NBER WORKING PAPER SERIES

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Working Paper 32342
http://www.nber.org/papers/w32342

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 2024

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NBER Working Paper No. 32342
April 2024
JEL No. D72,P0

ABSTRACT

Recent social movements stand out by their spontaneous nature and lack of stable leadership, raising doubts on their ability to generate political change. This article provides systematic evidence on the effects of protests on public opinion and political attitudes. Drawing on a database covering the quasi-universe of protests held in the United States, we identify 14 social movements that took place from 2017 to 2022, covering topics related to environmental protection, gender equality, gun control, immigration, national and international politics, and racial issues. We use Twitter data, Google search volumes, and high-frequency surveys to track the evolution of online interest, policy views, and vote intentions before and after the outset of each movement. Combining national-level event studies with difference-in-differences designs exploiting variation in local protest intensity, we find that protests generate substantial internet activity but have limited effects on political attitudes. Except for the Black Lives Matter protests following the death of George Floyd, which shifted views on racial discrimination and increased votes for the Democrats, we estimate precise null effects of protests on public opinion and electoral behavior.

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1. Introduction

In recent years, public demonstrations have seen a significant upsurge in the U.S. and around the world (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 and populism, 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 (Enikolopov, Makarin, and Petrova, 2020; Fergusson and Molina, 2019; Manacorda and Tesei, 2020), and, consequently a lack of stable leadership and organizational structure (De Witte, 2020; Keating, 2020; Serhan, 2019). This has made it more difficult for protesters to articulate consistent claims and sustain social movements beyond sudden outbreaks. In this context, despite their unprecedented size and frequency, descriptive evidence suggests that nonviolent campaigns have reached their lowest success rate in more than a century (Chenoweth, 2023).

Amidst these broader trends, the existing literature has focused heavily on exceptionally large movements and their influence on voting behavior. In the United States, for instance, much of recent research examines Black Lives Matter (BLM), with evidence pointing to significant effects on electoral outcomes, although findings remain mixed.[1] Yet, while BLM was one of the most important social movements of U.S. history, it only accounts for about 23% of protests held in the country from 2017 to 2022 and 13% of protest participants. The extent to which conclusions from such case studies, however important they are, generalize to protests of various intensity and to effects on broader political views beyond voting behavior remains unclear. We still know relatively little about the conditions under which protests change political attitudes and the channels through which they do so.

This paper provides systematic evidence on the effects of recent protests on individual attitudes. Combining a dataset on the near universe of protests held in the United States, social media and

[1] For instance, Reny and Newman (2021) document that the death of George Floyd led to a large nationwide increase in liberal racial attitudes, but that this increase was not higher or lower in areas more affected by Black Lives Matter protests. In contrast, Teeselink and Melios (2021) estimate that counties with greater protest intensity following the death of George Floyd saw a relative increase in Democratic vote shares between the 2016 and 2020 presidential elections.

Google search data, and high-frequency surveys including rich information on political views and vote intentions, we study the dynamics of 14 social movements that unfolded in the country since 2017. We find that most protests generate significant online activity but have only modest effects at best on public opinion and political attitudes. While Black Lives Matter protests may have influenced voters, we estimate precise null effects for most social movements and outcomes covered in our sample.

Our starting point was to build a new dataset mapping the evolution of online activity and political attitudes 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 waves 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 attitudes from five 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. Finally, 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.

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 and political attitudes 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 social 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 social movements.

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 social 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 social 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 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. However, this effect is close to null in both the simple-difference specification, when restricting the sample to independent movements, and in the difference-in-differences specification.

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 social 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 significant positive effects on both outcomes, but these effects are almost entirely driven by Black Lives Matter protests. Indeed, we find that the death of George Floyd led to a large and sustained 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 visible in both the simple-difference and difference-in-differences specifications, although results on the latter are not always robust to alternative specifications. For other movements in our sample, we find much more muted effects, and in most cases we estimate precise null effects of protests on policy views.

In the last part of our empirical analysis, we turn to the effects of protests on political attitudes and behavior, including turnout intentions, vote intentions for Donald Trump, and presidential approval before the 2020 U.S. presidential elections. The Nationscape survey allows us to precisely track the evolution of these outcomes in the months that preceded the election. We estimate null effects of protests on political attitudes. The exception is again Black Lives Matter protests, which did coincide with greater turnout intentions, lower vote intentions for Trump, and lower presidential approval, but even these findings are not fully robust to alternative specifications.

Based on this evidence, we conclude that the effects of social movements on opinions and political attitudes are generally quite weak. Across 14 social movements held in the United States from 2017 to 2021, the only movement for which we find significant effects on opinions and political attitudes is Black Lives Matter. Even in that case, the effects are sensitive to empirical specifications. One natural hypothesis could be that protest movements exhibit threshold behavior, with only movements such as BLM being sufficiently large and sustained to shift political attitudes. However, it is important to note that BLM was not the only large movement in our database. In fact, it was not even the largest: the 2017 Women's March, the 2018 Women's March, and the 2018 March for Our Lives protests in favor of gun control all mobilized a greater number of participants according to the CCC database. Yet, none of them consistently affected attitudes and political behavior beyond short-term increases in tweets and Google searches. Another hypothesis is that the exceptional national media coverage of the movement, rather than its size, made BLM stand out, and that media coverage is complementary to protests. One could also be concerned with measurement error of protests recorded in the CCC database, which could be greater for some movements than others and could explain null effects in some difference-in-differences specifications. Yet, we do find large and significant effects of protests on Twitter activity and Google searches in the corresponding areas, which suggests that the CCC data do capture meaningful geographic variation in protest intensity.

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.[2] Evidence on policy views is much scarcer and mixed, especially in the short

[2]A number of studies find that protests tilt local election outcomes in favor of the party closest to the movement: see for instance Casanueva (2021), Colombo et al. (2021), Lagios, Méon, and Tojerow (2021), Madestam et al. (2013), Teeselink and Melios (2021), and 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), the supply of female politicians (Moresi, 2022), or stock market valuations (Acemoglu, Hassan, and Tahoun, 2018).

run.[3] 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 Black Live Matters protests, which have received particular attention in recent years, we find that most other movements did not have any discernable effects. Second, the exceptionally high frequency and large sample size of the surveys used in our analysis allow us to track the effects of protests over time and to document potential pre-trends. By contrast, most existing studies rely on comparisons between two time periods. Finally, 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 and policy views among the general population and, finally, voting behavior.

The remainder of the paper is organized as follows. Section 2 presents the data and methodology. Sections 3, 4, and 5 study the effects of protests on the salience of issues raised by protesters, policy views, and political attitudes and behavior. Section 6 investigates how these effects vary across social movements. Section 7 concludes.

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 social movements (Section 2.1). Sections 2.2 and 2.3 present the Twitter, Google, and survey data with which we track the evolution of political attitudes. Finally, we outline the empirical specifications used to relate protests to public opinion (Section 2.4).

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, the CCC reports detailed information on marches, protests, strikes, demonstrations, riots,

[3] 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 in the short run. Some studies find that protests and strikes can shift attitudes in favor of protesters' claims (e.g., Branton et al., 2015; Enos, Kaufman, and Sands, 2019; Hertel-Fernandez, Naidu, and Reich, 2021; Mazumder, 2018; 2019; Pop-Eleches, Robertson, and Rosenfeld, 2022; Tertytchnaya and Lankina, 2020), but others document attitudinal backlash among subgroups of voters (e.g., Anduiza and Rico, 2022; Valentim, 2024).

and other political actions. 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 Social Movements

We identify major social 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 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 social 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. We then define a social movement as a period of large and sudden increase in protest intensity.[5]

With this approach, we are able to identify 14 major social 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 liberal political attitudes such as greater racial or gender equality, environmental protection, or gun control. We count the total number of protests that occurred two weeks after the beginning of each movement. The pro-gun-control March for Our Lives movement ranks first, with almost 5,500 protests, followed by George

[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 Figures B1 to B7 plot 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.

Floyd protests and the first Climate Strike. The first Women's March is the movement that gathered the greatest number of participants within two weeks after the beginning, with over 4 million protesters in January 2017. 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 220 (protests against the "Muslim ban") to 1,381 (George Floyd protests).

2.2. Twitter and Google Data

To estimate the effects of these social movements on the salience of and interest towards the corresponding topics, we match the CCC database with Twitter and Google data.

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 cities or counties with more or less protest intensity. Appendix Table C1 shows the keywords dictionary used for the data collection.

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. Time series of total search volumes can be collected either for daily, weekly, or monthly frequencies. The geographical unit of observation can be either the United States as a whole, individual U.S. states, or Designated Market Areas. We collect time series of search volumes for these combinations of frequencies and geographical units, drawing on 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. For each time period and geographical unit of observation, 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, 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. This makes it difficult to track the evolution of keywords that are rarely searched, especially in small geographical units. For instance, collecting daily Google search data at the DMA level will lead to many DMA-day cells bottom coded at zero, limiting the variation that can be exploited for the analysis. We thus face a trade-off between developing a more granular analysis and statistical precision. We come back to this in the results section.

2.3. Survey Data

To track the evolution of political attitudes before and after the unfolding of each social 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, and vote intentions for the 2020 presidential election.

The time coverage of the Nationscape survey allows us to cover five of our 15 social movements: the Climate Strike, Floyd protests, 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 social 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.

2.3.2. Gallup Poll Social Series

The Gallup Poll Social Series (GPSS) is a monthly survey run by Gallup since 2000. 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 social movement are considered to be. Second, it covers every month since 2000, allowing us to study the evolution of attitudes month-by-month for all social 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 social 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

Finally, 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 25 questions: six questions for environmental protection, three for gun control, four for immigration, four for racism, five 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 social 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 potential pre-trends in political attitudes before the outset of each movement. This difficulty is reinforced by the fact that the CCES did not ask the same questions every year. For most questions, we only have two years of data, one covering the pre-period and one covering the post-period.

2.4. Empirical Specifications

Having mapped social movements to Google searches, Twitter activity, and political attitudes, we consider three alternative specifications to estimate the effects of protests.

2.4.1. Simple Difference

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

$$y_{itqm} = \alpha + \sum_t \beta_t D_{tm} + X_{it}\zeta + \gamma_{qmc} + \varepsilon_{itqm}, \tag{1}$$

where y_{itqm} denotes respondent i's answer at time t to question q mapped to social movement m. Time is defined relative to the beginning of the movement. For the Twitter and Google analysis, i corresponds to geographical units, such as counties, and q corresponds to Twitter activity or Google search intensity. D_{tm} are time dummies taking value 1 if individual i is interviewed at time t for social movement m and 0 otherwise. We exclude the dummy corresponding to the period preceding the movement. γ_{qmc} are interacted question, movement, and county fixed effects. X_{it} is a vector of individual-level controls including ideological orientation, race, education, age, gender, employment status, and religion. The coefficients of interest β_t track the aggregate evolution of our outcome of interest before and after the outset of each movement.

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_{tm} by a single dummy $Post_{tm}$, which takes value 1 if individual i is interviewed after the outset of the social movement and 0 otherwise:

$$y_{itqm} = \alpha + \beta Post_{tm} + X_{it}\zeta + \gamma_{qmc} + \varepsilon_{itqm} \tag{2}$$

A natural concern with this approach is that social movements may be endogenous. If a third factor triggered both the social movement and the change in attitudes, outcomes could have changed even in the absence of protests. For instance, changes in racial attitudes in the United States might have been driven by the death of George Floyd, rather than by the protests that followed his death. We use two strategies to address this issue.

2.4.2. Simple Difference on Independent Movements

First, we restrict the analysis to seven social 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.

2.4.3. Difference-in-Differences

Second, we run a difference-in-differences specification comparing the evolution of outcomes of interest in locations with more or less protest intensity. More specifically, we estimate:

$$y_{itqm} = \alpha + \sum_t \phi_t(D_{tm} \times \text{Protest}_{cm}) + \sum_t \psi_t(D_{tm} \times \text{C}_{cm}) + X_{it}\zeta + \gamma_{qmc} + \lambda_{qmt} + \varepsilon_{itqm}, \quad (3)$$

where Protest_{cm} is a measure of protest intensity in location c during social movement m. The coefficients of interest, ϕ_t, capture the effect of greater protest intensity in a given location on the evolution of the outcome of interest. λ_{qmt} are interacted question, movement, and time fixed effects. C_{cm} is a vector of county-level time-invariant controls: the Democratic vote share in 2016, the Black population share in 2019, and the college graduate population share in 2019. These variables are strongly correlated with county-level protest intensity. We control for their interaction 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 with a larger fraction of Black voters, irrespective of local protests taking place in these counties. By controlling with this characteristic interacted with time, we ensure that we do not misattribute such changes to the impact of protests.

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

$$y_{itqm} = \alpha + \phi(Post_{tm} \times \text{Protest}_{cm}) + \psi(Post_{tm} \times \text{C}_{cm}) + X_{it}\zeta + \gamma_{qmc} + \lambda_{qmt} + \varepsilon_{itqm} \quad (4)$$

In our benchmark specification, we measure protest intensity as a dummy variable taking value 1 if there was any protest in location c in the 30 days that followed the beginning of each movement and 0 otherwise. We investigate the robustness of our results to alternative measures, such as the number of participants as a fraction of the population of each location.[6] While the number of participants is arguably a more precise measure of protest intensity, it is missing for the majority of protests covered by the CCC data, which motivates our use of a binary treatment in the main analysis. Our main figures also exclude county-level controls interacted with time; we compare results including and excluding these controls in the main regression tables. We cluster standard errors at the county level in both simple difference and difference-in-differences specifications.

Simple-difference and difference-in-differences specifications each have their specific advantages and inconvenients, 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 social movements on non-treated counties through channels such as media exposure. The simple-difference specification restricted to independent movements, while less well identified, has the advantage of capturing 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 social movements. We then consider the impact of protests on downstream outcomes that may be affected in the medium and long run: policy views, in Section 4, and political attitudes and behavior, in Section 5.

3. Social 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.

[6] The exception is the Google analysis, for which we only have data at the DMA level and thus define protest intensity as protesters over population in the benchmark specification. All DMAs would be in the treatment group if we were to define the treatment as the occurrence of at least one protest.

3.1. Simple Difference Specification

We start by presenting event study results on national trends in salience before and after the outset of each social movement. Figure 1 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. As visible from the figure, the average number of tweets increases sharply on the starting day of each movement. We observe some pretrends in the days 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 come back to their pre-period levels about ten days after. The development of social 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 2 extends this analysis to daily Google search volumes. The unit of observation is the United States as a whole. An observation corresponds to total searches for a given expression q associated with a given social movement m on a given day t. 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 social movement coincides with a sharp increase in search volumes for keywords associated with the corresponding movement. Appendix Figure A2 reproduces this result for the subset of independent movements.

Finally, Figure 3 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 sample of respondents representative of the U.S. population as a whole gives to the corresponding topics. The dependent variable is a dummy equal to 1 if an individual mentions topics related to the social movement among the three most important problems in the United States today. We normalize this dummy to have a mean of 0 and a standard deviation of 1, so as to make the results comparable across social movements. Protests coincide with a large increase in importance given to the corresponding topics, of about 0.15 standard deviations during the first month after the social movement started. The coefficient fades out to zero after three or four months. If one restricts the analysis to independent movements, this effect is much smaller, reaching about 0.05 standard deviations, and it disappears after one month (see Appendix Figure A3).

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 (with the exception of independent movements, for which there is no effect on the latter outcome). The magnitude of these effects is large: social movements are associated with an increase in Twitter and Google intensity of 0.9 and 1.7 standard deviations across all movements, and 0.6 and 0.7 standard deviations when restricting the sample to independent movements.

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 Black Lives Matter 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 A1. As columns 3 and 4 reveal, independent movements lead to an increase in searches for the word ‘protest’ of about 0.3 standard deviations, compared to 1.2 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 more significant change in salience after the beginning of each movement. Figure 4 presents results of the difference-in-differences specification using county-level tweet intensity as outcome. Tweet intensity increases much more on the start day of each movement in counties with at least one protest than in counties with no protest. On average, having a protest is associated with an increase in tweets mentioning keywords related to the movement of about 3 standard deviations. This effect gradually decreases until disappearing after about a week.

Figure 5 extends this result to Google search volumes. Because of issues with bottom-coding of daily search volumes (see Section 2.2), we focus on weekly searches.[7] The unit of observation is the DMA-keyword-week. The treatment is the total number of protesters as a share of the total population of each DMA. To make the results comparable, we normalize this continuous treatment to range from 0 to 1 for each social movement. As visible in the figure, Google searches rise much faster after the beginning of each movement in DMAs with greater protest intensity. Moving from the DMA with the lowest protest intensity to the DMA with the highest protest intensity is associated with a differential increase in search volumes equivalent to 0.5 standard deviations. Interestingly, searches already start rising slightly one week before the beginning of each movement, in line with the small anticipation effects visible in Figures 1 and 2. The coefficient reaches a peak on the starting week of the movement and goes back to zero after three weeks.

Finally, Figure 6 presents results using the GPSS survey. The results are less clear-cut, although we do observe a small rise in salience on the starting month of each movement.[8]

Table 3 complements the analysis with formal regression results. For each outcome, we report both baseline estimates and estimates controlling for county-level Democratic vote share, Black population share, and college-educated population share interacted with time. Indeed, as described in section 2.4.3, the occurrence of protests may be correlated with counties' political and demographic make-up. Therefore,the latter specification 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 social movement. In our benchmark specification, counties with at least one protest see a differential increase in Twitter intensity of 1.1 standard deviation, and a differential increase in Google searches of 0.5 standard deviation. These effects are much smaller (23% and 18% of the baseline estimates) after controlling for county characteristics interacted with time, but still significant at the 1 and 5% level respectively. Effects on issue importance measured with GPSS are small and not statistically significant in either specification.

[7] Appendix Figure A4 reproduces this result with daily DMA-level search volumes.

[8] An important drawback is that the GPSS survey was not run every single month, so the starting month is not covered for George Floyd and Families Belong Together protests.

4. Social 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 social 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 the set of questions changes across waves, there is often a unique pre or post wave available to estimate the effects of some social movements on corresponding attitudes. This precludes the possibility of a detailed analysis of aggregate trends in opinions.

Figure 7 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 social movement, the share of respondents stating an opinion is higher by about 1 percentage point. However, this effect is much less clear when limiting the analysis to independent movements. Although we do observe a slight increase, it is restricted to three weeks after and barely reaches statistical significance (see Appendix Figure A5).

Figure 8 extends this analysis to liberal attitudes. The dependent variable is a dummy variable equal to 1 if a respondent declares a liberal opinion, 0 if they declare a conservative opinion, and missing otherwise. We observe an increase in liberal attitudes immediately after the outset of a social movement, of about 0.5 to 1 percentage point. This effect is null when restricting the sample to independent movements, however (see Appendix Figure A6). In fact, we only observe aggregate changes in a few racial attitudes following the death of George Floyd, and in one environmental question after the Climate Strike. All other questions display null effects.

Table 4 presents results of regressions corresponding to these two outcomes. Social movements increase the share of respondents declaring an opinion and holding a liberal view by 0.7 percentage points and 0.8 percentage points, respectively. These effects are closer 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 9 investigates whether protest counties see a medium-run differential increase in the share of respondents with an opinion, compared to counties with no protest associated with the corresponding social movement. There is no evidence that treated counties saw a differential increase in the share of respondents with an opinion on the corresponding issues. Considering the upper bound of the 95 percent confidence interval, we can reject effects greater than 2 percentage points in any month after the beginning of each movement.

Figure 10 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, Figure 11 studies the year-to-year evolution of attitudes in treated versus control counties in the CCES survey. Because of the highly unbalanced nature of most political attitudes questions in this survey, attitudes can be tracked for more than two years for only nine questions covering four movements: the March for Science, March for Our Lives protests, Families Belong Together protests, and the first Women's March. Similarly as for responses to the Nationscape survey, we do not observe any differential increase in the fraction of respondents stating liberal views in protest counties. Three years after the outset of each movement, we can reject changes in the share of liberal attitudes exceeding 1 percentage point.

Table 5 presents corresponding regression results, with and without controlling for county characteristics interacted with time. All coefficients are close to zero and non-significant. Across both surveys and all outcomes, we can reject changes in policy views exceeding 1 percentage point.

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. Social 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 three complementary outcomes: turnout intentions, vote intentions, and presidential approval. Presidential approval is closely related to electoral behavior but it may be more malleable than vote intention. We use the Nationscape survey for all results in this section because it is the only source that covers these outcomes before and after each protest at a high frequency and with large sample sizes. The Nationscape survey allows us to track three questions from July 2019 to November 2020, corresponding to the months preceding the 2020 presidential election: whether the respondent intends to vote, whether the respondent would consider voting for Donald Trump, and whether the respondent approves of the way Donald Trump is handling his job as president. We show simple difference estimates in Section 5.1, and difference-in-difference estimates in Section 5.2.

5.1. Simple Differences

Figure 12 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 a dummy taking value 1 if the respondent declares intending to vote in the 2020 presidential election and 0 otherwise. There is no evidence that protests coincide with any increase in turnout; if anything, there is a slight drop in turnout intentions one week after the beginning of each movement, but the effect comes back to zero two weeks after.

Figure 13 reproduces this analysis, but focusing on vote intentions. The dependent variable takes value 1 if the respondent would consider voting for Donald Trump in the 2020 presidential election and 0 if they would not (unsure respondents, amounting to 10% of the sample, are set as missing). There is no significant change in aggregate vote intentions before and after protests. Considering the upper bound of the 95 percent confidence interval, we can reject positive or negative changes of more than 1 percentage point in the share of respondents who would consider voting for Trump.

One reason for these null effects could be that vote intentions are hard to move in the short run and tend to only vary in the medium to long run. We thus complement our analysis with a focus on presidential approval, which may be more malleable than vote intentions, making it a useful complementary outcome. Figure 14 extends the simple difference specification to presidential approval. Here, 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. Again, we find virtually no change in national-level presidential approval before and after the outset of social movements.

Appendix Figures A7, A8, and A9 show simple-difference effects on turnout intentions, vote intentions, and presidential approval for independent movements. Table 6 presents corresponding regression results. While vote intentions for Trump do not significantly change following the outset of an independent movement, we do observe a statistically significant decline in turnout and an increase in presidential approval, potentially reflecting backlash. One should be careful in interpreting this result, however, which is only visible in a subset of movements (see Figure 20) and does not extend to the difference-in-differences specification (as discussed in the next section).

5.2. Difference-in-Differences

We now turn to difference-in-differences specifications. Figures 15, 16, and 17 plot the corresponding event studies for turnout intentions, vote intentions, and presidential approval, respectively. For all three outcomes, the result is a precisely estimated null effect. We can reject any month-to-month change in turnout intentions greater than 2 percentage points and any change in support for Trump greater than 3 percentage points. Table 7 presents corresponding regression results.

6. Heterogeneity by Social Movement

Until now, we have pooled all social movements together in our analysis. One may wonder whether the positive effects we find on Google searches and Twitter intensity are driven by a specific movement. Similarly, the null effects on policy views and political behavior might hide significant heterogeneity, with some movements affecting policy views or vote intentions in one way and other movements affecting them in the opposite direction. In this section, we thus investigate how our main findings vary across social movements, starting with salience outcomes (Section 6.1), followed by policy views (Section 6.2) and political attitudes and behavior (Section 6.3).

6.1. Salience

We start by decomposing our results on the salience of political issues by social movement. Figure 18 presents coefficients associated with each movement separately for the Twitter data, Google data, and GPSS survey, for both the simple difference and difference-in-differences specifications.[9] Two main results stand out.

[9] As shown in Appendix Figure A10, we obtain similar results for the difference-in-differences specification after controlling for county characteristics interacted with time.

First, we observe positive effects of protests on tweets and Google searches across most movements, but the effects on the importance given by individuals to the corresponding political issues are restricted to fewer movements. Protests were associated with significant increases in Twitter intensity for ten out of fourteen movements, both in the simple difference and difference-in-differences specifications. The same holds for Google searches, which increased after the outset of most movements, although the estimates are statistically significant for a more restricted number of movements. By contrast, coefficients are positive and significant for only five movements in the simple difference specification using the GPSS survey, and for no movement at all in the difference-in-differences specification. This suggests that most movements were successful at raising attention and interest towards the corresponding political topics, but only a few led the general population to give significantly greater importance to the corresponding topics.

Second, a subset of movements had consistently larger effects across all outcomes and specifications. George Floyd protests, in particular, stand out as displaying some of the largest point estimates. The March for Our Lives and Families Belong Together movements, as well as protests related to the Muslim Ban and war with Iran, also display greater average coefficients. In contrast, Women's Marches and environmental protests had much smaller effects.

6.2. Policy Views

We now turn to the heterogeneous effects of social movements on policy views. The left panel of Figure 19 plots simple difference specifications using the Nationscape survey. The right panel plots difference-in-differences specifications using both the Nationscape and the CCES surveys. CCES survey waves are separated by one to two years depending on the outcome considered. This makes the simple-difference specification less credible over such long periods of time, so we do not report simple-difference estimates for this survey.

