The Limited Effects of U.S. Protests*

Amory Gethin Vincent Pons

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Abstract

Recent protest movements stand out by their spontaneous nature and lack of stable leadership, raising doubts on their ability to generate political change. In a context of high polarization, they may also fuel backlash. This article provides systematic evidence on the effects of protests on public opinion, political attitudes, and legislative policymaking. Drawing on a database covering the quasi-universe of protests held in the United States, we identify 14 protest waves that took place from 2017 to 2022, covering topics related to environmental protection, gender equality, racial issues, gun control, immigration, and national and international politics. We use Twitter data, Google search volumes, high-frequency surveys, official election results, and data on politician behavior to track the evolution of online interest, policy views, vote intentions, and policies proposed and adopted before and after the outset of each movement. Combining national-level event studies with difference-in-differences designs that exploit variation in local protest intensity, we find that protests generate substantial internet activity but have minimal effects on opinions, voting behavior, and a wide range of political outcomes. The Black Lives Matter protests following George Floyd's death are a notable exception, as they increased both support for the Democratic Party and legislative activity on racial issues. Finally, protest movements generally do not generate political backlash unless they become violent.

*Amory Gethin (agethin@worldbank.org): World Bank Development Research Group and World Inequality Lab - Paris School of Economics. Vincent Pons (vpons@hbs.edu): Harvard Business School, CEPR and NBER. We thank Rafael Di Tella, Teresa Esteban-Casanelles, Jean Lacroix, Eleni Kyrkopoulou, Jesse Shapiro, David Yang, and numerous seminar and conference participants for useful comments and discussions. Carlos Chávez Padilla, Leonardo Peñaloza-Pacheco, Marie Truffier-Blanc, and Neha Verma provided excellent research assistance. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

1. Introduction

In recent years, public demonstrations have seen a significant upsurge in the U.S. and around the world (Cantoni et al., 2024; Chenoweth, 2023; Ortiz et al., 2022). The multiplication of protests suggests that the electoral process is no longer able to settle major societal issues. This trend may thus be seen as another sign of democratic weakening, next to the rise in partisan polarization, the decline in voter turnout, and people's growing dissatisfaction with how democracy works. On the other hand, demonstrating is a form of political participation that has long been considered an essential feature of liberal democracies. It enables active citizens to voice their concerns outside of election periods and may help influence how other people think and vote and, ultimately, bring about political change. How successful the new wave of protests has been at doing so remains an open question. Distinctive features of many recent mobilizations include their spontaneous nature, the coordination of participants through social media rather than established entities such as parties or unions (Casanueva et al., 2025; Enikolopov, Makarin, and Petrova, 2020; Fergusson and Molina, 2019; Manacorda and Tesei, 2020), and, consequently a lack of stable leadership and organizational structure (Boyer et al., 2020; De Witte, 2020; Keating, 2020; Serhan, 2019). This has made it more difficult for protesters to articulate consistent claims and sustain protest movements beyond sudden outbreaks. At the same time, the weakly institutionalized nature of recent protests could allow new actors and claims to emerge and enable transgressive forms of contention conducive to political change (Tarrow, 2011; Tilly, 2004).

This paper provides systematic evidence on the effects of recent protests on individual attitudes, political behavior, and policymaking. Combining a dataset on the near universe of protests held in the United States, social media and Google search data, high-frequency surveys including rich information on political views and vote intentions, official election results, and policy outcomes, we study the dynamics of 14 protest movements that unfolded in the country from 2017 to 2022. We find that protests generate significant online activity but have limited effects on public opinion, political attitudes, and policies proposed and adopted in Congress. Black Lives Matter protests, which modestly influenced voters and policymakers, are an outlier: We find precise null effects for almost all other protest movements and outcomes covered in our sample.

Our starting point was to build a new dataset mapping the evolution of online activity, political attitudes, and policy outcomes with the occurrence of protests in the United States since 2017. Drawing on data from the Crowd Counting Consortium (CCC), which provides information on nearly all protests held in the U.S. during that period, we identify 14 protest movements covering topics related to environmental protection, gender equality, gun control, immigration, international affairs, national politics, and racial issues. These include large-scale movements such as Black

Lives Matter and the 2017 Women's March, which mobilized several million participants, but also movements of smaller magnitude such as protests against the 2017 Muslim Ban or the 2019 Climate Strike, which did not receive as much attention yet still mobilized several hundreds of thousands of protesters. The data allow us to observe the day of each movement's outset and the evolution of protests over time, as well as county-level variation in protest intensity.

We match the protests data with granular data on internet activity and political outcomes from ten sources. Data on online activity come from Twitter and Google Trends. We count the number of tweets and Google searches containing keywords related to each movement at a daily frequency. Data on political attitudes come from three surveys. The Nationscape survey, one of the largest public opinion surveys ever fielded in the United States, allows us to observe political opinions and vote intentions for repeated cross sections of about 1,000 adults every day from July 2019 to January 2021, for a total of about 500,000 respondents. The Cooperative Congressional Election Study covers similar topics and has the advantage of being available for a longer time period (2006-2022), but it is only fielded once a year and includes a more restrictive set of questions. The Gallup Poll Social Series (GPSS), a monthly survey run since 2000, records the problems seen as most important by U.S. citizens, providing a complementary view on the salience of political issues raised by protesters. In addition to these three surveys, we use official election results in presidential, House, gubernatorial, and local elections to study the effects of protests on turnout and electoral support for the Democratic Party. Finally, we exploit data on politicians' speeches and behavior, including video transcripts of local government meetings held in a large sample of cities, the universe of tweets published and of speeches pronounced by members of Congress, their ideology as measured by roll call votes, and their legislative activity as measured by sponsored and adopted congressional bills. Together, this rich set of outcomes allows us to track all the main steps of the causal chain, from increased awareness towards the issues raised by protesters to shifts in public opinion, voting behavior, and policymaking.

Our empirical analysis combines national-level event studies with difference-in-differences specifications exploiting variation in local protest intensity. The high frequency of our data first allows us to study how internet activity, political attitudes, and legislative activity evolve before and after the outset of each movement in the country as a whole. This event study specification has the advantage of directly identifying nationwide trend breaks: if a protest movement affects a certain outcome, we should expect to observe a significant change in this outcome following the outset of the movement. A natural concern is that such aggregate change may reflect the influence of other unobserved factors correlated with the beginning of the movement. For instance, racial attitudes may change due to the death of George Floyd and its discussion in the media rather than the protests that followed. We consider two alternative specifications to tackle this issue. First, we restrict the simple-difference analysis to six movements that we call "independent," in the sense that they were not immediately triggered by a particular event. Second, we run difference-in-differences specifications comparing the evolution of outcomes in counties with more or less protest intensity. This last specification has the advantage of better capturing local effects of protests, yet it cannot identify spillovers of protests beyond the county in which they took place, through channels such as national media and online coverage. We thus view these three specifications as providing different yet complementary perspectives on the political effects of protests.

Our first set of results relates to the effect of protests on the salience of issues raised by protesters, as measured by online activity and citizens' perception of the most important problem in the country. The outset of a protest movement coincides with a sharp increase in both tweets and Google searches related to the issues raised by protesters. This effect is large, statistically significant across all our specifications, and observed for most protest movements, but it is relatively short-lived: online salience recedes to baseline levels within two weeks after the beginning of the movement. Turning to the GPSS survey, we find no evidence that protests coincide with a significant nationwide increase in the fraction of respondents who consider that the issue raised by protesters is one of the three most important in the country.

We then turn to the effect of protests on policy views. The Nationscape survey allows us to track 25 questions before and after the beginning of five protest movements, while the CCES survey covers 25 questions over 10 movements. For each of these questions, we study both the fraction of respondents who declare having any opinion (not being "unsure" about the answer) and the fraction of liberal answers (for instance, whether the respondent is in favor of capping carbon emissions). We find small positive effects on both outcomes in the simple-difference specification, but these effects are entirely driven by Black Lives Matter protests. Indeed, the death of George Floyd led to a large increase in the fraction of respondents expressing more liberal attitudes on racial issues, in line with existing evidence (Reny and Newman, 2021). This effect is only visible in the simple-difference specification, however. For other movements in our sample, we estimate precise null effects of protests on policy views in all specifications.

We then analyze the effects of protests on political attitudes and behavior, including interest in politics, turnout intentions, vote intentions, and presidential approval. The Nationscape survey allows us to precisely track the evolution of these outcomes in the weeks before and after the outset of protest movements. We also study official county-level turnout and Democratic vote shares in presidential, House, gubernatorial, and local elections. Across all outcomes and specifications, we find no evidence that protests affected political attitudes.

Finally, we investigate the effects of protests on policymaking. Protest movements coincide with a large increase in local government meeting discussions, congressional tweets, speeches, and bills sponsored on topics related to protesters' claims in the simple-difference specification. However, these effects are null when restricting the sample to independent movements. We also estimate precise null effects of protests on all policymaking outcomes except local government meeting discussions and congressional tweets in the difference-in-differences specification.

We conclude by analyzing heterogeneity. Two results stand out. First, Black Lives Matter (BLM) protests were the only movement that consistently affected voting behavior and policymaking outcomes in both the simple-difference and difference-in-differences specifications. In particular, areas with greater BLM protest intensity saw an increase in both Democratic vote shares and race-related bills sponsored by Congress members elected in these areas. These sponsored bills did not translate into newly adopted laws, however, suggesting that the effects of BLM protests on actual policies was limited. Second, we generally do not find any evidence of backlash among any subgroup of individuals. Both in the simple-difference and difference-in-differences specifications, there is no heterogeneity in the effects of protests by ideology, age, gender, education, race, political knowledge, or type of news consumption. There is one exception: violent protests. While violent BLM protests generated more Twitter activity and more frequent discussions in local government meetings, they may also have led to a decline in turnout and in the share of respondents declaring liberal views on racial issues.

Based on this evidence, we conclude that the political effects of U.S. protests are generally weak. Across 14 protest movements held in the United States from 2017 to 2022, the only movement for which we find significant effects is BLM, and only for a subset of outcomes. One natural hypothesis could be that protest movements exhibit threshold behavior, so that only sufficiently large movements such as BLM can influence citizens and policymakers. However,BLM was not the only large movement in our database. In fact, it was not even the largest: the 2017 Women's March and the 2018 March for Our Lives protests in favor of gun control both mobilized a larger number of participants. Yet, none of them consistently affected attitudes and political behavior beyond short-term increases in tweets and Google searches. Another hypothesis is that it was the uniquely spontaneous, sustained, and transgressive nature of the BLM movement that enabled it to raise significant attention among citizens and policymakers, which in turn helped convert protest mobilization into political change. This challenges the view that less institutionalized and more decentralized protest movements are less likely to generate political results.

A large and growing literature studies the political effects of protests. There is evidence that specific movements may influence voting behavior, generally to the benefit of the party most favorable to protesters' claims.[1] Evidence on policy views and legislative policymaking is scarcer and more mixed.[2] Our analysis improves upon this work in three ways. First, unlike existing studies, we go beyond specific cases to systematically analyze all major movements that took place in the United States since 2017. Doing so has important implications for the generalizability of results documented in the literature: with the exception of BLM protests, which have received particular attention in recent years, we find that other movements did not have any discernable effects. Second, the richness of our data allows us to track the main elements of the causal chain linking protests to political outcomes, from online attention to salience, policy views, voting behavior, and policies proposed and adopted in Congress. This contrasts with existing studies, which generally restrict themselves to one type of outcome. Finally, the exceptionally high frequency of the social media, survey, and legislative making data used in our analysis allow us to track the effects of protests over time and to document potential pre-trends over long periods. By contrast, almost all existing studies in the literature rely on comparisons between only two time periods.

The remainder of the paper is organized as follows. Section 2 presents the data and methodology. Sections 3, 4, 5, and 6 study the effects of protests on the salience of issues raised by protesters, policy views, political attitudes and behavior, and policymaking. Section 7 investigates how these effects vary by movement, individual characteristic, party affiliation, and level of violence. Section 8 concludes.

[1] A number of studies find that protests tilt local election outcomes in favor of the parties or candidates closest to the movement (Casanueva, 2021; Colombo et al., 2021; Gillion and Soule, 2018; González, 2020; Lagios, Méon, and Tojerow, 2021; Larreboure and González, 2021; Madestam et al., 2013; Teeselink and Melios, 2021; Waldinger et al., 2023). On the other hand, several studies document that protests reduce trust in institutions and support for democracy (Ketchley and El-Rayyes, 2021; Sangnier and Zylberberg, 2017; Valentim, 2021). In some cases, they can also trigger electoral backlash or political polarization through heightened feelings of economic insecurity and demand for social control (Caprettini et al., 2024; Wang and Wong, 2021; Wasow, 2020). Existing studies have also documented effects of protests on other outcomes, such as economic redistribution (Archibong, 2022), reporting of sex crimes (Levy and Mattsson, 2023), or stock market valuations (Acemoglu, Hassan, and Tahoun, 2018; Ba, Rivera, and Whitefield, 2024; Ba, Rivera, and Whitefield, 2025).

[2] For instance, Hungerman and Moorthy (2023) provide evidence that 1970 Earth Day protests increased long-run support for the environment, but only among individuals who were school-aged at the time, suggesting null effects on the adult population. Haas et al. (2025) estimate null effects of protest exposure on opinions and vote intentions in a randomized control trial exposing pedestrians to climate strikes in Germany. Some studies do find that protests and strikes shift attitudes in favor of protesters' claims (e.g., Branton et al., 2015; Brehm and Gruhl, 2024; Enos, Kaufman, and Sands, 2019; Hertel-Fernandez, Naidu, and Reich, 2021; Mazumder, 2018; 2019; Pop-Eleches, Robertson, and Rosenfeld, 2022; Reny and Newman, 2021; Tertytchnaya and Lankina, 2020), but others document attitudinal backlash among subgroups of voters (e.g., Anduiza and Rico, 2022; Koob and Justesen, 2022; Valentim, 2024). Evidence on policy outcomes also varies across contexts and topics, covering outcomes as diverse as the supply of female politicians (Moresi, 2022) and roll call votes on minority-related issues (Gillion, 2012).

2. Data and Methodology

This section presents our data and empirical strategy. We first describe the database recording U.S. protests over the 2017-2022 period, as well as the method we use to identify major protest movements (Section 2.1). Sections 2.2, 2.3, 2.4, and 2.5 present the Twitter, Google, survey, election results, and policymaking data which we use to track the political effects of protests. Finally, we outline the empirical specifications used to relate protests to political outcomes (Section 2.6).

2.1. Protest Data

2.1.1. CCC Database

The starting point of our analysis is the database on political crowds in the United States since 2017 provided by the Crowd Counting Consortium (CCC). Drawing on various publicly available sources such as the media, social media accounts, and reviews of organization websites, the CCC compiles data on marches, protests, strikes, demonstrations, riots, and other political actions (Chenoweth et al., 2025).[3] The database provides detailed information on each protest, including its date, the city in which it took place, the protesters' requests, the number of participants, and the main actors involved. We focus on the period going from January 20th, 2017 (when the CCC data start) to May 31st, 2022 (when our survey data stop). During this period, the CCC database records a total of 110,000 independent events.

2.1.2. Identification of Protest Movements

We identify major protest movements in two steps.

First, we classify protests in the CCC database by topic and political orientation. In some instances, the CCC already records information on the "macroevent" associated with each protest, such as the 2017 Women's March, in which case we directly map protests to the topic related to each macroevent. This is the case for 30,000 protests. We manually classify the remaining 80,000 protests by relying on the "claims" variable, which provides a brief description of protest participants' main claims (for instance, "against racism, for social justice"). Drawing on these two

[3]More specifically, the CCC covers "any type of activity that...is carried out with the explicit purpose of articulating a grievance against a [political] target, or expressing support of a [political] target," but also further restricts the scope to events that are (1) "open to the public and free of charge" and (2) "nonviolent in the sense that they are not primarily organized to cause direct harm to any persons."

sources of information, we are able to categorize 92,000 protests (84%) into eight main topics: racism, environmental protection, gender equality, gun control, immigration, international affairs, national politics, and other miscellaneous topics.[4] Appendix Table B1 provides descriptive statistics. The most common issue is racism, representing 27% of all protests during the period. About 86% of protests are of liberal political orientation, while 14% are conservative.

Second, we identify protest movements that occurred during this period by exploiting major breaks in protest intensity by topic. Concretely, we plot the evolution of the number of protests and the number of participants by month for each of these eight topics. The time series show long periods of low protest intensity, interrupted by brief episodes of sharp spikes in protest activity. We define protest movements as periods of large and sudden increases in protest intensity.[5]

With this approach, we are able to identify 14 major protest movements that developed over the 2017-2022 period and for which survey data are available to cover political attitudes on the corresponding topic. Table 1 provides descriptive statistics on each movement. All movements are "liberal," in the sense that their claims are typically associated with progressive political attitudes such as greater racial or gender equality, environmental protection, or gun control. This finding is consistent with the tight association between protest participation and culturally liberal views documented in the literature (e.g., Kostelka and Rovny, 2019).[6] We sum the total number of protests and protesters during the month after the beginning of each movement. The first Women's March is the movement that gathered the greatest number of participants, with over 4 million protesters in January 2017, followed by the pro-gun-control March for Our Lives movement and the George Floyd protests. The smallest movements are the Women's March of October 2020 and the wave of protests against a potential war with Iran that took place in January 2020, both gathering fewer than 30,000 participants. Notice that figures on the number of participants are a lower bound, given that over half of events do not include information on participants and are bottom-coded at zero. The number of counties in which at least one protest occurred during a specific movement ranges from 188 (protests against the "Muslim ban") to 1,373 (George Floyd protests).

We estimate the effects of protest movements by combining the CCC data with data on outcomes capturing effects at different time horizons, from immediate responses, such as tweets and Google searches in the days following the protests, to long-run effects, such as election results several

[4]Other topics include protests related to the COVID-19 pandemic, strikes, and protests in support or against LGBTQ+ minorities. The remaining 16% of unclassified protests mostly consist in isolated events focused on local issues, which we do not attempt to classify given their sporadic and heterogeneous nature.

[5]Appendix Figure B1 plots the monthly evolution of protest intensity by topic (number of protests and number of protesters), highlighting the beginning of each movement with a black vertical line.

[6]We observe very few spikes in conservative protests during this period, and almost all of them display low protest intensity and geographical coverage. The one exception is protests against responses to the COVID-19 pandemic. Due to an insufficient number of outcomes related to this topic and the lack of any pre period (since COVID-19 was not an issue before the pandemic), we exclude this protest movement from our analysis.

years later. For each outcome, we conduct the analysis at the finest available geographic unit and the highest-frequency time unit. Appendix Table A1 lists all outcomes and the corresponding geographical and time units. We now present the data sources used for each outcome.

2.2. Twitter and Google Data

We use Twitter and Google data to estimate the effects of protest movements on the salience of and interest towards the corresponding topics.

2.2.1. Twitter Data

Using Twitter's API, we collect data on about 400,000 tweets covering the days immediately preceding and following the outset of each movement. Drawing on words mentioned in the "claims" variable of the CCC database, as well as newspaper and online reports, we first construct a dictionary of approximately 100 keywords. We then collect all tweets (1) tweeted during a window of two weeks before and after the beginning of the movement, (2) mentioning at least one of the keywords, and (3) providing information on the geolocation of the author. The resulting database allows us to measure how intensely the topic associated with each movement was discussed during our period of interest in counties with more or less protest intensity. Appendix Table C1 shows the keywords dictionary used for the data collection. We deliberately do not include the word 'protest' in this dictionary so that our results are not driven by tweets only mentioning that there was a protest on the day considered.

2.2.2. Google Data

We complement Twitter data with data on the intensity of Google searches associated with each topic. We rely on the Google Trends API, which allows us to collect information on the volume of searches made for a specific keyword or expression. We construct a database covering daily time series of total search volumes at the Designated Market Area (DMA) level, which is the smallest geographical unit of observation available. We use the same dictionary of keywords as the one used for the Twitter data.

Unlike publicly available Google Trends data, which normalize every time series to range from 0 to 100, we were able to get access to a restricted version of the API that covers actual search volumes. Search volumes are expressed relatively to all other keywords and expressions searched in the United States. Our dependent variable thus corresponds to the intensity of Google searches for keywords related to each movement in a given DMA, relatively to all other Google searches made in the U.S. during this period.

One difficulty is that the Google API bottom codes low search volumes at zero. In small DMAs, time series for keywords that are rarely searched display many zeros, which reduces variation in search volumes and our ability to detect changes in them. Our results thus provide a lower bound on the effects of protests on Google search intensity.

2.3. Survey Data

To track the evolution of political attitudes before and after the unfolding of each protest movement, we rely on three main survey datasets.

2.3.1. Nationscape

The Democracy Fund + UCLA Nationscape survey is one of the largest public opinion surveys ever conducted in the United States. It was fielded between July 2019 and January 2021. It interviewed repeated cross-sections of 500-2,000 adults every day during this period, amounting to a total of nearly 500,000 separate interviews. The survey questionnaire covers many questions on current political and social issues, including attitudes towards political institutions, attitudes towards specific social groups, opinions on a number of topics and policies, interest in politics, and vote intentions for the next presidential, House, Senate, and gubernatorial elections.

The time coverage of the Nationscape survey allows us to cover five of our 15 protest movements: the Climate Strike, the BLM protests, the Impeach Trump protests, and the last two Women's Marches. We were able to map 25 questions of the Nationscape survey to the topics covered by these movements. For instance, we classify the question "Women are just as capable of thinking logically as men" under the gender equality issue. This classification leaves us with four questions on environmental issues, four questions on national politics, seven questions on racism, and ten questions on gender equality. We dichotomize all variables and recode them so that 0 corresponds to a conservative opinion and 1 to a liberal opinion. The questionnaire also allows respondents to answer "Not sure" to each question, which we treat as a separate outcome of interest in the analysis, coding unsure respondents as 0 and those who expressed an opinion as 1. Appendix Table D1 lists these questions and shows the share of liberal answers to each of them. In our main analysis, we aggregate answers at the county level and track the evolution of opinions in the weeks before and after the outset of each movement.

