

# Does News Coverage of Hate-motivated Mass Shootings Generate More Hatred?\*

Andy Cao<sup>†</sup>

October, 2022

PRELIMINARY DRAFT - NOT FOR CIRCULATION

Click [here](#) for the latest version.

## Abstract

This paper investigates the role that the media play in promoting hatred through the news coverage of mass shootings. I first show through observational data that the media treat mass shootings differently depending on the motive behind the shooting. Any time a shooting targets a specific ethnicity/race/religion/gender, i.e., the shooting is hate-motivated, its news coverage differs in two respects: 1) higher coverage; 2) more focus on the shooter. I then show that there is more public interest in hate-motivated mass shootings, based on online searching behavior. Finally, I provide suggestive evidence that, immediately following a hate-motivated mass shooting, there is an increase in the number of hate crimes against the same victimized group. Based on these findings and the existing literature, I hypothesize that the way hate-motivated mass shootings are covered in the news contributes to spreading hatred. I test my hypotheses by conducting an online information provision experiment where I manipulate how a real past mass shooting targeting immigrants is reported in the news. In particular, I examine how, in the United States, Democrats and Republicans, who have different ex-ante views about immigration, react to news coverage that emphasizes the hate ideology or the identity and personal background of the shooter. Results from the experiment show that receiving details about the shooter's hate ideology increases Republicans' support for the shooter. Emphasis on the shooter's identity and background increases Democrats' support for both the shooter and the shooter's hate ideology. The latter finding is driven by the more right-leaning individuals within the Democrat sample.

*Keywords:* Media; mass shooting; hatred

*JEL Codes:* D91, K42, L82

---

\*I would like to especially thank my advisor Danila Serra for her guidance and support. I thank Elliott Ash, Andrew Barr, Alex Brown, Leonardo Bursztyn, Marco Castillo, Jennifer Doleac, Kwabena Donker, Catherine Eckel, Joanna Lahey, Judd Kessler, Silvana Krasteva, Jonathan Meer, Marco Palma, Ragan Petrie, Silvia Saccardo, Tim Salmon, Erik Snowberg, and numerous seminar participants for helpful comments. I am grateful for funding support from the Department of Economics and the College of Liberal Arts at Texas AM University. This study is approved by the Institutional Review Boards at TAMU (IRB2021-1000M). The online experiment is pre-registered on AsPredicted (#74996).

<sup>†</sup>Department of Economics, Texas A&M University. email: [andycao@tamu.edu](mailto:andycao@tamu.edu)

# 1 Introduction

Hate crimes have risen to their highest level in over a decade in the United States and have been elevated to top national threat priority.<sup>1</sup> The most extreme and dangerous hate crime is when the offender conducts a mass shooting targeting victims of a specific ethnicity, race, gender, sexual orientation, or religion. I call such act a hate-motivated mass shooting. Hate-motivated mass shootings receive great attention in the news and on social media. For instance, the 2022 Buffalo shooting<sup>2</sup> was headlined by the Wall Street Journal headline for four days straight after the shooting took place. During the same time, it was covered in Television news 767 times and was the most trending topic on Twitter.<sup>3</sup> A number of studies in criminology and social psychology suggest that media coverage of mass shootings could inspire more mass shootings through behavioral contagion (for example, see [Meindl & Ivy, 2017](#) and [Langman, 2018](#)). Relatedly, experimental investigations in the laboratory show that individuals are more likely to engage in anti-social behaviors when they get information about others engaging in such behavior (for example, see [Gino et al., 2009](#) and [Dimant, 2019](#)). This suggests that media coverage of hate-motivated mass shootings, by focusing on the shooter’s ideology and background, may induce or encourage others to express support for such ideology, leading to more hatred toward the victimized group.

In this paper, I employ quasi-experimental and experimental method to address the following questions. First, are hate-motivated shootings covered differently by the media in terms of intensity and content of coverage? Second, is there more public interest in hate-motivated shootings as compared to non-hate-motivated shootings, everything else being equal? Third, does emphasizing the ideology and/or the identity of the shooter in the coverage of hate-motivated mass shootings affect individuals’ attitudes toward the shooter and/or the shooter’s ideology, possibly leading to more hatred?

I categorize every notable mass shootings in the United States into hate-motivated mass shooting and non-hate-motivated mass shooting based on the shooter’s motive and the characteristics of the victims. Using data from the Internet Archive and the Vanderbilt Television News Archive, I compile a dataset of mass shooting news coverage. I find that the media gives differential treatment to mass shootings based on the nature of the shooting. Whenever a mass shooting is hate-motivated, it receives more news coverage, as measured by the number of news clips and the duration of news clips. Hate-motivated mass shootings on average receive more than three times the amount of coverage on national television networks. This difference is robust even after controlling for the number of casualties and a rich set of fixed effects. I then turn to examine the content of media coverage. For each mass shooting in my dataset, I scrape down news articles published within 14 days after the shooting. I use Natural Lan-

---

<sup>1</sup>See FBI’s release, [June 2021](#), and [October 2021](#).

<sup>2</sup>The shooting took place On May 14th, 2022, in Buffalo, New York. 10 Black people were killed.

<sup>3</sup>WSJ’s digital archive of top headlines can be accessed [here](#). The Buffalo shooting was headlined from May 15th to May 18th. Historical television news coverage can be found on the [Internet Archive](#). Historical Twitter Trends can be found on [Trend Calendar](#). The 2022 Buffalo shooting was the number 1 trending topic on May 15th, 2022.

guage Processing to identify whether a news article is about the shooter. I show that whenever a mass shooting is hate-motivated, news articles are 28.2 percent more likely to feature the shooter. Moreover, I show that a large proportion of these articles are related to the shooter’s ideology/motive.

Next, I investigate whether viewers exhibit similar bias in their news preference. I use Google Trends data to examine the online searching behavior related to each mass shooting. I show that people’s search interest value increases by 167 percent when a mass shooting is hate-motivated. A closer look at the searched terms suggests this gap is likely driven by the interest in the shooter. For more than 60 percent of the hate-motivated mass shootings, information related to the shooter is in the list of the most searched topics. In many cases, people directly used the name of the shooter and searched for the shooter’s manifesto. This pattern exactly matches media’s tendency to focus on the shooter when reporting hate-motivated mass shootings. One concern is that the prolonged exposure to the shooter could cause people to copy the shooter’s belief and behavior, i.e., become hateful toward the population targeted by the shooter, or in the most extreme case, commit hate crimes. To assess this possibility, I use the FBI’s hate crime data to compare the number of hate crimes targeting the same population before and after a hate-motivated mass shooting. Using an event study framework, I show that immediately following a hate-motivated mass shooting, there is an increase in the number of hate crimes against the same victimized group in the shooting. In contrast, there is no change in the number of hate crimes against other populations.

Based on my findings and the existing literature, I hypothesize that media coverage of hate-motivated mass shootings generates more support for the shooter and the shooter’s hate ideology, possibly leading to more hatred. However, it is challenging to establish causality using observational data. Indeed, even if there is a correlation between media consumption and hatred, that could simply be due to more hate-prone individuals self-selecting into watching or reading news that cover details of hate-motivated mass shootings, rather than to news coverage persuading individuals to be more hateful.

To overcome identification challenges, I employ an online information provision experiment (see [Haaland et al., 2020](#) for a review). I ask subjects to read a piece of news story about the 2019 El Paso shooting, which killed 23 people, including 8 Mexicans. The shooter posted a manifesto online with white nationalist and anti-immigrant themes minutes before the shooting. Subjects are randomly assigned to one of the four treatment conditions which vary in the level of informativeness. The No Hate treatment represents a streamlined version of news coverage. The news story only includes basic description of the shooting, such as the location and the number of victims. The Hate treatment is identical to the baseline treatment, except that the news story now mentions the shooting was targeted at the local Hispanic community and is possibly a hate crime. The Hate Ideology treatment builds on the Hate treatment and adds extra information on the shooter’s ideology, i.e., why he targeted the Hispanic population. Finally, the Hate Background treatment builds on the Hate Treatment and provides additional information on the shooter’s background, including name, photo, and quotations from former classmates hinting the shooter had a difficult childhood and was bullied at school by Hispanic

students. My outcome variables are measures of: 1) Interest in the shooting, measured by whether subjects ask to be shown more information at the end of the survey; 2) Attitudes toward the shooter, measured by survey questions on admiration for the shooter, justification for the shooter’s action, and sentencing option for the shooter; 3) Attitudes toward the ideology of the shooter, measured by an \$1 donation to an anti-immigrant organization or a pro-immigrant organization following the methodology used by [Bursztyn, Egorov, and Fiorin \(2020\)](#); 4) Hatred, measured by interest in accessing information on a white supremacy hate group.

Between Fall 2021 and Fall 2022, I recruited 2,400 American men to participate in the study via the online platform Prolific and CloudResearch. I stratified the recruitment and treatment assignment by political affiliation, with the aim of including an equal number of Republicans and Democrats in my sample. My final sample consists of 1199 Democrats and 1201 Republicans. This design choice allows me to test for possible heterogeneity in the impact of news reporting on individual attitudes, since the two parties have very polarized views regarding immigrants ([Card et al., 2022](#)).

I have four main findings from the experiment. My first finding is that subjects are not intrinsically more interested in hate-motivated than non-hate-motivated shootings. There is no significant difference in information demand between the No Hate treatment and the Hate treatment. This is true both for the Republican and the Democrat samples. This suggests that the higher public interest in hate-motivated mass shootings I observe in the online searching data is likely caused by either the higher intensity in media coverage of hate-motivated mass shootings as compared to non-hate motivated mass shootings, or in the way the two types of shootings are covered (i.e., the content of coverage). However, when subjects read the more informative news stories in the Hate Ideology treatment and the Hate Ideology Background treatment, they show significantly less demand for information on the shooting (both on the shooter and his ideology), than when such information is not provided, in the Hate treatment. Therefore, the higher public interest observed in the Google search data is more likely to be driven by the higher intensity of media coverage of hate-motivated shootings, rather than the differences in the content of media coverage.

My second finding is that the way the shooting is covered in the news affects subjects’ attitudes toward the shooter. To start with, both Democrat and Republican subjects decrease their support for the shooter when they know that the shooting is hate-motivated. They believe the shooter deserves a higher sentence, is less admirable, and his action less justifiable. This suggests that people have a natural distaste for hate crimes. However, the decrease in Republican subjects’ support goes away when they are provided additional information on the shooter’s ideology. I construct a standardized index of support for the shooter ([Anderson, 2008](#)) and show that Republican subjects in the Hate Ideology treatment increase their support for the shooter by 0.19 standard deviations relative to the Hate treatment (p-value=0.005). This suggests when Republican subjects are given details explaining the shooter’s ideas and beliefs about why he targets immigrants, they become more approving. In contrast, while knowing the shooter’s ideology does not affect Democrat subjects’ attitudes toward the shooter, knowing

the shooter’s background story about his childhood suffering increases their support for the shooter by 0.27 standard deviations (p-value=0.00).

My third finding is that when exposed to the news story that emphasizes the shooter’s background, Democrat subjects significantly increase their support for the shooter’s anti-immigrant ideology, as measured by donations to an anti-immigrant organization. In the experiment, about 75% of the subjects are randomly assigned to an anti-immigrant organization, while the rest of the 25% are assigned to a pro-immigrant organization. In both cases, near the end of the survey, subjects are given the description of the organization and asked whether they want to authorize a \$1 donation to the randomly assigned organization.<sup>4</sup> On average, the donation rate to the pro-immigrant organization is significantly higher in all treatments among both Republicans and Democrats. As expected, the donation rate to the anti-immigrant organization is significantly higher among Republicans (23.21 percent versus 14.49 percent, p-value=0.00). However, consistent with the increase in support for the shooter, Democrat subjects in the Hate Background treatment are 6.9 percentage points more likely to authorize a \$1 donation to the anti-immigrant organization relative to a mean of 11.4% in the Hate Treatment (p-value=0.037). In contrast, Republican subjects in the Hate Background treatment are 9.3 percentage points less likely to donate to the anti-immigrant organization relative to a mean of 27.8% in the Hate Treatment (p-value=0.022). This is surprising, given that Democrat subjects are generally known for their friendly attitudes toward immigrants. Further analysis shows that the treatment effect on Democrat subjects are driven by the more right-leaning individuals within the Democrat sample. There is no change in the donation rate to the pro-immigrant organization across different treatment conditions from either Democrat subjects or Republican subjects.

Finally, I provide suggestive evidence that exposure to the shooter’s background story increases Democrat subjects’ interest in white supremacy hate groups. At the end of the survey, subjects are given a brief description of a major hate group known for its white nationalist and white supremacy themes, and are told that this group shares similar ideology with the shooter. Subjects are then asked: “Would you like to know how to access its website”. I track whether subjects click on the links, which are provided if and only if subjects answered “yes” in the previous question. Results show that only 8.51 percent of Democrat subjects and 12.82 percent of Republican subjects requested the links (p-value=0.00), and even fewer subjects clicked on the links. Consistent with the increase in support for the shooter and the shooter’s ideology, Democrat subjects in the Hate Background treatment are 3.95 percentage points more likely to request the links to the hate group’s website. This difference is statistically significant (46.47 percent increase, p-value=0.076), despite the small sample size. However, knowing the shooter’s background story does not make Democrat subjects more likely to click on the links. While there is some evidence that Republican subjects in the Hate Ideology Treatment increases their likelihood of clicking on the links, the difference is not statistically

---

<sup>4</sup>The anti-immigrant organization is the Federation for American Immigration Reform. The pro-immigrant organization is the American Immigration Council.

significant (61.32 percent increase,  $p$ -value=0.265)

In summary, my experiment finds substantial variation in treatment effects based on subjects' baseline political stance. At the aggregate level, Republican subjects show higher support for the shooter, donate more to the anti-immigrant organization, and express higher interest in the white-supremacy hate group. A news story that emphasizes the shooter's anti-immigrant ideology increases Republican subjects' support for the shooter. A news story that emphasizes the shooter's identity and background, and highlights the shooter's struggles growing up increases Democrat subjects' support for the shooter, support for the shooter's ideology (more than 60 percent increase in donation rate to an anti-immigrant organization), and interest in white supremacy hate groups (suggestive evidence). Taken altogether, the heterogeneity in treatment effects suggests that Republican subjects respond to the shooter's ideology itself, while Democrat subjects respond to the shooter's traumatic background story which hints at the shooter being bullied by Hispanic students and possibly explains how the shooter developed his ideology.

My paper contributes to the literature on media coverage of mass shootings and its unintended consequences (see [Lankford & Madfis, 2018a](#) for a review). There has been a long-standing debate on how media should report mass shootings. Many studies point out that future offenders often find inspirations from past shooters ([Helfgott, 2015](#); [Kissner, 2016](#); [Lankford, 2016](#); [Meindl & Ivy, 2017](#); [Murray, 2017](#); [Langman, 2018](#); [Lee, 2018](#)). Some shooters even personally acknowledged that they were influenced and motivated by past mass shooters.<sup>5</sup> This suggests that media reporting on mass shootings, i.e., the victims, the suspect and his/her motives, may play a role in creating similar crimes. However, most research on this topic relies on correlational analysis and lacks proof of causality.<sup>6</sup> One important exception is [Jetter and Walker \(2022\)](#), who use exogenous variations in worldwide disaster deaths to show that news coverage of mass shootings causes more subsequent mass shootings. I extend [Jetter and Walker \(2022\)](#) by focusing on the effects of the content of mass shooting news coverage, rather than the intensity, and by focusing specifically on hate-motivated mass shootings. My experiment exogenously varies the information provided in the news story about a mass shooting to test how different kinds of information affect individuals' reactions to the crime, and in particular attitudes toward victims vis-à-vis the shooter. To the best of my knowledge, this is the first paper to causally show that media coverage of mass shootings can increase support for the shooter and the shooter's hateful ideology. The results from my experiment have important implications for media and policy makers.

More generally, my paper contributes to the vast literature that studies the influence of media on a variety of outcomes, including voting behavior and political opinions ([DellaVigna & Kaplan, 2007](#); [Gerber et al., 2009](#); [Martin & Yurukoglu, 2017](#)), immigration ([Couttenier et al., 2021](#); [Schneider-Strawczynski & Valette, 2021](#)), terrorism ([Jetter, 2017](#); [Durante & Zhu-](#)

---

<sup>5</sup>For instance, at least 32 attackers referred to the 1999 Columbine shooters as role models ([Langman, 2018](#)).

<sup>6</sup>Though researchers have proposed regulations such as calling for the media to stop publishing information about mass killers (for example, see [this](#) open letter signed by 149 scholars and professionals), such policies have never been tested and are largely ignored in practice.



ravskaya, 2018), criminal justice (Lim et al., 2015; Mastrorocco & Minale, 2018; Philippe & Ouss, 2018), socio-economic development (La Ferrara, 2016), and precautionary behavior during the Covid-19 pandemic (Bursztyn, Rao, et al., 2020; Simonov et al., 2020). However, there is little evidence of media’s ability to promote hatred. The exceptions are Yanagizawa-Drott (2014) and Adena et al. (2015), who examines the impact of government propaganda on mass violence, Ang (2020) who examines the impact of blockbuster film on racism, Bursztyn et al. (2019), Müller and Schwarz (2020), and Carr et al. (2020), who examines the impact of social media on racism. In previous work (Cao et al., 2022), I show that Donald Trump’s “Chinese Virus” tweets contributed to the rise of anti-Asian incidents. My paper focuses on news media, which represents a very different context. On the one hand, news media is (supposed to be) neutral and objective in nature. On the other hand, news media is people’s primary information source for criminal incidents and is therefore, especially hard to regulate. To the best of my knowledge, my paper is the first to document media’s differential treatment of mass shootings based on the underlying motive of the shooting. My experiment shows that the way hate-motivated mass shootings are covered in the news could lead to unintended consequences including more support for the shooter and more hatred against the victims. Thus, my paper extends the literature on media influence by showing that news media is capable of causing extreme behaviors.

Finally, my paper relates to the growing body of literature that uses information provision experiments (for a review, see Haaland et al., 2020). In particular, this paper adds to the studies on attitudes related to immigrants and immigration. Alesina et al. (2018) finds that providing true information about shares and origins of immigrants does not increase self-reported support for redistribution and donation to charity. Similarly, Grigorieff et al. (2020) finds that factual information about the characteristics of immigrants does not affect policy preferences measured by donation and petition. Bursztyn, Egorov, and Fiorin (2020) finds that information about Trump’s popularity increases individuals’ willingness to publicly express xenophobic views as measured by donation to an anti-immigrant organization. Haaland and Roth (2020) finds that providing subjects with research evidence on the labor market impacts of immigration makes subjects more supportive of immigration measured by self-reported views and petition signatures. My paper deviates from these studies in two ways. First, my information treatments resembles news articles that people may encounter regularly. I show that even a small variation in the news’ content about a mass shooting could affect how people feel towards immigrants. My findings suggest that narratives might be more effective in changing people’s attitudes than facts (Bénabou et al., 2018). Second, my outcome measures aim at capturing extreme behaviors such as support for the shooter and hatred, rather than strong support for immigration control. My paper shows that information experiments can be applied to study anti-social behaviors.

Overall, my paper highlights media’s role in spreading hatred. My findings provide important guidelines on media’s approach to mass shootings, and more broadly, other sensitive events. My experiment shows that it is desirable not to provide detailed information on shooter’s ideology, as well as the shooter’s identity and background to reduce the risk of hate crimes. The remainder of this paper is structured as follows. Section 2 presents evidence from observational

data. Section 3 introduces my hypotheses and experimental design. Section 4 presents results from the experiment. Section 5 concludes.

## 2 Evidence from observational data

This section contains my motivational analysis using observational data. Section 2.1 discusses how I categorize mass shootings in the US into hate-motivated and non-hate-motivated. Section 2.2 documents the difference in news coverage of hate-motivated mass shootings and non-hate-motivated mass shootings. Section 2.3 shows the difference in viewers' reactions. Section 2.4 provides evidence that following a hate-motivated mass shooting, there is an increase in the number of hate crimes against the same group that was targeted in the shooting.

### 2.1 Mass shootings in the US

I collect data for mass shootings in the United States from the list of the most notable mass shootings in the United States complied by Wikipedia.<sup>7</sup> Wikipedia defines a mass shooting as 4 or more shot in one incident.<sup>8</sup> The dataset contains 241 mass shootings in the United States from 1970 to March 2021.<sup>9</sup> I choose Wikipedia over other data sources for two reasons. First, it consists of mass shootings that attracted wide media coverage and public discussion. Second, these shootings tend to have a more complete description of the incident including the shooter's motive. These two features help me address my research questions.

For the purpose of this study, I divide notable mass shootings in the United States into two categories: hate-motivated mass shootings and other mass shootings. Based on the FBI's definition of a hate crime, I define a hate-motivated mass shooting as a mass shooting which is motivated, in whole or in part, by the offender's bias(es) against a: race, religion, sexual orientation, ethnicity, gender, gender identity. For each mass shooting in my dataset, I classify it as hate-motivated if it meets one of the following conditions:

1. The suspect explicitly admitted that the shooting was motivated by hatred/bias.
2. The majority of the victims belong to the same group such that the authorities were investigating the possibility of a hate crime against that group.

Note that if it is the latter case, there is a chance that the investigation failed to prove the shooting was a hate crime. Therefore, I could incorrectly label a mass shooting as hate-motivated when in reality it is not. However, since the shooting was investigated as a potential hate crime, being reported by the media as a potential hate crime, generated public discussion about hate crimes, it should still be classified as a hate-motivated mass shooting.

---

<sup>7</sup>Only shootings that have Wikipedia articles of their own are included in this list.

<sup>8</sup>Note that there is no agreement on how mass shooting is defined. Some agencies use a more restrictive definition, for example, Mother Jones defines a mass shooting as three or more shot and killed in one incident at a public place, excluding the perpetrators.

<sup>9</sup>This list is more inclusive compared to alternative sources such as Mother Jones (120 Mass shootings), Washington Post (180 Mass shootings), and The Violence Project (170 Mass shootings).



Based on my definition, 24 out of 241 (10%) mass shootings are identified as hate-motivated. A complete list of hate-motivated mass shootings is provided in Table A1 in the Appendix. Appendix Table A2 shows the descriptive statistics. On average, hate-motivated mass shootings are associated with slightly higher casualty. However, the difference is not statistically significant (the p-value of a t-test of equality is 0.13 and 0.67 respectively for the difference in mean of dead and injured).

## 2.2 News coverage of mass shootings in the US

In this section, I compile and analyze data on media coverage of the most notable mass shootings in the United States. I provide evidence that, compared to non-hate-motivated shootings, the media coverage of hate-motivated mass shootings: 1) lasts longer, in terms of the number of news segments per day, duration of news per day, 2) is more likely to focus on the shooter rather than the shooting itself.

### 2.2.1 The intensity of news coverage

To compare the level of media coverage of hate-motivated mass shootings versus other mass shootings, I use two data sources. First, I collect data from The Internet Archive, a digital library that archives clips of U.S. television news broadcasts since 2009. For each mass shooting in my dataset from 2009 to March 2021, I search for news by captions using three different keywords: <State Name Shooting>, <City Name> Shooting, <Suspect Name> Shooting.<sup>10</sup> I restrict the search to include only news clips that are published within 7 days since the shooting happened. My outcome of interest is the number of news clips returned from searching.

Figure 1 displays the total number of news clips in the 7 days following the shooting. Across all three specifications, hate-motivated mass shootings are associated with significantly higher number of news clips. This suggests that on average, hate-motivated mass shootings receive more media coverage compared with other mass shootings.

Next, I use an alternative data source to validate the pattern in Figure 1. I collect data from the Vanderbilt Television News Archive (VTNA) (Eisensee & Strömberg, 2007; Durante & Zhuravskaya, 2018; Jetter & Walker, 2022). VTNA’s core collection consists of regularly scheduled evening newscasts from ABC, CBS, NBC, CNN. For each mass shooting in my dataset, I search for its news coverage within 7 days the shooting took place. To maximize accuracy, I use the suspect’s name as a keyword.<sup>11</sup> This returned 1289 news clips for 223 mass shooting events.<sup>12</sup> I then construct a panel data of media coverage: I aggregate the total minutes of news coverage a shooting event received for each day within 7 days of the event. I then investigate the difference in the amount of coverage between hate-motivated mass shootings and other mass shootings.

<sup>10</sup>I exclude mass shootings with no identifiable suspect names. My final sample size is 124 mass shootings.

<sup>11</sup>I excluded mass shootings with no identifiable suspect names. My final sample size is 223 mass shootings.

<sup>12</sup>Note that the number of clips is much smaller than Internet Archive because VTNA only contains national newscasts.

Figure 2A shows that on average, hate-motivated mass shootings receive more news coverage per day, measured by the total duration of news in minutes. Figure 2B shows that on average, hate-motivated mass shootings are associated with higher number of news segments per day.

I formalize the graphical evidence in Figure 2 using regressions. Appendix Table A3 shows the estimated coefficients under different specifications. My dependent variable is the total amount of news coverage per day measured by minutes. Estimates from regressions confirm the graphical evidence presented earlier. The coefficient on Hate is positive and statistically significant even after controlling for casualty level and a rich set of fixed effects. Estimates from column 4 show that when there is no death, hate-motivated mass shootings on average receive 6.5 more minutes of news coverage per day. For every additional dead victim, hate-motivated mass shootings receive 0.72 more minutes of news coverage while non-hate-motivated mass shootings receive only 0.21 more minutes.

### 2.2.2 The content of news coverage

In this subsection, I present evidence that media coverage of hate-motivated mass shootings differs in content compared with other mass shootings: news stories on hate-motivated mass shootings tends to focus more on the shooter.

I collect data from Google News, one of the world’s largest news aggregators. For each mass shooting in my dataset that happened after 2006 (Google News was launched in 2006), I scrape down 50 news articles on Google News sorted by relevance.<sup>13</sup> I restrict my sample to articles that are published within 14 days after each shooting. I widened the scope from 7 days in prior analysis to 14 days because for a given event, there tends to be higher number of written news articles than the number of Television appearances. I use Octoparse to scrape down URLs and Python library Newspaper3K to extract data from each URL. This gives me 4396 valid news articles from various News agencies.<sup>14</sup> The top 3 sources are CNN, the New York Times, and the Washington Post. For each news article, I use NLP (Natural Language Processing) to obtain a set of keywords summarizing the article. I identify if a news article is about the shooter by examining whether the keywords of the article contains “suspect/shooter/gunman/perpetrator/killer/motive.” As a robustness check, I do the same exercise using the title of the news article instead.

Figure 3 plots the fraction of news articles about the suspect each day based on the article keywords and title respectively. The two approaches produce similar patterns. News articles about a hate-motivated mass shooting are more likely to involve stories about the shooter. Appendix Table A4 shows the difference in regression format. The dependent variable is an indicator variable that equals 1 if the news article focuses on the shooter. Estimates show that the difference is robust to controls and fixed effects. Column 4 shows that news articles on hate-motivated mass shootings are 5 percentage points more likely to focus on the shooter, which

---

<sup>13</sup>The number 50 is chosen based on an eyeball test of relevancy for returned results (the search might return irrelevant news articles) and computational constraints.

<sup>14</sup>I scraped down 5909 news articles. However, some are excluded from analysis due to missing information.

is a sizeable gap (21.28% increase) considering the proportion of news articles that involves shooters in non-hate-motivated mass shootings is 23.5 percent.

The next question in line is, what exactly do the news stories talk about when they feature the shooter? I provide evidence in Appendix Table A5 that more than 9% of all the new articles are related to the shooter’s ideology/motive, when the shooting is hate-motivated. In comparison, when the shooting is not motivated by hate, the fraction drops to less than 2%. Consider the recent Buffalo shooting on May 2022. After the shooting occurred, media immediately started reporting stories about the shooter and his white supremacy ideology. This is disturbing since this would translate to an increase in exposure to the shooter’s hateful ideology. Based on literature in criminology and psychology (see [Lankford & Madfis, 2018a](#) for a review), this could lead to behavioral contagion and other negative effects.

