from the same political party as the respondent. In Study 2, we find an increase in belief that the actions were justified, but the overall support is quite low. In Table S2, we present the coefficient estimates. Because nearly all respondents in Study 2 want to charge the assailant regardless of his party, the assailant's party has no discernible effect on support. This is consistent with prior work that shows partisan biases, especially with respect to deviations from democratic norms, are more about in-group love than out-group hate (Lelkes and Westwood, 2017; Westwood, Peterson and Lelkes, 2019).

Table S2: Respondents display a slight bias towards in-party assailants, though overall support is low.

	Study 1			Study 2		
	Justified	Support	Charged	Justified	Support	Charged
Out-party Suspect	−0.076	−0.246	0.075	−0.048	−0.231	0.007
	(0.037)	(0.144)	(0.029)	(0.017)	(0.052)	(0.007)
Intercept	0.157	2.139	0.892	0.068	1.401	0.989
	(0.025)	(0.099)	(0.020)	(0.012)	(0.037)	(0.005)
Observations	315	315	315	572	572	572

Likewise, we find almost no difference in support whether partisan information is provided. Consistently, respondents do not support the subject's actions, view the crime as unjustified, and want the assailant to be charged regardless of the information we provide. Where we find effects, they are relatively small and suggest that, at most, only a small share of the public supports political violence.

S2.6 Additional Results

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.98	3.06	0.19	0.44	0.92	0.76
	(0.08)	(0.15)	(0.02)	(0.06)	(0.02)	(0.05)
Apolitical Driver 2	0.70	−0.02	0.03	−0.00	−0.03	0.05
	(0.12)	(0.22)	(0.04)	(0.08)	(0.03)	(0.07)
Democrat Driver	0.73	0.15	0.00	−0.12	−0.05	0.08
	(0.12)	(0.20)	(0.04)	(0.08)	(0.03)	(0.06)
Republican Driver	0.16	0.05	0.05	−0.00	−0.03	−0.00
	(0.12)	(0.21)	(0.04)	(0.08)	(0.03)	(0.07)
Engaged Respondent		−1.48		−0.35		0.23
		(0.17)		(0.06)		(0.05)
Apolitical Driver 2 * Engaged Respondent		0.98		0.04		−0.11
		(0.26)		(0.09)		(0.07)
Democrat Driver * Engaged Respondent		0.69		0.14		−0.18
		(0.24)		(0.08)		(0.07)
Republican Driver * Engaged Respondent		0.03		0.05		−0.02
		(0.24)		(0.09)		(0.07)
Num. obs.	1002	1002	1002	1002	1002	1002

Table S3: Main outcome measures vs. the treatment condition and Engaged Respondent. The baseline category for the treatment is Apolitical Driver (Story 1). Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.98	2.23	0.19	0.26	0.92	0.93
	(0.08)	(0.12)	(0.02)	(0.04)	(0.02)	(0.02)
Apolitical Driver 2	0.70	0.50	0.03	−0.04	−0.03	−0.04
	(0.12)	(0.17)	(0.04)	(0.05)	(0.03)	(0.03)
Democrat Driver	0.73	0.45	0.00	−0.08	−0.05	−0.02
	(0.12)	(0.17)	(0.04)	(0.05)	(0.03)	(0.03)
Republican Driver	0.16	0.11	0.05	0.04	−0.03	−0.05
	(0.12)	(0.17)	(0.04)	(0.05)	(0.03)	(0.03)
Republican		−0.54		−0.16		−0.03
		(0.16)		(0.05)		(0.03)
Apolitical Driver 2 * Republican		0.42		0.14		0.03
		(0.24)		(0.07)		(0.05)
Democrat Driver * Republican		0.61		0.18		−0.07
		(0.23)		(0.07)		(0.06)
Republican Driver * Republican		0.10		0.01		0.04
		(0.23)		(0.07)		(0.05)
Num. obs.	1002	1002	1002	1002	1002	1002

Table S4: Main outcome measures vs. the treatment condition and party ID. The baseline category for the treatment is Apolitical Driver (Story 1). Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.33	0.27	0.91
	(0.15)	(0.04)	(0.03)
Apolitical Driver 2	0.45	−0.00	−0.04
	(0.21)	(0.06)	(0.04)
Democrat Driver	0.44	−0.07	−0.03
	(0.22)	(0.06)	(0.05)
Republican Driver	0.26	0.13	−0.04
	(0.21)	(0.07)	(0.04)
Weak Dem.	−0.67	−0.19	0.09
	(0.23)	(0.07)	(0.03)
Lean Dem.	0.07	0.23	0.09
	(0.44)	(0.17)	(0.03)
Lean Rep.	−0.93	−0.27	−0.11
	(0.39)	(0.04)	(0.18)
Weak Rep.	−0.81	−0.18	0.06
	(0.21)	(0.06)	(0.04)
Strong Rep.	−0.52	−0.17	−0.03
	(0.20)	(0.06)	(0.05)
Apolitical Driver 2 * Weak Dem.	0.58	0.04	−0.05
	(0.36)	(0.10)	(0.07)
Democrat Driver * Weak Dem.	0.38	0.14	0.03
	(0.35)	(0.11)	(0.05)
Republican Driver * Weak Dem.	−0.39	−0.17	0.01
	(0.32)	(0.09)	(0.06)
Apolitical Driver 2 * Lean Dem.	−0.49	−0.41	0.04
	(0.70)	(0.19)	(0.04)
Democrat Driver * Lean Dem.	−0.14	−0.33	−0.07
	(0.63)	(0.20)	(0.11)
Republican Driver * Lean Dem.	−0.66	−0.63	−0.10
	(0.58)	(0.17)	(0.14)
Apolitical Driver 2 * Lean Rep.	1.58	0.15	0.10
	(0.62)	(0.15)	(0.23)
Democrat Driver * Lean Rep.	1.02	0.07	−0.05
	(0.57)	(0.06)	(0.25)
Republican Driver * Lean Rep.	0.84	0.25	0.12
	(0.66)	(0.19)	(0.22)
Apolitical Driver 2 * Weak Rep.	0.58	0.00	0.01
	(0.33)	(0.09)	(0.06)
Democrat Driver * Weak Rep.	0.77	0.09	−0.06
	(0.35)	(0.10)	(0.08)
Republican Driver * Weak Rep.	−0.17	−0.20	−0.08
	(0.30)	(0.08)	(0.08)
Apolitical Driver 2 * Strong Rep.	0.30	0.18	0.02
	(0.31)	(0.09)	(0.07)
Democrat Driver * Strong Rep.	0.46	0.21	−0.04
	(0.30)	(0.09)	(0.08)
Republican Driver * Strong Rep.	−0.05	−0.03	0.10
	(0.31)	(0.09)	(0.07)
Num. obs.	998	998	998

Table S5: Main outcome measures vs. the treatment condition and 7-point party ID. The baseline category for the treatment is Apolitical Driver (Story 1), and the baseline category for 7-point party ID is Strong Democrat. Coefficients are from an ordinary least squares regression with HC1 standard errors. We note that this analysis was not pre-registered.

	Support	Justifed	Charged
(Intercept)	2.33	0.20	0.91
	(0.06)	(0.02)	(0.01)
Democrat Driver	0.19	0.05	−0.05
	(0.11)	(0.03)	(0.03)
Republican Driver	−0.02	−0.03	0.00
	(0.11)	(0.03)	(0.02)
Num. obs.	1002	1002	1002

Table S6: Main outcome measures vs. the treatment condition. The baseline category for the treatment is Apolitical Driver (Story 1). Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	2.26	2.41	0.17	0.24	0.90	0.92
	(0.09)	(0.09)	(0.02)	(0.03)	(0.02)	(0.02)
Out-Party Driver	0.05		−0.00		0.01	
	(0.13)		(0.03)		(0.03)	
In-Party Driver		0.11		0.02		−0.06
		(0.12)		(0.04)		(0.03)
Num. obs.	509	493	509	493	509	493

Table S7: Main outcome measures vs. whether R knew the attack was told the attack was apolitical or had political motives. Baseline category is apolitical driver (collapsing across stories 1 and 2). Coefficients are from an ordinary least squares regression with HC1 standard errors.

S2.7 Robustness

	Use Violence
(Intercept)	1.58
	(0.06)
Medium SD	0.16
	(0.08)
High SD	0.62
	(0.12)
Num. obs.	1000

Table S8: "How much do you feel it is justified for [R's In-Party] to use violence in advancing their political goals these days?" vs. social desirability (SD) scale. Baseline category is low social desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.17	0.15	0.92
	(0.10)	(0.03)	(0.02)
Democrat Driver	0.29	0.06	−0.08
	(0.17)	(0.05)	(0.04)
Republican Driver	0.22	−0.02	−0.06
	(0.17)	(0.04)	(0.04)
Medium SD	0.14	0.03	−0.00
	(0.14)	(0.04)	(0.03)
High SD	0.47	0.20	−0.06
	(0.17)	(0.05)	(0.04)
Democrat Driver * Medium SD	−0.21	0.01	0.01
	(0.24)	(0.07)	(0.06)
Republican Driver * Medium SD	−0.18	0.04	0.08
	(0.24)	(0.06)	(0.05)
Democrat Driver * High SD	−0.07	−0.04	0.12
	(0.30)	(0.09)	(0.07)
Republican Driver * High SD	−0.86	−0.12	0.17
	(0.31)	(0.09)	(0.06)
Num. obs.	1002	1002	1002

Table S9: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Baseline categories are Apolitical Driver (Story 1) for the treatment condition and low social-desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.02	0.10	0.94
	(0.10)	(0.02)	(0.02)
Democrat Driver	0.02	0.02	−0.04
	(0.16)	(0.04)	(0.04)
Republican Driver	0.13	−0.01	−0.02
	(0.18)	(0.04)	(0.03)
Medium Aggression	0.19	0.01	−0.01
	(0.14)	(0.03)	(0.03)
High Aggresion	0.83	0.30	−0.10
	(0.15)	(0.04)	(0.03)
Democrat Driver * Medium Aggression	0.11	0.03	−0.06
	(0.24)	(0.06)	(0.06)
Republican Driver * Medium Aggression	−0.18	−0.00	0.05
	(0.26)	(0.06)	(0.05)
Democrat Driver * High Aggresion	0.36	0.06	0.05
	(0.25)	(0.08)	(0.06)
Republican Driver * High Aggresion	−0.33	−0.08	0.03
	(0.26)	(0.08)	(0.06)
Num. obs.	1002	1002	1002

Table S10: Main outcome measures vs. the treatment condition interacted with the aggression scale. Baseline categories are Apolitical Driver (Story 1) for the treatment condition and low aggression. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.99	0.06	0.94
	(0.12)	(0.03)	(0.03)
Democrat Driver	−0.28	−0.14	−0.05
	(0.21)	(0.06)	(0.05)
Republican Driver	−0.13	−0.04	−0.08
	(0.22)	(0.06)	(0.05)
Pol. Interest	0.40	0.21	−0.04
	(0.28)	(0.08)	(0.06)
Democrat Driver * Pol. Interest	1.05	0.47	0.03
	(0.47)	(0.14)	(0.11)
Republican Driver * Pol. Interest	0.28	0.10	0.20
	(0.50)	(0.15)	(0.09)
Num. obs.	769	769	769

Table S11: Main outcome measures vs. the treatment condition interacted with the political interest scale. The baseline category is Apolitical Driver (Story 1) for the treatment condition. The political interest scale is a continuous variable. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.68	−0.04	0.90
	(0.20)	(0.06)	(0.04)
Democrat Driver	−0.07	0.01	−0.03
	(0.37)	(0.12)	(0.08)
Republican Driver	0.31	−0.02	0.12
	(0.38)	(0.11)	(0.06)
Moral Threat	0.20	0.07	0.00
	(0.06)	(0.02)	(0.01)
Democrat Driver * Moral Threat	0.07	0.01	−0.01
	(0.11)	(0.03)	(0.02)
Republican Driver * Moral Threat	−0.10	−0.01	−0.04
	(0.11)	(0.03)	(0.02)
Num. obs.	1002	1002	1002

Table S12: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are a moral threat to the nation and its people" (Moral Threat). The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.77	−0.04	0.93
	(0.13)	(0.03)	(0.03)
Democrat Driver	0.03	0.05	0.01
	(0.23)	(0.07)	(0.05)
Republican Driver	−0.12	0.02	0.05
	(0.22)	(0.05)	(0.04)
Human	0.22	0.09	−0.01
	(0.05)	(0.01)	(0.01)
Democrat Driver * Human	0.04	−0.00	−0.02
	(0.08)	(0.02)	(0.02)
Republican Driver * Human	0.04	−0.02	−0.02
	(0.08)	(0.02)	(0.02)
Num. obs.	1002	1002	1002

Table S13: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are less than human" (Human). The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.60	−0.07	0.91
	(0.19)	(0.06)	(0.04)
Democrat Driver	−0.08	0.13	−0.00
	(0.34)	(0.11)	(0.08)
Republican Driver	0.13	−0.02	0.04
	(0.34)	(0.10)	(0.07)
Evil	0.25	0.09	−0.00
	(0.06)	(0.02)	(0.01)
Democrat Driver * Evil	0.06	−0.03	−0.02
	(0.10)	(0.04)	(0.03)
Republican Driver * Evil	−0.05	−0.00	−0.01
	(0.11)	(0.03)	(0.02)
Num. obs.	993	993	993

Table S14: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are evil" (Evil). The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.20	0.14	0.91
	(0.06)	(0.02)	(0.01)
In-Party Driver	0.20	0.06	−0.06
	(0.11)	(0.03)	(0.03)
Out-Party Driver	0.01	−0.00	−0.01
	(0.11)	(0.03)	(0.03)
Injure Democrats	0.74	0.32	−0.02
	(0.18)	(0.05)	(0.04)
In-Party Driver * Injure Democrats	−0.08	−0.04	0.03
	(0.31)	(0.10)	(0.07)
Out-Party Driver * Injure Democrats	−0.06	−0.17	0.06
	(0.32)	(0.10)	(0.06)
Num. obs.	1002	1002	1002

Table S15: Main outcome measures vs. the treatment condition interacted with a 1 if the respondent responds "Yes" to "Have you ever wished that someone would physically injure one or more Democratic politicians?" (Injure Democrats). The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.20	0.14	0.91
	(0.06)	(0.02)	(0.01)
In-Party Driver	0.20	0.06	−0.06
	(0.11)	(0.03)	(0.03)
Out-Party Driver	0.01	−0.00	−0.01
	(0.11)	(0.03)	(0.03)
Injure Republicans	0.74	0.32	−0.02
	(0.18)	(0.05)	(0.04)
In-Party Driver * Injure Republicans	−0.08	−0.04	0.03
	(0.31)	(0.10)	(0.07)
Out-Party Driver * Injure Republicans	−0.06	−0.17	0.06
	(0.32)	(0.10)	(0.06)
Num. obs.	1002	1002	1002

Table S16: Main outcome measures vs. the treatment condition interacted with a 1 if the respondent responds "Yes" to "Have you ever wished that someone would physically injure one or more Republican politicians?" (Injure Republicans). The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.71	−0.03	0.95
	(0.10)	(0.03)	(0.02)
In-Party Driver	−0.03	−0.02	−0.04
	(0.17)	(0.05)	(0.04)
Out-Party Driver	−0.03	−0.05	−0.01
	(0.18)	(0.04)	(0.04)
Use Violence	0.36	0.13	−0.03
	(0.05)	(0.02)	(0.01)
In-Party Driver * Use Violence	0.10	0.04	−0.01
	(0.08)	(0.03)	(0.02)
Out-Party Driver * Use Violence	−0.01	0.00	0.01
	(0.08)	(0.03)	(0.02)
Num. obs.	1000	1000	1000

Table S17: Main outcome measures vs. the treatment condition interacted with "How much do you feel it is justified for [R's In-Party] to use violence in advancing their political goals these days?". The baseline category is Apolitical Driver (Story 1) for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	2.79	0.35	0.90
	(0.11)	(0.04)	(0.02)
In-Party Driver	0.30	0.10	−0.06
	(0.20)	(0.07)	(0.05)
Out-Party Driver	0.02	−0.06	−0.06
	(0.19)	(0.06)	(0.05)
Medium AP	−0.68	−0.19	0.01
	(0.15)	(0.05)	(0.03)
High AP	−0.64	−0.24	0.00
	(0.15)	(0.04)	(0.03)
In-Party Driver * Medium AP	−0.05	−0.15	0.00
	(0.26)	(0.08)	(0.07)
Out-Party Driver * Medium AP	−0.09	−0.03	0.09
	(0.26)	(0.07)	(0.06)
In-Party Driver * High AP	−0.29	−0.03	0.02
	(0.26)	(0.08)	(0.06)
Out-Party Driver * High AP	−0.09	0.09	0.10
	(0.26)	(0.08)	(0.06)
Num. obs.	1002	1002	1002

Table S18: Main outcome measures vs. the treatment condition interacted with the affective polarization scale. Baseline categories are Apolitical Driver (Story 1) for the treatment condition and low affective polarization. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S3 Study 2

S3.1 Sample Demographics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
age	1023	47.42	16.79	18	34	61	88
gender	1023						
... Female	523	51%					
... Male	500	49%					
race	1023						
... African American	139	14%					
... Asian	60	6%					
... Native American	25	2%					
... Other (please specify)	58	6%					
... Pacific Islander	2	0%					
... White/Caucasian	739	72%					
pid	1023						
... Democrat	489	48%					
... Republican	534	52%					

Table S19: Summary Statistics for Study 2

S3.2 Treatment Text

Iowa Man Arrested After Shooting A Woman at a [Democratic/Republican/Local Meeting

Steven Wright, 65, was arrested for attempted murder this afternoon in Des Moines. The Iowa local allegedly pulled a gun on a group of [Democrats/Republicans/locals] who were meeting in a neighboring house. Following a confrontation, Wright reportedly shot one of the attendees in the chest.

