Elite Cues and Non-compliance*

Zachary P Dickson[§] & **Sara B Hobolt**[†]

[§] London School of Economics z.dickson@lse.ac.uk
[†] London School of Economics s.b.hobolt@lse.ac.uk

Abstract

Political leaders increasingly use social media to speak directly to voters, but the extent to which elite cues shape offline political behavior remains unclear. In this article, we study the effects of elite cues on non-compliant behavior, focusing on a series of controversial tweets sent by US President Donald Trump calling for the "liberation" of Minnesota, Virginia and Michigan from state and local government COVID-19 restrictions. Leveraging the fact that Trump's messages exclusively referred to three specific US states, we adopt a generalized difference-in-differences design relying on spatial variation to identify the causal effects of the targeted cues. Our analysis shows that the President's messages led to an increase in movement, a decrease in adherence to stay-at-home restrictions, and an increase in arrests of white Americans for crimes related to civil disobedience and rebellion. These findings demonstrate the consequences of elite cues in polarized environments.

***Acknowledgements:** *The authors are grateful for generous support from the Volkswagen Foundation via The COVIDEU Project grant (Grant no. 9B051). Previous versions of this paper have benefited from the helpful comments of Florian Foos, Heike Klüver, Mik Laver, Toni Rodon, Jae-Jae Spoon, and Mads Thau as well as the reviewers and editors of the APSR. We are also thankful for comments and feedback from participants at the LSE Political Behavior Seminar, Nuffield Political Science Seminar, Polmeth Europe and both the Midwest and the European Political Science Association General Conferences.*

1 Introduction

Political elites are increasingly using social media platforms as a primary channel for communication with the public, a trend accentuated by the growing reliance of citizens on these platforms for political information (Geiger 2019). This shift provides political leaders with an opportunity to engage directly with their supporters. The significance of such messages are particularly pronounced during periods of crisis, when citizens turn to their leaders for guidance. In these crisis moments, it is reasonable to anticipate that messages from political figures would seek to foster unity and encourage citizen compliance with policy responses. However, when political polarization is high, elite communication can have the opposite effect and lead to greater public non-compliance and even defiance. This article investigates the impact of polarizing messages from political elites on behavior in the context of the COVID-19 pandemic.

There is a rich body of literature demonstrating that elite cues can have significant effects on citizens' political behavior and attitudes (Lupia and McCubbins 1998; Samuels and Zucco 2014; Lupia 1994; Brader and Tucker 2012). A consistent finding is that citizens tend to follow the cues of their preferred party or politicians when political elites are polarized (Leeper and Slothuus 2014). In the specific context of the COVID-19 pandemic, studies have shown that consistent and unified government messaging and public trust in governments led to higher levels of compliance with health-related measures (Jørgensen, Bor, and Petersen 2021; Jørgensen et al. 2021; Anderson and Hobolt 2022; Klüver et al. 2021). However, evidence from the United States suggests that not only was elite messaging on the COVID-19 pandemic highly polarized, there were also stark partisan differences in both support for and compliance with COVID-related measures among Republicans and Democrats (Gadarian, Goodman, and Pepinsky 2022; Allcott et al. 2020; Grossman et al. 2020; Roberts and Utych 2021; Bisbee and Lee 2022; Green et al. 2020).

This raises the question of whether specific elite messages can change people's behavior and even encourage non-compliance among partisan supporters. While the literature has shown that citizens' attitudes are often shaped by the cues of their preferred politicians, we know much less about whether specific elite cues – such as messages on social media – can cause a tangible change in the behavior of partisan followers. In this article, we address this question by examining the effects of President Trump's polarizing messages on non-compliance with state and local COVID-19 restrictions in the early days of the COVID-19 pandemic.

Specifically, we analyze the effects of a series of controversial tweets sent by President Trump calling for the "liberation" of Minnesota, Virginia and Michigan from COVID-19 restrictions at the height of the first wave of the pandemic in 2020. We leverage the fact that the President's messages exclusively referred to three specific US states, which allows us to adopt a difference-in-differences design relying on spatial and temporal discontinuities in the targeting and timing of the messages to identify and estimate the causal effects of the President's calls for liberation on non-compliant and rebellious behavior.

Our analysis proceeds in several steps. We start by examining the nature of the responses to the President's messages on social media, using topic models that highlight anti-government, radical and even violent rhetoric associated with the messages. We supplement this descriptive analysis by using geographic Internet search data, demonstrating the widespread impact of the messages on the daily search trends around the nation, with a greater concentration in the states targeted in the President's calls for liberation. We then turn to the primary analysis of the effects of the messages on non-compliant behavior. Using daily, county-level mobility data from Meta (Meta 2022) and Google (Google 2020), we find that the President's messages led to an increase in movement and a reduction in adherence to stay-at-home restrictions in Republican-majority counties in the targeted states. We show that these effects are not observed in Democratic-majority counties, nor were they driven simply by rebellion in states with Democratic governors. In other words, we find robust evidence that Trump's calls to action increased non-compliant behavior among supporters in the form of changes in mobility in the days following the messages.

We then investigate the spillover effects of the polarizing cues, focusing on more extreme forms of non-compliant behavior resulting in criminal arrests. Relying on daily arrests data from the FBI's National Incident-Based Reporting System (FBI 2022), we find that the President's messages were not only associated with anti-government rebellion and violent rhetoric on social media, they were also followed by an increase in arrests for crimes related to general disorder and rebellion – including assault, disorderly conduct, and vandalism – in the targeted states. Notably, we document this increase exclusively among white Americans, illustrating the heterogeneous effects of President Trump's calls to action. Our results are robust to a number of alternative explanations, specifications and estimation strategies.

This article thus makes three key contributions to the literature on elite cues. First, we provide robust causal evidence for the effects of elite cues on actual behavior across multiple outcomes. While there is a large body of literature demonstrating the effects of elite cues in experimental settings, studies have typically focused on citizens' self-reported preferences or attitudes (Tappin 2022; Druckman, Peterson, and Slothuus 2013; Slothuus and Bisgaard 2021). Our study provides an important test of whether elite cues on social media can not only shape citizens' support for policies, but also bring about changes in real-world behavior.

Second, our findings demonstrate that political elites can motivate behavioral changes by speaking directly to a subset of their supporters. While several studies have documented differences in behavior between Republicans and Democrats during the pandemic (Bisbee and Lee 2022; Grossman et al. 2020), our findings demonstrate heterogeneity in the effect of the cues across geographic lines as well. Specifically, we document that the President's messages caused an increase in non-compliant behavior in Republican-majority counties in the targeted states when compared only to Republican-majority counties elsewhere around the country. This contributes to the literature on micro-targeting by elites, as it shows that elites can strategically target their messages to specific subsets of their supporters.