### 2.3 Reactions to mass shootings in the US

In this last subsection, I showed that from the media’s side, hate-motivated mass shootings receive substantially higher news coverage compared to non-hate-motivated mass shootings. I now check whether similar differences exist from the viewer’s side, i.e., whether people are more interested in hate-motivated mass shootings, and more specifically, whether people are more likely to look for information about the shooter. I collect data from Google Trends. Google Trends provides access to search requests made to Google. The data is aggregated and normalized.<sup>15</sup> For each mass shooting in my dataset that happened after 2006 (Google Trends was launched in 2006), I download data from Google Trends using Python library pytrends. I restrict the time frame of data to reflect searching behaviors in the United States within 14 days of each shooting.

My first outcome of interest is the state-level search interest in each mass shooting. I plot the average number of regions with non-zero search interest and the average search interest across all the regions in Figure 4. The graph shows that people are much more interested in hate-motivated mass shootings. Regression estimates in Appendix Table A6 confirm this results. I use similar specifications as before. The dependent variable is the search interest of a mass shooting in a subregion. Column 4 shows that after controlling for the number of victims and fixed effects, the search interest value for hate-motivated mass shootings are on average 7.33 points higher compared to non-hate-motivated mass shootings. For every additional dead victim, the search interest for hate-motivated mass shootings increases by 0.74 while the search interest for non-hate-motivated mass shooting increases by only 0.4.

My second outcome of interest is people’s subject of interest when searching information for mass shootings. Recall that in section 2.2, I showed that news coverage on hate-motivated mass shootings are more likely to focus on the shooter. I now examine whether people shower higher search interest in the shooter when the shooting is hate-motivated. For each mass

---

<sup>15</sup>Each data point is divided by the total searches of the geography and time range it represents to compare relative popularity. The resulting numbers are then scaled on a range of 0 to 100 based on a topic’s proportion to all searches on all topics.

shooting event, I retrieve a list of related topics. These words and phrases are the most common topics that the users who searched for the mass shooting also searched for during the same search session.<sup>16</sup> Figure 5 displays the fraction of mass shootings that has “Suspect” on its list of related topics.<sup>17</sup> Whenever a hate-motivated mass shooting happens, about 60 percent of the time, “Suspect” is among the most searched topics on Google. In contrast, this ratio drops to less than 30 percent when the shooting is not hate-motivated. The regression analysis in Appendix Table A7 confirms this difference. However, the estimates lose statistical significance after adding control variables and fixed effects. In Appendix Table A8, I provide evidence that people often search for keywords related to the shooter’s motive. This search preference matches the media’s tendency to report more about the shooter and the shooter’s motive in hate-motivated mass shootings.

## 2.4 Hate crime before and after hate-motivated mass shootings

In Section 2.3, I showed that people show substantially more interest in the shooters of hate-motivated mass shootings, as reflected in online searching behaviors. This pattern matches the media’s reporting pattern shown in Section 2.2. Assuming that this prolonged exposure to the shooter leads to behavioral contagion, e.g., people copying the shooter, I should expect to see an increase in hatred toward the victimized group targeted by the shooter. In this section, I investigate this possibility by estimating an event study model that compares how the number of hate crimes targeting one group changes over time from 10 days before the occurrence of a hate-motivated mass shooting targeting that same group to 10 days after the shooting. I use the hate crime data from the FBI. The data is incident level and includes every hate crime incident from 1991 to 2019. During the same period, there are 21 hate-motivated mass shooting. I aggregate the data by date (10592 days) and calculate the number of hate crime incident per day nationwide. I then estimate the following specification via ordinary least squares:

$$y_{Gt} = \sum_{t=-5}^{t=5} \beta_t * HateShooting_t + \gamma_t + \epsilon_{Gt}$$

The outcome variable  $y_{Gt}$  is the number of hate crimes against group G on date t in the United States.  $HateShooting_t$  are indicator variables for being within 10 days from a hate-motivated mass shooting. Each indicator variable represent a two-day interval,  $t = -1$  is the omitted group. For example, if a hate-motivated mass shooting happened on date  $t$ ,  $\beta_1$  will measure the changes in the number of hate crimes on date  $t + 1$  and  $t + 2$ . The set of coefficients  $\beta_k$  reflects

---

<sup>16</sup>Google does not explicitly define what a search session is. Generally, a search session consists of all the search requests from a user within a given timeframe. A session lasts until there is inactivity. A common value for the inactivity threshold is 30 minutes and is sometimes described as the industry standard.

<sup>17</sup>People who searched for hate-motivated mass shootings are also more likely to search for topics that are related to the victims of the shooting. In particular, people search for the group that the victims belong to, i.e., race, religion. For example, those who searched for the Atlanta shooting in 2021 also searched for “Asian people,” “Asia,” “Asian Americans,” those who searched for the Poway shooting in 2019 also searched for “Synagogue,” “Chabad,” “Rabbi.”

the degree to which hate crime against group  $G$  changed before and after a hate-motivated mass shooting against group  $G$ .  $\gamma_t$  includes year fixed effect, month fixed effect, and day of the week fixed effect to control for changes over time in the rate of hate crimes. To examine possible heterogeneity by the types of mass shooting and hate crime, I investigate four different cases, the victimized group is African American, Latino, Jewish, and Gay respectively.

Figure 6 plots the resulting  $\beta_k$  estimates. The pink dotted line represents day 0 when a hate-motivated mass shooting happened. As the null estimates left of the link dotted line indicate, once all the fixed effects are controlled for, there is little difference in the pre-shooting trend in the number of hate crimes. Following a hate-motivated mass shooting, there's a large and statistically significant increase in the number of hate-crimes against the same victimized group targeted in the hate-motivated mass shooting. Consider the graph on the bottom left, the point estimate indicates that, relative to day 1 and day 2 before a hate-motivated mass shooting against Jewish took place, the number of hate crimes against Jewish increased by 3. This magnitude is large given that the daily average number of hate crime against Jewish is less than 3. The same pattern is also evident from the number of hate crimes against Black, Latino, and Gay, following a hate-motivated mass shooting against Black, Latino, and Gay respectively.

As a robustness check, I investigate whether the same pattern exists for the number of hate crimes against different victimized groups, i.e., following a hate-motivated mass shooting against African Americans, will there be an increase in the number of hate crimes against non-African Americans? To do so, I estimate a similar specification, except that the outcome variable is now the number of hate-crimes against non- $G$  on a particular day. Figure 7 plots the resulting  $\beta_k$  estimates. None of the estimate coefficients for post periods is significant, suggesting that the number of hate crimes against different victimized groups does not change before and after a hate-motivated mass shooting.

While my findings strongly suggest that following a hate-motivated mass shooting, there is an increase in hatred toward the group that was targeted in the shooting, there are limitations to my analyses. To begin with, with existing data, I can not prove that the increase in hatred is caused by news coverage of hate-motivated mass shootings. It is entirely possible that media is not responsible. For example, while people display higher interest in the shooters of hate-motivated mass shooting as shown in Section 2.3, this could simply reflect people's natural interest, which may have nothing to do with media coverage. The increase in hate crimes could be attributed to other reasons as well, such as victims' increased willingness to report, or the police's increased effort. In addition, FBI's hate crime data could be biased in two ways. First, as with most self-reported crime data, it suffers from under reporting (Pezzella et al., 2019). Second, It is sometimes difficult to determine whether an incident is a hate crime. The labeling process could be subjective to biases from law enforcement agencies.<sup>18</sup> Therefore, observational data is not sufficient to show media coverage of hate-motivated mass shootings

---

<sup>18</sup>The following is taken from the FBI's [webpage](#). "Only when a law enforcement investigation reveals sufficient evidence to lead a reasonable and prudent person to conclude that the offender's actions were motivated, in whole or in part, by his or her bias, should an agency report an incident as a hate crime."

causally generate more hatred.

## 2.5 Summary

In sum, using observational data from multiple sources, I found evidence that news coverage of hate-motivated mass shootings and non-hate-motivated mass shootings differ in two aspects. First, hate-motivated mass shootings receive more news coverage, as measured by the number of news clips, and the total length of coverage. Second, news coverage of hate-motivated mass shootings tends to focus more on the shooter such as the shooter’s ideology. Next, I showed that people’s reactions to hate-motivated mass shootings and non-hate-motivated mass shootings differ in similar manners. Namely, based on online searching data, I find that people show a higher interest in hate-motivated mass shootings, and this is possibly driven by the higher interest in the shooter. Finally, if the increase in exposure to the shooter results in an increase in hatred, then following a hate-motivated mass shooting, there should be an increase in the number of hate crimes against the same group that was targeted in the shooting. Using the FBI’s hate crime data and an event study framework, I provide evidence that there is indeed a rise in hatred post-shootings.

Based on these evidence and the existing literature, I hypothesize that the news coverage of hate-motivated mass shootings have unintended consequences, namely, it generates more hatred toward the victimized group. However, to provide causal evidence, one would have to overcome identification challenges. The ideal natural experiment would require exogenous variations in the way media covers mass shootings. This is extremely hard to achieve with observational data, making the implementation of an experiment especially desirable. In the next section, I formally lay out my hypotheses and describe the design and implementation of an online survey experiment aimed at testing my hypotheses.

## 3 Experimental Design

Based on my findings from observational data and the existing literature, I design and conduct an online information provision experiment to causally examine the impact of news coverage of hate-motivated mass shootings. My main treatment conditions simulate media’s tendency to focus on the shooter when covering hate-motivated mass shootings. In particular, I examine two aspects, 1) media’s focus on the shooter’s ideology, and 2) media’s focus on the shooter’s identity and background. This section introduces experimental design, treatment manipulations, hypotheses, outcome measures, and estimation strategy.

### 3.1 Outline

In order to causally study the impact of news coverage of hate-motivated mass shootings, I design and conduct an online information provision experiment. The structure of my experiment largely follows the growing literature on information provision experiments (for a review, see



Haaland et al., 2020). This methodology has been applied to answer policy-relevant questions in a variety of fields including sensitive topics such as attitudes toward immigration, labor market discrimination, and xenophobia (Alesina et al., 2018; Bursztyn, Egorov, & Fiorin, 2020; Grigorieff et al., 2020; Haaland & Roth, 2020). This methodology is ideal for my research for three reasons. First, I can exogenously vary the content of the news story on a mass shooting, generating the ideal variation I need to test my hypotheses. Second, I can vary one feature of the information set at a time to cleanly identify what specific content of the news story is affecting subjects' attitudes. Third, experiments conducted online provides a higher degree of anonymity compared with experiments conducted in the laboratory. Thus, participants in online experiments should feel more comfortable expressing their true views.<sup>19</sup>

In the experiment, participants are asked to read a piece of news story about a hate-motivated mass shooting against Hispanic immigrants. I implement different treatments where the content of the story is experimentally manipulated to either emphasize or do not emphasize the hateful nature of the shooting, the hateful ideology of the shooter, and the identity and background of the shooter. I subsequently measure participants' interest in the shooter's ideology and background, their attitudes toward the shooter (including admiration and justification for the shooter's action), their support for the hateful ideology of the shooter, and their interest in accessing information regarding a white supremacy hate group.

The news story in my experiment focuses on the 2019 El Paso shooting. This shooting has been described as the deadliest anti-Latino and anti-immigrants attack in recent U.S. history.<sup>20</sup> Twenty three people were killed in the shooting, including 8 Mexicans. Due to the high level of casualty, it received extensive media coverage in the United States. I choose this shooting for three reasons. First, the hateful motives behind the shooting is evident. The shooter Patrick Crusius explicitly admitted in his manifesto, that the shooting was motivated by anti-immigrant and anti-Hispanic ideology. Thus, this shooting clearly falls under the hate-motivated mass shooting category defined in this paper. Second, while there are other well-defined hate-motivated mass shootings targeting different populations such as people of certain race or sexual orientation, people might feel reluctant to express their true attitudes toward such populations in the modern society, given the potential of backlashes.<sup>21</sup> In comparison, discussion about immigrants and immigration are less frowned upon compared to other sensitive issues, since policies regarding immigration and anti-immigration are an essential part of the political agendas for both Democrats and Republicans. For example, recent survey evidence shows that college students think it is easier to have an open and honest conversation about immigration than racial inequality and gender-related topics.<sup>22</sup> Moreover, there exists a

---

<sup>19</sup>I formally address issues related to social desirability bias in Section 4.4.

<sup>20</sup>For example, see [this](#) article published by the New York Times.

<sup>21</sup>For example, the National Association of Scholars compiled a [list](#) of individuals who lost their job for offensive remarks. While the majority of cases are related to racism and gender, only less than 2% of the cases are related to immigrants and immigration.

<sup>22</sup>See the report on college free speech: [Link](#). On a related note, Ekins (2017) finds that among a list of 13 controversial topics, the majority of Americans believe speakers should be allowed to talk about deporting illegal immigrants at college campus.

variety of both anti- and pro-immigration organizations actively attempting to influence legislation.<sup>23</sup> With the rise of Donald Trump, the anti-immigrant sentiment has been increasingly mainstreamed over the last few years.<sup>24</sup> Third, since immigration is an issue that is explicitly polarized based on political leaning with the Republican party known to take a stricter stance, I can use subjects' political affiliation as a proxy to measure ex-ante attitudes toward the victimized group in the shooting, i.e., immigrants.

Figure 8 shows the outline of the experiment. Upon consent, subjects are first asked a series of demographic questions. Next, subjects are randomly assigned to one of the four information treatments where they are asked to read a piece of news story about a real past mass shooting. Finally, I measure my outcomes of interest, including subjects' interest in the shooter, subjects' attitudes toward the shooter, subjects' attitudes toward the shooter's anti-immigrant ideology, and subjects' interest in information about a white supremacy hate group.

I take several measures to improve data quality. First, before subjects are presented with the news story about the mass shooting, they are told that they will be asked to read a real piece of news story randomly selected from three categories: business, crime, and sports.<sup>25</sup> This design choice intends to mask the true objective of the survey, thus reducing participants' beliefs that the study aimed to measure their bias against the victimized group. Second, I offer rewards to ensure that subjects read the news story carefully. Before subjects see the news article, they are told that they have to answer two comprehension questions about the story, and they would be compensated \$0.2 for each correct answer. Third, in order to measure if subjects are paying attention, I include two attention checks in the survey following [Oppenheimer et al. \(2009\)](#), one pre-treatment, one post-treatment. Subjects are aware that their submission might get returned if they fail attention checks.<sup>26</sup> Finally, it is possible that subjects have seen news stories about the El Paso shooting before. In order to reduce recall bias, dates and locations are omitted from all treatments, with the exception of Treatment 4 mentioning the shooter's name.<sup>27</sup>

### 3.2 Treatments

I implement 4 different treatment conditions, where I experimentally manipulate the content of the news story in a way that progressively increases information about victims, motives and the shooter's background. To mimic real-life news as closely as possible, the wordings in all treatment conditions are adapted from real stories posted by major US media outlets.<sup>28</sup> Detailed survey script including the news story in each treatment condition are included in

---

<sup>23</sup>For example, see this [list](#) from Columbia University.

<sup>24</sup>For example, see this [report](#) from ADL.

<sup>25</sup>To maximize statistical power, 99.9% of the subjects saw the crime version of the survey.

<sup>26</sup>For example, see Prolific's [Attention and Comprehension Check Policy](#). An example of attention checks is provided in Appendix B.4.

<sup>27</sup>In the end of the survey, I asked subjects: "Before today, have you heard of the event described in the news story that you read?" 22.6 percent chose yes. I address this issue in detail in Section 4.4.3.

<sup>28</sup>Sources: [NPR](#), [The New York Times](#), [NBC](#), [BBC](#), [The Washington Post](#)

### **3.2.1 Treatment 1: No Hate**

The No Hate Treatment represents the most streamlined news coverage of mass shootings, featuring a basic description of the event, including when and where the shooting happened, the number of victims, and excerpts from interviews with witnesses. This news coverage does not mention the hate motive behind the shooting and does not provide information about the victimized group. Instead, the shooter’s motive is described as economic reasons according to an manifesto shared online.<sup>29</sup>

### **3.2.2 Treatment 2: Hate**

The Hate Treatment is identical to Treatment 1, with the exception that the news story now mentions the hate-motivated nature of the shooting, i.e., victims include at least 8 Mexicans, the attack was targeted at the local Hispanic community, authorities are investigating possible hate crime charges. This treatment represents the minimalistic news coverage of hate crimes. Although the news story discloses the possibility of a hate crime, no further details are given regarding why the shooter targeted Hispanic immigrants. Recall that in Section [2.3](#), I showed that people are more interested when the mass shooting is hate-motivated. This could simply be a natural preference regardless of how media reports the story. The comparison of the No Hate Treatment and the Hate Treatment allows me to examine whether people naturally react to hate-motivated mass shootings differently, regardless of the content and intensity of media coverage.

### **3.2.3 Treatment 3: Hate & Ideology**

The Hate Ideology Treatment builds on the Hate Treatment by adding details on the shooter’s ideology by providing excerpts from the shooter’s manifesto.<sup>30</sup>

The document claims that the attack was targeted at the local Hispanic community. It stated that Latin America immigrants represented a “Hispanic invasion.” It warned that white people were being replaced by foreigners.

The manifesto described an imminent attack and railed against immigrants, saying, “if we can get rid of enough people, then our way of life can be more sustainable.” It also detailed a plan to separate America into territories by race to save this country.

The author hoped his/her attack and words would inspire additional like-minded attacks and lead to a wider racial violence in pursuit of a white ethnostate.

---

<sup>29</sup>This is partially true according to the shooter’s manifesto.

<sup>30</sup>The wordings are taken directly from the shooter’s manifesto, and from an article published on [the New York Times](#).

In Section 2.2.2, I provide evidence that media coverage on hate-motivated mass shootings tends to focus on the shooter and the shooter’s ideology. In Section 2.3, I provide evidence that people show high interest in information related to the shooter and the shooter’s ideology. The matching preferences suggest whenever a hate-motivated mass shooting happens, there will be a high exposure to the shooter’s hateful beliefs and ideas. The comparison of the Hate Ideology Treatment and the Hate Treatment allows me to isolate the impact of media’s emphasis on the shooter’s hateful ideology on the audience’s attitudes toward the shooter and the victimized group.

### 3.2.4 Treatment 4: Hate & Background

The Hate Background Treatment builds on the Hate Treatment by adding details on the shooter’s identity and background, including his name, photo, and words from former classmates who saw the shooter depressed and bullied in high school:<sup>31</sup>

Police officers were interviewing the suspect, Patrick Crusius, a 21-year-old white man from Allen, Tex.

Investigators are looking into whether Crusius might have been radicalized online. But friends and former teachers and classmates say he might have been hardened, too, by the tensions in his changing community in real life.

Allison Pettitt, a classmate, said she saw Crusius pushed around in the hallways and “cussed out by some of the Spanish-speaking kids.” She said that bullying was common at the school and that teachers often ignored it. “He started getting more depressed closer to the end of junior year,” Pettitt said. “He started wearing a trench coat to school and becoming more antisocial and withdrawn.” Lesley Range-Stanton, a spokeswoman for Plano’s school district, declined to comment about whether Crusius was bullied, citing student privacy.

The Hate Background Treatment investigates how a news story with emphasis on the shooter’s identity and background story affects viewer’s attitudes. While the attention given to the shooter from the media combined with the high interest from the public will likely lead to an increase of exposure to the shooter’s ideology, it can also lead to an increase of exposure to other information related to the shooter. For example, people will likely encounter information about the identity and background of the shooter, including biography, life story, quotes from friends and neighbors’ depiction. Although media often portrays the shooter from various angles, I choose a story that hints at the shooter’s poor mental health condition because of its frequent occurrence on the news. The idea that there exists a link between mental illness and mass shootings is indeed often discussed in the media and in scholarly research. Despite increasing evidence that mental illness does not cause mass shootings, it is heavily debated. Depending on the criteria, the proportion of mass shootings associated with mental illness

---

<sup>31</sup>The wordings are taken from an article published on [The Washington Post](#).

varies from 4.7% to 78% across studies Parks et al. (2019). Consequently, news coverage of mass shootings and other violent events often features discussion about the offender’s mental health (Swanson et al., 2015; McGinty et al., 2016; DeFoster & Swalve, 2018; Duxbury et al., 2018). A database compiled by Mother Jones shows about 63.2% of mass shootings are linked to news stories about the shooter’s mental health.<sup>32</sup> Therefore, the Hate Background Treatment closely resembles the way that news outlets cover mass shootings. In section 2.3, I provide evidence that people frequently search for information related to the shooter following a hate-motivated mass shooting. This suggests that people will very likely encounter news stories about the shooter’s mental health sufferings either through direct news coverage or online searching. The comparison of the Hate Background Treatment and the Hate Treatment allows me to identify the impact of a stereotypical story about the shooter’s childhood suffering may have on the audience attitudes toward both the shooter and the shooter’s ideology.

### 3.3 Hypotheses

Building on existing literature and the patterns I found using observational data, I derive three hypotheses.

**Hypothesis 1.** *The Hate Ideology Treatment and the Hate Background treatment increases subjects’ interest in the shooter.*

Media plays an important role in informing the public of criminal incidents. Recent survey shows Americans rate crime as one of the most important news topics for daily life (Center, 2019). In section 2.3, I showed that compared to non-hate-motivated mass shootings, people show significantly higher interest in the shooter in hate-motivated mass shootings. Moreover, this pattern matches media’s tendency to focus on the shooter when covering hate-motivated mass shootings. The Hate Ideology Treatment and the Hate Background Treatment mimic the media’s emphasis on the shooter. Therefore, I hypothesize subjects in these two treatments will show higher interest in the shooting and the shooter.

**Hypothesis 2.** *The Hate Ideology Treatment increases subjects’ support for the shooter’s ideology.*

Existing studies in criminology and psychology argue that media coverage of mass shootings could generate negative consequences through behavioral contagion (see Lankford & Madfis, 2018a for a review), e.g., people might find inspiration from the shooter, endorse the shooter’s ideology, and possibly also imitate the shooter’s actions, leading to more crimes. In Section 2.2, I showed that whenever a hate-motivated mass shooting happens, news outlets tend to spend more time covering the shooter, including the shooter’s ideology. In Section 2.3, I showed

---

<sup>32</sup>This data can be accessed at <https://www.motherjones.com/politics/2012/12/mass-shootings-mother-jones-full-data/>. For more references on media’s portray of mass shooting and mental illness, see Klein, 2012; Saad, 2013; McGinty et al., 2014; Metzl & MacLeish, 2015; Fox & Fridel, 2016; Lankford & Cowan, 2020. Note that the FBI has been calling for the media to reduce coverage featuring the offender’s life stories. However this effort seems futile. See [here](#).

that people express more interest in the shooters of hate-motivated mass shootings. The combination of these two findings imply that, whenever a hate-motivated mass shooting occurs, the public is likely subject to an increased and prolonged exposure to the shooter’s hateful ideology. While recent literature suggests that positive information about a minority group can improve people’s attitude toward that minority group (Grigorieff et al., 2020; Haaland & Roth, 2020; Haaland & Roth, 2021; Song, 2021; Settele, 2022), the effect of negative information such as racism is largely unknown. It is entirely possible that exposure to such information about a minority group can increase anti-minority beliefs and behaviors. If that is the case, knowing the shooter’s anti-immigrant ideology could worsen people’s attitudes toward immigrants. In section 2.4, using an event study framework, I showed that immediately following a hate-motivated mass shooting, there is an increase in hate crimes against the same victimized group. Building on these findings and the existing literature, I hypothesize that the Hate Ideology Treatment, which mimics media’s emphasis on the shooter’s ideology when covering hate-motivated mass shootings, will increase subjects’ support for the shooter’s ideology.

**Hypothesis 3.** *The Hate Background Treatment increases subjects’ support for the shooter and the shooter’s ideology.*

As discussed in the previous subsection, it is common to find news stories that link mass shooter’s act to histories of abuse, being bullied, and difficult childhoods. Unsurprisingly, survey evidence shows the public blames mental health as the top reason for gun violence.<sup>33</sup> The Hate Background Treatment mimics media’s emphasis on the struggling of the shooter. On the one hand, this may increase people’s sympathy for the shooter. On the other hand, people might blame immigrants for the shooter’s suffering and thereby increase their anti-immigrant sentiments. Taken altogether, I hypothesize that subjects in the Hate Background Treatment will show higher support for the shooter and the shooter’s ideology.

**Hypothesis 4.** *The Hate Ideology Treatment and the Hate Background Treatment have differential impacts on subjects depending on their initial biases against immigrants.*

Conceptually, the Hate Ideology Treatment and the Hate Background Treatment can change people’s attitude in three ways. First, emphasis on the shooter may serve as a persuasion device (DellaVigna & Gentzkow, 2010). The Hate Ideology Treatment introduces the shooter’s hateful ideas to subjects and could persuade them to accept the ideas. Similarly, the Hate Background Treatment introduces the shooter’s struggles and could persuade subjects to increase sympathy for the shooter. This effect should be more pronounced for subjects whose prior toward the victimized group is neutral, i.e., near the middle of the distribution. Second, emphasis on the shooter may serve as a coordination device (Arias, 2019). The Hate Ideology Treatment spreads the shooter’s hateful ideas to all subjects and may thereby increase subjects’ perceived popularity of the hateful ideas. In a similar fashion, the Hate Background Treatment could change subjects’ perceived acceptability of supporting the shooter. Consequently, subjects with pre-existing bias may become more comfortable expressing support for the shooter and

---

<sup>33</sup>For example, click [here](#) and [here](#) to see the reports.



the hateful views given their updated beliefs. Taken together, I hypothesize that subjects with different initial bias against immigrants will respond differently to the Hate Ideology Treatment and the Hate Background Treatment.

### 3.4 Outcome measures

I have four primary outcomes: 1) interest in the shooter, 2) attitudes toward the shooter, 3) attitudes toward the shooter’s anti-immigrant ideology, 4) interest in a white supremacy hate group.

Specifically, my experiment aims at answering three questions. First, does the way the media covers hate-motivated mass shootings cause an increase in people’s interest in the shooting, the shooter and the shooter’s ideology? Second, does the way the media covers hate-motivated mass shootings affect the audience’s attitudes toward the shooter and/or the shooter’s ideology? In particular, by emphasizing the hateful ideology or by disclosing the shooter’s identity and background, could media coverage induce people to justify the crime and sympathize with the shooter, or to express support for the hate ideology, possibly leading to more hatred toward the victimized group? Third, does the effect of media coverage on hatred depend on people’s pre-existing views regarding the victimized group?

#### 3.4.1 Outcome 1: Interest in the shooter’s ideology and background

My first outcome attempts to address *Hypothesis 1*, i.e., whether media coverage of hate-motivated mass shootings causally increases the audience’s interests in the shooter. After subjects read the news story, I ask them if they would like to receive full access to the shooter’s manifesto and if they would like to receive more information on the shooter’s identity and background. Both questions are binary, subjects are told that if they choose yes, they would receive access to the information at the end of the survey ([Chopra et al., 2022](#)).

There are several reasons that make this outcome a valid behavioral measure. First, in a real-world setting, it is typical that readers would see the title or a preview of the story first and then decide to read the story, or search for additional information, as documented by the google search data I analyzed in Section 2.3 of this paper. Second, since subjects are paid a pre-specified reward upon completion of the survey, by choosing to receive more information, subjects are committing to spending more time on the survey, therefore paying a cost to access the additional information on the shooter. Third, one could argue that subjects interested in the shooter’s manifesto and background story could access the information provided at the end of the survey independently. They could search for such information by themselves after completing the survey, especially in the Hate Background Treatment where the identity of the shooter was disclosed. However, searching for information outside the survey would come at an additional cost (of time). Therefore, it is reasonable to believe that interested individuals would prefer to access such information while participating in the study.

### 3.4.2 Outcome 2: Attitudes toward the shooter

To test *Hypothesis 2A*, I ask subjects three survey questions that measures their support and sympathy for the shooter: 1) whether they admire the shooter’s courage, 2) whether they think the shooter’s action can be justified, 3) what is the appropriate sentencing for the shooter. Admiration and justification are asked on a 5-point Likert Scale. Sentencing options range from 10 years or less imprisonment to the death penalty. The exact survey script is provided in Appendix B.

Mass shooters often regard previous shooters as role models or inspiration. [Langman \(2018\)](#) shows this connection is mainly formed through heroic idolization and shared sympathy. Thus, I design my attitudinal measures to capture these two aspects. In addition, having three measures allows me to cross check the identified treatment effects. One might be concerned that having a group of similar outcomes is susceptible to bias due to multiple hypothesis testing. To address this concern, I compute a standardized index of support, as further explained in Section 3.6.