Two witnesses reported that Wright was upset that [Democrats/Republicans/people] were gathering in what Wright called a [Republican/Democratic/quiet] part of town. After aggressively arguing for several minutes, Wright reportedly aimed his gun at the woman and fired while calling her "a [Democratic/Republican/] maniac bent on ruining Iowa."

The victim later told reporters that she is sure she was shot "because she was trying to help organize [Democrats/Republicans/community events] in her neighborhood."

When deputies arrived, Wright was sitting on a couch next to a shotgun and stated that he was not coming out, the report states. Deputies were able to take him into custody without further incident. They located a pistol on his person with a magazine and six rounds of ammunition, the report continues.

S3.3 Engagement Question

In what state did the event covered by the article you just read occur?

- Iowa
- South Carolina
- Tennessee
- Michigan
- Texas
- Maine
- Oregon

S3.4 Outcome Questions

Do you support or oppose the actions of Steven Wright?

- Strongly Support
- Support
- Neither support nor oppose
- Oppose
- Strongly Oppose

Was the shooter justified or unjustified?

- Justified
- Unjustified

Should the shooter face criminal charges?

- Yes
- No

S3.5 Additional Results

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.53	2.35	0.07	0.26	0.98	0.91
	(0.05)	(0.17)	(0.01)	(0.06)	(0.01)	(0.04)
Democrat Shooter	−0.03	0.19	0.01	0.04	−0.00	−0.04
	(0.07)	(0.23)	(0.02)	(0.08)	(0.01)	(0.06)
Republican Shooter	0.02	0.14	0.05	0.11	−0.02	−0.04
	(0.07)	(0.23)	(0.02)	(0.08)	(0.01)	(0.06)
Engaged Respondent		−1.00		−0.23		0.08
		(0.17)		(0.06)		(0.04)
Democrat Shooter * Engaged Respondent		−0.27		−0.03		0.04
		(0.23)		(0.09)		(0.06)
Republican Shooter * Engaged Respondent		−0.21		−0.09		0.04
		(0.24)		(0.08)		(0.06)
Num. obs.	1023	1023	1023	1023	1023	1023

Table S20: Main outcome measures vs. the treatment condition and Engaged Respondent. The baseline category for the treatment is Apolitical Shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.53	1.54	0.07	0.06	0.98	0.99
	(0.05)	(0.07)	(0.01)	(0.02)	(0.01)	(0.01)
Democrat Shooter	−0.03	−0.07	0.01	0.03	−0.00	−0.01
	(0.07)	(0.10)	(0.02)	(0.03)	(0.01)	(0.01)
Republican Shooter	0.02	0.12	0.05	0.10	−0.02	−0.01
	(0.07)	(0.11)	(0.02)	(0.03)	(0.01)	(0.02)
Republican		−0.03		0.01		−0.02
		(0.10)		(0.03)		(0.02)
Democrat Shooter * Republican		0.08		−0.03		0.01
		(0.14)		(0.04)		(0.02)
Republican Shooter * Republican		−0.19		−0.08		−0.00
		(0.15)		(0.05)		(0.03)
Num. obs.	1023	1023	1023	1023	1023	1023

Table S21: Main outcome measures vs. the treatment condition and party ID. The baseline category for the treatment is Apolitical Shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.51	0.08	0.98
	(0.09)	(0.03)	(0.01)
Democrat Shooter	−0.10	0.00	0.01
	(0.13)	(0.04)	(0.02)
Republican Shooter	0.27	0.10	−0.01
	(0.15)	(0.05)	(0.02)
Weak Dem.	0.12	−0.06	0.02
	(0.15)	(0.03)	(0.01)
Lean Dem.	−0.11	−0.08	0.02
	(0.37)	(0.03)	(0.01)
Lean Rep.	−0.14	−0.08	0.02
	(0.22)	(0.03)	(0.01)
Weak Rep.	−0.03	−0.03	−0.01
	(0.15)	(0.04)	(0.03)
Strong Rep.	0.05	0.01	−0.01
	(0.13)	(0.04)	(0.02)
Democrat Shooter * Weak Dem.	−0.05	0.06	−0.04
	(0.20)	(0.06)	(0.03)
Republican Shooter * Weak Dem.	−0.49	−0.02	−0.01
	(0.21)	(0.07)	(0.03)
Democrat Shooter * Lean Dem.	0.55	0.14	−0.08
	(0.51)	(0.10)	(0.07)
Republican Shooter * Lean Dem.	0.33	0.15	0.01
	(0.96)	(0.22)	(0.02)
Democrat Shooter * Lean Rep.	0.03	−0.00	−0.11
	(0.31)	(0.04)	(0.10)
Republican Shooter * Lean Rep.	−0.18	−0.10	−0.08
	(0.32)	(0.05)	(0.09)
Democrat Shooter * Weak Rep.	0.12	0.00	0.01
	(0.20)	(0.06)	(0.03)
Republican Shooter * Weak Rep.	−0.29	−0.10	0.02
	(0.22)	(0.06)	(0.04)
Democrat Shooter * Strong Rep.	0.09	−0.01	−0.01
	(0.18)	(0.06)	(0.03)
Republican Shooter * Strong Rep.	−0.38	−0.08	−0.02
	(0.20)	(0.06)	(0.04)
Num. obs.	1023	1023	1023

Table S22: Main outcome measures vs. the treatment condition and 7-point party ID. The baseline categories are Apolitical Shooter and Strong Democrat. Coefficients are from an ordinary least squares regression with HC1 standard errors. We note that this analysis was not pre-registered.

	Support	Justifed	Charged
(Intercept)	1.53	0.07	0.98
	(0.05)	(0.01)	(0.01)
In-Party and Partisan	−0.07	0.02	−0.01
	(0.07)	(0.02)	(0.01)
Out-Party and Partisan	0.06	0.05	−0.00
	(0.07)	(0.02)	(0.01)
Num. obs.	1023	1023	1023

Table S23: Main outcome measures vs. the treatment condition. The baseline category for the treatment is Apolitical Shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S3.6 Robustness

	Use Violence
(Intercept)	1.60
	(0.06)
Medium SD	0.03
	(0.08)
High SD	0.06
	(0.10)
Num. obs.	1023

Table S24: "How much do you feel it is justified for [R's In-Party] to use violence in advancing their political goals these days?" vs. social desirability (SD) scale. Baseline category is low social desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.52	0.05	0.98
	(0.09)	(0.02)	(0.01)
In-Party and Partisan	−0.08	0.04	−0.02
	(0.11)	(0.03)	(0.02)
Out-Party and Partisan	−0.04	0.03	0.01
	(0.12)	(0.03)	(0.02)
Medium SD	0.02	0.01	0.00
	(0.11)	(0.03)	(0.02)
High SD	−0.02	0.06	−0.01
	(0.15)	(0.05)	(0.03)
In-Party and Partisan * Medium SD	−0.05	−0.02	0.01
	(0.15)	(0.04)	(0.03)
Out-Party and Partisan * Medium SD	0.14	0.04	−0.03
	(0.16)	(0.05)	(0.03)
In-Party and Partisan * High SD	0.19	−0.01	0.02
	(0.21)	(0.07)	(0.04)
Out-Party and Partisan * High SD	0.19	−0.01	−0.01
	(0.20)	(0.07)	(0.04)
Num. obs.	1023	1023	1023

Table S25: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Baseline categories are Apolitical Shooter for the treatment condition and low social-desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.34	0.02	0.99
	(0.06)	(0.01)	(0.01)
In-Party and Partisan	−0.13	0.00	−0.01
	(0.08)	(0.02)	(0.01)
Out-Party and Partisan	−0.08	0.04	0.00
	(0.08)	(0.02)	(0.01)
Medium Aggression	0.10	0.03	−0.02
	(0.10)	(0.02)	(0.02)
High Aggresion	0.48	0.13	−0.02
	(0.13)	(0.04)	(0.02)
In-Party and Partisan * Medium Aggression	−0.00	0.04	0.01
	(0.13)	(0.04)	(0.03)
Out-Party and Partisan * Medium Aggression	0.28	0.03	−0.01
	(0.15)	(0.04)	(0.03)
In-Party and Partisan * High Aggresion	0.18	0.03	−0.02
	(0.17)	(0.05)	(0.03)
Out-Party and Partisan * High Aggresion	0.20	0.01	−0.01
	(0.18)	(0.06)	(0.03)
Num. obs.	1023	1023	1023

Table S26: Main outcome measures vs. the treatment condition interacted with the aggression scale. Baseline categories are Apolitical Shooter for the treatment condition and low aggression. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.43	−0.01	0.97
	(0.10)	(0.03)	(0.02)
In-Party and Partisan	−0.07	0.05	−0.02
	(0.14)	(0.04)	(0.03)
Out-Party and Partisan	−0.08	0.05	0.01
	(0.16)	(0.05)	(0.03)
Pol. Interest	0.26	0.20	0.02
	(0.26)	(0.09)	(0.04)
In-Party and Partisan * Pol. Interest	−0.01	−0.07	0.02
	(0.36)	(0.11)	(0.06)
Out-Party and Partisan * Pol. Interest	0.39	0.01	−0.04
	(0.43)	(0.14)	(0.06)
Num. obs.	1023	1023	1023

Table S27: Main outcome measures vs. the treatment condition interacted with the political interest scale. The baseline category is Apolitical Shooter for the treatment condition. The political interest scale is a continuous variable. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.17	−0.03	1.03
	(0.09)	(0.03)	(0.02)
In-Party and Partisan	−0.12	−0.02	−0.05
	(0.13)	(0.04)	(0.02)
Out-Party and Partisan	−0.29	−0.06	−0.04
	(0.13)	(0.04)	(0.02)
Use Violence	0.22	0.06	−0.03
	(0.06)	(0.02)	(0.01)
In-Party and Partisan * Use Violence	0.02	0.02	0.02
	(0.08)	(0.03)	(0.02)
Out-Party and Partisan * Use Violence	0.22	0.07	0.02
	(0.09)	(0.03)	(0.02)
Num. obs.	1023	1023	1023

Table S28: Main outcome measures vs. the treatment condition interacted with "How much do you feel it is justified for [R's In-Party] to use violence in advancing their political goals these days?". The baseline category is Apolitical Shooter for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.70	0.11	0.96
	(0.10)	(0.03)	(0.02)
In-Party and Partisan	0.13	0.05	−0.02
	(0.15)	(0.05)	(0.03)
Out-Party and Partisan	0.14	0.05	0.00
	(0.15)	(0.05)	(0.03)
Medium AP	−0.26	−0.07	0.03
	(0.12)	(0.04)	(0.02)
High AP	−0.24	−0.07	0.02
	(0.13)	(0.04)	(0.02)
In-Party and Partisan * Medium AP	−0.32	−0.05	0.02
	(0.17)	(0.05)	(0.03)
Out-Party and Partisan * Medium AP	−0.09	−0.01	−0.00
	(0.19)	(0.06)	(0.03)
In-Party and Partisan * High AP	−0.26	−0.02	0.01
	(0.18)	(0.06)	(0.04)
Out-Party and Partisan * High AP	−0.16	0.01	−0.02
	(0.19)	(0.06)	(0.03)
Num. obs.	1023	1023	1023

Table S29: Main outcome measures vs. the treatment condition interacted with the affective polarization scale. Baseline categories are Apolitical Shooter for the treatment condition and low affective polarization. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S4 Study 3

S4.1 Sample Demographics

Variable	N	Percent
age4	1863	
... 30-44	463	25%
... 45-64	615	33%
... 65+	506	27%
... Under 30	279	15%
gender4	1863	
... Man	807	43%
... Non-binary	12	1%
... Other	1	0%
... Woman	1043	56%
race4	1863	
... Black	253	14%
... Hispanic	256	14%
... Other	113	6%
... White	1241	67%
pid3	1863	
... Democrat	967	52%
... Republican	896	48%

Table S30: Summary Statistics for Study 3

S4.2 Treatment Text

Iowa Man Arrested After Shooting A Woman at a [Democratic/Republican

Steven Wright, 65, was arrested for attempted murder this afternoon in Des Moines. The Iowa local allegedly pulled a gun on a group of [Democrats/Republicans] who were meeting in a neighboring house. Following a confrontation, Wright reportedly shot one of the attendees in the chest.

Two witnesses reported that Wright was upset that [Democrats/Republicans] were gathering in what Wright called a [Republican/Democratic] part of town. After aggressively arguing for several minutes, Wright reportedly aimed his gun at the woman and fired while calling her "a [Democratic/Republican] maniac bent on ruining Iowa."

The victim later told reporters that she is sure she was shot "because she was trying to help organize [Democrats/Republicans] in her neighborhood."

When deputies arrived, Wright was sitting on a couch next to a shotgun and stated that he was not coming out, the report states. Deputies were able to take him into custody without further incident. They located a pistol on his person with a magazine and six rounds of ammunition, the report continues.

S4.3 Engagement Question

In what state did the event covered by the article you just read occur?

- Iowa
- South Carolina
- Tennessee
- Michigan
- Texas
- Maine
- Oregon

S4.4 Outcome Questions

Do you support or oppose the actions of Steven Wright?

- Strongly Support
- Support
- Neither support nor oppose
- Oppose
- Strongly Oppose

Was the shooter justified or unjustified?

- Justified
- Unjustified

Should the shooter face criminal charges?