2.3.2. Gallup Poll Social Series

The Gallup Poll Social Series (GPSS) is a monthly survey run by Gallup since 2000 on a sample representative of the full U.S. population. The sample size is much lower than that of the Nationscape survey, generally reaching about 1,000 respondents per month. Despite this low sample size, the GPSS has two advantages. First, it asks respondents about the three most important problems of the country at the time of the survey. This question usefully complements the analysis of opinions in Nationscape by providing a direct measure of how important the topics corresponding to each protest movement are considered to be. Second, it covers every month since 2000, allowing us to study the county-level evolution of attitudes month-by-month for all protest movements identified in the CCC database (from 2017 to 2022).

As in the case of Nationscape, we manually map the most important problems mentioned by respondents to the topic covered by each movement. For instance, respondents mentioning "Race Relations" as one of the most important problems are mapped to the issue of racism. We then define our outcome of interest as taking value 1 if the respondent mentioned the corresponding topic among the three most important problems in the country and 0 otherwise.

2.3.3. Cooperative Congressional Election Study

We complement these two surveys with the Cooperative Election Study (previously called Cooperative Congressional Election Study, CCES). The CCES is a representative survey that has been fielded by YouGov every year since 2006. It includes 60,000 respondents in recent election years, and 20,000 respondents in non-election years. Like Nationscape, it covers information on vote intentions and past voting behavior, together with questions on policy views. As for Nationscape, we associate questions on policy views with each topic of interest. We were able to map 23 questions: six questions for environmental protection, three for gun control, four for immigration, four for racism, three for gender equality, one for national politics (presidential approval), one related to Iran, and one related to the Muslim Ban. Appendix Table D2 provides more detail.

The main advantage of CCES over Nationscape is that it covers a longer time period, allowing us to study 10 of the 15 protest movements identified in the CCC database (no question related to the remaining five movements is available). Its main weakness is that it is only fielded once a year, which limits our ability to identify long pre-trends in political attitudes before the outset of each movement. This difficulty is reinforced by the fact that the CCES did not always ask the same questions every year. For this reason, we can only track the county-level evolution of opinions over four time periods, from two years before to two years after the outset of each movement.

2.4. Official Election Results

We complement the survey data with official election results to study long-run changes in voting behavior. County-level vote shares in presidential (1980-2024), House (2004-2024), and gubernatorial elections (1990-2022) as well as turnout in general elections (1992-2022) are available from the David Leip's Atlas.[7]

Local election results for city councils, county executives, county legislatures, and mayors are available from the American local government elections database (Benedictis-Kessner et al., 2023). It covers a sample of about 1,400 cities, counties, and school districts with a population of at least 50,000 in 2020. We map all geographical units in this database to counties and construct county-level Democratic vote shares. The resulting panel covers about 600 counties, accounting for 78% of the U.S. population.

2.5. Policymaking

Finally, we consider five policymaking outcomes: local government meetings, congressional tweets, congressional speeches, congressional ideology, and congressional bills.

2.5.1. Local Government Meetings

Data on local government meetings come from the Local View database (Barari and Simko, 2023), which records video transcripts of about 150,000 local government meetings held in almost 1,000 cities across the United States from 2012 to 2023. We map cities to counties and count the number of videos mentioning each keyword related to each movement in each county-day.

2.5.2. Congressional Tweets

We use data from `https://github.com/alexlitel/congresstweets` on the universe of tweets published by members of Congress over 2017-2021. The data indicate the author, date, and content of each tweet. We identify all Congress members and map them to their congressional districts. As for the general Twitter data, we count the number of tweets mentioning keywords related to each movement. This gives us a measure of how intensely the topic associated with each movement was discussed by Congress members.

[7] While the Nationscape survey also records vote intentions for the next Senatorial elections, we do not include these elections in our analysis of official election outcomes as the results are only available at the state level.

2.5.3. Congressional Speeches

We collect the universe of speeches made by Congress members from `congress.gov`, including about 350,000 speeches from 2016 to 2024. We count the number of keywords related to each topic of interest and mentioned by each Congress member, giving us a dataset at the day-congressional district level.

2.5.4. Congressional Ideology

Data on Congress members' ideology come from Voteview (Lewis et al., 2025), which infers their ideology from roll call votes. We use Nokken-Poole scores, which allow Congress members' ideal points to change across legislatures. We focus on the first dimension of these scores, which is the one displaying the greatest variation and the most commonly used in existing work.

2.5.5. Congressional Bills

Finally, we collect data on bills sponsored and adopted in Congress from `congress.gov`, including about 35,000 bills sponsored from 2016 to 2021. The data provide information on the sponsors and co-sponsors of each bill, the title and text of the bill, and the dates at which it was sponsored and potentially engrossed (that is, voted by at least one Chamber) and passed. We use text analysis to attribute topic scores ranging from 0 to 10 to each bill, where 0 means that the bill is completely unrelated to a given topic (such as racial issues) and 10 that the bill is strongly related to that topic. We then average the topic scores of bills sponsored or co-sponsored by a given Congress member on a given week.

2.6. Empirical Specifications

Having mapped protest movements to Google searches, Twitter activity, political attitudes, and policymaking outcomes, we use both simple-difference and difference-in-differences specifications to estimate the effects of protests.

2.6.1. Simple Difference

We first investigate whether the unfolding of protest movements coincides with nationwide changes in political outcomes. We consider the following simple-difference specification:

$$y_{ctqm} = \alpha + \sum_t \beta_t D_t + \gamma_{qmc} + \varepsilon_{ctqm}, \tag{1}$$

where y_{ctqm} denotes the value of a given outcome y in location c at time t for item q mapped to protest movement m. We standardize all outcomes to have a mean of 0 and a standard deviation of 1 within each movement-item. Time is defined relative to the beginning of the movement, with symmetric time windows for all outcomes except Twitter and election results.[8] Depending on the outcome considered, items q can be keywords (Twitter), survey questions (Nationscape, CCES), or types of elections (vote intentions, election results). Geographical units c are counties (e.g., for election results), DMAs (for Google searches), or congressional districts (e.g., for congressional bills). Each geographical unit receives the same weight in the main regressions, and we investigate the robustness of our results to weighting units by population. D_t are time dummies taking value 1 if location c is observed at time t and 0 otherwise. We exclude the dummy corresponding to the period -1 preceding the beginning of the movement. γ_{qmc} are interacted item, movement, and county fixed effects. The coefficients of interest β_t track the aggregate evolution of our outcome of interest before and after the outset of each movement. Standard errors are two-way clustered at the movement-location and movement-time levels.

In addition to this event study specification, we also present regression results comparing outcomes before and after the outset of each movement. We then replace time dummies D_t by a single dummy $Post_t$, which takes value 1 if location c is observed after the outset of the protest movement and 0 otherwise:

$$y_{ctqm} = \alpha + \beta Post_t + \gamma_{qmc} + \varepsilon_{ctqm}. \tag{2}$$

This approach is most relevant for outcomes measured at high frequency. Then, a break in the series that exactly coincides with the beginning of a protest movement likely reflects the effect of the movement rather than chance. A possible concern is if protest movements are triggered by external factors and such factors generate changes in political outcomes on their own. Then, we risk to misinterpret these changes as the effects of protests. For instance, changes in racial attitudes in the United States might have been driven by the death of George Floyd rather than the protests

[8] For Twitter, we collected only one week of tweets in the pre period to limit costs. For election results, only two to three elections are available in the post period; we keep more elections in the pre period to investigate pre-trends over a longer horizon.

that followed his death.

To address this this issue, we restrict some of our simple-difference regressions to seven protest movements that we call independent, in the sense that they were not triggered by a specific event: the March for Science, the Climate Strike, and the four Women's Marches. These movements did not directly arise from a particular event and were planned months in advance. In particular, the second, third, and fourth Women's Marches deliberately happened almost exactly one year after the previous one. We can thus more confidently consider a change in outcome coinciding with the beginning of these movements as their causal impact. The downside is that the sample is restricted to a subset of movements and that these movements tend to be weaker than those triggered by an external event.

The concern that simple-difference results may partly capture the effects of external events that triggered protests is further addressed by our second empirical strategy.

2.6.2. Difference-in-Differences

Our difference-in-differences specification compares the evolution of outcomes of interest in locations with more or less protest intensity. Specifically, we estimate:

$$y_{ctqm} = \alpha + \sum_t \phi_t (D_t \times \text{Protest}_{cm}) + \sum_t \psi_t (D_t \times \text{C}_{cm}) + \gamma_{qmc} + \lambda_{qmt} + \varepsilon_{ctqm}, \tag{3}$$

where Protest_{cm} is a measure of protest intensity in location c during protest movement m. The coefficients of interest, ϕ_t, capture the effect of greater protest intensity in a location on the evolution of the outcome of interest. λ_{qmt} are interacted item, movement, and time fixed effects. C_{cm} is a time-invariant control measuring *protest propensity* in location c for movement m. We construct this variable by training a LASSO model relating protest intensity during movement m to a vector of county-level time-invariant controls (as in, e.g., Büyükeren, Makarin, and Xiong, 2026): the Democratic vote share in 2016, the composition of the population by race and education, median income, the unemployment rate, and overall protest intensity in location c outside of the movement considered.[9] These variables are strongly correlated with protest intensity, explaining about one quarter of the county-level variation in protest participation across movements. We control for protest propensity interacted with time dummies to account for differences in time trends across counties that may be unrelated to protest intensity. For instance, the death of George Floyd and its coverage by the national media may have triggered more dramatic changes in attitudes in counties

[9]Our main conclusions are robust to controlling for all these variables separately in the regression rather than controlling for protest propensity alone (see Appendix Figure A10). We also report event studies for all outcomes without controlling for protest propensity interacted with time in Appendix Figures A5 to A8.

with a larger fraction of Black voters, irrespective of local protests taking place in these counties. By controlling for protest propensity interacted with time, we ensure that we do not misattribute such changes to the impact of protests. In other words, we estimate how a given location responds to a specific wave of protests in that location, relative to the changes one would otherwise have observed given its demographic and political composition. As we show below, controlling for protest propensity is crucial to address the endogeneity of protests and the pre-trends present in some outcomes.

Similarly as for the simple difference specifications, we also present regression results comparing outcomes before and after the outset of each movement:

$$y_{ctqm} = \alpha + \phi(Post_t \times \text{Protest}_{cm}) + \psi(Post_t \times \text{C}_{cm}) + \gamma_{qmc} + \lambda_{qmt} + \varepsilon_{ctqm}. \tag{4}$$

In our benchmark specification, we measure protest intensity as a continuous variable equal to the total number of protest participants in location c in the 30 days that followed the beginning of each movement, expressed as a fraction of the total population of location c. We standardize this variable so that it has a standard deviation of 1 for each protest movement and takes a minimum value of 0, in locations with no protester. We winsorize protest intensity at the 99th percentile across geographical units to limit the influence of outlier locations that concentrated very large numbers of protesters. Our main figures include controls for protest propensity interacted with time, and our main tables show both specifications including and excluding these controls. We cluster standard errors at the movement-location level, which is the level of the treatment.[10]

One potential issue relates to the quality of the data on the number of protest participants. In the CCC, the number of participants is missing for about half of the protests. These cases often correspond to very small events, so we code them as having zero participants in our benchmark specification. When it is available, one may also be concerned that the number of protesters is misreported. For these reasons, we conduct two robustness checks. First, we compare county-level protest participants recorded in CCC to self-reported protest participation in the CCES survey. We find a significant correlation between these two measures of protest intensity, even after controlling for a range of other county-level variables (see Appendix Table B2). Second, we investigate the robustness of our results to using alternative empirical specifications, such as coding protest intensity as a dummy equal to 1 if there was any protest in location c and 0 otherwise, dropping counties with no information on protest participants altogether, or winsorizing protest intensity at the 97th instead of the 99th percentile.[11]

[10]For electoral outcomes, we cluster standard errors at the county level rather than the county-movement level to account for the fact that the same counties and elections are observed across all movements.

[11]The results of these robustness checks are shown in Appendix Figure A10.

Our simple-difference and difference-in-differences specifications each have their specific advantages, making them complementary. County-level difference-in-differences are arguably better causally identified, yet they can only capture local effects of protests in treated counties. As a result, by construction, this specification cannot measure spillover effects of protest movements on non-treated counties through channels such as media exposure. The simple-difference specification restricted to independent movements, while less well identified, captures both direct and indirect effects since it tracks the evolution of outcomes at the national level.

We now turn to presenting the main results, focusing on three sets of outcomes. First, we investigate the effect of protests on Google searches, Twitter intensity, and the importance given by the general population to the issues raised by protesters (Section 3). We expect these outcomes to be affected immediately after the outset of protest movements and to shape downstream effects on political behavior such as vote choice (e.g., Le Pennec and Pons, 2023). We then consider the impact of protests on outcomes that may be affected in the medium and long run: policy views, in Section 4, political attitudes and behavior, in Section 5, and policymaking outcomes, in Section 6.

3. Protest Movements and Salience

This section presents results on the effect of protests on the salience of the corresponding political issues, drawing on Google, Twitter, and GPSS data. We start by presenting results for the simple difference specification for all movements (Section 3.1). Section 3.2 turns to difference-in-differences estimates.

3.1. Simple Difference Specification

We start by presenting event study results on national trends in salience before and after the outset of each protest movement. Figure 1, panel (a) plots results of the simple-difference specification using Twitter data. The unit of observation is the county. The dependent variable is the total number of tweets related to the topic associated with each movement divided by the county's population, standardized to have a mean of 0 and a standard deviation of 1 for each movement. As visible from the figure, the average number of tweets increases sharply on the starting day of each movement, by about 0.1 standard deviations, which is statistically significant at the 5% level. We observe some pretrends in the day immediately preceding each movement, which likely capture people tweeting about upcoming protests. However, there is still a clear jump in tweet intensity on the exact day of the movement outset. This effect starts declining immediately after the beginning of the movement, until tweets go back to their pre-period levels about ten days after. The development of protest movements thus coincides with a significant increase in Twitter activity. Appendix Figure A1 reproduces the same figure after restricting the sample to independent movements. The results are qualitatively similar, although the effect is slightly smaller.

Figure 1, panel (b) extends this analysis to daily Google search volumes. The unit of observation is the DMA. An observation corresponds to total searches for an expression q associated with a protest movement m on a day t in DMA c. Time series of searches for each expression are normalized to have a mean of 0 and a standard deviation of 1. The results are similar to those obtained with Twitter data. The outset of a protest movement coincides with a sharp 0.1 standard deviations increase in search volumes for keywords associated with the corresponding movement, which is significant at the 1% level. Appendix Figure A1 reproduces this result for the subset of independent movements.

Finally, Figure 1, panel (c) presents results of the simple-difference specification using the GPSS survey. While the Google and Twitter data allow us to track salience at a particularly high frequency among social media and Internet users, this survey has the advantage of capturing medium-run monthly-level changes in the importance that a representative sample of respondents gives to the corresponding topics. The dependent variable is the fraction of individuals in county c who mention topics related to the protest movement among the three most important problems in the United States today, normalized to have a mean of 0 and a standard deviation of 1. Protests coincide with a small and non-significant 0.05 standard deviations increase in importance given to the corresponding topics during the first month after the protest movement started. In the subsample of independent movements, this effect is close to null (see Appendix Figure A1).

Table 2 presents results of regressions comparing each of these three outcomes before and after the outset of each movement. We include all movements in columns 1 through 3, and restrict the analysis to independent movements in columns 4 through 6. In line with the graphical evidence discussed above, protests are associated with significant increases in Twitter intensity, Google searches, as well as the importance given to the corresponding issues. All effects are smaller for independent movements and the effect on salience measured using GPSS is not significant in that subsample.

There are two potential reasons why we obtain smaller effects when focusing on independent movements than in the full sample. First, independent movements are smaller. Indeed, they are associated with about 600 protests each on average, as compared to 1,800 protests for other movements (see Table 1). One should then naturally expect independent movements to have smaller effects on aggregate Twitter activity and Google searches. Alternatively, the effects of independent movements may capture the specific impact of protests, while the effects of other movements may capture the impact both of protests and of the event that triggered them (such as the death of

George Floyd in the case of BLM protests).

To distinguish between these two explanations, we compare our baseline results with effects on Google searches of the word "protest" specifically. If the effect on searches for "protest" is smaller for independent movements than for other movements, as in our baseline results, this suggests that differences in the scale of the two types of movements may be driving the gap between our two estimates. On the contrary, if searches for "protest" do not differ between the two types of movements, other unobserved factors might be at play.

We show the results of this test in Appendix Table A2. As columns 3 and 4 reveal, independent movements lead to an increase in searches for the word 'protest' of about 0.02 standard deviations, compared to 0.07 standard deviations in the case of all movements. This gap is even larger as the one observed for all keywords in our database (columns 1 and 2). These results provide evidence supporting the first explanation: independent movements have smaller effects because these movements are weaker, not because omitted factors exaggerate the effect of other factors.

3.2. Difference-in-Differences

We now investigate whether locations with greater protest intensity experience a larger change in salience after the beginning of each movement. Figure 2, panel (a) presents the results of the difference-in-differences specification using county-level tweet intensity as outcome. Tweet intensity increases much more on the first day of each movement in counties with greater protest intensity. On average, a one standard deviation increase in protest intensity is associated with an increase in tweets mentioning keywords related to the movement of about 0.4 standard deviations, which is significant at the 5% level. This effect quickly decreases and disappears after about four days.

Figure 2, panel (b) extends this result to Google search volumes. The unit of observation is the DMA-keyword-day. We find that Google searches increase slightly faster (by 0.03 standard deviations, significant at the 10% level) after the beginning of each movement in DMAs with greater protest intensity. However, this small effect is restricted to the exact day of the protest, after which the coefficient goes back to zero.

Finally, 2, panel (c) presents results using the GPSS survey. The effects are less precisely estimated due to the small sample size of the survey, but we find no evidence that salience rises differentially in counties with greater protest intensity.[12]

Table 3 complements the graphical analysis with formal regression results. For each outcome, we

[12]A limitation of the GPSS survey is that it was not run every single month, so the starting month is not covered for the George Floyd and Families Belong Together protests.

report estimates both with and without controlling for location-level protest propensity interacted with time.[13] Indeed, as described in Section 2.6.2, the occurrence of protests may be correlated with counties' political and demographic make-up, so controlling for protest propensity predicted by sociodemographic factors and interacted with time is useful to check that we are capturing the impact of local protests rather than differential trends in different types of counties after the beginning of the protest movement. In our benchmark specification (controlling for protest propensity), increasing protest intensity by one standard deviation leads to a differential increase in Twitter intensity of 0.13 standard deviations. This effect is more than twice smaller than the one estimated without controlling for time interacted protest propensity. Effects on Google searches are positive without the control but null with it. Effects on issue importance measured with GPSS are small and not statistically significant either way. These results are robust to a range of alternative specifications, including using a binary treatment, excluding counties with missing protest participation, winsorizing the 97th percentile of protest participation, and weighting observations by population (see Appendix Figure A10).

4. Protest Movements and Policy Views

We now turn to analyzing the effect of protests on policy views. Section 4.1 presents results on aggregate changes in policy views, while Section 4.2 turns to difference-in-differences estimates.

4.1. Simple Differences

We start again by comparing the evolution of policy views before and after the outset of protest movements using a simple-difference design. We focus on the Nationscape survey, which provides high-frequency measures of individual opinions. Since the CCES survey only occurs at a yearly level and consistent questions are only available for a few years, credible simple-difference event studies cannot be estimated with this survey.

Figure 3, panel (a) studies whether protests coincide with aggregate changes in the share of respondents declaring an opinion on each question—that is, not declaring "Not Sure." There is some evidence that protests increase the proportion of respondents having an opinion. Three weeks after the outset of a protest movement, the share of respondents stating an opinion is higher by 0.05 standard deviations (equivalent to about 1 percentage point in the average movement and significant at the 1% level). However, this effect drops to zero after four weeks and is even less clear

[13] The number of observations is slightly smaller when controlling for protest propensity due to missing values in variables used to predict protest propensity in a few locations, in particular Alaskan counties.

when limiting the analysis to independent movements (see Appendix Figure A2).

Figure 3, panel (b) extends this analysis to liberal attitudes. The dependent variable is the share of respondents declaring a liberal rather than a conservative opinion on a given question. There is no evidence that respondents become significantly more or less liberal after the outset of protest movements. The same null effect holds when restricting the sample to independent movements (see Appendix Figure A2).

Table 4 presents results of regressions corresponding to these two outcomes. Protest movements increase the share of respondents declaring an opinion by 0.02 standard deviations, which is significant at 1%. The share of respondents holding liberal views increases by about 0.01 standard deviations, which is significant at the 10% level. The effects are very close to zero and non-significant when restricting the sample to independent movements.

4.2. Difference-in-Differences

We now turn to difference-in-differences specifications. Figure 4, panel (a) investigates whether counties with greater protest intensity in a given movement see a differential increase in the share of respondents with an opinion on the corresponding issues. We do not find any such evidence. These results and all other difference-in-differences results using the Nationscape survey are robust to considering a wider time window of six months rather than six weeks (see Appendix Figure A9). Considering the upper bound of the 95 percent confidence interval, we can reject effects greater than 0.1 standard deviation (about 5 percentage points) per standard deviation of protest intensity in any week after the beginning of each movement.

Figure 4, panel (b) extends this analysis to liberal attitudes. Again, we estimate a precise null effect: counties with greater protest intensity do not see any differential change in attitudes in either a conservative or liberal direction.

Finally, 4, panel (c) studies the year-to-year evolution of attitudes in counties with greater protest intensity in the CCES survey. Attitudes can be tracked continuously over a period of four years surrounding each movement for 23 questions covering 10 out of our 14 movements. We observe a small but non-significant differential increase in the fraction of respondents stating liberal views. One year after the outset of each movement, we can reject changes in the share of liberal attitudes exceeding 0.07 standard deviations (about 2 percentage points) per standard deviation of protest intensity.

Table 5 presents corresponding regression results. All effects on outcomes based on the Nationscape survey are close to zero and non-significant. We can generally reject changes in policy views exceeding 0.06 standard deviations (1-2 percentage points). Controlling for protest propensity interacted with time, the coefficient for CCES is positive but small and only significant at the 10% level. As for the effects on salience, these results are robust across alternative empirical specifications (see Appendix Figure A10).

Taken together, these findings suggest that local protests do not lead to any significant change in policy views in the counties in which the protests took place. One possible concern is that our difference-in-difference design will miss effects of protests that took place outside the county but that people heard about in the media or through discussions with friends or relatives. However, as discussed in Section 3, local protest intensity does lead to large increases in Google and Twitter activity in the corresponding counties. We infer that protests do have local effects on issue salience, but that these effects are not sufficiently strong to change individuals' policy views.