### 3.4.3 Outcome 3: attitudes toward the shooter’s ideology

I test *Hypothesis 2B* by measuring subjects’ attitude toward the shooter’s ideology (Anti-Hispanic, Anti-immigrant). Ideally, my goal is to measure hatred towards the victimized group and willingness to commit crimes against them. However, this is challenging from both a design and ethical perspective. As a workaround, I construct a behavioral measure of subjects’ support for anti-immigration. To do so, subjects are told that they will be given the opportunity to authorize a \$1 donation to one randomly chosen organization. The organization will either be an anti-immigrant or a pro-immigrant organization.<sup>34</sup> Subjects see a brief description of only their randomly assigned organization before authorizing to donate. Subjects are also explicitly told that if they authorize the donation, the \$1 will not be deducted from their payoff, they are simply authorizing it. This donation setup follows the methodology introduced by [Bursztyn, Egorov, and Fiorin \(2020\)](#) in the context of measuring anti-immigrant sentiment.<sup>35</sup> An alternative design would be to ask subjects to make donations out of their own money. However, given the sensitive nature of the causes supported by the organizations of interest, subjects might feel more reluctant to make the donation.

In the experiment, about 75% of the subjects are assigned to The Federation for American Immigration Reform (FAIR, an anti-immigrant organization), while about 25% of the subjects are assigned to American Immigration Council (AIC, a pro-immigrant organization). The primary outcome of interest is the willingness to authorize donations to FAIR. To make sure that donating to FAIR captures more of a resentment and hatred toward immigrants instead

---

<sup>34</sup>In the experiment, subjects know that the organization will be randomly selected, but do not know it is restricted to two immigration organizations.

<sup>35</sup>Donation to organizations is widely used as an outcome measure in information provision experiment. For example, see [Alesina et al., 2018](#); [Bursztyn, Egorov, & Fiorin, 2020](#); [Bursztyn, Haaland, et al., 2020](#); [Grigorieff et al., 2020](#); [Haaland & Roth, 2021](#).

of reasonable support for stricter immigration policy, I made it clear in the description of FAIR, that this is an anti-immigrant organization with ties to white-supremacy groups and has made many racist comments. The pro-immigrant organization and the randomization of subjects to be shown one of the two organizations serve three purposes. First, it reduces experimenter demand effects by masking the true intent of the experiment. Subjects are told that one organization will be randomly selected and only see the chosen organization. Thus, it should be more difficult to relate the experiment to anti-immigrant sentiment. Second, the donation to the pro-immigrant organization serves as a robustness check. Assuming that the support for anti-immigration and pro-immigration are mutually exclusive, then the change in donation rate to the two organizations should move in opposite directions. Thus, if one treatment condition increases the donation rate to the anti-immigrant organization, it should decrease the donation rate to the pro-immigrant organization. Measuring subjects' donation to the pro-immigrant organization allows me to cross check the treatment effect on support for anti-immigrant. Finally, it is possible that the news coverage of hate-motivated mass-shootings have differential impact on attitudes towards the shooter and attitudes toward the victims. The emphasis on the hate ideology of the shooter may, for instance, increase support for the shooter from some individuals, and increase support for the victimized group from other individuals. My design allows me to test for this possibility.

#### 3.4.4 Outcome 4: Interest in a white supremacy hate group

To further test *Hypothesis 2B*, I construct a more direct measure of hatred by measuring subjects' interest in a white supremacy hate group. Subjects are given a brief description of a hate group named Stormfront, the oldest and one of the largest hate site, then asked if they want to receive links to access its website. If subject expresses interest, they will receive links at the end of the survey. I then track whether subjects clicked on the provided links.<sup>36</sup>

This measure complements the donation outcome for several reasons. First, the interest in hate group is a closer proxy for hatred. Many shooters wrote and post manifestos on online hate groups before committing the shooting. Second, it is possible that subjects hate immigrants but do not donate to an anti-immigrant organization. This might be because they do not trust the organization, might be because they do not think a \$1 donation will make a difference. In comparison, subject can access the hate group and “do things” by themselves. Third, it is possible that the treatment effects do not immediately translate into instant action. Many past mass shooters admitted that they are radicalized online.<sup>37</sup> The interest in hate group can capture this intermediate effect.

One might be concerned that subjects may simply request and click on the links out of curiosity rather than hatred. To minimize this concern, I make sure that subjects are aware

---

<sup>36</sup>The clicking is tracked using JavaScript embedded in the Qualtrics survey. Subjects are not aware that their clicking can be tracked.

<sup>37</sup>For example, the 2022 Buffalo supermarket shooter references a 4chan board devoted to guns, and says he was radicalised by the /pol/ or “politically incorrect” board. For further information see [this](#) article published by BBC.

that this hate group is founded by long-time white supremacist and is actively promoting white supremacy. If requests and clicks are driven by curiosity, then I should expect to see a large volume of requests and clicks. I address this issue again in Section 4.2.4.

### 3.4.5 Other survey measures to detect mechanism

My secondary analysis aims at identifying the mechanism behind the treatment effects. My treatments of interest are the Hate Ideology Treatment and the Hate Background Treatment, the news stories presented in both treatments provide extra information about the shooter. As discussed in *Hypothesis 4*, news coverage that focuses on the shooter can affect people's attitude through two channels. First, news stories that provide details on the shooter's anti-immigrant ideologies may persuade viewers into accepting the shooter's beliefs. Similarly, news stories that provide details on the shooter's struggles (traumatic childhood, bullied) may persuade viewers into sympathizing with the shooter. Second, news stories may change people's perception about the local popularity of anti-immigrant sentiment. Thus, people with an initial bias towards immigrant might find it more comfortable expressing support for the shooter and the shooter's ideology.

First, to examine whether news stories about the shooter can persuade people with no initial bias against immigrants to hate immigrants, I measure subjects' baseline attitudes before the information treatment. I elicit subjects' opinions on 6 political issues including abortion, same-sex marriage, gun control, minimum wage, build the wall, and citizenship for children of illegal immigrants.<sup>38</sup> Although my primary interest is the two immigration-related questions, the four questions on other political issues can reduce experimenter demand effect. It also helps me evaluate the subject's political stance more generally. Detailed survey script is provided in Appendix B.4.1. If the persuasion mechanism is present, I should expect to see less treatment effects for subjects with strong initial bias since they are already persuaded.

Second, to examine whether news stories about the shooter can change subjects' perceived popularity of the shooter and the shooter's ideology, I elicit subjects' perception of social norms. After subjects complete the survey module on the attitudes toward the shooter described in Section 3.4.2, all subjects except for the first 200 are asked to guess the option that was chosen the most by the first 200 subjects. Subjects are paid \$0.2 for each correct guess.<sup>39</sup> Similarly, I elicit subjects' perceived popularity of anti-immigrant sentiment. After subjects complete the donation question described in Section 3.4.3, they are asked to report what they think is the percentage of previous subjects who authorized the donation. Subjects are rewarded \$0.2 if the difference between their guess and the true answer is less than or equal to 2. If the treatment effects operate through the social norm channel, I should expect subjects' perception of social norms to move in the same direction as their actual behavior across different treatments.

Admittedly, the two mechanisms could coexist at the same time and it is difficult to disentangle them perfectly. These additional survey questions allow me to gain more insight into

---

<sup>38</sup>These topics are taken from popular political issues on [iSideWith.com](https://www.isidewith.com).

<sup>39</sup>See Appendix B.3.9 for the survey script.

what is behind the treatment effects.

### 3.5 Sample and Procedure

I recruit survey participants from two online recruiting platforms, Prolific and CloudResearch. Studies that compare data quality of behavioral research across online platforms consistently find that Prolific and CloudResearch produce high quality data that is comparable to laboratory experiment (Gupta et al., 2021; Peer et al., 2022). Recruiting from two platforms is important for my research as it allows me to cross check my findings and increases the reliability of my results. In addition, both platforms strictly forbid researchers from asking participants for their identifiable information. This enforced anonymity protects participants' privacy and is especially important for research on sensitive topics as it minimizes experimenter demand effects and social desirability bias. Finally, it is worth pointing out that recent evidence shows that the size of experimenter demand effect in online survey experiments is small. The knowledge of the experiment's purpose has no detectable effect on participants' behaviors (De Quidt et al., 2018; Mummolo & Peterson, 2019).

To maximize statistical power within my budget constraint, I only recruited subjects who met all the following conditions:

1. Identified themselves as Republican or Democrat.
2. Identified themselves as male.
3. Currently resides in the United States.
4. Has a Minimum approval rate of 95%.<sup>40</sup>

I target both Republicans and Democrats for two reasons. First, It is well established that Americans' attitudes about race and gender are divided by partisanship (for example, Horowitz et al., 2017; Doherty et al., 2019). Recent survey evidence shows that while the majority of Democrats perceive establishing a path to legal status for immigrants as the top priority in immigration policy, the majority Republicans prioritize increasing border security and deportations of illegal immigrants.<sup>41</sup> Moreover, political speeches on immigration has become increasingly polarized. Computational analysis of US congressional speeches and presidential communications shows that Republicans are more likely to frame immigration in negative terms such as "crime" and "threats," while Democrats tend to use more positive framing such as "family" and "contribution" (Card et al., 2022). Thus, it is very likely that people who identify as Democrats and people who identify as Republicans will have very different views about immigration and immigrants. Since immigrant is the population that was targeted in the shooting on the news story, Stratifying the recruitment and the randomization by political affiliation allows me to test *Hypothesis 3*, i.e., whether the emphasis of the media coverage on the shooter and the shooter's ideology has a differential impact on the audience based on ex-ante biases towards the victimized group.

---

<sup>40</sup>A user's approval rate is the number of approved submissions divided by the number of total submissions.

<sup>41</sup>For example, click [here](#) to see a report by Pew Research Center.

I recruit male subjects because men are far more likely to commit hate crimes than women. According to the FBI, the most common hate crime offense are vandalism, simple assault, and aggravated assault.<sup>42</sup> While the FBI does not publish hate crime statistics by sex, it is evident that men commits these offenses far more often than women. Men account for 76.5% of arrests for aggravate assault, 70.6% of arrests for other assaults, and 76.8% of arrests for vandalism.<sup>43</sup> Although it is possible that women express more hatred than men, data suggests they do so in a less violent and extreme manner. In addition, since gender is not the focus of my study, recruiting only male subjects allows me to eliminate gender heterogeneity and increases statistical power. The experimental procedure including the inclusion restriction was preregistered on AsPredicted (#74996).

### 3.6 Estimation Strategy

I tests the effects of the information treatments on subjects' outcome measures by estimating the following equation using OLS on the full sample:

$$Y_i = \alpha + \beta_1 T_{1i} + \beta_2 T_{3i} + \beta_3 T_{4i} + \delta X_i + \epsilon_i \quad (1)$$

Where  $Y_i$  is the 4 sets of outcome variables described in Section 3.4.  $T_{1i}$  is an indicator variable that equals 1 if subject  $i$  is assigned to the No Hate Treatment, 0 otherwise. Similarly,  $T_{3i}$  is an indicator variable for the Hate Ideology Treatment,  $T_{4i}$  is an indicator variable for the Hate Background Treatment. The Hate Treatment is the omitted group in regression analysis.  $X$  is a set of individual characteristics measured before the information treatment: age, education level, income level, an indicator variable that equals 1 if the subject is White or Caucasian, an index for fame-seeking personality constructed using the Big 5 modesty measure (Konstabel et al., 2012),<sup>44</sup> an index for political stance constructed using subjects' stated views on a list of controversial political issues as described in Section 3.4.5, and an indicator variable that equals 1 if the subject is recruited from CloudResearch.  $\beta_1$  captures the extent to which people naturally react to hate-motivated mass shootings differently.  $\beta_2$  and  $\beta_3$  capture the impacts of media emphasis on the shooter's ideology and media emphasis on the shooter's background on viewers' attitudes.

In order to statistically test whether there are heterogeneous treatment effects by baseline bias toward immigrants as specified in *Hypothesis 3*, I estimate equation 1 separately for the Democrat sample and the Republican sample. In addition, I estimate equation 2 below, where I pool the two samples and include interactions between the treatment dummies and a dummy

---

<sup>42</sup>See FBI's 2020 hate crime statistics [here](#).

<sup>43</sup>See FBI's latest release [here](#).

<sup>44</sup>The literature on mass shootings points out that shooters often have a desire for fame and attention (Bushman, 2018; Langman, 2018; Lankford & Madfis, 2018b; Silva & Greene-Colozzi, 2019).



for political affiliations.

$$\begin{aligned}
Y_i = & \alpha + \beta_1 T_{1i} + \beta_2 T_{3i} + \beta_3 T_{4i} \\
& + \beta_4 T_{1i} * Republican_i + \beta_5 T_{3i} * Republican_i + \beta_6 T_{4i} * Republican_i \\
& + \gamma Republican_i + \delta X_i + \epsilon_i
\end{aligned} \tag{2}$$

$Republican_i$  is a dummy that equals to 1 if subject  $i$  is from the Republican sample. In this specification,  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  capture the treatment effects on subjects from the Democrat sample, whom I hypothesize to hold less ex-ante bias towards immigrants.  $\beta_4$ ,  $\beta_5$ ,  $\beta_6$  capture the differential impacts of treatments on subjects from the Republican sample, whom I hypothesize to hold stronger ex-ante bias.

Since I have three outcome measures for attitudes toward the shooter, one concern would be multiple hypothesis testing causing false rejection of true null hypotheses. To address this concern, I construct a standardized index of support using responses to all three questions. I first standardize the response to each question with respect to the mean and standard deviation of the Hate Treatment. I then construct an inverse covariance weighted index using [Anderson \(2008\)](#)'s method. In addition, I report the sharpened False Discovery Rate (FDR) q-values in the Appendix.

As a secondary analysis, I examine possible mechanisms as specified in Section 3.4.5. In addition to investigating whether there are heterogeneous treatment effects between the Democrat sample and the Republican sample, I examine whether there are heterogeneous treatment effects within each sub-sample by estimating the following equation.

$$\begin{aligned}
Y_i = & \alpha + \beta_1 T_{1i} + \beta_2 T_{3i} + \beta_3 T_{4i} \\
& + \beta_4 T_{1i} * Political_i + \beta_5 T_{3i} * Political_i \\
& + \beta_6 T_{4i} * Political_i + \gamma Political_i + \delta X_i + \epsilon_i
\end{aligned} \tag{3}$$

Where  $Political_i$  is an index for subject  $i$ 's political stance constructed using the subject's response to six controversial political issue questions as explained in Section 3.4.5. An answer that aligns with the Democratic Party ideology will be coded as a 0, an answer that aligns with the Republican Party ideology will be coded as a 1. To generate an index, I calculate the average of the responses to all six questions, weighted by the inverse covariance matrix as [Anderson \(2008\)](#). The index is a continuous variable between 0 and 1 where a higher value represents a more right-leaning political stance. If the news treatments are persuading people with no initial bias against immigrants to hold bias, I should expect to see stronger treatment effects for people who are closed to the center of the political distribution, i.e., right-leaning Democrats and left-leaning Republicans. If that is the case, the estimated  $\beta_5$  and  $\beta_6$  should be positive for the Democrat sample, and negative for the Republican sample.

To examine whether changes in the perception of social norm serve as the mechanism behind the treatment effects. I estimate the same specification as equation 1, except that the outcome variables are replaced with the elicited norm measures. I conduct this exercise using the pooled sample, as well as the two sub-samples separately.

## 4 Results

In this section, I present the results from my experiment. Section 4.1 reports descriptive statistics of my sample. Section 4.2 reports treatment effects. Section 4.3 reports results from secondary analyses to identify the mechanism. Section 4.4 reports results from several robustness checks.

### 4.1 Descriptive Statistics

I recruited 1600 subjects from Prolific between Fall 2021 to Summer 2022. I recruited 800 subjects from CloudResearch in Fall 2022. I stratified the recruitment and treatment assignment by political affiliation such that there is an equal number of Democrats and Republicans in each treatment condition. The experiment was programmed in Qualtrics. Subjects were paid \$2.67 for completing the survey,<sup>45</sup> and had the chance to earn up to \$1.2 of bonus payment.<sup>46</sup> The average completion time is around 16 minutes. The actual hourly earning translates into around \$14/hour, which is considerably high for online surveys.<sup>47</sup> In terms of data quality, 83.58% of subjects answered both comprehension questions correctly, 86.38% subjects passed both attention checks.

Table 1 reports demographic characteristics of my sample. Panel A reports the demographics of the full sample. Panel B and Panel C report the demographics of the Democrat sample and the Republican sample respectively. The last column of the table reports the p-value of an ANOVA test against the null hypothesis that subjects across the four experimental treatment conditions are not jointly different from each other. Subjects on average are around 38 years old and college educated. Overall, the full sample and the two sub-samples are balanced across different treatment conditions except for two instances. I account for these imbalances in the empirical analysis by controlling for the imbalanced variables.

There are several differences in demographics between the Democrat sample and the Republican sample. Panel A of Appendix Table A9 reports test statistics for the Democrat sample vs Republican sample. On average, subjects from the democrat sample are younger, have higher education, lower income, less likely to be white, less fame-seeking. Unsurprisingly, the political index shows that the Democrat sample is much more left-leaning compared to the Republican sample (0.08 vs 0.62, p-value=0).<sup>48</sup>

In addition, there are several differences in demographics between Prolific subjects and CloudResearch subjects. Panel B of Appendix Table A9 shows that on average, subjects from

---

<sup>45</sup>The completion fee for subjects who participated before April 2022 is \$2.17. Prolific increased its minimum wage from \$6.5 to \$8 an hour in April 2022. Thus, the completion fee for subsequent experiments is increased to \$2.67.

<sup>46</sup>As explained in Section 3.4, the incentivized norm questions are unavailable for the first 200 subjects in each sample. The maximum bonus for the initial 200 subjects is \$0.4 from answering comprehension questions correctly.

<sup>47</sup>For example, the average earnings on MTurk is \$2 per hour (Hara et al., 2018).

<sup>48</sup>The distribution of political stance is shown in Appendix Figure A1.

the Prolific sample are younger, more educated, have higher income, and more left-leaning. To account for the difference in recruiting platform in the regression analysis, I control for a dummy that equals 1 if the subject is recruited from CloudResearch. One concern is subjects who are registered on CloudResearch could also be registered on Prolific. Thus, it is possible that the same person will participate in the experiment twice. To investigate this possibility, I additionally ask subjects from CloudResearch two questions in the end of the survey: 1) Are you registered on other recruiting platforms other than MTurk? 2) Have you seen this survey before on a different platform? While about 13% of CloudResearch subjects are also registered Prolific, only about 1% (10 subjects) say they saw the same survey before. Therefore, this concern is trivial.

## 4.2 Treatment Effects

In this subsection, I compare different contents of news coverage and examine whether news coverage of hate-motivated mass shootings causally increased hatred. Section 4.2.1 tests *Hypothesis 1* by examining the treatment effect on information demand. Section 4.2.2 tests *Hypothesis 2A* by examining the treatment effect on support for the shooter. Section 4.2.3 and Section 4.2.4 test *Hypothesis 2B* by examining the treatment effect on donation rate to the anti-immigrant organization and the treatment effect on interest in white supremacy hate group. As specified in my pre-analysis plan, I also investigate heterogeneous treatment effects by political affiliation.

### 4.2.1 Treatment effects on public interest

I test *Hypothesis 1*, i.e., whether media coverage of hate-motivated mass shootings increases viewers' interest. Panel A of Table 2 reports estimates from equation 1 using the full sample. The dependent variables are an indicator variable that equals 1 if the subject requests to receive the shooter's full manifesto, and an indicator variable that equals 1 if the subject requests to receive more information about the shooter's background. For each variable, I report estimates without controls in odd columns, and estimates with controls in even columns.

I start by comparing the information demand in the No Hate Treatment and the Hate Treatment. The two treatment conditions are identical, except that the Hate Treatment mentions the hateful nature of the shooting. In Section 2, I showed that the media has a tendency to focus on the shooter in hate-motivated mass shootings. Moreover, the online searching behavior after mass shootings reveals that people show much higher interest when the shooting is hate-motivated. One possible explanation is hate crimes simply draw more attention from people, regardless of what the media does. In which case subjects in the Hate Treatment should show higher information demand compared to subjects in the No Hate Treatment.

Estimates in Panel A of Table 2 shows the contrary: subjects' information demand significantly decreased when they learn that the shooting is hate-motivated. Compared with subjects in the Hate Treatment, subjects in the No Hate Treatment are 5.7 percentage points more likely to request information about the shooter's ideology, and 5.9 percentage points more

likely to request information about the shooter’s background. This pattern shows that people are not naturally more interested in hate-motivated mass shootings. If anything, the decrease in information demand in the Hate Treatment suggests that people have a natural distaste for hate crimes. This implies that the difference in viewer’s interest displayed in the observational data is likely to be caused by media coverage instead of viewer’s natural preferences, either through the difference in content, or the difference in intensity/duration.

I then investigate whether differences in the content of news coverage causes difference in public interest. Recall that compared to subjects in the Hate Treatment, subjects in the Hate Ideology Treatment saw additional information on the shooter’s ideology, and subjects in the Hate Background Treatment saw additional information on the shooter’s background. Estimates in Panel A of Table 2 show that subjects who are assigned to the more informative treatment conditions show significantly less interest in receiving more information. In fact, the decrease in information demand is the largest when subjects read the news story that covers that information. Subjects in the Hate Ideology Treatment are 8.25 percentage points less likely to request information about the shooter’s ideology (compared to a mean of 43.59 percent in the Hate Treatment). Subjects in the Hate Background Treatment are 12.57 percentage points less likely to request information about the shooter’s background (compared to a mean of 55.74 percent in the Hate Treatment). The results are robust to the inclusion of control variables. These findings rule out the possibility that people’s high interest in hate-motivated mass shootings is driven by the content of news coverage. Instead, public interest is more likely to be driven by media’s tendency to spend more time covering hate-motivated mass shootings as shown in section 2.2.1.

Panel B and Panel C of Table 2 report estimates separately for the Democrat sample and the Republican sample. In the baseline treatment (Hate), Democrat subjects show slightly lower interest in the shooter’s manifesto (0.407 vs 0.465,  $p$ -value=0.149). The signs of the coefficients on the treatment dummies are largely consistent with that of the full sample. Subjects from both samples show lower interest in the more informative treatment conditions.

#### 4.2.2 Treatment effects on support for the shooter

I test *Hypothesis 2A*, i.e., whether the news emphasis on ideology and background of the shooter increases viewers’ support for the shooter. As described in section 3.4.2, I ask subjects three questions to measure their attitude towards the shooter: 1) How much they admire the shooter’s courage, 2) How much they believe the shooter’s action can be justified, 3) What they think the sentencing for the shooter should be. To construct an overall measure of support, I use Anderson (2008)’s method and the responses to all three questions to generate an index of support standardized around the control mean as described in Section 3.6. Thus, the index is displayed in standard deviations from the mean of the Hate Treatment.

In section 2, I showed that media has a tendency to report stories about the ideology and background of the shooter in hate-motivated mass shootings. Moreover, there is an increase in the number of hate crimes against the same population that was targeted in the shooting. If the

increase in hate crime is because of the media’s focus on the shooter that caused some people to admire, worship, or even copying the shooter, I should expect subjects in the Hate Ideology Treatment and the Hate Background Treatment to show higher support for the shooter as measured by the index.

Appendix Table A10 reports estimates from equation 1 for all three attitudinal measures and shows that they move in the same direction. Panel A of Table 3 reports estimates where the outcome variable is the support index using the same specification and the full sample. All the coefficients on treatment dummies are positive and significant. Across all treatments, subjects in the No Hate Treatment who are not informed of the shooting’s hateful nature exhibit the strongest support for the shooter. Compared to subjects in the Hate Treatment who learns that the shooting is possibly a hate crime, subjects in the No Hate Treatment significantly increase their support for the shooter by about 0.22 standard deviations. The decrease in support when subjects learn the hateful nature of the shooting is consistent with the decrease in interest shown in the last section. However, this decrease is partially mitigated when subjects are shown additional information about the shooter’s ideology in the Hate Ideology Treatment and the shooter’s background information in the Hate Background Treatment. In fact, subjects in the Hate Ideology Treatment and the Hate Background Treatment show significantly higher support for the shooter compared to subjects in the Hate Treatment. Knowing either the shooter’s ideology or the shooter’s background make subjects more supportive by about 0.12 standard deviations. The results are robust to the inclusion of control variables. These findings provide support for *Hypothesis 2A*, the news emphasis on the shooter’s ideology and background increases support for the shooter.

Panel B and Panel C of Appendix Table A10 show regressions on all three attitudinal measures separately for two sub-samples. On the aggregate level, Republican subjects show higher admiration for the shooter, higher justification for the shooter’s action, but choose harsher sentencing options for the shooter.<sup>49</sup> This pattern is consistent with Republican’s tougher attitude against immigrants, and Democrat’s stronger opposition to using the death penalty.<sup>50</sup> Panel B and Panel C of Table 3 show the regression on the standardized support index for two sub-samples separately. For both the Democrat sample and the Republican sample, the coefficient on No Hate is positive and significant. Thus, the decrease in support for the shooter when subjects learn the shooting is hate-motivated is true for regardless of ex-ante bias towards the victims. However, the coefficients on Hate Ideology and Hate Background show substantial heterogeneous treatment effects. The Hate Ideology Treatment significantly increases Republican subjects’ support for the shooter by 0.188 standard deviations, but has no effect on Democrat subjects. This finding is consistent with Demszky et al. (2019), who uses Twitter data to show that Republicans are more likely to focus on the shooter’s ideology when discussing a mass shooting. In contrast, the Hate Background Treatment significantly increases Democrat subjects’ support for the shooter by 0.265 standard deviations, but has no effect on Republican subjects. These results are confirmed by the analysis shown in column 5

---

<sup>49</sup>A t-test for mean comparison returns a p-value of 0 for all three variables.

<sup>50</sup>For example, see [This report](#).

and column 6 of Table A11, which reports estimates from equation 2 that includes interaction terms between the treatment dummies and party dummy. In fact, the level increase is almost identical for Democrat subjects in the Hate Background Treatment and Republican subjects in the Hate Ideology Treatment. The differential treatment effects provide support for *Hypothesis 3*.

It is worth pointing out that the overall level of support for the shooter shown in the experiment is quite low. The majority of subjects strongly disagree that they admire the shooter’s courage, and strongly disagree that the shooter’s action can be justified. Thus, one might question the magnitude of effect given the low baseline level. I discuss this concern in more detail in Section 4.5.

### 4.2.3 Treatment effects on support for the shooter’s ideology

I now investigate *Hypothesis 2B*: whether the news emphasis on the shooter increases viewers’ support for the shooter’s ideology, measured by donation to an anti-immigrant organization.

In the last section, I showed that subjects show higher support for the shooter when they read a news story that mentions either the shooter’s ideology or background. However, it is not clear whether this increase in support actually translates into action. It is possible that people dislikes the shooter’s hateful ideology but simply idolize the shooter as a person for other reasons. If there is indeed an increase in support for the shooter’s ideology, subjects in the Hate Ideology Treatment and the Hate Background Treatment should be more likely to authorize the donation to the anti-immigrant organization. Panel A of Table 4 reports estimates from equation 1 using the full sample. The dependent variable in column 1 and column 2 is an indicator variable that equals 1 if the subject authorized an 1\$ donation to the anti-immigrant organization. As a robustness check, I also similarly examine how the treatments affect donation to the pro-immigration organization in column 3 and column 4. First, at the baseline level, the donation rate to the pro-immigrant organization (63.8%) is considerably higher than the donation rate to the anti-immigrant organization (17.8%). This is consistent with the difference in the framing used when describing the organizations: FAIR (anti-immigrant) is described as an organization with ties to white supremacy and racism, while AIC (pro-immigrant) is described using neutral language, as an organization working to improve the US immigration system. Second, in contrast to the increase in support for the shooter shown in the last section, there’s no difference in the donation rate to either organization across all treatment conditions. None of the coefficients on treatment dummies are statistically different from zero. Therefore, there is no evidence that the content of media coverage affected the support for the shooter’s anti-immigrant ideology.