- Yes
- No

S4.5 Additional Results

Table S31: Study 3: Passing Engagement Test by Incentive Arm

	Dependent variable:
	Passed
Out-Party Shooter	0.010
	(−0.041, 0.060)
Incentivized	0.059*
	(0.009, 0.110)
Out-Party Shooter X Incentivized	−0.047
	(−0.118, 0.025)
Constant	0.787***
	(0.751, 0.823)
Observations	1,863
R^2	0.003
Adjusted R^2	0.002
Residual Std. Error	0.392 (df = 1859)
F Statistic	2.081 (df = 3; 1859)
Note:	*p<0.05; **p<0.01; ***p<0.001

Table S32: Study 3: Justification, Support and Charges by Political Alignment by Incentive Arm

	Dependent variable:		
	Support	Justification	Charged
	(1)	(2)	(3)
OutParty Shooter	0.162*	−0.052**	−0.028*
	(0.032, 0.292)	(−0.091, −0.014)	(−0.056, −0.001)
Incentivized	−0.031	−0.040*	0.004
	(−0.162, 0.100)	(−0.078, −0.001)	(−0.023, 0.032)
Incentivized X OutParty	0.051	0.084**	0.017
	(−0.134, 0.237)	(0.029, 0.139)	(−0.023, 0.056)
Intercept	1.540***	0.127***	0.959***
	(1.446, 1.633)	(0.099, 0.154)	(0.939, 0.978)
Observations	1,863	1,863	1,863
R^2	0.009	0.005	0.003
Adjusted R^2	0.007	0.004	0.002
Residual Std. Error (df = 1859)	1.020	0.301	0.217
F Statistic (df = 3; 1859)	5.346**	3.227*	2.170
Note:			*p<0.05; **p<0.01; ***p<0.001

Table S33: Trolling, Justifcation, Support and Charges by Political Alignment

	Dependent variable:		
	Support	Justification	Charged
	(1)	(2)	(3)
OutParty Shooter	0.176***	−0.022	−0.020*
	(0.089, 0.263)	(−0.048, 0.005)	(−0.040, −0.001)
Shark Bite	2.281***	0.392***	−0.159***
	(1.915, 2.647)	(0.280, 0.503)	(−0.242, −0.075)
Shark Bite X OutParty	−0.176	0.211**	0.032
	(−0.666, 0.313)	(0.062, 0.360)	(−0.080, 0.143)
Intercept	1.459***	0.096***	0.965***
	(1.398, 1.521)	(0.077, 0.114)	(0.951, 0.979)
Observations	1,863	1,863	1,863
R^2	0.150	0.093	0.016
Adjusted R^2	0.149	0.092	0.014
Residual Std. Error (df = 1859)	0.945	0.288	0.215
F Statistic (df = 3; 1859)	109.514***	63.546***	9.780***
Note:			*p<0.05; **p<0.01; ***p<0.001

Table S34: Cheerleading, Justifcation, Support and Charges by Political Alignment

	Dependent variable:		
	Support	Justification	Charged
	(1)	(2)	(3)
OutParty Shooter	0.203***	−0.004	−0.028**
	(0.110, 0.297)	(−0.032, 0.023)	(−0.048, −0.009)
Cheerleader	0.886***	0.288***	−0.196***
	(0.583, 1.188)	(0.199, 0.378)	(−0.260, −0.131)
Cheerleader X OutParty	−0.155	−0.088	0.158**
	(−0.614, 0.304)	(−0.223, 0.048)	(0.060, 0.256)
Intercept	1.481***	0.093***	0.970***
	(1.415, 1.548)	(0.073, 0.112)	(0.956, 0.984)
Observations	1,863	1,863	1,863
R^2	0.034	0.029	0.021
Adjusted R^2	0.033	0.027	0.020
Residual Std. Error (df = 1859)	1.007	0.297	0.215
F Statistic (df = 3; 1859)	22.115***	18.507***	13.589***
Note:			*p<0.05; **p<0.01; ***p<0.001

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.57	2.34	0.08	0.23	0.97	0.92
	(0.04)	(0.14)	(0.01)	(0.04)	(0.01)	(0.02)
Republican Shooter	0.10	0.21	0.03	0.09	−0.03	−0.11
	(0.06)	(0.19)	(0.02)	(0.06)	(0.01)	(0.04)
Engaged Respondent		−0.94		−0.18		0.06
		(0.14)		(0.04)		(0.02)
Republican Shooter * Engaged Respondent		−0.18		−0.08		0.10
		(0.20)		(0.07)		(0.05)
Num. obs.	1863	1863	1863	1863	1863	1863

Table S35: Main outcome measures vs. the treatment condition and Engaged Respondent. The baseline category for the treatment is Democrat shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Support	Justifed	Justifed	Charged	Charged
(Intercept)	1.57	1.53	0.08	0.09	0.97	0.98
	(0.04)	(0.06)	(0.01)	(0.02)	(0.01)	(0.01)
Republican Shooter	0.10	0.27	0.03	0.02	−0.03	−0.05
	(0.06)	(0.10)	(0.02)	(0.03)	(0.01)	(0.02)
Republican		0.08		−0.02		−0.02
		(0.08)		(0.03)		(0.01)
Republican Shooter * Republican		−0.36		0.02		0.04
		(0.13)		(0.04)		(0.02)
Num. obs.	1863	1863	1863	1863	1863	1863

Table S36: Main outcome measures vs. the treatment condition and party ID. The baseline category for the treatment is Democrat shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.48	0.07	0.98
	(0.08)	(0.02)	(0.01)
Republican Shooter	0.22	0.02	−0.02
	(0.11)	(0.02)	(0.01)
Weak Dem.	0.15	0.06	−0.00
	(0.13)	(0.05)	(0.01)
Weak Rep.	−0.03	−0.03	−0.03
	(0.12)	(0.02)	(0.02)
Strong Rep.	0.22	0.02	−0.02
	(0.10)	(0.03)	(0.01)
Republican Shooter * Weak Dem.	0.13	0.00	−0.08
	(0.21)	(0.07)	(0.04)
Republican Shooter * Weak Rep.	−0.06	0.07	0.01
	(0.18)	(0.05)	(0.04)
Republican Shooter * Strong Rep.	−0.45	0.00	0.00
	(0.15)	(0.04)	(0.02)
Num. obs.	1863	1863	1863

Table S37: Main outcome measures vs. the treatment condition and 7-point party ID (without independents). The baseline category for the treatment is Democrat shooter, and the baseline category for 7-point party ID is Strong Democrat. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Support	Justifed	Charged
(Intercept)	1.52	0.11	0.96
	(0.04)	(0.01)	(0.01)
Out-Party Shooter	0.19	−0.01	−0.02
	(0.06)	(0.02)	(0.01)
Num. obs.	1863	1863	1863

Table S38: Main outcome measures vs. the treatment condition. The baseline category for the treatment is In-Party shooter. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S5 Study 4

S5.1 Sample Demographics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
age	1009	45.2	17.44	18	30	60	90
gender	1009						
... Female	510	51%					
... Male	499	49%					
race	1009						
... African American	160	16%					
... Asian	30	3%					
... Native American	19	2%					
... Other	43	4%					
... Pacific Islander	2	0%					
... White/Caucasian	755	75%					
pid	1009						
... Democrat	540	54%					
... Republican	469	46%					

Table S39: Summary Statistics for Study 4

S5.2 Engagement Vignette and Question

Bringing back sea otters to the Oregon Coast just got a high-level endorsement. The federal budget for this new year includes a directive to study sea otter reintroduction.

The proviso making sea otter fans happy was tucked away deep in the new federal budget. It directs the U.S. Fish and Wildlife Service to study the feasibility and cost of reestablishing the charismatic marine mammals where they were once hunted to near-extinction along the Pacific Coast.

Bob Bailey leads the Elakha Alliance, a group that wants to bring wild sea otters back. His organization instigated the congressional action.

"I'm very pleased. This is very timely," Bailey said in an interview. "It will definitely help U.S. Fish and Wildlife Service develop a strategic approach for how best to conserve and protect sea otters."

What state is receiving funding to study the reintroduction of sea otters?

- Oregon
- Alaska
- Washington
- California
- Texas
- Florida
- Louisiana

S5.3 Treatment Text

Jon James Fishnick was convicted last week of [crime]. He was arrested by police [description].

Table S40: Crime and Crime Description Text for Study 4

Crime	Description
protesting without a permit	after leading a protest against [outparty] on the grounds of the county courthouse. He made no effort to acquire the necessary permit for the protest and refused to leave when asked by police.
vandalism	after he cut down several large signs expressing support for candidates of the [outparty].
assault	for throwing rocks at peaceful [outparty] protesters. Although no one was seriously injured, paramedics bandaged a man with a head wound.
arson	as he attempted to run from a fire he started at the local [outparty] headquarters. Although he waited for the building to close for the night, several adjacent buildings were still occupied.
assault with a deadly weapon	after driving his car into a crow of [outparty] protesters. Although no one was killed, several individuals were seriously injured and one spent a month in the hospital.",
murder	after surveillance footage was found showing Fisknick stabbing a prominent [outparty] to death. Fisknick targeted the victim because he stopped Fisknick from voting in the last election. Fisknick claims the victim wanted to stop [inparty] voters.

S5.4 Outcome Questions

The judge is expected to sentence Fishnick next week. We are interested in what sentence you think is appropriate:

- Community service
- 1 - 3 days in jail
- 4 - 30 days in jail
- 2 - 3 months in jail
- 4 - 6 months in jail
- 7 months to 1 year in jail
- 2 - 5 years in prison
- 6 - 10 years in prison
- 11 - 15 years in prison
- 16 - 20 years in prison
- More than 20 years in prison

Would you support or oppose a pardon for Jon James Fishnick?

- Strongly Support
- Support
- Neither support nor oppose
- Oppose
- Strongly Oppose

S5.5 Additional Results

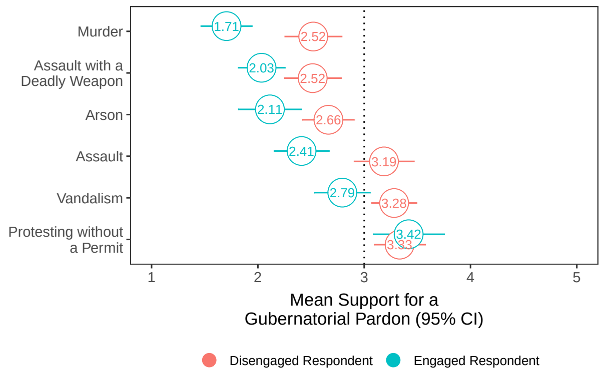

Figure S2: Support for a Mean Support for a Gubernatorial Pardon by Attention

	Pardon	Pardon	Nullify	Nullify
(Intercept)	2.48	2.66	0.04	0.04
	(0.10)	(0.13)	(0.02)	(0.02)
Assault	0.40	0.52	0.27	0.32
	(0.15)	(0.19)	(0.04)	(0.06)
Assault w/Deadly Weapon	−0.20	−0.15	0.04	0.08
	(0.14)	(0.19)	(0.03)	(0.04)
Murder	−0.33	−0.14	0.02	0.04
	(0.14)	(0.19)	(0.02)	(0.03)
Protest w/out Permit	0.88	0.67	0.52	0.47
	(0.14)	(0.18)	(0.04)	(0.05)
Vandalism	0.60	0.62	0.46	0.39
	(0.13)	(0.17)	(0.04)	(0.05)
Engaged Respondent		−0.55		−0.01
		(0.20)		(0.03)
Assault * Engaged Respondent		−0.22		−0.13
		(0.28)		(0.08)
Assault w/Deadly Weapon * Engaged Respondent		0.07		−0.07
		(0.26)		(0.05)
Murder * Engaged Respondent		−0.27		−0.05
		(0.27)		(0.05)
Protest w/out Permit * Engaged Respondent		0.64		0.13
		(0.28)		(0.09)
Vandalism * Engaged Respondent		0.06		0.20
		(0.26)		(0.08)
Num. obs.	991	991	1009	1009

Table S41: Main outcome measures vs. treatment condition and the engagement test. Pardon is a Likert scale “Would you support or oppose a pardon for Jon James Fishnick?” Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and failure for the engagement test. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Pardon	Nullify	Nullify
(Intercept)	2.48	2.76	0.04	0.05
	(0.10)	(0.15)	(0.02)	(0.02)
Assault	0.40	0.25	0.27	0.25
	(0.15)	(0.21)	(0.04)	(0.06)
Assault w/Deadly Weapon	−0.20	−0.50	0.04	0.02
	(0.14)	(0.20)	(0.03)	(0.03)
Murder	−0.33	−0.51	0.02	−0.00
	(0.14)	(0.20)	(0.02)	(0.03)
Protest w/out Permit	0.88	0.56	0.52	0.49
	(0.14)	(0.20)	(0.04)	(0.06)
Vandalism	0.60	0.53	0.46	0.42
	(0.13)	(0.19)	(0.04)	(0.06)
Republican		−0.57		−0.01
		(0.19)		(0.03)
Assault * Republican		0.28		0.04
		(0.29)		(0.08)
Assault w/Deadly Weapon * Republican		0.63		0.05
		(0.27)		(0.05)
Murder * Republican		0.38		0.03
		(0.28)		(0.05)
Protest w/out Permit * Republican		0.67		0.06
		(0.28)		(0.09)
Vandalism * Republican		0.14		0.10
		(0.26)		(0.08)
Num. obs.	991	991	1009	1009

Table S42: Main outcome measures vs. treatment condition and party ID. Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and Democrats. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.86	0.03
	(0.18)	(0.02)
Assault	0.27	0.34
	(0.26)	(0.07)
Assault w/Deadly Weapon	−0.42	0.06
	(0.26)	(0.04)
Murder	−0.56	0.03
	(0.24)	(0.04)
Protest w/out Permit	0.54	0.45
	(0.24)	(0.07)
Vandalism	0.57	0.42
	(0.22)	(0.06)
Weak Dem.	−0.36	0.07
	(0.35)	(0.07)
Lean Dem.	−0.86	−0.03
	(0.18)	(0.02)
Lean Rep.	−0.46	−0.03
	(0.41)	(0.02)
Weak Rep.	−0.96	−0.03
	(0.29)	(0.02)
Strong Rep.	−0.58	0.02
	(0.24)	(0.04)
Assault * Weak Dem.	0.02	−0.34
	(0.45)	(0.12)
Assault w/Deadly Weapon * Weak Dem.	−0.14	−0.16
	(0.42)	(0.08)
Murder * Weak Dem.	0.29	−0.13
	(0.48)	(0.08)
Protest w/out Permit * Weak Dem.	0.19	0.06
	(0.50)	(0.15)
Vandalism * Weak Dem.	−0.40	−0.06
	(0.45)	(0.17)
Assault * Lean Dem.	−0.02	−0.09
	(0.34)	(0.23)
Assault w/Deadly Weapon * Lean Dem.	0.59	0.10
	(0.57)	(0.16)
Murder * Lean Dem.	−0.10	−0.03
	(0.37)	(0.04)
Protest w/out Permit * Lean Dem.	0.30	0.38
	(0.56)	(0.17)
Vandalism * Lean Dem.	0.10	0.33
	(0.35)	(0.23)
Assault * Lean Rep.	0.33	−0.01
	(0.94)	(0.29)
Assault w/Deadly Weapon * Lean Rep.	−0.38	−0.06
	(0.50)	(0.04)
Murder * Lean Rep.	−0.84	−0.03
	(0.44)	(0.04)
Protest w/out Permit * Lean Rep.	1.56	0.30
	(0.50)	(0.23)
Vandalism * Lean Rep.	−0.37	0.38
	(0.69)	(0.19)
Assault * Weak Rep.	0.26	−0.20
	(0.41)	(0.12)
Assault w/Deadly Weapon * Weak Rep.	0.68	0.00
	(0.39)	(0.06)
Murder * Weak Rep.	0.52	0.04
	(0.41)	(0.06)
Protest w/out Permit * Weak Rep.	0.70	0.20
	(0.39)	(0.12)
Vandalism * Weak Rep.	0.09	0.10
	(0.37)	(0.12)
Assault * Strong Rep.	0.24	−0.01
	(0.36)	(0.10)
Assault w/Deadly Weapon * Strong Rep.	0.64	0.02
	(0.36)	(0.07)
Murder * Strong Rep.	0.49	−0.01
	(0.34)	(0.06)
Protest w/out Permit * Strong Rep.	0.65	0.03
	(0.35)	(0.11)
Vandalism * Strong Rep.	0.21	0.08
	(0.32)	(0.10)
Num. obs.	990	1008

Table S43: Main outcome measures vs. treatment condition and 7-point party ID. Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and Strong Democrats. Coefficients are from an ordinary least squares regression with HC1 standard errors. We note that this analysis was not pre-registered.