Finally, our findings illustrate the substantive effects that polarizing elite messages on social media can have on real-world behavior in a crisis, even when such behavior is potentially costly to the individual. The context of the pandemic is particularly revealing as it allows us to demonstrate that Trump's messages mobilized citizens to act in ways that go against official rules and guidance, even when there were potential costs associated with breaking such rules, including personal health risks.

2 Elite Cues and Public Compliance

"Trump's practice of charismatic populism portrayed him as uniquely knowledgeable, with a particular authority that other politicians and health leaders lacked...he demanded the media spotlight" write Gadarian, Goodman and Pepinsky in their authoritative account of the politics of the pandemic in the US, concluding that "Trump's decisions made the pandemic worse" (Gadarian, Goodman, and Pepinsky 2022, 273–74). Studies have argued that Trump's leadership worsened the outcome of the pandemic in the US in a number of ways, including encouraging less social distancing (Roberts and Utych 2021; Grossman et al. 2020; Bisbee and Lee 2022), reducing mask wearing (Hahn 2021), and undermining trust in science agencies (Hamilton and Safford 2021; Gadarian, Goodman, and Pepinsky 2022).

While there is little doubt that Trump was a highly unusual leader and conspicuous media presence, these claims about how he shaped pandemic outcomes raise broader questions about the ways in which the messages of political elites can influence outcomes in moments of crisis. In this article, we are not focusing on the effect of policy choices, but more specifically on the extent to which elite messaging on social media can influence the behavior of citizens. Particularly, we are interested in identifying the causal effects of specific polarizing elite messages opposing COVID-related restrictions on citizens' adherence to such restrictions and, in turn, on more radical instances of non-compliance.

There is a large body of literature demonstrating that elite cues can have significant effects on citizens' behavior and attitudes, as well as their support for public policies. Messages from political actors are among the most widely available and influential information shortcuts in politics, and individuals respond to cues based on their perceived credibility and trustworthiness (Arceneaux 2008; Arceneaux and Johnson 2013; Leeper and Slothuus 2014; Lupia and McCubbins 1998; Tesler 2012). Social media have made it easier for politicians to address their supporters directly. In a polarized political context, citizens will often interpret cues from the perspective of in-groups and out-groups. Specifically, the literature shows that citizens tend to follow the cues of their preferred party or politicians (Nicholson 2012; Brader and Tucker 2012; Samuels and Zucco 2014; Tappin, Berinsky, and Rand 2023). In the US, partisan identities are powerful social identities that provide a lens through which people observe the world (Campbell et al. 1960; Green, Palmquist, and Schickler 2004; Iyengar and Simon 2000; Theodoridis 2017; Mason 2018). Partisan cues thus shape how citizens perceive policies and the political world and have been shown to activate partisan biases even on traditionally nonpartisan issues (Druckman 2001; Kam 2005).

In what ways do elite cues matter during a crisis? We might expect elite cues to be particularly important in moments of heightened uncertainty as the one experienced in early-2020 at the start of the COVID-19 pandemic. As with any crisis situation, the pandemic presented citizens with the daunting challenge of navigating a new, complex and changing information environment. In crises in general, citizens will often "rally 'round the flag", and evidence from the first phase of the pandemic suggests that citizens around the world became more supportive of and receptive to their political leaders (De Vries et al. 2021; Baekgaard et al. 2020; Bol et al. 2021; Lupu and Zechmeister 2021). However, unlike much of the world – where mainstream politicians sought to present a united front in response to the pandemic (Barari et al. 2020; Anderson and Hobolt 2022; De Vries et al. 2021) – the response in the US was deeply politicized and polarized along partisan lines, with different positions taken by Democratic and Republican party leaders both on the threat posed by COVID-19 and the appropriate response (Allcott et al. 2020; Roberts and Utych 2021; Bisbee and Lee 2022). For example, Green et al. (2020) analyzed the rhetoric surrounding COVID-19 by Congress members and show that while Democrats highlighted the public health threat, Republicans placed greater emphasis on China and businesses. Likewise, Gadarian, Goodman, and Pepinsky (2022) describe President Trump's response to the pandemic as polarizing and divisive.

In such a polarized environment, we would expect the effect of elite cues to be conditioned by the partisanship of the receiver. In other words, we would expect Republican partisans to be more receptive to the messages of Republican politicians, such as Donald Trump, whereas Democratic partisans would be less receptive and may even shift their opinion in the opposite direction. Indeed, studies have shown that Republican partisans were generally less supportive of COVID-19 measures and less likely to comply (Allcott et al. 2020; Gadarian, Goodman, and Pepinsky 2022). Survey evidence shows that Democrats were typically more likely to see COVID-19 as a major threat and more supportive than Republicans in their stated support and willingness to comply with such measures (Van Green and Tyson 2020; Gadarian, Goodman, and Pepinsky 2022). Moreover, more Republican counties typically displayed lower levels of compliance with social distancing measures than Democratic counties, further highlighting a partisan disconnect (Roberts and Utych 2021; Bisbee and Lee 2022).

Yet, while the evidence reveals clear differences in partisan attitudes and behaviors in the US during the crisis, it is challenging to examine empirically whether these differences are caused by elite rhetoric. Some studies have made important contributions to examining the role of elite cues during the pandemic. Bursztyn et al. (2020) use county-level variation in television consumption of two Fox News programs (Sean Hannity and Tucker Carlson) and find that differences in viewership predict differences in COVID-related health outcomes. Two other important studies examine the effect of elite cues on compliance of social distancing rules more directly. Grossman et al. (2020) show that a governor's tweets encouraging social distancing have a meaningful impact on social distancing behaviors, and the effect is larger in Democrat-leaning counties. Similarly, Bisbee and Lee (2022) reveal that the partisan gap in Americans' social distancing behaviors is exaggerated by President Trump's pronouncements on the seriousness of the virus. They leverage changes in Trump's evaluation of the pandemic revealed in his tweets to show an increase in mobility in Republican-leaning counties when Trump issued anti-lockdown tweets.

We build on these studies, and the wider literature on elite cues, to examine the effects of polarizing elite rhetoric on citizens' behaviour. Specifically, our focus is on President Trump's calls for the "liberation" of Michigan, Minnesota and Virginia at the height of the initial outbreak of COVID-19. Given that Trump's liberate tweets targeted three specific states, and were so widely read and commented upon, we focus on estimating the causal effects of the messages on compliance in those states compared to non-targeted states. Our general expectation is that non-compliance increased in the targeted states.