5. Protest Movements and Political Attitudes and Behavior

Beyond affecting policy views, protests could generate political change by changing how people vote. We turn to this dimension by analyzing four complementary outcomes: turnout, vote choice, presidential approval, and interest in politics. The Nationscape survey allows us to study these outcomes before and after each protest wave at a high frequency and with large sample sizes. We combine these individual-level survey data with a longer-run analysis exploiting official county-level turnout and election results. We show simple difference estimates in Section 5.1, and difference-in-difference estimates in Section 5.2. We restrict the simple-difference analysis to the Nationscape survey, given that elections are too distant in time to detect trend breaks in election results before and after protest outbreaks and attribute these changes to the protests.

5.1. Simple Differences

Figure 5, panel (a) plots the aggregate evolution of turnout intentions during the weeks before and after the outset of each movement, as measured in the Nationscape survey. The dependent variable is the fraction of respondents who declare intending to vote in the 2020 presidential election, standardized to have a mean of 0 and a standard deviation of 1. There is no evidence that protests coincide with any increase or decrease in turnout intentions.

Figure 5, panel (b) reproduces this analysis, but focusing on vote intentions. The Nationscape survey records vote intentions in presidential, House, Senate, and gubernatorial elections. We combine these different questions in a pooled specification in which the unit of observation is the county-week-election type. The dependent variable is the fraction of respondents who would consider voting for the Democratic Party in the next elections. Respondents who do not state a vote intention are excluded from both the numerator and denominator. There is no significant change in aggregate vote intentions after the protests. Considering the upper bound of the 95 percent confidence interval, we can reject positive or negative changes of more than 0.05 standard deviations (about 2 percentage points) in the share of respondents who would consider voting for the Democratic Party in any of the weeks following the protests.

One reason for these null effects could be that turnout and vote intentions may be hard to change in the short run. We thus complement our analysis by considering presidential approval and political interest, which are closely related to electoral behavior but may be more malleable. In the survey, presidential approval takes values ranging from 1 (for respondents who strongly disapprove Donald Trump's way of handling his job as president) to 4 (for those who strongly approve it). Political interest also ranges from 1 (for respondents who hardly follow at all what's going on in government) to 4 (for those who follow it most of the time). For each of these two variables, we average individual responses by county and standardize them to have a mean of 0 and a standard deviation of 1. As shown in Figure 5, panels (c) and (d), we do not find any systematic change in presidential approval or political interest after the outset of protest movements.

We obtain similar null results on all outcomes when conducting the event studies in the subset of independent movements (Appendix Figure A3). Table 6 presents the simple-difference regression results for the full sample and the subset of independent movements. All coefficients are close to zero and statistically non-significant. For most outcomes, we can reject changes in attitudes greater than 0.03 standard deviations. The only exception is a statistically significant negative change in turnout intentions for independent movements, which seems to be driven by pretrends rather than a trend break (see Appendix Figure A3).

5.2. Difference-in-Differences

We now turn to difference-in-differences estimates of the effects on turnout intentions, vote intentions, presidential approval, political interest, as well as county-level Democratic vote shares and turnout in counties with higher protest intensity. As shown in Figure 6, we find a null effect for all six outcomes. Table 7 presents corresponding regression results. Without controlling for protest propensity interacted with time, the only significant effect is on the Democratic vote share. However, this effect is entirely driven by large pretrends (see Appendix Figure A7, panel (e)), highlighting the importance of accounting for the endogeneity of protests' location, especially for slow-moving outcomes such as vote shares. When controlling for protest propensity interacted with time, we find precise null effects for all outcomes except official turnout, for which we find a small positive effect driven by pretrends in t = -3 (Figure 6, panel (f)). These findings generally hold across different empirical specifications (see Appendix Figure A10).[14]

6. Protests and Policymaking

Beyond the general population, protests may also affect the way policymakers communicate with voters and the policies they propose and adopt. In this section, we study the effects of protests on five policymaking outcomes: local government meetings, congressional tweets, congressional speeches, congressional ideology, and congressional bills. We present the simple-difference and difference-in-differences results in Sections 6.1 and 6.2, respectively.

6.1. Simple Difference

Figure 7 presents simple-difference event studies for local government meetings, congressional tweets, congressional speeches, and congressional bills sponsored before and after the outset of each movement. All dependent variables are standardized to have a mean of 0 and a standard deviation of 1 within each movement. We do not consider congressional ideology in the simple difference specification since this outcome is measured too infrequently (every other year). Protests coincide with a significant increase in local government meeting discussions related to the issues raised by protesters, which starts in the week immediately following movements' outset and persists for about five weeks (panel (a)). An increase in the number of mentions of keywords related to the issues raised by protesters is also visible in both congressional tweets (panel (b)) and congressional speeches (panel (c)). This spike is concentrated on the day of the movements' outset and disappears the following day. Finally, congressional bills sponsored in Congress also become more closely related to the topics raised by protesters (panel (d)). The average topic score increases in the first week and returns to its baseline value after about four weeks. Hence, protests coincide with increased effort by Congress members to propose bills related to the issues raised by the protesters. However, these efforts do not succeed in generating any change in adopted policies: there is no evidence of any increase in engrossed bills in the months following the beginning of protest movements (panel (e)).[15]

Appendix Figure A4 displays the same event studies for independent movements. The same pattern

[14] The one exception is election results, for which we find a large effect of protests when using a binary version of the treatment. However, this effect is entirely driven by large pretrends, with no evidence of any trend break around the timing of protests (see Appendix Figure A11).

[15] Results on engrossed bills in Figure 8 use the same timing as for sponsored bills, that is, t corresponds to the month in which a bill was sponsored. Our results are robust to using the month in which a bill was engrossed instead.

as in Figure 7 holds for congressional tweets, but the coefficient is not statistically significant. For the other four outcomes, there is no evidence of any significant change after the outset of protest movements.

Table 8 presents the corresponding regression results. Protests coincide with an increase in all policymaking outcomes of about 0.03-0.07 standard deviations, with coefficients significant at the 10% level, with the exception of engrossed bills for which we estimate a null effect (columns 1 to 4). However, only local government meetings display a significant coefficient when focusing on independent movements (columns 6 to 10), and this effect is primarily driven by pretrends (Appendix Figure A4, panel (a)).

6.2. Difference-in-Differences

We present difference-in-differences results in Figure 8. The unit of observation is the congressional district for all outcomes except local government meetings, for which it is the county. Local government meeting participants become more likely to mention movement-related keywords in counties with greater protest intensity, although the estimates are noisy (panel (a)). Protests also modestly affect the content of congressional tweets and speeches: Congress members elected in congressional districts with greater protest intensity are slightly more likely to mention keywords related to protesters' claims in the days following the outset of protest waves (panels (b) and (c)). When it comes to congressional bills and ideology, however, the event studies suggest precise null effects. There is no evidence that Congress members elected in districts with greater protest intensity become more or less conservative in the terms following the protests (panel (d)). The bills that they sponsor (panel (e)) or succeed in getting adopted by at least one Chamber (panel (f)) do not become more related to the protesters' claims either.

Table 9 presents the corresponding regression results. After controlling for protest propensity interacted with time, we find no significant effect of protests on any policymaking outcome.[16] We can reject effects exceeding 0.05 standard deviations for all outcomes except congressional tweets. We conclude that while protests might slightly raise policymakers' attention towards the topics raised by protesters as visible in their Twitter activity, this short-run increase in salience does not translate into significant ideological or policy changes overall.

[16] Appendix Figure A10 shows that these null effects extend to alternative specifications.

7. Heterogeneity

In the previous sections, we pooled all protest movements together in our analysis. In this section, we investigate how protests' effects vary across movements and people. The positive effects we find on Twitter activity and some policy outcomes may be driven by a specific movement or by specific types of voters and policymakers. Conversely, the null overall effects on policy views, voting behavior, and policymaking might hide movement-specific effects of opposite signs.

7.1. Heterogeneity by Movement

To explore heterogeneity across protest movements, we first run the following simple-difference specification:

$$y_{ctqm} = \alpha + \sum_{m} \beta_m Post_t \times D_m + \gamma_{qmc} + \varepsilon_{ctqm}. \tag{5}$$

Where D_m takes 1 for protest movement m and 0 otherwise. The coefficients β_m measure the change in outcome y after the outset of movement m.

One movement stands out from this analysis: the BLM protests that followed the killing of George Floyd. We find little heterogeneity across other movements. For this reason, we focus on comparing BLM to other movements in the main text and show detailed results for each specific movement in Appendix Figures A12 and A13.

As shown in Figure 9, panel (a), the simple difference coefficient is positive, significant at the 1 or 5% level, and much larger for BLM than other movements for all outcomes except political interest and engrossed bills. For non-BLM movements, we only observe positive and significant effects on tweets, Google searches, and policymaking outcomes. While both BLM and other movements coincided with significant changes in online activity, attention among policymakers, and the content of bills sponsored in Congress, only BLM protests were followed by significant changes in opinions and political attitudes among the general population.

We extend this heterogeneity analysis to the difference-in-differences specification with the following specification:

$$y_{ctqm} = \alpha + \sum_{m} \phi_m (Post_t \times \text{Protest}_{cm}) + \sum_{m} \psi_m (Post_t \times \text{C}_{cm}) + \gamma_{qmc} + \lambda_{qmt} + \varepsilon_{ctqm}. \tag{6}$$

Figure 9, panel (b) presents the results. Relative to the simple-difference specification, the coefficients are smaller and fewer of them are positive and significant. For movements other than the BLM protests, the only dependent variable significantly affected by protests is tweets. We estimate precise null effects for all other outcomes. By contrast, we observe positive effects of BLM protests not only on tweets but also on some policymaking outcomes, namely congressional tweets and speeches and congressional bills sponsored. In other words, BLM protests did lead Congress members elected in districts with greater protest intensity to propose more bills related to racial issues. We do not find any effect on engrossed bills, however, suggesting that these legislative efforts did not translate into actual policy adoption.[17] We also find positive effects of BLM protests (but not of other protest movements) on the Democratic vote share in subsequent elections, although this effect is quantitatively small.

Why were BLM so much more effective at convincing voters and policymakers than all other movements in our sample? One possible reason is that the BLM movement mobilized a particularly large number of participants. However, the first two Women's Marches and the March for Our Lives movement gathered a similar or even larger number of protesters. Another possibility is that the topic of racial injustice found greater resonance among citizens and policymakers than other topics, due to its specific importance in U.S. politics and history. A third complementary interpretation is that the BLM protest movement was particularly disruptive and sustained. Indeed, almost all other movements in our sample took place over a single day, and most of them were planned in advance by established organizations.[18] In contrast to these more "contained" forms of contention, BLM protests gradually unfolded over several weeks and were largely spontaneous and leaderless. Such "transgressive" contention (Tarrow, 2011; Tilly, 2004) may be more conducive to agenda-setting and more likely to change voters and policymakers' views and behavior.

A related hypothesis is that the BLM protests were more likely to include violence, and that violent protests are more likely than peaceful demonstrations to attract attention and produce effects. We investigate this possibility by estimating heterogeneous treatment effects by protest violence. The CCC database reports information on whether there was any incident during each protest. We define a protest as violent if there were any police arrests, injuries among participants or policemen, or property damage. Violent protests are rare: across all movements, only about 750 protests were violent (3.5% of all protests). However, about 90% of these violent protests were associated with

[17]For instance, the first weeks of June 2020 saw the introduction of many bills related to racial issues, such as H.Res.988 "condemning all acts of police brutality, racial profiling, and the use of excessive and militarized force throughout the country," S.Res.602 "recognizing that the murder of George Floyd by officers of the Minneapolis Police Department is the result of pervasive and systemic racism that cannot be dismantled without, among other things, proper redress in the courts," and S.Res.613 "calling for justice for George Floyd and opposing calls to defund the police." However, none of these bills were engrossed by Congress.

[18]With the exception of March for Our Lives, which took place over two days (March 14 and 24, 2018), all protest waves were concentrated around a single day. Protests against the Muslim Ban and the War in Iran did unfold spontaneously, with initially weak institutional underpinnings, but they were also concentrated around a single day.

BLM protests. BLM was thus unique in that respect in comparison to other movements in our sample.

We compare the effects of violent and non-violent protests by running a difference-in-differences specification with two separate treatments for violent and non-violent protest intensity:

$$\begin{aligned} y_{ctqm} = \quad & \alpha + \phi_1(Post_t \times \text{Protest}_{cm}^{\text{violent}}) + \phi_2(Post_t \times \text{Protest}_{cm}^{\text{non-violent}}) \\ & +\psi_1(Post_t \times \text{C}_{cm}^{\text{violent}}) + \psi_2(Post_t \times \text{C}_{cm}^{\text{non-violent}}) + \gamma_{qmc} + \lambda_{qmt} + \varepsilon_{ctqm}. \end{aligned} \tag{7}$$

The treatment variables $\text{Protest}_{cm}^{\text{violent}}$ and $\text{Protest}_{cm}^{\text{non-violent}}$ measure the number of participants in violent and non-violent protests, expressed as a share of a given unit's population and standardized to have a mean of 0 and a standard deviation of 1 as in the main specification. $\text{C}_{cm}^{\text{violent}}$ and $\text{C}_{cm}^{\text{non-violent}}$ are violent and non-violent protest propensity, estimated using the same methodology as for overall protest propensity. Given that BLM was the only movement in our sample with a significant number of violent protests, we focus on BLM protests in this analysis.

Appendix Figure A15 presents the results. We observe, first, that violent protests generated substantially more attention on Twitter than non-violent protests. We also find a positive effect of violent protest intensity on political interest and local government meeting discussions on racial issues.[19] Second, in contrast to non-violent protests, violent protests did not increase Democratic vote shares and congressional bills sponsored on racial issues (although the differences between the coefficients are not statistically significant). For individual opinions, we even find some suggestive evidence of backlash: counties with greater violent protest intensity saw a relative decline in the share of respondents expressing liberal opinions on racial issues in both the Nationscape and CCES surveys. Together, these findings suggest that violent protests may raise more attention but are not more effective at generating political change than peaceful demonstrations and that they may even be counter-productive. In sum, the impact of BLM protests may result from the specific importance of racial issues in the U.S. and the transgressive form of contention expressed by these protests, but it cannot be explained by its violent components.

[19] For example, the video of the municipal council of Fayetteville, North Carolina held on May 31st, 2020 mentions: “We’ve called this emergency session as a opportunity for the council to hear the latest information so that we can share with you, our citizens and constituents, regarding the events, the very tragic events that took place in our community on last night. As you know many cities across the country are grappling with the same thing, that people have hijacked noble calls to bring and highlight social institutional racism change and injustice, hijacked for other purposes to exploit the situation in the family of George Floyd and it caused havoc and chaos, and to trespass and destroy property and communities and cities across the country last night that made its way into our city in Fayetteville.”

7.2. Heterogeneity by Individual Characteristic

We now explore effect heterogeneity by voters' characteristics, focusing on survey outcomes for which data on individual characteristics are available. The simple-difference specification takes the following form:

$$y_{zctqm} = \alpha + \sum_{z} \beta_z (Post_t \times D_z) + \gamma_{zqmc} + \varepsilon_{zctqm} \tag{8}$$

Where D_z takes value 1 for individual characteristic z and 0 otherwise. We aggregate responses from voters sharing a characteristic and pool questions from our three surveys (GPSS, Nationscape, and CCES) in the same specification. The unit of observation is thus the characteristic-county-time-question-movement. For instance, one observation corresponds to average turnout intentions in Nationscape among women in a given county at a given time period. The coefficients β_z capture the extent to which opinions and political attitudes change in a specific subgroup following the outset of protest movements.

Similarly, the difference-in-differences specification takes the form:

$$\begin{aligned} y_{zctqm} = \alpha + \sum_{z} \phi_z (Post_t \times D_z \times \text{Protest}_{cm}) \quad &+ \textstyle\sum_z \psi_z (Post_t \times D_z \times \text{C}_{cm}) \\ &+ \gamma_{zqmc} + \varepsilon_{zctqm} \end{aligned} \tag{9}$$

Figure 10 presents the results.[20] We find no evidence of heterogeneity in either specification. We also find no subgroup with clearly identified positive or negative effects. On average, protests do not seem to have any impact on any subgroup, defined by ideology, age, gender, education, race, interest in politics, or news consumption. In particular, we do not observe effects of opposite signs on liberal and conservative voters, indicating that null overall effects on survey questions do not mask a combination of positive effects on voters sympathetic to liberal protests and backlash among others.

7.3. Heterogeneity by Congress Members' Party

Figure 11 finally turns to heterogeneity by Congress members' party affiliation. Our empirical specification is the same as in Section 7.2, except that z corresponds to Congress members' political party (Democrat or Republican) rather than individual characteristics.

As panel (a) shows, protests are followed by a much larger increase in tweets, speeches, and

[20] Appendix Figure A14 provides detailed results by survey and outcome.

sponsored bills related to protesters' claims among Democrats legislators than among Republicans. Republicans do tweet and talk a bit more about protest-related topics, but the effects are smaller than for Democrats and we find a precise null effect for bill sponsorship by Republicans. Panel (b) shows the results of the difference-in-differences specification. These effects are null for both Democrat and Republican Congress members: on average, greater protest intensity in their district affected neither their speeches nor their behavior.

8. Conclusion

We study the effects of protests on online interest, policy views, political attitudes, and policy-making focusing on 14 major protest movements that took place in the United States from 2017 to 2022. The high frequency and large sample size of our data allow us to precisely track the evolution of our outcomes of interest in the days and months that preceded and followed the outset of each protest wave. Our approach significantly improves upon existing work by providing a comprehensive view on the impact of protests on attitudes and on the underlying channels. This considerably increases the external validity of results relative to preexisting studies focusing on specific case studies.

Overall, protests coincide with large increases in online interest, as measured by tweets containing keywords related to the topic of the movement. This effect is visible in both nationwide event studies and difference-in-differences specifications comparing counties with more or less protest intensity. It is present for most protest movements but relatively short-lived: online interest decreases to baseline levels a few days after the beginning of the protest movement. Furthermore, despite this increase in salience, protests do not significantly affect policy views, political behavior, and public policies: we generally estimate precise null effects on public opinion, election results, and bills proposed and adopted in Congress. The protests triggered by the death of George Floyd constitute an important exception, as they were followed by an increase in liberal attitudes on racial issues, votes received by the Democrats, and race-related bills introduced in Congress. However, this effect is not always robust to alternative specifications, and we cannot exclude that it was partly driven by the death of George Floyd itself and its coverage in national media rather than the related protests. Overall, our findings point to the limited success of recent protest movements at shifting the beliefs and behavior of U.S. voters and policymakers, at least in the short and medium run.

Our results raise important questions on the effectiveness of recent protest movements at bringing about political change. Why were the BLM protests the only ones coinciding with significant changes in political attitudes? One possible explanation is that this movement stood out due to its spontaneity, persistence, and intense coverage in traditional and social media. This calls for further research on the channels through which voters and political leaders access information and become persuaded or not by protesters' claims.

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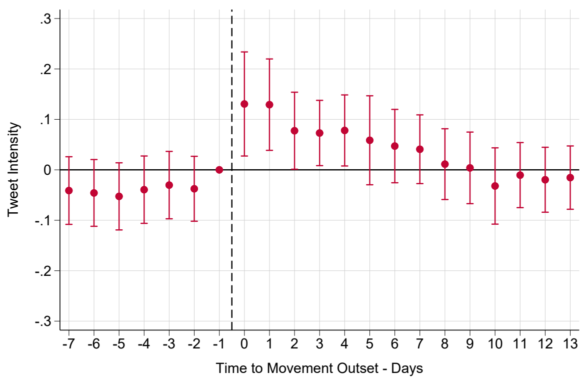
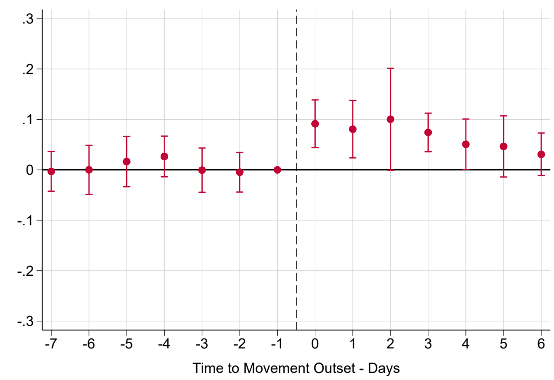
Figure 1 – Protests and Salience: Simple Difference

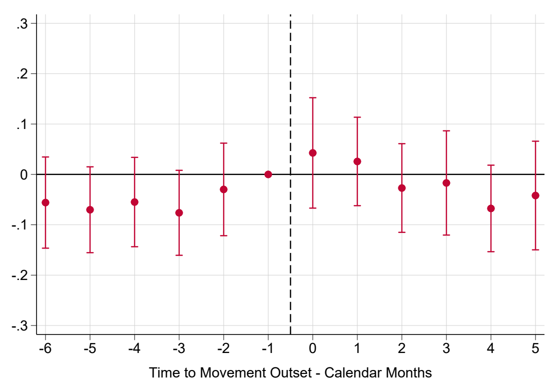
(a) Twitter



(b) Google



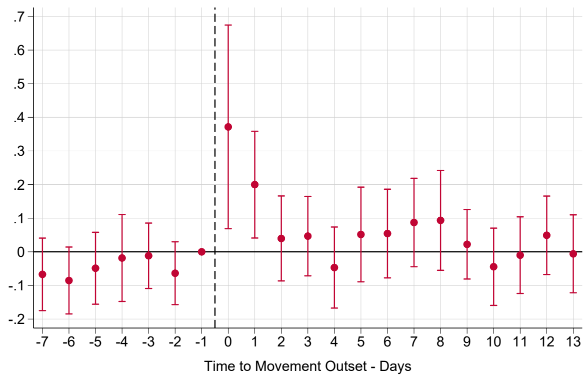
(c) GPSS



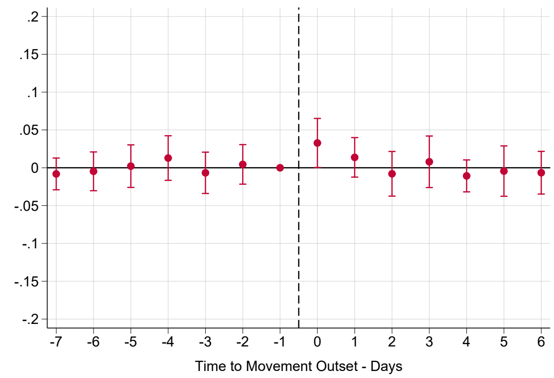
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). Twitter: the dependent variable is the number of tweets related to a given issue. Google: the dependent variable is the number of Google searches for a given keyword. GPSS: the dependent variable is the share of respondents mentioning a given issue as one of the most important problems of the country. All dependent variables are standardized to have a mean of 0 and a standard deviation of 1.