S5.6 Robustness

	Pardon	Nullify
(Intercept)	2.48	0.04
	(0.17)	(0.02)
Assault	0.28	0.32
	(0.24)	(0.07)
Assault w/Deadly Weapon	−0.58	0.05
	(0.21)	(0.04)
Murder	−0.36	0.04
	(0.23)	(0.04)
Protest w/out Permit	0.71	0.53
	(0.22)	(0.07)
Vandalism	0.39	0.51
	(0.21)	(0.07)
Medium SD	−0.25	−0.01
	(0.22)	(0.03)
High SD	0.44	0.04
	(0.29)	(0.05)
Assault * Medium SD	0.18	−0.04
	(0.32)	(0.10)
Assault w/Deadly Weapon * Medium SD	0.62	−0.02
	(0.29)	(0.05)
Murder * Medium SD	0.02	−0.04
	(0.31)	(0.05)
Protest w/out Permit * Medium SD	0.47	0.02
	(0.30)	(0.09)
Vandalism * Medium SD	0.46	−0.03
	(0.28)	(0.09)
Assault * High SD	0.14	−0.13
	(0.41)	(0.11)
Assault w/Deadly Weapon * High SD	0.41	0.01
	(0.37)	(0.08)
Murder * High SD	0.10	−0.04
	(0.39)	(0.07)
Protest w/out Permit * High SD	−0.02	−0.08
	(0.40)	(0.12)
Vandalism * High SD	0.15	−0.16
	(0.38)	(0.11)
Num. obs.	991	1009

Table S44: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Pardon is a Likert scale “Would you support or oppose a pardon for Jon James Fishnick?” Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and low social-desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.04	0.06
	(0.14)	(0.03)
Assault	0.60	0.36
	(0.23)	(0.08)
Assault w/Deadly Weapon	−0.27	−0.01
	(0.18)	(0.04)
Murder	−0.33	−0.02
	(0.20)	(0.04)
Protest w/out Permit	1.30	0.59
	(0.21)	(0.07)
Vandalism	0.90	0.56
	(0.19)	(0.07)
Medium Aggression	0.32	−0.02
	(0.21)	(0.04)
High Aggresion	1.00	−0.02
	(0.24)	(0.04)
Assault * Medium Aggression	−0.28	−0.08
	(0.32)	(0.11)
Assault w/Deadly Weapon * Medium Aggression	−0.04	0.04
	(0.27)	(0.06)
Murder * Medium Aggression	−0.28	0.03
	(0.27)	(0.06)
Protest w/out Permit * Medium Aggression	−0.28	−0.04
	(0.32)	(0.11)
Vandalism * Medium Aggression	−0.55	0.02
	(0.28)	(0.10)
Assault * High Aggresion	−0.40	−0.18
	(0.35)	(0.10)
Assault w/Deadly Weapon * High Aggresion	0.42	0.14
	(0.32)	(0.07)
Murder * High Aggresion	0.30	0.06
	(0.33)	(0.06)
Protest w/out Permit * High Aggresion	−0.96	−0.19
	(0.34)	(0.10)
Vandalism * High Aggresion	−0.26	−0.33
	(0.32)	(0.09)
Num. obs.	991	1009

Table S45: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Pardon is a Likert scale “Would you support or oppose a pardon for Jon James Fishnick?” Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and low aggression. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	1.76	0.05
	(0.19)	(0.03)
Assault	0.54	0.14
	(0.28)	(0.08)
Assault w/Deadly Weapon	0.31	0.04
	(0.26)	(0.05)
Murder	−0.23	−0.03
	(0.27)	(0.04)
Protest w/out Permit	1.68	0.74
	(0.29)	(0.08)
Vandalism	1.17	0.64
	(0.26)	(0.08)
Pol. Interest	1.28	−0.05
	(0.43)	(0.04)
Assault * Pol. Interest	−0.35	0.28
	(0.60)	(0.15)
Assault w/Deadly Weapon * Pol. Interest	−1.16	0.04
	(0.61)	(0.11)
Murder * Pol. Interest	−0.25	0.06
	(0.63)	(0.08)
Protest w/out Permit * Pol. Interest	−1.36	−0.40
	(0.62)	(0.15)
Vandalism * Pol. Interest	−1.31	−0.21
	(0.60)	(0.17)
Num. obs.	750	759

Table S46: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. The political interest scale is a continuous variable. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	1.60	0.06
	(0.37)	(0.05)
Assault	0.60	0.38
	(0.51)	(0.13)
Assault w/Deadly Weapon	−0.66	−0.10
	(0.49)	(0.10)
Murder	−0.69	−0.12
	(0.46)	(0.06)
Protest w/out Permit	1.48	0.73
	(0.49)	(0.13)
Vandalism	1.00	0.78
	(0.46)	(0.12)
Moral Threat	0.25	−0.00
	(0.11)	(0.01)
Assault * Moral Threat	−0.05	−0.03
	(0.15)	(0.04)
Assault w/Deadly Weapon * Moral Threat	0.13	0.04
	(0.14)	(0.03)
Murder * Moral Threat	0.11	0.04
	(0.14)	(0.02)
Protest w/out Permit * Moral Threat	−0.16	−0.07
	(0.14)	(0.04)
Vandalism * Moral Threat	−0.10	−0.10
	(0.13)	(0.03)
Num. obs.	991	1009

Table S47: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are a moral threat to the nation and its people" (Moral Threat). Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	1.85	0.05
	(0.20)	(0.04)
Assault	0.55	0.26
	(0.31)	(0.09)
Assault w/Deadly Weapon	−0.42	−0.03
	(0.27)	(0.06)
Murder	−0.44	−0.08
	(0.27)	(0.04)
Protest w/out Permit	1.50	0.72
	(0.29)	(0.09)
Vandalism	0.52	0.80
	(0.26)	(0.08)
Human	0.24	−0.00
	(0.07)	(0.01)
Assault * Human	−0.06	0.00
	(0.11)	(0.03)
Assault w/Deadly Weapon * Human	0.08	0.03
	(0.10)	(0.02)
Murder * Human	0.04	0.04
	(0.10)	(0.02)
Protest w/out Permit * Human	−0.23	−0.08
	(0.10)	(0.03)
Vandalism * Human	0.02	−0.12
	(0.09)	(0.03)
Num. obs.	991	1009

Table S48: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are less than human" (Human). Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.18	0.08
	(0.34)	(0.05)
Assault	0.15	0.36
	(0.50)	(0.13)
Assault w/Deadly Weapon	−0.83	−0.04
	(0.45)	(0.09)
Murder	−0.76	−0.04
	(0.44)	(0.08)
Protest w/out Permit	1.48	0.72
	(0.47)	(0.13)
Vandalism	0.08	0.78
	(0.42)	(0.11)
Evil	0.10	−0.01
	(0.11)	(0.02)
Assault * Evil	0.07	−0.03
	(0.16)	(0.04)
Assault w/Deadly Weapon * Evil	0.21	0.03
	(0.15)	(0.03)
Murder * Evil	0.13	0.02
	(0.14)	(0.02)
Protest w/out Permit * Evil	−0.21	−0.07
	(0.16)	(0.04)
Vandalism * Evil	0.18	−0.11
	(0.14)	(0.04)
Num. obs.	989	1007

Table S49: Main outcome measures vs. the treatment condition interacted with a Likert scale for "[R's out-party] are evil" (Evil). Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.28	0.05
	(0.10)	(0.02)
Assault	0.39	0.32
	(0.16)	(0.05)
Assault w/Deadly Weapon	−0.17	0.04
	(0.14)	(0.03)
Murder	−0.35	0.01
	(0.14)	(0.03)
Protest w/out Permit	1.02	0.54
	(0.15)	(0.05)
Vandalism	0.65	0.53
	(0.14)	(0.05)
Injure Democrats	0.99	−0.02
	(0.27)	(0.03)
Assault * Injure Democrats	−0.20	−0.21
	(0.36)	(0.08)
Assault w/Deadly Weapon * Injure Democrats	−0.04	0.02
	(0.38)	(0.06)
Murder * Injure Democrats	0.13	0.02
	(0.38)	(0.06)
Protest w/out Permit * Injure Democrats	−0.67	−0.12
	(0.37)	(0.11)
Vandalism * Injure Democrats	−0.03	−0.36
	(0.36)	(0.09)
Num. obs.	991	1009

Table S50: Main outcome measures vs. the treatment condition interacted with a 1 if the respondent responds "Yes" to "Have you ever wished that someone would physically injure one or more Democratic politicians?" (Injure Democrats). Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.28	0.05
	(0.10)	(0.02)
Assault	0.39	0.32
	(0.16)	(0.05)
Assault w/Deadly Weapon	−0.17	0.04
	(0.14)	(0.03)
Murder	−0.35	0.01
	(0.14)	(0.03)
Protest w/out Permit	1.02	0.54
	(0.15)	(0.05)
Vandalism	0.65	0.53
	(0.14)	(0.05)
Injure Republicans	0.99	−0.02
	(0.27)	(0.03)
Assault * Injure Republicans	−0.20	−0.21
	(0.36)	(0.08)
Assault w/Deadly Weapon * Injure Republicans	−0.04	0.02
	(0.38)	(0.06)
Murder * Injure Republicans	0.13	0.02
	(0.38)	(0.06)
Protest w/out Permit * Injure Republicans	−0.67	−0.12
	(0.37)	(0.11)
Vandalism * Injure Republicans	−0.03	−0.36
	(0.36)	(0.09)
Num. obs.	991	1009

Table S51: Main outcome measures vs. the treatment condition interacted with a 1 if the respondent responds “Yes” to “Have you ever wished that someone would physically injure one or more Republican politicians?” (Injure Republicans). Pardon is a Likert scale “Would you support or oppose a pardon for Jon James Fishnick?” Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	1.63	0.00
	(0.15)	(0.02)
Assault	0.37	0.29
	(0.22)	(0.07)
Assault w/Deadly Weapon	−0.25	0.03
	(0.20)	(0.04)
Murder	−0.37	0.02
	(0.21)	(0.04)
Protest w/out Permit	1.56	0.71
	(0.23)	(0.07)
Vandalism	0.87	0.78
	(0.21)	(0.07)
Use Violence	0.43	0.02
	(0.07)	(0.01)
Assault * Use Violence	0.02	−0.01
	(0.09)	(0.03)
Assault w/Deadly Weapon * Use Violence	0.07	0.01
	(0.10)	(0.02)
Murder * Use Violence	0.08	0.00
	(0.10)	(0.02)
Protest w/out Permit * Use Violence	−0.33	−0.11
	(0.11)	(0.03)
Vandalism * Use Violence	−0.13	−0.16
	(0.10)	(0.03)
Num. obs.	990	1008

Table S52: Main outcome measures vs. the treatment condition interacted with "How much do you feel it is justified for [R's In-Party] to use violence in advancing their political goals these days?". Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Pardon	Nullify
(Intercept)	2.94	0.05
	(0.18)	(0.03)
Assault	0.51	0.27
	(0.26)	(0.07)
Assault w/Deadly Weapon	−0.28	0.07
	(0.26)	(0.05)
Murder	−0.27	0.07
	(0.26)	(0.05)
Protest w/out Permit	0.44	0.44
	(0.23)	(0.07)
Vandalism	0.51	0.27
	(0.24)	(0.07)
Medium AP	−0.52	−0.00
	(0.25)	(0.04)
High AP	−0.92	−0.01
	(0.22)	(0.04)
Assault * Medium AP	−0.30	−0.10
	(0.34)	(0.10)
Assault w/Deadly Weapon * Medium AP	0.06	−0.03
	(0.34)	(0.07)
Murder * Medium AP	−0.25	−0.10
	(0.35)	(0.06)
Protest w/out Permit * Medium AP	0.58	0.10
	(0.34)	(0.11)
Vandalism * Medium AP	−0.03	0.25
	(0.33)	(0.10)
Assault * High AP	0.01	0.09
	(0.35)	(0.10)
Assault w/Deadly Weapon * High AP	0.24	−0.04
	(0.33)	(0.06)
Murder * High AP	0.17	−0.08
	(0.32)	(0.06)
Protest w/out Permit * High AP	0.81	0.15
	(0.33)	(0.10)
Vandalism * High AP	0.43	0.32
	(0.31)	(0.10)
Num. obs.	991	1009

Table S53: Main outcome measures vs. the treatment condition interacted with the affective polarization scale. Pardon is a Likert scale "Would you support or oppose a pardon for Jon James Fishnick?" Nullify is a binary indicator of whether the respondent gave Fishnick community service. Baseline categories are arson for the treatment condition and low affective polarization. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S6 Study 5

Our second PAP includes a study 5. We completed this study, but trimmed it from the main manuscript for space and for clarity. Our plan is to consider this for a future publication, but we present the major result below and report all preregistered analysis to comply with our PAP.

In this study we asked individuals to estimate how many Democrats and Republicans support political violence. One half of the sample just answered these questions. The other half was offered a cash incentive for being within 3 percentage points of the correct answer (the group mean from the study). We presented the same engagement vignette from study 3 (see page S5.2).

The major result is that individuals dramatically overestimate group support for political violence among their own party (see Figure S3) and among the out-party. This is consistent for both those offered an incentive and those not offered the incentive.

Figure S3: Respondents Dramatically Overestimate Group Support for Violence.

S6.1 Sample Demographics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
age	1030	46.67	16.97	18	32	61	92
gender	1030						
... Female	524	51%					
... Male	506	49%					
race	1030						
... African American	155	15%					
... Asian	72	7%					
... Native American	27	3%					
... Other (please specify)	57	6%					
... Pacific Islander	2	0%					
... White/Caucasian	717	70%					
pid	1030						
... Democrat	518	50%					
... Republican	512	50%					

Table S54: Summary Statistics for Study 5

S6.2 Engagement Vignette and Question

Bringing back sea otters to the Oregon Coast just got a high-level endorsement. The federal budget for this new year includes a directive to study sea otter reintroduction.

The proviso making sea otter fans happy was tucked away deep in the new federal budget. It directs the U.S. Fish and Wildlife Service to study the feasibility and cost of reestablishing the charismatic marine mammals where they were once hunted to near-extinction along the Pacific Coast.

Bob Bailey leads the Elakha Alliance, a group that wants to bring wild sea otters back. His organization instigated the congressional action.

"I'm very pleased. This is very timely," Bailey said in an interview. "It will definitely help U.S. Fish and Wildlife Service develop a strategic approach for how best to conserve and protect sea otters."

What state is receiving funding to study the reintroduction of sea otters?

- Oregon
- Alaska
- Washington
- California
- Texas
- Florida
- Louisiana

S6.3 Treatment Text

S6.3.1 No Incentive Prompt

We are interested in how Americans perceive supporters of the two main political parties.

Just give us your best guesses to the questions below.

(Please do not look answer up though; we are interested in your perceptions! Each page has a time limit before it auto-advances.)

S6.3.2 Incentive Prompt

We are interested in how Americans perceive supporters of the two main political parties.

Just give us your best guesses to the questions below.

We will give you $.50 for each response that comes within 3 percentage points of the correct answer.

(Please do not look answer up though; we are interested in your perceptions! Each page has a time limit before it auto-advances.)