Building on the literature on elite cues discussed above, we can develop specific expectations about the effects of Trump's messages on citizens' behavior during the pandemic. We argue that the impact of elite cues on citizen behavior is conditional on the specific context. The context of the COVID-19 pandemic had two core features that are relevant to the anticipated effects of elite cues. First, it was a time of great uncertainty among the public about the nature and risks of COVID-19, as well as how to respond to these risks. This uncertainty meant that people were likely more receptive to elite cues, as they lacked strong predispositions about how to behave in a pandemic and were likely seeking further information and guidance. Second, the pandemic in the US was characterized – as discussed above – by a highly polarized political environment with conflicting messages by Republicans and Democrats. In such a polarized environment, we expect that when partisans receive messages from a recognizable partisan source, they will evaluate the message through a partisan lens. If the messenger and recipient share a partisan identity, the recipient will trust the message and respond accordingly; whereas, if the messenger and recipient lie on opposite sides of the partisan divide, the recipient will mistrust the source and reject the message. This means that we expect Republicans to be receptive and respond to the messages of President Trump, while we would expect Democrats to reject the messages.

This leads us to the following hypotheses:

> *H1:* Individuals in states targeted by Trump's messages are less compliant with COVID-19 stay-at-home orders in the days following the tweets than individuals in states that were not targeted in the messages.

> *H1a:* The effects of Trump's messages on non-compliance are observed in predominantly Republican counties.

We go one step further to examine the effects of President Trump's calls for liberation not just on compliance with social distancing measures, but also with more extreme forms of non-compliant behavior. Specifically, we examine the degree to which Trump's messages inspired criminal activities more broadly. Evidence suggests that COVID-19 crime rates fell in the first phase of the pandemic, mainly attributed to the stay-at-home-orders in place that led to a drop in the types of minor offenses that are typically committed in the community in peer groups (Stickle and Felson 2020; Boman and Gallupe 2020). Studies in criminology have suggested that the lockdowns altered the social dynamics often associated with minor offending, as individuals (often young males) had less access to the peer groups in which criminal behavior often occurs (Boman and Gallupe 2020; Lopez and Rosenfeld 2021).

We would thus expect that if Trump's messages encouraged people *not* to comply with the stay-at-home orders, this could also spill over into other criminal activities – such as disorderly conduct, vandalism, destruction of property, and assault – in the targeted states. Similar to our expectations for mobility, we expect the effects of the cues on such non-compliant behavior to be concentrated only among individuals most receptive to Trump's messages, i.e. Republican partisans and Trump supporters. Since we do not know the partisan affiliation of individual arrestees (see below), we consider the degree to which effects are heterogeneous across racial groups. This is an admittedly crude measure; however, the literature consistently shows that non-white Americans are much less likely to be Republican partisans and Trump supporters compared to white Americans (Sides, Tesler, and Vavreck 2017). For example, a Pew Research

Center study shows that only 6% of Black voters and 28% of Hispanic voters supported Trump in 2016 compared to 54% of white voters (and 62% of white male voters) (Doherty, Kiley, and Johnson 2018). Considering these demographic patterns in voting behavior and support for Trump, we expect non-white voters in general to be less receptive to Trump's cues, and we would therefore expect Trump's cues to have a disproportionate effect on crime rates among white Americans. This leads to our final hypothesis:

> *H2:* Individuals in states targeted by Trump's messages are more likely to commit crimes in the days following the tweets than individuals in states that were not targeted in the messages. This effect is likely to be less pronounced for non-white compared to white individuals.

In the following section, we discuss the details and context of the specific messages before empirically testing the hypotheses.

2.1 President Trump's Calls for Liberation

On April 17, 2020, President Trump broadcast three separate messages to his 80+ million Twitter followers that read as follows: "LIBERATE MICHIGAN", "LIBERATE MINNESOTA", and "LIBERATE VIRGINIA" (Collins and Zadrozny 2020).[1] At that point in time, and in the surrounding days, each of the three states targeted by Trump were under stay-at-home mandates from state governments to slow the spread of the COVID-19 virus. Despite the President tending to downplay the threat posed by COVID-19 in early stages of the pandemic (Wolfe and Dale 2020), the President's calls for rebellion against state governments on April 17 were widely seen as a highly conspicuous policy reversal. Just one day previous on April 16, President Trump issued guidelines for phasing out the COVID-19 restrictions that expressed the administration's commitment to "empower Governors to tailor the phased reopening to address the situation in their state."[2] Moreover, only a few days prior he had spoken warmly about the state governors, describing relations in positive terms: "I'm proud to say that some of them [US governors], I think, are friends. In some cases, they're Democrats, but I think they like me, and

1. President Trump's full message to Virginia was "LIBERATE VIRGINIA, and save your great 2nd Amendment. It is under siege!"

2. President Donald J. Trump Is Beginning the Next Phase In Our Fight Against Coronavirus: Guidelines for Opening Up America Again *White House Archives*. April 16, 2020.

I actually like them."[3] The President's tweets thus constituted a sharp reversal, contradicting his previous expressions of warmth for the state governors and his administration's guidance that would "...allow governors to take a phased and deliberate approach to reopening their individual states."[4]

According to media reporting of the tweets, Trump's calls for liberation were widely seen as encouraging citizens to disobey the stay-at-home orders in place, and even as an incitement of violence and rebellion (Collins and Zadrozny 2020; Fallows 2020). The word *liberate*, which means to set free or deliver, carries specific connotations of rebellion and insurrection against unjust and oppressive rule. For this reason, many at the time interpreted the messages as a call for rebellion against state and local governments. For instance, former Assistant Attorney General for National Security Mary McCord stated that "it's not at all unreasonable to consider Trump's tweets about 'liberation' as at least tacit encouragement to citizens to take up arms against duly elected state officials of the party opposite his own" (McCord 2020).