Figure 2 – Protests and Salience: Difference-in-Differences

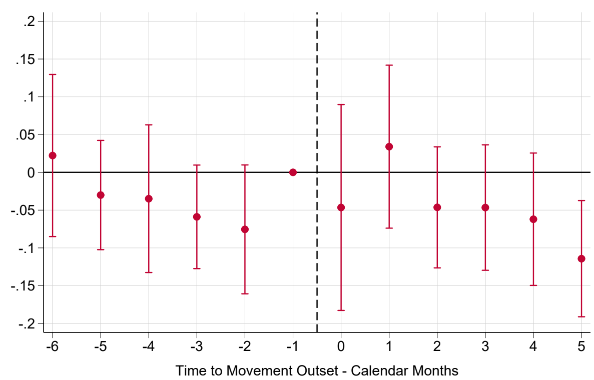
(a) Twitter



(b) Google



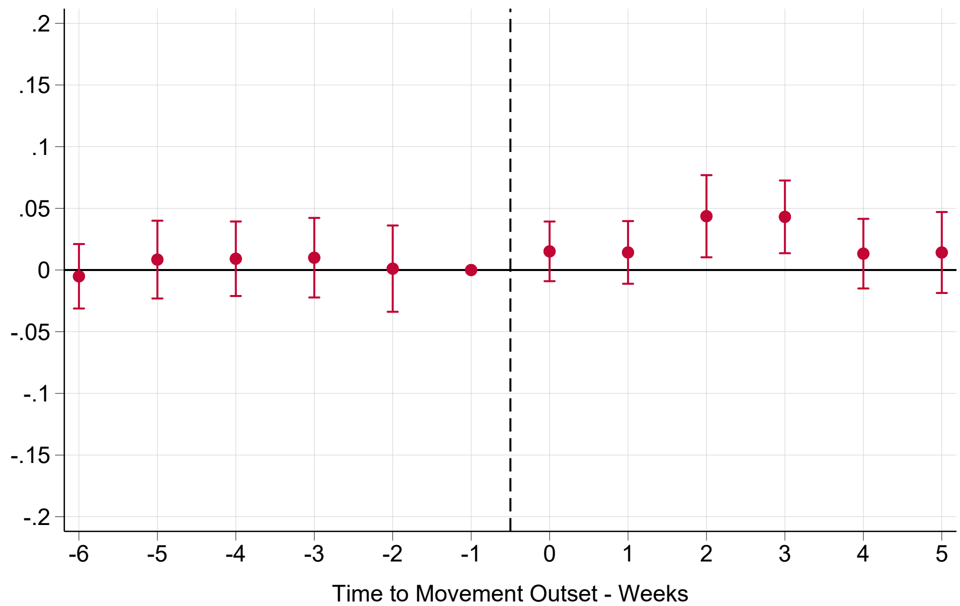
(c) GPSS



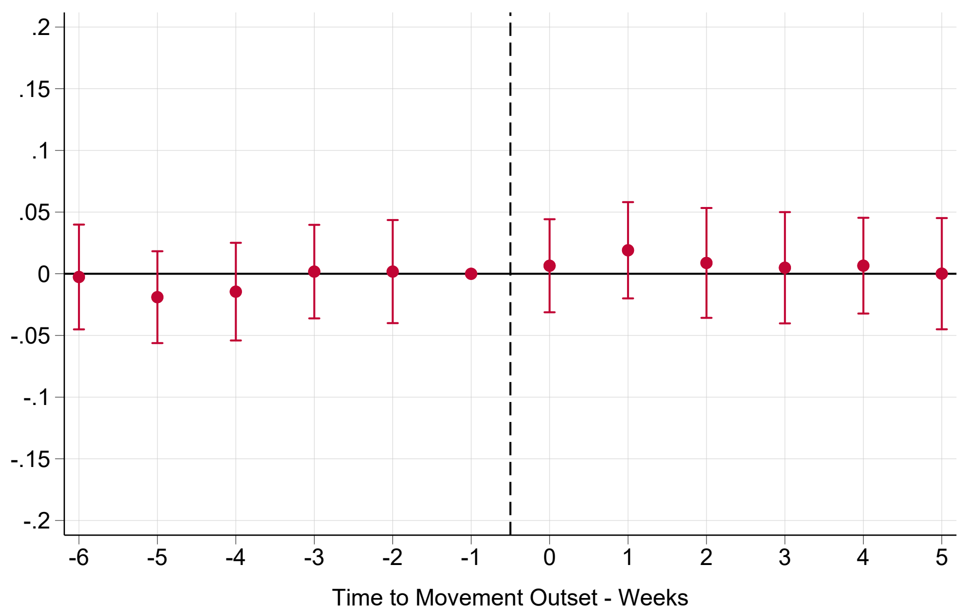
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 3 – Protests and Opinions: Simple Difference

(a) Nationscape: Having an Opinion



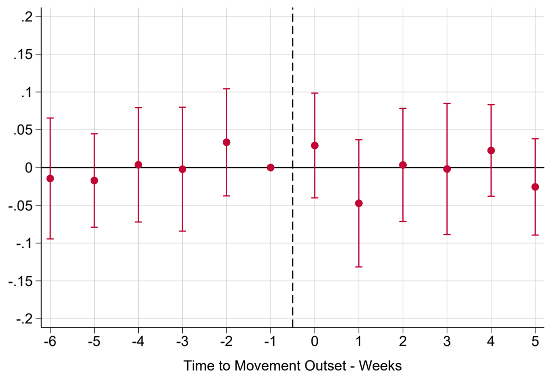
(b) Nationscape: Liberal Attitudes



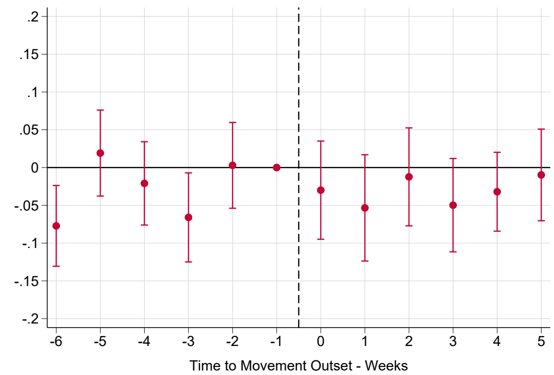
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). Having an opinion: the dependent variable is a dummy taking value 1 if the respondent has an opinion on a given issue and 0 otherwise. Liberal attitudes: the dependent variable is a dummy taking value 1 if the respondent has a liberal opinion on a given issue and 0 if they have a conservative opinion. All dependent variables are standardized to have a mean of 0 and a standard deviation of 1.

Figure 4 – Protests and Opinions: Difference-in-Differences

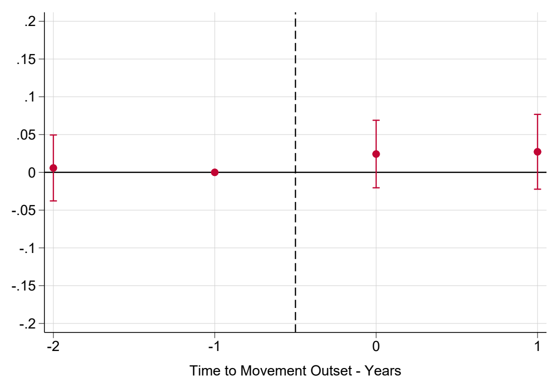
(a) Nationscape: Having an Opinion



(b) Nationscape: Liberal Attitudes



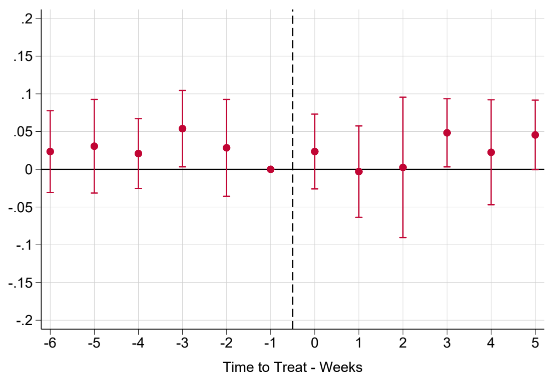
(c) CCES: Liberal Attitudes



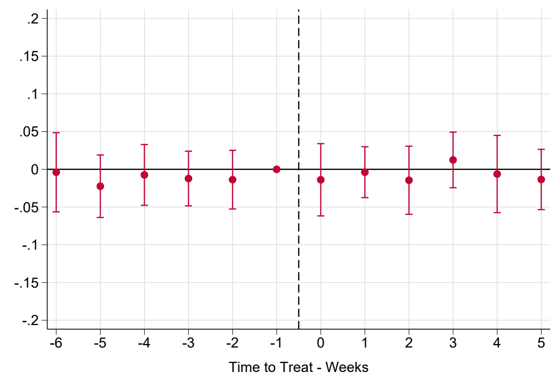
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 5 – Protests and Political Attitudes: Simple Difference

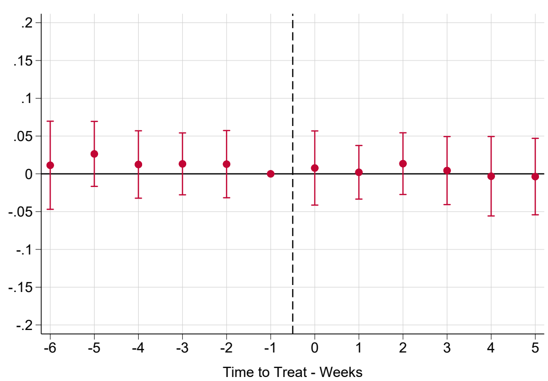
(a) Turnout Intentions



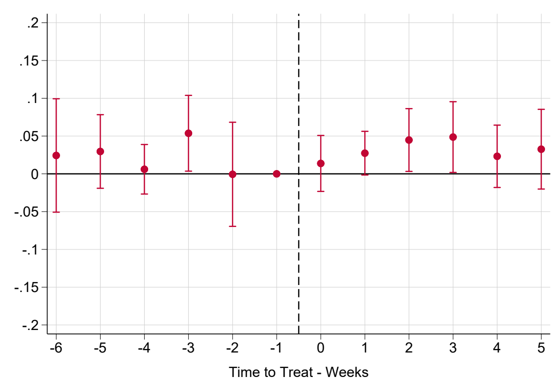
(b) Vote Intentions



(c) Presidential Approval



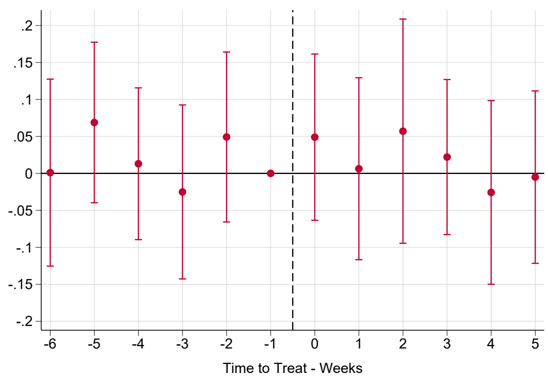
(d) Political Interest



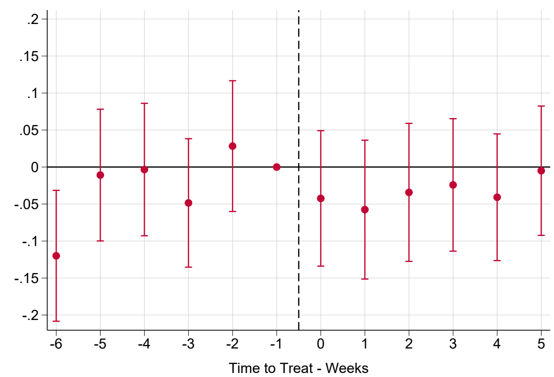
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). Turnout intentions: the dependent variable is a dummy taking value 1 if the respondent declares intending to vote in the 2020 presidential election and 0 otherwise. Vote intentions: the dependent variable is a dummy taking value 1 if the respondent declares considering voting for the Democratic party in the next elections (presidential, House, Senate, or gubernatorial) and 0 otherwise. Presidential approval: the dependent variable takes values ranging from 1 to 4, with 1 corresponding to respondents strongly disapproving Donald Trump's way of handling his job as president and 4 corresponding to those strongly approving it. Political interest: the dependent variable takes values ranging from 1 to 4, with 1 corresponding to respondents hardly following at all what's going on in government and 4 corresponding to those following what's going on in government most of the time. All dependent variables are standardized to have a mean of 0 and a standard deviation of 1.

Figure 6 – Protests and Political Attitudes: Difference-in-Differences

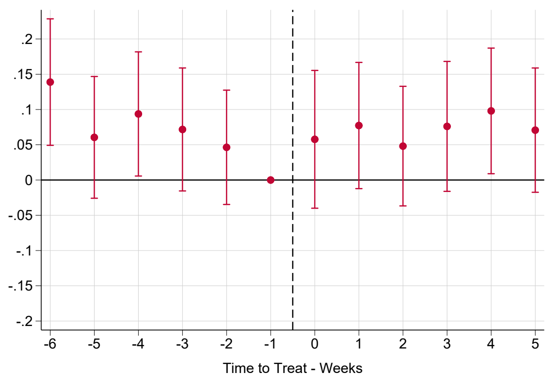
(a) Turnout Intentions



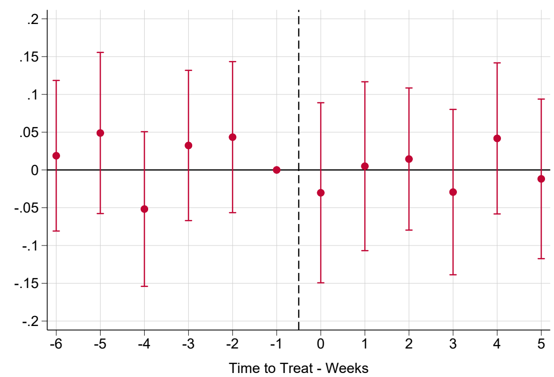
(b) Vote Intentions



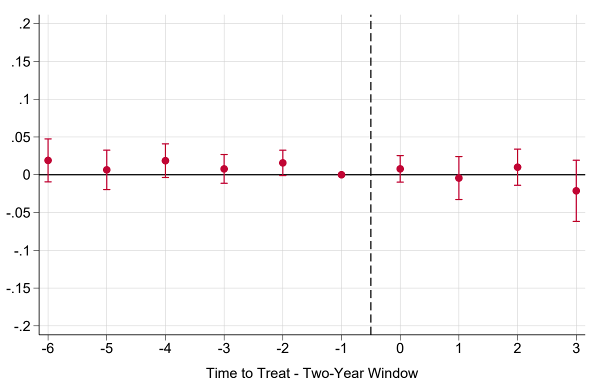
(c) Presidential Approval



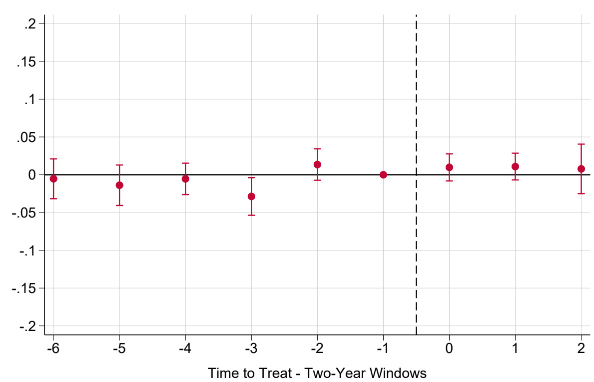
(d) Political Interest



(e) Election Results: Democratic Vote Share



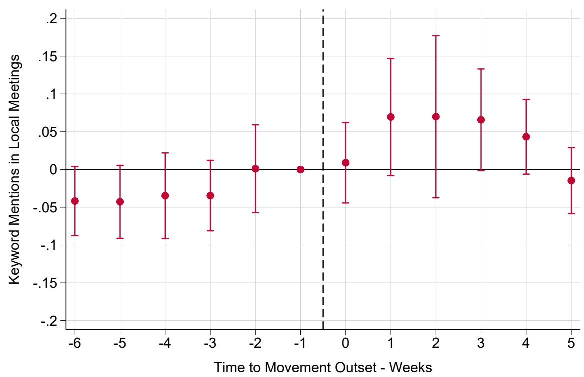
(f) Election Results: Turnout



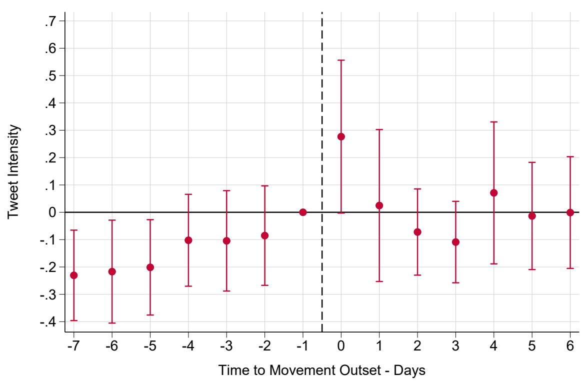
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 7 – Protests and Policymaking: Simple Difference

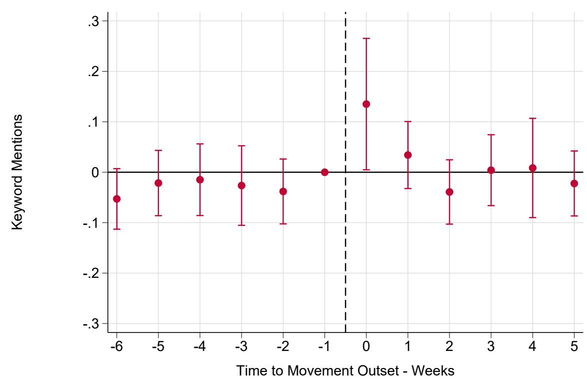
(a) Local Government Meetings



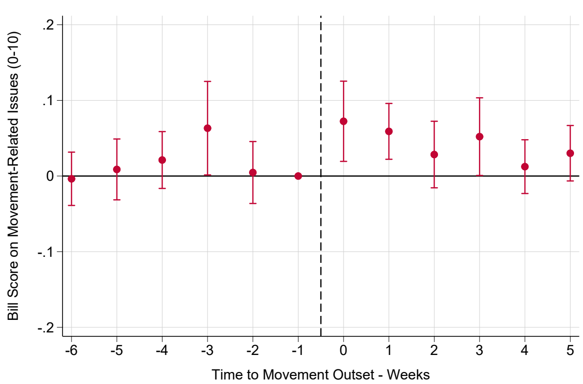
(b) Congressional Tweets



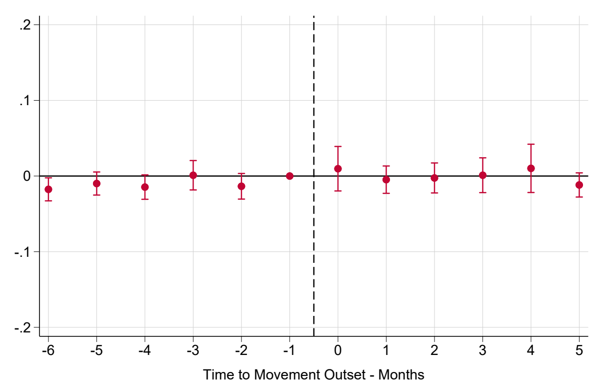
(c) Congressional Speeches



(d) Congressional Bills Sponsored



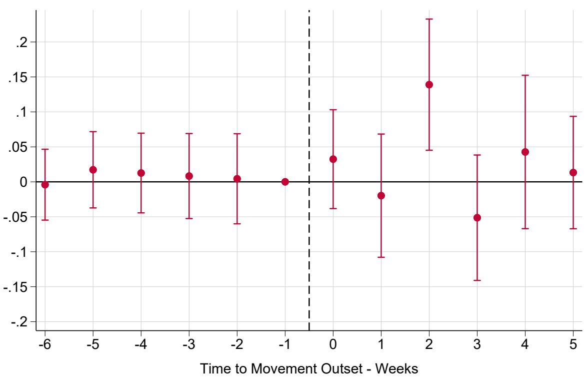
(e) Congressional Bills Engrossed



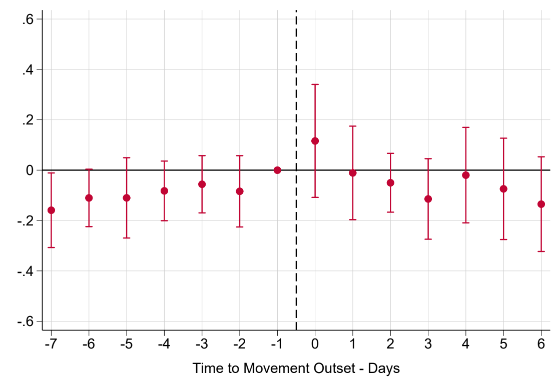
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). Congressional tweets: the dependent variable is the number of tweets related to a given issue. Congressional speeches: the dependent variable is the number of keyword mentions related to a given issue in congressional speeches. Local government meetings: the dependent variable is the number of local government meeting videos mentioning keywords related to a given issue. Congressional bills sponsored: the dependent variable is the number of sponsored or co-sponsored congressional bills related to a given issue. All dependent variables are standardized to have a mean of 0 and a standard deviation of 1.