S6.4 Outcome Questions

What percentage of Republicans do you think...? (forced sum to 100%)

- Support using violence in advancing their political goals
- Oppose using violence in advancing their political goals

What percentage of Democrats do you think...? (forced sum to 100%)

- Support using violence in advancing their political goals
- Oppose using violence in advancing their political goals

S6.5 Additional Results

Note these shorthand labels for the main outcome measures:

- "Rep. Dist." = the distance between the respondent's perception for Republicans and the true percentage of Republicans who support using violence.
- "Dem. Dist." = the distance between the respondent's perception for Democrats and the true percentage of Democrats who support using violence.
- "Rep. Sup." = respondent's perception of the percentage of Republicans who support using violence.
- "Dem. Sup." = respondent's perception of the percentage of Democrats who support using violence.
- "In-Party Sup." = respondent's perception of the percentage of members of their in-party who support using violence.
- "Out-Party. Sup." = respondent's perception of the percentage of members of their out-party who support using violence.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	30.38	29.06	36.22	35.01	29.71	41.52
	(1.21)	(0.93)	(1.35)	(1.10)	(1.07)	(1.32)
Incentivized	−2.01	2.06	−1.19	3.15	0.90	1.06
	(1.64)	(1.30)	(1.82)	(1.50)	(1.49)	(1.75)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S55: Main outcome measures vs. treatment condition. Baseline category for treatment condition is No Incentive. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	34.42	29.51	40.30	35.03	33.70	41.64
	(2.02)	(1.63)	(2.27)	(1.91)	(1.88)	(2.28)
Incentivized	−4.60	0.73	−3.31	2.32	−0.61	−0.39
	(2.69)	(2.24)	(2.97)	(2.57)	(2.51)	(2.98)
Engaged Respondent	−6.49	−0.73	−6.57	−0.04	−6.41	−0.19
	(2.51)	(1.98)	(2.81)	(2.33)	(2.27)	(2.79)
Incentivized * Engaged Respondent	4.16	2.13	3.41	1.33	2.43	2.31
	(3.39)	(2.75)	(3.75)	(3.16)	(3.11)	(3.68)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S56: Main outcome measures vs. treatment condition and Engaged Respondent. Baseline categories are No Incentive and Disengaged Respondent. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.
(Intercept)	43.90	31.32	51.81	38.43
	(1.80)	(1.28)	(1.90)	(1.45)
Incentivized	−3.48	1.22	−3.19	1.69
	(2.39)	(1.80)	(2.52)	(2.01)
Republican	−26.32	−4.41	−30.35	−6.65
	(2.14)	(1.86)	(2.36)	(2.17)
Incentivized * Republican	1.25	1.45	2.07	2.58
	(2.87)	(2.59)	(3.14)	(2.98)
Num. obs.	1030	1030	1030	1030

Table S57: Main outcome measures vs. treatment condition and party ID. Baseline categories are No Incentive and Democrat. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.
(Intercept)	46.42	31.82	54.28	38.91
	(2.23)	(1.65)	(2.38)	(1.86)
Incentivized	−5.51	1.83	−5.13	2.61
	(2.99)	(2.30)	(3.16)	(2.54)
Weak Dem.	−8.10	−2.02	−8.09	−2.18
	(3.82)	(2.74)	(4.04)	(3.13)
Lean Dem.	1.14	3.62	2.27	5.53
	(10.87)	(5.52)	(10.90)	(5.59)
Lean Rep.	−27.80	−2.36	−29.28	−7.37
	(5.79)	(5.76)	(6.42)	(7.87)
Weak Rep.	−25.47	−6.08	−28.77	−8.09
	(3.04)	(2.58)	(3.40)	(3.04)
Strong Rep.	−31.24	−4.34	−35.92	−6.46
	(2.63)	(2.52)	(2.93)	(2.91)
Incentivized * Weak Dem.	7.93	−1.35	7.97	−1.95
	(5.07)	(3.85)	(5.34)	(4.35)
Incentivized * Lean Dem.	−12.84	−6.98	−15.83	−10.55
	(14.10)	(8.30)	(14.64)	(9.30)
Incentivized * Lean Rep.	−1.46	1.35	−0.37	6.21
	(6.79)	(8.32)	(7.48)	(10.21)
Incentivized * Weak Rep.	4.41	0.07	5.80	−0.31
	(4.23)	(3.71)	(4.66)	(4.35)
Incentivized * Strong Rep.	3.52	1.07	3.92	2.23
	(3.52)	(3.42)	(3.88)	(3.89)
Num. obs.	1030	1030	1030	1030

Table S58: Main outcome measures vs. treatment condition and 7-point party ID. Baseline categories are No Incentive and Strong Democrat Democrat. Coefficients are from an ordinary least squares regression with HC1 standard errors. We note that this analysis was not pre-registered.

S6.6 Robustness

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	30.53	29.94	35.75	35.44	28.36	42.83
	(2.02)	(1.64)	(2.28)	(1.93)	(1.80)	(2.27)
Incentivized	−3.10	2.76	−2.08	3.91	1.49	0.34
	(2.82)	(2.26)	(3.14)	(2.63)	(2.54)	(3.06)
Medium SD	−0.74	−0.86	0.30	0.22	0.46	0.07
	(2.75)	(2.17)	(3.08)	(2.53)	(2.40)	(3.01)
High SD	0.73	−2.55	1.61	−2.49	5.50	−6.37
	(3.24)	(2.45)	(3.64)	(2.94)	(3.00)	(3.53)
Incentivized * Medium SD	0.04	−1.14	−0.74	−1.50	−0.13	−2.12
	(3.74)	(2.97)	(4.15)	(3.42)	(3.36)	(4.00)
Incentivized * High SD	5.95	−0.95	6.55	−0.70	−2.33	8.18
	(4.48)	(3.57)	(4.94)	(4.17)	(4.16)	(4.81)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S59: Main outcome measures vs. the treatment condition interacted with the social desirability scale. Baseline categories are No Incentive for the treatment condition and low social-desirability. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	26.34	30.93	31.28	36.32	27.29	40.31
	(1.96)	(1.70)	(2.23)	(2.02)	(1.88)	(2.26)
Incentivized	−2.36	0.75	−1.33	2.36	0.71	0.32
	(2.66)	(2.32)	(2.99)	(2.70)	(2.56)	(3.01)
Medium Aggression	0.91	−2.89	1.81	−1.68	1.76	−1.63
	(2.94)	(2.32)	(3.29)	(2.73)	(2.69)	(3.21)
High Aggresion	10.59	−2.86	12.35	−2.29	5.32	4.73
	(2.83)	(2.30)	(3.17)	(2.72)	(2.57)	(3.20)
Incentivized * Medium Aggression	1.71	0.75	1.71	−0.74	−1.36	2.33
	(3.92)	(3.19)	(4.35)	(3.69)	(3.64)	(4.24)
Incentivized * High Aggresion	0.72	3.57	0.11	3.47	2.77	0.80
	(3.91)	(3.22)	(4.35)	(3.71)	(3.62)	(4.30)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S60: Main outcome measures vs. the treatment condition interacted with the aggression scale. Baseline categories are No Incentive for the treatment condition and low aggression. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	28.14	26.46	33.26	31.61	27.57	37.29
	(2.07)	(1.56)	(2.32)	(1.84)	(1.88)	(2.25)
Incentivized	−3.55	3.32	−2.96	4.15	0.48	0.72
	(3.02)	(2.39)	(3.35)	(2.75)	(2.81)	(3.21)
Pol. Interest	6.04	6.99	7.99	9.18	5.77	11.40
	(4.65)	(3.44)	(5.09)	(3.91)	(4.18)	(4.80)
Incentivized * Pol. Interest	3.59	−3.60	4.07	−3.06	0.76	0.25
	(6.71)	(5.25)	(7.29)	(5.83)	(6.14)	(6.78)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S61: Main outcome measures vs. the treatment condition interacted with the political interest scale. The baseline category is No Incentive for the treatment condition. The political interest scale is a continuous variable. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	22.93	31.83	27.53	37.83	26.06	39.30
	(2.08)	(1.68)	(2.33)	(1.98)	(1.93)	(2.35)
Incentivized	−1.21	1.26	0.13	2.12	1.38	0.86
	(2.78)	(2.25)	(3.08)	(2.61)	(2.58)	(3.04)
Use Violence	4.49	−1.68	5.24	−1.70	2.20	1.34
	(1.06)	(0.82)	(1.16)	(0.96)	(0.94)	(1.21)
Incentivized * Use Violence	−0.54	0.50	−0.86	0.64	−0.32	0.09
	(1.38)	(1.07)	(1.52)	(1.23)	(1.24)	(1.52)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S62: Main outcome measures vs. the treatment condition interacted with “How much do you feel it is justified for [R’s In-Party] to use violence in advancing their political goals these days?”. The baseline category is No Incentive for the treatment condition. Coefficients are from an ordinary least squares regression with HC1 standard errors.

	Rep. Dist.	Dem. Dist.	Rep. Sup.	Dem. Sup.	In-Party Sup.	Out-Party Sup.
(Intercept)	31.89	28.94	38.26	35.25	34.32	39.20
	(1.86)	(1.57)	(2.08)	(1.81)	(1.85)	(2.03)
Incentivized	−0.62	0.80	0.08	1.46	−0.47	2.01
	(2.59)	(2.22)	(2.87)	(2.53)	(2.60)	(2.78)
Medium AP	−2.12	2.13	−1.95	2.08	−4.67	4.81
	(2.83)	(2.19)	(3.12)	(2.57)	(2.58)	(3.00)
High AP	−2.63	−1.74	−4.49	−2.84	−9.81	2.49
	(2.97)	(2.35)	(3.34)	(2.74)	(2.61)	(3.31)
Incentivized * Medium AP	−6.23	1.42	−6.63	1.96	0.29	−4.96
	(3.74)	(3.11)	(4.12)	(3.57)	(3.57)	(4.01)
Incentivized * High AP	2.47	2.27	3.29	3.05	4.50	1.84
	(4.12)	(3.24)	(4.59)	(3.73)	(3.69)	(4.41)
Num. obs.	1030	1030	1030	1030	1030	1030

Table S63: Main outcome measures vs. the treatment condition interacted with the affective polarization scale. Baseline categories are No Incentive for the treatment condition and low affective polarization. Coefficients are from an ordinary least squares regression with HC1 standard errors.

S7 Passing Engagement and Demographic Traits

One concern is that our engagement measure is acting as a proxy for demographic differences. To address this concern we predict passing the engagement check with a series of demographic variables: sex (male or female), age, race (white or non-white), partisanship (Democrat or Republican), education (less than high school, high school, college, and advanced degree) and income. We find no systematic effects. Age predicts passing in study 1 and study 2. In study 1 white respondents and more educated respondents are more likely to pass, though this are no similar effects in study 2 and study 3.

Table S64: Predicting Passing the Engagement Check Studies 1-3

	Study 1	Study 2	Study 3
	(1)	(2)	(3)
Age	0.008	0.001	0.007
	(0.001)	(0.001)	(0.001)
Male	0.009	−0.044	−0.003
	(0.029)	(0.026)	(0.032)
White	0.100	0.015	0.067
	(0.037)	(0.032)	(0.039)
Republican	−0.025	0.007	−0.027
	(0.030)	(0.028)	(0.033)
Advanced Degree	0.199	0.048	−0.092
	(0.100)	(0.087)	(0.112)
College	0.290	0.028	−0.102
	(0.095)	(0.082)	(0.109)
High School	0.242	0.025	−0.108
	(0.093)	(0.081)	(0.107)
$100k +	−0.017	0.007	0.067
	(0.046)	(0.040)	(0.050)
$30k-39k	0.018	0.041	0.043
	(0.050)	(0.044)	(0.057)
$40k-49k	0.004	0.083	0.051
	(0.053)	(0.049)	(0.058)
$50k-59k	−0.024	0.029	0.004
	(0.057)	(0.047)	(0.060)
$60k-69k	0.059	−0.026	0.066
	(0.064)	(0.053)	(0.072)
$70k-79k	−0.119	−0.107	−0.033
	(0.061)	(0.054)	(0.060)
$80k-89k	0.066	0.018	0.011
	(0.068)	(0.059)	(0.088)
$90k-99k	0.062	−0.005	0.044
	(0.064)	(0.059)	(0.075)
Intercept	0.020	0.721	0.135
	(0.096)	(0.087)	(0.112)
Observations	1,002	1,023	1,009

S8 Correlates of Violence (Aggression Tables)

Table S65: Support for Violence by Aggression

	Dependent variable:			
	Our Measure (Engaged)	Our Measure (Full Sample)	Kalmoe-Mason (Engaged)	Kalmoe-Ma
	(1)	(2)	(3)	
Buss Perry (0-1)	0.203***	0.426***	0.667***	0
	(0.095, 0.312)	(0.313, 0.539)	(0.517, 0.817)	(0.6
Intercept	0.049**	0.031	0.093***	
	(0.015, 0.083)	(−0.008, 0.070)	(0.045, 0.141)	(0.0
Observations	279	339	833	
R^2	0.047	0.140	0.084	
Adjusted R^2	0.043	0.137	0.083	
Residual Std. Error	0.178 (df = 277)	0.227 (df = 337)	0.422 (df = 831)	0.425
F Statistic	13.527*** (df = 1; 277)	54.723*** (df = 1; 337)	76.096*** (df = 1; 831)	157.070**
Note:				*p<0.05; **p

Table S66: Support for Violence by Aggression Binned in Terciles

	Dependent variable:			
	Our Measure (Engaged)	Our Measure (Full Sample)	Kalmoe-Mason (Engaged)	Kalmoe-M
	(1)	(2)	(3)	
Buss Perry - Medium	0.067**	0.095**	0.149***	
	(0.018, 0.117)	(0.035, 0.156)	(0.080, 0.217)	(0
Buss Perry - High	0.085**	0.170***	0.296***	
	(0.034, 0.136)	(0.110, 0.230)	(0.225, 0.368)	(0
Intercept	0.056***	0.066**	0.130***	
	(0.024, 0.089)	(0.026, 0.106)	(0.083, 0.177)	(0
Observations	279	339	833	
R^2	0.044	0.086	0.074	
Adjusted R^2	0.037	0.080	0.072	
Residual Std. Error	0.178 (df = 276)	0.234 (df = 336)	0.425 (df = 830)	0.43
F Statistic	6.321** (df = 2; 276)	15.720*** (df = 2; 336)	33.184*** (df = 2; 830)	62.507*
Note:				*p<0.05; **

S9 Partial Identification under Nonignorable Engagement

Suppose we observe survey question outcomes Y_i measuring support for political violence for each respondent i. Some respondents are engaged ($E_i = 1$) while other respondents are disengaged ($E_i = 0$); engagement at the time of the survey is thought to be a function of the incentives of the survey, the respondent, the time the respondent takes the survey, and so on. In theory, each respondent has an engaged potential outcome $Y_i(1)$ that they respond with if they are engaged when taking the survey and a disengaged potential outcome $Y_i(0)$ that they respond with if they are disengaged when taking the survey. That is,

$$Y_i = \begin{cases} Y_i(1) & E_i = 1 \\ Y_i(0) & E_i = 0 \end{cases} \tag{1}$$

Note that, by using potential outcomes (POs), we capture the fact that the respondents who are engaged at the time of the survey might by systematically different from respondents who are disengaged at the time of the survey. That is, $\mathbb{E}[Y_i(1) \mid E_i = 1] \neq \mathbb{E}[Y(1) \mid E_i = 0]$. This is analogous to treatment ignorability (where E_i is the "treatment") in causal inference.

The target, or estimand, of our analysis is the population-level support for violence on the engaged PO, $\mathbb{E}[Y(1)]$. The disengaged support for violence $Y_i(0)$ is not necessarily related to $Y_i(1)$ — it might be a random response or based on a fixed-response strategy such as always picking the middle position on a Likert scale — so it is ignored in the following analysis.