To further examine how these messages were received by citizens, we analyzed the responses of individuals who engaged with them on Twitter. Hundreds of thousands of users liked, shared and replied to the liberate messages. Relying on topic models of the messages that "quote-tweeted" one of the three liberate messages, Figure 1 presents the top-10 most common topics.[5]

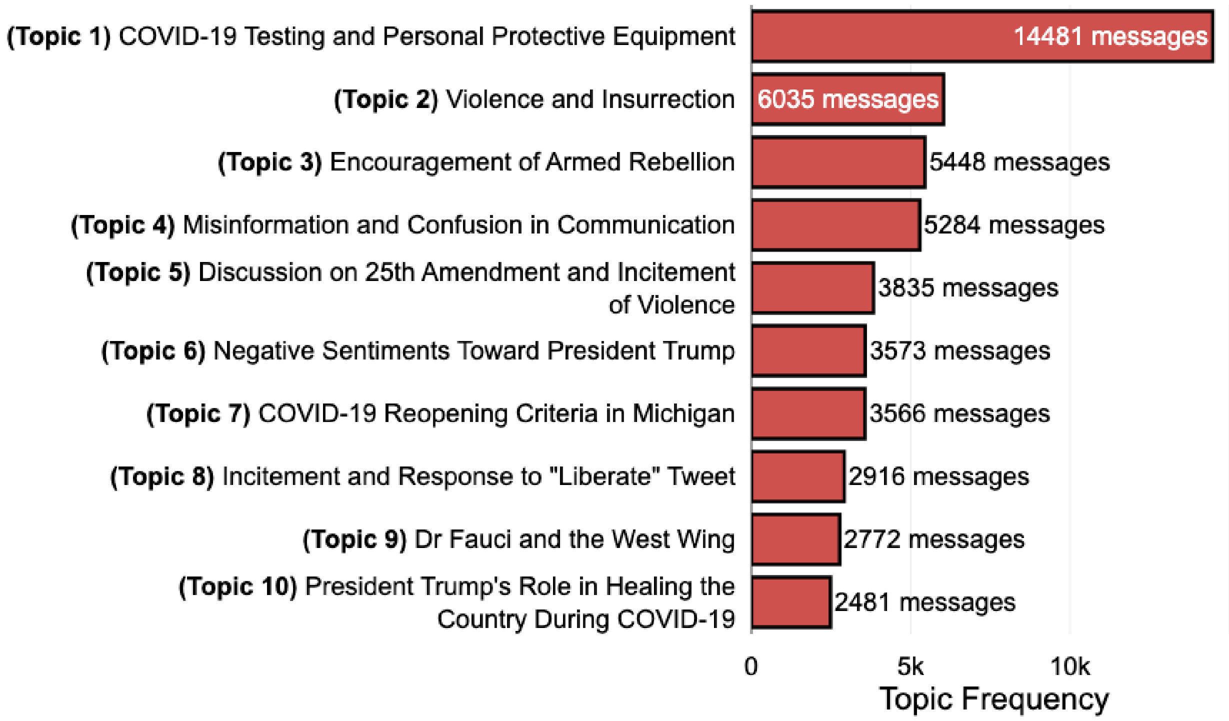
In Figure 1, the interpreted topics are presented, along with the number of messages that corresponds to the given topic. Calls for greater testing and personal protective equipment include the largest proportion of the messages, while calls for violence, rebellion and insurrection are also prominent. Additionally, many of the messages express opposition to the President's messages, with a significant number of messages conveying negative sentiments toward the President and calling for Trump to play a role in healing the nation. While the results of the topic model provide a high level description of the largest categories of specific underlying messages, they also mask some of the extreme content within many of the messages. For example, some specific messages include "Patriots it's time to hit the streets!" and "It is time to fight. Take your State back." Several messages also appear to interpret Trump's calls for liberation as an endorsement of the far-right extremist group "Boogaloo Boys" (Collins and

3. Remarks by President Trump in Press Briefing. *White House Archives*. April 14, 2020.

4. Remarks by President Trump, Vice President Pence, and Members of the Coronavirus Task Force in Press Briefing. *White House Archives*. April 16, 2020.

5. The topic model included 143,171 quote tweets. Further details of the topic model analysis are available in Appendix C.

Figure 1: Top-10 Topics of LIBERATE Quote Tweets



Note: Top-10 topics from 143,171 messages quote tweeting President Trump's 'Liberate' tweets. Further details about the topic model are provided in Appendix C.

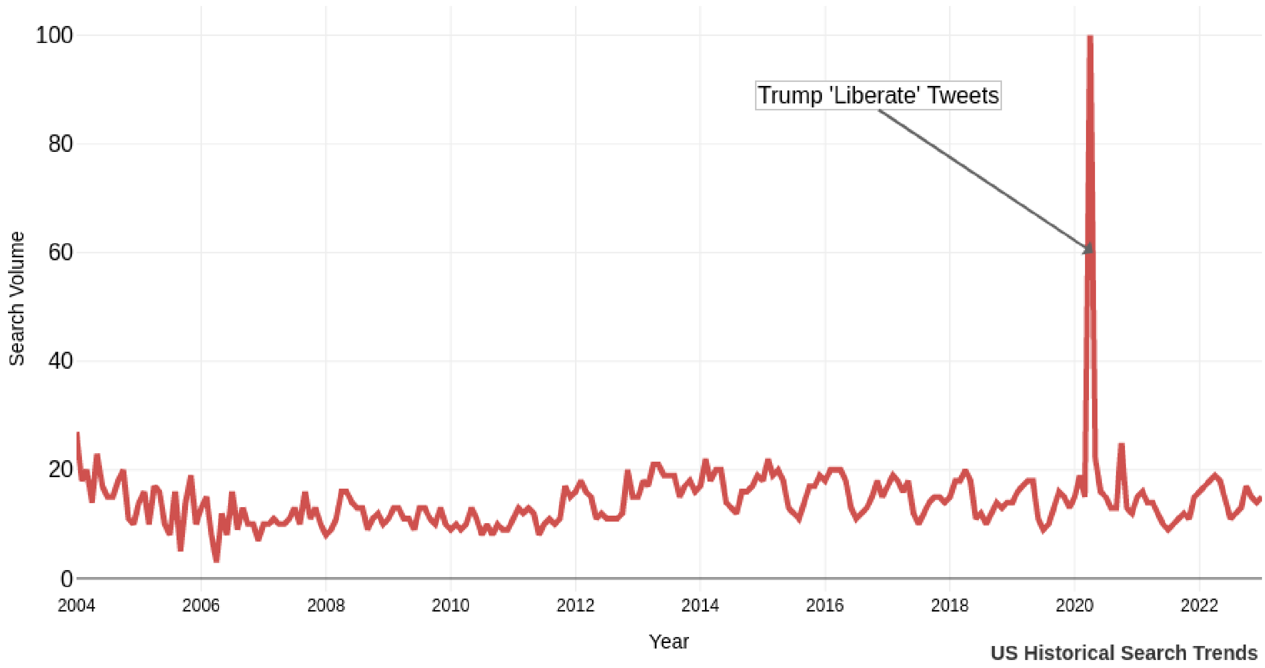
Zadrozny 2020). For example, specific messages included "YOOOO TRUMP JUST SAID TO KICK OFF THE BOOGALOO" and "Boogaloo activated by presidential decree."