While the estimates from the full sample does not support *Hypothesis 2B*, the null results could be due to two reasons. First, it is possible that my news treatments are not strong enough to generate changes in behavior. As shown in Section 2.2, the intensity of media coverage on hate-motivated mass shootings is high. It is likely that news viewers are repeatedly exposed to stories about the shooter’s ideology and background. Thus, a one time exposure in my



experiment might not be sufficient. Second, it is also possible that there is heterogeneity in treatment effects as suggested in *Hypothesis 3*, and this heterogeneity caused the overall lack of effects.

I investigate heterogeneous treatment effects by estimating equation 1 separately for the Democrat sample and Republican sample. Estimates are reported in Panel B and Panel C of Table 4. First, consistent with the partisan and ideological differences on immigration policy, Republican subjects are significantly more likely to donate to the anti-immigrant organization (0.278 vs 0.114 in the Hate Treatment,  $p\text{-value}=0$ ), and significantly less likely to donate to the pro-immigrant organization compared to Democrat subjects (0.457 vs 0.778 in the Hate Treatment,  $p\text{-value}=0$ ). The coefficient on the Hate Background Treatment shows substantial heterogeneous treatment effects by political affiliation. Democrat subjects significantly increase their likelihood of donating to the anti-immigrant organization by about 7 percentage points (61% increase) when they are given background information of the shooter. This pattern is consistent with the increase in support for the shooter as shown in the last subsection. In contrast, the same treatment condition significantly decreases Republican subjects' likelihood of donating to the anti-immigrant organization by 9.3 percentage points (33% decrease). These results are confirmed by the estimates shown in column 7 and column 8 of Table A11. When the news story contains information shooter's background, subjects from the Democrat sample who are generally characterized by their friendly attitude towards immigrants, become more anti-immigrants, subjects from the Republican sample who are generally characterized by their unfavorable attitude towards immigrants, decreases their support for anti-immigrant ideology. The contrasting treatment effects on Democrats and Republicans support *Hypothesis 3*.

In contrast, the likelihood of donating to the pro-immigrant organization is not statistically different across different treatment conditions for either Democrat subjects or Republican subjects. While I expect the information treatments to affect the support for pro-immigrant in opposite directions, there are several factors that can explain the null effect. First, by design, only 25% of the subjects are given the opportunity to donate to the pro-immigrant organization. Thus, the small sample size might not be statistically sufficient to detect any variation. Second, people might not perceive AIC (pro-immigrant) as the opposite of FAIR (anti-immigrant). By design, FAIR is described in strong language to make sure subjects understand the organization's stance. In compassion, AIC is described in neutral language as an organization whose goal is to improve the immigration system of United States. Thus, it is possible that subjects with anti-immigrant sentiment would nevertheless donate to AIC. Third, the results might be caused by social desirability bias. In particular, donating to a pro-immigrant organization may be perceived as especially desirable. Thus, subjects would authorize the donation regardless of the news story they see. I discuss issues related to social desirability bias in more detail in Section 4.4.

#### 4.2.4 Treatment effects on interest in hate group

To further test *Hypothesis 2B*, I examine the treatment effect on subjects' interest in a white-supremacy hate group named Stormfront. In the survey, subjects are shown a description of the hate group, and are asked if they would like to receive links to the hate group's website. I examine two outcomes: 1) whether a subject requested the links, 2) whether a subject actually clicked on the links after requesting them. First, it is worth pointing out that the fraction of subjects who expressed interest is extremely low. At the aggregate level, only 10.67% of the subjects requested the links for accessing Stormfront's website, and only 1.04% of the subjects clicked on the links. The low volume of requests and clicks shows that the interest in hate group is unlikely to be driven by pure curiosity. Therefore, the variation in interest is at least partially capturing the change in hatred. However, consistent with the null result in donation rate, subjects' interest does not vary by treatment conditions. Table 5 presents estimates from equation 1. There is no statistically significant difference in the percentage of subjects who requested the links or the percentage of subjects who clicked on the links across different treatment conditions. This result does not support *Hypothesis 2B*.

Panel B and Panel C of Table 5 report the estimates from equation 1 separately for the Democrat sample and the Republican sample. First, consistent with the higher support for the shooter and the higher donation rate to the anti-immigrant organization shown in previous subsections, Republican subjects are more likely to request the links for access at the baseline (0.13 vs 0.067, p-value=0.01). Second, for both samples, the percentage of subjects who requested the links does not seem to vary much across different treatments.

There is some evidence that the Hate Background Treatment increases Democrat subjects' likelihood of requesting the links by 4 percentage points (60% increase, p-value=0.076). This pattern is consistent with the increase in support for the shooter and the shooter's ideology shown in previous subsections. When Democrat subjects learn about the shooter's background story, they increase their support for the shooter measured by admiration, justification, and sentencing for the shooter, they increase their support for the shooter's ideology measured by a \$1 donation to an anti-immigrant organization, and they show higher interest in white supremacy hate groups. However, my sample size is not large enough for a more precise estimate. Moreover, the same treatment does not change Democrat subjects' likelihood of clicking on the links. Column 9 to column 12 of Table A11 presents estimates from the fully saturated model including interaction terms between treatment dummies and party dummy. None of the coefficients are statistically significant after controlling for demographic variables. Therefore, the estimates presented in Table 5 are susceptible to bias and should be interpreted with caution.

### 4.3 Secondary analyses

In the last section, I showed that knowing the shooter's background story increases Democrat subjects' support for the shooter, support for the shooter's ideology, and interest in white-

supremacy hate groups (suggestive evidence). In contrast, knowing the shooter’s ideology increases Republican subjects’ support for the shooter. In this section, I conduct several secondary analyses as specified in Section 3.6.

First, I examine whether there are heterogeneous treatment effects within each sub-sample by estimating equation 3. If the news treatments persuaded people to develop bias against immigrants, then the treatment effects should be driven by subjects who are positioned near the middle of the political spectrum, i.e., right-leaning Democrats and left-leaning Republicans. This population is likely to be neutral toward immigrants and thus may be especially subjective to media’s influence. Table 6 report the estimates. Panel A reports estimates for the Democrat sample. The coefficient on the interaction term between the political index and the dummy for the Hate Background Treatment is positive and significant. This shows that the observed treatment effects of knowing the shooter’s background story on Democrat subjects are entirely driven by the right leaning subjects within the Democrat sample. The magnitude of the point estimates are large. For example, for Democrat subjects in the Hate Background Treatment, a 0.1 increase (about 0.7 standard deviations) in the political index will increase their likelihood of donating to the anti-immigrant organization by 6.7 percentage points. In comparison, there is little heterogeneity within the Republican sample. The interaction terms between the political index and the treatment dummies are largely insignificant. One concern is the political index is constructed using the subject’s view on six diverse political issue questions and does not necessarily capture the subject’s attitude toward immigrants. To address this concern, I measure subjects’ attitude toward immigrants using only two political issue questions related to immigration. The results shown in Appendix Table A12 are largely consistent with Table 6. These findings provide support that the news treatments are persuading right-leaning Democrats to develop hatred toward immigrants. This is also consistent with Song (2021), who shows that racial progressive content on Twitter makes racial moderates more progressive, but has little effect on racial progressives and conservatives.

Second, I examine social norms as a possible mechanism for the treatment effects. As described in Section 3.4, I elicit subjects’ perception of social norms on the support for the shooter. I incentivize subjects to guess what they think is the option that was chosen the most by previous survey participants when asked: 1) How much they admire the shooter’s courage, 2) How much they believe the shooter’s action can be justified, 3) What they think the sentencing for the shooter should be. Subjects are rewarded \$0.2 for each correct guess. To construct an overall measure of norm perception, I standardize the response to each of the three norm questions around the control mean and use Anderson (2008)’s method to generate an index of norms. Similarly, after subjects makes the decision to donate, I incentivize them to guess what percentage of previous subjects authorized the donation. Table 7 reports estimates from equation 1 where the dependent variables are the aforementioned norm variables. Results show that subjects from both parties overestimate the social norms. For example, Democrat subjects in the Hate Treatment guessed 24% of previous survey participants authorized the donation when the true percentage is only 11%. However, the movement of subjects’ norm perceptions between treatments is closely aligned with the movement of their actual behaviors.

Democrat subjects who are shown the background story of the shooter and Republican subjects who are shown the ideology of the shooter significantly increase their their perceived popularity of the shooter. This shows that news coverage can shift subjects' perceptions of social norms. The change in acceptability of supporting the shooter and the shooter's ideology might explain the observed treatment effects.

Third, I examine whether news stories about the shooter motivate people who are seeking attention to copy the shooter. Table ?? presents estimates from equation ?. The regression specification includes treatment dummies as well as the interaction terms between the treatment dummies and an index measuring fame-seeking personality. First, Panel A shows the estimates using the full sample. The coefficients on the Fame Seeking Index is positive and significant for three main outcome measures. This suggests subjects with higher propensity for fame-seeking show higher support for the shooter, show higher support for the shooter's ideology, and show higher interest in the white supremacy hate group. The same pattern also shows in Panel B and Panel C where the estimates are based on the sub-samples. However, some of the estimates lose statistical significance possibly due to the smaller sample size. Second, this effect does not seem to differ across treatment conditions. None of the coefficients on the interaction terms are significant, with the exception of Democrat subjects in the Hate Background Treatment. This suggests that the treatment effects are not different for individuals with high propensity for fame-seeking.

## 4.4 Robustness Checks

In this subsection, I address several concerns that may threaten the validity of my results, including experimenter demand effect, inattention, recall bias, social desirability bias, and multiple hypothesis testing.

### 4.4.1 Experimenter demand effect

One concern is that my results might be driven by experimenter demand effect. For example, subjects might correctly guessed the true purpose of the experiment and thus change their behavior. In addition, since my outcome measures are particularly sensitive, my results could be especially vulnerable to bias. There are several features of my design that help address this concern. First, my experiments were conducted online. The procedure is completely anonymous. I do not have any access to the participants' identifying information. The anonymous environment should help alleviate experimenter demand effect. In addition, recent literature shows that demand effects observed in experiments and surveys are modest at best ([De Quidt et al., 2018](#)). Moreover, online survey experiments are particularly resistant to demand effects ([Mummolo & Peterson, 2019](#)).

Second, as described in Section 3, my survey implements extra layers of randomization intended to cover the true purpose of my study and reduce demand effects. One might also be concerned that participants are self-selecting into the study. However, the selection bias should be minimal. Appendix Figure A2 shows a screenshot of the study's advertisement on Prolific,

which describes the study in neutral language. Moreover, more than 90% of the participants who started the study completed the study.

Third, I ask participants an open-ended question in the end of the survey “If you had to guess, what do you think is the purpose of our study?” If the subject’s response contains words related to any of the following roots: 1)immigrant, 2)race, 3)hate, I identify that subject as correctly guessed the purpose of the study and may be prone to bias. Appendix Table A13 reports the average percentage of subjects who guessed correctly in each treatment condition. Column 1 shows that 18% of subjects overall are able to correctly guess the purpose of my study. The high proportion could be due to the diverse keywords I used for identification. Column 2 to column 4 show that only 8%,6%, and 6% of subjects guessed correctly if I restrict keywords to those related to only one of the three roots. To examine whether there is significant difference in experimenter demand effect across different treatments conditions, I estimate equation 1 where the dependent variable is a dummy that equals 1 if subject correctly guessed the purpose of the experiment. Results are reported in Appendix Table A14. Overall, subjects in the Hate Treatment are significantly more accurate than subjects in the No Hate Treatment. While there is little difference between the Hate Treatment and the Hate Background Treatment, subjects in the Hate Ideology are 4 percentage points more likely to correctly guess the experiment’s purpose (p-value=0.066). I then examine whether my results still hold if I exclude the 18% of subjects who correctly guess the purpose of my study from regressions. The estimates reported in Appendix Table 8 are very similar in magnitude compared to the main estimates in Section 4.2. More importantly, the coefficients remain statistically significant. Thus, my findings are unlikely to be driven by experimenter demand effect.

#### 4.4.2 Inattention

One concern with online survey experiment is subjects might not pay enough attention to the survey because there is no experimenter to monitor the progress. In the worst case, subjects can simply click through the whole survey by giving random responses to every question. A typical reason for poor data quality is subjects feel they are underpaid. As discussed in Section 4.1, The hourly wage in my experiment is around \$14, which is well above the average payment for online labor markets. In addition, subjects understand that they must answer some questions correctly to earn the highest amount of bonus payment. Finally, I include two attention checks in the survey. Subjects understand that they may not get paid if they failed the attention checks.

As shown in Section 4.1, 86% of the subjects passed both attention checks. Appendix Table A14 shows that the likelihood of subjects passing attention checks are largely the same across different treatment conditions, with the exception that Republican subjects in the Hate-Background Treatment are about 9 percentage points more likely to pass the attention checks. To investigate whether the 14% of subjects who failed both attention checks biased my results, I exclude those subjects and ran the same regression specifications. Table 9 reports the estimates. Although the size of the magnitude is smaller, the coefficients remain statistically significant.

Thus, my findings are unlikely to be driven by subjects not paying attention.

#### 4.4.3 Recall bias

Since the shooting I use in my experiment happened in 2019 and received nation wide attention, it is possible that subjects have seen news stories about it before. If that is the case, my results might be biased because subjects have been “treated” before. To minimize this possibility, I omitted the dates, locations, and names in the news story, except in the Hate Background Treatment, where the shooter’s name is mentioned. Nevertheless, about 22% of the subjects acknowledged in the exit survey that they have heard of the shooting before. Appendix Table A14 shows that subjects are least likely to recognize the shooting in the No Hate Treatment where the least information is given. Reassuringly, even in the Hate Ideology Treatment and the Hate Background Treatment where more information about the shooter is given, subjects are not more likely to recognize the shooting.

To investigate whether the 22% of the subjects who recognized the shooting causes bias in my results, I exclude these subjects and run the same regression specifications. The estimates are shown in Table 10. While the effects of the Hate Background Treatment on Democrat subjects’ support for the shooter and the shooter’s ideology are still evident, the treatment effects on the Republican sample are largely lost. Overall, the estimates are smaller in magnitude compared to the estimates presented in Section 4.2. There are two reasons that might explain why the treatment effects are weaker when excluding subjects who know the shooting before. First, since I am dropping about 22% of my whole sample, I have less statistical power to detect meaningful variations. Second, as shown in Section 2.2, the news coverage on hate-motivated mass shootings is intense and usually focuses on the shooter. Thus, subjects who recognized the shooting in my experiment have been treated before participating in my experiment. If there is a positive correlation between treatment intensity and treatment effect, then it explains why the treatment effects excluding subjects who have been treated repeatedly are smaller in size. This also suggests that the treatment effects I found are likely to be an underestimate since in real life, people are likely to receive more than a one-time exposure.

#### 4.4.4 Social desirability bias

One might be concerned that my results are affected by social desirability bias given that my outcomes are measuring socially inappropriate behaviors. For example, One of my main outcome variables is the donation to an anti-immigrant organization, which in many people’s eyes might be socially inappropriate. Thus, people might feel prone to act in a socially desirable way, i.e., not donating to the anti-immigrant organization, which could bias my results.

To assess this possibility, I use the Marlowe-Crowne social desirability scale to measure a subject’s propensity for acting in a socially desirable way (Crowne & Marlowe, 1960). This module is included as part of the demographics questions in a subset of the CloudResearch sample. I use the 7-item X1 scale as described in Fisher (1993) and construct a social desirability



index using [Anderson \(2008\)](#)'s method.<sup>51</sup> Appendix Table [A15](#) reports the correlation between the main outcome variables and the social desirability index. Results show that subjects' social desirability index is negatively correlated with the support for the shooter. In comparison, the social desirability index does not predict the likelihood of donating to the anti-immigrant organization or the interest in hate groups, although the sign of all coefficients is negative. An additional concern is subjects' social desirability bias might be stronger in some treatments. For example, this effect could be more salient in the Hate Ideology Treatment and the Hate Background Treatment, since the news stories in both conditions hint that the shooter is motivated by anti-immigrant. If that is the case, then the estimated treatment effects should be biased downward. Following [Dhar et al. \(2022\)](#), I estimate the following equation.

$$\begin{aligned}
Y_i = & \alpha + \beta_1 T_{1i} + \beta_2 T_{3i} + \beta_3 T_{4i} \\
& + \beta_4 T_{1i} * HighSD_i + \beta_5 T_{3i} * HighSD_i + \beta_6 T_{4i} * HighSD_i \\
& + \gamma HighSD_i + \delta X_i + \epsilon_i
\end{aligned} \tag{4}$$

Where  $Y_i$  is my outcome variable,  $HighSD_i$  is an indicator variable that equals 1 if subject  $i$  has an above-median social desirability index, and other variables are define similarly as before. The coefficients on the interaction terms between  $HighSD_i$  and the treatment dummies should tell me whether there is stronger social desirability bias in different treatment conditions. Table [11](#) shows the results. Having a above-median social desirability index makes the subject significantly less likely to request links for the hate group website. This effect is not significantly for other primary outcome measures, although all signs are negative. More importantly, this effect is largely the same across different treatment conditions. The coefficients on the interaction terms are not significantly different from zero, with the exception of the No Hate Treatment. This pattern is reassuring and shows that the treatment effects are similar in magnitude for subjects with a low versus high propensity to give the socially desirable response. Thus, my results are unlikely to be affected by social desirability bias.

#### 4.4.5 Multiple hypothesis testing

I have six primary outcome measures, including: 1) information demand for the shooter's manifesto, 2) information demand for the shooter's background, 3) index of support for the shooter, 4) support for the shooter's ideology measured by donation to an anti-immigrant organization, 5) whether the subject requested links to a hate group's website, 6) whether the subject clicked on the links to the hate group's website.

A common issue of having multiple outcome measures is that more hypotheses are being tested, thereby increasing the probability of false rejections. To address this concern, I compute the sharpened False Discovery Rate (FDR) q-values and report in Table [12](#) ([Benjamini et al., 2006](#)).<sup>52</sup> The treatment effects on support for the shooter are robust to multiple hypothesis corrections. The coefficients on Hate Ideology and Hate Background remain significant.

<sup>51</sup>Survey script is provided in Appendix [B.4.2](#).

<sup>52</sup>The FDR is the expected proportion of rejections that are type I errors (false rejections). I used [Anderson \(2008\)](#)'s code.

However, the treatment effect on Democrat subjects' support for the shooter's ideology loses statistical significance. The corrected p-value is 0.164.

## 4.5 Discussion of effect sizes

In previous sections, I showed that subjects from the Democrat sample significantly increase their support for the shooter and the shooter's anti-immigrant ideology when they read a news story that contains information about the shooter's background. It is worth pointing out that both the effect size and the baseline level are relatively small. For example, When asked if they admire the shooter's courage on a 5-point Likert scale, about 91 percent of all the subjects chose strongly disagree (a value of 1). Similarly, when asked if they think the shooter's action can be justified, about 84 percent of the subjects chose 1. Despite the small magnitude, my results are meaningful for two reasons.

First, as discussed in the last section, the treatment effects detected from my experiment are likely to be underestimated since it's a one time exposure. In real life, people will likely encounter news stories about the shooter's ideology or background repeatedly. Thus, the small magnitude of treatment effects does not diminish its significance. Admittedly, the index of support for the shooter is constructed using self-reported attitudinal responses, and thus does not necessarily predict change in behaviors. However, literature in criminology shows mass shooters may find inspiration from previous shooters. This connection often starts from admiration and sympathy, then becomes stronger over time [Langman \(2018\)](#). Thus, it is possible that the self-reported increase in support for the shooter could translate into behavioral change in the future. To investigate this possibility, Appendix Table [A16](#) shows support for the shooter strongly predicts support for the shooter's ideology and interest in hate groups. Therefore, even though the observed treatment effects might be driven by a small fraction of subjects, it is nevertheless alarming.

Second, it should be noted that the observed treatment effect on donation rate is comparable with other papers using similar methodology. The review paper by [Haaland et al. \(2020\)](#) points out that the effect size on behavioral measures are typically small in information experiments. While donation to a charity organization is commonly used as an outcome measure in information experiments, many studies find very little difference between the treatment group and the control group. For example, [Settele \(2022\)](#) uses donation to an NGO for women right, [Grigorieff et al. \(2020\)](#) uses donation to a pro-immigrant charity, [Haaland and Roth \(2021\)](#) uses donation to a pro-black civil rights organization. However, all three studies do not find statistically significant treatment effect on donation. Two exceptions are [Bursztyn, Egorov, and Fiorin \(2020\)](#), who found an increase of 50 percent in donation rate to an anti-immigrant organization, and [Bursztyn, Haaland, et al. \(2020\)](#), who found an increase of 23 percent in donation rate to a pro-black organization. In comparison, I find a 62 percent increase in donation rate to an anti-immigrant organization from the Democrat sample. This magnitude is larger than [Bursztyn, Egorov, and Fiorin \(2020\)](#) and [Bursztyn, Haaland, et al. \(2020\)](#).

## 5 Conclusion

In this paper, I study whether news coverage of hate-motivated mass shootings increases hatred. In the first part of my analysis, I use observational data from multiple sources to provide evidence that 1) hate-motivated mass shootings receive higher media coverage which often focuses on the shooter; 2) people show higher interest in hate-motivated mass shootings, and in particular, the shooter; 3) immediately following a hate-motivated mass shooting targeting a specific group, there's an increase in the number of hate crimes against the same victimized group. Based on these findings and guided by the existing literature, I hypothesize that the way the media covers hate-motivated mass shootings causally generates more hatred. In the second part of my analysis, I employ an online experiment to test my research hypothesis. In the experiment, subjects are asked to read a piece of news story about the 2019 El Paso shooting that targeted Hispanic immigrants. Each subject is randomly assigned to one of the four treatment conditions that vary in the level of informativeness, i.e., whether the news story discloses the shooting was targeting Hispanic immigrants, and whether it covers the shooter's hateful ideology (white supremacy, anti-immigrant) or background (name, photo, childhood). I then measure subjects' interest in the shooter, attitudes toward the shooter, the shooter's ideology, and interest in a white supremacy hate group.

My first finding from the experiment is that subjects are not more interested in hate-motivated than non-hate-motivated shootings. This suggests that the higher public interest in hate shootings I observed in the search data is likely due to the fact that these crimes receive more media coverage, rather than to the fact that subjects are intrinsically more interested in them. My second finding is that providing more information on the shooter's background significantly increases support for the shooter from Democrat subjects, providing more information on the shooter's ideology significantly increases support for the shooter from Republican subjects. My third finding is that consistent with the increase in support for the shooter, Democrat subjects who read the news story that emphasizes the shooter's background significantly increase their support for the shooter's anti-immigrant ideology as measured by donations to anti-immigrant organization. My fourth finding is there is suggestive evidence that the news story with emphasis on the shooter's background increases Democrat subjects interest in a white supremacy hate group.

Overall, this paper shows that news coverage of mass shootings could have unintended consequences. In particular, news stories could positively affect viewers' attitude toward the shooter, and negatively affect viewers' attitude toward the victims. Thus, my findings provide support for the argument that media coverage of sensitive topics should be regulated. This paper has implications for future work. To start with, my experiment studies the reaction to a specific mass shooting from a specific group of subjects. Subsequent research should examine the reaction to a different mass shooting from a broader audience. Second, my experiment focuses on how different types of media coverage change viewer's attitudes toward the victimized group in the shooting. It would also be interesting to see whether media coverage changes how the victimized group feels toward the shooter's group. Again, consider the 2019 El Paso

shooting as an example, will immigrants become more resentful toward white people after they saw news stories about the shooter's white supremacy ideology? Third, my treatments vary in the amount of information about the shooter. Many people argue that media should shift attention from shooters to victims and survivors.<sup>53</sup> Future work should investigate whether and how news coverage that emphasizes the victims' stories and backgrounds may affect viewers' attitudes toward the victimized group and the shooter's ideology, possibly leading to less hatred.

---

<sup>53</sup>For example, see the [No Notoriety Campaign](#), and <https://www.reportingonmassshootings.org/>

## References

- Adena, M., Enikolopov, R., Petrova, M., Santarosa, V., & Zhuravskaya, E. (2015). Radio and the rise of the nazis in prewar germany. *The Quarterly Journal of Economics*, 130(4), 1885–1939.
- Alesina, A., Miano, A., & Stantcheva, S. (2018). *Immigration and redistribution* (Tech. Rep.). National Bureau of Economic Research.
- Anderson, M. 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.
- Ang, D. (2020). The birth of a nation: Media and racial hate.
- Arias, E. (2019). How does media influence social norms? experimental evidence on the role of common knowledge. *Political Science Research and Methods*, 7(3), 561–578.
- Bénabou, R., Falk, A., & Tirole, J. (2018). *Narratives, imperatives, and moral reasoning* (Tech. Rep.). National Bureau of Economic Research.
- Benjamini, Y., Krieger, A. M., & Yekutieli, D. (2006). Adaptive linear step-up procedures that control the false discovery rate. *Biometrika*, 93(3), 491–507.
- Bursztyn, L., Egorov, G., Enikolopov, R., & Petrova, M. (2019). *Social media and xenophobia: evidence from russia* (Tech. Rep.). National Bureau of Economic Research.
- Bursztyn, L., Egorov, G., & Fiorin, S. (2020). From extreme to mainstream: The erosion of social norms. *American economic review*, 110(11), 3522–48.
- Bursztyn, L., Haaland, I. K., Rao, A., & Roth, C. P. (2020). *Disguising prejudice: Popular rationales as excuses for intolerant expression* (Tech. Rep.). National Bureau of Economic Research.
- Bursztyn, L., Rao, A., Roth, C. P., & Yanagizawa-Drott, D. H. (2020). *Misinformation during a pandemic* (Tech. Rep.). National Bureau of Economic Research.
- Bushman, B. J. (2018). Narcissism, fame seeking, and mass shootings. *American behavioral scientist*, 62(2), 229–241.
- Cao, A., Lindo, J. M., & Zhong, J. (2022). *Can social media rhetoric incite hate incidents? evidence from trump’s” chinese virus” tweets* (Tech. Rep.). National Bureau of Economic Research.
- Card, D., Chang, S., Becker, C., Mendelsohn, J., Voigt, R., Boustan, L., ... Jurafrsky, D. (2022). Computational analysis of 140 years of us political speeches reveals more positive but increasingly polarized framing of immigration. *Proceedings of the National Academy of Sciences*, 119(31), e2120510119.
- Carr, J., Clifton-Sprigg, J., James, J., & Vujic, S. (2020). *Love thy neighbour? brexit and hate crime* (Tech. Rep.). IZA Discussion Papers.

- Center, P. R. (2019). For local news, americans embrace digital but still want strong community connection. *Pew Research Center*.
- Chopra, F., Haaland, I., & Roth, C. (2022). Do people demand fact-checked news? evidence from us democrats. *Journal of Public Economics*, 205, 104549.
- Couttenier, M., Hatte, S., Thoenig, M., & Vlachos, S. (2021). Anti-muslim voting and media coverage of immigrant crimes. *The Review of Economics and Statistics*, 1–33.
- Crowne, D. P., & Marlowe, D. (1960). A new scale of social desirability independent of psychopathology. *Journal of consulting psychology*, 24(4), 349.
- DeFoster, R., & Swalve, N. (2018). Guns, culture or mental health? framing mass shootings as a public health crisis. *Health communication*, 33(10), 1211–1222.
- DellaVigna, S., & Gentzkow, M. (2010). Persuasion: empirical evidence. *Annu. Rev. Econ.*, 2(1), 643–669.
- DellaVigna, S., & Kaplan, E. (2007). The fox news effect: Media bias and voting. *The Quarterly Journal of Economics*, 122(3), 1187–1234.
- Demszky, D., Garg, N., Voigt, R., Zou, J., Gentzkow, M., Shapiro, J., & Jurafsky, D. (2019). Analyzing polarization in social media: Method and application to tweets on 21 mass shootings. *arXiv preprint arXiv:1904.01596*.
- De Quidt, J., Haushofer, J., & Roth, C. (2018). Measuring and bounding experimenter demand. *American Economic Review*, 108(11), 3266–3302.
- Dhar, D., Jain, T., & Jayachandran, S. (2022). Reshaping adolescents’ gender attitudes: Evidence from a school-based experiment in india. *American Economic Review*, 112(3), 899–927.
- Dimant, E. (2019). Contagion of pro-and anti-social behavior among peers and the role of social proximity. *Journal of Economic Psychology*, 73, 66–88.
- Doherty, C., Kiley, J., & Asheer, N. (2019). In a politically polarized era, sharp divides in both partisan coalitions. *PEW Research*.
- Durante, R., & Zhuravskaya, E. (2018). Attack when the world is not watching? us news and the israeli-palestinian conflict. *Journal of Political Economy*, 126(3), 1085–1133.
- Duxbury, S. W., Frizzell, L. C., & Lindsay, S. L. (2018). Mental illness, the media, and the moral politics of mass violence: The role of race in mass shootings coverage. *Journal of Research in Crime and Delinquency*, 55(6), 766–797.
- Eisensee, T., & Strömberg, D. (2007). News droughts, news floods, and us disaster relief. *The Quarterly Journal of Economics*, 122(2), 693–728.
- Ekins, E. E. (2017). The state of free speech and tolerance in america; attitudes about free speech, campus speech, religious liberty, and tolerance of political expression. *Findings From the Cato Institute*.