In our model, engagement E_i is not direclty observed. We only observe whether the respondent passes an engagement check: $C_i = 1$ if the check is passed and $C_i = 0$ if the check is failed. $P(C_i = 1)$ is the share of respondents who pass the check in the population. We assume that engaged respondents pass the check with probability 1, and disengaged respondents pass the check with probability β:

$$P(C_i = 1 \mid E_i = 1) = 1 \tag{2}$$

$$P(C_i = 1 \mid E_i = 0) = \beta, \tag{3}$$

where β is known, such as $\beta = 1/K$ for an engagement check with K response options. Given this structure, the share of respondents who are engaged, $\pi = P(E_i = 1)$, is point identified:

$$P(C_i = 1) = \pi + (1 - \pi)\beta \implies \pi = \frac{P(C_i = 1) - \beta}{1 - \beta}. \tag{4}$$

Note that $\pi \leq P(C_i = 1)$ with a strict inequality if $\beta > 0$. This captures the fact that some of the respondents who pass the check are disengaged (and passed the check by mere chance). We make one further assumption that the disengaged PO is (mean) independent of passing the check among disengaged respondents:

$$\mathbb{E}[Y_i(0) \mid C_i = 0, E_i = 0] = \mathbb{E}[Y_i(0) \mid C_i = 1, E_i = 0]. \tag{5}$$

That is, disengaged respondents who pass the check shirk on Y_i in the same way as disengaged respondents who fail the check. Thus, the researcher should randomize the check response options to guarantee shirking strategies are independent (over the disengaged population) of passing the check.

To obtain identification results for the target $\mathbb{E}[Y_i(1)]$, we first point identify $\mu = \mathbb{E}[Y_i(1) \mid E_i = 1]$. To see how, note that the population average observed outcome satisfies

$$\begin{aligned} \mathbb{E}[Y_i] &= \mathbb{E}[Y_i \mid E_i = 1]\pi + \mathbb{E}[Y_i \mid E_i = 0](1 - \pi) \\ &= \mathbb{E}[Y_i(1) \mid E_i = 1]\pi + \mathbb{E}[Y_i(0) \mid E_i = 0](1 - \pi) \\ &= \mu\pi + \mathbb{E}[Y_i(0) \mid E_i = 0, C_i = 0](1 - \pi) \\ &= \mu\pi + \mathbb{E}[Y_i(0) \mid C_i = 0](1 - \pi), \end{aligned}$$

since $C_i = 0 \implies E_i = 0$. This leads to

$$\mu = \frac{\mathbb{E}[Y_i] - \mathbb{E}[Y_i \mid C_i = 0](1 - \pi)}{\pi} \tag{6}$$

With this result, we can partially identify $\mathbb{E}[Y_i(1)]$ using an analogous tower argument.

$$\begin{aligned} \theta = \mathbb{E}[Y_i(1)] &= \mathbb{E}[Y_i(1) \mid E_i = 1]\pi + \mathbb{E}[Y_i(1) \mid E_i = 0](1 - \pi) \\ &= \mu\pi + \lambda(1 - \pi) \end{aligned}$$

where $\lambda = \mathbb{E}[Y_i(1) \mid E_i = 0]$ is the population average engaged PO. Putting this together, we have

$$\begin{aligned}\theta(\lambda) &= \mathbb{E}[Y_i] + (\lambda - \mathbb{E}[Y_i \mid C_i = 0])(1-\pi) \\ &= \mathbb{E}[Y_i] + \frac{\lambda}{1-\beta}\,\mathbb{E}[(1-C_i)] - \frac{1}{1-\beta}\,\mathbb{E}[Y_i(1-C_i)]\end{aligned}$$

where the first expression for $\theta(\lambda)$ is more interpretable in terms of the model, but the second expression is written in terms of statistical targets (and suggests the Delta method). Note that one should not analyze this last expression as a function of β all-else-held-fixed, since the distribution of C_i depends on β.

If $\lambda \in \Lambda$, then the partial identification bounds are $[\theta_l, \theta_u] = [\inf_{\lambda \in \Lambda} \theta(\lambda), \sup_{\lambda \in \Lambda} \theta(\lambda)] = [\theta(\inf \Lambda), \theta(\sup \Lambda)]$ by monotonicity. Notably, if the outcomes Y_i are binary, and $\Lambda = [a, b]$ where $a \geq 0, b \leq 1$, then $[\theta_l, \theta_u] = [\theta(a), \theta(b)]$.

To construct confidence intervals, we adapt the results of Imbens and Manski (2004, §4). The sampling distributions of $\hat{\theta}_l, \hat{\theta}_u$ can be obtained from a straightforward application of the Delta method on the vector of sample means $\frac{1}{N}\sum_{i=1}^{N}(Y_i, F_i, Y_i F_i)'$ where $F_i = 1 - C_i$.

Table S67: Crosswalk between PAP study labels and manuscript study labels

PAP	PAP Label	Manuscript Label
PAP 1	Study 1	Study 1
PAP 1	Study 2	Study 4
PAP 2	Study 1 (Replication)	Study 2
PAP 2	Study 3	Study 45 (Appendix only)
PAP 3	Study 1 (Replication)	Study 3

S10 Pre Analysis Plans

Note: the study labels in these PAPs does not match the final document. We provide a crosswalk in Table S67.

S10.1 PAP1 (Study 1 and Study 4

Pre-Analysis Plan: Support for Political Violence

Justin Grimmer   Clayton Nall   Matt Tyler   Sean J. Westwood

September 7, 2021

Contents

1 Preliminary Notes

- This is the pre-analysis plan for a survey experiment on support for political violence. There are two experiments in the survey.
- All of the code excerpted below is included in our upload to OSF along with our PAP. We excerpt it into the PAP to facilitate peer review.
- In the code that follows we use raw codings, though we may standardize for interpretability.
- We will conduct a multiple testing correction following Anderson (2008).
- This is an updated PAP based on a pretest of 50 respondents. It corrects several coding issues and specifies that we will also look at results by attentiveness.

2 Data Cleaning

We will clean the data for the survey as follows:

```
library(tidyverse)
library(psy)
library(qualtRics)
library(gtools)
data <- read_csv("data/data.csv")

table(data$gc)
data <- data %>%
filter(gc==1)

#recode leaners
data$Q10[data$Q11 == "Democratic Party"] <- "Democrat"
data$Q10[data$Q11 == "Republican Party"] <- "Republican"
data$pid <- data$Q10
data$pid <- as.factor(data$pid)

# covariates
data$gender <- as.factor(data$Q4)
data$income <- as.factor(data$Q7)
data$education <- as.factor(data$Q8)
data$age <- data$Q14
data$race <- data$Q5

# strong partisans
data$Q12<-recode(data$Q12, "Strong Republican" = 1, "Not a strong Republican" = 0)
data$Q13<-recode(data$Q13, "Strong Democrat" = 1, "Not a strong Democrat" = 0)
```

```
data$strongpartisan <- 0
data$strongpartisan[data$pid=="Republican"] <- data$Q12[data$pid=="Republican"]
data$strongpartisan[data$pid=="Democrat"] <- data$Q13[data$pid=="Democrat"]

#recode experiments and conditions

data$experiment <- recode(data$experiment, "1" = "Vignette", "2" = "Sentencing")

#study 1
data$cell <- NA
data$cell[data$version == 1 & data$partisantreatment == 1] <-
"Republican and Partisan"
data$cell[data$version == 2 & data$partisantreatment == 1] <-
"Republican and Non-Partisan"
data$cell[data$version == 1 & data$partisantreatment == 2] <-
"Democrat and Partisan"
data$cell[data$version == 2 & data$partisantreatment == 2] <-
"Democrat and Non-Partisan"

# create controls

#affpol
data$affectivepolarization <- NA
data$inparty <- NA
data$outparty <- NA

data$inparty[which(data$pid=="Democrat")] <-
data$Q30_2[which(data$pid=="Democrat")]
data$inparty[which(data$pid=="Republican")] <-
data$Q31_2[which(data$pid=="Republican")]

data$outparty[which(data$pid=="Republican")] <-
data$Q30_2[which(data$pid=="Republican")]
data$outparty[which(data$pid=="Democrat")] <-
data$Q31_2[which(data$pid=="Democrat")]

data$affectivepolarization <- data$inparty -data$outparty

data$affectivepolarization <-
quantcut(data$affectivepolarization, q=3,
labels = c("Low", "Medium", "High"))


# Marlow-Crowne
```

```
data$Q20<-recode(as.character(data$Q20), "TRUE" = 1, "FALSE" = 0)
data$Q21<-recode(as.character(data$Q21), "TRUE" = 1, "FALSE" = 0)
data$Q22<-recode(as.character(data$Q22), "TRUE" = 1, "FALSE" = 0)
data$Q23<-recode(as.character(data$Q23), "TRUE" = 1, "FALSE" = 0)
data$Q24<-recode(as.character(data$Q24), "TRUE" = 1, "FALSE" = 0)
data$Q25<-recode(as.character(data$Q25), "TRUE" = 1, "FALSE" = 0)
data$Q26<-recode(as.character(data$Q26), "TRUE" = 1, "FALSE" = 0)
data$Q27<-recode(as.character(data$Q27), "TRUE" = 1, "FALSE" = 0)
data$Q28<-recode(as.character(data$Q28), "TRUE" = 1, "FALSE" = 0)
data$Q29<-recode(as.character(data$Q29), "TRUE" = 1, "FALSE" = 0)

data$marlowcrowne <- (data$Q20 + data$Q21 + data$Q22 +
data$Q23 + data$Q24 + data$Q25 + data$Q26 + data$Q27 + data$Q28 + data$Q29)/10

data$marlowcrowne <- quantcut(data$marlowcrowne, q=3, labels = c("Low",
"Medium", "High"))

# Short-Form Buss-Perry Aggression Questionnaire
data$Q63<-recode(data$Q63, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q64<-recode(data$Q64, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q65<-recode(data$Q65, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q66<-recode(data$Q66, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q67<-recode(data$Q67, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q68<-recode(data$Q68, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q69<-recode(data$Q69, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q70<-recode(data$Q70, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q71<-recode(data$Q71, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q72<-recode(data$Q72, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q73<-recode(data$Q73, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q75<-recode(data$Q65, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)

data$bussperry <- (data$Q63 + data$Q64 + data$Q65 + data$Q66 + data$Q67 +
data$Q68 + data$Q69 + data$Q70 + data$Q71 + data$Q72 + data$Q73 +
```

```
data$Q75)/12

data$bussperry <- quantcut(data$bussperry, q=3, labels = c("Low",
"Medium", "High"))

# Kalmoe-Mason
data$Q32<-recode(data$Q32, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)
data$Q33<-recode(data$Q33, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)
data$Q34<-recode(data$Q34, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)

data$Q35<-recode(data$Q35, "Yes" = 1, "No" = 0)
data$Q35<-recode(data$Q36, "Yes" = 1, "No" = 0)

data$Q77<-recode(data$Q77, "1 - Not at all" = 1, "2"=2, "3"=3,
"4"=4,"5 - A great deal" = 5)
names(data)
#political engagement index
data$Q16<-recode(data$Q16, "Yes" = 1, "No" = 0)
data$Q17<-recode(data$Q17, "Yes" = 1, "No" = 0)
data$Q18<-recode(data$Q18, "Yes" = 1, "No" = 0)

data$partscale <- (data$Q16 + data$Q17 + data$Q18)/3

data$partscale <- quantcut(data$partscale, q=3, labels = c("Low",
"Medium", "High"))
```

Note: We do not expect missing data because our Qualtics survey is set to "force response", but if there is missing data we will recode all missing data to its mean.

3 Study 1

3.1 Primary DVs

There are three primary variables of interest:

1. Do you support or oppose the actions of [Stan Gimm/Thomas Kelly]?
2. Was the driver justified or unjustified?
3. Should the driver face criminal charges?

```
# recode DVs

study1$supportactions <- NA
study1$supportactions[study1$partisantreatment==1] <-
study1$Q44[study1$partisantreatment==1]
study1$supportactions[study1$partisantreatment==2] <-
study1$Q50[study1$partisantreatment==2]
study1$supportactions <- recode(study1$supportactions,
"Strongly support" = 5, "Support"=4, "Neither support nor oppose"=3,
"Oppose"=2,"Strongly oppose" = 1)

study1$justified <- NA
study1$justified[study1$partisantreatment==1] <-
study1$Q45[study1$partisantreatment==1]
study1$justified[study1$partisantreatment==2] <-
study1$Q51[study1$partisantreatment==2]
study1$justified <-recode(study1$justified,
"Justified" = 1, "Unjustified" = 0)

study1$charged <- NA
study1$charged[study1$partisantreatment==1] <-
study1$Q46[study1$partisantreatment==1]
study1$charged[study1$partisantreatment==2] <-
study1$Q52[study1$partisantreatment==2]
study1$charged <-recode(study1$charged, "Yes" = 1, "No" = 0)
```

3.2 Factual Attention Check

We will ask each respondent to recall which state was mentioned in the treatment vignette.

```
# attention check
study1$passed <- 0
study1$passed[study1$Q43 == "Florida" & study1$partisantreatment==1] <- 1
study1$passed[study1$Q49 == "Oregon" & study1$partisantreatment==2] <- 1

table(study1$passed, study1$partisantreatment)
table(study1$passed)
```

3.3 Treatments

The design is a four cell design:

1. Democratic subject and partisan crime

2. Democratic subject and non-partisan crime
3. Republican subject and partisan crime
4. Republican subject and non-partisan crime

We will code the treatments as noted above.

3.4 Hypothesis tests

We expect support for violence to be low across all three dependent variables for all conditions. Specifically, we expect that tolerance for political violence will be no different from tolerance for non-political violence.

We will look for an effect in three different ways: by cell, by cell collapsing by party and between the partisan and non-partisan cells after collapsing by party. We will also look at the main results by attentiveness (those passing the factional attention check). Expecting support for violence to be larger for those who randomly click/don't pay attention.

```
# raw support (by condition)
table(study1$supportactions, study1$cell)
table(study1$supportactions, study1$cell)
table(study1$supportactions, study1$cell)

# raw support (pooled)
prop.table(table(study1$supportactions))
prop.table(table(study1$supportactions))
prop.table(table(study1$supportactions))

# Main results (general support)
summary(lm(supportactions ~ cell, data = study1))
summary(lm(justified ~ cell, data = study1))
summary(lm(charged ~ cell, data = study1))

# by attentiveness
summary(lm(supportactions ~ cell*passed, data = study1))
summary(lm(justified ~ cell*passed, data = study1))
summary(lm(charged ~ cell*passed, data = study1))

# Main results (general support by party)
summary(lm(supportactions ~ cell*pid, data = study1))
summary(lm(justified ~ cell*pid, data = study1))
summary(lm(charged ~ cell*pid, data = study1))

# Main results by in- and out-party
```

```
study1$alignment <- NA
study1$alignment[study1$version == 1 &
study1$partisantreatment == 1 & study1$pid == "Democrat"] <-
"Out-Party and Partisan"
study1$alignment[study1$version == 2 &
study1$partisantreatment == 1 & study1$pid == "Democrat"] <-
"Out-Party and Non-Partisan"
study1$alignment[study1$version == 1 &
study1$partisantreatment == 2 & study1$pid == "Democrat"] <-
"In-Party and Partisan"
study1$alignment[study1$version == 2 &
study1$partisantreatment == 2 & study1$pid == "Democrat"] <-
"In-Party and Non-Partisan"

study1$alignment[study1$version == 1 &
study1$partisantreatment == 1 & study1$pid == "Republican"] <-
"In-Party and Partisan"
study1$alignment[study1$version == 2 &
study1$partisantreatment == 1 & study1$pid == "Republican"] <-
"In-Party and Non-Partisan"
study1$alignment[study1$version == 1 &
study1$partisantreatment == 2 & study1$pid == "Republican"] <-
"Out-Party and Partisan"
study1$alignment[study1$version == 2 &
study1$partisantreatment == 2 & study1$pid == "Republican"] <-
"Out-Party and Non-Partisan"

study1$alignment <- as.factor(study1$alignment)

summary(lm(supportactions ~ alignment, data = study1))
summary(lm(justified ~ alignment, data = study1))
summary(lm(charged ~ alignment, data = study1))

# main result, comparing the two out-party treatments

t.test(study1$supportactions[study1$alignment ==
"Out-Party and Partisan"],
study1$supportactions[study1$alignment ==
"Out-Party and Non-Partisan"])
t.test(study1$justified[study1$alignment ==
"Out-Party and Partisan"],
```

```
study1$justified[study1$alignment ==
"Out-Party and Non-Partisan"])
t.test(study1$charged[study1$alignment ==
"Out-Party and Partisan"],
study1$charged[study1$alignment ==
"Out-Party and Non-Partisan"])
```

3.5 Heterogenous Treatment Effects

We have no clear predictions for heterogeneous treatment effects. However, we will explore whether our treatment varies by party

```
# Main results (general support by party)
summary(lm(supportactions ~ cell*pid, data = study1))
summary(lm(justified ~ cell*pid, data = study1))
summary(lm(charged ~ cell*pid, data = study1))
```

3.6 Robustness

The literature identifies several possible mechanisms that might prompt a person to support violence. Here we account for the most common: political engagement, affective polarization, social desirability (Marlow-Crowne Social Desirability Scale), and aggression (Buss-Perry Aggression Questionnaire. We also include six items from prior work that reportedly predict support for partisan violence: three measures of moral disengagement and three measures of prospective partisan violence(Kalmoe and Mason, forthcoming).