To explore the wider public reach of the President's messages, we looked at Internet search trends. Focusing on the keyword *liberate*, we examined historical and state-level search history in the United States. As shown in Figure 2, at no other point in the twenty-year history that Google has tracked search data was the term *liberate* searched more frequently than in April 2020.

Although it is clear that the President's messages were widely seen and discussed, we further examined the spatial distribution of Internet search trends across the country. Focusing on the week following the President's messages, Figure 3 presents the spatial distribution of Internet searches for *liberate* across the country from April 17-23.[6] The figure suggests that searches

6. The Google Trends data presented in Figure 3 constitute between-state comparisons which are normalized and scaled between 0-100 for the 50 states from April 17-23. Between-state comparisons can only be made with static Google Trends data, which means that the data are normalized/scaled over the time range of April 17-23).

Figure 2: Historical Internet Search Trends for 'Liberate'

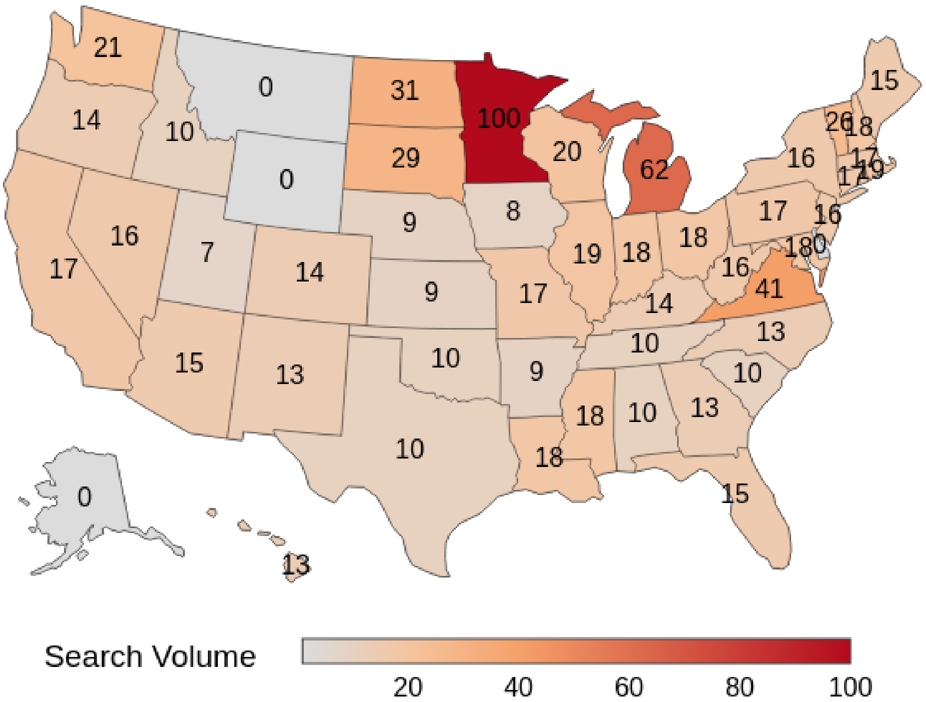


Note: Historical Google Trends searches for *liberate* in the United States. Google Trends data are normalized and scaled according to time period and geography to represent the relative popularity of a search term on a range between 0 and 100 (Google 2020).

for "liberate" were generally higher in the three states targeted by the President. During the week following the messages, Minnesota had the highest search volume in the country and was followed by Michigan (62) and Virginia (41).

Both the Internet search trend data as well as the topic models of the quote tweets suggest that the President's messages were widely seen and discussed, and that they were interpreted as calls for rebellion and violence. We therefore expect that the President's messages had an effect on the behavior of citizens – and specifically supporters – in the days following the messages, encouraging them to engage in non-compliant behavior in the targeted states. Despite the mixed messaging by the President in the days leading up to this, the tweets calling for rebellion against the restrictions on April 17 offered a clear and unambiguous declaration of the President's stance on the issue, which we expect would have resonated with his supporters and would be concentrated in the states targeted in his messages. In the next section, we present our empirical strategy for testing this expectation.

Figure 3: Internet Search Trends for "Liberate" from April 17-23



Note: Google Search Trends for *liberate* on April 17-23. Google Trends data are normalized and scaled in order to represent the relative popularity of the search term on a range between 0 and 100 for all 50 states for a given time period. (Google 2020).

3 Research Design

3.1 Data and Variables

To examine the extent to which President Trump's messages affected public behavior, we focus on three different outcomes of non-compliance, each measured daily: movement, daily time spent at home, and arrests for crimes related to disorderly conduct and rebellion. Daily movement and time spent at home data are available at the county level and are based on mobile phone locations. Our primary source of mobility comes from Meta's (previously Facebook) Data for Good project (Meta 2022). The movement range data tracks daily movement through the Facebook application and were released to researchers and public health experts to aid in combating the spread of COVID-19. There are two types of data available from Meta: movement range data and "stay put" data. The movement range data measures the distance people travel from their home area. The "stay put" data are calculated using the fraction of the population that remains in a single location for the entire day.[7]

Both measurements of mobility capture daily change in relation to normalized averages established by Meta during the months prior to the initial lockdowns and restrictions. Meta's mobility data are especially valuable for our analysis, because in combination they provides measures of both the extent to which individuals traveled, as well as the percent of the population that remained in a single location for the day. We refer to the former of the two as movement data and the latter of the two as compliance with stay-at-home measures.

To measure criminal activity, we rely on arrest data from the FBI's National Incident-Based Reporting System (NIBRS) (FBI 2022). These data are available at the level the arrest and include information on the type of crime for which the arrest was made, as well as demographic characteristics of the offender. 45 US states (and the District of Columbia) reported arrests in 2020 to NIBRS, including the three states that were targeted by the President's messages. We identify four crimes that are potentially related to disorderly conduct and rebellion (Stickle and Felson 2020; Boman and Gallupe 2020), namely arrests for Assault (simple and aggravated), Disorderly Conduct, and Destruction/Damage/Vandalism of Property. We present descriptive statistics for arrests for these crimes in Appendix I.

In the cases of both the mobility and the arrest data, there are several limitations and the potential for non-random missing data. In Appendix F we provide a comprehensive discussion of the limitations of the data used in the analysis. To summarize, we expect non-random missing data to work against our hypothesized effects of the cues. For the mobility data, Meta protects user privacy by setting the threshold for county-level data at 300 individual observations. Therefore, missing data are more likely in extremely rural areas, which are also most likely to be more susceptible to the President's messages (Gimpel et al. 2020). For the arrest data, we expect that well-documented racial biases in policing practices may mask the true number of arrests of white Americans either through limited focus on areas most frequented by these individual by law enforcement personnel or greater leniency in the case that crimes are indeed committed (Knox, Lowe, and Mummolo 2020; Hoekstra and Sloan 2022; Grosjean, Masera, and Yousaf 2023). We offer a further discussion of the limitations of the data in Appendix F.