- Fisher, R. J. (1993). Social desirability bias and the validity of indirect questioning. *Journal of consumer research*, 20(2), 303–315.
- Fox, J. A., & Fridel, E. E. (2016). The tenuous connections involving mass shootings, mental illness, and gun laws. *Violence and Gender*, 3(1), 14–19.
- Gerber, A. S., Karlan, D., & Bergan, D. (2009). Does the media matter? a field experiment measuring the effect of newspapers on voting behavior and political opinions. *American Economic Journal: Applied Economics*, 1(2), 35–52.
- Gino, F., Gu, J., & Zhong, C.-B. (2009). Contagion or restitution? when bad apples can motivate ethical behavior. *Journal of Experimental Social Psychology*, 45(6), 1299–1302.
- Grigorieff, A., Roth, C., & Ubfal, D. (2020). Does information change attitudes toward immigrants? *Demography*, 57(3), 1117–1143.
- Gupta, N., Rigotti, L., & Wilson, A. (2021). The experimenters’ dilemma: Inferential preferences over populations. *arXiv preprint arXiv:2107.05064*.
- Haaland, I., & Roth, C. (2020). Labor market concerns and support for immigration. *Journal of Public Economics*, 191, 104256.
- Haaland, I., & Roth, C. (2021). Beliefs about racial discrimination and support for pro-black policies. *The Review of Economics and Statistics*, 1–38.
- Haaland, I., Roth, C., & Wohlfart, J. (2020). Designing information provision experiments.
- Hara, K., Adams, A., Milland, K., Savage, S., Callison-Burch, C., & Bigham, J. P. (2018). A data-driven analysis of workers’ earnings on amazon mechanical turk. In *Proceedings of the 2018 chi conference on human factors in computing systems* (pp. 1–14).
- Helfgott, J. B. (2015). Criminal behavior and the copycat effect: Literature review and theoretical framework for empirical investigation. *Aggression and violent behavior*, 22, 46–64.
- Horowitz, J. M., Parker, K., & Stepler, R. (2017). Wide partisan gaps in us over how far the country has come on gender equality. *Pew Research Center*, 18.
- Jetter, M. (2017). The effect of media attention on terrorism. *Journal of Public Economics*, 153, 32–48.
- Jetter, M., & Walker, J. K. (2022). News coverage and mass shootings in the us. *European Economic Review*, 104221.
- Kissner, J. (2016). Are active shootings temporally contagious? an empirical assessment. *Journal of Police and Criminal Psychology*, 31(1), 48–58.
- Klein, J. (2012). Bully society, the. In *Bully society, the*. New York University Press.
- Konstabel, K., Lönnqvist, J.-E., Walkowitz, G., Konstabel, K., & Verkasalo, M. (2012). The ‘short five’(s5): Measuring personality traits using comprehensive single items. *European Journal of Personality*, 26(1), 13–29.

- La Ferrara, E. (2016). Mass media and social change: Can we use television to fight poverty? *Journal of the European Economic Association*, 14(4), 791–827.
- Langman, P. (2018). Different types of role model influence and fame seeking among mass killers and copycat offenders. *American Behavioral Scientist*, 62(2), 210–228.
- Lankford, A. (2016). Fame-seeking rampage shooters: Initial findings and empirical predictions. *Aggression and violent behavior*, 27, 122–129.
- Lankford, A., & Cowan, R. G. (2020). Has the role of mental health problems in mass shootings been significantly underestimated? *Journal of Threat Assessment and Management*, 7(3-4), 135.
- Lankford, A., & Madfis, E. (2018a). Don't name them, don't show them, but report everything else: A pragmatic proposal for denying mass killers the attention they seek and deterring future offenders. *American behavioral scientist*, 62(2), 260–279.
- Lankford, A., & Madfis, E. (2018b). Media coverage of mass killers: Content, consequences, and solutions. *American Behavioral Scientist*, 62(2), 151–162.
- Lee, K. J. (2018). Mass shootings and media contagion theory: Social media's influence on frequency of incidents. *Elon Journal of Undergraduate Research in Communications*, 9(2), 27–35.
- Lim, C. S., Snyder Jr, J. M., & Strömberg, D. (2015). The judge, the politician, and the press: newspaper coverage and criminal sentencing across electoral systems. *American Economic Journal: Applied Economics*, 7(4), 103–35.
- Martin, G. J., & Yurukoglu, A. (2017). Bias in cable news: Persuasion and polarization. *American Economic Review*, 107(9), 2565–99.
- Mastorocco, N., & Minale, L. (2018). News media and crime perceptions: Evidence from a natural experiment. *Journal of Public Economics*, 165, 230–255.
- McGinty, E. E., Kennedy-Hendricks, A., Choksy, S., & Barry, C. L. (2016). Trends in news media coverage of mental illness in the united states: 1995–2014. *Health Affairs*, 35(6), 1121–1129.
- McGinty, E. E., Webster, D. W., Jarlenski, M., & Barry, C. L. (2014). News media framing of serious mental illness and gun violence in the united states, 1997-2012. *American journal of public health*, 104(3), 406–413.
- Meindl, J. N., & Ivy, J. W. (2017). Mass shootings: The role of the media in promoting generalized imitation. *American journal of public health*, 107(3), 368–370.
- Metzl, J. M., & MacLeish, K. T. (2015). Mental illness, mass shootings, and the politics of american firearms. *American journal of public health*, 105(2), 240–249.
- Müller, K., & Schwarz, C. (2020). From hashtag to hate crime: Twitter and anti-minority sentiment. *Available at SSRN 3149103*.

- Mummolo, J., & Peterson, E. (2019). Demand effects in survey experiments: An empirical assessment. *American Political Science Review*, 113(2), 517–529.
- Murray, J. L. (2017). Mass media reporting and enabling of mass shootings. *Cultural Studies Critical Methodologies*, 17(2), 114–124.
- Oppenheimer, D. M., Meyvis, T., & Davidenko, N. (2009). Instructional manipulation checks: Detecting satisficing to increase statistical power. *Journal of experimental social psychology*, 45(4), 867–872.
- Parks, J., Bechtold, D., Shelp, F., Lieberman, J., & Coffey, S. (2019). Mass violence in america: Causes, impacts and solutions.
- Peer, E., Rothschild, D., Gordon, A., Evernden, Z., & Damer, E. (2022). Data quality of platforms and panels for online behavioral research. *Behavior Research Methods*, 54(4), 1643–1662.
- Pezzella, F. S., Fetzer, M. D., & Keller, T. (2019). The dark figure of hate crime underreporting. *American Behavioral Scientist*, 0002764218823844.
- Philippe, A., & Ouss, A. (2018). “no hatred or malice, fear or affection”: media and sentencing. *Journal of Political Economy*, 126(5), 2134–2178.
- Saad, L. (2013). Americans fault mental health system most for gun violence. *Gallup Politics*, 20.
- Schneider-Strawczynski, S., & Valette, J. (2021). Media coverage of immigration and the polarization of attitudes.
- Settele, S. (2022). How do beliefs about the gender wage gap affect the demand for public policy? *American Economic Journal: Economic Policy*, 14(2), 475–508.
- Silva, J. R., & Greene-Colozzi, E. A. (2019). Fame-seeking mass shooters in america: Severity, characteristics, and media coverage. *Aggression and Violent Behavior*, 48, 24–35.
- Simonov, A., Sacher, S. K., Dubé, J.-P. H., & Biswas, S. (2020). *The persuasive effect of fox news: non-compliance with social distancing during the covid-19 pandemic* (Tech. Rep.). National Bureau of Economic Research.
- Swanson, J. W., McGinty, E. E., Fazel, S., & Mays, V. M. (2015). Mental illness and reduction of gun violence and suicide: bringing epidemiologic research to policy. *Annals of epidemiology*, 25(5), 366–376.
- Yanagizawa-Drott, D. (2014). Propaganda and conflict: Evidence from the rwandan genocide. *The Quarterly Journal of Economics*, 129(4), 1947–1994.

# Tables

Table 1: Online Experiment - Summary Statistics and Balance Tests

	All	T1	T2	T3	T4	ANOVA p-value
<b>Panel A - Full Sample (N = 2400)</b>						
Age	38.26 (13.16)	37.36 (12.64)	38.79 (13.44)	38.03 (13.29)	38.85 (13.22)	0.16
Education level	3.76 (1.10)	3.78 (1.14)	3.80 (1.08)	3.75 (1.14)	3.70 (1.05)	0.47
Income level	7.11 (3.36)	7.18 (3.42)	7.28 (3.35)	7.17 (3.38)	6.83 (3.26)	0.10*
White	0.74 (0.44)	0.73 (0.44)	0.75 (0.43)	0.74 (0.44)	0.74 (0.44)	0.88
Political index	0.36 (0.35)	0.35 (0.34)	0.36 (0.35)	0.36 (0.35)	0.36 (0.35)	0.80
Fame-seeking index	2.71 (0.88)	2.76 (0.89)	2.69 (0.91)	2.68 (0.87)	2.69 (0.84)	0.33
Observations	2,400	602	601	597	600	
<b>Panel B - Democrat Sample (N = 1199)</b>						
Age	37.81 (12.95)	36.90 (13.06)	38.86 (13.33)	36.95 (12.44)	38.54 (12.88)	0.12
Education level	3.82 (1.08)	3.85 (1.12)	3.77 (1.06)	3.73 (1.10)	3.92 (1.05)	0.15
Income level	6.75 (3.33)	6.77 (3.44)	6.98 (3.35)	6.68 (3.33)	6.56 (3.21)	0.48
White	0.69 (0.46)	0.67 (0.47)	0.71 (0.45)	0.67 (0.47)	0.70 (0.46)	0.59
Political index	0.08 (0.14)	0.07 (0.12)	0.08 (0.15)	0.09 (0.15)	0.07 (0.15)	0.66
Fame-seeking index	2.56 (0.89)	2.59 (0.90)	2.54 (0.94)	2.54 (0.88)	2.58 (0.84)	0.86
Observations	600	301	300	297	301	
<b>Panel C - Republican Sample (N = 1201)</b>						
Age	38.70 (13.35)	37.82 (12.22)	38.71 (13.56)	39.11 (14.02)	39.15 (13.57)	0.59
Education level	3.70 (1.12)	3.71 (1.15)	3.82 (1.11)	3.78 (1.19)	3.48 (1.01)	0.00***
Income level	7.48 (3.35)	7.59 (3.36)	7.57 (3.34)	7.65 (3.36)	7.09 (3.31)	0.15
White	0.79 (0.41)	0.78 (0.41)	0.78 (0.41)	0.80 (0.40)	0.79 (0.41)	0.92
Political index	0.64 (0.26)	0.62 (0.27)	0.64 (0.26)	0.64 (0.27)	0.64 (0.25)	0.51
Fame-seeking index	2.85 (0.84)	2.94 (0.84)	2.84 (0.85)	2.83 (0.84)	2.80 (0.83)	0.21
Observations	600	301	301	300	299	

*Notes:* A total of 2400 individuals participated in the online experiment. Subjects are recruited from Prolific and CloudResearch. This table reports the mean of each demographic variable across different treatment conditions. The corresponding standard deviation is reported in parentheses. Education level is a categorical variable ranging from Less than high school (1) to Doctorate (7). Income level is a categorical variable ranging from Less than \$10,000 (1) to \$15,000 or more (12). Political index ranges from 0 to 1, a higher value means more right-leaning. Fame-seeking index ranges from 1 to 5, a higher value means more fame-seeking.

Table 2: Treatment effects on interest

	A: Full Sample				B: Democrat				C: Republican			
	Manifesto		Background		Manifesto		Background		Manifesto		Background	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
No Hate (T1)	0.057** (0.028)	0.050* (0.028)	0.059** (0.029)	0.055* (0.029)	0.055 (0.040)	0.047 (0.040)	0.058 (0.040)	0.056 (0.040)	0.060 (0.040)	0.057 (0.040)	0.060 (0.040)	0.060 (0.040)
Hate Ideology (T3)	-0.083*** (0.028)	-0.086*** (0.028)	-0.057** (0.029)	-0.058** (0.029)	-0.016 (0.040)	-0.026 (0.040)	-0.001 (0.040)	-0.004 (0.040)	-0.148*** (0.040)	-0.146*** (0.040)	-0.111*** (0.040)	-0.111*** (0.040)
Hate Background (T4)	-0.034 (0.028)	-0.036 (0.028)	-0.126*** (0.029)	-0.125*** (0.029)	-0.031 (0.040)	-0.030 (0.040)	-0.135*** (0.040)	-0.130*** (0.040)	-0.037 (0.040)	-0.038 (0.040)	-0.117*** (0.040)	-0.114*** (0.041)
Control Mean	0.436	0.436	0.557	0.557	0.407	0.407	0.563	0.563	0.465	0.465	0.551	0.551
Observations	2,400	2,400	2,400	2,400	1,199	1,199	1,199	1,199	1,201	1,201	1,201	1,201
R-squared	0.011	0.031	0.019	0.024	0.004	0.032	0.020	0.033	0.023	0.039	0.023	0.027
T1=T3 p-value	0.000***	0.000***	0.000***	0.000***	0.077*	0.066*	0.145	0.141	0.000***	0.000***	0.000***	0.000***
T1=T4 p-value	0.001***	0.002***	0.000***	0.000***	0.031**	0.052*	0.000***	0.000***	0.016**	0.019**	0.000***	0.000***
T3=T4 p-value	0.090*	0.075*	0.016**	0.019**	0.706	0.921	0.001***	0.002***	0.006***	0.007***	0.897	0.937
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*Notes:* This table presents results from OLS regressions. Panel A shows the results for the full sample. Panel B shows the results for the Democrat sub-sample. Panel C shows the results for the Republican sub-sample. The dependent variable in columns that are labeled Manifesto is an indicator variable that equals 1 if the subject requested to be shown the shooter's manifesto. The dependent variable in columns that are labeled Background is an indicator variable that equals 1 if the subject requested to be shown the shooter's Background. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, and a dummy for the Hate Background Treatment. The Hate Treatment is the omitted group. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 3: Treatment effects on support for the shooter

	Index of support for the shooter					
	A: Full Sample		B: Democrat		C: Republican	
	(1)	(2)	(3)	(4)	(5)	(6)
No Hate (T1)	0.217*** (0.050)	0.194*** (0.048)	0.189*** (0.070)	0.168** (0.066)	0.246*** (0.070)	0.234*** (0.067)
Hate Ideology (T3)	0.122** (0.050)	0.117** (0.048)	0.057 (0.070)	0.035 (0.067)	0.174** (0.071)	0.188*** (0.067)
Hate Background (T4)	0.121** (0.050)	0.126*** (0.048)	0.280*** (0.070)	0.265*** (0.066)	0.001 (0.071)	0.043 (0.068)
Control Mean	0.000	0.000	0.000	0.000	0.000	0.000
Observations	2,400	2,400	1,199	1,199	1,201	1,201
R-squared	0.008	0.071	0.016	0.121	0.015	0.114
T1=T3 p-value	0.055*	0.109	0.059*	0.045**	0.307	0.494
T1=T4 p-value	0.054*	0.163	0.191	0.143	0.001***	0.005***
T3=T4 p-value	0.993	0.836	0.001***	0.001***	0.015**	0.032**
Control Variables	No	Yes	No	Yes	No	Yes

*Notes:* This table presents results from OLS regressions. Panel A shows the results for the full sample. Panel B shows the results for the Democrat sub-sample. Panel C shows the results for the Republican sub-sample. The dependent variable in each panel is an index measuring support for the shooter that is standardized around the control mean (Hate Treatment) of each sample. The estimates are represented in standard deviations from the control mean. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, and a dummy for the Hate Background Treatment. The Hate Treatment is the omitted group. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1



Table 4: Treatment effects on support for the shooter's ideology

	A: Full Sample				B: Democrat				C: Republican			
	Donation		Donation		Donation		Donation		Donation		Donation	
	anti-immigrant	pro-immigrant	anti-immigrant	pro-immigrant	anti-immigrant	pro-immigrant	anti-immigrant	pro-immigrant	anti-immigrant	pro-immigrant	anti-immigrant	pro-immigrant
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
No Hate (T1)	-0.006 (0.028)	-0.007 (0.027)	-0.060 (0.050)	-0.053 (0.044)	0.028 (0.035)	0.021 (0.034)	-0.077 (0.062)	-0.067 (0.061)	-0.033 (0.042)	-0.037 (0.042)	-0.016 (0.070)	-0.035 (0.065)
Hate Ideology (T3)	-0.016 (0.027)	-0.016 (0.027)	-0.048 (0.052)	-0.041 (0.046)	0.020 (0.034)	0.013 (0.033)	-0.086 (0.065)	-0.082 (0.063)	-0.046 (0.041)	-0.045 (0.041)	0.017 (0.073)	-0.004 (0.067)
Hate Background (T4)	-0.016 (0.027)	-0.016 (0.026)	-0.038 (0.053)	-0.034 (0.047)	0.071** (0.034)	0.069** (0.033)	0.047 (0.065)	0.039 (0.064)	-0.101** (0.041)	-0.093** (0.041)	-0.099 (0.075)	-0.095 (0.070)
Control Mean	0.198	0.198	0.623	0.623	0.114	0.114	0.778	0.778	0.278	0.278	0.457	0.457
Observations	1,665	1,665	735	735	842	842	357	357	823	823	378	378
R-squared	0.000	0.045	0.002	0.211	0.006	0.088	0.015	0.087	0.008	0.034	0.007	0.184
T1=T3 p-value	0.718	0.746	0.819	0.787	0.818	0.817	0.882	0.807	0.760	0.853	0.640	0.625
T1=T4 p-value	0.693	0.753	0.666	0.678	0.205	0.141	0.059*	0.098*	0.104	0.179	0.249	0.371
T3=T4 p-value	0.975	0.991	0.843	0.885	0.128	0.085*	0.051*	0.070*	0.180	0.237	0.121	0.189
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*Notes:* This table presents results from OLS regressions. Panel A shows the results for the full sample. Panel B shows the results for the Democrat sub-sample. Panel C shows the results for the Republican sub-sample. The dependent variable in columns that are labeled “Donation anti-immigrant” is an indicator variable that equals 1 if the subject authorized the 1\$ donation to the anti-immigration organization. The dependent variable in columns that are labeled “Donation pro-immigrant” is an indicator variable that equals 1 if the subject authorized the 1\$ donation to the pro-immigration organization. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, and a dummy for the Hate Background Treatment. The Hate Treatment is the omitted group. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 5: Treatment effects on interest in hate group

	A: Full Sample				B: Democrat				C: Republican			
	Links requested		Links clicked		Links requested		Links clicked		Links requested		Links clicked	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
No Hate (T1)	0.015 (0.018)	0.009 (0.018)	-0.007 (0.006)	-0.007 (0.006)	0.016 (0.023)	0.012 (0.022)	-0.003 (0.007)	-0.003 (0.007)	0.013 (0.027)	0.012 (0.027)	-0.010 (0.009)	-0.011 (0.009)
Hate Ideology (T3)	0.007 (0.018)	0.006 (0.018)	0.007 (0.006)	0.007 (0.006)	0.018 (0.023)	0.013 (0.022)	0.003 (0.007)	0.004 (0.007)	-0.003 (0.027)	0.002 (0.027)	0.010 (0.009)	0.010 (0.009)
Hate Background (T4)	0.012 (0.018)	0.012 (0.018)	-0.005 (0.006)	-0.005 (0.006)	0.040* (0.023)	0.040* (0.022)	0.003 (0.007)	0.004 (0.007)	-0.016 (0.027)	-0.007 (0.027)	-0.013 (0.009)	-0.013 (0.009)
Control Mean	0.098	0.098	0.012	0.012	0.067	0.067	0.007	0.007	0.130	0.130	0.017	0.017
Observations	2,400	2,400	2,400	2,400	1,199	1,199	1,199	1,199	1,201	1,201	1,201	1,201
R-squared	0.000	0.039	0.003	0.008	0.003	0.058	0.001	0.012	0.001	0.036	0.006	0.012
T1=T3 p-value	0.677	0.854	0.022**	0.020**	0.961	0.965	0.338	0.360	0.553	0.705	0.032**	0.024**
T1=T4 p-value	0.868	0.862	0.774	0.732	0.307	0.216	0.346	0.370	0.286	0.482	0.724	0.790
T3=T4 p-value	0.802	0.721	0.045**	0.047**	0.332	0.236	0.985	0.983	0.636	0.745	0.013**	0.012**
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*Notes:* This table presents results from OLS regressions. Panel A shows the results for the full sample. Panel B shows the results for the Democrat sub-sample. Panel C shows the results for the Republican sub-sample. The dependent variable in columns that are labeled Requested is an indicator variable that equals 1 if the subject requested to be shown links to access the website of a white supremacy hate group. The dependent variable in columns that are labeled Clicked is an indicator variable that equals 1 if the subject clicked on the provided links. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, and a dummy for the Hate Background Treatment. The Hate Treatment is the omitted group. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 6: Heterogeneous treatment effects within sub-samples

	A: Democrat sample				B: Republican sample			
	Index	Donation	Links	Links	Index	Donation	Links	Links
	Support	anti-immigrant	requested	clicked	Support	anti-immigrant	requested	clicked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No Hate (T1)	0.104 (0.075)	0.026 (0.039)	0.014 (0.025)	-0.005 (0.008)	0.661*** (0.175)	0.036 (0.109)	0.079 (0.070)	-0.023 (0.024)
Hate Ideology (T3)	0.013 (0.075)	0.005 (0.038)	0.008 (0.025)	0.002 (0.008)	0.104 (0.176)	0.060 (0.109)	0.001 (0.071)	0.014 (0.025)
Hate Background (T4)	0.072 (0.073)	0.020 (0.037)	0.006 (0.025)	-0.013 (0.008)	0.049 (0.183)	-0.140 (0.112)	0.058 (0.074)	-0.028 (0.026)
Political Index (PI)	0.493 (0.323)	0.247 (0.174)	0.081 (0.109)	-0.031 (0.034)	-0.089 (0.184)	0.150 (0.111)	0.067 (0.074)	0.001 (0.026)
No Hate * PI	0.847* (0.496)	-0.074 (0.260)	-0.028 (0.168)	0.024 (0.053)	-0.686*** (0.256)	-0.116 (0.160)	-0.107 (0.103)	0.020 (0.036)
Hate Ideology * PI	0.339 (0.442)	0.128 (0.224)	0.076 (0.150)	0.034 (0.047)	0.132 (0.254)	-0.162 (0.157)	0.002 (0.102)	-0.005 (0.035)
Hate Background * PI	2.605*** (0.439)	0.671*** (0.229)	0.448*** (0.149)	0.225*** (0.047)	-0.011 (0.264)	0.071 (0.162)	-0.102 (0.106)	0.023 (0.037)
Control Mean	0.000	0.114	0.067	0.007	0.001	0.278	0.130	0.017
Observations	1,199	842	1,199	1,199	1,201	823	1,201	1,201
R-squared	0.151	0.102	0.068	0.036	0.124	0.037	0.037	0.013
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* This table presents results from OLS regressions. Panel A shows the results for the Democrat sample. Panel B shows the results for the Republican sample. The dependent variables in each panel from left to right are: (1) a standardized index measuring support for the shooter, (2) a dummy that equals 1 if the subject authorized the \$1 donation to the anti-immigrant organization, (3) a dummy that equals 1 if the subject requested to be shown links to access the website of a white supremacy hate group, (4) a dummy that equals 1 if the subject clicked on the provided links about the hate group. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, a dummy for the Hate Background Treatment, Political Index (PI), and interaction terms between the treatment dummies and the Political Index. The Hate Treatment is the omitted group. Political Index (PI) is an index that measures the subject's political stance, a higher value means more right-leaning. Control variables include age, income, education, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subject is recruited from CloudResearch. Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 7: Social norm as a mechanism

	A: Full Sample		B: Democrat		C: Republican	
	Index	Donation	Index	Donation	Index	Donation
	support	anti-immigrant	support	anti-immigrant	support	anti-immigrant
	norm	norm	norm	norm	norm	norm
	(1)	(2)	(3)	(4)	(5)	(6)
No Hate (T1)	0.122** (0.048)	0.000 (0.017)	0.042 (0.067)	0.005 (0.023)	0.189*** (0.065)	-0.007 (0.024)
Hate Ideology (T3)	0.096** (0.048)	-0.002 (0.017)	0.032 (0.067)	0.010 (0.023)	0.146** (0.065)	-0.016 (0.023)
Hate Background (T4)	0.103** (0.048)	-0.016 (0.017)	0.262*** (0.067)	0.050** (0.023)	-0.003 (0.065)	-0.078*** (0.023)
Control Mean	0.000	0.275	-0.000	0.240	-0.000	0.308
Observations	2,400	1,665	1,199	842	1,201	823
R-squared	0.059	0.034	0.129	0.089	0.087	0.071
T1=T3 p-value	0.586	0.915	0.888	0.835	0.501	0.703
T1=T4 p-value	0.680	0.347	0.001	0.052	0.003	0.003
T3=T4 p-value	0.894	0.397	0.001	0.079	0.023	0.007
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* This table presents results from OLS regressions. Panel A shows the results for the Democrat sample. Panel B shows the results for the Republican sample. The dependent variables in each panel from left to right are: (1) a standardized index measuring the social norm of support for the shooter, (2) subjects' guess on the percentage of previous survey participants who authorized the \$1 donation to the anti-immigrant organization. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, and a dummy for the Hate Background Treatment. The Hate Treatment is the omitted group. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 8: Treatment effects excluding subjects who guessed the experiment's purpose

	A: Full Sample				B: Democrat				C: Republican			
	Index	Donation	Links	Links	Index	Donation	Links	Links	Index	Donation	Links	Links
	support	anti-immigrant	requested	clicked	support	anti-immigrant	requested	clicked	support	anti-immigrant	requested	clicked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
No Hate (T1)	0.194*** (0.052)	-0.011 (0.030)	0.011 (0.019)	-0.005 (0.006)	0.174** (0.072)	0.039 (0.038)	0.014 (0.025)	-0.004 (0.008)	0.227*** (0.073)	-0.059 (0.045)	0.012 (0.030)	-0.005 (0.010)
Hate Ideology (T3)	0.147*** (0.055)	-0.006 (0.030)	0.019 (0.020)	0.010 (0.007)	0.028 (0.075)	0.035 (0.038)	0.022 (0.026)	0.000 (0.008)	0.251*** (0.078)	-0.040 (0.047)	0.018 (0.032)	0.021* (0.011)
Hate Background (T4)	0.143*** (0.054)	-0.020 (0.030)	0.018 (0.020)	-0.002 (0.007)	0.280*** (0.075)	0.082** (0.038)	0.040 (0.026)	0.004 (0.008)	0.038 (0.076)	-0.119** (0.046)	-0.001 (0.031)	-0.007 (0.011)
Control Mean	0.001	0.206	0.101	0.011	0.000	0.112	0.069	0.009	0.001	0.289	0.131	0.012
Observations	1,960	1,368	1,960	1,960	991	704	991	991	969	664	969	969
R-squared	0.076	0.043	0.035	0.007	0.143	0.098	0.055	0.014	0.126	0.032	0.034	0.014
T1=T3 p-value	0.374	0.860	0.691	0.024	0.043	0.918	0.737	0.586	0.752	0.693	0.849	0.013
T1=T4 p-value	0.326	0.761	0.715	0.608	0.135	0.229	0.290	0.323	0.011	0.194	0.680	0.842
T3=T4 p-value	0.941	0.638	0.971	0.090	0.001	0.202	0.490	0.674	0.008	0.102	0.570	0.011
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* This table presents results from OLS regressions excluding subjects who correctly guessed that the purpose of the experiment is related to at least one of the following: (1) immigrants, (2) racism, (3) Hate. Panel A shows the results for the full sample. Panel B shows the results for the Democrat sub-sample. Panel C shows the results for the Republican sub-sample. The dependent variables in each panel from left to right are: (1) a standardized index measuring support for the shooter, (2) a dummy that equals 1 if the subject authorized the \$1 donation to the anti-immigrant organization, (3) a dummy that equals 1 if the subject requested to be shown links to access the website of a white supremacy hate group, (4) a dummy that equals 1 if the subject clicked on the provided links about the hate group. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, and a dummy for the Hate Background Treatment. The Hate Treatment is the omitted group. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 9: Treatment effects excluding subjects who failed all attention checks