George Floyd protests again stand out as displaying the largest average effects. At the national level, the outset of the movement was associated with a 4 percentage point increase in the share of respondents declaring an opinion on racial issues, mirrored by a 4 percentage point increase in liberal views. We also observe positive effects on liberal attitudes in the difference-in-differences specification, in the order of 1-2 percentage points, although we stress that these effects are only statistically significant in the CCES survey and not robust to the inclusion of county-level controls.[10] This suggests that the death of George Floyd led to large changes in attitudes on racial issues at the national level, but the local effects of the protests that followed were much more muted.

[10] See Appendix Figure A11.

The individual effects of other social movements are much less clear. The 2019 climate strike is associated with a small nationwide increase in the share of respondents with an opinion, but a negative coefficient on liberal views and a null effect in all difference-in-differences specifications. Effects estimated with the CCES survey are positive in the case of Muslim Ban protests, negative for three movements, and close to zero for all others. Furthermore, all CCES coefficients are close to null when controlling for county-level characteristics, suggesting that the effects reflect differential trends in different types of counties rather than causal effects of local protest intensity.

6.3. Political Attitudes and Behavior

Finally, we investigate the effects of protests on political attitudes and behavior, focusing on the five movements covered by the Nationscape survey. Consistently with results on policy views, George Floyd protests are the only social movement that generated consistent effects across several outcomes. As shown in Figure 20, these protests were associated with a nationwide 2-3 percentage point decrease in the proportion of respondents intending to vote for Donald Trump, a significant increase in turnout intentions, and a drop in presidential approval. These results extend to the difference-in-differences specifications, although the coefficients are smaller and not always statistically significant.[11]

Other social movements do not display any consistent effect. If anything, the Third Women's March led to an increase in vote intentions for Trump and presidential approval, but these effects drop to zero in the difference-in-differences specification. The other three movements display coefficients close to zero and non-significant across all outcomes.

7. Conclusion

We study the effects of protests on online interest, policy views, and political attitudes, focusing on 14 major social 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 social movement. 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 and Google

[11] Appendix Figure A12 presents similar results for the difference-in-differences specification after controlling for county characteristics interacted with time.

searches containing keywords related to the topic of the movement. This effect is visible in both event studies and difference-in-differences specifications comparing counties with more or less protest intensity. It is present for most protest waves but relatively short-lived: online interest decreases to baseline levels about ten days after the beginning of the social movement. Furthermore, despite this increase in salience, protests do not significantly affect policy views and political behavior: we generally estimate precise null effects on public opinion and vote intentions regarding the 2020 U.S. presidential election. The protests triggered by the death of George Floyd constitute an important exception, as they were followed by a sharp increase in liberal attitudes on racial issues and vote intentions for the Democrats. However, this effect is not always robust to alternative specifications, and we cannot exclude that it was 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 waves at shifting the beliefs and behavior of the U.S. electorate, at least in the short run.

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

References

Acemoglu, Daron, Tarek A Hassan, and Ahmed Tahoun (2018). "The power of the street: Evidence from Egypt's Arab Spring". In: *The Review of Financial Studies* 31.1, pp. 1–42.

Anduiza, Eva and Guillem Rico (2022). "Sexism and the far-right vote: The individual dynamics of gender backlash". In: *American Journal of Political Science*.

Archibong, Belinda (2022). "Protest matters: The effects of protests on economic redistribution". SSRN 4029312.

Branton, Regina, Valerie Martinez-Ebers, Tony E Carey Jr, and Tetsuya Matsubayashi (2015). "Social protest and policy attitudes: The case of the 2006 immigrant rallies". In: *American Journal of Political Science* 59.2, pp. 390–402.

Caprettini, Bruno, Marcel Caesmann, Hans-Joachim Voth, and David Yanagizawa-Drott (2024). "Going Viral: Protests and Polarization in 1932 Hamburg". Working Paper.

Casanueva, Annalí (2021). "Can Chants in the Street Change Parliament's Tune? The Effects of the 15M Social Movement on Spanish Elections". Working Paper.

Chenoweth, Erica (2023). "Can nonviolent resistance survive COVID-19?" In: *Rights at Stake and the COVID-19 Pandemic*. Routledge, pp. 134–146.

Colombo, Francesco, Alessandro Ferrara, Foteini-Maria Vassou, Fabrizio Bernardi, and Elias Dinas (2021). "From the Streets to the Voting Booth: The Electoral Effect of Grassroots Mobilization Against the Far-Right". SSRN 3826965.

De Witte, Melissa (June 4, 2020). "Leaderless, decentralized protest is a strength and a weakness, warns civil rights scholar Clayborne Carson". In: *Stanford News*.

Enikolopov, Ruben, Alexey Makarin, and Maria Petrova (2020). "Social media and protest participation: Evidence from Russia". In: *Econometrica* 88.4, pp. 1479–1514.

Enos, Ryan D, Aaron R Kaufman, and Melissa L Sands (2019). "Can violent protest change local policy support? Evidence from the aftermath of the 1992 Los Angeles riot". In: *American Political Science Review* 113.4, pp. 1012–1028.

Fergusson, Leopoldo and Carlos Molina (2019). "Facebook causes protests". CEDE Working paper 41.

Hertel-Fernandez, Alexander, Suresh Naidu, and Adam Reich (2021). "Schooled by strikes? The effects of large-scale labor unrest on mass attitudes toward the labor movement". In: *Perspectives on Politics* 19.1, pp. 73–91.

Hungerman, Daniel and Vivek Moorthy (2023). "Every day is earth day: Evidence on the long-term impact of environmental activism". In: *American Economic Journal: Applied Economics* 15.1, pp. 230–258.

Keating, Joshua (June 9, 2020). “The George Floyd Protests Show Leaderless Movements Are the Future of Politics”. In: *Slate*.

Ketchley, Neil and Thoraya El-Rayyes (2021). “Unpopular protest: Mass mobilization and attitudes to democracy in post-Mubarak Egypt”. In: *The Journal of Politics* 83.1, pp. 291–305.

Lagios, Nicolas, Pierre-Guillaume Méon, and Ilan Tojerow (2021). “Does it Pay Off to Demonstrate Against the Far Right?” Working Paper.

Levy, Ro’ee and Martin Mattsson (2023). “The effects of social movements: Evidence from# MeToo”. SSRN 3496903.

Madestam, Andreas, Daniel Shoag, Stan Veuger, and David Yanagizawa-Drott (2013). “Do political protests matter? evidence from the tea party movement”. In: *The Quarterly Journal of Economics* 128.4, pp. 1633–1685.

Manacorda, Marco and Andrea Tesei (2020). “Liberation technology: Mobile phones and political mobilization in Africa”. In: *Econometrica* 88.2, pp. 533–567.

Mazumder, Soumyajit (2018). “The persistent effect of US civil rights protests on political attitudes”. In: *American Journal of Political Science* 62.4, pp. 922–935.

– (2019). “Black lives matter for Whites’ racial prejudice: assessing the role of social movements in shaping racial attitudes in the United States”. Working Paper.

Moresi, Alessandra (2022). “The Impact of the 2017 Women’s March on Female Political Representation”. SSRN 4040171.

Ortiz, Isabel, Sara Burke, Mohamed Berrada, Hernán Saenz Cortés, Isabel Ortiz, Sara Burke, Mohamed Berrada, and Hernán Saenz Cortés (2022). “An analysis of world protests 2006–2020”. In: *World protests: A study of Key protest issues in the 21st century*. Springer, pp. 13–81.

Pop-Eleches, Grigore, Graeme Robertson, and Bryn Rosenfeld (2022). “Protest participation and attitude change: evidence from Ukraine’s Euromaidan revolution”. In: *The Journal of Politics* 84.2, pp. 625–638.

Reny, Tyler T and Benjamin J Newman (2021). “The opinion-mobilizing effect of social protest against police violence: Evidence from the 2020 George Floyd protests”. In: *American political science review* 115.4, pp. 1499–1507.

Sangnier, Marc and Yanos Zylberberg (2017). “Protests and trust in the state: Evidence from African countries”. In: *Journal of Public Economics* 152, pp. 55–67.

Serhan, Yasmeen (Nov. 19, 2019). “The Common Element Uniting Worldwide Protests”. In: *The Atlantic*.

Teeselink, Bouke Klein and Georgios Melios (2021). “Weather to protest: The effect of black lives matter protests on the 2020 presidential election”. SSRN 3809877.

Tertytchnaya, Katerina and Tomila Lankina (2020). “Electoral protests and political attitudes under electoral authoritarianism”. In: *The Journal of Politics* 82.1, pp. 285–299.

Valentim, António (2024). “Repeated Exposure and Protest Outcomes: How Fridays for Future Protests Influenced Voters”. Working Paper.

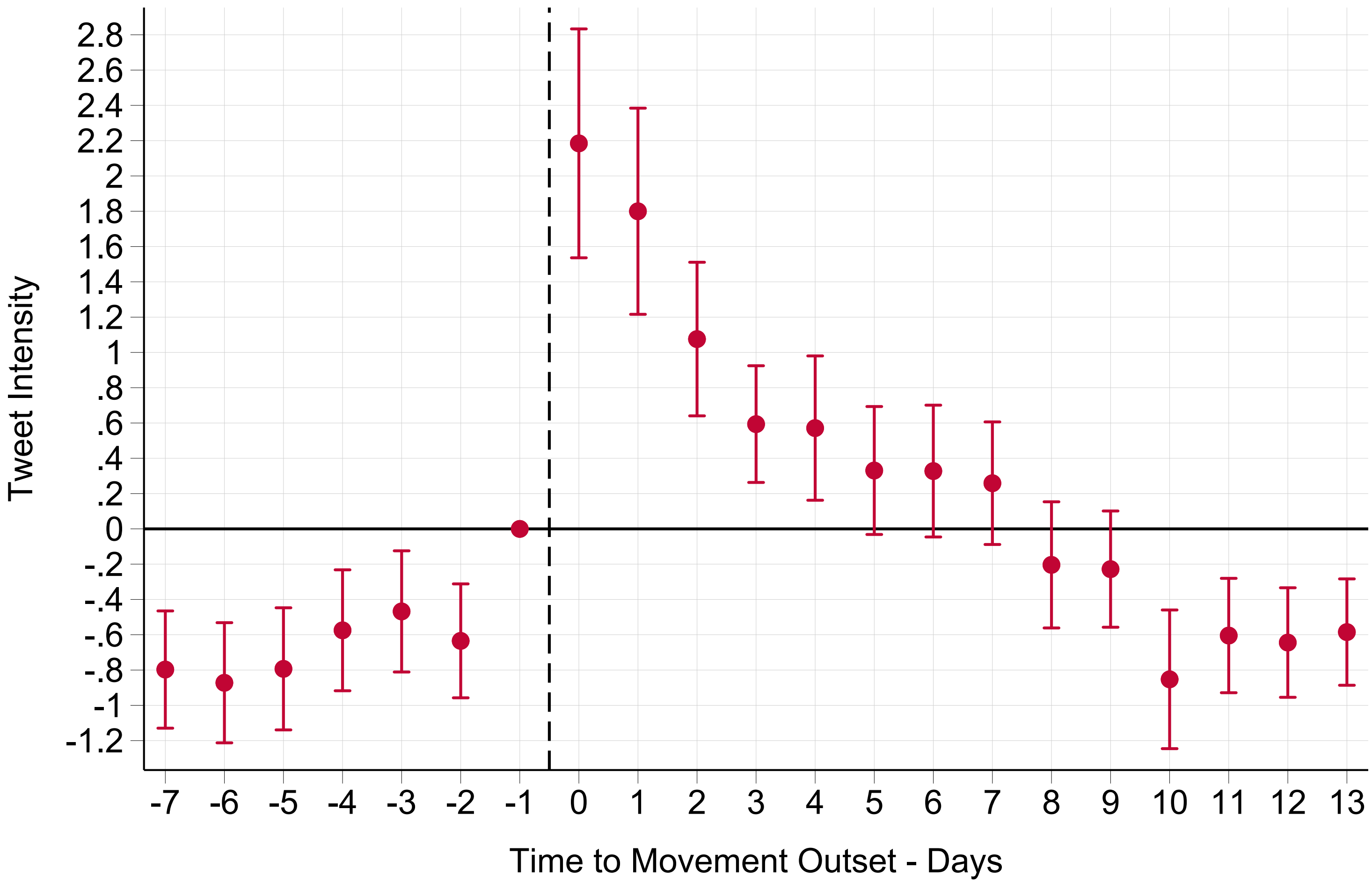
Valentim, Vicente (2021). “Creating critical citizens? Anti-austerity protests and public opinion”. In: *Electoral Studies* 72, pp. 1023–39.

Waldinger, Maria, Marc Fabel, Helmut Rainer, Matthias Flückiger, Markus Ludwig, and Sebastian Wichert (2023). “The Power of Youth: Fridays for Future Climate Protests”, Reverse Intergenerational Value Transmission, and Adults’ Political Behavior”. SSRN.

Wang, Ye and Stan Hok-Wui Wong (2021). “Electoral impacts of a failed uprising: Evidence from Hong Kong’s Umbrella Movement”. In: *Electoral Studies* 71, p. 102336.

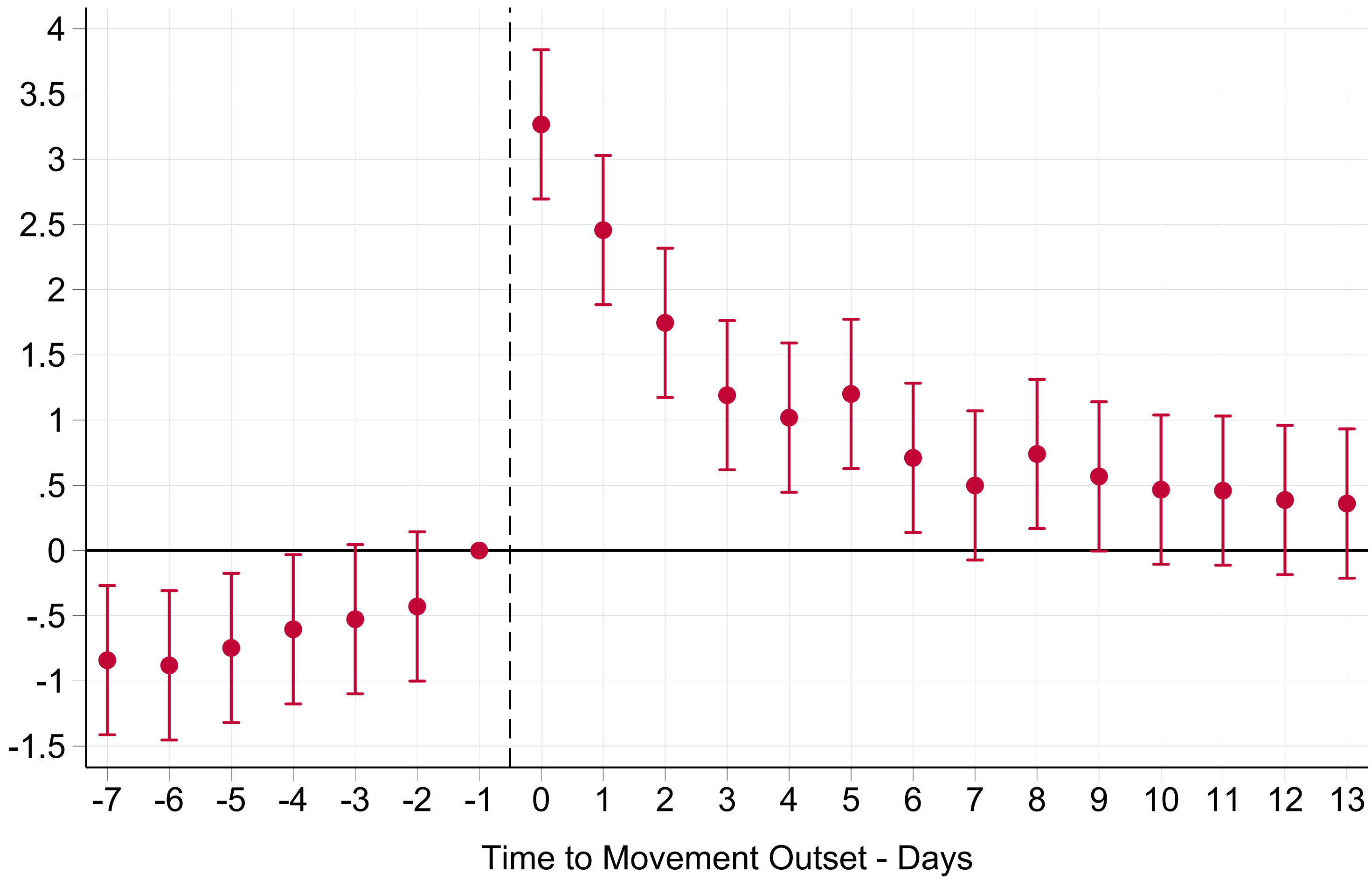
Wasow, Omar (2020). “Agenda seeding: How 1960s black protests moved elites, public opinion and voting”. In: *American Political Science Review* 114.3, pp. 638–659.

Figure 1 – Protests and Salience: Twitter Activity, Simple Difference



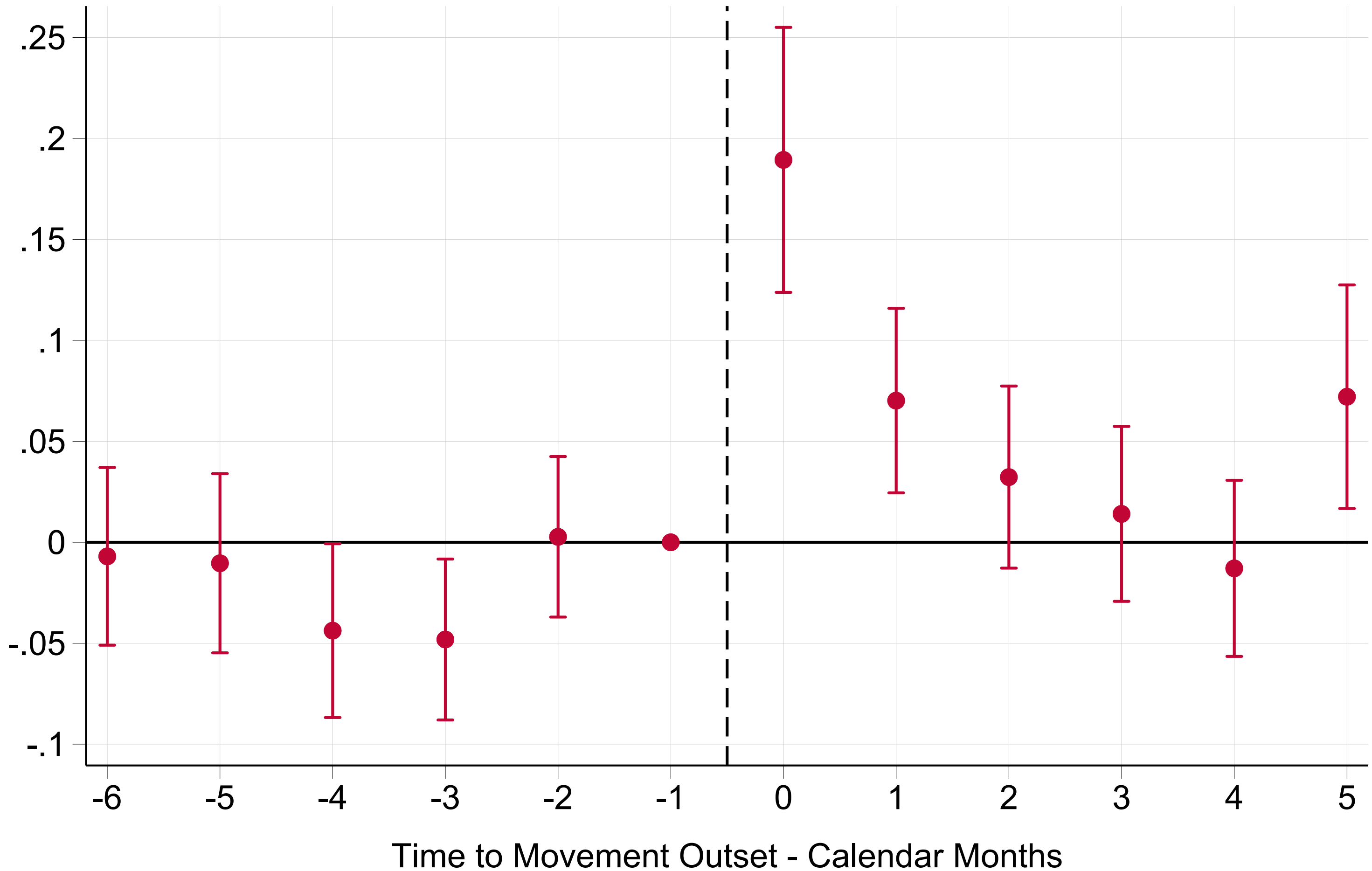
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). The dependent variable is the number of tweets related to a given issue, standardized to have a mean of 0 and a standard deviation of 1.

Figure 2 – Protests and Salience: Google Search Intensity, Simple Difference



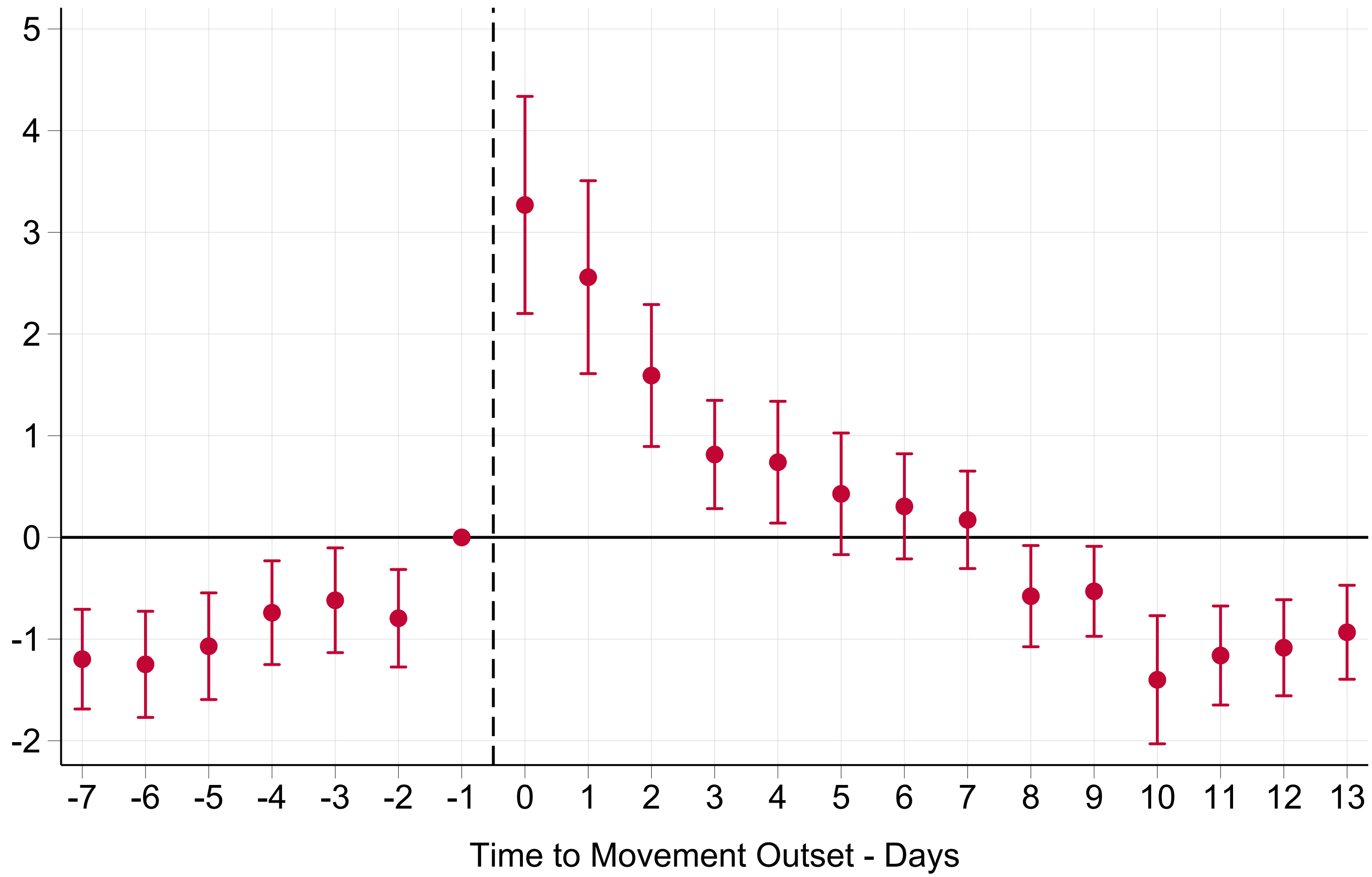
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). The dependent variable is the number of Google searches for a given keyword, standardized to have a mean of 0 and a standard deviation of 1.