7. More on the methodology of the mobility data is available directly from Meta Research (Meta 2022).

3.2 Identification Strategy

We adopt a generalized difference-in-differences design to estimate the effects of the cues on mobility and arrests related to civil disobedience following the President's messages. The focus of our analysis is on the extent to which President Trump's cues motivated non-compliant behavior in the areas that were explicitly targeted in his messages. Our identification strategy therefore takes advantage of the spatial and temporal discontinuities in the intended targets (i.e. Michigan, Minnesota and Virginia vs the rest of the country) and timing (i.e. before and after April 17, 2020) of President Trump's calls for liberation. In the primary analysis, the "treatment" group includes counties within states that were explicitly targeted by the President (Michigan, Minnesota and Virginia), while the "control" group includes counties within states around the country that were not targeted but were under the same statewide stay-at-home orders.

Although the cues were directed specifically to the citizens of Michigan, Virginia and Minnesota, the President's messages were seen widely, which is evidenced by the widespread national media coverage and the dramatic increase in online search behavior on April 17 in the rest of the country, shown above in Figure 2 and Figure 3. It is therefore likely that the President's messages had an effect on the behavior of in-group partisans around the country when it comes to the outcomes we study as well. This is a feature rather than a flaw in our design. Given that the effects of the cues were not limited to in-group partisans in the targeted states alone, our research design offers a robust, yet clear test case for the effect of elite cues on political behavior. In other words, because the "control group" in the difference-in-differences design is not entirely "untreated", the extent to which the President's messages have a detectable effect on the behaviors of individuals in the targeted states in relation to the control states is conservative. At the same time, however, the President's explicit targeting of residents in three and only three states provides a clear and identifiable treatment group, which we argue allows us to clearly identify the causal effects of the cues on multiple behavioral outcomes.

The primary assumptions of our difference-in-differences design necessitate that the treated and control groups would have followed the same trajectory in the absence of the treatment. This assumption is commonly known as the parallel trends assumption and is a crucial assumption in difference-in-differences designs (Card and Krueger 1993). Our primary identifying assumption is therefore that trends in mobility and arrests in Michigan, Virginia and Minnesota would have followed the same trajectory as trends in mobility and arrests—*in the absence of the President's messages*—in the rest of the country in the days following April 17. We take several steps to ensure that this is a credible assumption.

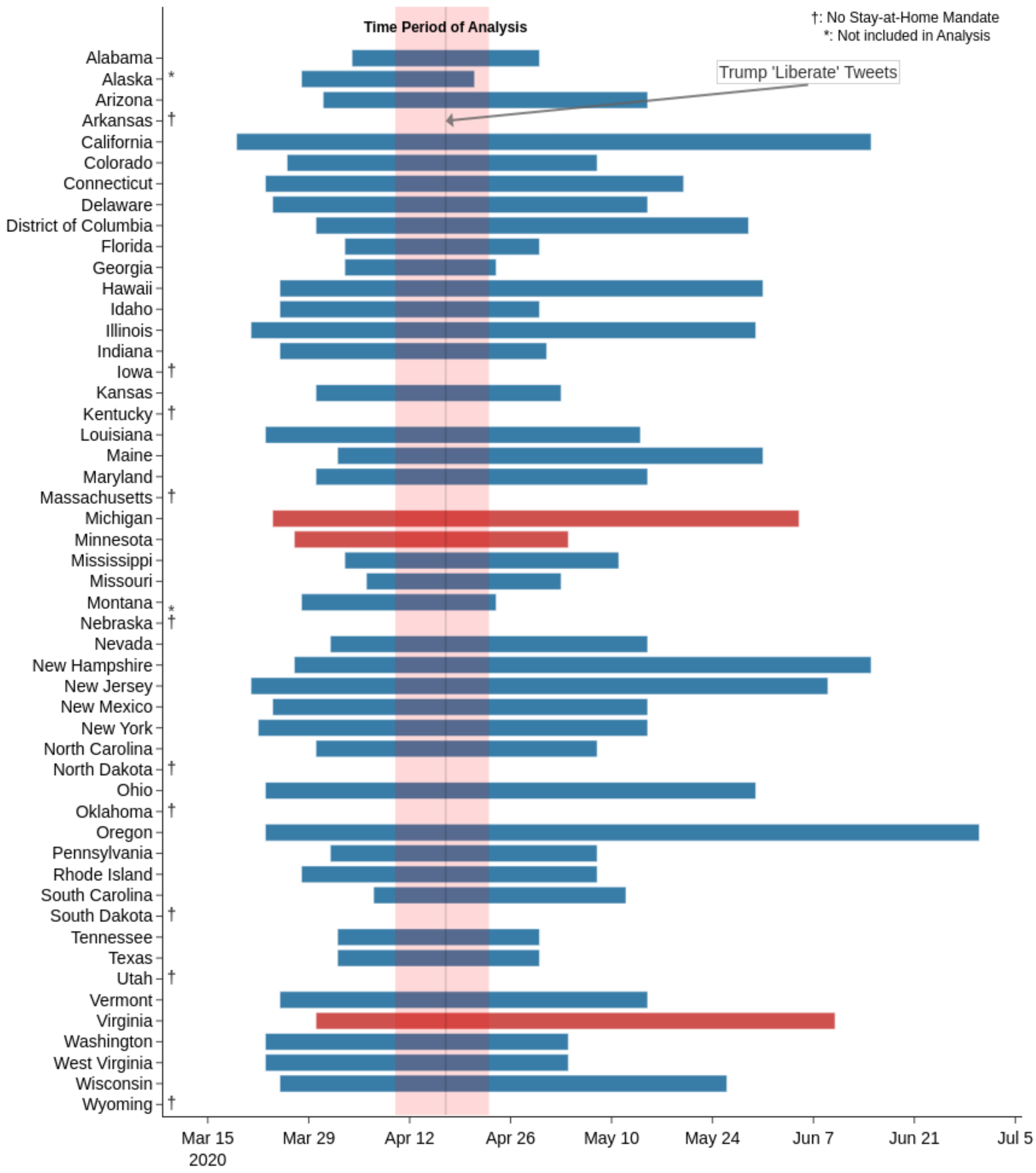
First, we ensure that equal comparisons are made between the treatment and control groups (e.g. the targeted and non-targeted states) by including only states that were under statewide stay-at-home orders during the entire period of analysis. This ensures that the treatment and control groups are comparable in terms of the extent of the restrictions in place, and that the decision to violate the stay-at-home orders is not confounded by geographic differences in the anticipated costs associated with breaking local COVID-19 restrictions. We further detail the extent of the restrictions in each state in Appendix D and we present the states that were included in the analysis in Figure 4. In the figure, each of the states that were under statewide stay-at-home or shelter-in-place orders are presented with the time periods of the initial restrictions. The figure also indicates the three states that were targeted by President Trump's messages in red. In total, 40 of the US states (and Washington DC) met the inclusion criteria for the analysis.