In all cases except for the Kalmoe-Mason items we create indexes by taking the mean of summed scale items. We then bin each variable into terciles. We will treat the Kalmoe-Mason items as separate predictors, though we may combine Q35 and Q36 into a single item coded to record attitudes toward the out-party.

The literature, based on correlational survey data, predicts that as affective polarization, political engagement and aggression increase so too does tolerance for political violence.

We also predict that social desirability will increase support for prospective political violence (Kalmoe-Mason), but not for support for actual political violence measured though our experiment. We suspect that this will be especially among strong partisans.

Finally, we predict that support for prospective violence poorly does not moderate support for violence in our experiments.

```
# Prospective violence and social desirability

summary(lm(Q77 ~ marlowcrowne, data = study1))
```

```
summary(lm(Q77 ~ marlowcrowne, data = study1[]))

#marlow-crowne
summary(lm(supportactions ~ alignment * marlowcrowne,
data = study1))
summary(lm(justified ~ alignment * marlowcrowne,
data = study1))
summary(lm(charged ~ alignment * marlowcrowne,
data = study1))

#buss-perry
summary(lm(supportactions ~ alignment * bussperry,
data = study1))
summary(lm(justified ~ alignment * bussperry,
data = study1))
summary(lm(charged ~ alignment * bussperry,
data = study1))

#political interest

summary(lm(supportactions ~ alignment * partscale,
data = study1))
summary(lm(justified ~ alignment * partscale,
data = study1))
summary(lm(charged ~ alignment * partscale,
data = study1))

#kalmoe mason

summary(lm(supportactions ~ alignment * Q32,
data = study1))
summary(lm(justified ~ alignment * Q32,
data = study1))
summary(lm(charged ~ alignment * Q32,
data = study1))

summary(lm(supportactions ~ alignment * Q33,
data = study1))
summary(lm(justified ~ alignment * Q33,
data = study1))
summary(lm(charged ~ alignment * Q33,
data = study1))
```

```
summary(lm(supportactions ~ alignment * Q34,
data = study1))
summary(lm(justified ~ alignment * Q34,
data = study1))
summary(lm(charged ~ alignment * Q34,
data = study1))

summary(lm(supportactions ~ alignment * Q35,
data = study1))
summary(lm(justified ~ alignment * Q35,
data = study1))
summary(lm(charged ~ alignment * Q35,
data = study1))

summary(lm(supportactions ~ alignment * Q36,
data = study1))
summary(lm(justified ~ alignment * Q36,
data = study1))
summary(lm(charged ~ alignment * Q36,
data = study1))

summary(lm(supportactions ~ alignment * Q77,
data = study1))
summary(lm(justified ~ alignment * Q77,
data = study1))
summary(lm(charged ~ alignment * Q77,
data = study1))

#affpol
summary(lm(supportactions ~ alignment * affectivepolarization,
data = study1))
summary(lm(justified ~ alignment * affectivepolarization,
data = study1))
summary(lm(charged ~ alignment * affectivepolarization,
data = study1))
```

4 Study 2

4.1 Primary DVs

There are three primary variables of interest:

1. The length of the recommended sentence.
2. Support for a possible pardon
3. Support for nullifying the conviction by imposing community service.

```
study2$nullify <- 0
study2$nullify[study2$Q53 == "Community service"] <- 1
study2$pardon <- recode(study2$Q76, "Strongly support" = 5, "Support"=4,
"Neither support nor oppose"=3, "Oppose"=2,"Strongly oppose" = 1)
```

4.2 Treatments

This is a six cell randomized design with six different partisan crimes.

```
$crime = array("vandalism",
"protesting without a permit",
"assault",
"arson",
"assault with a deadly weapon",
"murder"
);
```

4.3 Factual Attention Check

We will include an unrelated vignette on sea otter reintroduction. Following this vignette we will ask what state the story covers.

```
    # check for attentiveness
study1$passed <- 0
study2$passed[study1$Q82 == "Oregon"] <- 1
```

4.4 Hypothesis tests

We expect that support (with all measures) will decrease as the severity of the crime increases. We will also look at results by attentiveness, expecting that support for nullification is driven by random/inattentive responding.

```
# main results
table(study2$Q53, study2$item.crime)
#main result - pardon
summary(lm(pardon~item.crime, data=study2))
# main result - nullification
```

```
summary(lm(nullify~item.crime, data=study2))

# by attentiveness
# main results
table(study2$Q53, study2$item.crime, study2$passed)
#main result - pardon
summary(lm(pardon~item.crime*passed, data=study2))
# main result - nullification
summary(lm(nullify~item.crime*passed, data=study2))
```

4.5 Heterogeneous treatment effects

Again, we look at difference by PID with no predictions.

```
# by pid

# main results
table(study2$Q53, study2$item.crime, study2$pid)
#main result - pardon
summary(lm(pardon~item.crime*pid, data=study2))
# main result - nullification
summary(lm(nullify~item.crime*pid, data=study2))
```

4.6 Robustness

We use the same robustness measures from study 1

```
# robustness

#marlow-crowne
summary(lm(pardon ~ alignment * marlowcrowne, data = study2))
summary(lm(nullify ~ alignment * marlowcrowne, data = study2))

#buss-perry
summary(lm(pardon ~ alignment * bussperry, data = study2))
summary(lm(nullify ~ alignment * bussperry, data = study2))

#political interest

summary(lm(pardon ~ alignment * partscale, data = study2))
```

```
summary(lm(nullify ~ alignment * partscale, data = study2))

# kalmoe-mason

summary(lm(pardon ~ alignment * Q32, data = study2))
summary(lm(nullify ~ alignment * Q32, data = study2))

summary(lm(pardon ~ alignment * Q33, data = study2))
summary(lm(nullify ~ alignment * Q33, data = study2))

summary(lm(pardon ~ alignment * Q34, data = study2))
summary(lm(nullify ~ alignment * Q34, data = study2))

summary(lm(pardon ~ alignment * Q35, data = study2))
summary(lm(nullify ~ alignment * Q35, data = study2))

summary(lm(pardon ~ alignment * Q36, data = study2))
summary(lm(nullify ~ alignment * Q36, data = study2))

summary(lm(pardon ~ alignment * Q77, data = study2))
summary(lm(nullify ~ alignment * Q77, data = study2))

# affpol
summary(lm(pardon ~ alignment * affectivepolarization, data = study2))
summary(lm(nullify ~ alignment * affectivepolarization, data = study2))
```

References

Anderson, Michael L. 2008. "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American statistical Association* 103(484):1481–1495.

S10.2 PAP2 (Study 2 and Study 5

Pre-Analysis Plan: Support for Political Violence

Justin Grimmer   Clayton Nall   Matt Tyler   Sean J. Westwood

September 7, 2021

Contents

1 Preliminary Notes

- This is the pre-analysis plan for a survey experiment on support for political violence. There are two experiments in the survey.
- All of the code excerpted below is included in our upload to OSF along with our PAP. We excerpt it into the PAP to facilitate peer review.
- In the code that follows we use raw codings, though we may standardize for interpretability.
- We will conduct a multiple testing correction following Anderson (2008).

2 Data Cleaning

We will clean the data for the survey as follows:

```
library(tidyverse)
library(psy)
library(gtools)

data <- read_csv("data/data2.csv")

table(data$gc)
data <- data %>%
filter(gc==1)

#recode leaners
data$Q10[data$Q11 == "Democratic Party"] <- "Democrat"
data$Q10[data$Q11 == "Republican Party"] <- "Republican"
data$pid <- data$Q10
data$pid <- as.factor(data$pid)

# covariates
data$gender <- as.factor(data$Q4)
data$income <- as.factor(data$Q7)
data$education <- as.factor(data$Q8)
data$age <- data$Q14
data$race <- data$Q5

# strong partisans
data$Q12<-recode(data$Q12, "Strong Republican" = 1,
"Not a strong Republican" = 0)
data$Q13<-recode(data$Q13, "Strong Democrat" = 1,
"Not a strong Democrat" = 0)
```

```
data$strongpartisan <- 0
data$strongpartisan[data$pid=="Republican"] <- data$Q12[data$pid=="Republican"]
data$strongpartisan[data$pid=="Democrat"] <- data$Q13[data$pid=="Democrat"]

#recode experiments and conditions

data$experiment <- recode(data$experiment,
"1" = "Vignette (Rep)", "2" = "Expressiveness")

#study 1
data$cell <- NA
data$cell[data$version == 1] <- "Democrat Shooter"
data$cell[data$version == 2] <- "Republican Shooter"
data$cell[data$version == 3] <- "Shooter"

#study 2
data$study3cell <- NA
data$study3cell[data$payprompt == 1] <- "No Incentive"
data$study3cell[data$payprompt == 2] <- "Incentive"

# create controls

#affpol
data$affectivepolarization <- NA
data$inparty <- NA
data$outparty <- NA

data$inparty[which(data$pid=="Democrat")] <-
data$Q30_2[which(data$pid=="Democrat")]
data$inparty[which(data$pid=="Republican")] <-
data$Q31_2[which(data$pid=="Republican")]

data$outparty[which(data$pid=="Republican")] <-
data$Q30_2[which(data$pid=="Republican")]
data$outparty[which(data$pid=="Democrat")] <-
data$Q31_2[which(data$pid=="Democrat")]

data$affectivepolarization <- data$inparty -data$outparty

data$affectivepolarization <-
quantcut(data$affectivepolarization, q=3,
labels = c("Low", "Medium", "High"))


# Marlow-Crowne
```

```
data$Q20<-recode(as.character(data$Q20), "TRUE" = 1, "FALSE" = 0)
data$Q21<-recode(as.character(data$Q21), "TRUE" = 1, "FALSE" = 0)
data$Q22<-recode(as.character(data$Q22), "TRUE" = 1, "FALSE" = 0)
data$Q23<-recode(as.character(data$Q23), "TRUE" = 1, "FALSE" = 0)
data$Q24<-recode(as.character(data$Q24), "TRUE" = 1, "FALSE" = 0)
data$Q25<-recode(as.character(data$Q25), "TRUE" = 1, "FALSE" = 0)
data$Q26<-recode(as.character(data$Q26), "TRUE" = 1, "FALSE" = 0)
data$Q27<-recode(as.character(data$Q27), "TRUE" = 1, "FALSE" = 0)
data$Q28<-recode(as.character(data$Q28), "TRUE" = 1, "FALSE" = 0)
data$Q29<-recode(as.character(data$Q29), "TRUE" = 1, "FALSE" = 0)

data$marlowcrowne <- (data$Q20 + data$Q21 + data$Q22 +
data$Q23 + data$Q24 + data$Q25 + data$Q26 + data$Q27 + data$Q28 + data$Q29)/10

data$marlowcrowne <- quantcut(data$marlowcrowne, q=3, labels = c("Low",
"Medium", "High"))

# Short-Form Buss-Perry Aggression Questionnaire
data$Q63<-recode(data$Q63, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q64<-recode(data$Q64, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q65<-recode(data$Q65, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q66<-recode(data$Q66, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q67<-recode(data$Q67, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q68<-recode(data$Q68, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q69<-recode(data$Q69, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q70<-recode(data$Q70, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q71<-recode(data$Q71, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q72<-recode(data$Q72, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q73<-recode(data$Q73, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)
data$Q75<-recode(data$Q65, "1- Very unlike me" = 1, "2"=2,
"3"=3, "4"=4,"5- Very like me" = 5)

data$bussperry <- (data$Q63 + data$Q64 + data$Q65 + data$Q66 + data$Q67 +
data$Q68 + data$Q69 + data$Q70 + data$Q71 + data$Q72 + data$Q73 +
```

```
data$Q75)/12

data$bussperry <- quantcut(data$bussperry, q=3, labels = c("Low",
"Medium", "High"))

# Kalmoe-Mason
data$Q32<-recode(data$Q32, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)
data$Q33<-recode(data$Q33, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)
data$Q34<-recode(data$Q34, "Strongly agree" = 5, "Somewhat agree"=4,
"Neither agree nor disagree"=3, "Somewhat disagree"=2,"Strongly disagree" = 1)

data$Q35<-recode(data$Q35, "Yes" = 1, "No" = 0)
data$Q35<-recode(data$Q36, "Yes" = 1, "No" = 0)

data$Q77<-recode(data$Q77, "1 - Not at all" = 1, "2"=2, "3"=3,
"4"=4,"5 - A great deal" = 5)
names(data)
#political engagement index
data$Q16<-recode(data$Q16, "Yes" = 1, "No" = 0)
data$Q17<-recode(data$Q17, "Yes" = 1, "No" = 0)
data$Q18<-recode(data$Q18, "Yes" = 1, "No" = 0)

data$partscale <- (data$Q16 + data$Q17 + data$Q18)/3

data$partscale <- quantcut(data$partscale, q=3, labels = c("Low",
"Medium", "High"))
```

Note: We do not expect missing data because our Qualtics survey is set to "force response", but if there is missing data we will recode all missing data to its mean.

3 Study 1 (Replication)

This is a replication of a prior study that was based on real events. Here we replicate with a contrived news story that is identical for both Democrats and Republicans. We also alter the context of the event to a shooting.

3.1 Primary DVs

There are three primary variables of interest:

1. Do you support or oppose the actions of Steven Wright?

2. Was the shooter justified or unjustified?
3. Should the shooter face criminal charges?

```
# recode DVs
study1$supportactions <- NA
study1$supportactions <- study1$Q44
study1$supportactions <- recode(study1$supportactions,
"Strongly support" = 5, "Support"=4,
"Neither support nor oppose"=3,
"Oppose"=2,"Strongly oppose" = 1)

study1$justified <- NA
study1$justified <- study1$Q45
study1$justified <-recode(study1$justified,
"Justified" = 1, "Unjustified" = 0)

study1$charged <- NA
study1$charged <- study1$Q46

study1$charged <-recode(study1$charged,
"Yes" = 1, "No" = 0)
```

3.2 Factual Attention Check

We will ask each respondent to recall which state was mentioned in the treatment vignette.

```
study1 <- data[data$experiment == "Vignette (Rep)",]

# attention check
study1$passed <- 0
study1$passed[study1$Q43 == "Iowa"] <- 1

table(study1$passed, study1$cell)
table(study1$passed)
```

3.3 Treatments

The design is a three cell design:

1. Democratic subject and partisan crime
2. Republican subject and partisan crime
3. Non-partisan crime

We will code the treatments as noted above.