Figure 3 – Protests and Salience: GPSS, Simple Difference



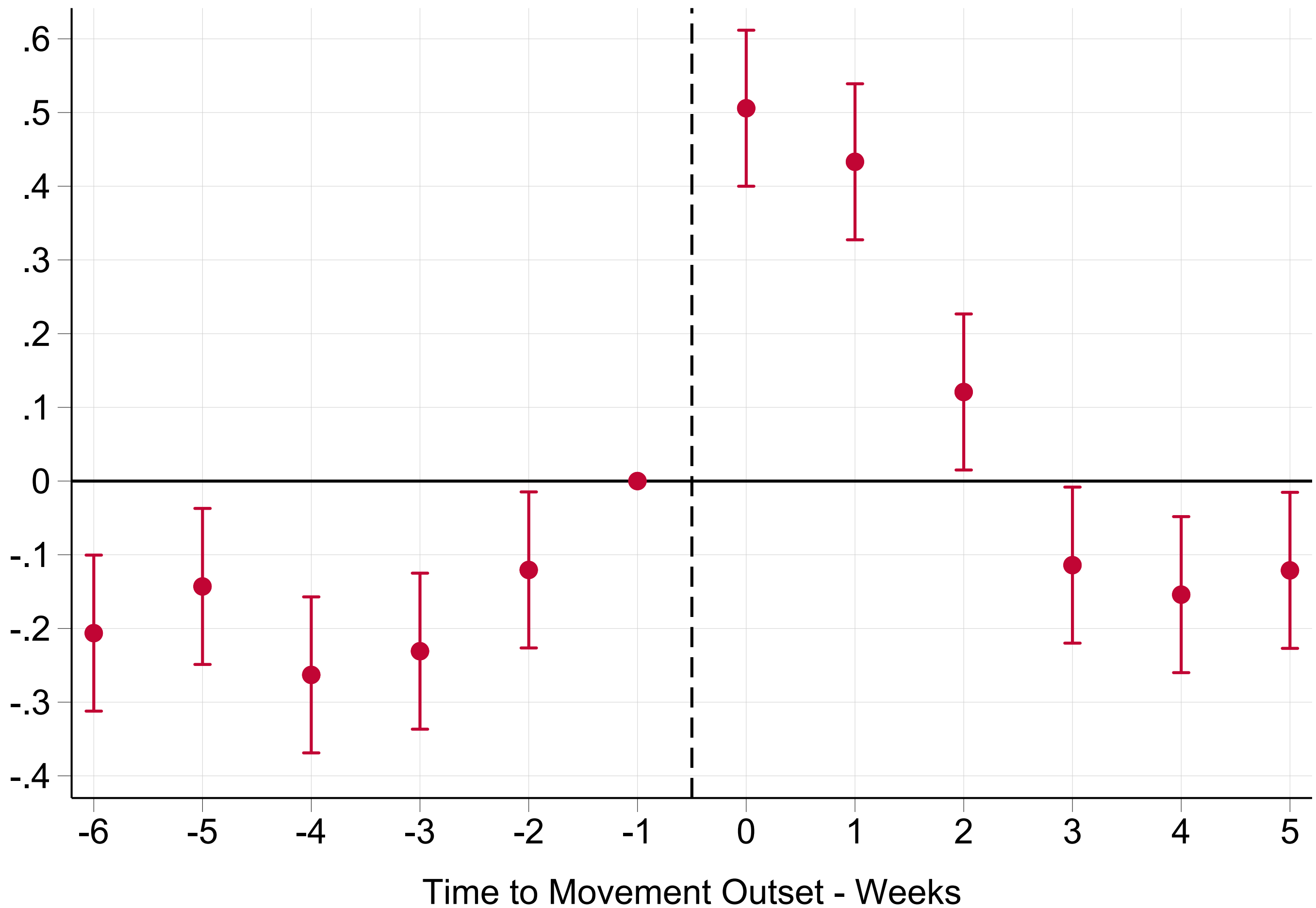
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). The dependent variable is the share of respondents mentioning a given issue as one of the most important problems of the country, standardized to have a mean of 0 and a standard deviation of 1.

Figure 4 – Protests and Salience: Twitter Activity, Difference-in-Differences



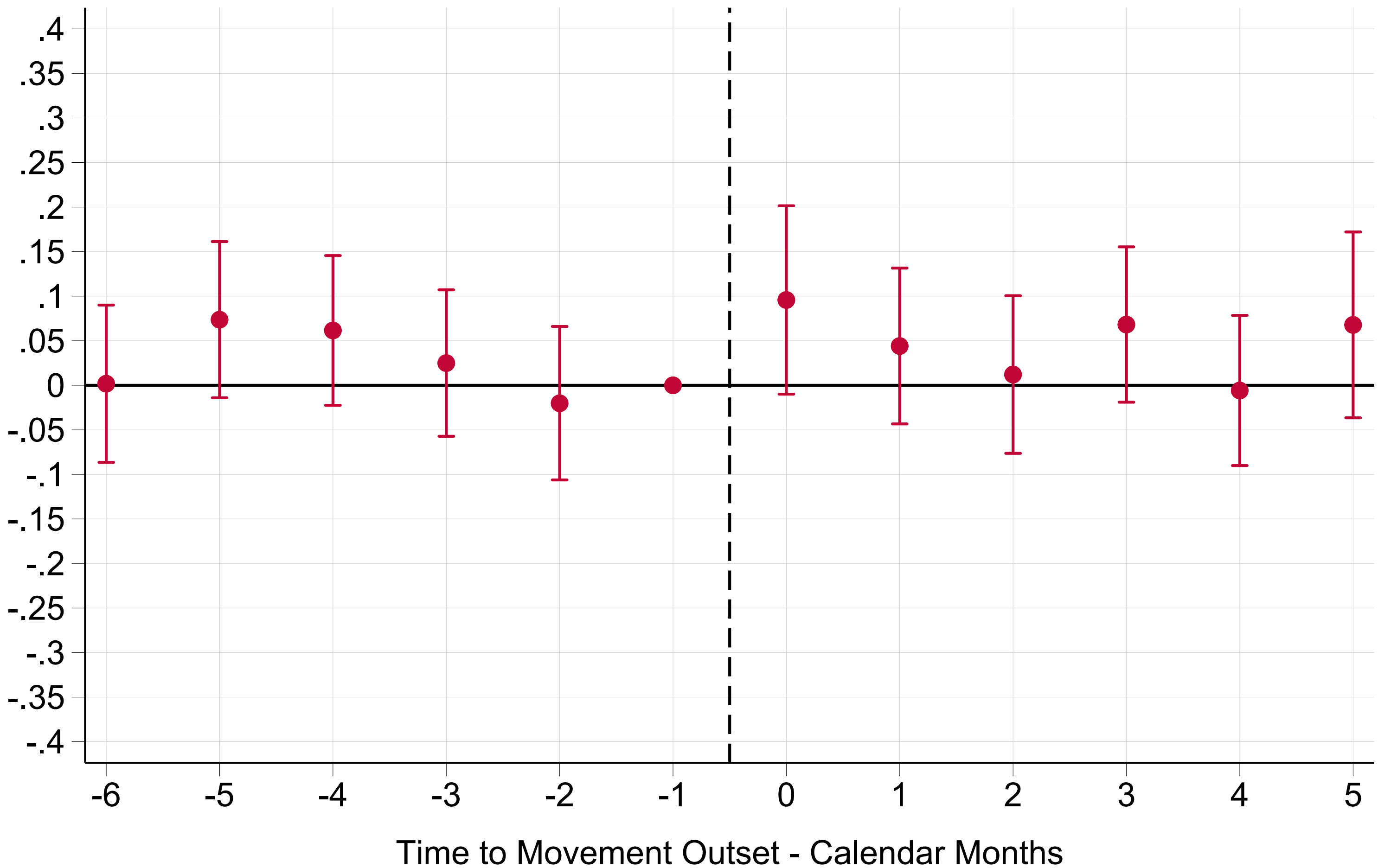
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 5 – Protests and Salience: Google Search Intensity, Difference-in-Differences



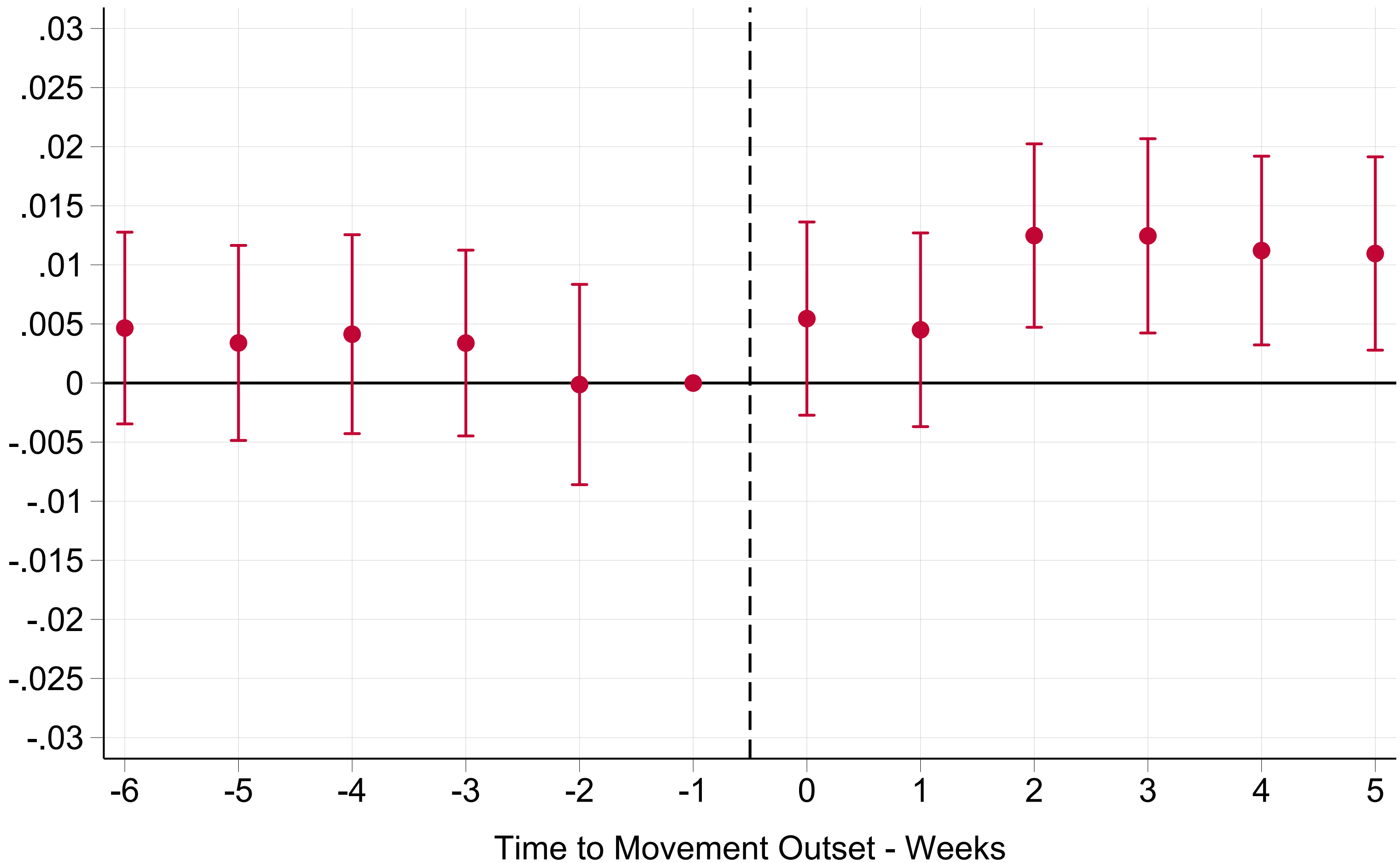
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 6 – Protests and Salience: GPSS, Difference-in-Differences



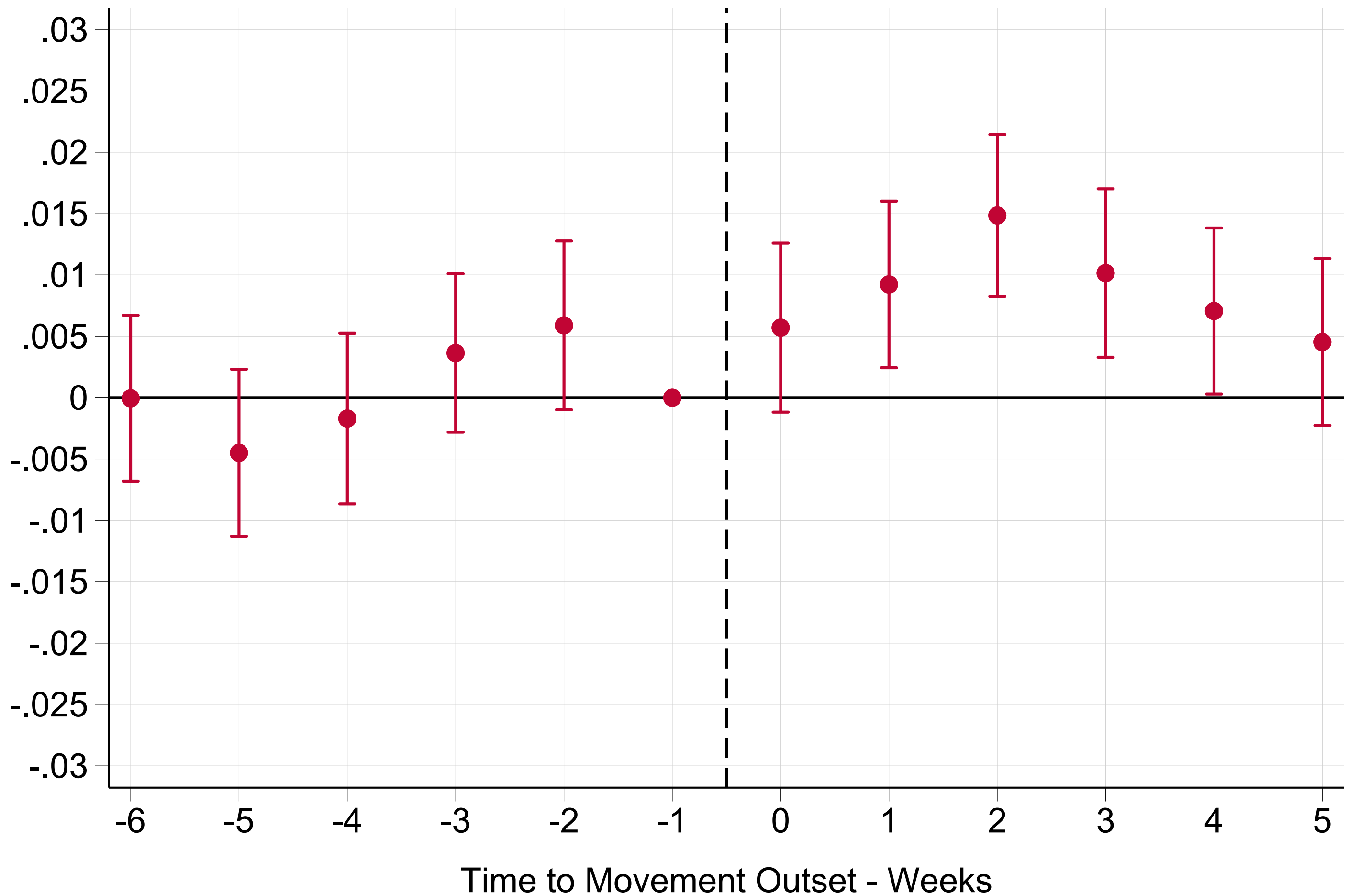
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 7 – Protests and Having an Opinion: Nationscape, Simple Difference



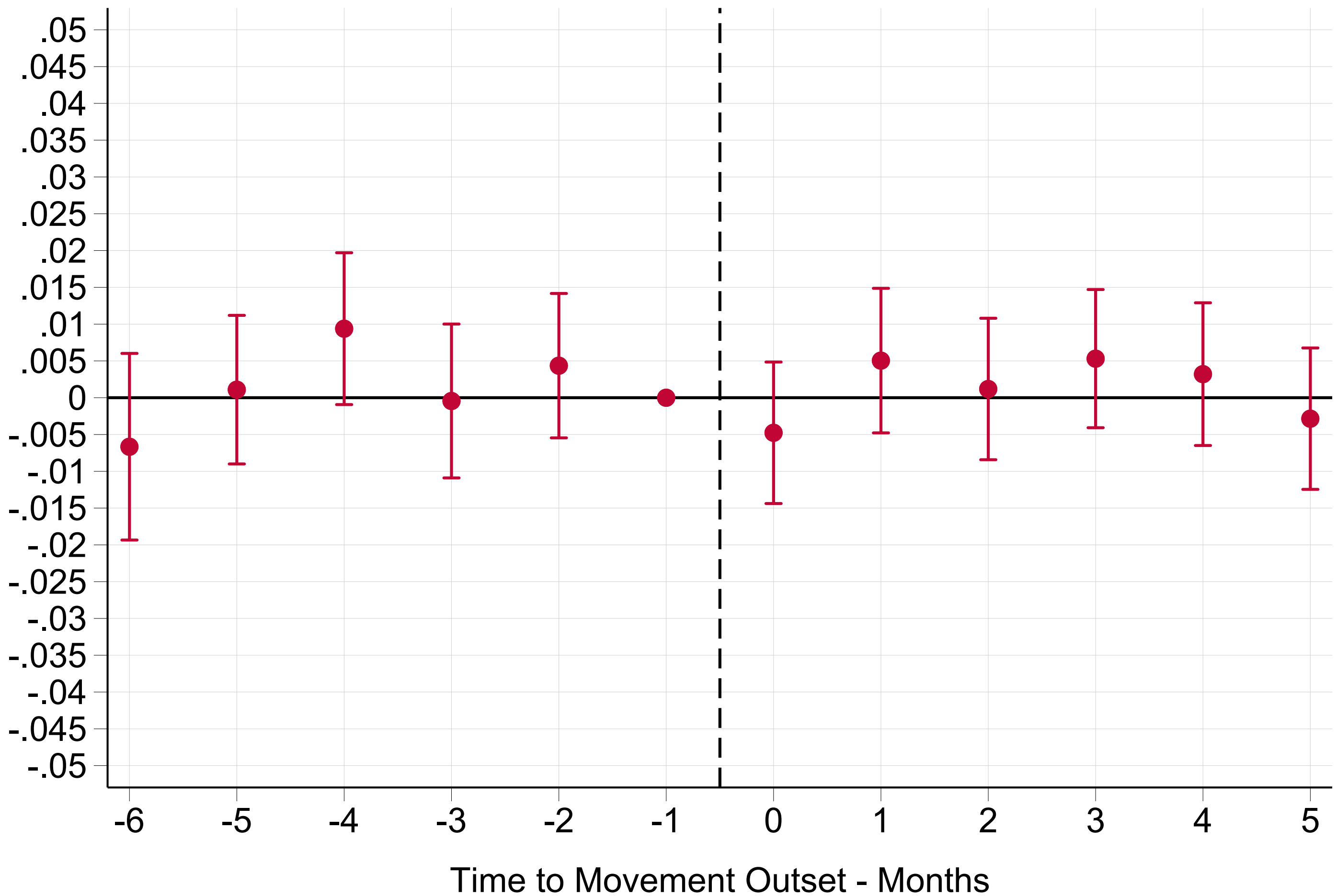
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). The dependent variable is a dummy taking value 1 if the respondent has an opinion on a given issue and 0 otherwise.

Figure 8 – Protests and Liberal Attitudes: Nationscape, Simple Difference



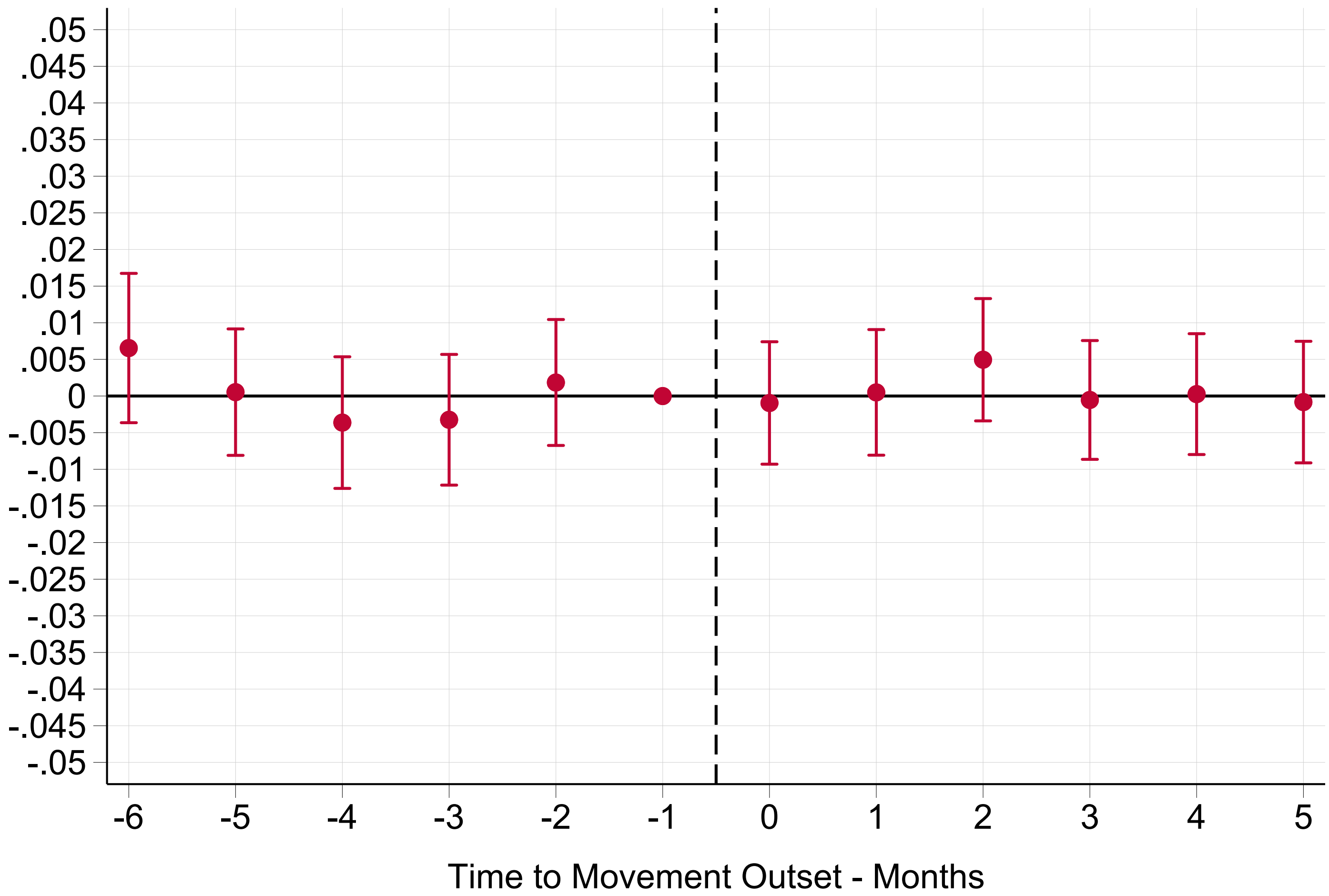
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). The dependent variable is a dummy taking value 1 if the respondent has a liberal opinion on a given issue and 0 if they have a conservative opinion.