The second way we ensure the parallel trends assumption is met in our analysis is through considering different compositions of the treatment and control groups. We do so in two ways. First, we include analyses that examine only counties that are similar in their partisan composition. Specifically, we estimate the effects of the cues in majority-Republican counties[8] (in targeted states) using only majority-Republican counties elsewhere around the country (that were also under the same state-wide COVID-19 restrictions) as the control group. This approach ensures that we compare the effects of the cues in targeted Republican-majority counties against *only* the behavior of counties with a similar partisan composition (i.e. Republican-majority counties) elsewhere around the country that were *not* explicitly targeted in the President's messages.

Second, we estimate the effects of the cues in the targeted states against *only* the behavior of individuals in states with a Democratic governor elsewhere around the country that were not explicitly targeted in the President's messages. This approach follows the logic that President

8. We use data from the 2016 Presidential Election to assess partisanship at the county level. Data from the 2020 Presidential Election was not used to avoid potential post-treatment bias.

Figure 4: US State Stay-at-Home Orders in 2020



Note: Bars indicate duration of initial state stay-at-home orders. Red bars indicate the states that were targeted in President Trump's messages. States with missing bars did not issue (mandatory) state-wide stay-at-home orders. States with an asterisk (∗) or that did not issue a stay-at-home mandate were not included in the analysis.

Trump may have targeted the three states because they were governed by Democratic governors, and therefore the President's messages may have a greater effect because individuals may rebel against the authority of Democratic governors. By considering only states that were governed by Democrats, this approach ensures that the outcomes we examine are not a function of the partisan affiliation of the state governor.

Finally, we provide additional evidence to support the parallel trends assumption by testing for pre-trends in the outcome variables in the pre-treatment period using the methods described in Liu, Wang, and Xu (2022). The results of these tests do not indicate the presence of pre-treatment trends between any of the treatment–control group compositions we examine. The results of this analysis are presented in Appendix J.

3.3 Estimation

For estimation, we consider several recent advances in the econometrics literature that provide estimators intended to recover causal estimates in generalized difference-in-differences settings with observational data. In our primary strategy, we estimate the effects of the cues using matrix completion methods (Athey et al. 2021; Liu, Wang, and Xu 2022). Matrix completion treats the treated outcomes as missing values and uses a low-rank matrix completion approach to estimate the missing counterfactual outcomes against which the actual treated outcomes are compared. This approach allows for estimating the "missing" (e.g. counterfactual) outcomes in the targeted states after the messages were sent using data from the non-targeted states, effectively approximating the outcome variable of interest in the absence of the cues.

We additionally estimate the effects of the cues using several other estimators that are appropriate for our setting, including Mahalanobis matching (Imai, Kim, and Wang 2023), trajectory balancing with kernel balancing weights (Hazlett and Xu 2018), interactive fixed effects (Bai 2009), and an event study design with two-way fixed effects. We provide further details of these estimators and the results in Appendix K. In brief, the results of the alternative estimators are qualitatively consistent with the results of the matrix completion estimates in the primary analysis, suggesting that the substantive findings are insensitive to our estimation decisions.

In the analysis of mobility, we estimate the effects of the cues on movement and compliance with stay-at-home orders, with the unit of analysis being the county-day. In the analysis of arrests, we estimate the effects of the cues on arrests for crimes related to civil disobedience and rebellion, with the unit of analysis being the state-day. Given that both sources of data measure aggregated behavior at the county (mobility) and state (arrests) level, inferences rely on the assumption that group behavior reflects the behavior of individuals within the said group (King 2013). In other words, we cannot rule out the possibility of ecological inferences due to data limitations. However, we expect that this limitation works against our theoretical expectations. Given expected heterogeneity in the partisan composition of a county – and our theoretical expectation that it is in-group partisans who are most susceptible to the cues – the "treated" counties that undoubtedly include out-group partisans (e.g. Democrats) who are not responsive to the cues would shrink the county-level estimates toward zero. In addition, we provide several assurances and robustness checks aimed at minimizing alternative explanations for the results we observe. Further examination of alternative explanations and robustness checks are provided in subsection 5.1, as well as in Appendix K and Appendix P.

4 Mobility Results

We first examine the cumulative effects of the President's messages on mobility. Table 1 and Table 2 present the estimates for the effects of the President's messages on movement and stay-at-home compliance, respectively. Each column includes the estimates from a different modelling strategy articulated previously in subsection 3.2. Model 1 includes estimates for the effects of the cues on movement in all counties within the targeted states. Model 2 uses only Democratic-majority counties in the targeted states as the control group. Model 3 follows the same partisan format with only Republican-majority counties for the treated and control groups. Model 4 uses only counties in states with Democratic governors as the control group and all counties in the targeted states as the treatment group (all three of which had Democratic governors at the time).

Of particular interest for the hypothesized effects of the cues on in-group partisan behavior are the results in Republican majority counties. These results – presented in Model 3 in Table 1 and Table 2 – provide the most direct test of our expectations and suggest that the cues had significant effects. Specifically, the results indicate that the President's messages led to an increase in movement and a decrease in stay-at-home compliance in the days following the messages. In the cases of both movement and stay-at-home compliance, the effects of the cues are greatest in magnitude in Republican-majority counties, however, they are similarly detectable at the

Table 1: Cumulative Effect of "Liberate" Cues on Movement

	Movement			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	1.746***	-0.660	2.311***	1.720***
Standard error	(0.261)	(0.397)	(0.279)	(0.289)
CI lower (2.5%)	1.234	-1.438	1.763	1.153
CI upper (97.5%)	2.258	0.119	2.859	2.286
P-value	0.000	0.097	0.000	0.000
County	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
N obs.	29,064	5,516	23,548	13,902

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Model 1 estimates the effect of the cues on movement in all counties within the targeted states. Model 2 uses only Democrat-majority counties in the targeted states as the treatment group and Democratic-majority counties elsewhere around the country under the same stay-at-home orders as the control groups. Model 3 follows the same partisan format with only Republican-majority counties for the treated and control groups. Model 4 uses only counties in states with Democratic governors as the control group and all counties in the targeted states as the treatment group.

state level (Model 1) and in the case that only counties in states with Democratic governors are considered as the control group (Model 4).