Figure 8 – Protests and Policymaking: Difference-in-Differences

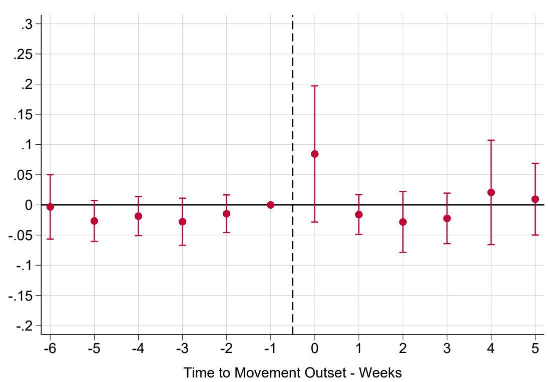
(a) Local Government Meetings



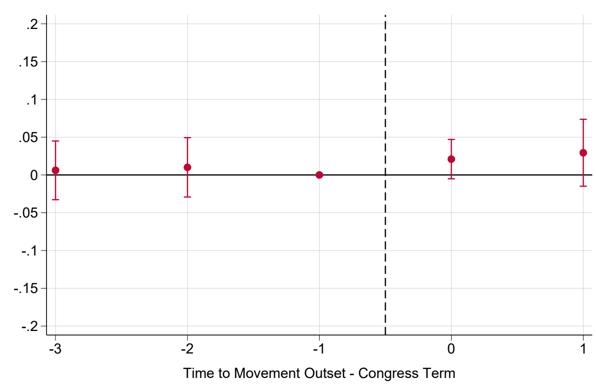
(b) Congressional Tweets



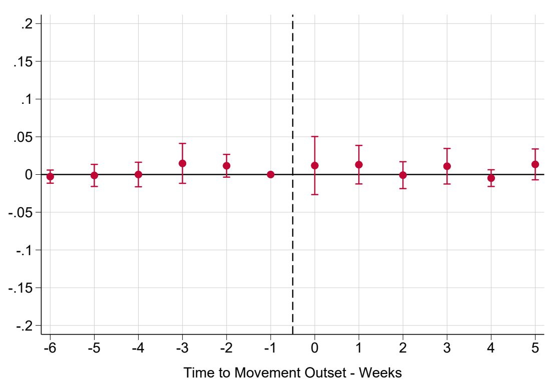
(c) Congressional Speeches



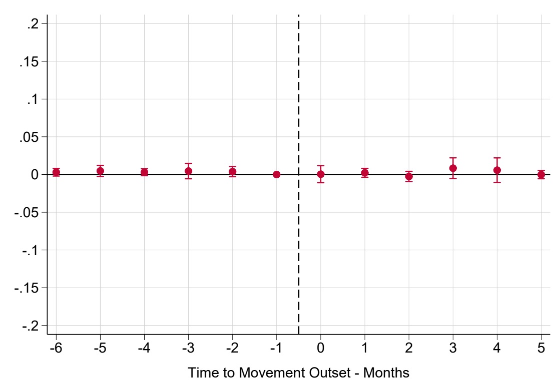
(d) Congressional Ideology



(e) Congressional Bills Sponsored



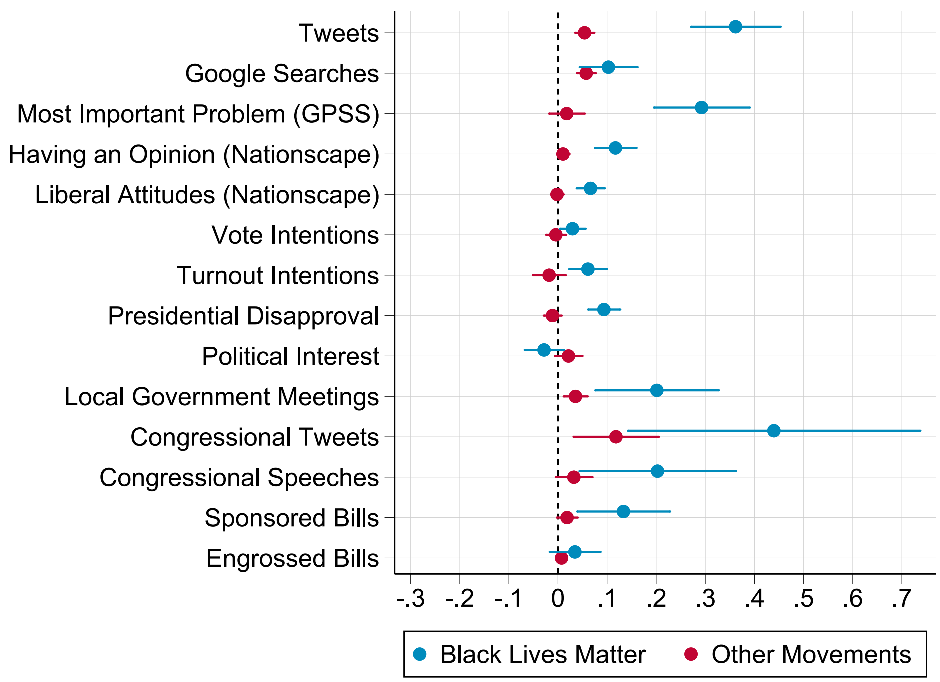
(f) Congressional Bills Engrossed



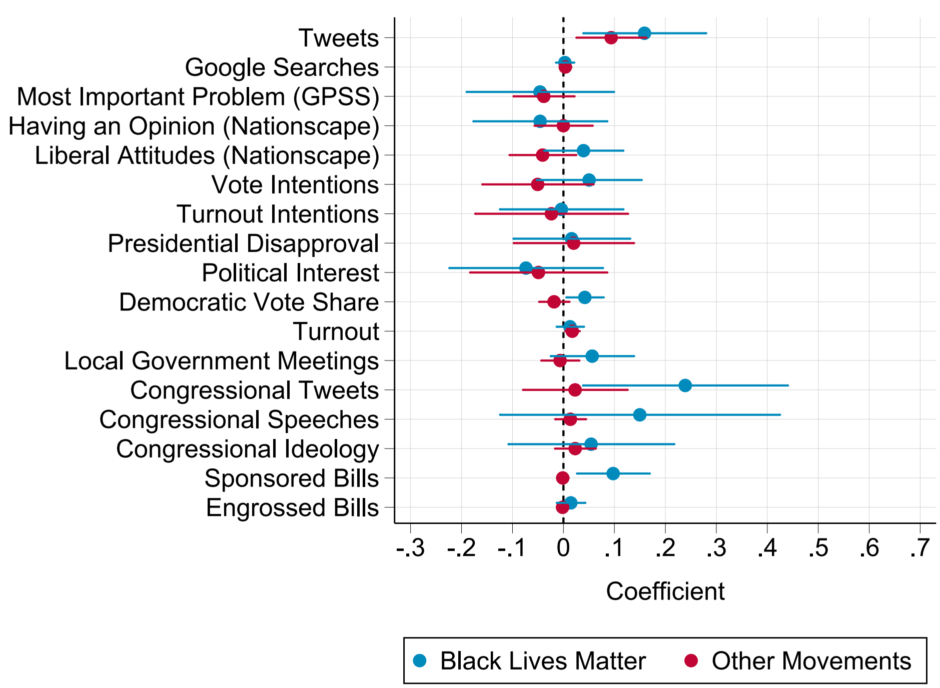
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 9 – Heterogeneity by Movement: BLM versus Other Movements

(a) Simple Difference



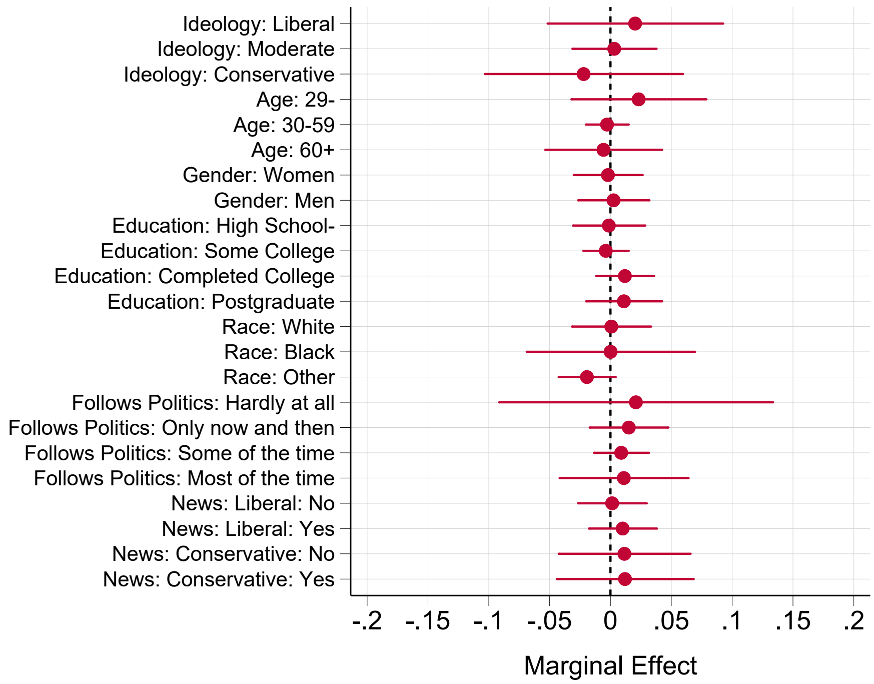
(b) Difference-in-Differences



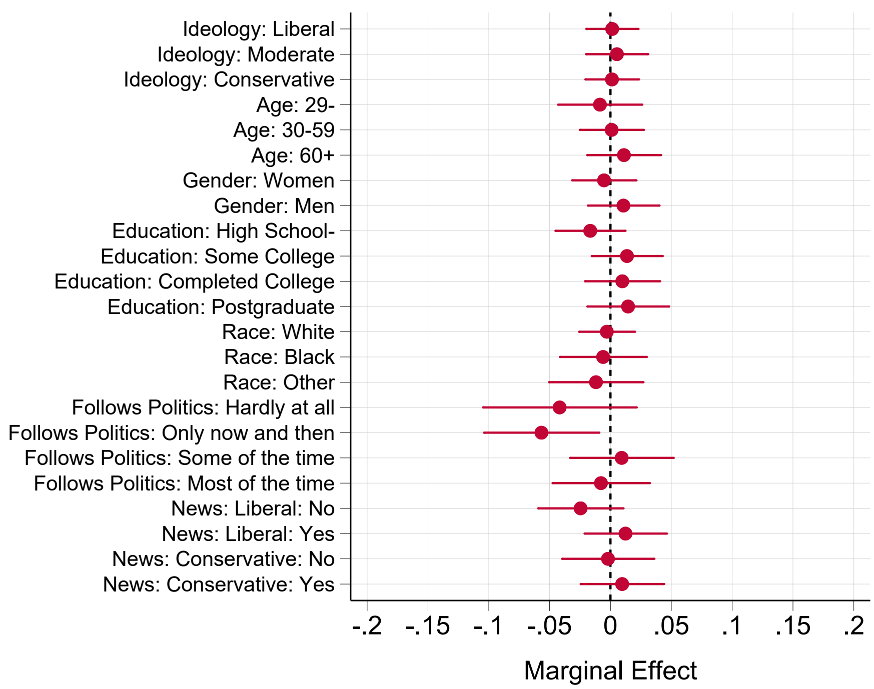
Notes: Panel (a) reports point estimates and 95% robust confidence intervals for the β_m in equation (5). Panel (b) reports point estimates and 95% robust confidence intervals for the ϕ_m in equation (6).

Figure 10 – Heterogeneity by Individual Characteristic

(a) Simple Difference



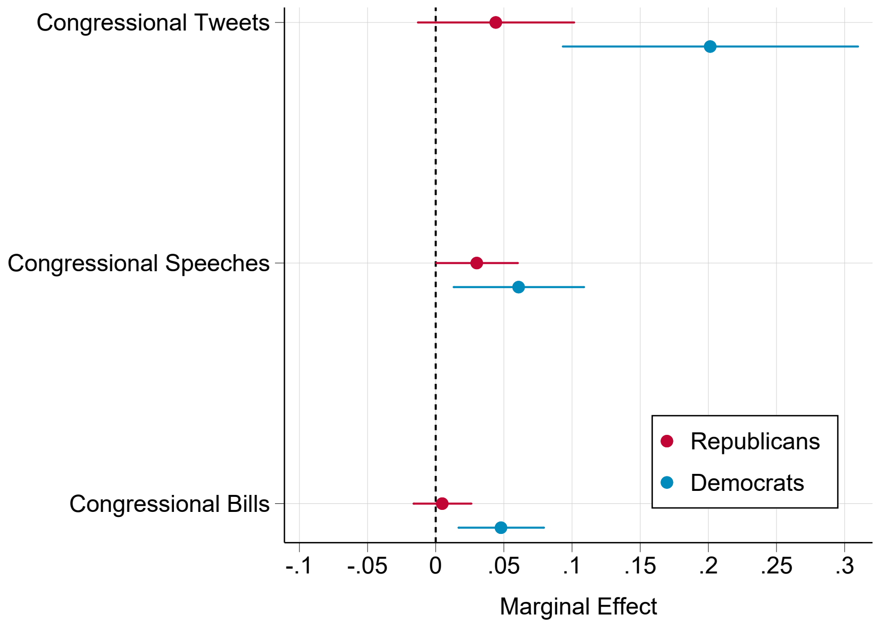
(b) Difference-in-Differences



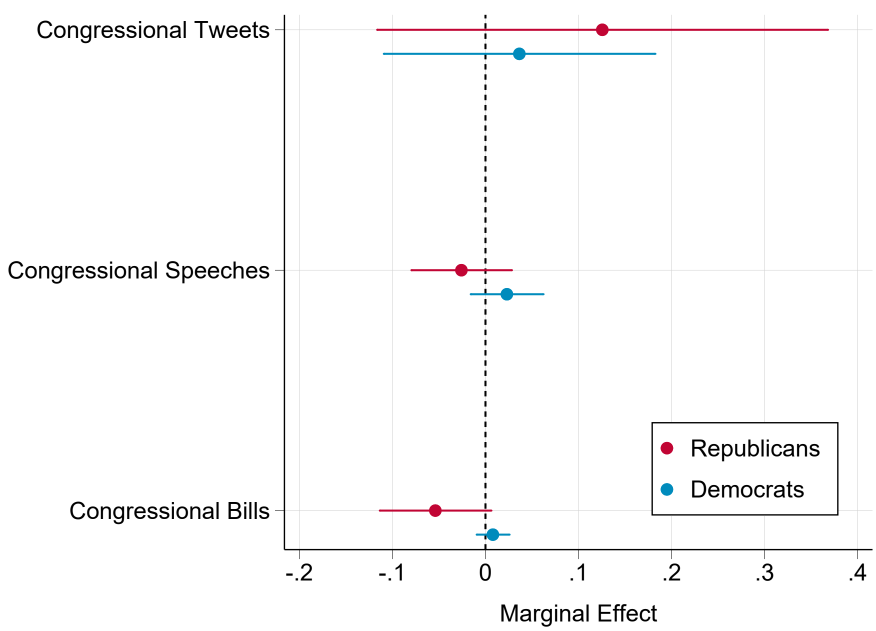
Notes: Panel (a) reports point estimates and 95% robust confidence intervals for the β_z in equation (8). Panel (b) reports point estimates and 95% robust confidence intervals for the ϕ_z in equation (9).

Figure 11 – Heterogeneity by Party

(a) Simple Difference



(b) Difference-in-Differences



Notes: Panel (a) reports point estimates and 95% robust confidence intervals for the β_m in equation (5). Panel (b) reports point estimates and 95% robust confidence intervals for the ϕ_m in equation (6).

Table 1 – Descriptive Statistics by Protest Movement

Topic	Date	Movement	Protests	Protesters	Counties
Environmental Protection	2017/04/22	March For Science	513	796,882	395
Environmental Protection	2019/09/20	Climate Strike	1,444	433,587	628
Gender Equality	2017/01/21	Women's March 1	824	4,245,716	522
Gender Equality	2018/01/20	Women's March 2	488	2,257,816	364
Gender Equality	2020/01/18	Women's March 3	327	356,434	244
Gender Equality	2020/10/17	Women's March 4	450	25,736	306
Gun Control	2018/03/14	March for Our Lives	5,431	3,206,449	1012
Immigration	2017/01/28	Muslim Ban	460	311,531	188
Immigration	2018/06/30	Families Belong Together	1,100	519,879	590
Immigration	2019/07/12	Lights for Liberty	828	120,292	511
International Affairs	2020/01/03	War with Iran	540	12,894	298
National Politics	2018/11/08	Mueller Investigation	914	36,590	651
National Politics	2019/12/17	Impeach Trump	668	94,361	447
Racism	2020/05/25	George Floyd	7,802	2,404,010	1373

Notes: This table reports descriptive statistics on each protest movement. Date is the date marking the beginning of the movement. Protests is the number of protests that took place during the month following the outset of the movement. Protesters is the total number of participants in these protests. Counties is the number of counties in which at least one protest took place during the month following the outset of the movement.

Table 2 – Protests and Salience: Simple Difference

	All Movements			Independent Movements		
	(1) Twitter	(2) Google	(3) GPSS	(4) Twitter	(5) Google	(6) GPSS
Post Protest	0.114***	0.063***	0.035*	0.083***	0.029***	0.013
	(0.013)	(0.009)	(0.018)	(0.012)	(0.007)	(0.011)
N	616,028	523,320	70,572	264,012	261,660	28,979
Time Window	1 Week	1 Week	6 Months	1 Week	1 Week	6 Months

Notes: This table reports simple difference estimates corresponding to equation (2), separately for all movements (columns 1 to 3) and independent movements only (columns 4 to 6). We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated (number of weeks or months on each side of the window). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3 – Protests and Salience: Difference-in-Differences

	Twitter		Google		GPSS	
	(1) Without Controls	(2) With Controls	(3) Without Controls	(4) With Controls	(5) Without Controls	(6) With Controls
Post Protest × Treatment	0.292***	0.134***	0.018***	0.004	-0.022	-0.040
	(0.035)	(0.040)	(0.004)	(0.005)	(0.025)	(0.028)
N	616,028	612,374	523,320	519,904	26,630	26,554
Time Window	1 Week	1 Week	1 Week	1 Week	6 Months	6 Months

Notes: This table reports difference-in-differences estimates corresponding to equation (4), before and after controlling for county characteristics interacted with time ($Post_{tm} \times \mathrm{C}_{cm}$ in equation (4)). We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated (number of weeks or months on each side of the window). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4 – Protests and Opinions: Simple Difference

	All Movements		Independent Movements	
	(1) Nationscape Any Opinion	(2) Nationscape Opinion	(3) Nationscape Any Opinion	(4) Nationscape Opinion
Post Protest	0.020***	0.013*	0.005	0.001
	(0.007)	(0.007)	(0.007)	(0.007)
N	264,576	462,646	199,174	306,672
Time Window	6 Weeks	6 Weeks	6 Weeks	6 Weeks

Notes: This table reports simple difference estimates corresponding to equation (2), separately for all movements (columns 1 to 2) and independent movements only (columns 3 to 4). We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated (number of weeks on each side of the window). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5 – Protests and Opinions: Difference-in-Differences

	Nationscape Any Opinion		Nationscape Opinion		CCES Opinion	
	(1) Without Controls	(2) With Controls	(3) Without Controls	(4) With Controls	(5) Without Controls	(6) With Controls
Post Protest $\times$ Treatment	-0.004	-0.013	0.002	0.000	0.058***	0.029*
	(0.023)	(0.027)	(0.021)	(0.027)	(0.014)	(0.018)
N	75,102	74,992	129,240	129,052	136,046	135,786
Time Window	6 Weeks	6 Weeks	6 Weeks	6 Weeks	2 Years	2 Years

Notes: This table reports difference-in-differences estimates corresponding to equation (4), before and after controlling for county characteristics interacted with time ($Post_{tm} \times \mathrm{C}_{cm}$ in equation (4)). We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated (number of weeks or years on each side of the window). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6 – Protests and Political Attitudes: Simple Difference

	All Movements				Independent Movements			
	(1) Vote Intention	(2) Turnout Intention	(3) Presidential Approval	(4) Political Interest	(5) Vote Intention	(6) Turnout Intention	(7) Presidential Approval	(8) Political Interest
Post Protest	0.003	-0.004	-0.009	0.012	0.007	-0.042**	0.006	0.003
	(0.009)	(0.015)	(0.009)	(0.012)	(0.011)	(0.020)	(0.010)	(0.015)
N	203,807	71,150	81,537	83,281	119,193	42,500	49,380	50,428
Time Window	6 Weeks	6 Weeks	6 Weeks	6 Weeks	6 Weeks	6 Weeks	6 Weeks	6 Weeks

Notes: This table reports simple difference estimates corresponding to equation (2), separately for all movements (columns 1 to 4) and independent movements only (columns 5 to 8). We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated (number of weeks on each side of the window). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7 – Protests and Political Attitudes: Difference-in-Differences

	Vote Intention		Turnout Intention		Presidential Approval		Political Interest		Democratic Vote Share		Turnout	
	(1) Without Controls	(2) With Controls	(3) Without Controls	(4) With Controls	(5) Without Controls	(6) With Controls	(7) Without Controls	(8) With Controls	(9) Without Controls	(10) With Controls	(11) Without Controls	(12) With Controls
Post Protest × Treatment	0.004	0.001	-0.014	-0.016	-0.005	-0.017	-0.072*	-0.062	0.121***	-0.007	0.002	0.016***
	(0.033)	(0.042)	(0.040)	(0.050)	(0.034)	(0.042)	(0.040)	(0.052)	(0.017)	(0.013)	(0.008)	(0.006)
N	58,728	58,636	19,990	19,954	21,800	21,766	22,108	22,072	1,208,778	1,208,580	342,982	342,982
Time Window	6 Weeks	6 Weeks	6 Weeks	6 Weeks	6 Weeks	6 Weeks	6 Weeks	6 Weeks	6 Years	6 Years	4 Years	4 Years

Notes: This table reports difference-in-differences estimates corresponding to equation (4), before and after controlling for county characteristics interacted with time ($Post_{tm} \times \mathrm{C}_{cm}$ in equation (4)). We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated (number of weeks or years on each side of the window). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8 – Protests and Policymaking: Simple Difference

	All Movements					Independent Movements				
	(1) Local Meetings	(2) Congressional Tweets	(3) Congressional Speeches	(4) Sponsored Bills	(5) Engrossed Bills	(6) Local Meetings	(7) Congressional Tweets	(8) Congressional Speeches	(9) Sponsored Bills	(10) Engrossed Bills
Post Protest	0.066***	0.151***	0.045**	0.027**	0.014	0.054***	0.082	0.001	0.018	0.000
	(0.018)	(0.043)	(0.019)	(0.011)	(0.010)	(0.016)	(0.068)	(0.019)	(0.014)	(0.013)
N	315,144	46,450	649,125	512,736	512,736	153,168	17,623	278,100	219,744	219,744
Time Window	6 Weeks	1 Week	6 Weeks	6 Weeks	6 Weeks	6 Weeks	1 Week	6 Weeks	6 Weeks	6 Weeks