	A: Full Sample				B: Democrat				C: Republican			
	Index	Donation	Links	Links	Index	Donation	Links	Links	Index	Donation	Links	Links
	support	anti-immigrant	requested	clicked	support	anti-immigrant	requested	clicked	support	anti-immigrant	requested	clicked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
No Hate (T1)	0.187*** (0.052)	0.006 (0.029)	0.007 (0.018)	-0.006 (0.006)	0.180*** (0.068)	0.014 (0.034)	0.009 (0.022)	-0.003 (0.007)	0.214*** (0.077)	-0.006 (0.046)	0.009 (0.029)	-0.010 (0.010)
Hate Ideology (T3)	0.121** (0.053)	-0.007 (0.028)	0.001 (0.018)	0.004 (0.006)	0.043 (0.069)	-0.004 (0.034)	0.008 (0.023)	0.001 (0.007)	0.191** (0.077)	-0.014 (0.046)	-0.008 (0.029)	0.008 (0.010)
Hate Background (T4)	0.132** (0.052)	-0.007 (0.028)	0.007 (0.018)	-0.008 (0.006)	0.243*** (0.068)	0.074** (0.034)	0.043* (0.022)	0.000 (0.007)	0.045 (0.076)	-0.087* (0.045)	-0.025 (0.029)	-0.018* (0.010)
Control Mean	0.001	0.188	0.093	0.012	0.000	0.116	0.063	0.007	0.002	0.263	0.126	0.017
Observations	2,073	1,449	2,073	2,073	1,089	766	1,089	1,089	984	683	984	984
R-squared	0.056	0.050	0.040	0.008	0.120	0.100	0.062	0.010	0.087	0.037	0.036	0.012
T1=T3 p-value	0.204	0.635	0.718	0.090	0.045	0.601	0.962	0.571	0.765	0.876	0.567	0.082
T1=T4 p-value	0.286	0.625	0.990	0.728	0.352	0.074	0.131	0.617	0.026	0.077	0.231	0.396
T3=T4 p-value	0.828	0.996	0.706	0.040	0.004	0.021	0.124	0.945	0.053	0.103	0.537	0.009
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* This table presents results from OLS regressions excluding subjects who failed all attention checks in the survey. Panel A shows the results for the full sample. Panel B shows the results for the Democrat sub-sample. Panel C shows the results for the Republican sub-sample. The dependent variables in each panel from left to right are: (1) a standardized index measuring support for the shooter, (2) a dummy that equals 1 if the subject authorized the \$1 donation to the anti-immigrant organization, (3) a dummy that equals 1 if the subject requested to be shown links to access the website of a white supremacy hate group, (4) a dummy that equals 1 if the subject clicked on the provided links about the hate group. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, and a dummy for the Hate Background Treatment. The Hate Treatment is the omitted group. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1



Table 10: Treatment effects excluding subjects who recognized the shooting

	A: Full Sample				B: Democrat				C: Republican			
	Index	Donation	Links	Links	Index	Donation	Links	Links	Index	Donation	Links	Links
	support	anti-immigrant	requested	clicked	support	anti-immigrant	requested	clicked	support	anti-immigrant	requested	clicked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
No Hate (T1)	0.106** (0.049)	-0.014 (0.031)	0.002 (0.020)	-0.007 (0.006)	0.074 (0.069)	0.013 (0.039)	0.009 (0.026)	-0.000 (0.008)	0.147** (0.067)	-0.042 (0.047)	0.002 (0.029)	-0.014 (0.009)
Hate Ideology (T3)	0.020 (0.050)	-0.044 (0.031)	-0.008 (0.020)	-0.000 (0.006)	-0.034 (0.070)	0.006 (0.039)	0.015 (0.027)	0.004 (0.008)	0.058 (0.069)	-0.096** (0.046)	-0.026 (0.030)	-0.004 (0.009)
Hate Background (T4)	0.097* (0.051)	0.001 (0.031)	0.020 (0.020)	-0.004 (0.006)	0.236*** (0.072)	0.086** (0.040)	0.045 (0.027)	0.006 (0.008)	0.007 (0.069)	-0.075 (0.046)	0.005 (0.030)	-0.013 (0.009)
Control Mean	0.000	0.200	0.098	0.011	-0.001	0.111	0.069	0.005	0.001	0.280	0.126	0.017
Observations	1,800	1,245	1,800	1,800	879	610	879	879	921	635	921	921
R-squared	0.063	0.042	0.035	0.005	0.144	0.090	0.053	0.011	0.098	0.038	0.038	0.013
T1=T3 p-value	0.079	0.326	0.622	0.239	0.116	0.861	0.807	0.586	0.189	0.248	0.333	0.280
T1=T4 p-value	0.867	0.622	0.357	0.608	0.021	0.060	0.181	0.444	0.040	0.473	0.915	0.928
T3=T4 p-value	0.125	0.141	0.166	0.524	0.000	0.041	0.281	0.818	0.462	0.648	0.294	0.335
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* This table presents results from OLS regressions excluding subjects who correctly guessed that the purpose of the experiment is related to at least one of the following: (1) immigrants, (2) racism, (3) Hate. Panel A shows the results for the full sample. Panel B shows the results for the Democrat sub-sample. Panel C shows the results for the Republican sub-sample. The dependent variables in each panel from left to right are: (1) a standardized index measuring support for the shooter, (2) a dummy that equals 1 if the subject authorized the \$1 donation to the anti-immigrant organization, (3) a dummy that equals 1 if the subject requested to be shown links to access the website of a white supremacy hate group, (4) a dummy that equals 1 if the subject clicked on the provided links about the hate group. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, and a dummy for the Hate Background Treatment. The Hate Treatment is the omitted group. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 11: Robustness check for social desirability bias

	Index support		Donation anti-immigrant		Hate links requested		Hate links clicked	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No Hate (T1)	0.182 (0.189)	0.229 (0.188)	-0.124 (0.099)	-0.091 (0.099)	-0.031 (0.065)	-0.033 (0.065)	0.019 (0.015)	0.019 (0.015)
Hate Ideology (T3)	0.217 (0.188)	0.260 (0.184)	0.056 (0.097)	0.071 (0.096)	-0.056 (0.065)	-0.051 (0.064)	0.019 (0.014)	0.021 (0.014)
Hate Background (T4)	0.075 (0.188)	0.091 (0.186)	-0.110 (0.096)	-0.088 (0.097)	-0.075 (0.065)	-0.070 (0.064)	-0.000 (0.014)	-0.003 (0.014)
High SD	-0.163 (0.186)	-0.154 (0.183)	-0.032 (0.094)	-0.031 (0.093)	-0.117* (0.064)	-0.130** (0.063)	-0.000 (0.014)	-0.003 (0.014)
T1 * High SD	0.012 (0.263)	-0.077 (0.259)	0.248* (0.134)	0.236* (0.132)	-0.014 (0.090)	-0.023 (0.090)	-0.019 (0.020)	-0.019 (0.020)
T3 * High SD	0.020 (0.263)	-0.069 (0.258)	-0.132 (0.134)	-0.155 (0.132)	0.035 (0.091)	0.018 (0.089)	-0.019 (0.020)	-0.021 (0.020)
T4 * High SD	0.114 (0.262)	0.124 (0.258)	-0.016 (0.131)	-0.026 (0.130)	0.052 (0.090)	0.058 (0.089)	0.000 (0.020)	0.003 (0.020)
Constant	0.100 (0.139)	-0.183 (0.278)	0.241*** (0.073)	-0.173 (0.143)	0.205*** (0.048)	0.033 (0.096)	0.000 (0.011)	-0.057*** (0.022)
Observations	399	399	280	280	399	399	399	399
R-squared	0.015	0.073	0.046	0.104	0.027	0.073	0.014	0.048
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes

*Notes:* This table presents results from OLS regressions. SD Index is an index ranging from 0 to 1 that measures a subject's propensity to give the socially desirable response. The dependent variables in each panel from left to right are: (1) a standardized index measuring support for the shooter, (2) a dummy that equals 1 if the subject authorized the \$1 donation to the anti-immigrant organization, (3) a dummy that equals 1 if the subject requested to be shown links to access the website of a white supremacy hate group, (4) a dummy that equals 1 if the subject clicked on the provided links about the hate group. High SD is a dummy that equals 1 if the subject has a above-median social desirability index. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, a dummy for the Hate Background Treatment, High SD, and the interaction terms between the treatment dummies and High SD. The Hate Treatment is the omitted group. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

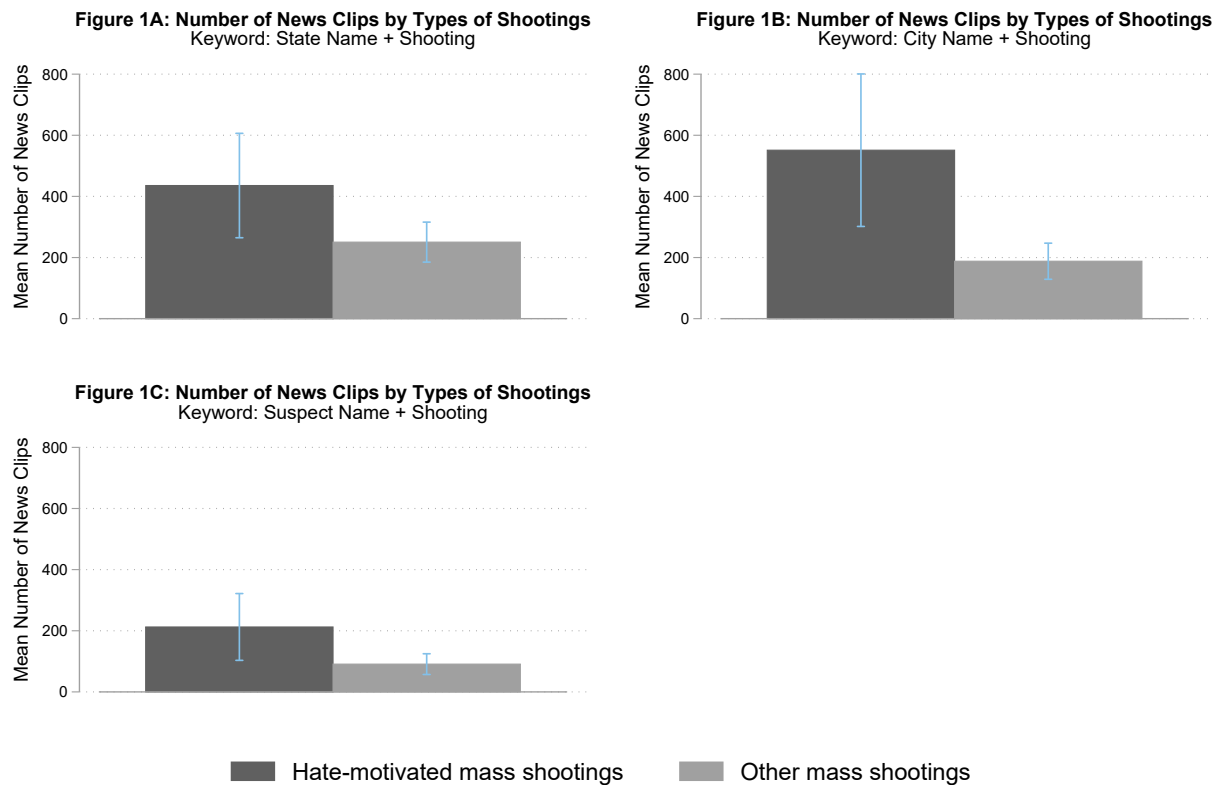
Table 12: Correction for Multiple Hypothesis Testing

	(1)	(2)	(3)	(4)	(5)	(6)
	Demand manifesto	Demand background	Index support	Donation anti-immigrant	Hate links requested	Hate links clicked
Panel A: Full sample						
No Hate	0.050 (0.078) [0.145]	0.055 (0.052) [0.108]	0.194 (0.000) [0.001]	-0.008 (0.773) [0.660]	0.009 (0.611) [0.619]	-0.007 (0.242) [0.300]
Hate Ideology	-0.087 (0.002) [0.012]	-0.058 (0.044) [0.107]	0.115 (0.017) [0.050]	-0.017 (0.524) [0.577]	0.005 (0.762) [0.660]	0.007 (0.254) [0.300]
Hate Background	-0.036 (0.199) [0.284]	-0.125 (0.000) [0.001]	0.126 (0.009) [0.035]	-0.016 (0.549) [0.577]	0.012 (0.489) [0.577]	-0.005 (0.409) [0.518]
Control Mean	0.436	0.557	0.001	0.198	0.098	0.012
Observations	2,400	2,400	2,400	1,665	2,400	2,400
R-squared	0.031	0.024	0.072	0.045	0.040	0.009
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Democrat sample						
No Hate	0.047 (0.235) [0.778]	0.056 (0.167) [0.57]	0.169 (0.011) [0.064]	0.021 (0.526) [1]	0.012 (0.585) [1]	-0.003 (0.719) [1]
Hate Ideology	-0.026 (0.511) [1]	-0.004 (0.927) [1]	0.034 (0.609) [1]	0.013 (0.697) [1]	0.013 (0.562) [1]	0.004 (0.587) [1]
Hate Background	-0.030 (0.448) [1]	-0.130 (0.001) [0.011]	0.264 (0.000) [0.002]	0.069 (0.037) [0.164]	0.039 (0.078) [0.281]	0.004 (0.600) [1]
Control Mean	0.407	0.563	0.000	0.114	0.067	0.007
Observations	1,199	1,199	1,199	842	1,199	1,199
R-squared	0.032	0.033	0.118	0.087	0.057	0.013
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Republican sample						
No Hate	0.057 (0.155) [0.275]	0.060 (0.140) [0.275]	0.234 (0.001) [0.005]	-0.037 (0.377) [0.477]	0.012 (0.660) [0.591]	-0.011 (0.254) [0.378]
Hate Ideology	-0.146 (0.000) [0.005]	-0.111 (0.006) [0.021]	0.187 (0.005) [0.021]	-0.045 (0.274) [0.378]	0.002 (0.952) [0.699]	0.010 (0.264) [0.378]
Hate Background	-0.038 (0.350) [0.477]	-0.114 (0.005) [0.021]	0.043 (0.529) [0.478]	-0.093 (0.022) [0.052]	-0.007 (0.790) [0.699]	-0.013 (0.162) [0.275]
Control Mean	0.465	0.551	0.001	0.278	0.130	0.017
Observations	1,201	1,201	1,201	823	1,201	1,201
R-squared	0.039	0.027	0.113	0.034	0.036	0.013
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* This table presents results from OLS regressions. All variables follow the same notation as before. Standard p-values are reported in parentheses, under the coefficients. FDR-adjusted p-values, computed following [Anderson \(2008\)](#) are reported in square brackets below.

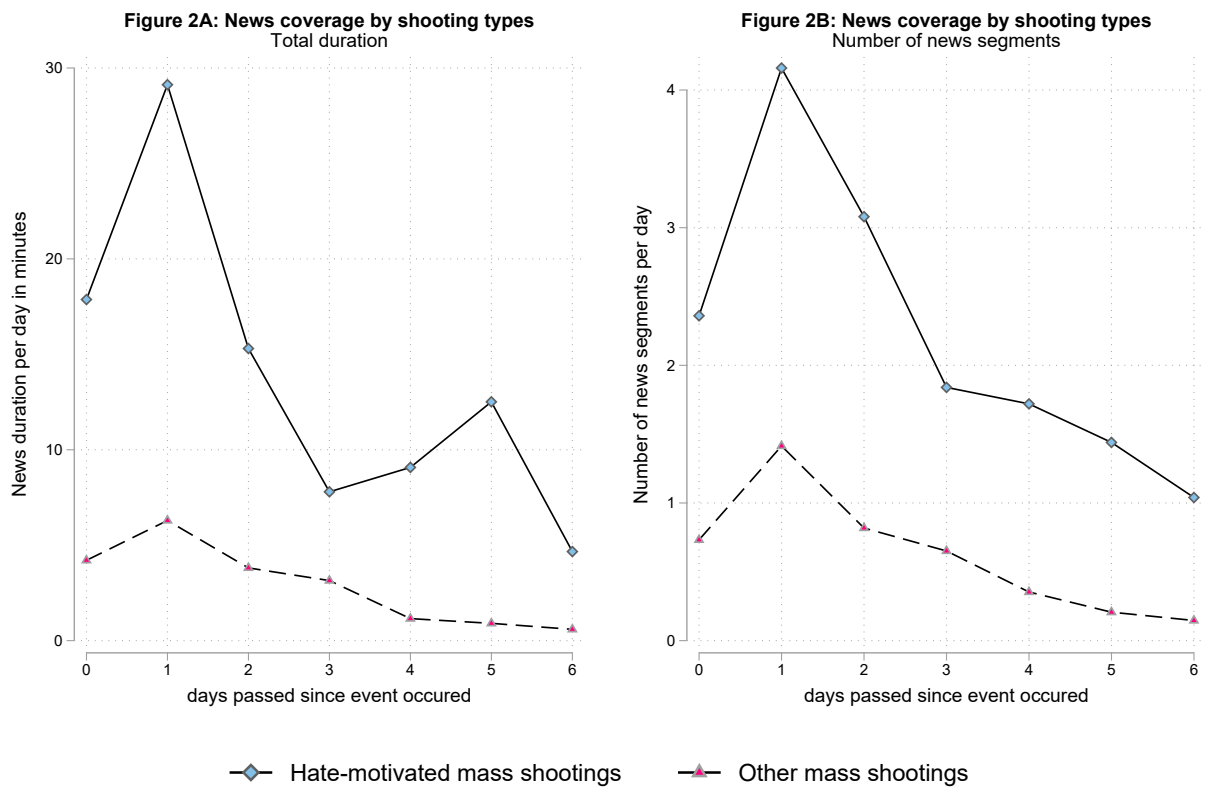
# Figures

Figure 1: Number of News Clips



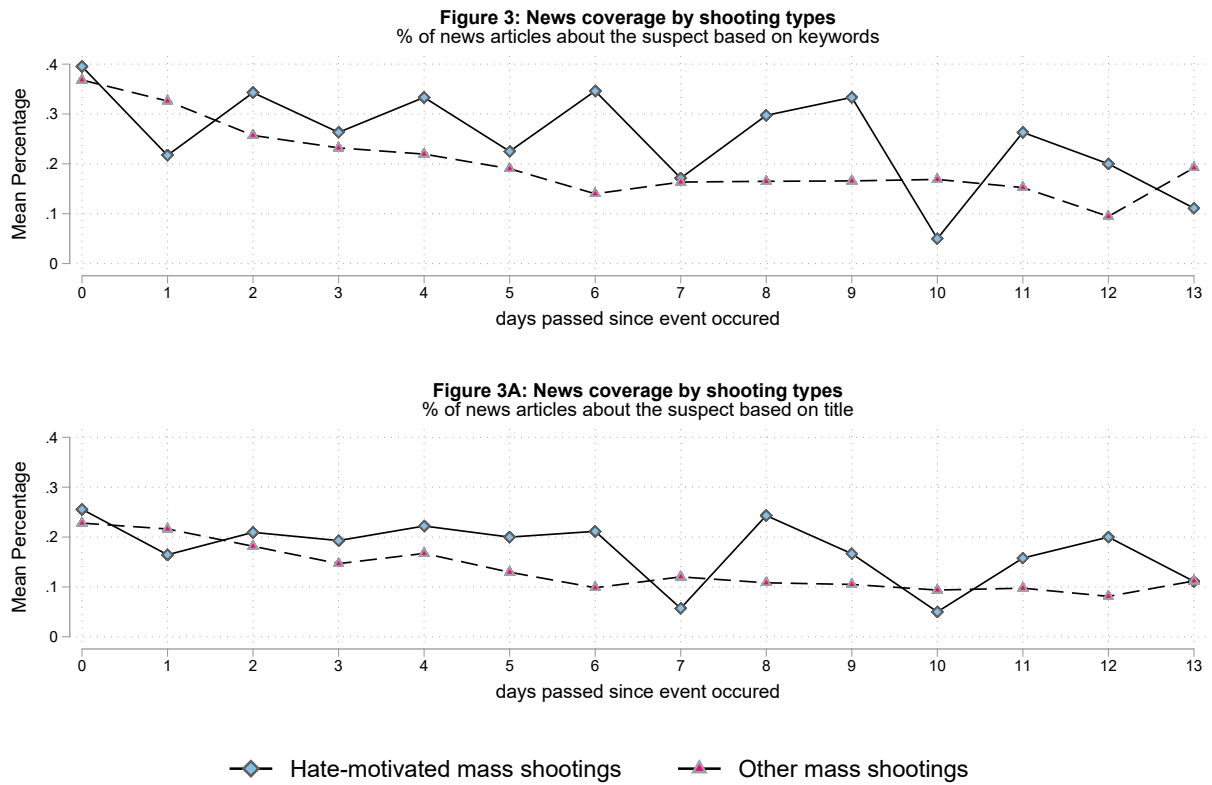
*Notes:* This graph plots the number of returned news clips when searching using the Internet Archive. The dark gray bar plots the average number of news clips for hate-motivated mass shootings, in the 7 days following the shooting. The light gray bar plots the average number of news clips for other mass shootings. Error bars reflect 95% confidence intervals. Only news that are published within 7 days since the shooting happened are included.

Figure 2: Total minutes on evening TV news broadcasts



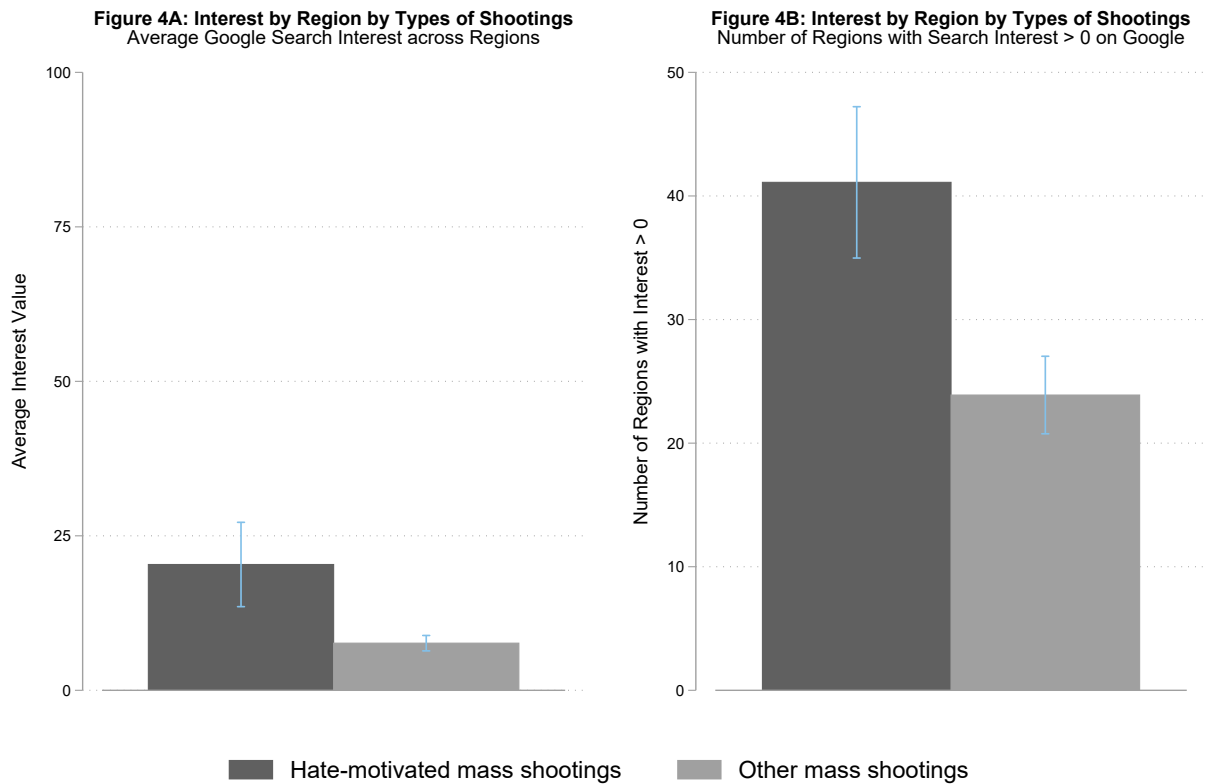
*Notes:* This graph displays the intensity of media coverage of mass shootings using data from VTNA. Panel A plots the total duration of news in minutes. Panel B plots the number of news segments per day. The X-axis represents the number of days passed since the shooting occurred. The diamond solid line plots the average media coverage for hate-motivated mass shootings while the triangle dashed line does the same for other mass shootings.

Figure 3: Percentage of news articles about the shooter



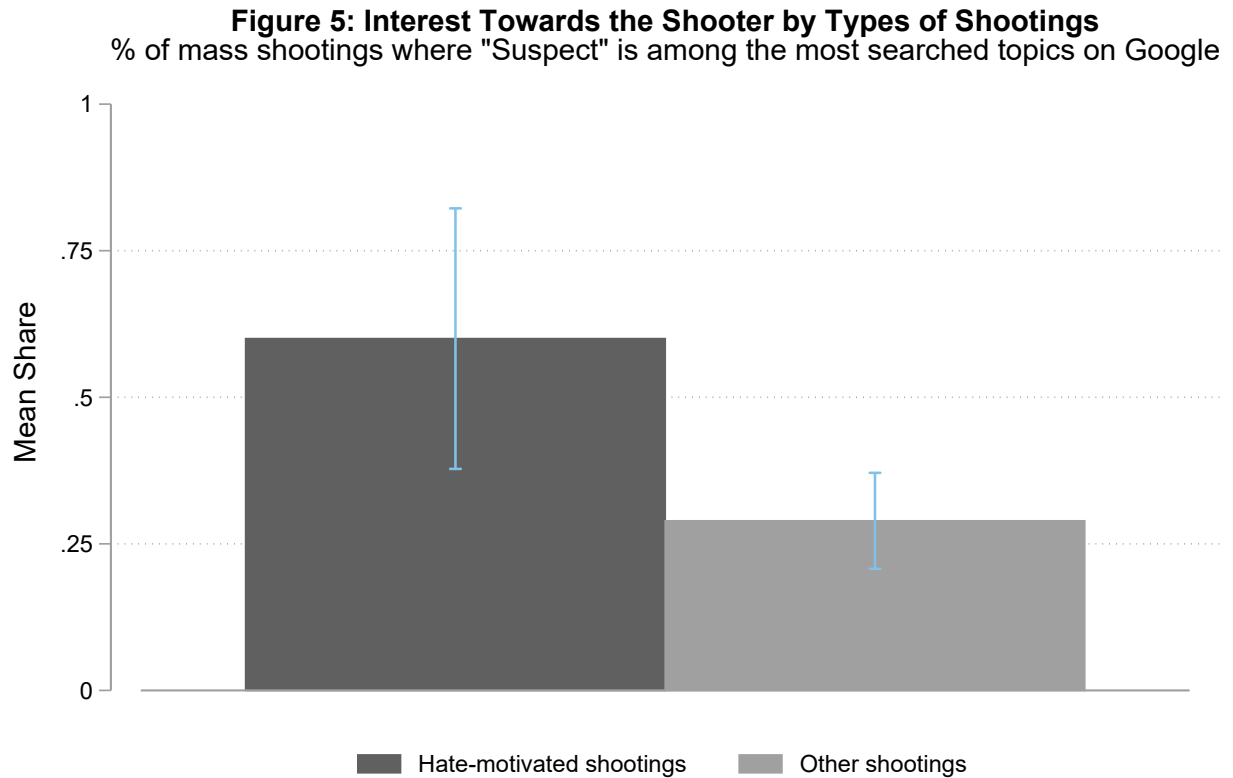
*Notes:* This graph displays the fraction of news articles that focuses on the shooter. Panel A uses the titles of news articles for identification. Panel B uses keywords. The X-axis represents the number of days passed since the shooting occurred. The diamond solid line plots the fraction for hate-motivated mass shootings while the triangle dashed line plots the fraction for other mass shootings.