Figure 9 – Protests and Having an Opinion: Nationscape, Difference-in-Differences



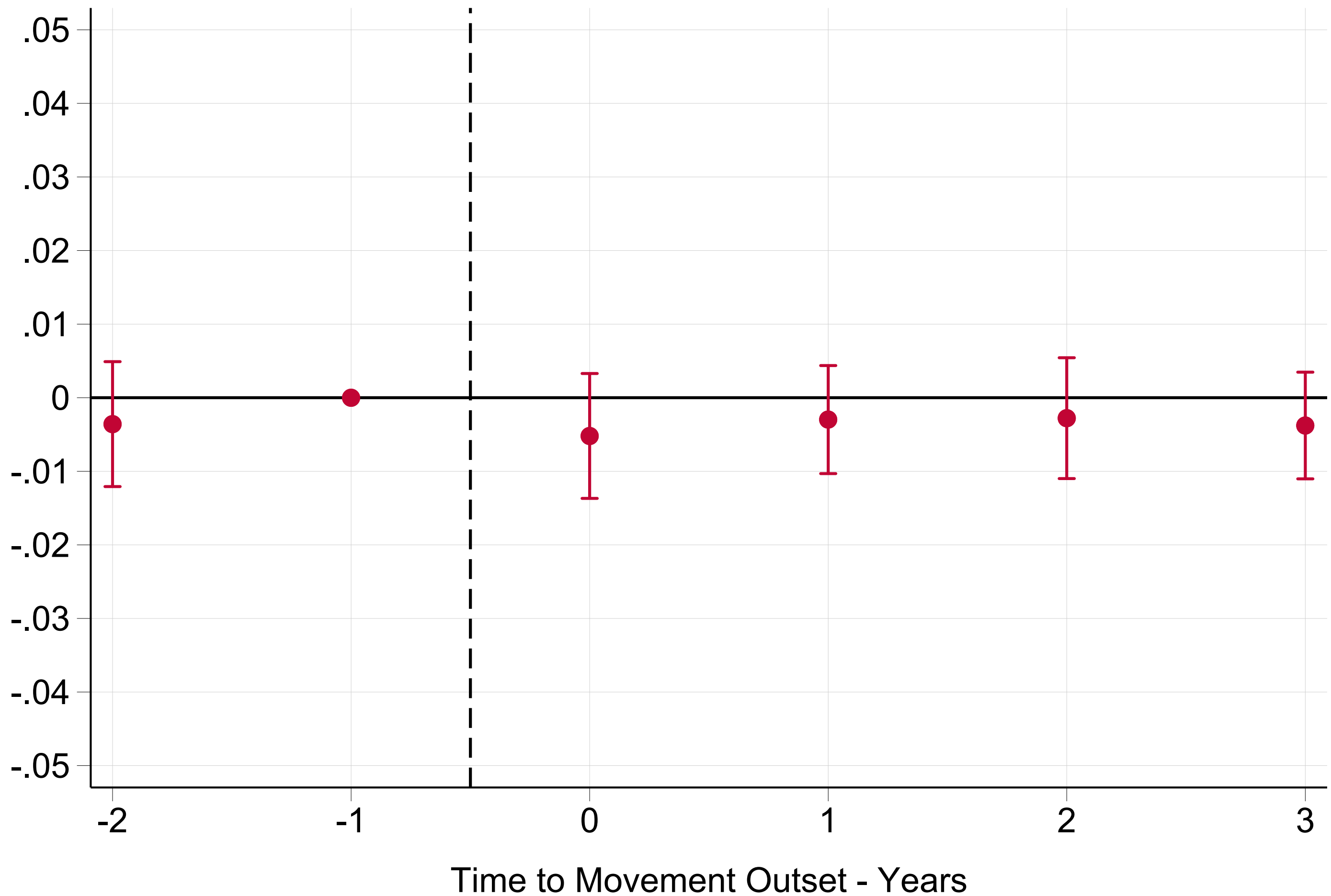
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 10 – Protests and Liberal Attitudes: Nationscape, Difference-in-Differences



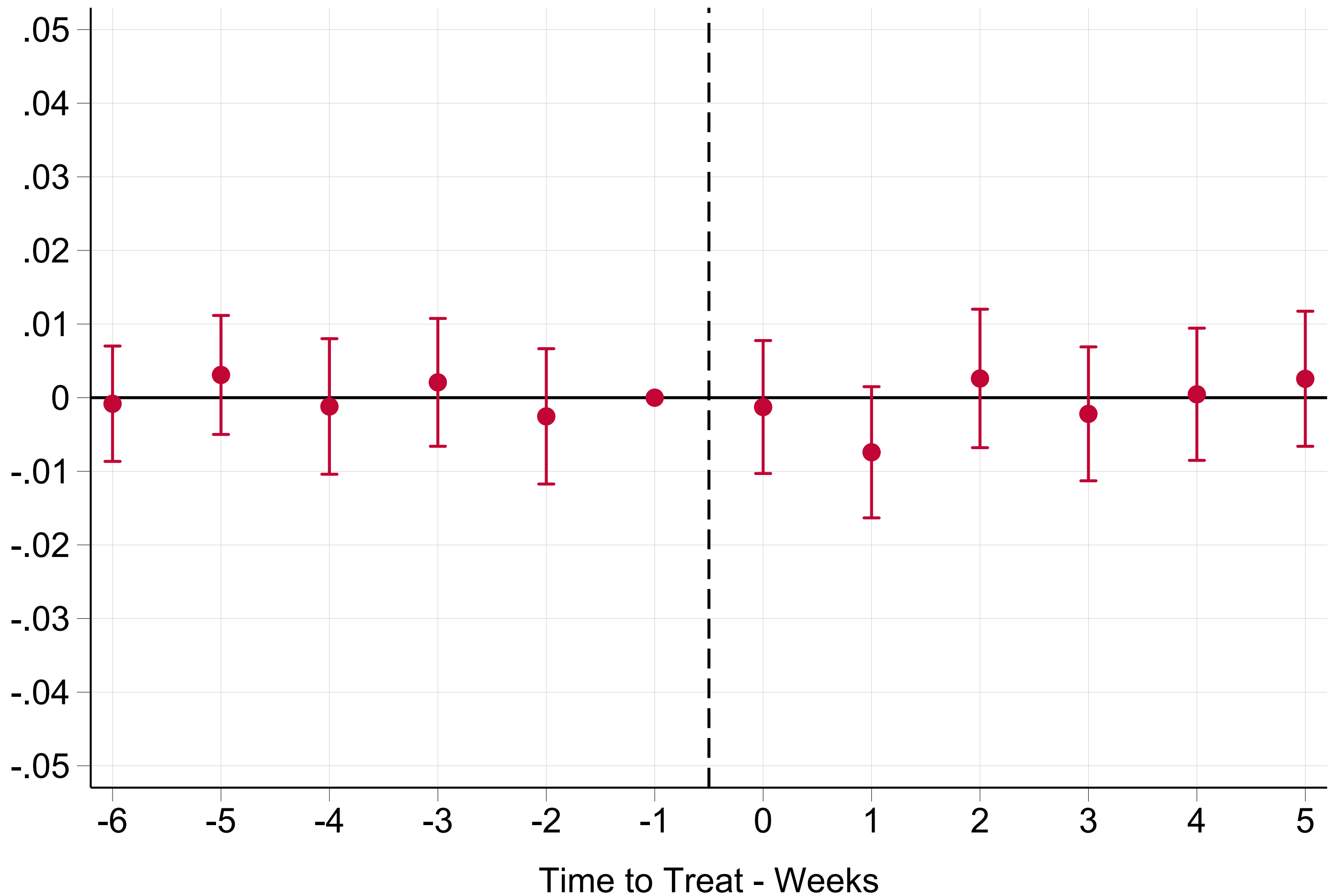
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 11 – Protests and Liberal Attitudes: CCES, Difference-in-Differences



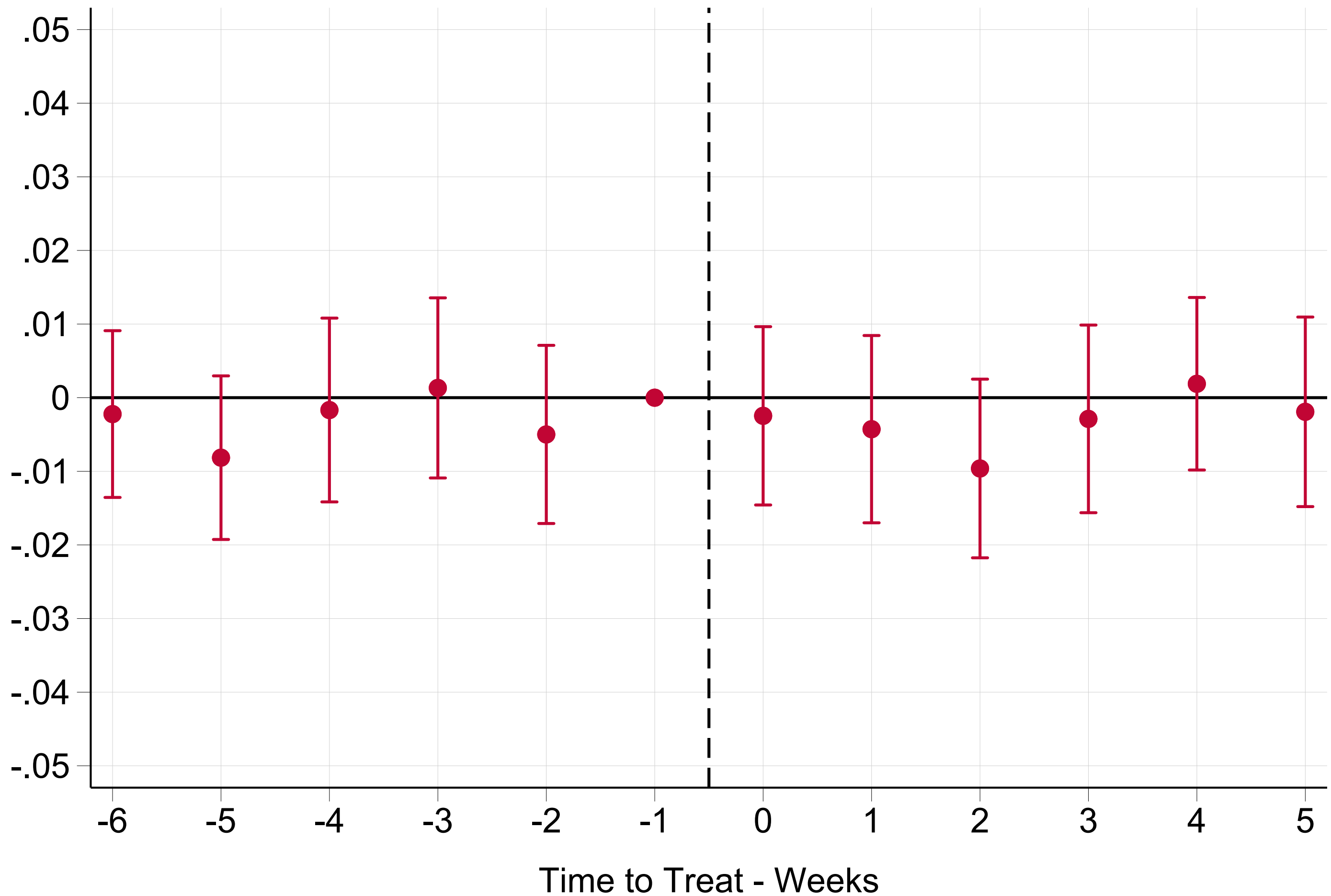
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 12 – Protests and Turnout Intentions: Simple Difference



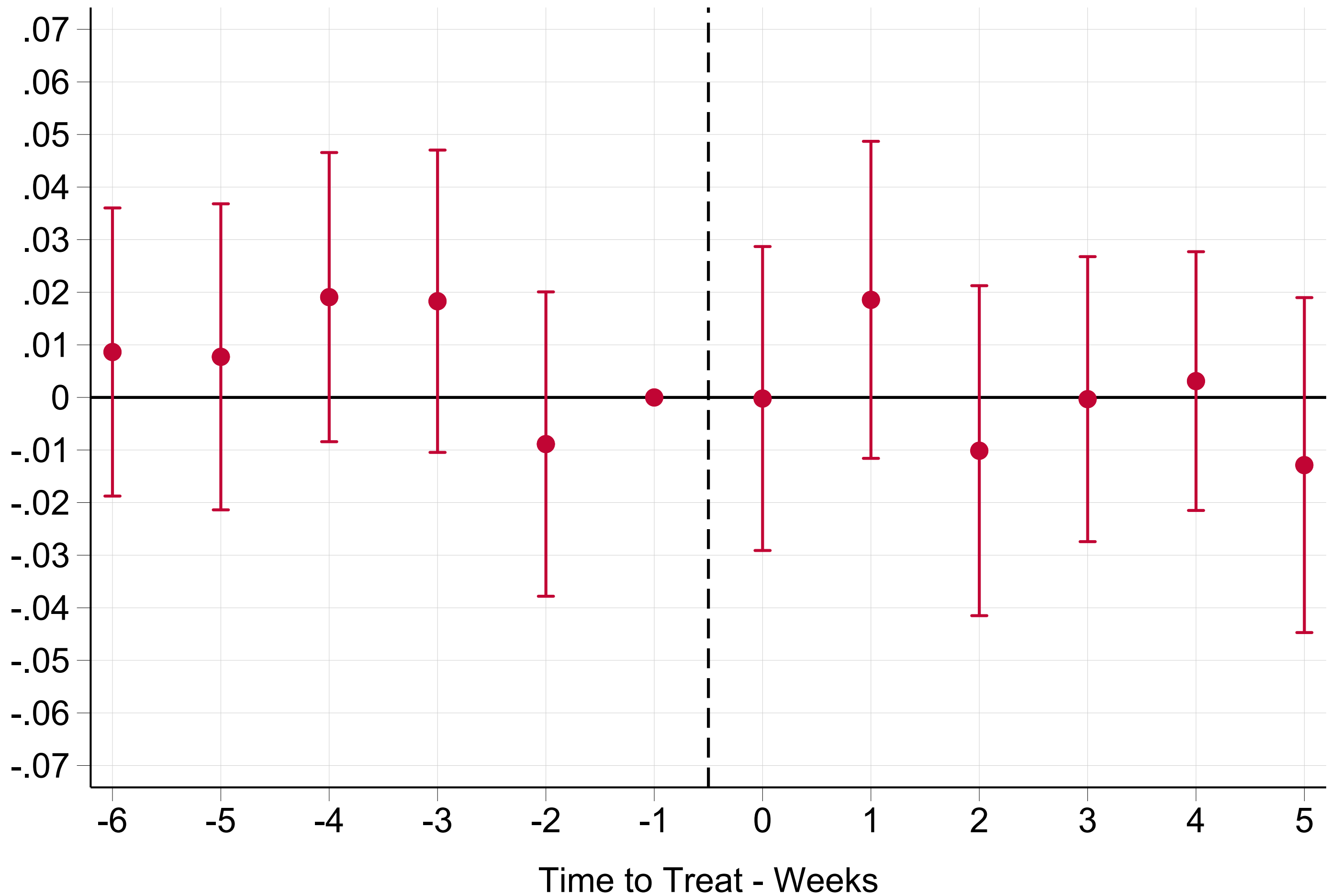
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). The dependent variable is a dummy taking value 1 if the respondent declares intending to vote in the 2020 presidential election and 0 otherwise.

Figure 13 – Protests and Vote Intentions: Simple Difference



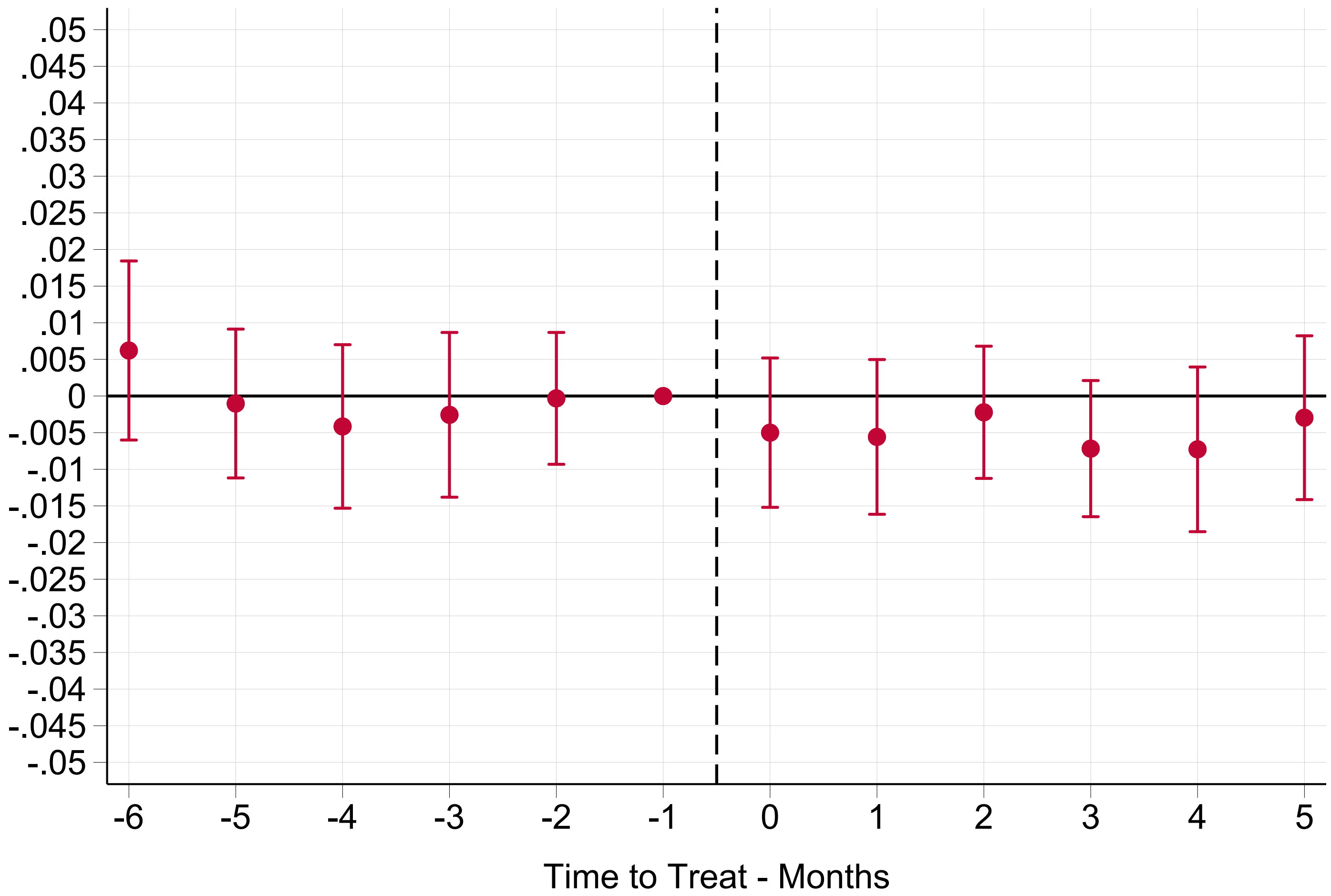
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). The dependent variable is a dummy taking value 1 if the respondent declares considering voting for Donald Trump in the 2020 presidential election and 0 otherwise.

Figure 14 – Protests and Presidential Approval: Simple Difference



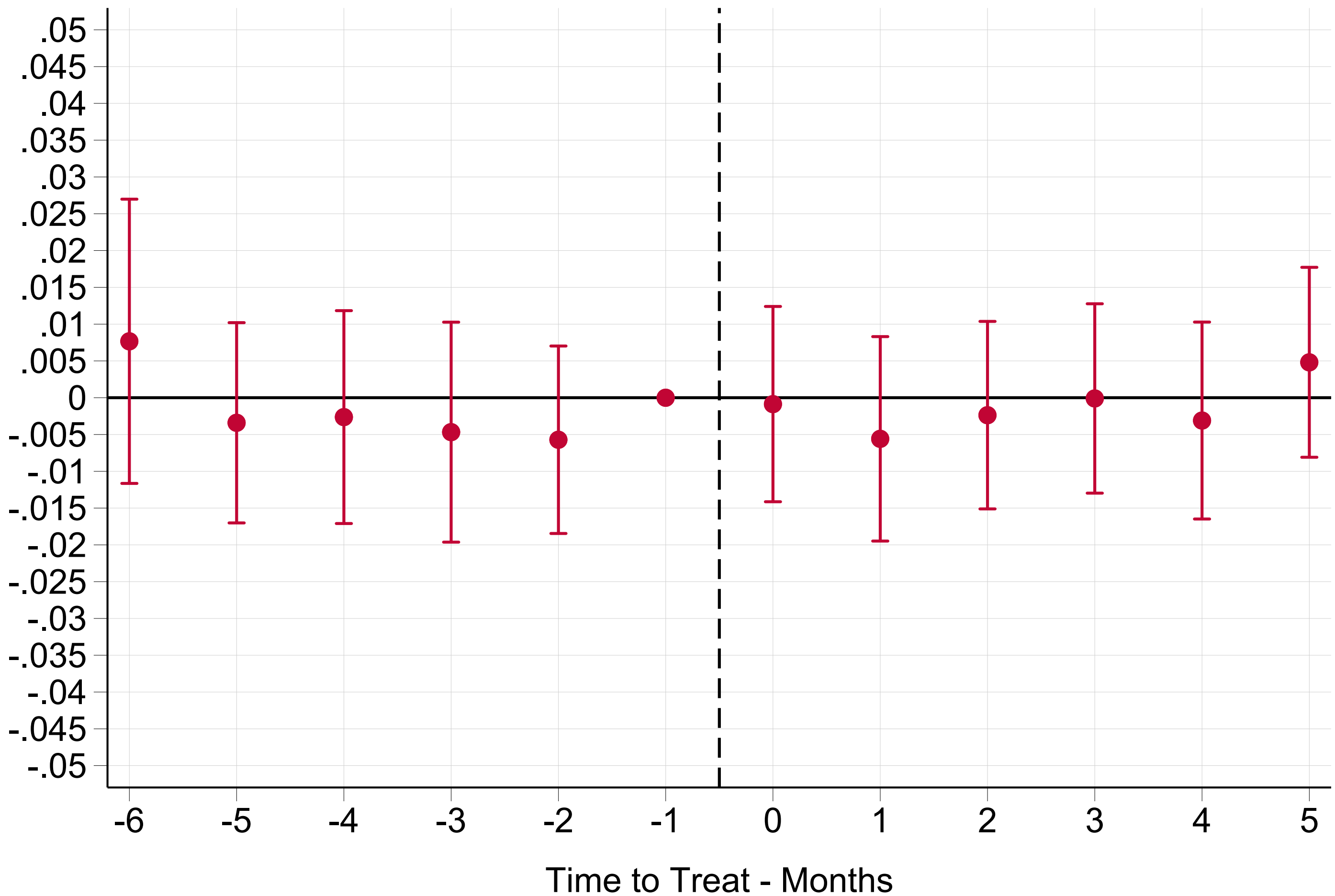
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1). The dependent variable takes values ranging from 1 to 4, with 1 corresponding to respondents strongly disapproving Donald Trump's way of handling his job as president and 4 corresponding to those strongly approving it.