Notes: This table reports simple difference estimates corresponding to equation (2), separately for all movements (columns 1 to 5) and independent movements only (columns 6 to 10). We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated (number of weeks on each side of the window). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9 – Protests and Policymaking: Difference-in-Differences

	Local Meetings		Congressional Tweets		Congressional Speeches		Congressional Ideology		Sponsored Bills		Engrossed Bills	
	(1) Without Controls	(2) With Controls	(3) Without Controls	(4) With Controls	(5) Without Controls	(6) With Controls	(7) Without Controls	(8) With Controls	(9) Without Controls	(10) With Controls	(11) Without Controls	(12) With Controls
Post Protest × Treatment	0.052***	0.020	0.099***	0.044	0.033**	0.023	0.021**	0.026	0.006	0.004	-0.000	-0.001
	(0.018)	(0.020)	(0.035)	(0.047)	(0.015)	(0.018)	(0.010)	(0.020)	(0.005)	(0.006)	(0.001)	(0.002)
N	315,144	314,592	46,450	46,450	531,771	531,771	37,758	37,758	512,736	512,736	2,183,052	2,183,052
Time Window	6 Weeks	6 Weeks	1 Week	1 Week	6 Weeks	6 Weeks	2 Years	2 Years	6 Weeks	6 Weeks	6 Months	6 Months

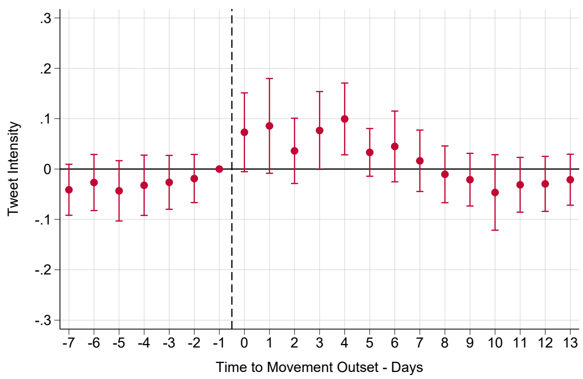
Notes: This table reports difference-in-differences estimates corresponding to equation (4), before and after controlling for county characteristics interacted with time ($Post_{tm} \times \mathrm{C}_{cm}$ in equation (4)). We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated (number of weeks or years on each side of the window). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Online Appendix

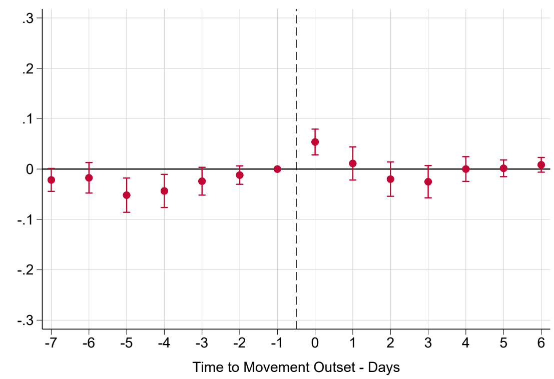
A. Additional Figures and Tables

Figure A1 – Protests and Salience: Simple Difference on Independent Movements

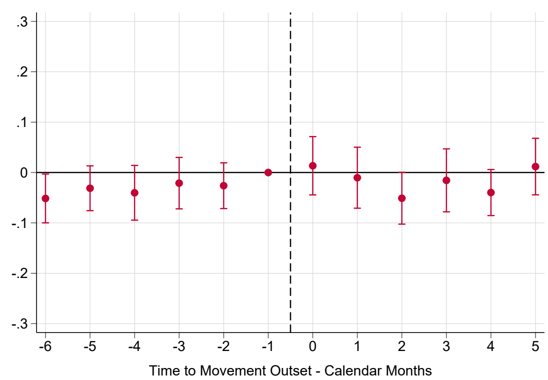
(a) Twitter



(b) Google



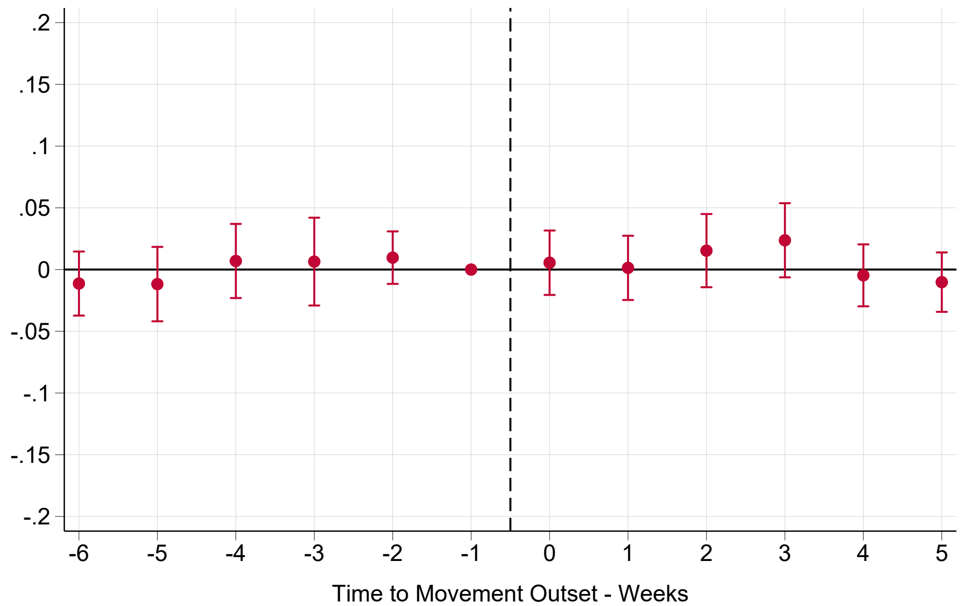
(c) GPSS



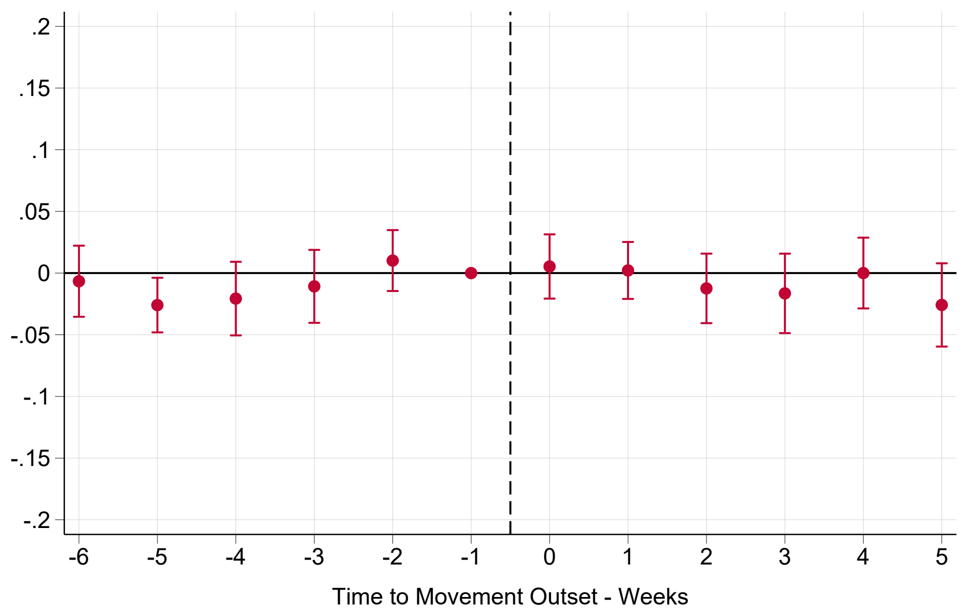
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1).

Figure A2 – Protests and Opinions: Simple Difference on Independent Movements

(a) Nationscape: Having an Opinion



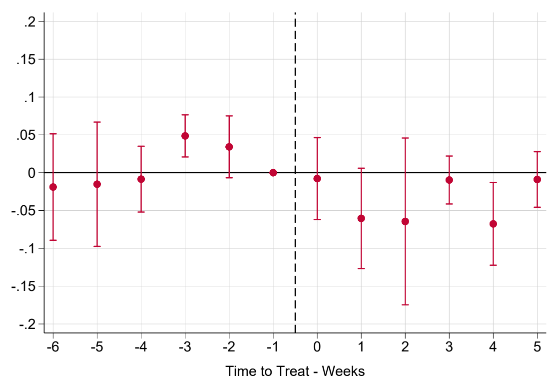
(b) Nationscape: Liberal Attitudes



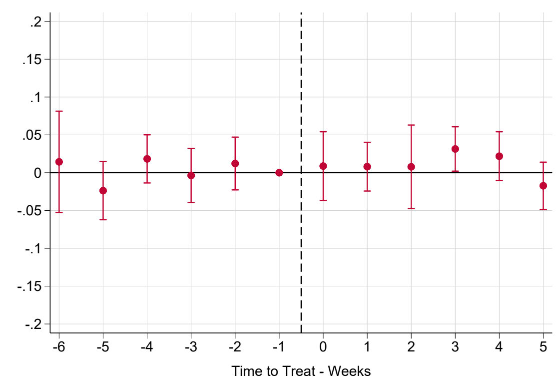
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1).

Figure A3 – Protests and Political Attitudes: Simple Difference on Independent Movements

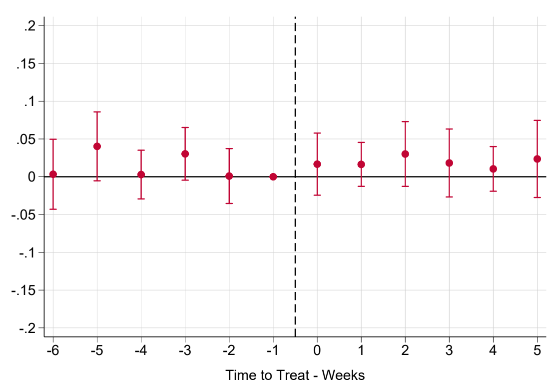
(a) Turnout Intentions



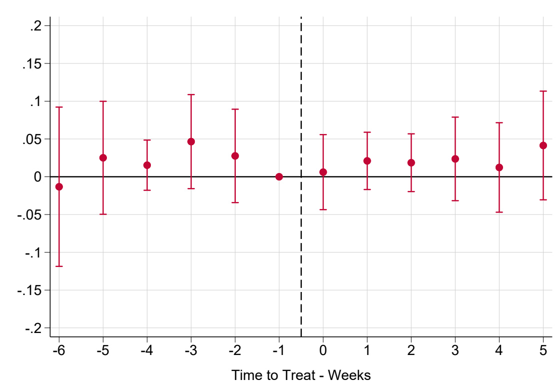
(b) Vote Intentions



(c) Presidential Approval



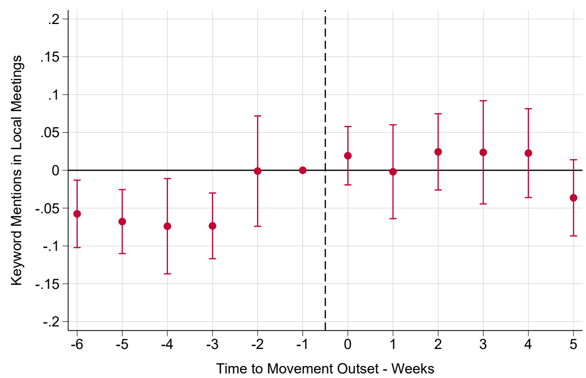
(d) Political Interest



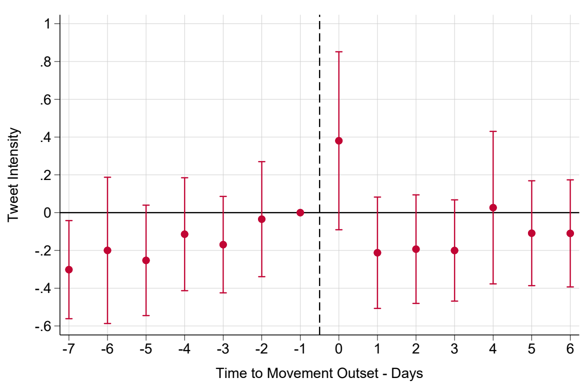
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1).

Figure A4 – Protests and Policymaking: Simple Difference on Independent Movements

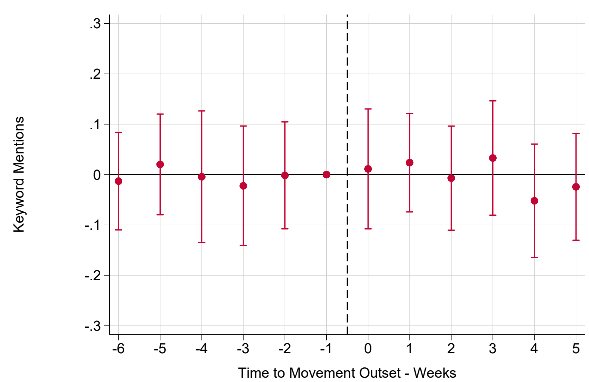
(a) Local Government Meetings



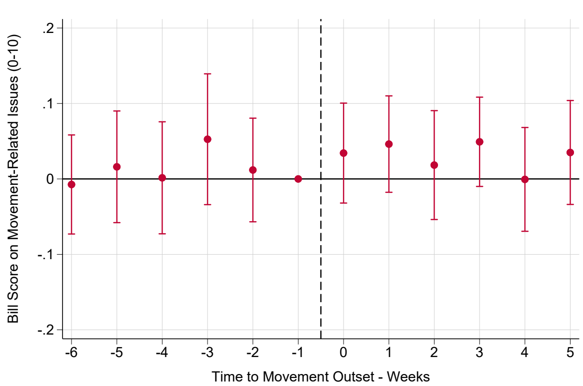
(b) Congressional Tweets



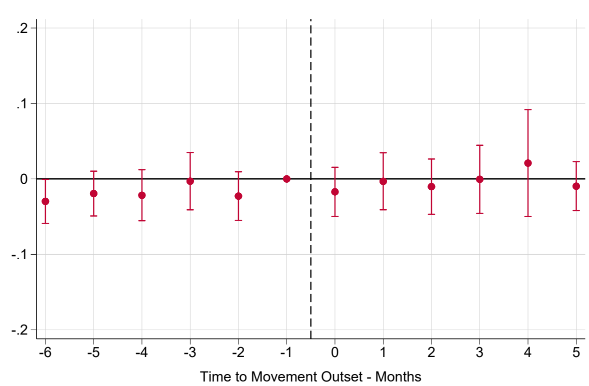
(c) Congressional Speeches



(d) Congressional Bills Sponsored



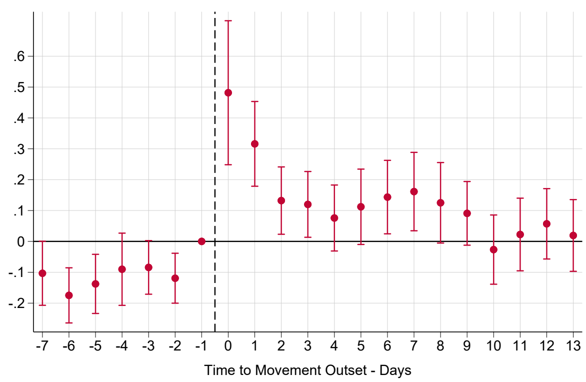
(e) Congressional Bills Engrossed



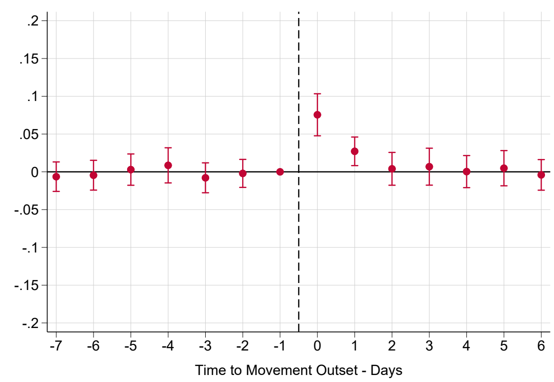
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1).

Figure A5 – Protests and Salience: Difference-in-Differences without Protest Propensity Control

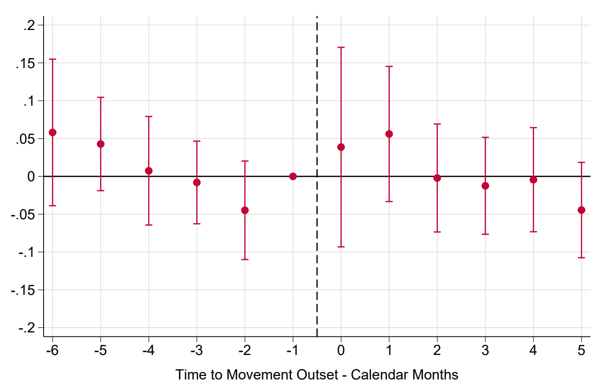
(a) Twitter



(b) Google



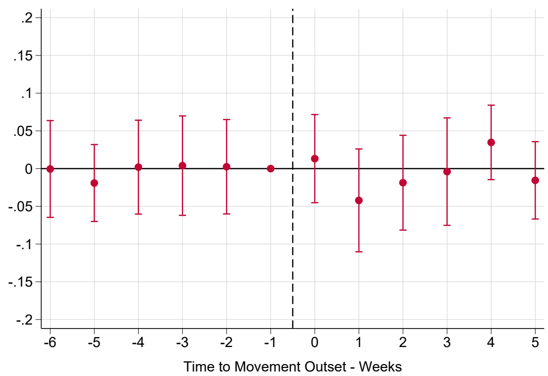
(c) GPSS



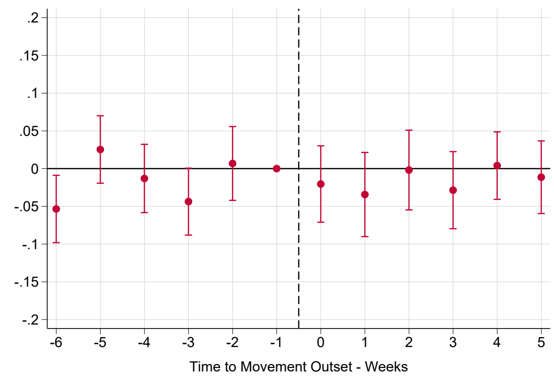
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3). Estimates do not control for protest propensity interacted with time.

Figure A6 – Protests and Opinions: Difference-in-Differences without Protest Propensity Control

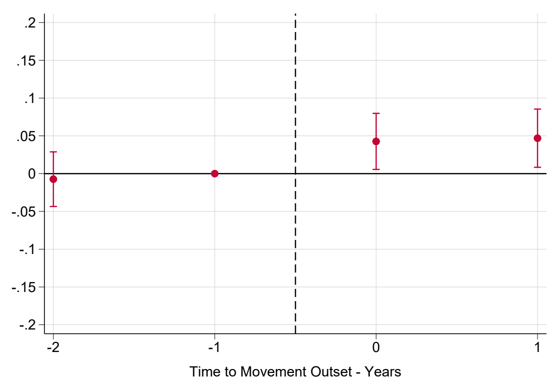
(a) Nationscape: Having an Opinion



(b) Nationscape: Liberal Attitudes



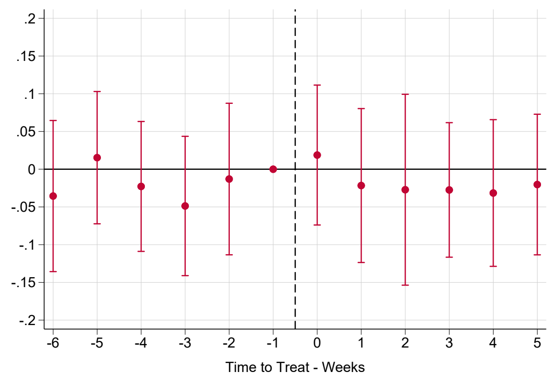
(c) CCES: Liberal Attitudes



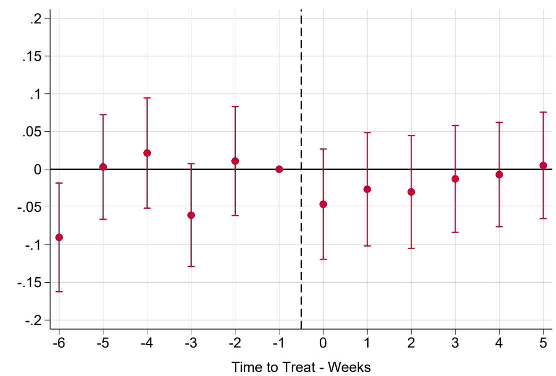
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3). Estimates do not control for protest propensity interacted with time.