3.4 Hypothesis tests

We expect support for violence to be low across all three dependent variables for all conditions. Specifically, we expect that tolerance for political violence will be no different from tolerance for non-political violence.

We will look for an effect in three different ways: by cell, by cell collapsing by party and between the partisan and non-partisan cells after collapsing by party. We will also look at the main results by attentiveness (those passing the factional attention check). Expecting support for violence to be larger for those who randomly click/don't pay attention.

```
# raw support (by condition)
round(prop.table(table(study1$supportactions,
study1$cell),1),2)
table(study1$justified, study1$cell)
table(study1$charged, study1$cell)

# raw support (pooled)
prop.table(table(study1$supportactions))
prop.table(table(study1$justified))
prop.table(table(study1$charged))

# Main results (general support)
summary(lm(supportactions ~ cell, data = study1))
summary(lm(justified ~ cell, data = study1))
summary(lm(charged ~ cell, data = study1))

# raw support (by condition) and attentiveness
round(prop.table(table(study1$supportactions,
study1$cell, study1$passed),1),2)
table(study1$justified, study1$cell, study1$passed)
table(study1$charged, study1$cell, study1$passed)

# by attentiveness
summary(lm(supportactions ~ cell*passed, data = study1))
summary(lm(justified ~ cell*passed, data = study1))
summary(lm(charged ~ cell*passed, data = study1))

# Main results (general support by party)
summary(lm(supportactions ~ cell*pid, data = study1))
summary(lm(justified ~ cell*pid, data = study1))
summary(lm(charged ~ cell*pid, data = study1))

# Main results by in- and out-party
```

```
study1$alignment <- NA
study1$alignment[study1$version == 1 &
study1$pid == "Democrat"] <- "In-Party and Partisan"
study1$alignment[study1$version == 2  &
study1$pid == "Democrat"] <- "Out-Party and Partisan"

study1$alignment[study1$version == 1 &
study1$pid == "Republican"] <- "Out-Party and Partisan"
study1$alignment[study1$version == 2 &
study1$pid == "Republican"] <- "In-Party and Partisan"

study1$alignment[study1$version == 3] <- "Non-Partisan"

study1$alignment <- as.factor(study1$alignment)

summary(lm(supportactions ~ alignment, data = study1))
summary(lm(justified ~ alignment, data = study1))
summary(lm(charged ~ alignment, data = study1))

# main result, comparing the out-party treatments to control

t.test(study1$supportactions[study1$alignment ==
"Out-Party and Partisan"], study1$supportactions[study1$alignment ==
"Non-Partisan"])

t.test(study1$justified[study1$alignment ==
"Out-Party and Partisan"],
study1$justified[study1$alignment == "Non-Partisan"])

t.test(study1$charged[study1$alignment == "Out-Party and Partisan"],
study1$charged[study1$alignment == "Non-Partisan"])

# main result, comparing the in-party treatments to control

t.test(study1$supportactions[study1$alignment == "In-Party and Partisan"],
study1$supportactions[study1$alignment == "Non-Partisan"])

t.test(study1$justified[study1$alignment == "In-Party and Partisan"],
study1$justified[study1$alignment == "Non-Partisan"])

t.test(study1$charged[study1$alignment == "In-Party and Partisan"],
```

```
study1$charged[study1$alignment == "Non-Partisan"])
```

3.5 Heterogenous Treatment Effects

We have no clear predictions for heterogeneous treatment effects. However, we will explore whether our treatment varies by party

3.6 Robustness

The literature identifies several possible mechanisms that might prompt a person to support violence. Here we account for the most common: political engagement, affective polarization, social desirability (Marlow-Crowne Social Desirability Scale), and aggression (Buss-Perry Aggression Questionnaire. We also include six items from prior work that reportedly predict support for partisan violence: three measures of moral disengagement and one measure of prospective partisan violence (Kalmoe and Mason, forthcoming).

In all cases except for the Kalmoe-Mason item we create indexes by taking the mean of summed scale items. We then bin each variable into terciles. We will treat the Kalmoe-Mason items as separate predictors, though we may combine Q35 and Q36 into a single item coded to record attitudes toward the out-party.

The literature, based on correlational survey data, predicts that as affective polarization, political engagement and aggression increase so too does tolerance for political violence.

We also predict that social desirability will increase support for prospective political violence (Kalmoe-Mason), but not for support for actual political violence measured though our experiment. We suspect that this will be especially among strong partisans.

Finally, we predict that support for prospective violence poorly does not moderate support for violence in our experiments.

```
# robustness

# Prospective violence and social desirability

summary(lm(Q77 ~ marlowcrowne, data = study1))

summary(lm(Q77 ~ marlowcrowne, data = study1[]))

#marlowe-crowne
summary(lm(supportactions ~ alignment * marlowcrowne,
data = study1))
summary(lm(justified ~ alignment * marlowcrowne,
data = study1))
summary(lm(charged ~ alignment * marlowcrowne,
data = study1))
```

```
#buss-perry
summary(lm(supportactions ~ alignment * bussperry,
data = study1))
summary(lm(justified ~ alignment * bussperry, data = study1))
summary(lm(charged ~ alignment * bussperry, data = study1))

#political interest

summary(lm(supportactions ~ alignment * partscale,
data = study1))
summary(lm(justified ~ alignment * partscale, data = study1))
summary(lm(charged ~ alignment * partscale, data = study1))

#kalmoe mason

summary(lm(supportactions ~ alignment * Q77, data = study1))
summary(lm(justified ~ alignment * Q77, data = study1))
summary(lm(charged ~ alignment * Q77, data = study1))

#affpol
summary(lm(supportactions ~ alignment * affectivepolarization,
data = study1))
summary(lm(justified ~ alignment * affectivepolarization,
data = study1))
summary(lm(charged ~ alignment * affectivepolarization,
data = study1))
```

4 Study 3

4.1 Primary DVs

1. Estimated Republican support for political violence.
2. Estimated Democratic support for political violence.

We will recode this variable in two ways. First, we will compute the distance of each response from the true population value. Second, we will pool in-party and out-party responses.

```
study3$repsupport <- study3$Q93_1
study3$demsupport <- study3$Q90_1

study3$inpartysupport <- NA
```

```
study3$outpartysupport <- NA

study3$inpartysupport[study3$pid == "Democrat"] <-
study3$demsupport[study3$pid == "Democrat"]
study3$outpartysupport[study3$pid == "Democrat"] <-
study3$repsupport[study3$pid == "Democrat"]

study3$inpartysupport[study3$pid == "Republican"] <-
study3$repsupport[study3$pid == "Republican"]
study3$outpartysupport[study3$pid == "Republican"] <-
study3$demsupport[study3$pid == "Republican"]

true_dem <- X
true_rep <- Y

#compute distance
study3$repdistance <- abs(study3$repsupport - true_rep)
study3$demdistance <- abs(study3$demsupport - true_dem)
```

4.2 Treatments

There are two experimental cells: one where we offer a cash incentive for correct responding and one where we offer no such incentive.

4.3 Factual Attention Check

We will include an unrelated vignette on sea otter reintroduction. Following this vignette we will ask what state the story covers.

```
    # check for attentiveness
study3$passed <- 0
study3$passed[study3$Q82 == "Oregon"] <- 1
```

4.4 Hypothesis tests

We expect that without incentives individuals will over-estimate group support for political violence. We further expect inattentiveness to increase support for partisan violence.

```
# main results
summary(lm(repdistance~study3cell, data=study3))
summary(lm(demdistance~study3cell, data=study3))

summary(lm(repsupport~study3cell, data=study3))
```

```
summary(lm(demsupport~study3cell, data=study3))

summary(lm(inpartysupport~study3cell, data=study3))
summary(lm(outpartysupport~study3cell, data=study3))


# by attentiveness
# main results
# main results
summary(lm(repdistance~study3cell*passed, data=study3))
summary(lm(demdistance~study3cell*passed, data=study3))

summary(lm(repsupport~study3cell*passed, data=study3))
summary(lm(demsupport~study3cell*passed, data=study3))

summary(lm(inpartysupport~study3cell*passed, data=study3))
summary(lm(outpartysupport~study3cell*passed, data=study3))
```

4.5 Heterogeneous treatment effects

Again, we look at difference by PID with no predictions.

```
# by pid

# main results
summary(lm(repdistance~study3cell*pid, data=study3))
summary(lm(demdistance~study3cell*pid, data=study3))

summary(lm(repsupport~study3cell*pid, data=study3))
summary(lm(demsupport~study3cell*pid, data=study3))
```

4.6 Robustness

We use the same robustness measures from study 1

```
# robustness

#marlow-crownesummary(lm(repdistance~study3cell,
data=study3))
summary(lm(demdistance~study3cell* marlowcrowne,
data=study3))
```

```
summary(lm(repsupport~study3cell* marlowcrowne,
data=study3))
summary(lm(demsupport~study3cell* marlowcrowne,
data=study3))

summary(lm(inpartysupport~study3cell* marlowcrowne,
data=study3))
summary(lm(outpartysupport~study3cell* marlowcrowne,
data=study3))


#buss-perry
summary(lm(repdistance~study3cell* bussperry, data=study3))
summary(lm(demdistance~study3cell* bussperry, data=study3))

summary(lm(repsupport~study3cell* bussperry, data=study3))
summary(lm(demsupport~study3cell* bussperry, data=study3))

summary(lm(inpartysupport~study3cell* bussperry, data=study3))
summary(lm(outpartysupport~study3cell* bussperry, data=study3))


#political interest
summary(lm(repdistance~study3cell* partscale, data=study3))
summary(lm(demdistance~study3cell* partscale, data=study3))

summary(lm(repsupport~study3cell* partscale, data=study3))
summary(lm(demsupport~study3cell* partscale, data=study3))

summary(lm(inpartysupport~study3cell* partscale, data=study3))
summary(lm(outpartysupport~study3cell* partscale, data=study3))

#kalmoe mason

summary(lm(repdistance~study3cell * Q77, data=study3))
summary(lm(demdistance~study3cell * Q77, data=study3))

summary(lm(repsupport~study3cell * Q77, data=study3))
summary(lm(demsupport~study3cell * Q77, data=study3))

summary(lm(inpartysupport~study3cell * Q77, data=study3))
```

```
summary(lm(outpartysupport~study3cell * Q77, data=study3))



#affpol
summary(lm(repdistance~study3cell* affectivepolarization,
data=study3))
summary(lm(demdistance~study3cell* affectivepolarization,
data=study3))

summary(lm(repsupport~study3cell* affectivepolarization,
data=study3))
summary(lm(demsupport~study3cell* affectivepolarization,
data=study3))

summary(lm(inpartysupport~study3cell* affectivepolarization,
data=study3))
summary(lm(outpartysupport~study3cell* affectivepolarization,
data=study3))
```

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S10.3 PAP3 (Study 3

Pre-Analysis Plan: Support for Political Violence - 3

Justin Grimmer   Clayton Nall   Matt Tyler   Sean J. Westwood

December 22, 2021

Contents

1 Preliminary Notes

- This is the pre-analysis plan for a replication of a survey experiment on support for political violence.
- We use the treatment text from a prior study — "Study 1 (replication)" with some modifications.
- For this replication we remove the apolitical treatments.
- We removed all covariates except the general Kalmoe-Mason measure (with an updated response scale).
- We randomize a pre-treatment prompt to incentivize careful and thoughtful responding.

2 Data cleaning

This will proceed using the code from the last PAP with the alterations noted above.

3 Study 1 (Replication)

3.1 Primary DVs

There are three primary variables of interest:

1. Do you support or oppose the actions of Steven Wright?
2. Was the shooter justified or unjustified?
3. Should the shooter face criminal charges?

3.2 Factual Attention Check

We will ask each respondent to recall which state was mentioned in the treatment vignette. This is the same as the original study.

3.3 Treatments

The design is a four cell design:

1. Democratic suspect X Attention Incentivized
2. Republican suspect X Attention Incentivized
3. Democratic suspect X Attention Not Incentivized
4. Republican suspect X Attention Not Incentivized

3.4 Hypothesis tests

The primary analysis will compare distributions and means from the three different possible outcome scales by cell. We will group respondents and treatments into two groups ”in-group” and ”out-group”

The primary analysis will compare distributions and means from the three different possible outcome scales.

3.5 Heterogenous Treatment Effects

We have no clear predictions for heterogeneous treatment effects. However, we will explore whether our treatment varies by party, responses to a pre-treatment partisan cheerleading question (from Shafner and Luks 2018) and a pre-treatment survey trolling question (from the ANES).

S10.4 PAP3 (Study 2 Replication and Survey Addition

Pre-Analysis Plan: Support for Political Violence - 3

Justin Grimmer Clayton Nall Matt Tyler Sean J. Westwood

September 7, 2021

Contents

1 Preliminary Notes

- This is the pre-analysis plan for a partial replication of a survey experiment on support for political violence.
- We use the treatment text from a prior study — "Study 1 (replication)" with some modifications.
- For this replication we remove the apolitical treatments and only provide in-party vignettes.
- We removed all covariates except for social desirability and the the general Kalmoe-Mason measure (with an updated response scale).
- We only measure justification. Additionally, we randomize the outcome question and scale between three options detailed below.

2 Data cleaning

This will proceed using the code from the last PAP with the alterations noted above.

3 Study 1 (Replication)

This is a replication of a prior study that was based on real events. Here we replicate with a contrived news story that is identical for both Democrats and Republicans. We also alter the context of the event to a shooting.

3.1 Primary DVs

There are is one primary variable of interest. We however, randomize the outcome scale and question stem:

1. Was the shooter justified or unjustified?
   Justified or Unjustified
2. How justified was the shooter?
   Not at all, a little, a moderate amount, a lot and a great deal
3. How justified was the shooter?
   Not at all, a little, a moderate amount, a lot, a great deal and don't know

3.2 Factual Attention Check

We will ask each respondent to recall which state was mentioned in the treatment vignette. This is the same as the original study.

3.3 Treatments

The design does not vary the treatment other than ensuring co-partisanship.

1. Democratic subject and partisan crime (always copartisan)

2. Republican subject and partisan crime (always copartisan)

3.4 Hypothesis tests

We expect that inattentive respondents will randomly respond when presented with a dicotemous outcome scale and will select a don't know when that option is available.

We expect support for violence to be low across all three versions of the question.

We expect support for violence to be larger for those who randomly click/don't pay attention.

The primary analysis will compare distributions and means from the three different possible outcome scales.

3.5 Heterogenous Treatment Effects

We have no clear predictions for heterogeneous treatment effects. However, we will explore whether our treatment varies by party.

3.6 Robustness

The literature identifies several possible mechanisms that might prompt a person to support violence. Here we account for the most common: political engagement, affective polarization, social desirability (Marlow-Crowne Social Desirability Scale), and aggression (Buss-Perry Aggression Questionnaire. We also include six items from prior work that reportedly predict support for partisan violence: three measures of moral disengagement and one measure of prospective partisan violence (Kalmoe and Mason, forthcoming).

In all cases except for the Kalmoe-Mason item we create indexes by taking the mean of summed scale items. We then bin each variable into terciles. We will treat the Kalmoe-Mason item as a separate predictors.

3.7 Robustness

We use the same robustness measures from study 1

4 Survey Questions

We also include two pre-treatment survey questions.

First, we replicate the original Kalmoe-Mason justification question with the original unbalanced scale:

“How much do you feel it is justified for $e://Field/p to use violence in advancing their political goals these days?”

- Not at all
- A little
- A moderate amount
- A lot
- A great deal

Next, we ask those who select any option other than “Not at all”:

“You reported that it is justified to use violence in advancing their political goals. What kind of violent crimes do think are justified?

Please be specific.”

This is an open-end question.

4.1 Analysis

This is exploratory analysis. We intend to analyze open-ended responses to identify patterns in what kinds of crimes respondents are thinking of. This will either be done by humans or via machine learning.

S11 APSR Formatted Version of Manuscript Citations

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