Figure 15 – Protests and Turnout Intentions: Difference-in-Differences



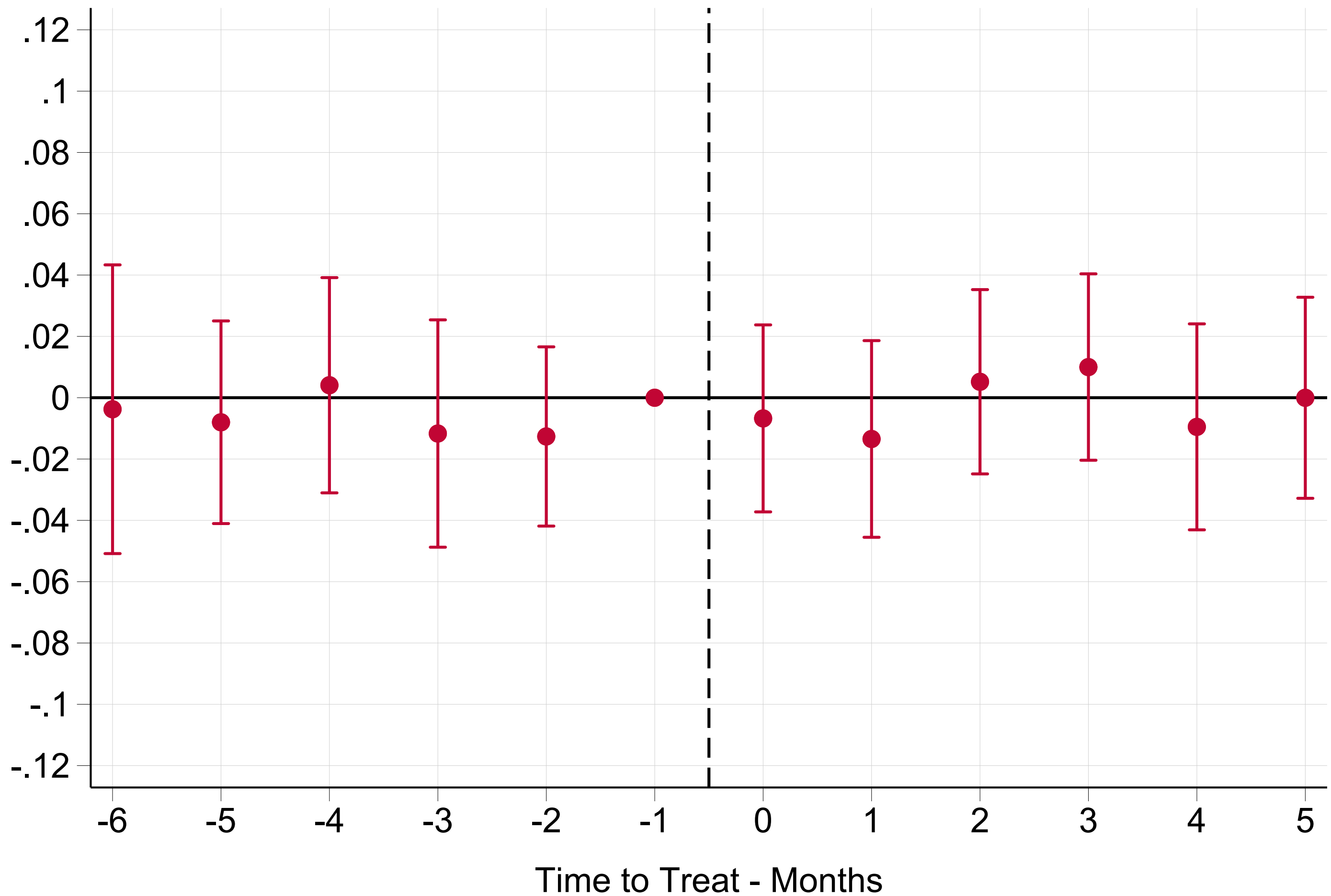
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 16 – Protests and Vote Intentions: Difference-in-Differences



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

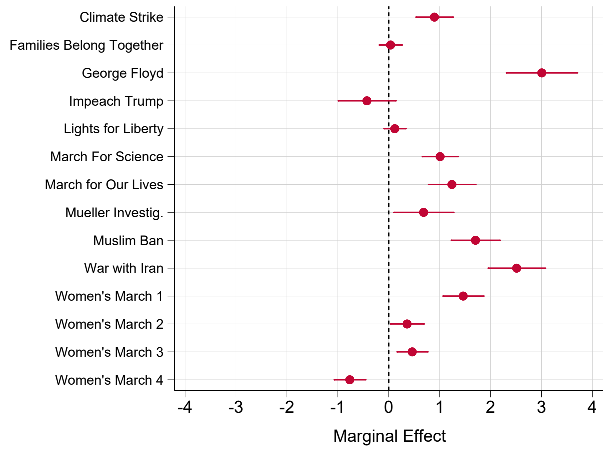
Figure 17 – Protests and Presidential Approval: Difference-in-Differences



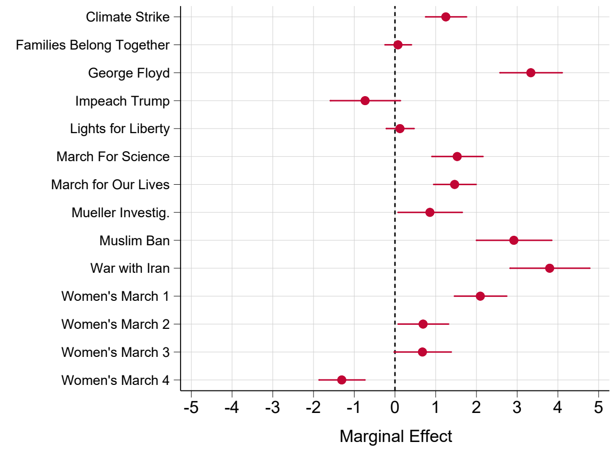
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure 18 – Heterogeneity by Movement: Salience

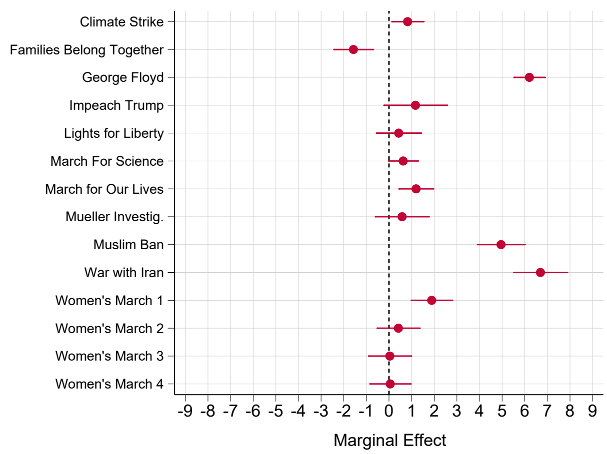
(a) Twitter: Simple Difference



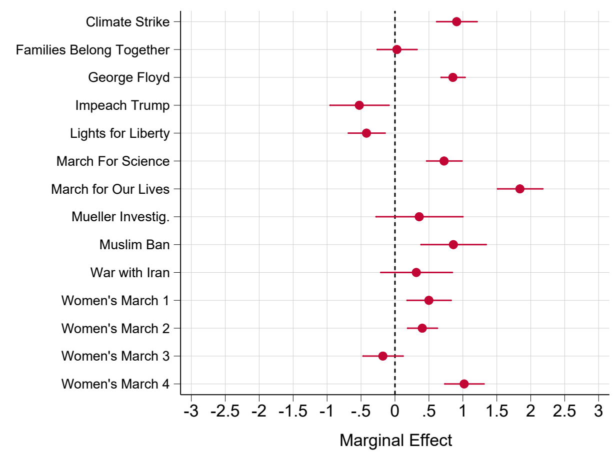
(b) Twitter: Difference-in-Differences



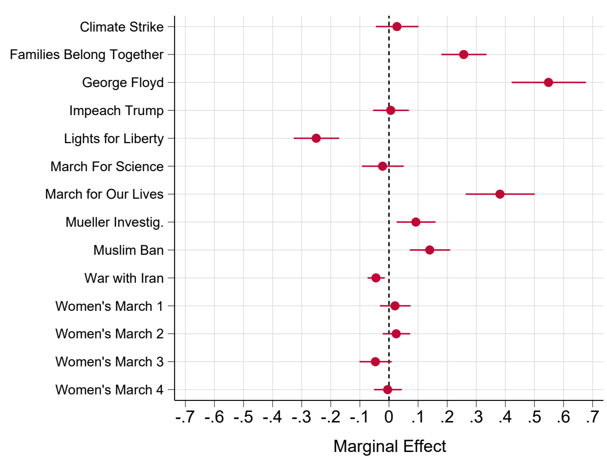
(c) Google: Simple Difference



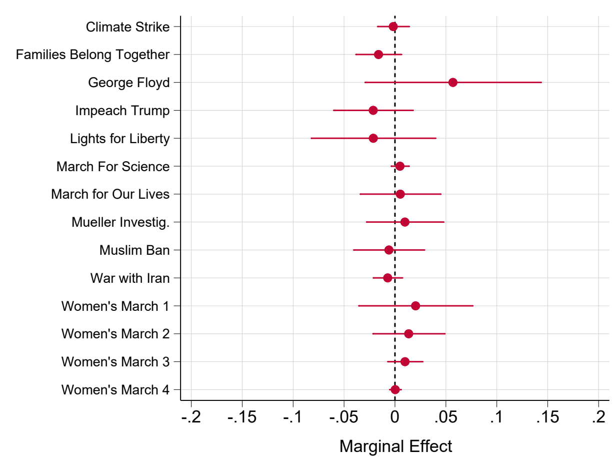
(d) Google: Difference-in-Differences



(e) GPSS: Simple Difference



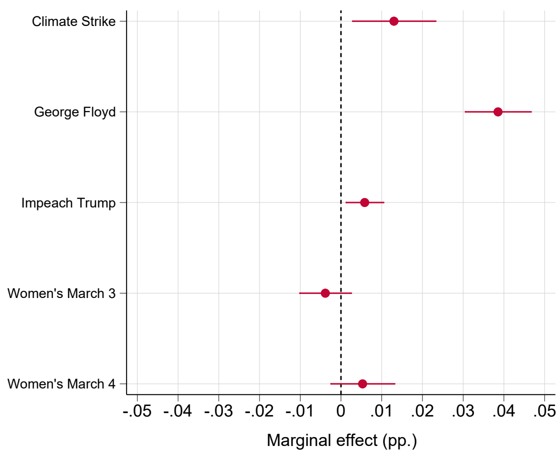
(f) GPSS: Difference-in-Differences



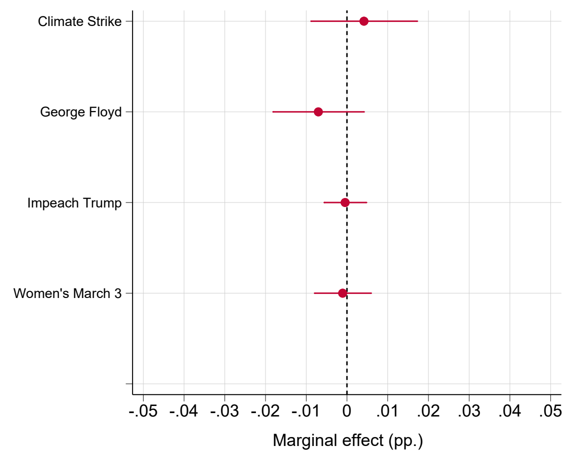
Notes: The figure reports heterogeneous treatment effects by movement for both the simple difference and difference-in-differences specifications. Panels (a) and (c) report point estimates and 95% robust confidence intervals for β in equation (2). Panels (b), (d), and (e) report point estimates and 95%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

Figure 19 – Heterogeneity by Movement: Opinions

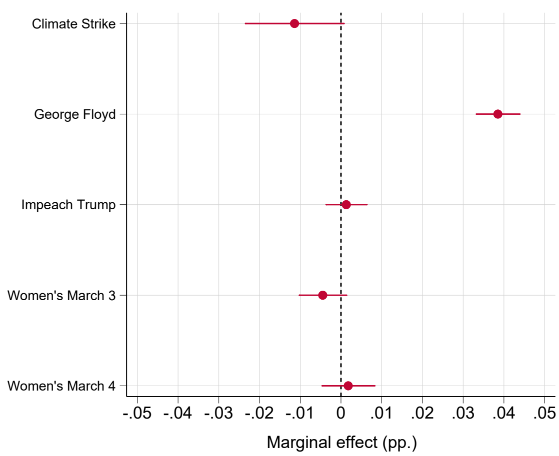
(a) Nationscape, Any Opinion: Simple Difference



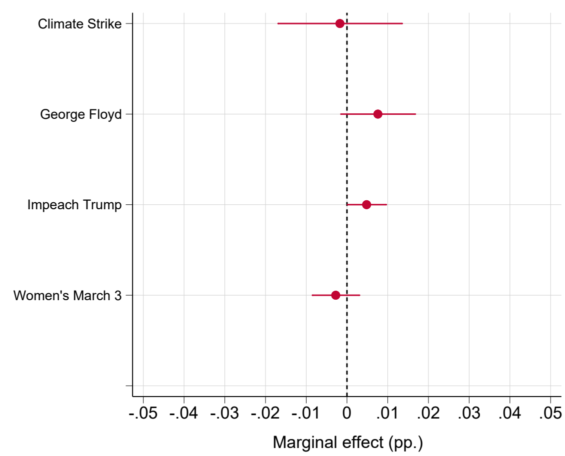
(b) Nationscape, Any Opinion: Difference-in-Differences



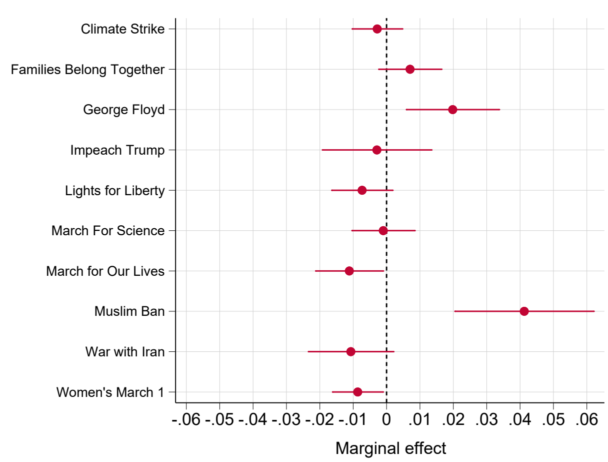
(c) Nationscape, Opinion: Simple Difference



(d) Nationscape, Opinion: Difference-in-Differences



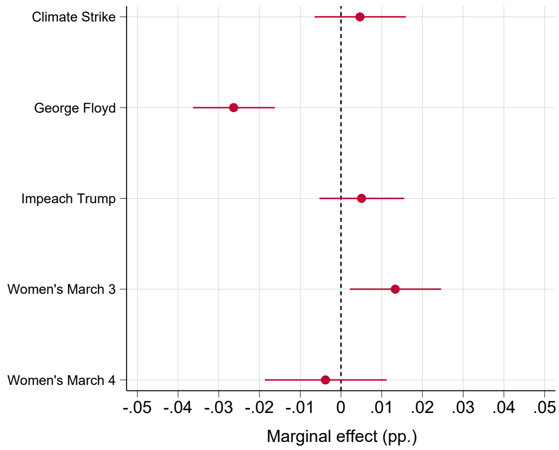
(e) CCES: Difference-in-Differences



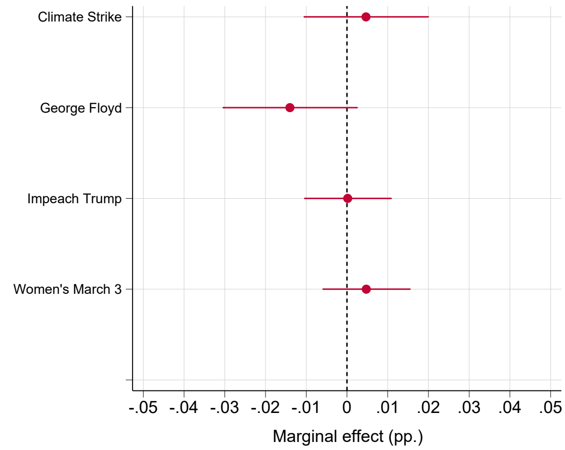
Notes: The figure reports heterogeneous treatment effects by movement for both the simple difference and difference-in-differences specifications. Panels (a), (c), and (e) report point estimates and 95% robust confidence intervals for β in equation (2). Panels (b), (d), and (f) report point estimates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

Figure 20 – Heterogeneity by Movement: Political Attitudes

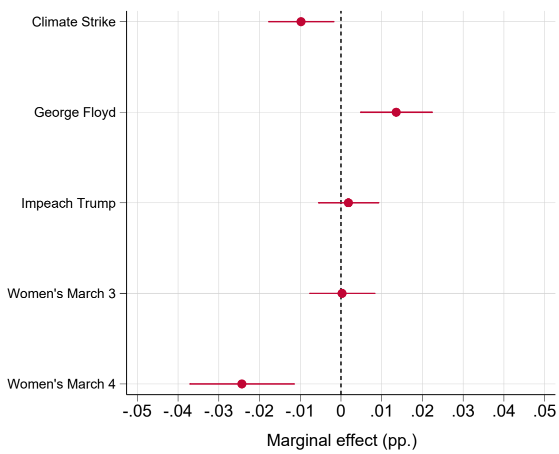
(a) Trump: Simple Difference



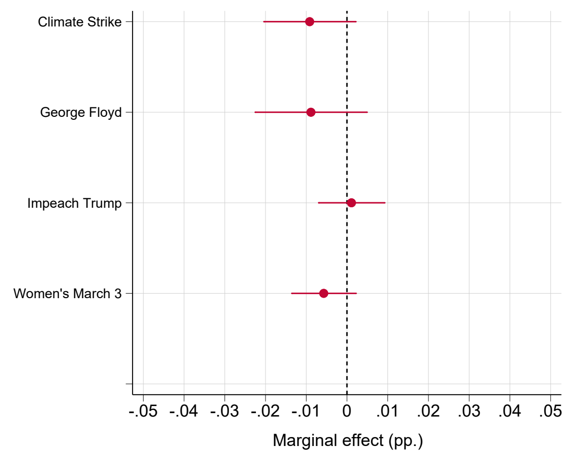
(b) Trump: Difference-in-Differences



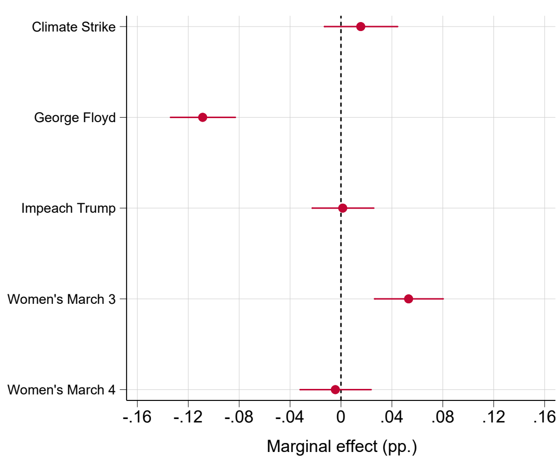
(c) Turnout: Simple Difference



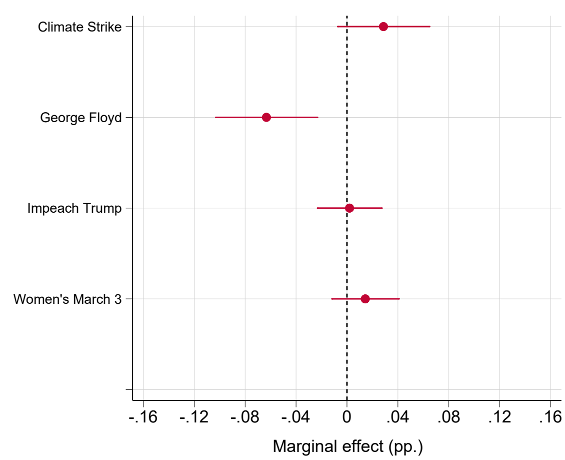
(d) Turnout: Difference-in-Differences



(e) Presidential Approval:
Simple Difference



(f) Presidential Approval:
Difference-in-Differences



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

Table 1 – Descriptive Statistics by Social Movement

Topic	Date	Movement	Protests	Protesters	Counties
Environmental Protection	2017/04/22	March For Science	497	796,682	399
Environmental Protection	2019/09/20	Climate Strike	1,420	429,933	630
Gender Equality	2017/01/21	Women's March 1	686	4,208,710	527
Gender Equality	2018/01/20	Women's March 2	461	2,255,752	379
Gender Equality	2020/01/18	Women's March 3	309	350,084	261
Gender Equality	2020/10/17	Women's March 4	428	25,558	322
Gun Control	2018/03/14	March for Our Lives	5,395	3,202,686	1018
Immigration	2017/01/28	Muslim Ban	316	241,420	223
Immigration	2018/06/30	Families Belong Together	282	43,884	599
Immigration	2019/07/12	Lights for Liberty	756	115,602	511
International Affairs	2020/01/09	War with Iran	485	12,456	298
National Politics	2018/11/08	Mueller Investigation	898	32,940	652
National Politics	2019/12/17	Impeach Trump	644	86,762	452
Racism	2020/05/25	George Floyd	5,392	1,974,568	1381

Notes: This table reports descriptive statistics on each social movement. Date is the date marking the beginning of the movement. Protests is the number of protests that took place within two weeks 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 within two weeks 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	0.879***	1.658***	0.010***	0.571***	0.666***	0.000
	(0.061)	(0.115)	(0.002)	(0.073)	(0.099)	(0.002)
N	922,908	4,984	128,969	395,535	2,492	64,433
Time Window	2 Weeks	2 Weeks	6 Months	2 Weeks	2 Weeks	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, months, or years 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	1.110***	0.255***	0.530***	0.096**	0.017	0.007
	(0.097)	(0.065)	(0.040)	(0.046)	(0.018)	(0.020)
N	922,908	915,222	149,520	148,096	128,969	128,228
Time Window	2 Weeks	2 Weeks	2 Weeks	2 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, months, or years 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	0.007***	0.008***	0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
N	815,704	1,526,293	596,296	966,132
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 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, months, or years 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	-0.001	-0.001	0.001	0.000	-0.003	-0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
N	2,259,910	2,253,411	4,511,747	4,498,659	5,630,336	5,609,279
Time Window	6 Months	6 Months	6 Months	6 Months	1 Year	1 Year

Notes: This table reports difference-in-differences estimates corresponding to equation (4), before and after controlling for county characteristics interacted with time ($Post_{tm} \times$ 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, months, 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)	(2)	(3)	(4)	(5)	(6)
	Trump	Turnout	Presidential Approval	Trump	Turnout	Presidential Approval
Post Protest	-0.001	-0.002	-0.008	0.006	-0.008***	0.022**
	(0.003)	(0.002)	(0.006)	(0.004)	(0.003)	(0.009)
N	267,785	251,273	300,298	154,837	148,623	179,976
Time Window	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 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, months, or years on each side of the window). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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

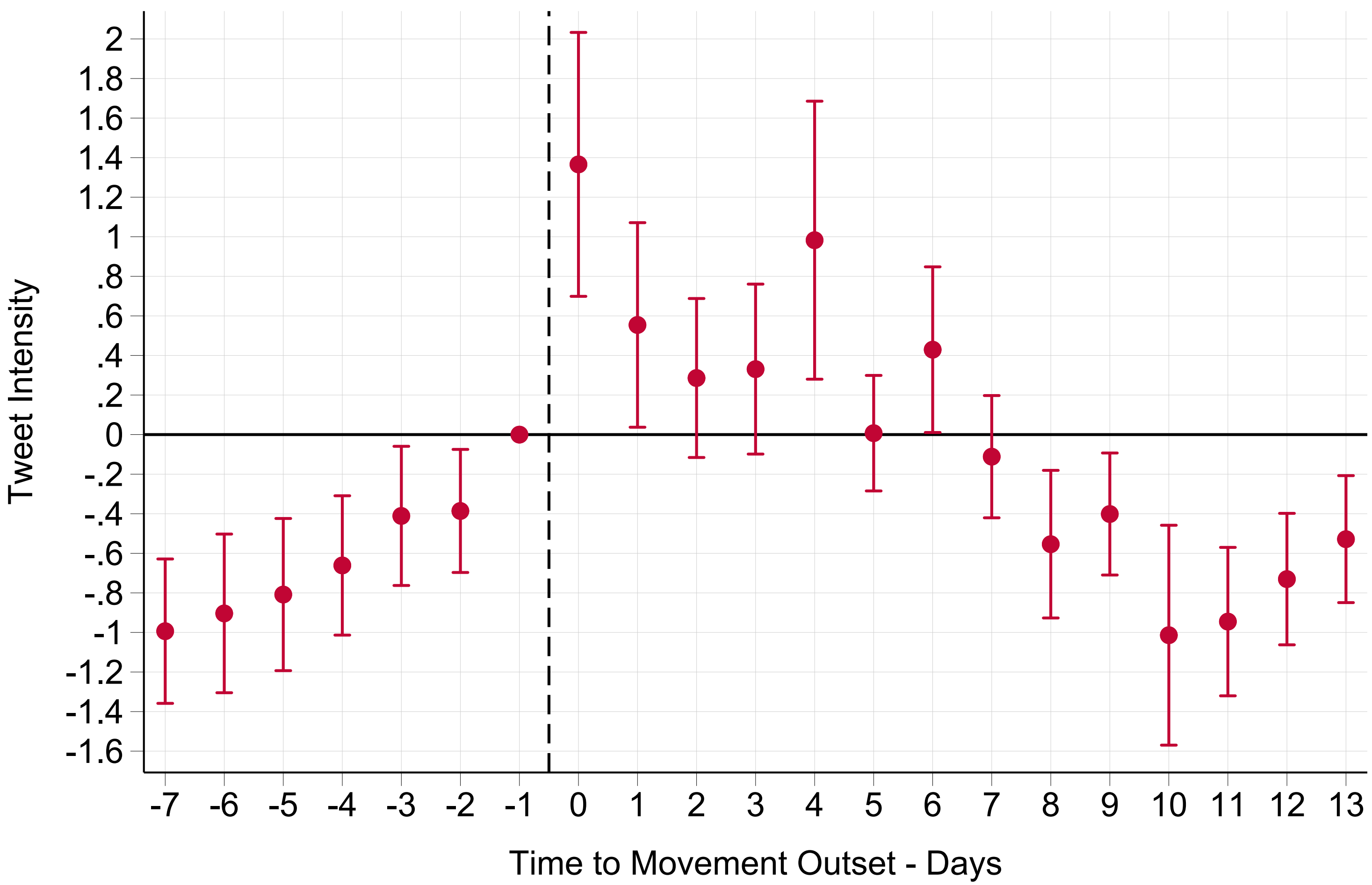
	Trump		Turnout		Presidential Approval	
	(1) Without Controls	(2) With Controls	(3) Without Controls	(4) With Controls	(5) Without Controls	(6) With Controls
Post Protest × Treatment	0.001	0.001	-0.004	-0.003	0.003	0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.009)	(0.010)
N	865,143	862,612	831,913	829,455	932,847	930,167
Time Window	6 Months	6 Months	6 Months	6 Months	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 ($Post_{tm} \times$ 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, months, or years on each side of the window). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Online Appendix