Figure A7 – Protests and Political Attitudes: Difference-in-Differences without Protest Propensity Control

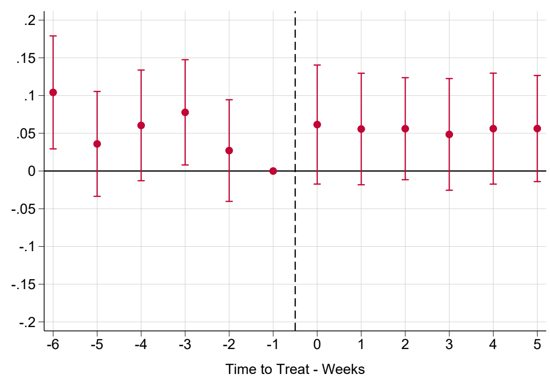
(a) Turnout Intentions



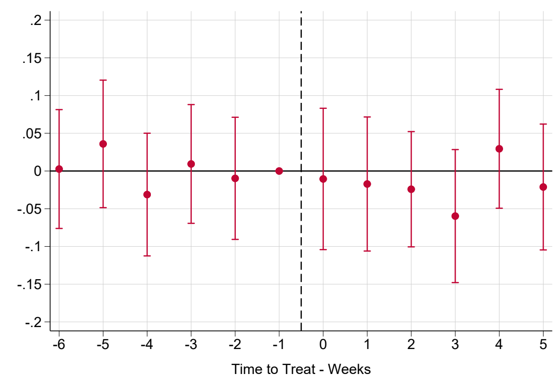
(b) Vote Intentions



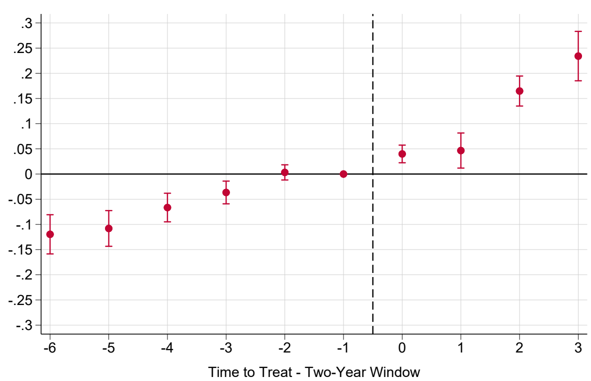
(c) Presidential Approval



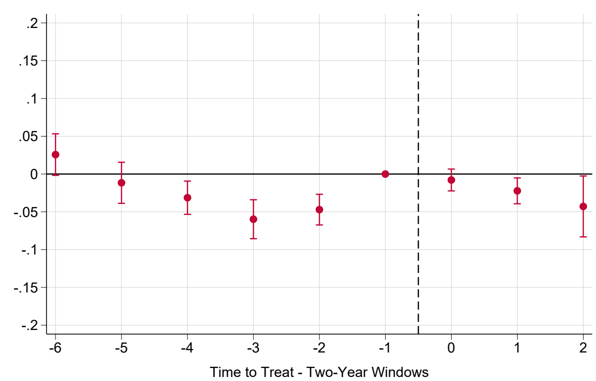
(d) Political Interest



(e) Election Results: Democratic Vote Share



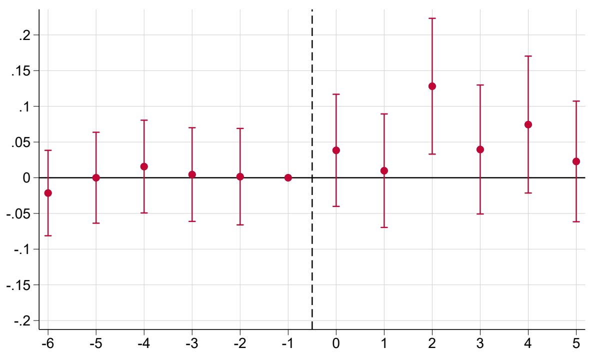
(f) Election Results: Turnout



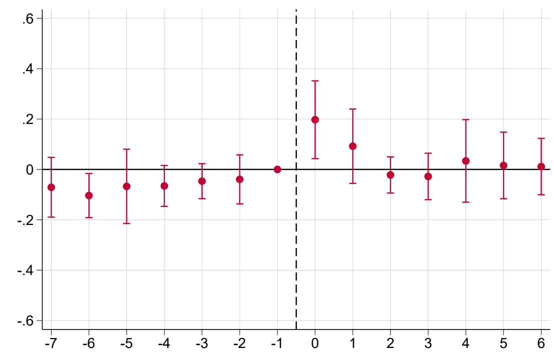
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3). Estimates do not control for protest propensity interacted with time.

Figure A8 – Protests and Policymaking: Difference-in-Differences without Protest Propensity Control

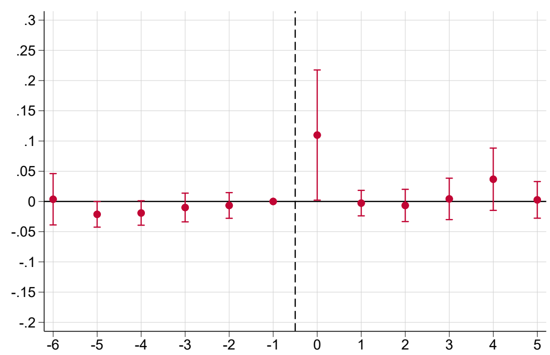
(a) Local Government Meetings



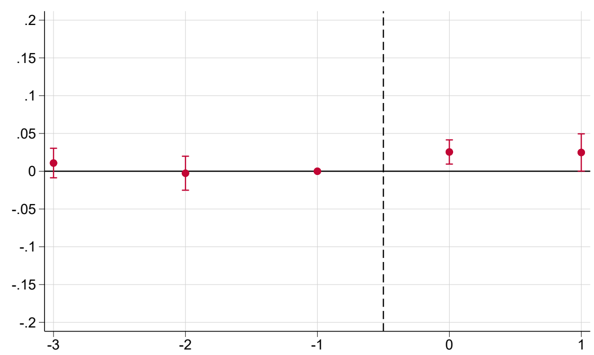
(b) Congressional Tweets



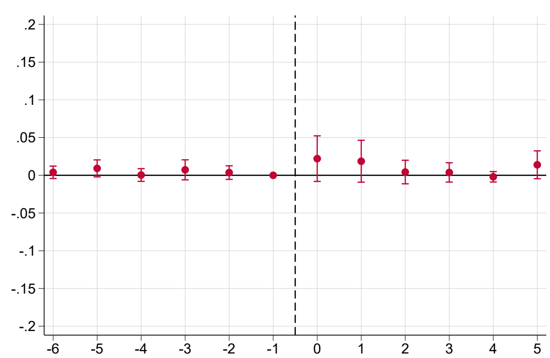
(c) Congressional Speeches



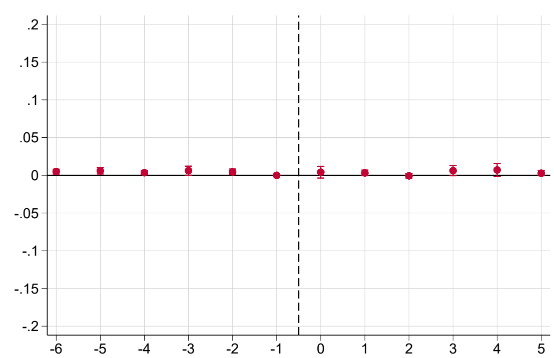
(d) Congressional Ideology



(e) Congressional Bills Sponsored



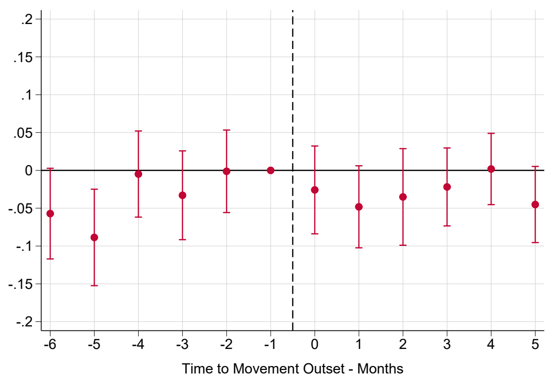
(f) Congressional Bills Engrossed



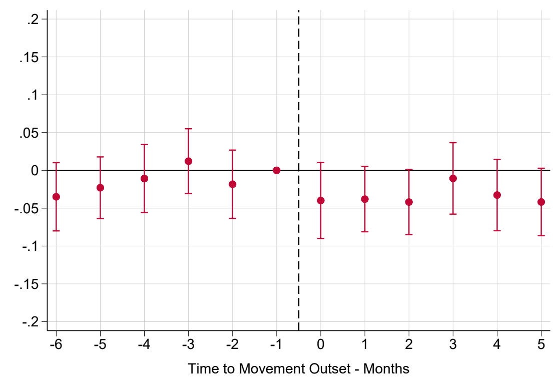
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3). Estimates do not control for protest propensity interacted with time.

Figure A9 – Nationscape Survey, Difference-in-Differences: Long-Run Effects

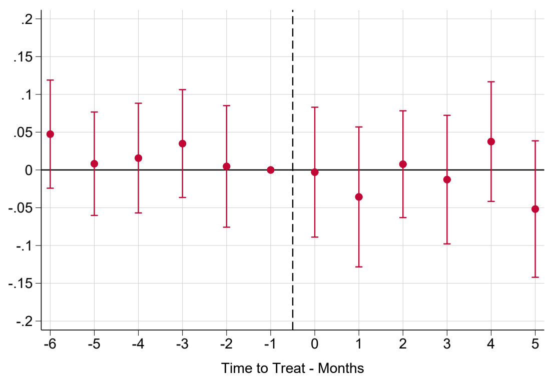
(a) Having an Opinion



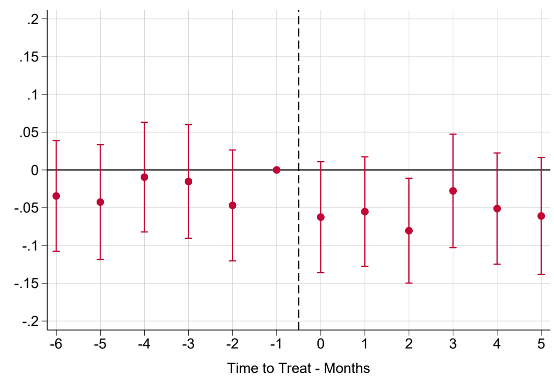
(b) Liberal Attitudes



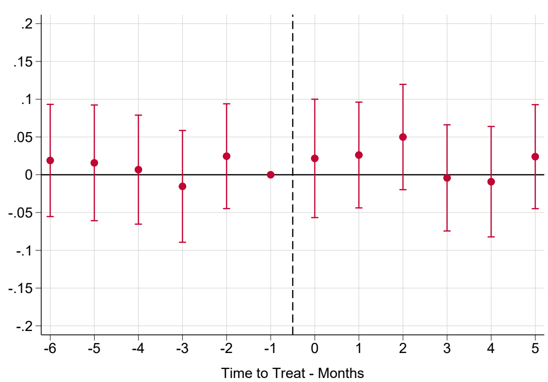
(c) Turnout Intentions



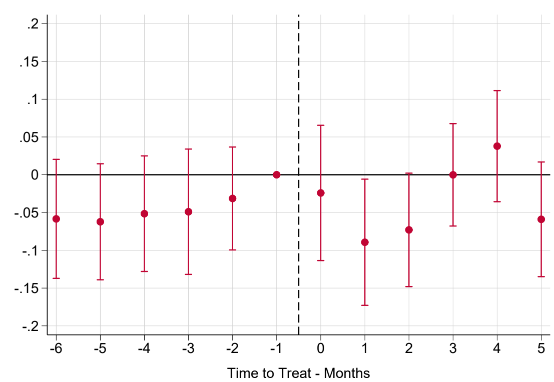
(d) Vote Intentions



(e) Presidential Approval

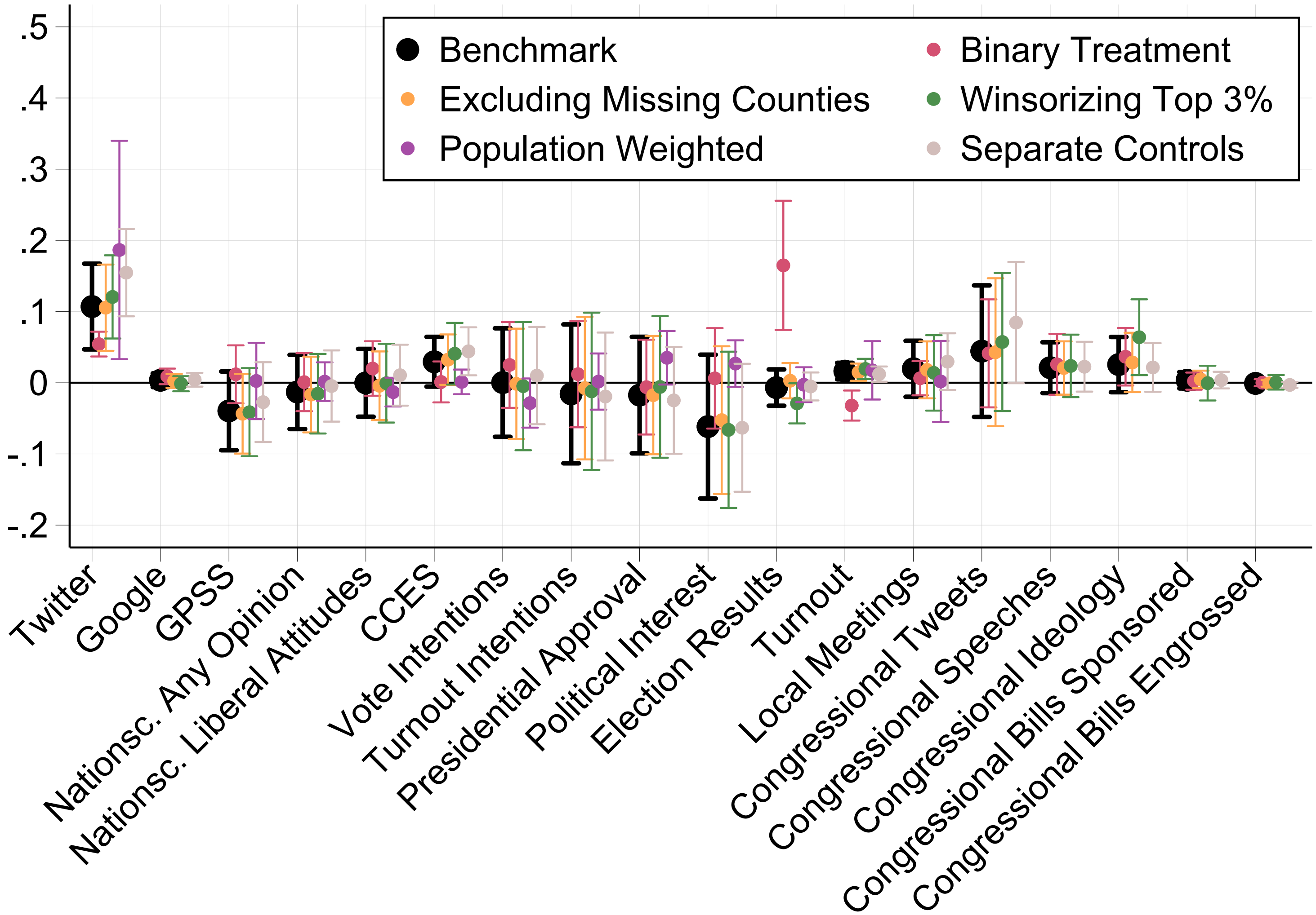


(f) Political Interest



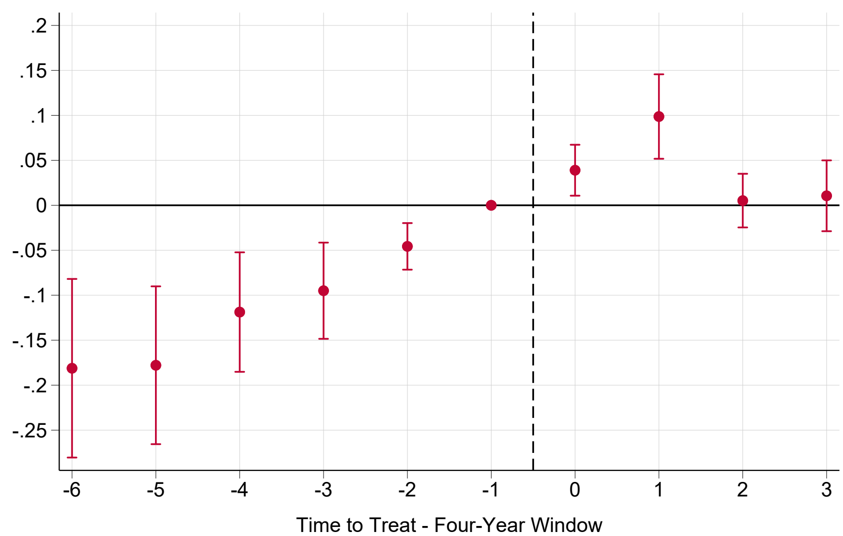
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure A10 – Robustness to Alternative Specifications



Notes: This figure reports difference-in-differences estimates corresponding to ϕ in equation (4) for alternative empirical specifications. Benchmark: benchmark specification reported in the main text. Binary Treatment: protest intensity coded as a binary variable taking 1 if there was any protest in the geographical unit and 0 otherwise. Excluding Missing Counties: exclude counties with no information on the number of protesters from the analysis. Winsorizing Top 3%: winsorize the 97th percentile of protest intensity instead of the 99th percentile. Population Weighted: weight observations by the total population of each unit. Separate Controls: control for the full set of county-level controls interacted with time instead of protest propensity interacted with time.

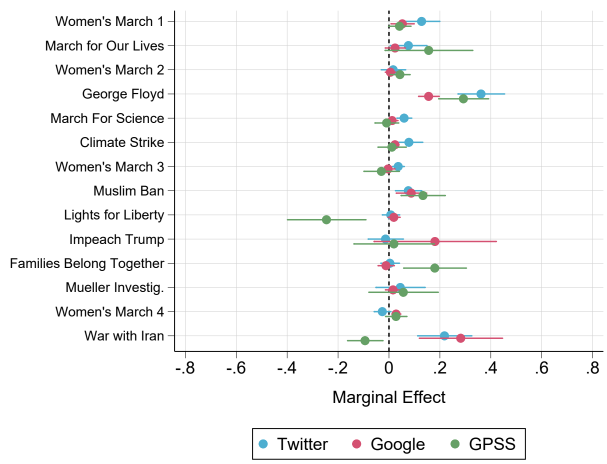
Figure A11 – Election Results, Difference-in-Differences: Binary Treatment



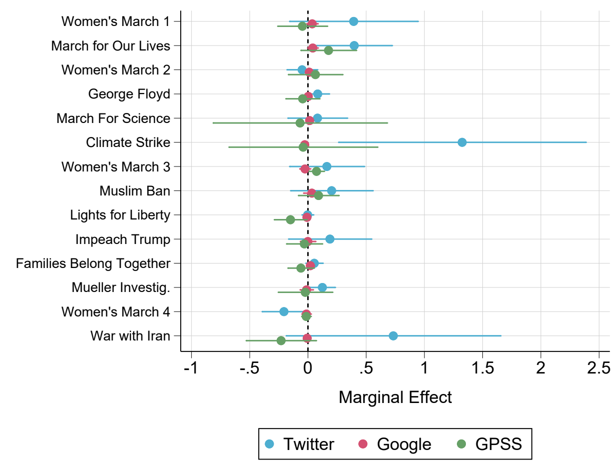
Notes: This figure reports difference-in-differences estimates corresponding to ϕ in equation (4). Protest intensity coded as a binary variable taking 1 if there was any protest in the geographical unit and 0 otherwise

Figure A12 – Heterogeneity by Movement: Salience and Opinions

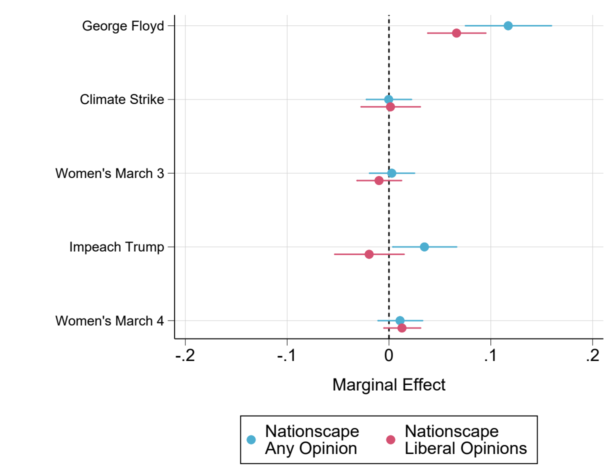
(a) Salience: Simple Difference



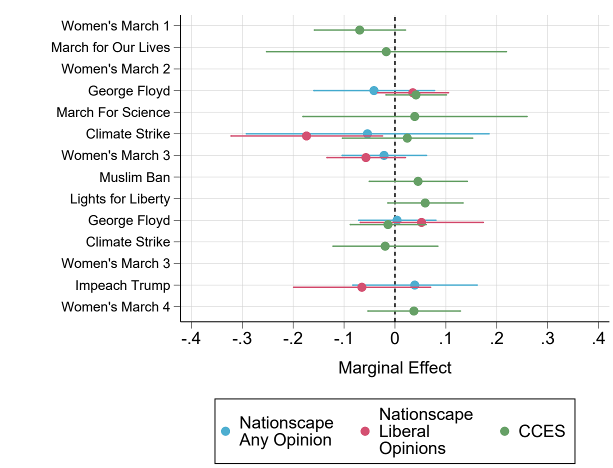
(b) Salience: Difference-in-Differences



(c) Opinions: Simple Difference



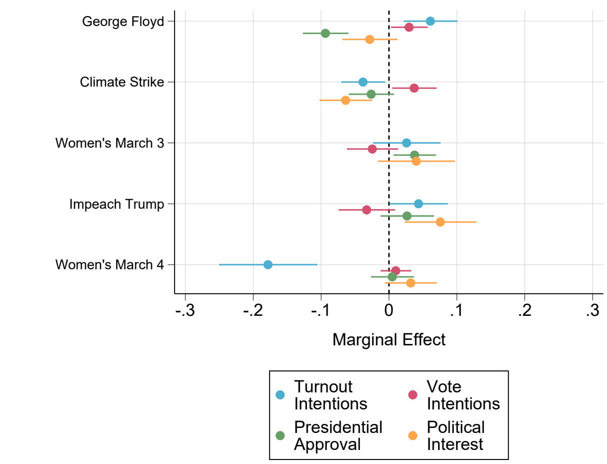
(d) Opinions: Difference-in-Differences



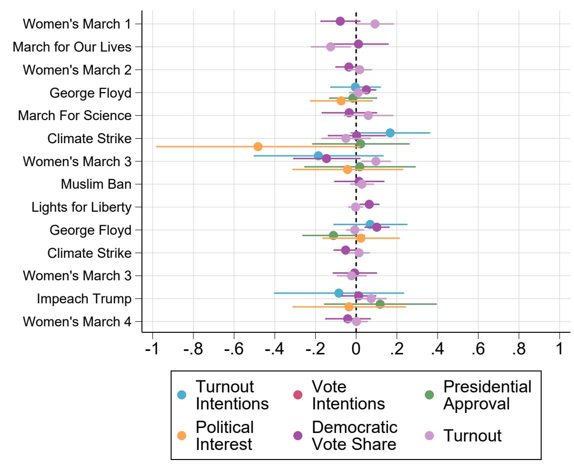
Notes: The figure reports heterogeneous treatment effects by movement for both the simple difference and difference-in-differences specifications. Panels (a) and (c) report point estimates and 95% robust confidence intervals for β in equation (2). Panels (b), (d), and (e) report point estimates and 95% robust confidence intervals for ϕ in equation (4).