Figure 4: Interest in mass shootings measured by online searching behavior



*Notes:* Google divides the United States into 51 subregions based on geography. For each subregion, Google calculates a search interest value, ranging from 0 to 100. A value of 100 would indicate in that subregion, the total search volume related to a given shooting divided by the total search volume is the highest in the United States. A value of 50 would indicate a subregion where searches about a given shooting are half as popular as the location that has a value of 100. Panel A shows the average search interest value across all subregions. Panel B shows the average number of subregions with a search interest value that is greater than 0. The data is restricted to reflect searching behaviors in the United States within 14 days since each shooting happened. The dark gray bar represents hate-motivated mass shootings while the light gray bar represents non-hate-motivated mass shootings. Error bars reflect 95% confidence intervals.

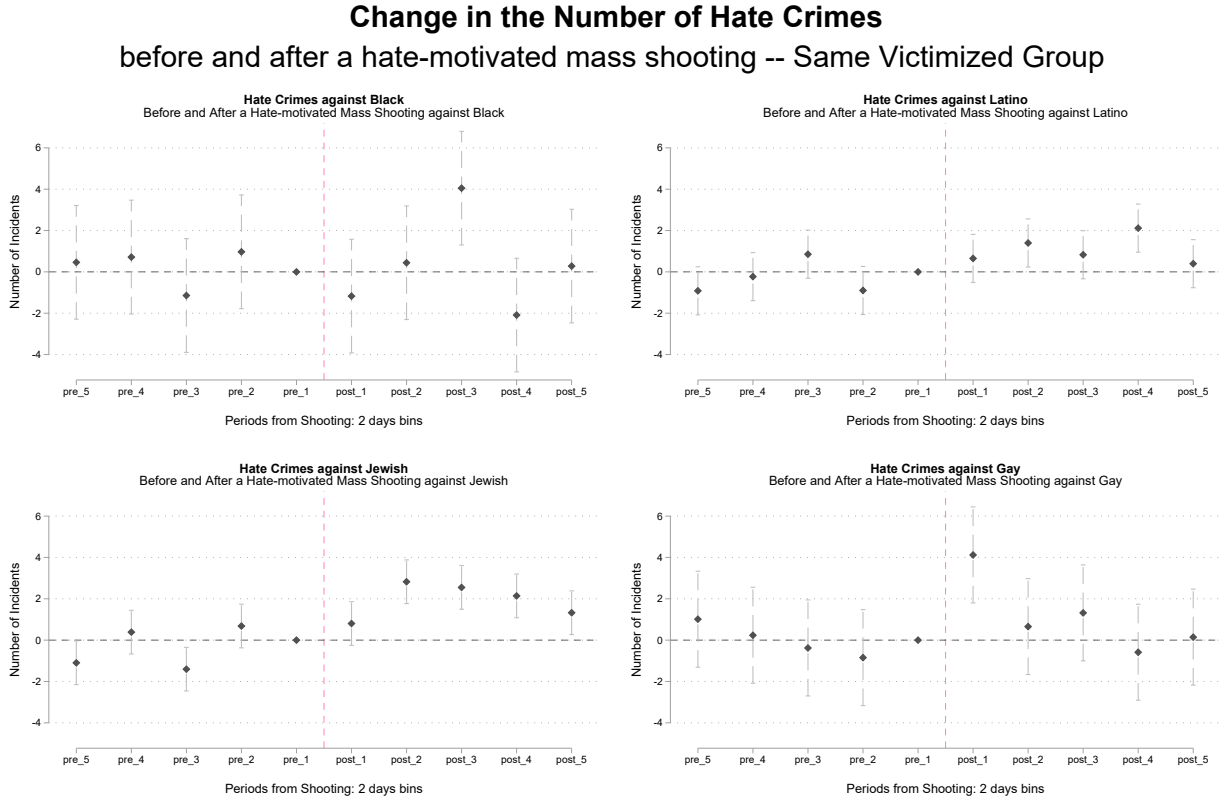
Figure 5: Interest in the Shooter measured by online searching behavior



*Notes:* This graph shows the fraction of mass shootings that has "Suspect" on its list of related topics. For each keyword, Google returns at most 25 topics sorted by popularity. A topic includes all search terms related to it. Thus, for each mass shooting, the list of related topics contains the most common terms that users who searched for the mass shooting also searched for during the same search session. The data is restricted to reflect searching behaviors in the United States within 14 days since the shooting happened. The dark gray bar represents hate-motivated mass shootings while the light gray bar represents non-hate-motivated mass shootings. Error bars reflect 95% confidence intervals.

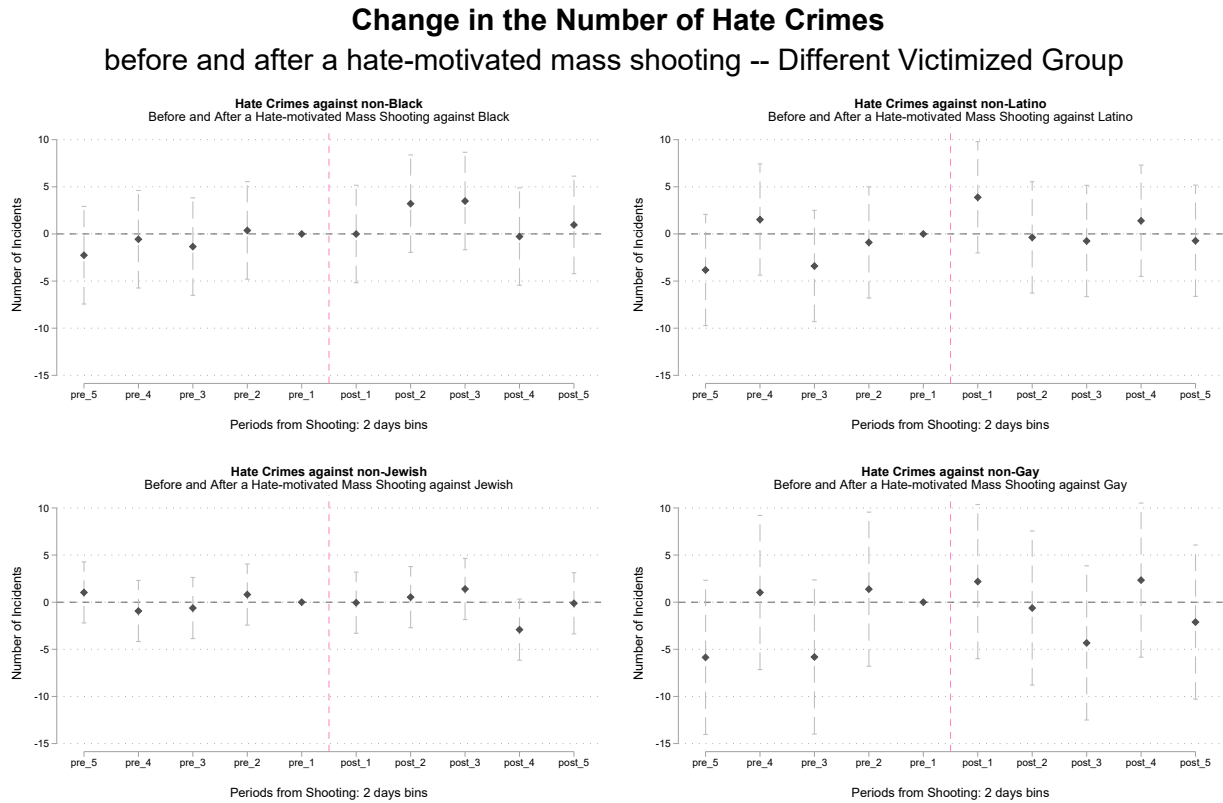


Figure 6: Change in the number of hate crimes targeting the same population



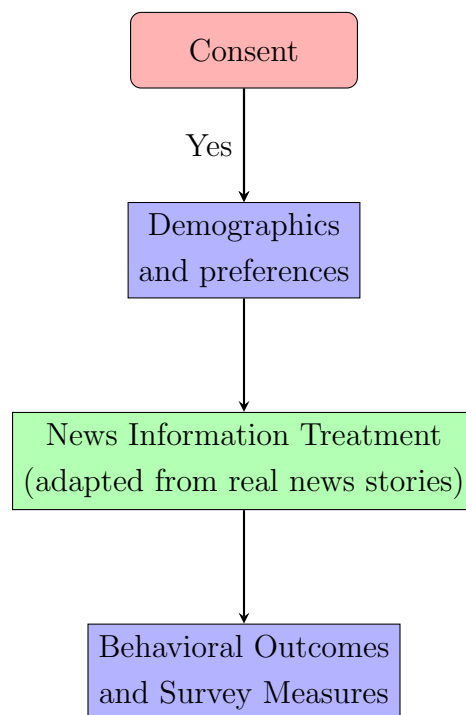
*Notes:* This graph plots the estimated  $\beta_k$  coefficients as explained in Section 2.4. The dependent variable in Panel A, B, C, D is the daily number of hate crimes nation wide against African Americans, Latino, Jewish, and Gay respectively. The data is incident-level hate crime data from the FBI. The pink dotted line represents day 0 when a hate-motivated mass shooting happened. Each point on the X-axis represents a 2-day interval. For example, *post*<sub>1</sub> covers day 1 and day 2. *pre*<sub>1</sub> is the omitted group. I additionally control for year fixed effect, month fixed effect, and day of the week fixed effect, and the intensity of news coverage on each hate-motivated mass shooting 7 days following the shooting. Error bars reflect 95% confidence intervals.

Figure 7: Change in the number of hate crimes targeting different populations



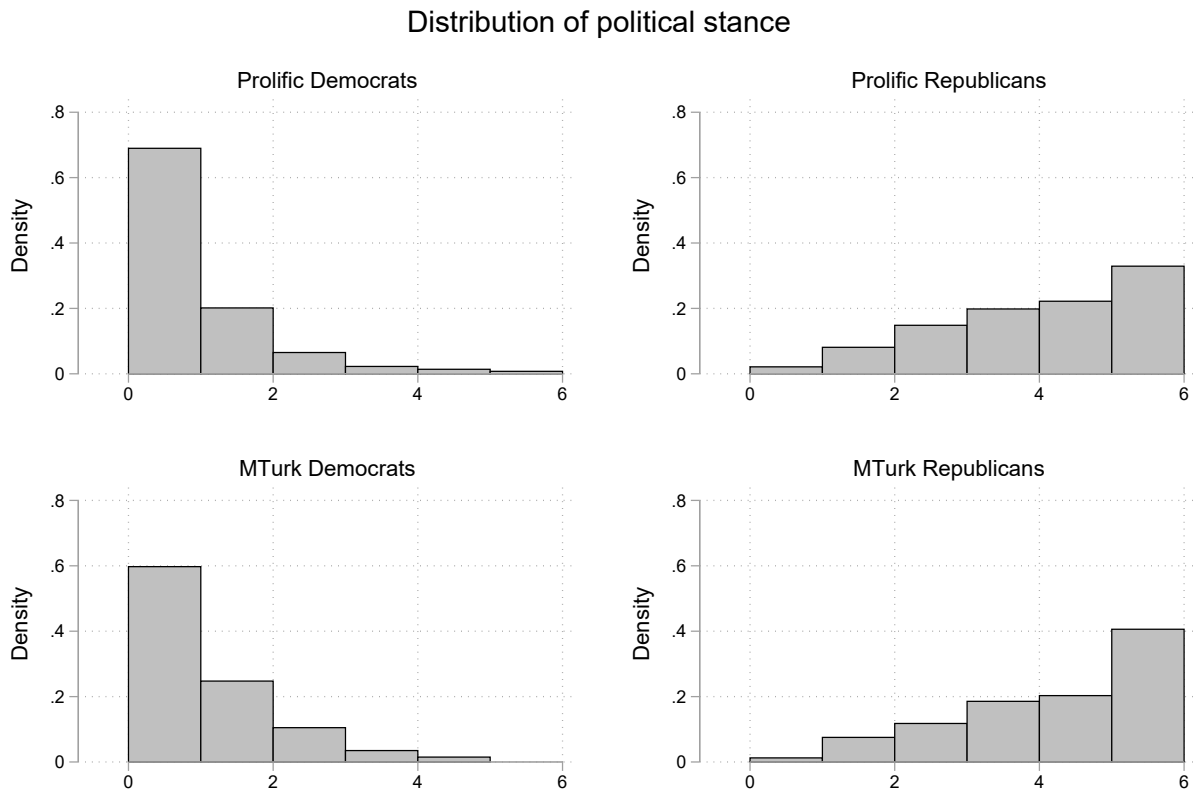
*Notes:* The estimates presented in this graph serve as a robustness check for the results shown in Figure 6. The dependent variable in Panel A, B, C, D is the daily number of hate crimes nation wide excluding the ones targeting African Americans, Latino, Jewish, and Gay respectively. The data is incident-level hate crime data from the FBI. The pink dotted line represents day 0 when a hate-motivated mass shooting happened. Each point on the X-axis represents a 2-day interval. For example, *post*<sub>1</sub> covers day 1 and day 2. *pre*<sub>1</sub> is the omitted group. I additionally control for year fixed effect, month fixed effect, and day of the week fixed effect, and the intensity of news coverage on each hate-motivated mass shooting 7 days following the shooting. Error bars reflect 95% confidence intervals.

Figure 8: Outline of experiment



## A Appendix A: additional tables and figures

Figure A1: Distribution of political stance



*Notes:* This graph shows the distribution of political stance. I elicit subjects' opinions on 6 political issues including abortion, same-sex marriage, gun control, minimum wage, build the wall, and citizenship for children of illegal immigrants. An answer that aligns with the Democratic Party ideology will be coded as a 0, an answer that aligns with the Republican Party ideology will be coded as a 1. The political stance is calculated as the summation of all responses.

Table A1: List of hate-motivated mass shootings

Date	Location	Dead	Type
March 16, 2021	Atlanta, Georgia	8	Anti-Asian
December 10, 2019	Jersey City, New Jersey	6	Anti-Jew
December 6, 2019	Pensacola, Florida	4	Islamic terrorism
August 3, 2019	El Paso, Texas	23	Anti-Hispanic
April 27, 2019	Poway, California	1	Anti-Jew
November 2, 2018	Tallahassee, Florida	3	Anti-female
October 27, 2018	Pittsburgh, Pennsylvania	11	Anti-Jew
September 24, 2017	Antioch, Tennessee	1	Anti-White
April 13, 2017	Fresno, California	4	Anti-White
July 17, 2016	Baton Rouge, Louisiana	4	Anti-White
July 7, 2016	Dallas, Texas	6	Anti-White
June 12, 2016	Orlando, Florida	50	Anti-Gay
December 2, 2015	San Bernardino, California	16	Islamic terrorism
August 26, 2015	Moneta, Virginia	3	Anti-White
July 16, 2015	Chattanooga, Tennessee	6	Islamic terrorism
June 17, 2015	Charleston, South Carolina	9	Anti-Black
May 23, 2014	Isla Vista, California	7	Anti-female
August 5, 2012	Oak Creek, Wisconsin	7	Anti-Sikh
November 5, 2009	Fort Hood, Texas	14	Islamic terrorism
July 28, 2006	Seattle, Washington	1	Anti-Jew
August 10, 1999	Los Angeles, California	1	Anti-Jew
July 2, 1999	Illinois and Indiana	3	Anti-Jew, Anti-Black, Anti-Asian
November 3, 1979	Greensboro, North Carolina	5	Anti-Black
December 31, 1972	New Orleans, Louisiana	10	Anti-White

Table A2: Summary statistics of shootings

	<b>Hate-motivated</b>	<b>Non-hate-motivated</b>
# Dead	8.46	6.20
# Injured	10.29	7.84
# Observations	24	217

*Notes:* A hate-motivated mass shooting is defined as a mass shooting which is motivated, in whole or in part, by the offender's bias(es) against a: race, religion, sexual orientation, ethnicity, gender, gender identity.

Table A3: Total minutes per day on evening TV news broadcasts

	Total minutes of news coverage per day			
	(1)	(2)	(3)	(4)
Hate	11.066*** (0.979)	10.259*** (0.935)	6.192*** (1.222)	6.456*** (1.311)
#Dead		0.323*** (0.050)	0.181*** (0.057)	0.207*** (0.069)
#Injured		0.067*** (0.013)	0.080*** (0.013)	0.084*** (0.014)
#Dead * Hate			0.511*** (0.100)	0.515*** (0.111)
Constant	2.904*** (0.321)	0.295 (0.412)	1.101** (0.439)	2.343 (3.330)
Observations	1,561	1,561	1,561	1,561
R-squared	0.076	0.165	0.179	0.297
Fixed Effects				YES

*Notes:* Column 1 shows an OLS regression of the total minutes of news coverage per day on a dummy for hate-motivated mass shootings. Column 2 additionally controls for the number of dead victims and the number of injured victims. Column 3 adds an interaction term between the number of dead victims and hate. Column 4 adds a set of fixed effects, including days since shooting fixed effect (from day 0, i.e., the day the shooting happened, to day 6, i.e., the 6th day since the shooting happened), day of the week fixed effect, month fixed effect, year fixed effect. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A4: Percentage of news articles about the shooter

	Percentage of news articles about the shooter							
	Based on Keywords				Based on Title			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hate	0.043** (0.018)	0.046** (0.018)	0.068*** (0.024)	0.050** (0.025)	0.033** (0.015)	0.032** (0.016)	0.052** (0.021)	0.050** (0.022)
#Dead		-0.001 (0.001)	0.001 (0.001)	-0.001 (0.002)		0.000 (0.001)	0.001 (0.001)	-0.000 (0.001)
#Injured		0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
#Dead * Hate			-0.003 (0.002)	-0.002 (0.002)			-0.002 (0.002)	-0.002 (0.002)
Constant	0.235*** (0.007)	0.239*** (0.009)	0.232*** (0.010)	0.436*** (0.154)	0.156*** (0.006)	0.154*** (0.008)	0.149*** (0.008)	0.303** (0.133)
Observations	4,396	4,396	4,396	4,396	4,396	4,396	4,396	4,396
R-squared	0.001	0.001	0.002	0.049	0.001	0.001	0.002	0.033
Fixed Effects				YES				YES

*Notes:* The dependent variable for Column 1 through Column 4 is an indicator variable that equals 1 if the news article is about the shooter based on the keywords. Column 1 shows an OLS regression of an indicator on a dummy for hate-motivated mass shootings. Column 2 additionally controls for the number of dead victims and the number of injured victims in each shooting. Column 3 adds an interaction term between the number of dead victims and hate. Column 4 adds a set of fixed effects, including days since shooting fixed effect (from day 0, i.e., the day the shooting happened, to day 13, i.e., the 13th day since the shooting happened), day of the week fixed effect, month fixed effect, year fixed effect. Column 5 to Column 8 uses the same specifications as Columns 1 to Column 4, except that the dependent variable is identified based on the title of the news article. Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$



Table A5: Percentage of news articles about the shooter's motive

	Percentage of news articles about the shooter's motive			
	(1)	(2)	(3)	(4)
Hate	0.074*** (0.007)	0.071*** (0.007)	0.080*** (0.009)	0.079*** (0.010)
#Dead		0.001 (0.000)	0.001** (0.001)	0.001 (0.001)
#Injured		-0.000 (0.000)	-0.000* (0.000)	-0.000 (0.000)
#Dead * Hate			-0.001 (0.001)	-0.001 (0.001)
Constant	0.017*** (0.003)	0.014*** (0.003)	0.012*** (0.004)	0.114* (0.060)
Observations	4,396	4,396	4,396	4,396
R-squared	0.025	0.026	0.026	0.050
Fixed Effects				YES

*Notes:* The dependent variable is an indicator variable that equals 1 if the keywords of the news article contains “motive, ideology, manifesto, reason, racial, race, hate” Column 1 shows an OLS regression of an indicator on a dummy for hate-motivated mass shootings. Column 2 additionally controls for the number of dead victims and the number of injured victims in each shooting. Column 3 adds an interaction term between the number of dead victims and hate. Column 4 adds a set of fixed effects, including days since shooting fixed effect (from day 0, i.e., the day the shooting happened, to day 13, i.e., the 13th day since the shooting happened), day of the week fixed effect, month fixed effect, year fixed effect. Column 5 to Column 8 uses the same specifications as Columns 1 to Column 4, except that the dependent variable is identified based on the title of the news article. Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table A6: Interest in mass shootings measured by online searching behavior

	State-level search interest on Google			
	(1)	(2)	(3)	(4)
Hate	12.733*** (0.581)	11.253*** (0.576)	7.130*** (0.755)	7.334*** (0.790)
#Dead		0.474*** (0.035)	0.252*** (0.044)	0.404*** (0.046)
#Injured		0.008 (0.008)	0.033*** (0.008)	0.019** (0.009)
#Dead * Hate			0.519*** (0.062)	0.340*** (0.066)
Constant	7.629*** (0.212)	4.662*** (0.272)	5.799*** (0.302)	-2.260 (1.894)
Observations	7,650	7,650	7,650	7,650
R-squared	0.059	0.103	0.111	0.170
Fixed Effects				YES

*Notes:* The dependent variable is the search interest value of a mass shooting in a subregion, as explained in Figure 4. Google divides the United States into 51 subregions based on geography. Thus, for each shooting, there are 51 observations. The data is restricted to reflect searching behaviors in the United States within 14 days since each shooting happened. Column 1 shows an OLS regression of search interest value on a dummy for hate-motivated mass shootings. Column 2 additionally controls for the number of dead victims and the number of injured victims in each shooting. Column 3 adds an interaction term between the number of dead victims and hate. Column 4 adds month fixed effect and year fixed effect. Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table A7: Interest in the shooter by online searching behavior

	=1 if “Suspect” is among the most searched topics			
	(1)	(2)	(3)	(4)
Hate	0.311*** (0.112)	0.294** (0.114)	0.126 (0.148)	0.031 (0.144)
#Dead		0.006 (0.007)	-0.004 (0.009)	0.006 (0.008)
#Injured		-0.000 (0.002)	0.001 (0.002)	-0.001 (0.002)
#Dead * Hate			0.021* (0.012)	0.018 (0.012)
Constant	0.289*** (0.042)	0.260*** (0.055)	0.307*** (0.060)	-0.347 (0.275)
Observations	141	141	141	141
R-squared	0.053	0.058	0.079	0.401
Fixed Effects				YES

*Notes:* The dependent variable is an indicator variable that equals 1 if “Suspect” is in the list of the most searched topics related to the shooting. Column 1 shows an OLS regression of an indicator on a dummy for hate-motivated mass shootings. Column 2 additionally controls for the number of dead victims and the number of injured victims in each shooting. Column 3 adds an interaction term between the number of dead victims and hate. Column 4 adds a set of fixed effects, month fixed effect and year fixed effect. Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table A8: Interest in the shooter's motive by online searching behavior

	=1 if motive is among the most searched topics			
	(1)	(2)	(3)	(4)
Hate	0.175*** (0.051)	0.170*** (0.048)	0.188*** (0.063)	0.181*** (0.067)
#Dead		0.001 (0.003)	0.002 (0.004)	0.002 (0.004)
#Injured		0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)
#Dead * Hate			-0.002 (0.005)	-0.004 (0.006)
Constant	0.025 (0.019)	-0.001 (0.023)	-0.006 (0.026)	-0.100 (0.128)
Observations	141	141	141	141
R-squared	0.079	0.216	0.217	0.388
Fixed Effects				YES

*Notes:* The dependent variable is an indicator variable that equals 1 if the most searched topics contains any of the following: “motive, ideology, manifesto, reason, racial, race, hate”. Column 1 shows an OLS regression on a dummy for hate-motivated mass shootings. Column 2 additionally controls for the number of dead victims and the number of injured victims in each shooting. Column 3 adds an interaction term between the number of dead victims and hate. Column 4 adds month fixed effect and year fixed effect. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A9: Summary Statistics and Balance Tests

	A: By political affiliation			B: By recruiting platform		
	Democrat (1)	Republican (2)	t-test (1)=(2)	Prolific (3)	CloudResearch (4)	t-test (3)=(4)
Age	37.81 (12.95)	38.70 (13.35)	0.10*	37.48 (13.07)	39.82 (13.20)	0.00***
Education level	3.82 (1.08)	3.70 (1.12)	0.01***	3.79 (1.14)	3.70 (1.04)	0.09*
Income level	6.75 (3.33)	7.48 (3.35)	0.00***	7.36 (3.39)	6.62 (3.25)	0.00***
White	0.69 (0.46)	0.79 (0.41)	0.00***	0.75 (0.43)	0.72 (0.45)	0.11
Political index	0.08 (0.14)	0.64 (0.26)	0.00***	0.35 (0.35)	0.38 (0.36)	0.05**
Fame-seeking index	2.56 (0.89)	2.85 (0.84)	0.00***	2.69 (0.86)	2.74 (0.90)	0.27
Observations	1,199	1,201		1,601	799	

*Notes:* This table reports the mean of each demographic variable for the Democrat sample (1), the Republican sample (2), the Prolific sample (3), and the CloudResearch sample (4). The corresponding standard deviation is reported in parentheses. t-test of inequality between (1) and (2), and t-test of inequality between (3) and (4) are reported in the last column of each panel. Education level is a categorical variable ranging from Less than high school (1) to Doctorate (7). Income level is a categorical variable ranging from Less than \$10,000 (1) to \$15,000 or more (12). Political index ranges from 0 to 1, a higher value means more right-leaning. Fame-seeking index ranges from 1 to 5, a higher value means more fame-seeking.