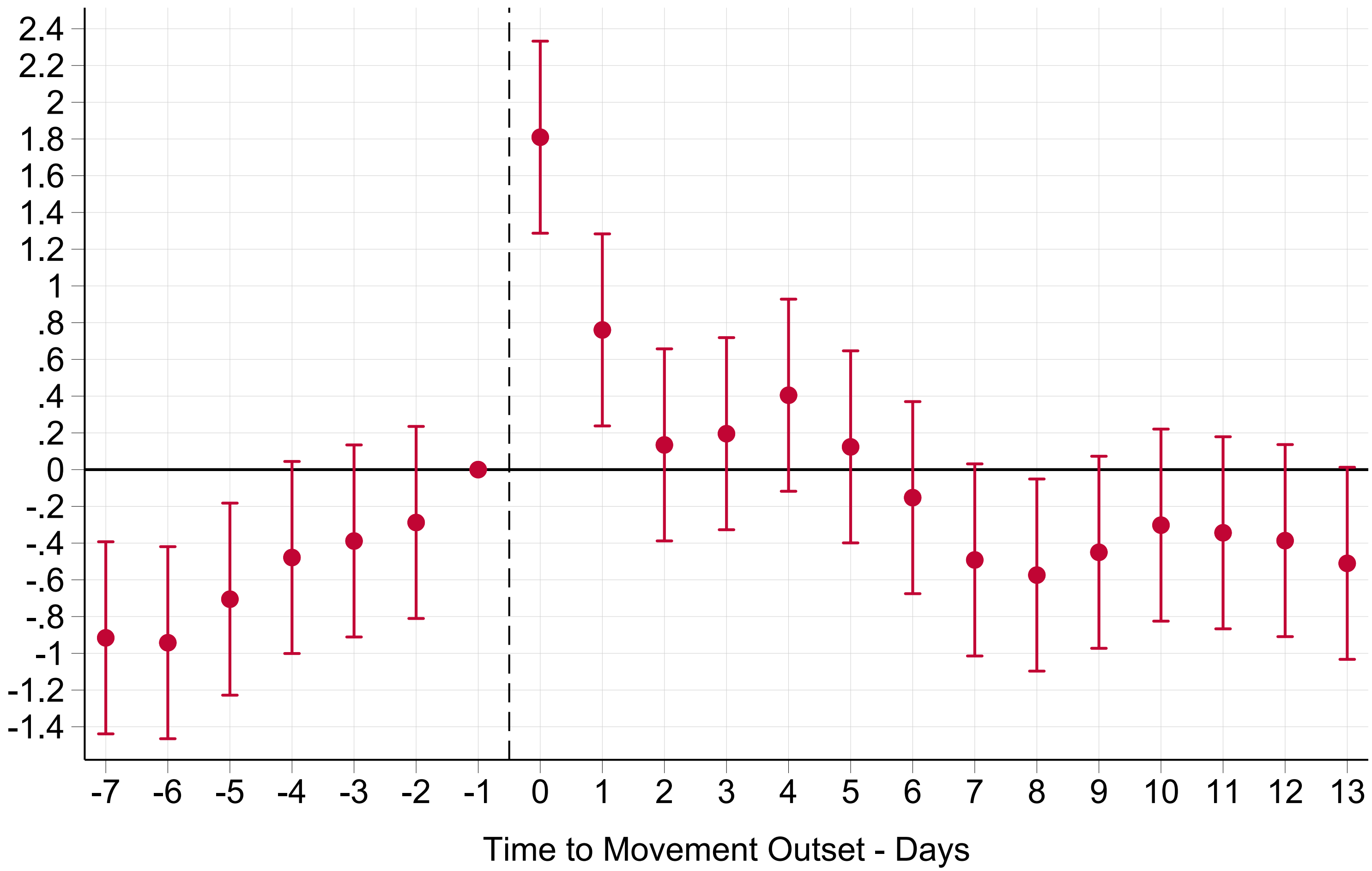
A. Additional Figures and Tables

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



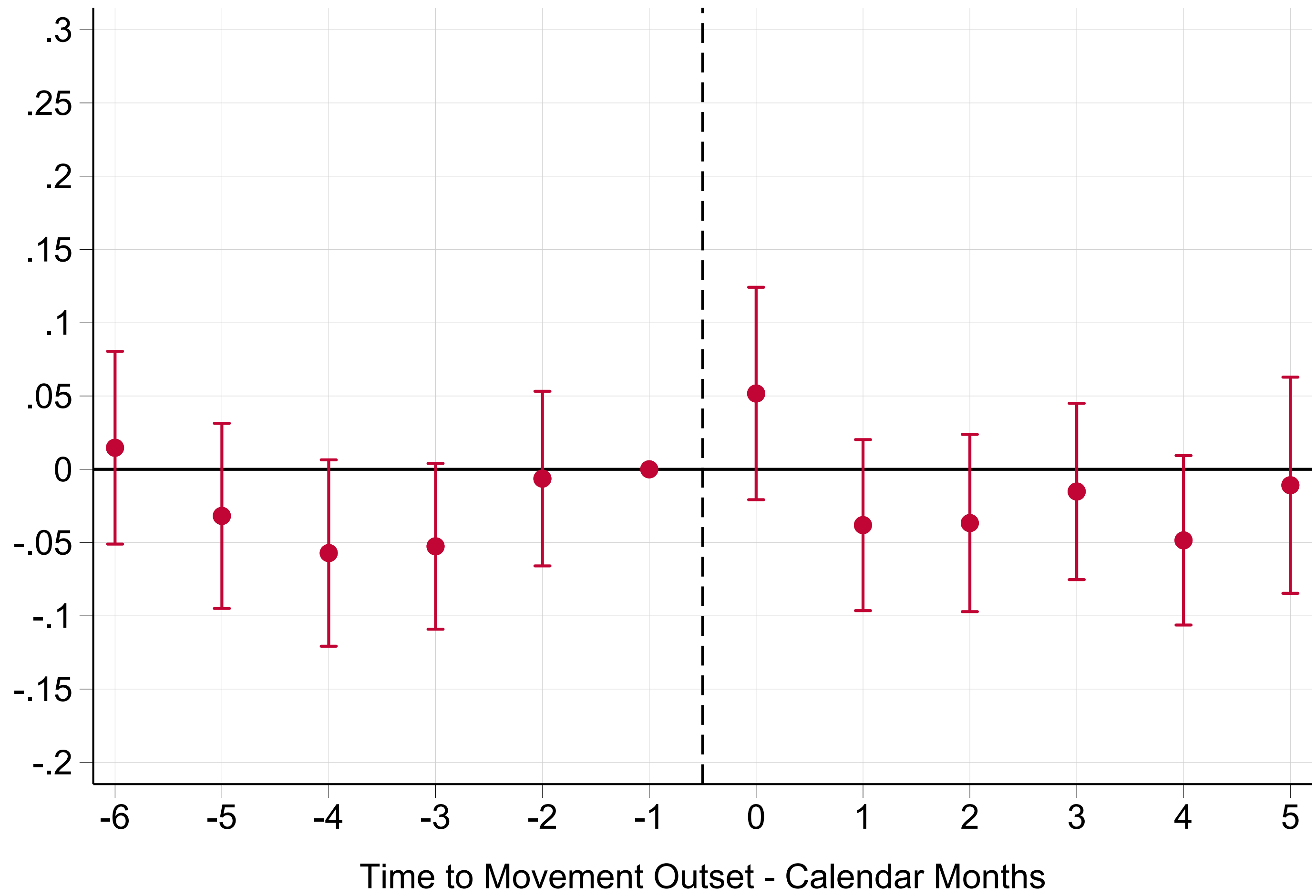
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1).

Figure A2 – Protests and Salience: Google Search Intensity, Simple Difference on Independent Movements



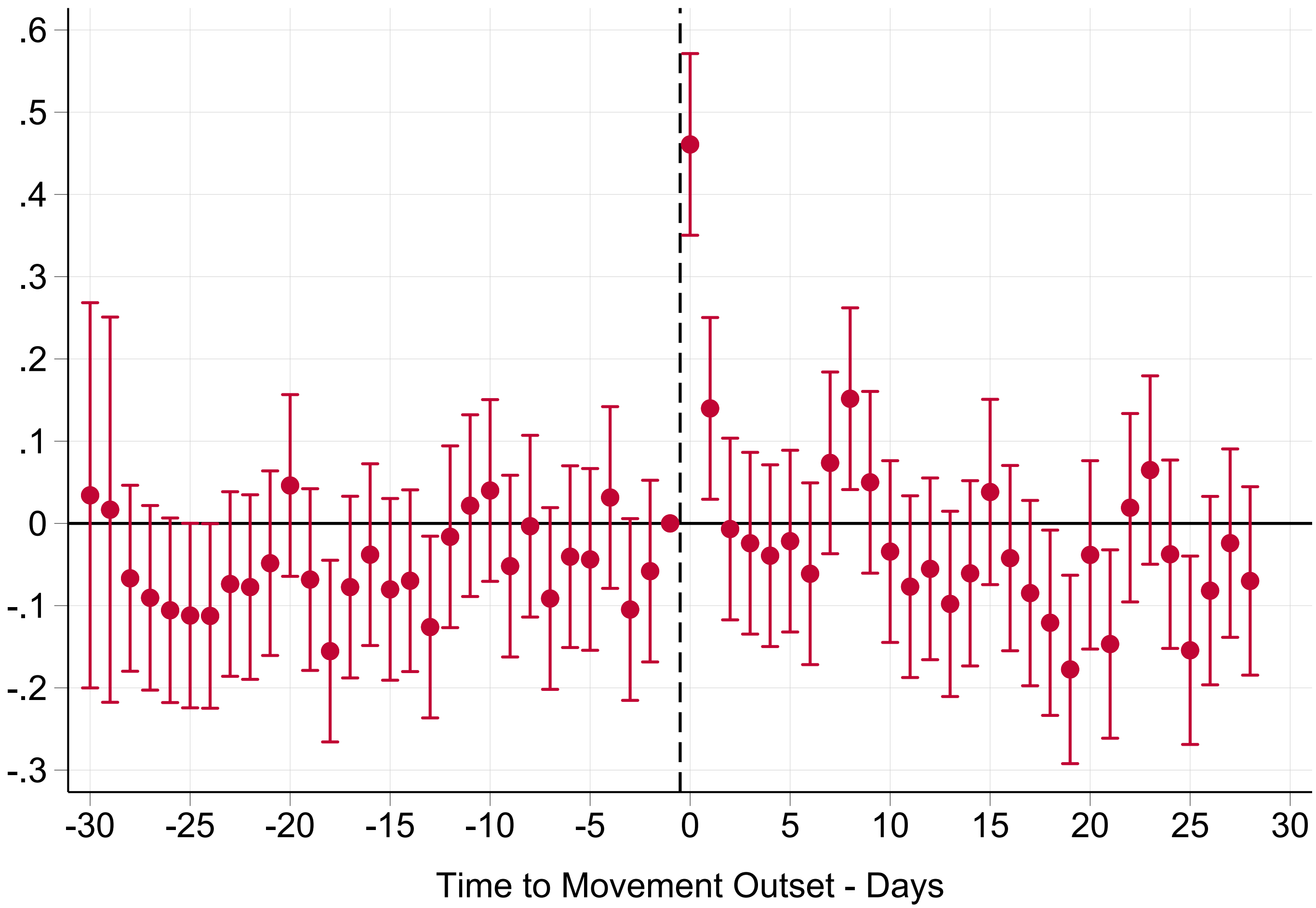
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1).

Figure A3 – Protests and Salience: GPSS, Simple Difference on Independent Movements



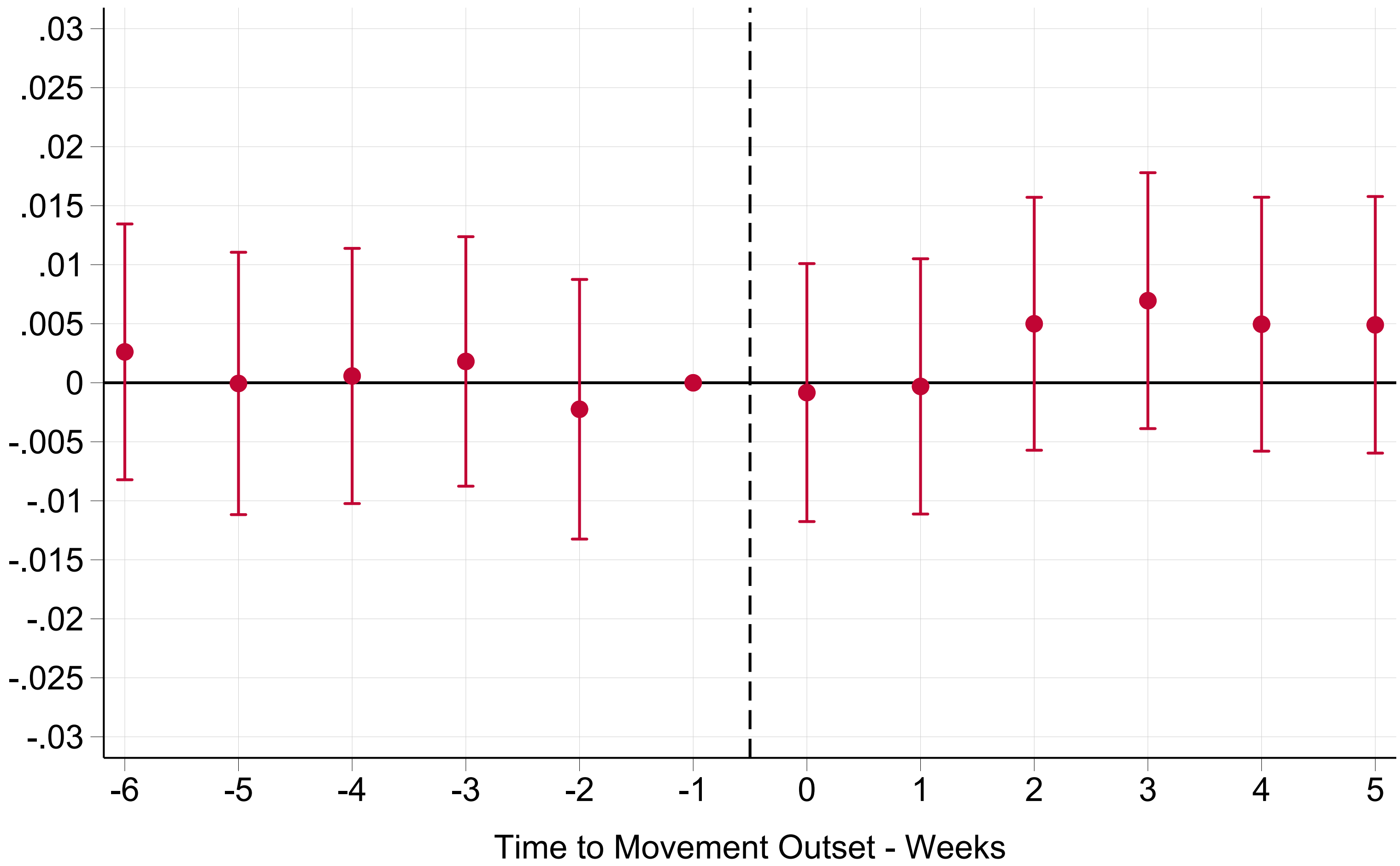
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1).

Figure A4 – Protests and Salience: Google Search Intensity, Difference-in-Differences (Daily)



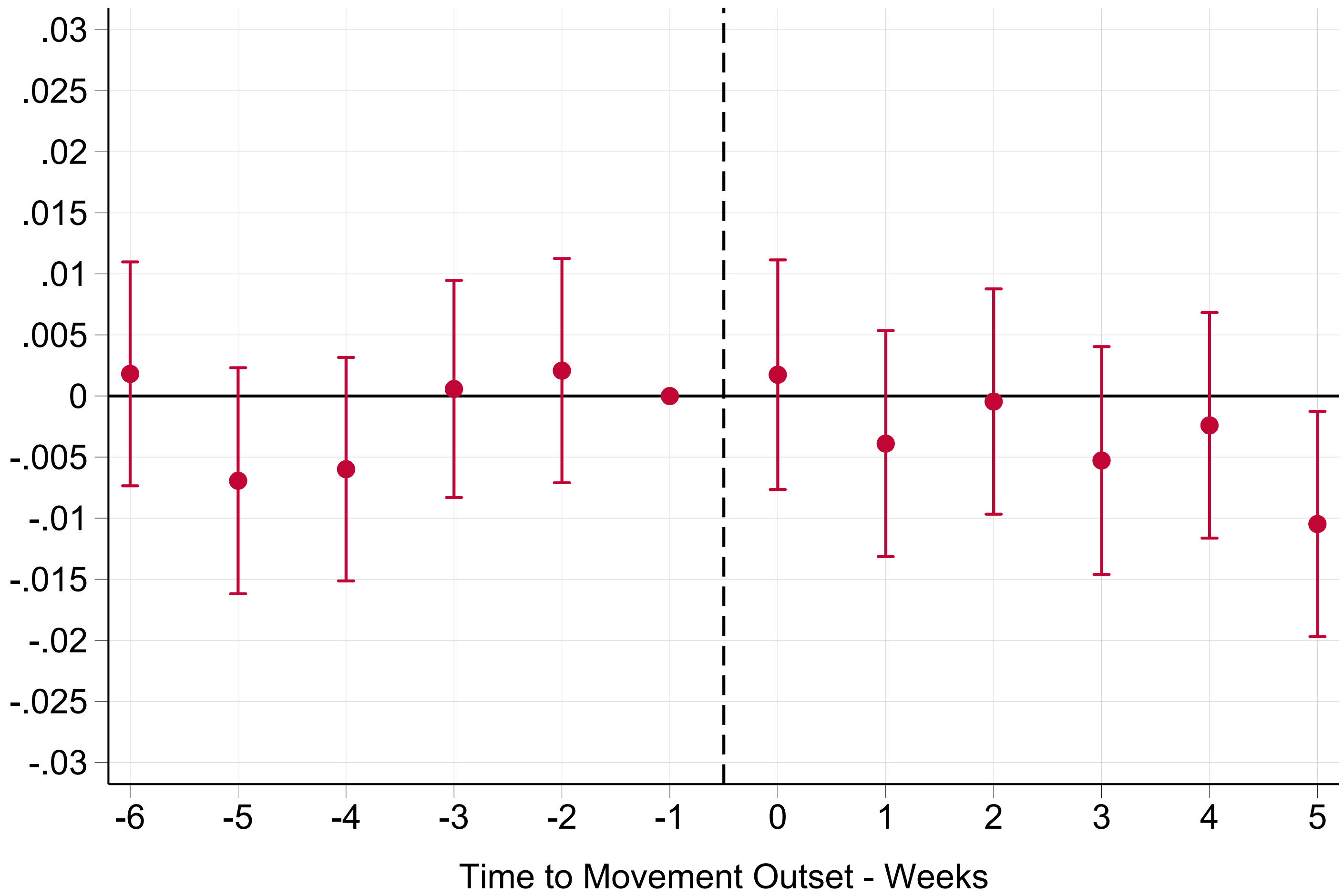
Notes: The figure reports point estimates and 95% robust confidence intervals for the ϕ_t in equation (3).

Figure A5 – Protests and Having an Opinion: Nationscape, Simple Difference on Independent Movements



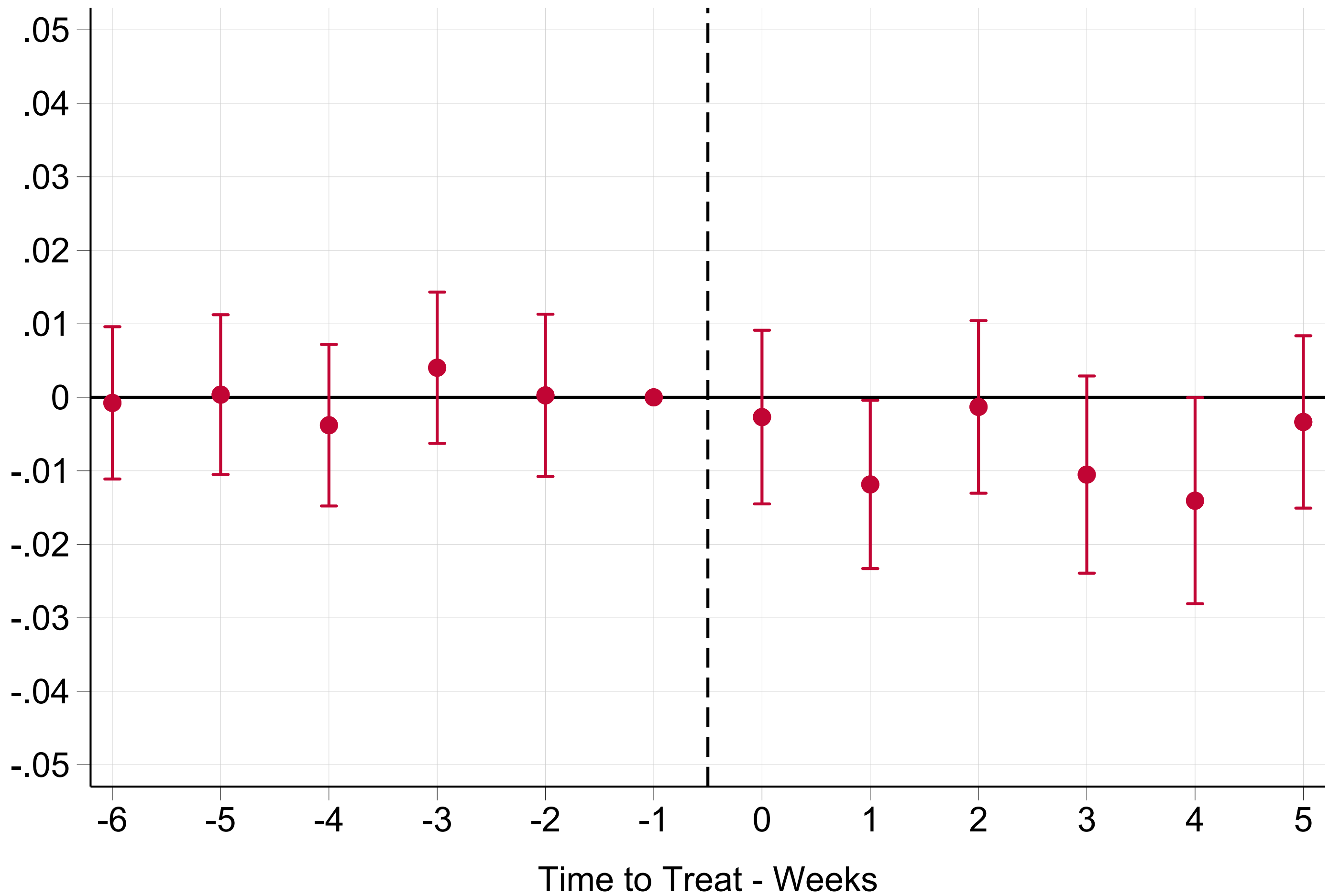
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1).