Figure A13 – Heterogeneity by Movement: Political Attitudes and Policymaking

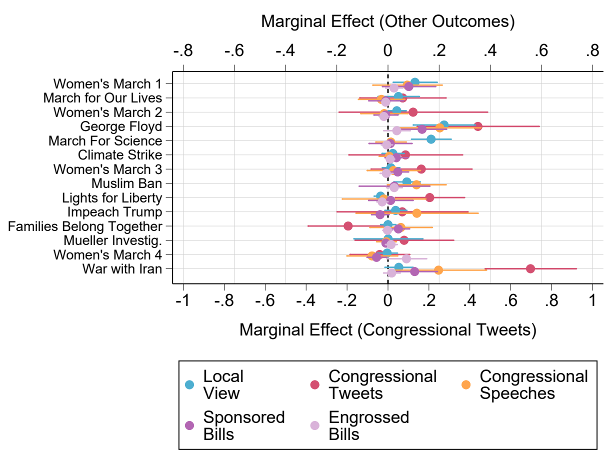
(a) Political Attitudes: Simple Difference



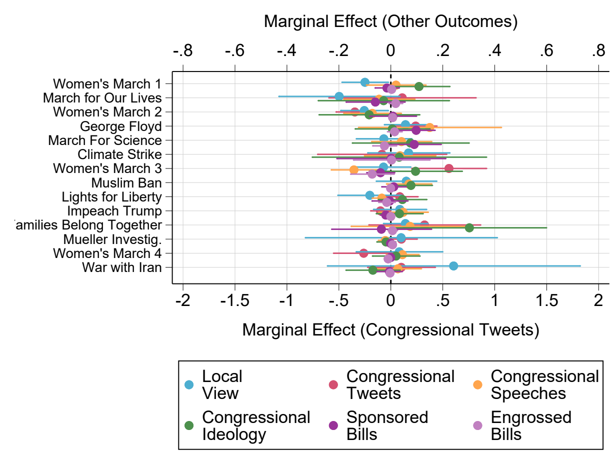
(b) Political Attitudes: Difference-in-Differences



(c) Policymaking: Simple Difference



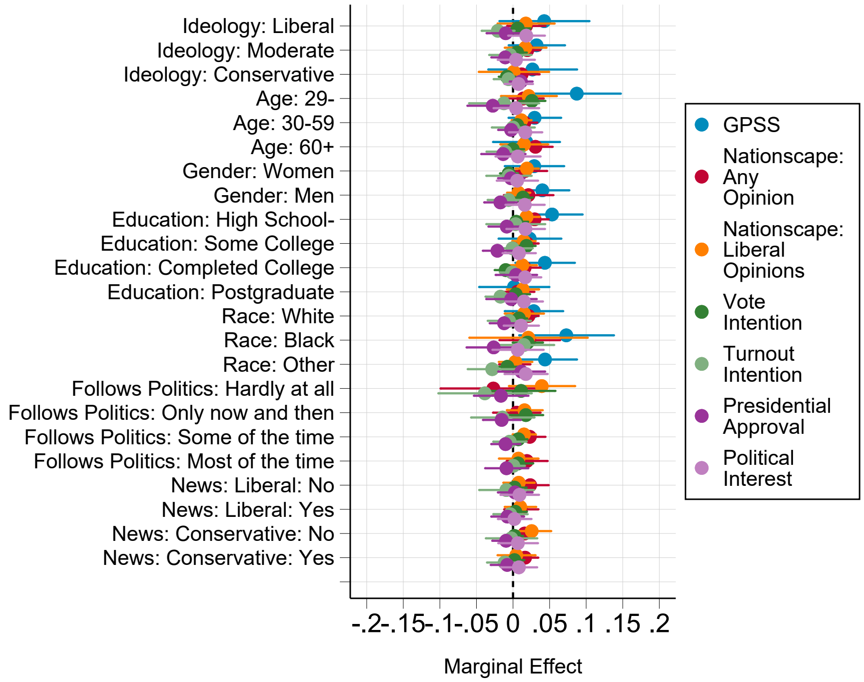
(d) Policymaking: Difference-in-Differences



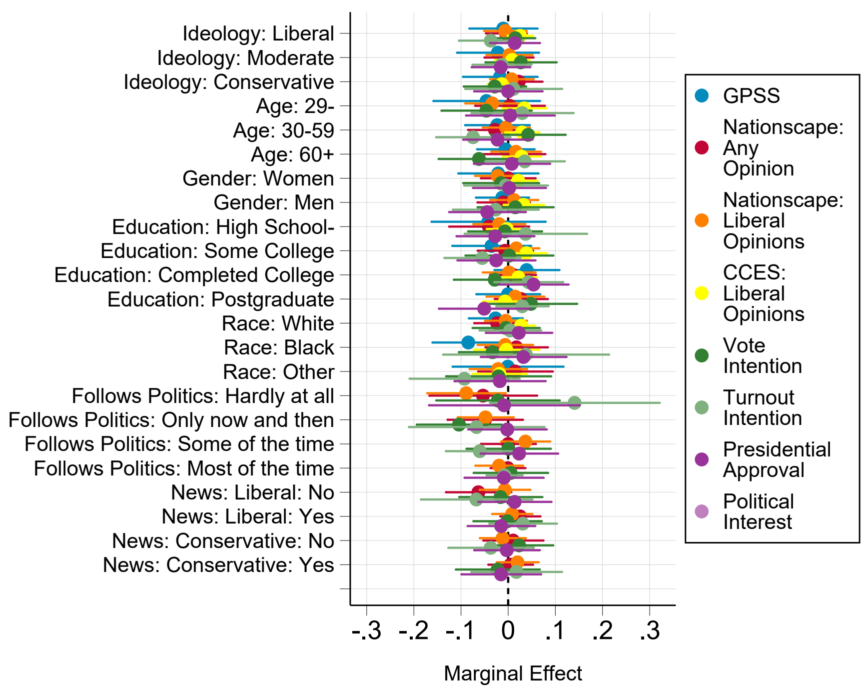
Notes: The figure reports heterogeneous treatment effects by movement for both the simple difference and difference-in-differences specifications. Panels (a) and (c) report point estimates and 95% robust confidence intervals for β in equation (2). Panels (b), (d), and (e) report point estimates and 95% robust confidence in tervals for ϕ in equation (4).

Figure A14 – Heterogeneity by Individual Characteristic: Results by Outcome

(a) Simple Difference

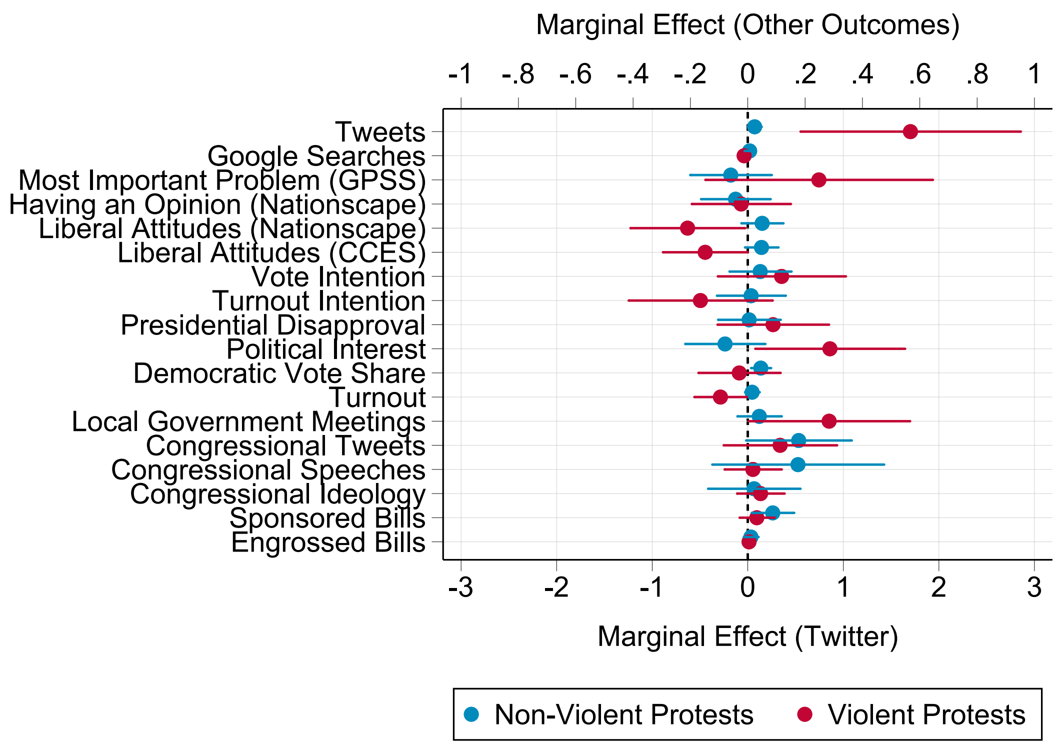


(b) Difference-in-Differences



Notes: The figure reports heterogeneous treatment effects by individual characteristic and by outcome for both the simple difference and difference-in-differences specifications. Panel (a) reports point estimates and 95% robust confidence intervals for β_z in equation (8). Panel (b) reports point estimates and 95% robust confidence intervals for ϕ_z in equation (9).

Figure A15 – Heterogeneity by Protest Violence



Notes: The figure reports point estimates and 95% robust confidence intervals for ϕ_1 and ϕ_2 in equation (7).

Table A1 – Geographical and Time Units of Analysis by Outcome

Outcome	Geographical Unit	Time Unit	Pre-Periods	Post-Periods
Tweets	County	Day	7	14
Google Searches	DMA	Day	7	7
Most Important Problem (GPSS)	County	Month	6	6
Having an Opinion (Nationscape)	County	Week	6	6
Liberal Attitudes (Nationscape)	County	Week	6	6
Liberal Attitudes (CCES)	County	Week	6	6
Vote Intentions (Nationscape)	County	Week	6	6
Turnout Intentions (Nationscape)	County	Week	6	6
Presidential Approval (Nationscape)	County	Week	6	6
Political Interest (Nationscape)	County	Week	6	6
Election Results: Democratic Vote Share	County	Two-Year Period	6	4
Election Results: Turnout	County	Two-Year Period	6	3
Local Government Meetings	County	Week	6	6
Congressional Tweets	Congressional District	Day	7	7
Congressional Speeches	Congressional District	Week	6	6
Congressional Ideology	Congressional District	Two-Year Period	3	2
Sponsored Bills	Congressional District	Week	6	6
Engrossed Bills	Congressional District	Month	6	6

Notes: This table reports the geographical and time units used in the analysis for each outcome.

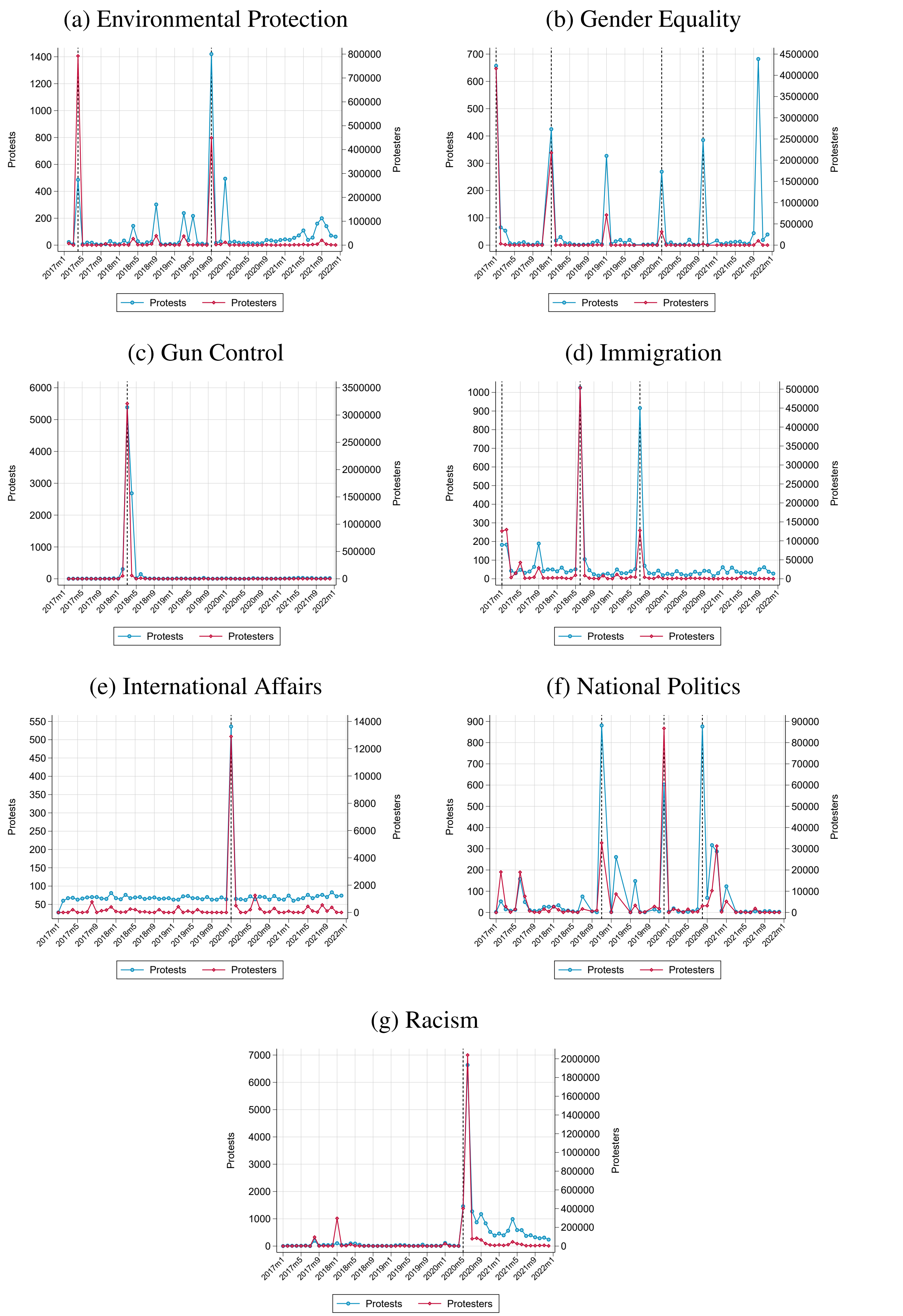
Table A2 – Protests and Salience: Simple Difference, Google Searches for All Words versus Searches for ‘Protest’

	Searches for All Words		Searches for Protest	
	(1) All Movements	(2) Independent Movements	(3) All Movements	(4) Independent Movements
Post Protest	0.052***	0.020***	0.071***	0.015*
	(0.007)	(0.005)	(0.022)	(0.007)
N	1,046,640	523,320	82,320	35,280
Time Window	2 Weeks	2 Weeks	2 Weeks	2 Weeks

Notes: This table reports simple difference estimates corresponding to equation (2), separately for all keywords (columns 1 and 2) and the word ‘protest’ only (columns 3 and 4). Columns (1) and (2) reproduce columns (2) and (6) in Table 2. We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B. Protest Data

Figure B1 – Protests in the United States, 2017-2021



Notes: The figure reports the monthly number of protests (left axis) and number of protest participants (right axis) in the United States over the 2017-2021 period.

Table B1 – Protest Data: Descriptive Statistics by Topic

	Protests	Protesters
Racism	24,863	3,785,925
Gun Control	10,381	3,491,667
National Politics	9,707	1,678,827
Gender Equality	8,025	8,453,840
Environmental Protection	7,027	1,528,965
International Affairs	6,698	258,420
Immigration	5,756	1,297,414
Other	19,963	6,336,017

Notes: The table reports the total number of protests and protesters in the United States by topic over the 2017-2021 period.

Table B2 – Protest Data: Correlation with Survey-Reported Protest Participation

	(1) Without Controls	(2) With Controls
Protesters/Population (CCES)	0.130***	0.040***
	(0.004)	(0.004)
N	7,296	7,272
R-Squared	0.15	0.39

Notes: The table reports results of regressions relating county-level protest intensity in the past year as measured in the CCC database to protest participation in the past year as reported by respondents in the CCES survey. The unit of observation is the county-year. The survey and protest data are matched over three time periods corresponding to the survey questions asked in three waves of the CCES about past protest participation: September 2017 to September 2018, October 2018 to October 2019, and September 2019 to September 2020. Column (1) regresses protest intensity measured in CCC on protest intensity measured in CCES. Column (2) controls for year fixed effects, the composition of the population by race and education, the unemployment rate, median income, and the 2016 Democratic vote share.

C. Twitter and Google Data

Table C1 – Twitter and Google Keyword Dictionary

Topic	Movement	Keywords
Environmental Protection	Climate Strike	biodiversity; climate; climate action; climate change; climate justice; climate march; climate strike; deforestation; environmental justice; fossil fuels; global warming; green new deal; greenhouse effect; greenhouse gas; greta thunberg; nuclear; paris agreement; pollution; renewable resources; sustainable
Environmental Protection	March For Science	bill nye; biodiversity; climate; climate action; climate change; climate march; deforestation; environmental justice; environmental protection agency; fossil fuels; global warming; greenhouse effect; greenhouse gas; march for science; neil degrasse tyson; nuclear; nye; paris agreement; pollution; renewable resources; science; science guy; sustainable
Gender Equality	Women's Marches	abortion; abortion rights; domestic violence; feminism; feminist; lgbtq; pro choice; pro life; roe wade; women; women rights; women's march
Gun Control	March for Our Lives	assault weapon; bump stock; bump stocks; gun control; gun laws; gun rights; gun safety; gun violence; march for our lives; march life; march lives; national rifle association; never again; nra; rifle; second amendment; weapon

Immigration	Families Belong Together	abolish ice; border wall; children jail; children separated; concentration camps; daca; deportation; detention camps; families belong together; families together; ice; separation families; zero tolerance
Immigration	Lights for Liberty	border wall; concentration camps; daca; deportation; detention camps; ice; lights for liberty; lights liberty; s386; zero tolerance
Immigration	Muslim Ban	immigration ban; immigration order; muslim ban; no ban; no fear; no hate; no wall; unamerican; welcome
International Affairs	War with Iran	iran; no war; nuclear; out of iraq; sanctions on iran; soleimani; war with iran
National Politics	Impeach Trump	above the law; impeach; impeach trump; remove; trump
National Politics	Mueller Investig.	above the law; mueller; mueller probe; no one is above the law; protect mueller; robert mueller; russia investigation
Racism	George Floyd	all lives matter; antiracism; back the blue; bipoc; black lives matter; blue lives matter; civil rights; defund police; defund the police; george floyd; justice; police brutality; police lives matter; race; racial; racial justice; racism; slavery; support police; white lives matter; white supremacy

Notes: The table reports the list of keywords used to collect the Twitter and Google Trends data for each movement.

D. Survey Data

Table D1 – Nationscape: List of Questions Related to Policy Views

Topic	Question	% Positive
Environmental Protection	Cap carbon emissions	74%
Environmental Protection	Disagree removing barriers to oil and gas drilling	48%
Environmental Protection	Green New Deal	59%
Environmental Protection	Large-scale investment in technology for environment	77%
Gender Equality	Disagree never permit abortion	72%
Gender Equality	Disagree women complaining about harassment cause more problems	46%
Gender Equality	Discrimation against women	39%
Gender Equality	Not allow employers to decline coverage of abortion in insurance	51%
Gender Equality	Not more comfortable with man as boss	33%
Gender Equality	Not require waiting period and ultrasound before abortion	47%
Gender Equality	Permit abortion at any time	29%
Gender Equality	Permit abortion in cases other than rape etc.	65%
Gender Equality	Permit late term abortion	31%
Gender Equality	Women just as capable of thinking logically	85%
National Politics	How favorable is your impression of: Biden	50%
National Politics	How favorable is your impression of: Trump	52%
National Politics	Impeach Trump	49%
National Politics	Presidential approval	51%
Racism	Alright for blacks and whites to date	74%
Racism	Disagree Blacks should work their way out like other minorities	26%
Racism	Discrimation against blacks	55%
Racism	Don’t prefer that relatives marry from same race	36%
Racism	Generations of slavery have created difficult conditions	49%
Racism	Grant reparation payments to the descendants of slaves	32%
Racism	How favorable is your impression of: Blacks	83%

Notes: The table reports the list of questions related to policy views used in the Nationscape survey and shows the share of liberal answers to each question.

Table D2 – CCES: List of Questions Related to Policy Views

Topic	Question	% Positive
National Politics	Job approval - President Trump	59%
Environmental Protection	EPA strengthen enforcement of Clean Air Act	61%
Environmental Protection	EPA regulate C02 emissions	68%
Environmental Protection	State require minimum amt of renewable fuels	64%
Environmental Protection	Raise fuel efficiency for average automobile	69%
Environmental Protection	Withdraw the United States from the Paris Climate Agreement.	62%
Environmental Protection	Repeal the Clean Power Plant Rules	61%
Gun Control	Ban assault rifles	65%
Gun Control	Easier to obtain concealed-carry permit	63%
Gun Control	Background checks for all sales	90%
Immigration	Increase the number of border patrols	45%
Immigration	Grant legal status to all illegal immigrants with jobs	62%
Immigration	Build a wall between the U.S. and Mexico.	64%
Immigration	Reduce legal immigration	60%
International Affairs	Withdraw US from the Iran Nuclear Accord	49%
Immigration	Ban Muslims from immigrating to the U.S.	54%
Racism	white people have advantages	55%
Racism	Racial problems are rare, isolated situations	64%
Racism	Other minorities overcame prejudice	39%
Racism	Hard for Blacks to overcome slavery, discrimination	48%
Gender Equality	Make abortions illegal in all circumstances	84%
Gender Equality	Permit abortion only if rape, incest or woman’s life in danger	56%
Gender Equality	Always allow a woman to obtain an abortion	61%

Notes: The table reports the list of questions related to policy views used in the CCES survey and shows the share of liberal answers to each question.