Table A10: Treatment effects on support for the shooter

	A: Full Sample			B: Democrat			C: Republican		
	Admire (1)	Justify (2)	Sentence (3)	Admire (4)	Justify (5)	Sentence (6)	Admire (7)	Justify (8)	Sentence (9)
No Hate (T1)	0.123*** (0.039)	0.113** (0.046)	0.212*** (0.059)	0.077* (0.044)	0.056 (0.055)	0.201*** (0.073)	0.175*** (0.064)	0.178** (0.072)	0.246*** (0.090)
Hate Ideology (T3)	0.086** (0.039)	0.054 (0.046)	0.136** (0.059)	0.013 (0.044)	-0.001 (0.055)	0.059 (0.073)	0.155** (0.064)	0.112 (0.072)	0.226** (0.090)
Hate Background (T4)	0.058 (0.039)	0.061 (0.046)	0.177*** (0.059)	0.124*** (0.044)	0.139** (0.055)	0.252*** (0.073)	0.003 (0.064)	0.005 (0.073)	0.121 (0.091)
Control Mean	1.126	1.250	1.781	1.067	1.150	1.906	1.186	1.349	1.657
Observations	2,400	2,400	2,383	1,199	1,199	1,190	1,201	1,201	1,193
R-squared	0.049	0.048	0.084	0.147	0.091	0.063	0.044	0.065	0.118
T1=T3 p-value	0.347	0.207	0.197	0.152	0.306	0.052*	0.751	0.362	0.827
T1=T4 p-value	0.097*	0.268	0.549	0.287	0.133	0.476	0.007***	0.017**	0.169
T3=T4 p-value	0.473	0.878	0.492	0.013**	0.012**	0.008***	0.017**	0.140	0.246
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* This table presents results from OLS regressions. Panel A shows the results for the full sample. Panel B shows the results for the Democrat sub-sample. Panel C shows the results for the Republican sub-sample. The dependent variables in each panel are respectively: admiration for the shooter (5 point Likert-scale), justification for the shooter's action (5 point Likert-scale), and sentencing option for the shooter (6 options ranging from 10 years or less imprisonment to death penalty). The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, and a dummy for the Hate Background Treatment. The Hate Treatment is the omitted group. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A11: Heterogeneous treatment effect by political affiliations

	Demand manifesto		Demand background		Index support		Donation anti-immigrant		Hate links requested		Hate links clicked	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
No Hate (T1)	0.055 (0.040)	0.046 (0.040)	0.058 (0.040)	0.055 (0.040)	0.190** (0.083)	0.140* (0.081)	0.028 (0.039)	0.020 (0.038)	0.016 (0.025)	0.007 (0.025)	-0.003 (0.008)	-0.004 (0.008)
Hate Ideology (T3)	-0.016 (0.040)	-0.026 (0.040)	-0.001 (0.040)	-0.004 (0.040)	0.058 (0.084)	0.028 (0.081)	0.020 (0.038)	0.014 (0.038)	0.018 (0.025)	0.011 (0.025)	0.003 (0.008)	0.003 (0.008)
Hate Background (T4)	-0.031 (0.040)	-0.033 (0.040)	-0.135*** (0.040)	-0.133*** (0.040)	0.282*** (0.083)	0.243*** (0.081)	0.071* (0.038)	0.061 (0.037)	0.040 (0.025)	0.034 (0.025)	0.003 (0.008)	0.003 (0.008)
Republican (Rep)	0.058 (0.040)	0.003 (0.048)	-0.012 (0.040)	-0.041 (0.049)	0.030 (0.083)	0.008 (0.098)	0.163*** (0.038)	0.043 (0.046)	0.063** (0.025)	0.022 (0.030)	0.010 (0.008)	0.001 (0.010)
No Hate * Rep	0.005 (0.057)	0.009 (0.056)	0.002 (0.057)	0.002 (0.057)	0.136 (0.118)	0.178 (0.114)	-0.060 (0.055)	-0.053 (0.054)	-0.003 (0.036)	0.004 (0.035)	-0.007 (0.012)	-0.006 (0.012)
Hate Ideology * Rep	-0.132** (0.057)	-0.119** (0.056)	-0.110* (0.057)	-0.107* (0.057)	0.171 (0.118)	0.217* (0.114)	-0.065 (0.054)	-0.060 (0.053)	-0.020 (0.036)	-0.011 (0.035)	0.007 (0.012)	0.007 (0.012)
Hate Background * Rep	-0.006 (0.057)	-0.006 (0.056)	0.018 (0.057)	0.017 (0.057)	-0.269** (0.118)	-0.181 (0.115)	-0.172*** (0.053)	-0.155*** (0.053)	-0.056 (0.036)	-0.043 (0.035)	-0.017 (0.012)	-0.016 (0.012)
Control Mean (Hate & Dem)	0.407	0.407	0.563	0.563	0.001	0.001	0.114	0.114	0.067	0.067	0.007	0.007
Observations	2,400	2,400	2,400	2,400	2,400	2,400	1,665	1,665	2,400	2,400	2,400	2,400
R-squared	0.015	0.034	0.023	0.028	0.015	0.077	0.019	0.050	0.006	0.040	0.005	0.010
T1=T3 p-value	0.076	0.069	0.145	0.142	0.112	0.166	0.835	0.869	0.965	0.870	0.414	0.407
T1=T4 p-value	0.031	0.047	0.000	0.000	0.272	0.204	0.250	0.267	0.355	0.286	0.422	0.409
T3=T4 p-value	0.706	0.871	0.001	0.002	0.007	0.008	0.167	0.196	0.380	0.369	0.987	0.995
T1+T1*Rep=0 p-value	0.135	0.167	0.138	0.155	0.000	0.000	0.399	0.396	0.597	0.659	0.228	0.227
T3+T3*Rep=0 p-value	0.000	0.000	0.006	0.006	0.006	0.002	0.230	0.226	0.908	0.982	0.224	0.214
T4+T4*Rep=0 p-value	0.356	0.331	0.004	0.004	0.884	0.447	0.008	0.013	0.529	0.704	0.109	0.119
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*Notes:* This table presents results from OLS regressions. The dependent variables from left to right are: (1) an indicator variable that equals 1 if the subject requested to be shown the shooter's manifesto, (2) an indicator variable that equals 1 if the subject requested to be shown the shooter's Background, (3) a standardized index measuring support for the shooter, (4) a dummy that equals 1 if the subject authorized the \$1 donation to the anti-immigrant organization, (5) a dummy that equals 1 if the subject requested to be shown links to access the website of a white supremacy hate group, (6) a dummy that equals 1 if the subject clicked on the provided links about the hate group. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, and a dummy for the Hate Background Treatment, a dummy for Republican subjects, and the interaction terms between treatment assignment and party affiliation. Democrat subjects in the Hate Treatment is the omitted group. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A12: Heterogeneous treatment effects within sub-samples

	A: Democrat sample				B: Republican sample			
	Index	Donation	Links	Links	Index	Donation	Links	Links
	Support (1)	anti-immigrant (2)	requested (3)	clicked (4)	Support (5)	anti-immigrant (6)	requested (7)	clicked (8)
No Hate (T1)	0.115 (0.076)	0.024 (0.038)	0.016 (0.025)	-0.008 (0.008)	0.605*** (0.193)	0.059 (0.122)	0.054 (0.078)	-0.032 (0.027)
Hate Ideology (T3)	0.010 (0.076)	0.011 (0.037)	0.018 (0.025)	0.005 (0.008)	0.091 (0.191)	-0.036 (0.125)	-0.053 (0.077)	-0.009 (0.027)
Hate Background (T4)	0.138* (0.076)	0.057 (0.038)	0.004 (0.025)	-0.004 (0.008)	0.003 (0.203)	-0.152 (0.131)	-0.048 (0.081)	-0.034 (0.028)
Unfriendly	0.051 (0.122)	0.110* (0.063)	0.027 (0.040)	-0.012 (0.013)	-0.046 (0.154)	-0.010 (0.099)	0.016 (0.062)	-0.016 (0.021)
No Hate * Unfriendly	0.198 (0.169)	-0.043 (0.085)	-0.030 (0.055)	0.024 (0.018)	-0.426** (0.206)	-0.116 (0.130)	-0.049 (0.083)	0.023 (0.029)
Hate Ideology * Unfriendly	0.142 (0.169)	0.028 (0.086)	-0.020 (0.055)	-0.004 (0.018)	0.113 (0.204)	-0.011 (0.132)	0.065 (0.082)	0.022 (0.028)
Hate Background * Unfriendly	0.521*** (0.168)	0.027 (0.083)	0.151*** (0.055)	0.035** (0.017)	0.046 (0.215)	0.065 (0.138)	0.046 (0.086)	0.023 (0.030)
Control Mean	0.000	0.114	0.067	0.007	0.001	0.278	0.130	0.017
Observations	1,199	842	1,199	1,199	1,201	823	1,201	1,201
R-squared	0.083	0.069	0.062	0.013	0.118	0.034	0.039	0.013
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* This table presents results from OLS regressions. Panel A shows the results for the Democrat sample. Panel B shows the results for the Republican sample. The dependent variables in each panel from left to right are: (1) a standardized index measuring support for the shooter, (2) a dummy that equals 1 if the subject authorized the \$1 donation to the anti-immigrant organization, (3) a dummy that equals 1 if the subject requested to be shown links to access the website of a white supremacy hate group, (4) a dummy that equals 1 if the subject clicked on the provided links about the hate group. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, a dummy for the Hate Background Treatment, Political Index (PI), and interaction terms between the treatment dummies and the Political Index. The Hate Treatment is the omitted group. Unfriendly is an indicator that equals 1 if the subject support building a wall along the U.S. southern border, or does not support children of illegal immigrants to be granted legal citizenship. Control variables include age, income, education, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and in indicator variable that equals 1 if the subject is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1



Table A13: Experimenter demand effect

	All	T1	T2	T3	T4	T1=T2	T3=T2	T4=T2
Immigrant	0.08	0.04	0.08	0.12	0.07	0.01***	0.013**	0.748
Race	0.06	0.02	0.05	0.08	0.07	0.006***	0.045***	0.268
Hate	0.06	0.02	0.09	0.07	0.07	0.00***	0.308	0.167
One of the above three	0.18	0.08	0.21	0.25	0.20	0.000***	0.114	0.732

*Notes:* This table reports the percentage of subjects who are able to correctly guess the purpose of the experiment. The first row reports the percentage of subjects whose response is related to immigrant. The second row reports the percentage of subjects whose response is related to race. The third row reports the percentage of subjects whose response is related to hate. The last row reports the percentage of subjects whose response is related to immigrant or race or hate. The last three columns report p-value from t-test.

Table A14: Robustness checks

	A: Full Sample			B: Democrat			C: Republican		
	Guessed purpose correctly (1)	Passed all attention checks (2)	Recognize the shooting (3)	Guessed purpose correctly (4)	Passed all attention checks (5)	Recognize the shooting (6)	Guessed purpose correctly (7)	Passed all attention checks (8)	Recognize the shooting (9)
No Hate (T1)	-0.123*** (0.022)	0.019 (0.020)	-0.053** (0.025)	-0.143*** (0.031)	0.023 (0.023)	-0.069* (0.036)	-0.106*** (0.032)	0.019 (0.031)	-0.034 (0.034)
Hate Ideology (T3)	0.040* (0.022)	0.012 (0.020)	-0.002 (0.025)	-0.018 (0.031)	0.007 (0.023)	-0.019 (0.036)	0.099*** (0.031)	0.020 (0.031)	0.019 (0.034)
Hate Background (T4)	-0.008 (0.022)	0.051*** (0.020)	0.036 (0.025)	-0.056* (0.031)	0.016 (0.023)	0.047 (0.036)	0.030 (0.032)	0.088*** (0.031)	0.027 (0.035)
Control Mean	0.208	0.844	0.256	0.230	0.897	0.280	0.186	0.791	0.233
Observations	2,400	2,400	2,400	1,199	1,199	1,199	1,201	1,201	1,201
R-squared	0.038	0.034	0.021	0.035	0.024	0.037	0.053	0.041	0.012
T1=T3 p-value	0.000	0.737	0.040	0.000	0.499	0.161	0.000	0.971	0.130
T1=T4 p-value	0.000	0.100	0.000	0.004	0.787	0.001	0.000	0.028	0.081
T3=T4 p-value	0.027	0.048	0.120	0.221	0.685	0.063	0.031	0.031	0.814
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* This table presents results from OLS regressions. Panel A shows the results for the full sample. Panel B shows the results for the Democrat sample. Panel C shows the results for the Republican sample. The dependent variables in each panel from left to right are: (1) a dummy that equals 1 if the subject correctly guessed the purpose of the experiment, (2) a dummy that equals 1 if the subject passed both attention checks, (3) A dummy that equals 1 if the subject recognized the shooting. The independent variables include a dummy for the No Hate Treatment, a dummy for the Hate Ideology Treatment, and a dummy for the Hate Background Treatment. The Hate Treatment is the omitted group. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A15: The correlation between social desirability bias and outcome measures

	Index support		Donation anti-immigrant		Hate links requested		Hate links clicked	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SD Index	-0.207 (0.181)	-0.249 (0.182)	-0.008 (0.096)	-0.021 (0.095)	-0.072 (0.063)	-0.100 (0.063)	-0.017 (0.014)	-0.021 (0.014)
Constant	0.292** (0.128)	0.091 (0.269)	0.198*** (0.069)	-0.157 (0.138)	0.163*** (0.044)	0.025 (0.094)	0.016 (0.010)	-0.037* (0.021)
Observations	399	399	280	280	399	399	399	399
R-squared	0.003	0.058	0.000	0.059	0.003	0.043	0.004	0.034
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes

*Notes:* This table presents results from OLS regressions. SD Index is an index ranging from 0 to 1 that measures a subject's propensity to give the socially desirable response. The dependent variables in each panel from left to right are: (1) a standardized index measuring support for the shooter, (2) a dummy that equals 1 if the subject authorized the \$1 donation to the anti-immigrant organization, (3) a dummy that equals 1 if the subject requested to be shown links to access the website of a white supremacy hate group, (4) a dummy that equals 1 if the subject clicked on the provided links about the hate group. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table A16: Correlation between attitudinal measures and behavioral outcome

	A: Full sample			B: Democrat			C: Republican		
	Donation anti-immigrant	Hate links Requested	Hate links clicked	Donation anti-immigrant	Hate links Requested	Hate links clicked	Donation anti-immigrant	Hate links Requested	Hate links clicked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Index of support	0.105*** (0.011)	0.083*** (0.007)	0.013*** (0.002)	0.110*** (0.016)	0.071*** (0.011)	0.016*** (0.004)	0.095*** (0.016)	0.084*** (0.010)	0.010*** (0.004)
Constant	-0.021 (0.048)	0.031 (0.032)	-0.009 (0.011)	0.013 (0.057)	0.017 (0.039)	-0.015 (0.013)	-0.053 (0.089)	0.069 (0.057)	-0.005 (0.020)
Observations	1,665	2,400	2,400	842	1,199	1,199	823	1,201	1,201
R-squared	0.092	0.089	0.017	0.129	0.086	0.028	0.066	0.090	0.013
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

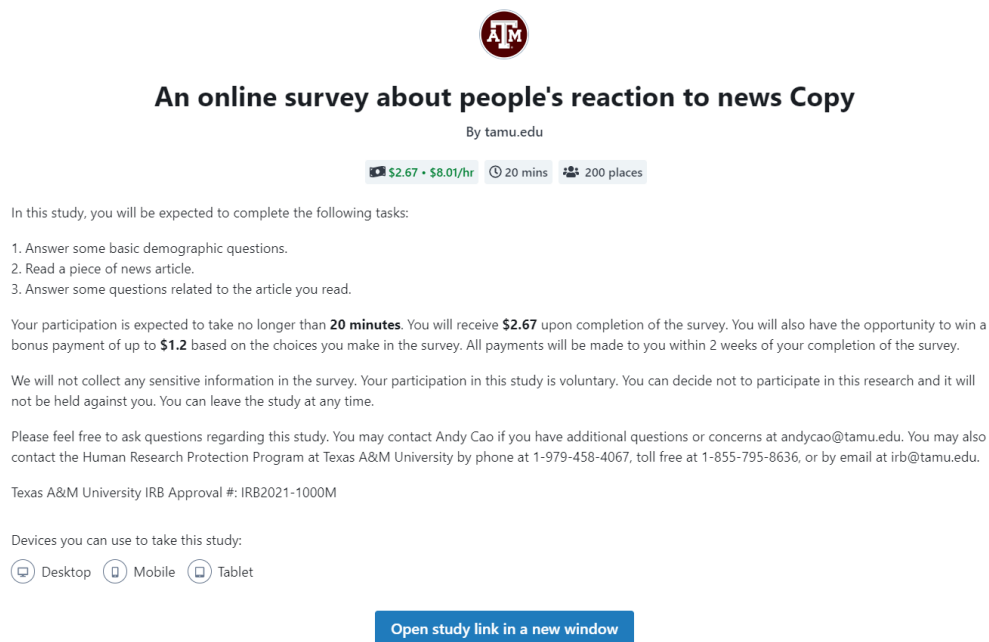
*Notes:* This table presents results from OLS regressions. The dependent variables in each panel from left to right are: (1) a dummy that equals 1 if the subject authorized the \$1 donation to the anti-immigrant organization, (2) a dummy that equals 1 if the subject requested to be shown links to access the website of a white supremacy hate group, (3) a dummy that equals 1 if the subject clicked on the provided links about the hate group. The independent variable is the standardized index of support for the shooter. Control variables include age, income, education, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subject is recruited from CloudResearch. Estimates with controls are reported in odd columns. Estimates without controls are reported in even columns. Control variables include age, income, education, an index measuring political stance, an index measuring fame-seeking personality, an indicator variable that equals 1 if the subject is white, and an indicator variable that equals 1 if the subjects is recruited from CloudResearch. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## B Appendix B survey materials

Appendix B.1 shows the recruiting advertisement of the study. Appendix B.2 shows each of the four information treatments. Appendix B.3 shows my main outcome measures. Appendix B.4 shows other survey questions mentioned in the paper. To view the complete survey interactively, please visit [https://tamu.qualtrics.com/jfe/form/SV\\_e4pM5zr0oXP3Xvg](https://tamu.qualtrics.com/jfe/form/SV_e4pM5zr0oXP3Xvg)

### B.1 Advertisement

Figure A2: Study description on Prolific



The image is a screenshot of a survey advertisement on the Prolific platform. At the top center is the Texas A&M University logo. Below it, the title "An online survey about people's reaction to news Copy" is displayed in bold, followed by "By tamu.edu". A green bar indicates the payment of "\$2.67 + \$8.01/hr", a timer for "20 mins", and "200 places" available. The text describes the tasks: answering demographic questions, reading a news article, and answering related questions. It states that participation takes no longer than 20 minutes and offers a bonus payment of up to \$1.2. It also mentions that the study is voluntary and that sensitive information will not be collected. Contact information for Andy Cao and the Human Research Protection Program is provided, along with the Texas A&M University IRB Approval #: IRB2021-1000M. At the bottom, there are icons for Desktop, Mobile, and Tablet, and a blue button that says "Open study link in a new window".

### B.2 Information Treatments

#### B.2.1 Treatment 1: No Hate

A gunman opened fire Saturday in a grocery store and around a nearby shopping mall, leaving 20 people dead and 26 injured. The suspect is in custody and police say no officers fired their weapons while arresting him.

The police and FBI are investigating whether an anonymous “manifesto,” shared on an online forum, was written by the gunman. The document claims that the attack was motivated by economic reasons.

The store where the shooting took place is a popular destination among tourists. The Department of Justice has called the shooting an act of domestic terrorism.

One witness said she was shopping with her husband when they heard gunfire.



“People were panicking and running, saying that there was a shooter,” “They were running close to the floor, people were dropping on the floor.” She and her husband ran through a stock room before taking cover with other customers.

### **B.2.2 Treatment 2: Hate**

A gunman opened fire Saturday in a grocery store and around a nearby shopping mall, leaving 20 people dead and 26 injured. The suspect is in custody and police say no officers fired their weapons while arresting him.

The victims include at least 8 Mexicans, law enforcement officials said. The police and FBI are investigating whether an anonymous white nationalist “manifesto,” shared on an online forum, was written by the gunman. The document claims that the attack was targeted at the local Hispanic community.

The store where the shooting took place is a popular destination among Mexican tourists. The Department of Justice has called the shooting an act of domestic terrorism and federal authorities say they are investigating possible hate crimes charges. One witness said she was shopping with her husband when they heard gunfire. “People were panicking and running, saying that there was a shooter,” “They were running close to the floor, people were dropping on the floor.” She and her husband ran through a stock room before taking cover with other customers.

### **B.2.3 Treatment 3: Hate Ideology**

A gunman opened fire Saturday in a grocery store and around a nearby shopping mall, leaving 20 people dead and 26 injured. The suspect is in custody and police say no officers fired their weapons while arresting him.

The victims include at least 8 Mexicans, law enforcement officials said. The police and FBI are investigating whether an anonymous white nationalist “manifesto,”



shared on an online forum, was written by the gunman.

The document claims that the attack was targeted at the local Hispanic community. It stated that Latin America immigrants represented a “Hispanic invasion.” It warned that white people were being replaced by foreigners.

The manifesto described an imminent attack and railed against immigrants, saying, “if we can get rid of enough people, then our way of life can be more sustainable.” It also detailed a plan to separate America into territories by race to save this country.

The author hoped his/her attack and words would inspire additional like-minded attacks and lead to a wider racial violence in pursuit of a white ethnostate.

The store where the shooting took place is a popular destination among Mexican tourists. The Department of Justice has called the shooting an act of domestic terrorism and federal authorities say they are investigating possible hate crimes charges. One witness said she was shopping with her husband when they heard



gunfire. “People were panicking and running, saying that there was a shooter,” “They were running close to the floor, people were dropping on the floor.” She and her husband ran through a stock room before taking cover with other customers.

#### B.2.4 Treatment 4: Hate Background

A gunman opened fire Saturday in a grocery store and around a nearby shopping mall, leaving 20 people dead and 26 injured. The suspect is in custody and police say no officers fired their weapons while arresting him.

The victims include at least 8 Mexicans, law enforcement officials said. The police and FBI are investigating whether an anonymous white nationalist “manifesto,” shared on an online forum, was written by the gunman. The document claims that the attack was targeted at the local Hispanic community.

The store where the shooting took place is a popular destination among Mexican tourists. The Department of Justice has called the shooting an act of domestic terrorism and federal authorities say they are investigating possible hate crimes charges. One witness said she was shopping with her husband when they heard



gunfire. “People were panicking and running, saying that there was a shooter,” “They were running close to the floor, people were dropping on the floor.” She and her husband ran through a stock room before taking cover with other customers.

Police officers were interviewing the suspect, Patrick Crusius, a 21-year-old white man from Allen, Tex. Investigators are looking into whether Crusius might have been radicalized online. But friends and former teachers and classmates say he might have been hardened, too, by the tensions in his changing community in real life.

Allison Pettitt, a classmate, said she saw Crusius pushed around in the hallways and “cussed out by some of the Spanish-speaking kids.” She said that bullying was common at the school and that teachers often ignored it. “He started getting more depressed closer to the end of junior year,” Pettitt said. “He started wearing a trench coat to school and becoming more antisocial and withdrawn.” Lesley Range-Stanton, a spokeswoman for Plano’s school district, declined to comment about whether Crusius was bullied, citing student privacy.



## **B.3 Outcome measures**

### **B.3.1 Interest in the shooter**

The news story mentioned an anonymous manifesto. The manifesto was published on an online forum 19 minutes before the first 911 call that alerted the authorities to the mass shooting at the mall.

Would you like to read the anonymous manifesto? If you choose “Yes” we will provide you with access to the complete manifesto at the end of the survey. If you choose “No” you will proceed with the survey without receiving access.

- Yes
- No

Since the shooting happened, authorities have released more information about the suspect of the shooting.

Would you like to know more about the suspect? E.g., age, background. If you choose “Yes” we will provide you with more information at the end of the survey. If you choose “No” you will proceed with the survey without receiving information.

- Yes
- No

### **B.3.2 Justification for the shooter (No Hate)**

Justification is a defense in a criminal case, by which a defendant who committed the crime as defined, claims they did no wrong, because committing the crime advanced some social interest or vindicated a right of such importance that it outweighs the wrongfulness of the crime.

Now think about the news story you just read. The police has confirmed that the suspect was the author of the manifesto, which claims that the attack was motivated by economic reasons. On a scale of 5, do you think the suspect’s reason for the attack satisfies the justification defense?



### **B.3.3 Justification for the shooter (Hate)**

Justification is a defense in a criminal case, by which a defendant who committed the crime as defined, claims they did no wrong, because committing the crime advanced some social interest or vindicated a right of such importance that it outweighs the wrongfulness of the crime.

Now think about the news story you just read. The police has confirmed that the suspect was the author of the manifesto, which claims that the attack was targeted at the local Hispanic community.

On a scale of 5, do you think the suspect's reason for the attack satisfies the justification defense?

### **B.3.4 Sentencing for the shooter**

Now think about the other people who are taking this survey. What do you think is the sentencing option that most other people would choose?

- 10 years or less imprisonment
- 11 to 20 years imprisonment
- 21 to 39 years imprisonment
- Life imprisonment with parole after a minimum of 30 years
- Life imprisonment without parole
- Death Penalty
- Other, please specify

### **B.3.5 Admiration for the shooter**

In your own opinion, how much do you agree or disagree with the following statement?

“Even though what the shooter did was wrong, it took a lot of courage to do what he did, and I admire him for that.”

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

### **B.3.6 Support for the shooter's ideology (anti-immigrant)**

As part of the study, we will now randomly select an organization. You will have the opportunity to authorize a \$1 donation to that organization. You will learn about the organization in the next page.

Your decision will NOT affect your payoff from the survey. If you choose to authorize the \$1 donation, this money will NOT be deducted from your payment, we will simply make the donation on your behalf.

We will post the total amount of donation made on our website once the study is published. All results reported will be in an aggregate format, your individual decision is strictly anonymous. If you are interested, you can visit this website for updates.

The organization randomly selected for you is the Federation for American Immigration Reform (FAIR).

The Federation for American Immigration Reform (FAIR) is a non profit, anti-immigration organization in the United States. The group publishes position papers, organizes events, and runs campaigns in order to advocate for changes in U.S. immigration policy.

FAIR leaders have ties to white supremacist groups and eugenicists and have made many anti-immigration statements. FAIR's founder, John Tanton, has expressed his wish that America remain a majority-white population: a goal to be achieved, presumably, by limiting the number of nonwhites who enter the country.

Would you like to authorize a \$1 donation to FAIR?

### **B.3.7 Support for the shooter's ideology (pro-immigrant)**

As part of the study, we will now randomly select an organization. You will have the opportunity to authorize a \$1 donation to that organization. You will learn about the organization in the next page.

Your decision will NOT affect your payoff from the survey. If you choose to authorize the \$1 donation, this money will NOT be deducted from your payment, we will simply make the donation on your behalf.

We will post the total amount of donation made on our website once the study is published. All results reported will be in an aggregate format, your individual decision is strictly anonymous. If you are interested, you can visit this website for updates.

The organization randomly selected for you is the American Immigration Council (AIC).

The American Immigration Council is a Washington, D.C.-based 501(c)(3) non-profit organization and advocacy group. It advocates for immigrants to the United States.

The American Immigration Council works to strengthen America by shaping how America thinks about and acts towards immigrants and immigration and by working toward a more fair and just immigration system that opens its doors to those in need of protection and unleashes the energy and skills that immigrants bring.

Would you like to authorize a \$1 donation to AIC?

### **B.3.8 Interest in a white-supremacy hate group**

There are organizations/groups whose goals and activities are primarily or substantially based on a shared antipathy towards people of one or more other different races, religions, ethnicities/nationalities/national origins, genders, and/or sexual identities.

Some of these organizations/groups share similar ideology as the author of the manifesto.

One example of such group is Stormfront. Created by former Alabama Klan boss and long-time white supremacist Don Black in 1995, Stormfront was the first major hate site on the Internet. Claiming more than 300,000 registered members as of May 2015 (though far fewer remain active), the site has been a very popular online forum for white nationalists. In its own words, “Our mission is to provide information not available in the controlled news media and to build a community of White activists working for the survival of our people.”

Stormfront was filtered out from Google Search due to its controversial content. Would you like to know how to access its website?

If you choose “Yes”, we will provide you with relevant information at the end of the survey. If you choose “No”, you will proceed with the survey without receiving access.

### **B.3.9 Example of norm elicitation**

Earlier this month, 200 participants on MTurk participated in this survey. We asked these participants the same questions as the ones you are answering, including the last question you just saw: “On a scale of 1 to 5, do you think the suspect’s reason for the attack satisfies the justification defense?”

Now, we ask you to think about the answers of these 200 previous participants and guess what option most of them chose. You will win a bonus payment of \$0.2 if your guess is correct.

200 participants were asked: “On a scale of 1 to 5, do you think the suspect’s reason for the attack satisfies the justification defense?”

I think most people chose:

## **B.4 Other survey questions**

### **B.4.1 Measuring political stance**

- What is your stance on abortion?
  - Pro-life
  - Pro-choice
- Do you support the legalization of same sex marriage?

- Yes
  - No
- Should there be more restrictions on the current process of purchasing a gun?
  - Yes
  - No
- What is your stance on abortion?
  - Pro-life
  - Pro-choice
- Should the government raise the federal minimum wage?
  - Yes
  - No
- Should the U.S. build a wall along the southern border?
  - Yes
  - No
- Should children of illegal immigrants be granted legal citizenship?
  - Yes
  - No

#### **B.4.2 Measuring social desirability bias**

- Do you agree or disagree with the following statement? I'm always willing to admit it when I make a mistake
  - Agree
  - Disagree
- Do you agree or disagree with the following statement? I like to gossip at times
  - Agree
  - Disagree
- Do you agree or disagree with the following statement? There have been occasions when I took advantage of someone
  - Agree
  - Disagree
- Do you agree or disagree with the following statement? I sometimes try to get even rather than forgive and forget
  - Agree

- Disagree
- Do you agree or disagree with the following statement? At times I have really insisted on having things my own way
  - Agree
  - Disagree
- Do you agree or disagree with the following statement? I have never been irked when people expressed ideas very different from my own
  - Agree
  - Disagree
- Do you agree or disagree with the following statement? I have never deliberately said something that hurt someone's feelings
  - Agree
  - Disagree

#### **B.4.3 Example of attention checks**

Thank you again for participating in our study. It is very important that you read and answer each question carefully. To show that you are paying attention, please choose both “Extremely displeased” and “slightly pleased” on the question below.

- How pleased are you with the weather today?
  - Extremely displeased
  - Moderately displeased
  - Slightly displeased
  - Neither pleased nor displeased
  - Slightly pleased
  - Moderately pleased
  - Extremely pleased