Figure A6 – Protests and Liberal Attitudes: Nationscape, Simple Difference on Independent Movements



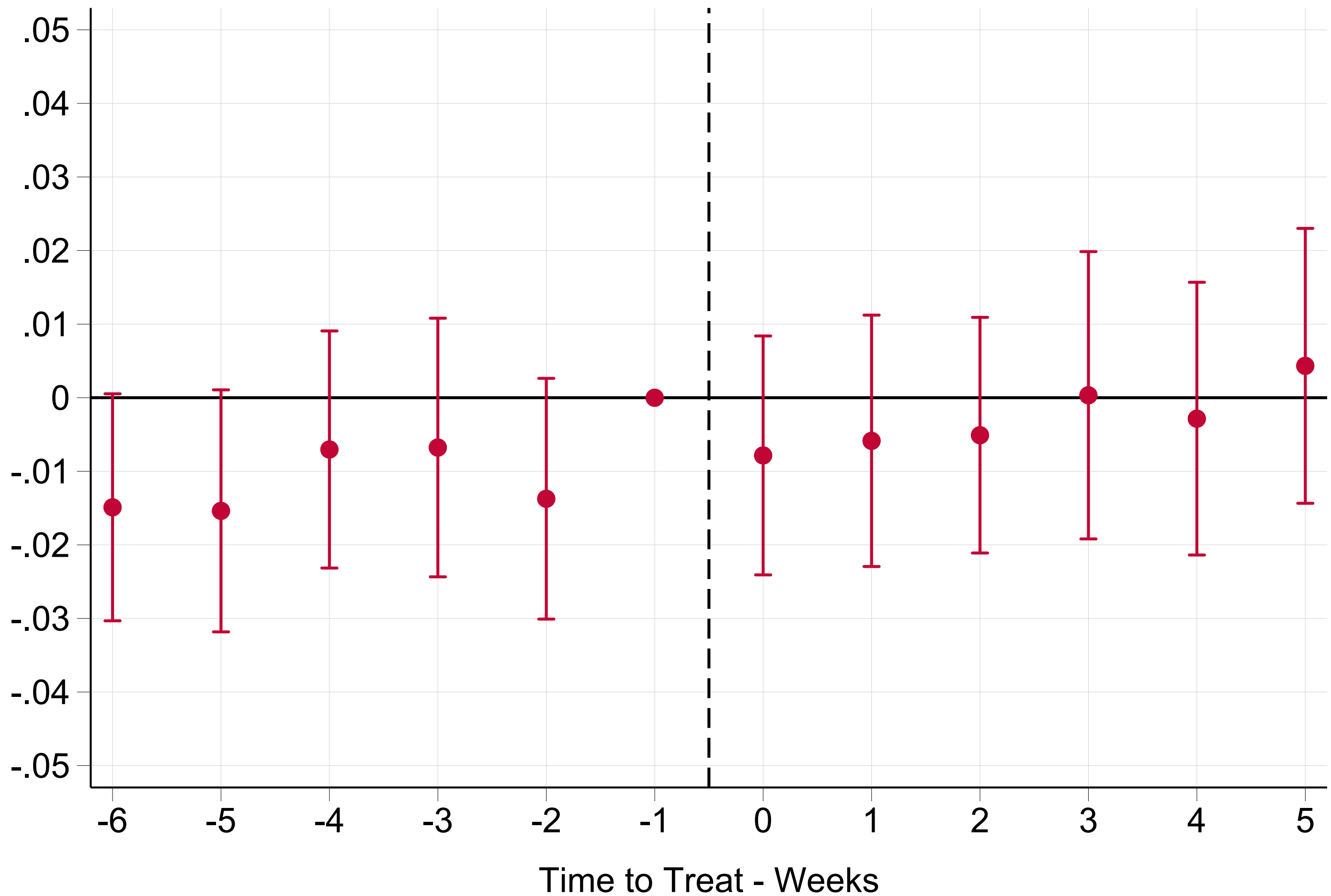
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1).

Figure A7 – Protests and Turnout Intentions: Simple Difference on Independent Movements



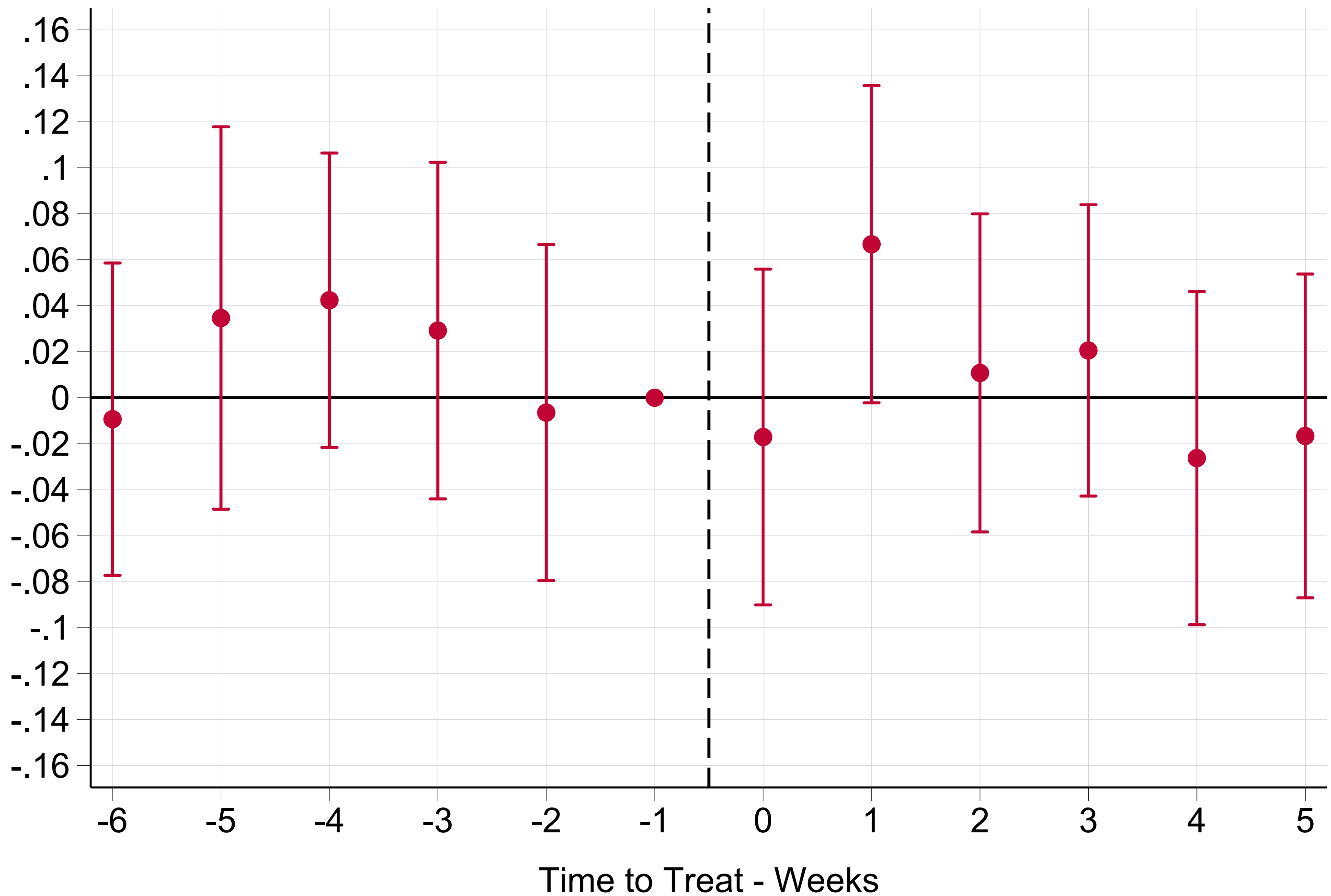
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_t in equation (1).

Figure A8 – Protests and Vote Intentions: Simple Difference on Independent Movements



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

Figure A9 – Protests and Presidential Approval: Simple Difference on Independent Movements



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

Table A1 – 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	1.658***	0.666***	1.243***	0.261**
	(0.115)	(0.099)	(0.342)	(0.106)
N	4,984	2,492	392	168
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2 – Protests and Salience: Difference-in-Differences, Continuous Treatment

	Twitter		Google		GPSS	
	(1) Without Controls	(2) With Controls	(3) Without Controls	(4) With Controls	(5) Without Controls	(6) With Controls
Post Protest × Treatment	0.278***	0.222***	0.530***	0.096**	0.004	-0.006
	(0.044)	(0.069)	(0.040)	(0.046)	(0.007)	(0.006)
N	922,908	915,222	149,520	148,096	128,969	128,228
Time Window	2 Weeks	2 Weeks	2 Weeks	2 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)). The treatment is the number of protesters as a share of county population, standardized to take a mean of 0 and a standard deviation of 1 for each movement. We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3 – Protests and Opinions: Difference-in-Differences, Continuous Treatment

	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 × Treatment	0.000	-0.000	-0.001***	-0.001**	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	2,259,910	2,253,411	4,511,747	4,498,659	5,630,336	5,609,279
Time Window	6 Months	6 Months	6 Months	6 Months	1 Year	1 Year

Notes: This table reports difference-in-differences estimates corresponding to equation (4), before and after controlling for county characteristics interacted with time ($Post_{tm} \times \text{C}_{cm}$ in equation (4)). The treatment is the number of protesters as a share of county population, standardized to take a mean of 0 and a standard deviation of 1 for each movement. We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

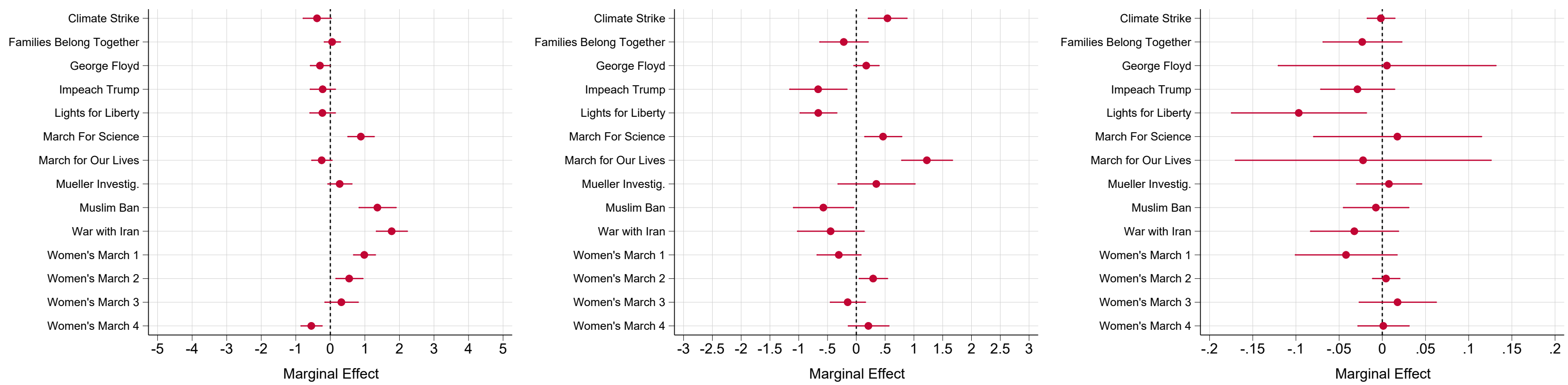
Table A4 – Protests and Political Attitudes: Difference-in-Differences, Continuous Treatment

	Trump		Turnout		Presidential Approval	
	(1) Without Controls	(2) With Controls	(3) Without Controls	(4) With Controls	(5) Without Controls	(6) With Controls
Post Protest × Treatment	-0.000	-0.000*	-0.000	0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
N	865,143	862,612	831,913	829,455	932,847	930,167

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)). The treatment is the number of protesters as a share of county population, standardized to take a mean of 0 and a standard deviation of 1 for each movement. We report standard errors in parentheses, the number of observations, and the time window over which the regression is estimated. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A10 – Heterogeneity by Movement: Salience, Difference-in-Differences With County Controls

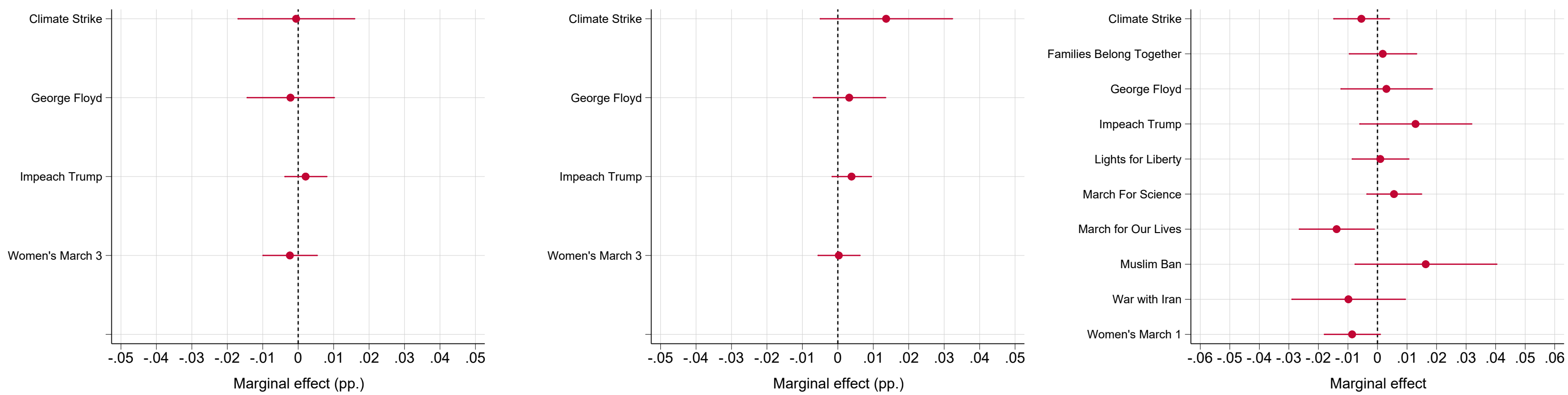
(a) Twitter (b) Google (c) GPSS



Notes: The figure reports heterogeneous treatment effects by movement for the difference-in-differences specification. Each panel reports point estimates and 95% robust confidence intervals for ϕ in equation (4). Estimates control for county-level Democratic vote shares in 2016, county-level Black population shares in 2019, and county-level college graduate population shares in 2019 interacted with time.

Figure A11 – Heterogeneity by Movement: Opinions, Difference-in-Differences With County Controls

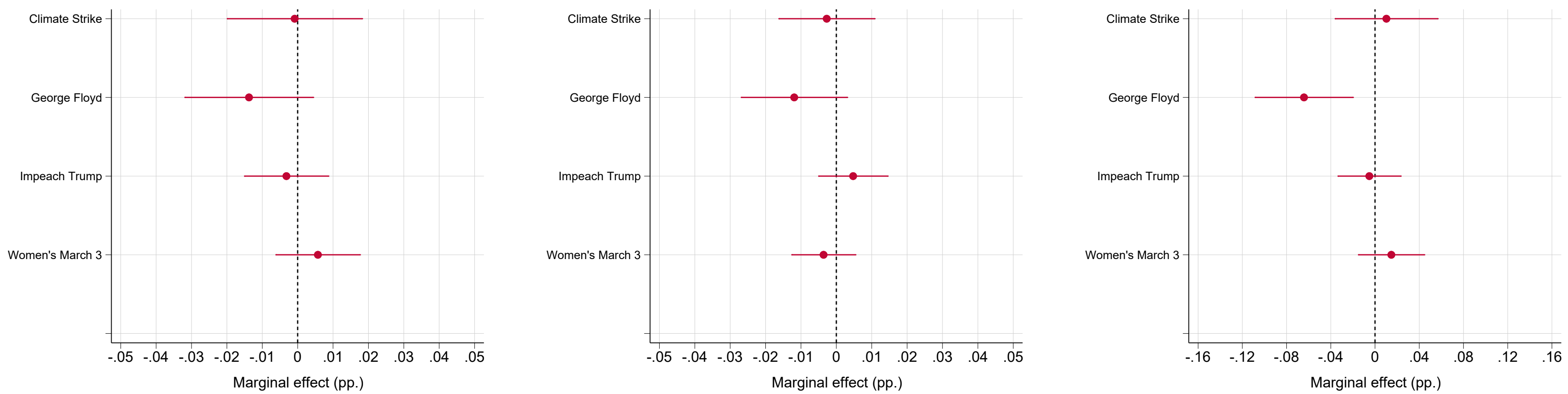
(a) Nationscape, Any Opinion (b) Nationscape, Opinion (c) CCES



Notes: The figure reports heterogeneous treatment effects by movement for the difference-in-differences specification. Each panel reports point estimates and 95% robust confidence intervals for ϕ in equation (4). Estimates control for county-level Democratic vote shares in 2016, county-level Black population shares in 2019, and county-level college graduate population shares in 2019 interacted with time.

Figure A12 – Heterogeneity by Movement: Political Attitudes, Difference-in-Differences With County Controls

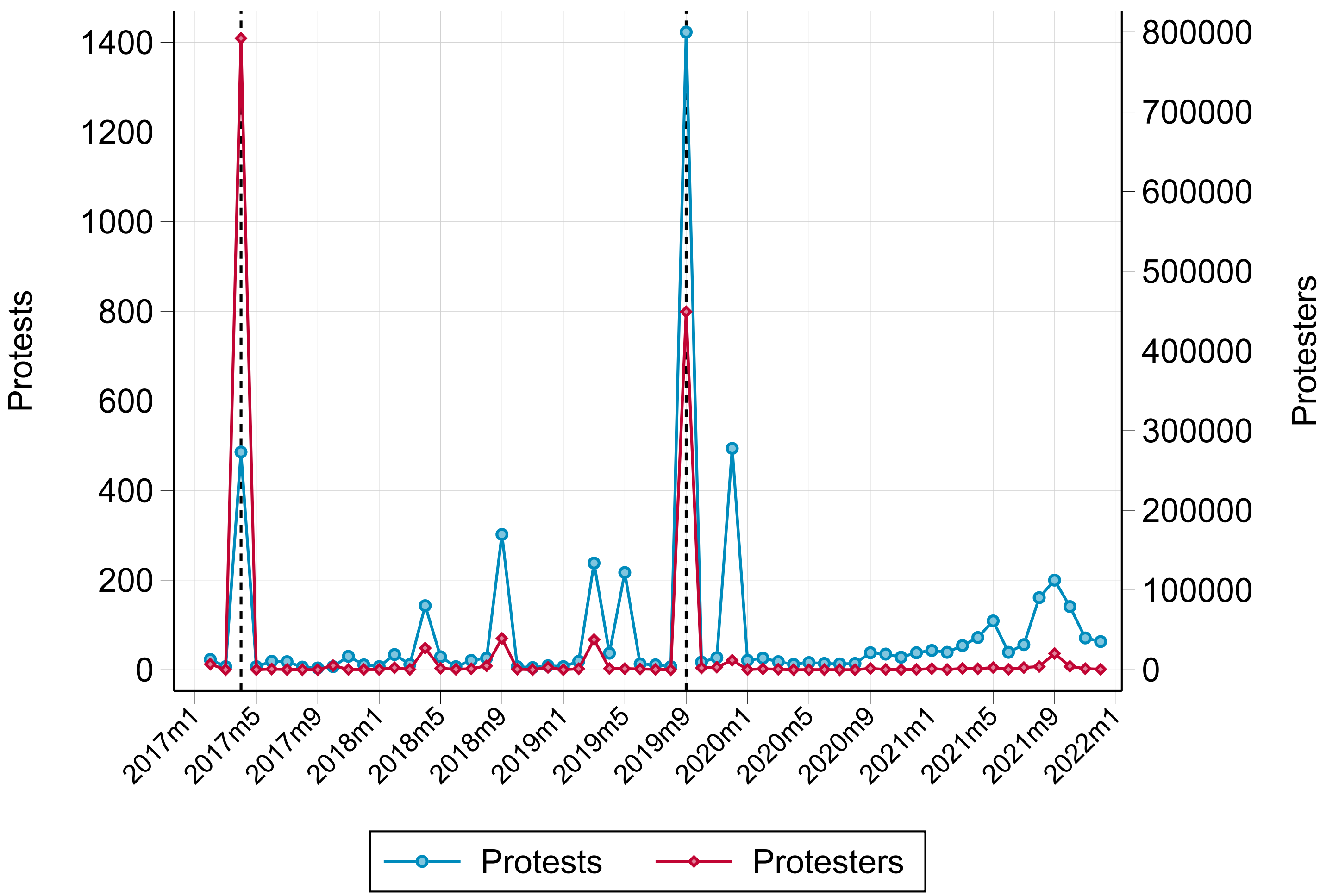
(a) Trump (b) Turnout (c) Presidential Approval



Notes: The figure reports heterogeneous treatment effects by movement for the difference-in-differences specification. Each panel reports point estimates and 95% robust confidence intervals for ϕ in equation (4). Estimates control for county-level Democratic vote shares in 2016, county-level Black population shares in 2019, and county-level college graduate population shares in 2019 interacted with time.

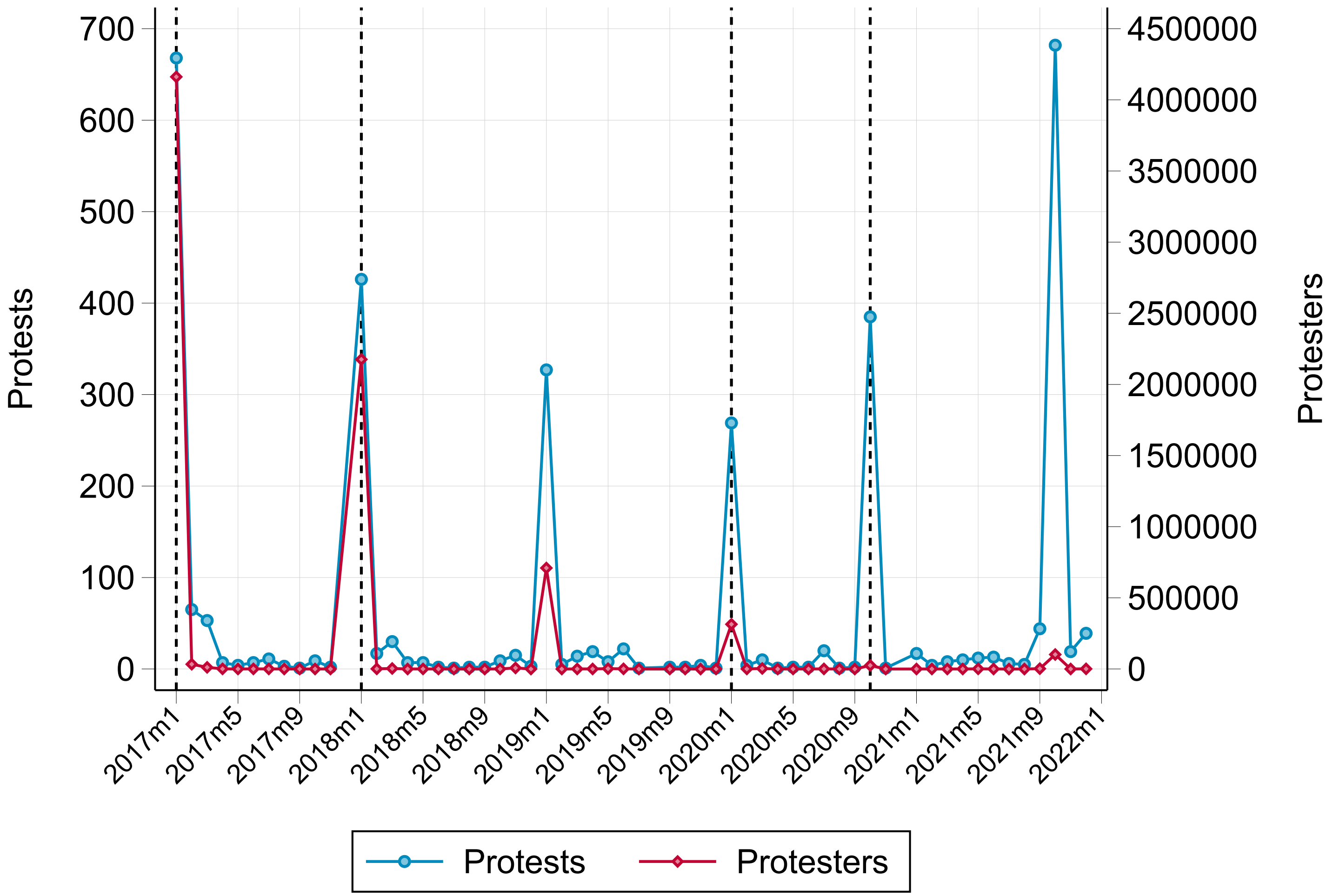
B. Protest Data

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



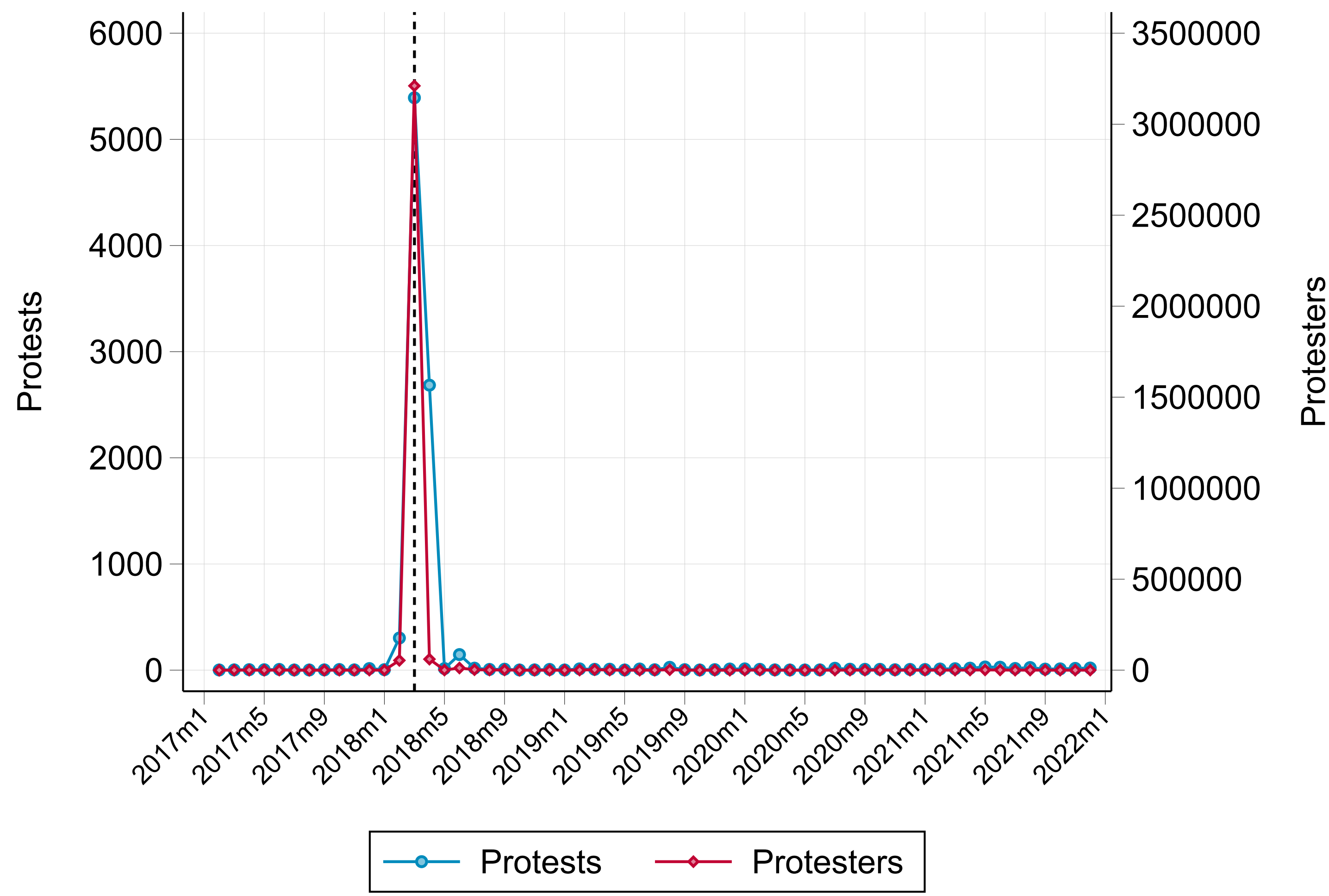
Notes: The figure reports the monthly number of protests (left axis) and number of protest participants (right axis) in the United States over the 2017-2021 period.

Figure B2 – Protests in the United States, 2017-2021: Gender Equality



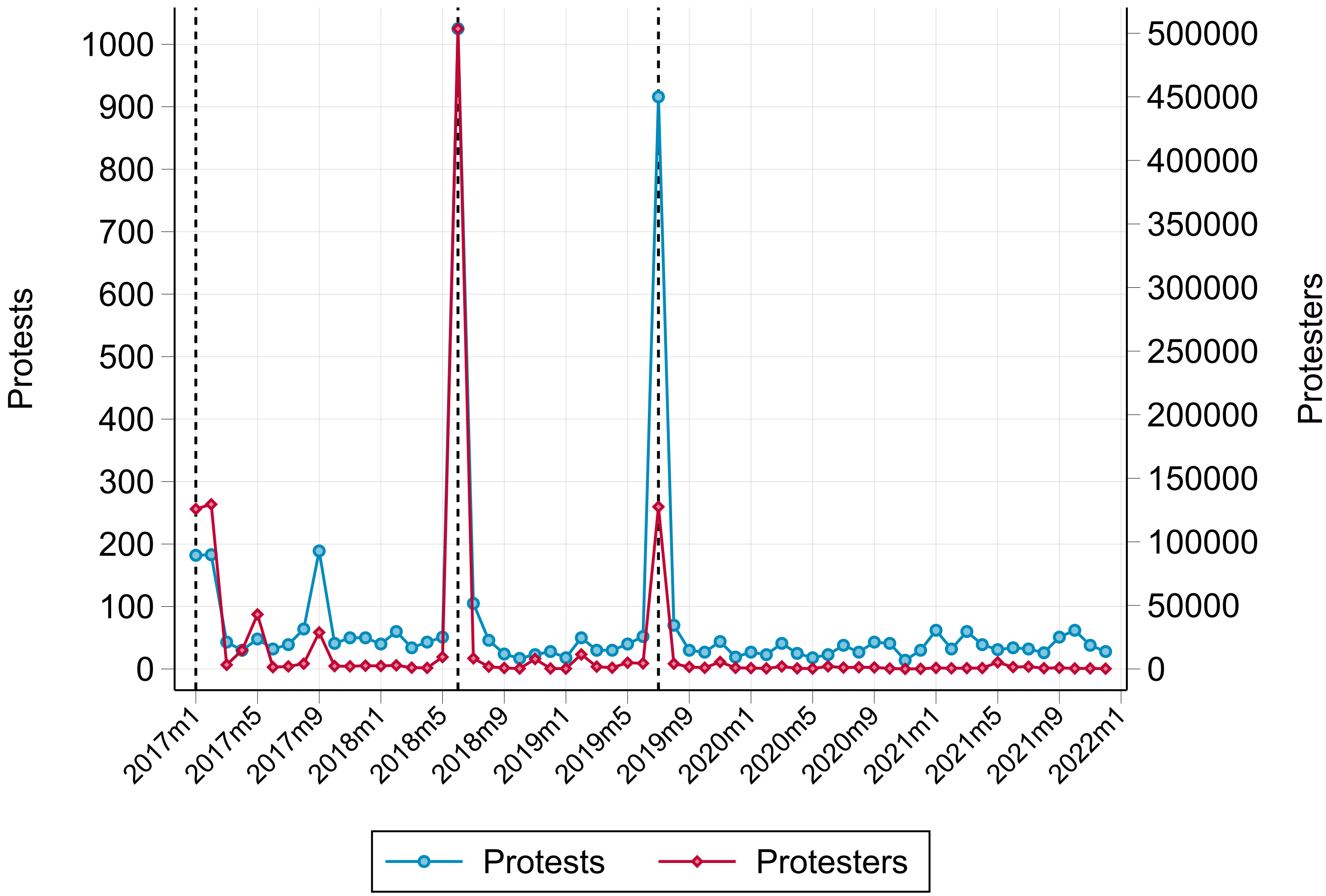
Notes: The figure reports the monthly number of protests (left axis) and number of protest participants (right axis) in the United States over the 2017-2021 period.

Figure B3 – Protests in the United States, 2017-2021: Gun Control



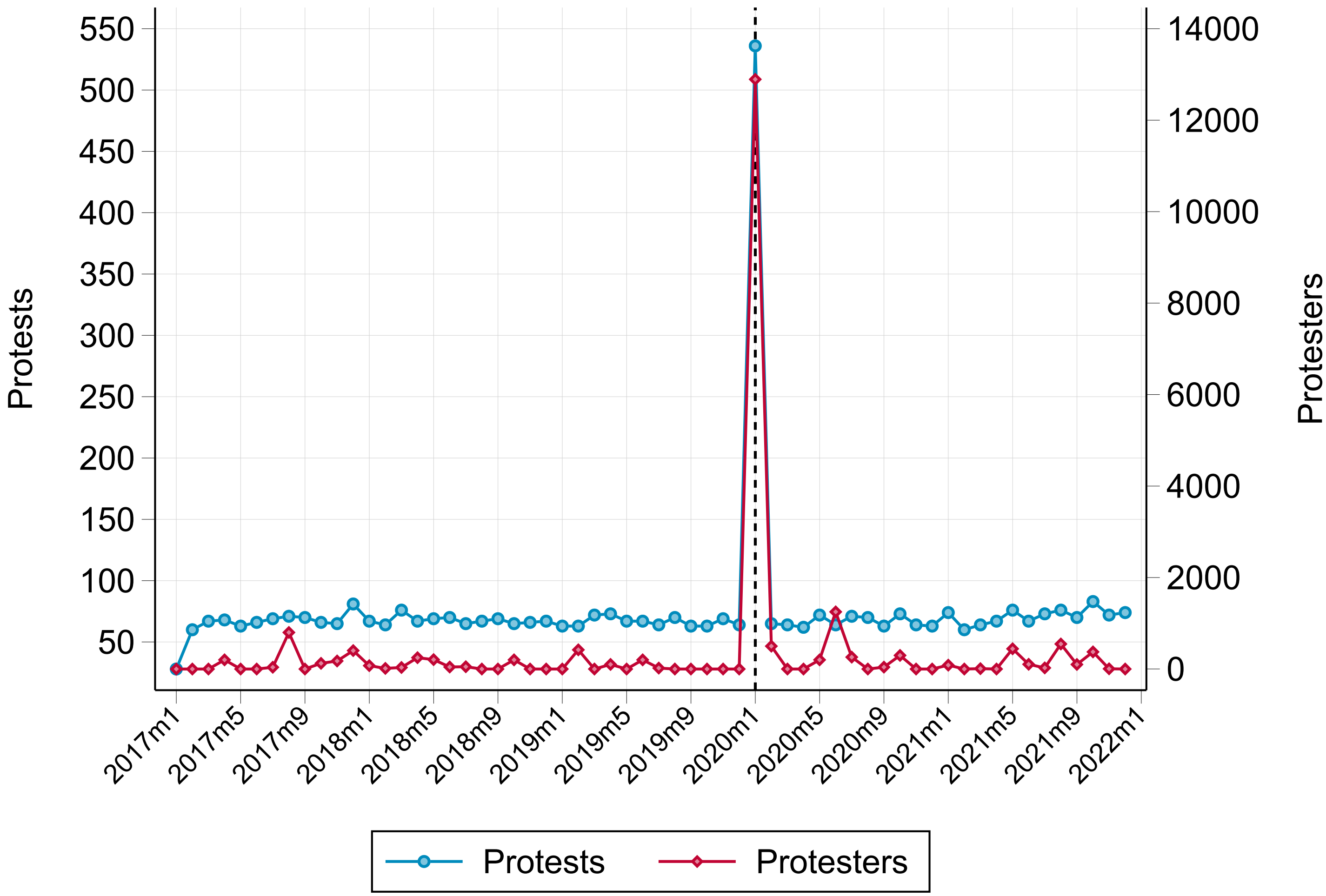
Notes: The figure reports the monthly number of protests (left axis) and number of protest participants (right axis) in the United States over the 2017-2021 period.

Figure B4 – Protests in the United States, 2017-2021: Immigration



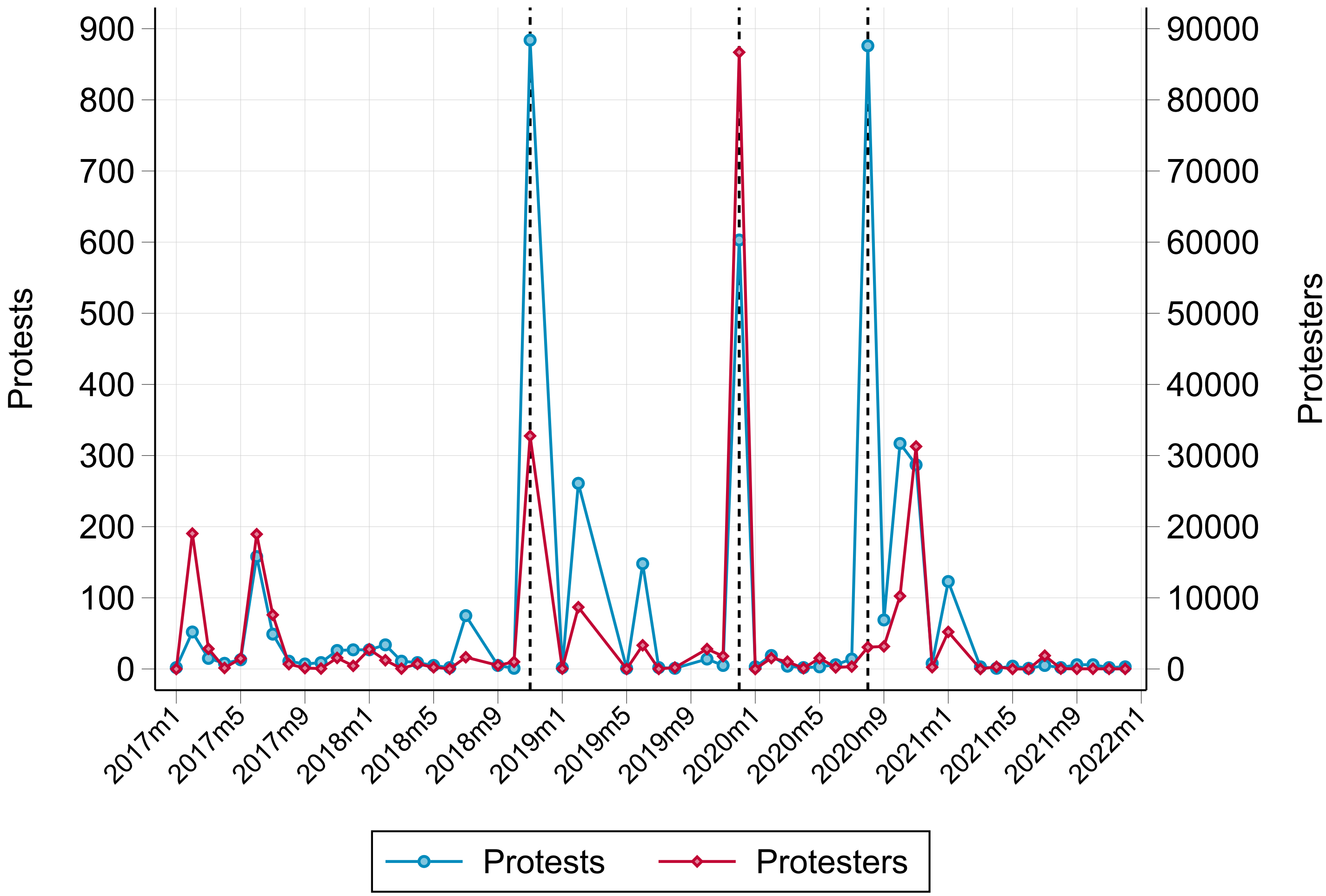
Notes: The figure reports the monthly number of protests (left axis) and number of protest participants (right axis) in the United States over the 2017-2021 period.

Figure B5 – Protests in the United States, 2017-2021: International Affairs



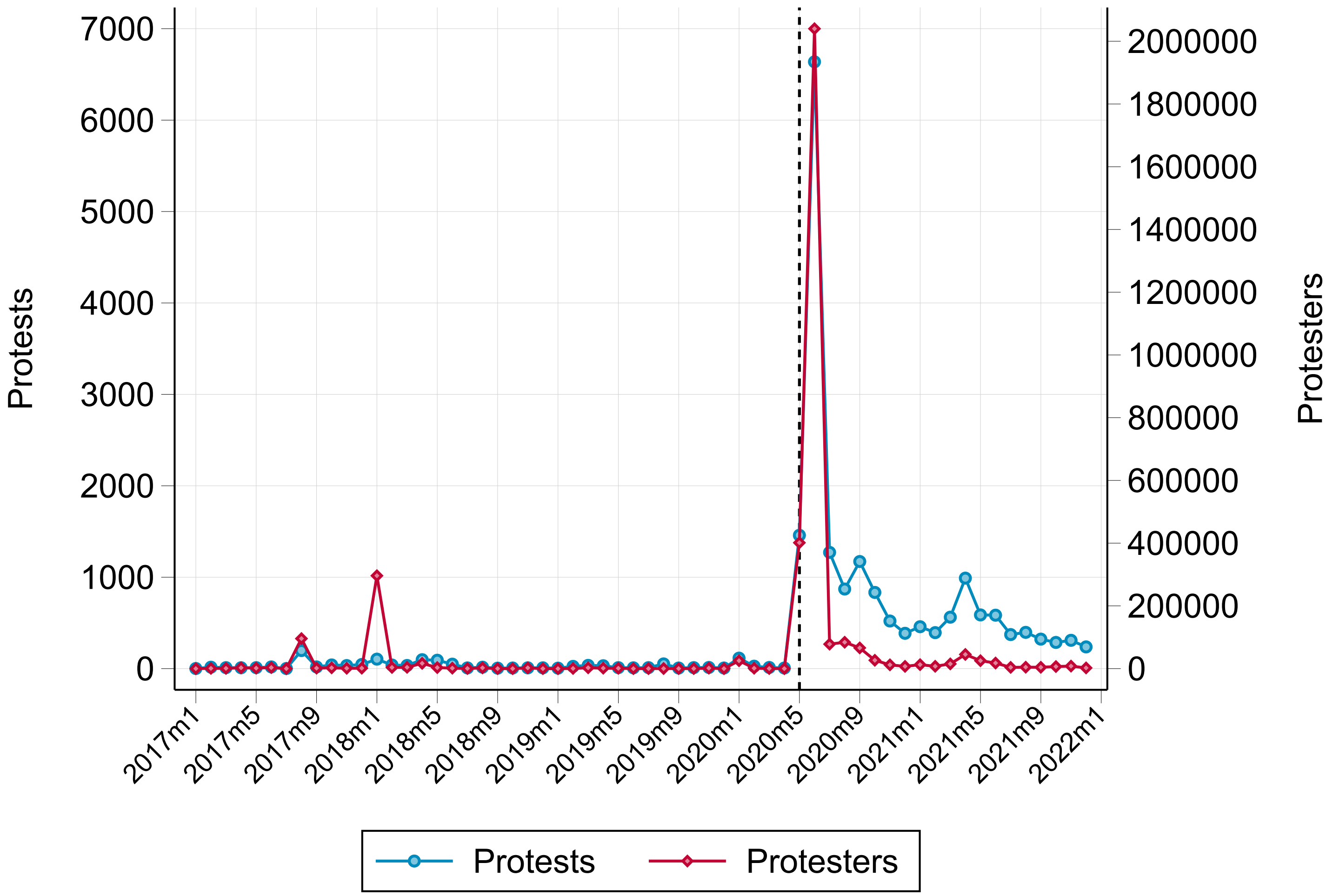
Notes: The figure reports the monthly number of protests (left axis) and number of protest participants (right axis) in the United States over the 2017-2021 period.

Figure B6 – Protests in the United States, 2017-2021: National Politics



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.

Figure B7 – Protests in the United States, 2017-2021: Racism



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	24,869	3,786,081
Gun Control	10,388	3,493,235
National Politics	9,712	1,678,828
Gender Equality	8,049	8,456,764
Environmental Protection	7,037	1,529,120
International Affairs	6,701	258,468
Immigration	5,756	1,297,414
Other	20,010	6,356,234

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

C. Twitter and Google Data

Table C1 – Twitter and Google Keyword Dictionary

Topic	Movement	Keyword
Environmental Protection	Climate Strike	biodiversity
Environmental Protection	Climate Strike	climate
Environmental Protection	Climate Strike	climate action
Environmental Protection	Climate Strike	climate change
Environmental Protection	Climate Strike	climate justice
Environmental Protection	Climate Strike	climate march
Environmental Protection	Climate Strike	climate strike
Environmental Protection	Climate Strike	deforestation
Environmental Protection	Climate Strike	environmental justice
Environmental Protection	Climate Strike	fossil fuels
Environmental Protection	Climate Strike	global warming
Environmental Protection	Climate Strike	green new deal
Environmental Protection	Climate Strike	greenhouse effect
Environmental Protection	Climate Strike	greenhouse gas
Environmental Protection	Climate Strike	greta thunberg
Environmental Protection	Climate Strike	nuclear
Environmental Protection	Climate Strike	paris agreement
Environmental Protection	Climate Strike	pollution
Environmental Protection	Climate Strike	renewable resources
Environmental Protection	Climate Strike	sustainable
Environmental Protection	March For Science	neil degrasse tyson

Environmental Protection	March For Science	bill nye
Environmental Protection	March For Science	biodiversity
Environmental Protection	March For Science	climate
Environmental Protection	March For Science	climate action
Environmental Protection	March For Science	climate change
Environmental Protection	March For Science	climate march
Environmental Protection	March For Science	deforestation
Environmental Protection	March For Science	environmental justice
Environmental Protection	March For Science	environmental protection agency
Environmental Protection	March For Science	fossil fuels
Environmental Protection	March For Science	global warming
Environmental Protection	March For Science	greenhouse effect
Environmental Protection	March For Science	greenhouse gas
Environmental Protection	March For Science	march for science
Environmental Protection	March For Science	nuclear
Environmental Protection	March For Science	nye
Environmental Protection	March For Science	paris agreement
Environmental Protection	March For Science	pollution
Environmental Protection	March For Science	renewable resources
Environmental Protection	March For Science	science
Environmental Protection	March For Science	science guy
Environmental Protection	March For Science	sustainable
Gender Equality	Women’s Marches	roe wade
Gender Equality	Women’s Marches	abortion
Gender Equality	Women’s Marches	abortion rights

Gender Equality	Women’s Marches	domestic violence
Gender Equality	Women’s Marches	feminism
Gender Equality	Women’s Marches	feminist
Gender Equality	Women’s Marches	lgbtq
Gender Equality	Women’s Marches	pro choice
Gender Equality	Women’s Marches	pro life
Gender Equality	Women’s Marches	women
Gender Equality	Women’s Marches	women rights
Gender Equality	Women’s Marches	women’s march
Gun Control	March for Our Lives	assault weapon
Gun Control	March for Our Lives	bump stock
Gun Control	March for Our Lives	bump stocks
Gun Control	March for Our Lives	gun control
Gun Control	March for Our Lives	gun laws
Gun Control	March for Our Lives	gun rights
Gun Control	March for Our Lives	gun safety
Gun Control	March for Our Lives	gun violence
Gun Control	March for Our Lives	march for our lives
Gun Control	March for Our Lives	march life
Gun Control	March for Our Lives	march lives
Gun Control	March for Our Lives	national rifle association
Gun Control	March for Our Lives	never again
Gun Control	March for Our Lives	nra
Gun Control	March for Our Lives	rifle
Gun Control	March for Our Lives	second amendment

Gun Control	March for Our Lives	weapon
Immigration	Families Belong Together	daca
Immigration	Families Belong Together	ice
Immigration	Families Belong Together	abolish ice
Immigration	Families Belong Together	border wall
Immigration	Families Belong Together	children jail
Immigration	Families Belong Together	children separated
Immigration	Families Belong Together	concentration camps
Immigration	Families Belong Together	deportation
Immigration	Families Belong Together	detention camps
Immigration	Families Belong Together	families belong together
Immigration	Families Belong Together	families together
Immigration	Families Belong Together	separation families
Immigration	Families Belong Together	zero tolerance
Immigration	Lights for Liberty	daca
Immigration	Lights for Liberty	ice
Immigration	Lights for Liberty	border wall
Immigration	Lights for Liberty	concentration camps
Immigration	Lights for Liberty	deportation
Immigration	Lights for Liberty	detention camps
Immigration	Lights for Liberty	lights for liberty
Immigration	Lights for Liberty	lights liberty
Immigration	Lights for Liberty	s386
Immigration	Lights for Liberty	zero tolerance
Immigration	Muslim Ban	immigration ban

Immigration	Muslim Ban	immigration order
Immigration	Muslim Ban	muslim ban
Immigration	Muslim Ban	no ban
Immigration	Muslim Ban	no fear
Immigration	Muslim Ban	no hate
Immigration	Muslim Ban	no wall
Immigration	Muslim Ban	unamerican
Immigration	Muslim Ban	welcome
International Affairs	War with Iran	iran
International Affairs	War with Iran	no war
International Affairs	War with Iran	nuclear
International Affairs	War with Iran	out of iraq
International Affairs	War with Iran	sanctions on iran
International Affairs	War with Iran	soleimani
International Affairs	War with Iran	war with iran
National Politics	Impeach Trump	above the law
National Politics	Impeach Trump	impeach
National Politics	Impeach Trump	impeach trump
National Politics	Impeach Trump	remove
National Politics	Impeach Trump	trump
National Politics	Mueller Investig.	above the law
National Politics	Mueller Investig.	mueller
National Politics	Mueller Investig.	mueller probe
National Politics	Mueller Investig.	no one is above the law
National Politics	Mueller Investig.	protect mueller

National Politics	Mueller Investig.	robert mueller
National Politics	Mueller Investig.	russia investigation
Racism	George Floyd	all lives matter
Racism	George Floyd	bipoc
Racism	George Floyd	blue lives matter
Racism	George Floyd	george floyd
Racism	George Floyd	white lives matter
Racism	George Floyd	antiracism
Racism	George Floyd	back the blue
Racism	George Floyd	black lives matter
Racism	George Floyd	civil rights
Racism	George Floyd	defund police
Racism	George Floyd	defund the police
Racism	George Floyd	justice
Racism	George Floyd	police brutality
Racism	George Floyd	police lives matter
Racism	George Floyd	race
Racism	George Floyd	racial
Racism	George Floyd	racial justice
Racism	George Floyd	racism
Racism	George Floyd	slavery
Racism	George Floyd	support police
Racism	George Floyd	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	49%
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 Obama	41%
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%
Gender Equality	Allow employers to decline coverage of abortions in insurance plans	58%
Gender Equality	Prohibit the expenditure of funds authorized or appropriated by federal law for any abortion	56%

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.