In the specification that includes only Democrat-majority counties, the estimates are not statistically distinguishable from zero at conventional levels. This suggests that the President's messages did not have significant effects on movement or stay-at-home compliance in Democrat-majority counties. This is consistent with the expectation that the President's messages would have a greater effect on in-group partisans, and also shows that out-group partisans (e.g. Democratic-majority counties) did not respond to the President in the same manner.

4.1 Dynamic Effects of Elite Cues

To further understand the ways in which the effects of the cues developed over time, we used the same estimation procedures to examine the effects dynamically. Figure 5 provides the estimated coefficients over time.

Figure 5 suggests only subtle deviation from the baseline in the lead up to the *liberate* messages, with no clear pre-treatment trends in the targeted states.[9] However, the estimates

9. Several estimates are statistically distinguishable from zero in the time leading up to the messages. One

Table 2: Cumulative Effect of "Liberate" Cues on Stay-at-home Compliance

	Stay-at-home Compliance			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	-0.868***	0.078	-1.090***	-0.802***
Standard error	(0.121)	(0.243)	(0.122)	(0.129)
CI lower	-1.104	-0.399	-1.329	-1.055
CI upper	-0.631	0.555	-0.850	-0.550
P-value	0.000	0.748	0.000	0.000
County	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
N obs.	29,064	5,516	23,548	13,902

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

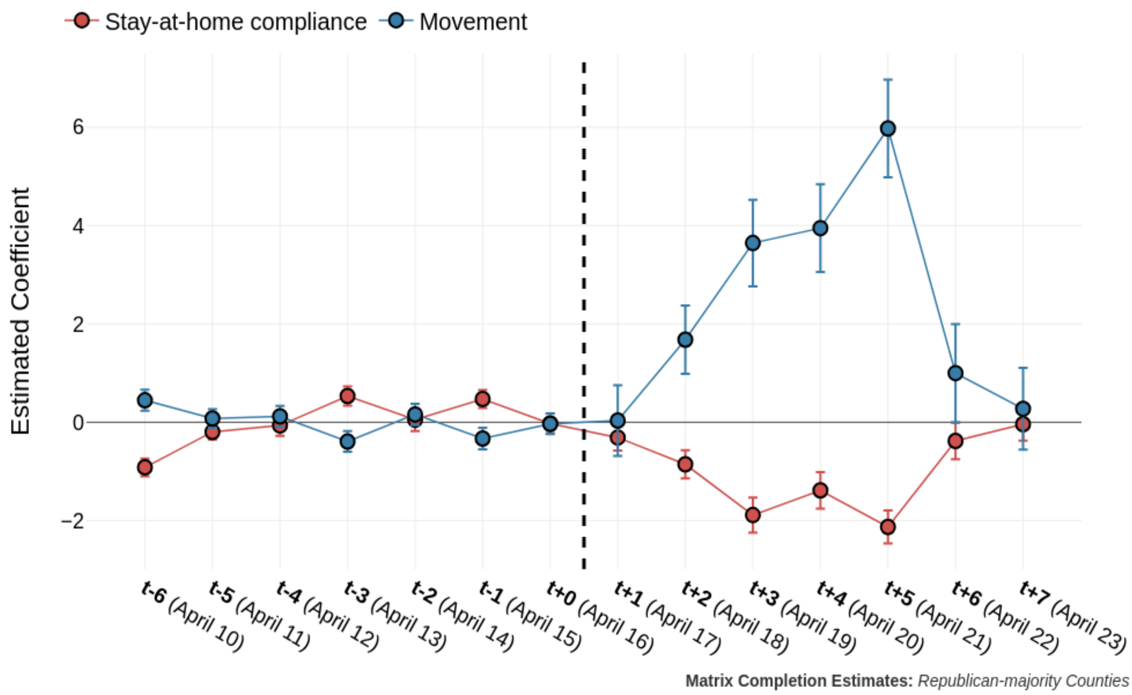
Note: Model 1 estimates the effect of the cues on movement in all counties within the targeted states. Model 2 uses only Democrat-majority counties in the targeted states as the treatment group and democratic-majority counties elsewhere around the country under the same stay-at-home orders as the control groups. Model 3 follows the same partisan format with only Republican-majority counties for the treated and control groups. Model 4 uses only counties in states with Democratic governors as the control group and all counties in the targeted states as the treatment group.

indicate a sharp increase in movement and a decrease in stay-at-home compliance in the days following the President's messages. In Republican-majority counties, movement increases near linearly for the following four days, peaking on April 21 before returning to similar levels as other Republican majority counties on the 22nd and 23rd. The compliance estimates indicate a similar pattern but in reverse, with compliance decreasing—though not as sharply as movement increased—in the following five days before returning to similar levels as other Republican-majority counties on April 22nd and 23rd.

While the dynamic effects of the cues is significant in the days following the messages, the effects are relatively short-lived, as we would expect. Namely, the estimates suggest that both movement and stay-at-home compliance return to similar levels as other Republican-majority counties within a week of the President's messages. In Appendix G, we provide suggestive

reason for this is likely due to idiosyncratic differences in holiday time off around Good Friday (April 10) and Easter (April 12). While neither day is a federal public holiday, some employers provide paid time off and several states have state-wide public holidays. Estimates are nearly identical when we do not include states with state-wide public holidays for Easter. Moreover, when reducing the post-treatment ATT estimates by the worst-case (maximum) pre-treatment parallel trends violation, a statistically meaningful effect is still reliably identifiable for both outcomes (Rambachan and Roth 2023; Manski and Pepper 2018). Additionally, we provide further evidence to empirically support a lack of trends in the outcome variable, as well as event study estimates from OLS regressions in which pre-treatment estimates are not distinguishable from zero, in Appendix J and Appendix K.

Figure 5: Dynamic Effects of "Liberate" Cues on Mobility in Republican Counties



Note: Matrix completion coefficient estimates and 95% confidence intervals for the effect of the cues on movement (blue) and stay-at-home compliance (red) in Republican-majority counties (e.g. Model 3 in Table 1 and Table 2). The control group includes Republican-majority counties around the country that were not targeted in the President calls for liberation and were under the same mandatory state restrictions.

evidence that the effects of the cues may become undetectable around April 22 due to an increase in movement in the control group rather than a decrease in movement in the treatment group. This may suggest that individuals in the control group (e.g. Republican partisans that were residents of the states targeted in Trump's messages) may have been influenced by increased mobility by their in-group partisan peers in the targeted states.

5 Criminal Behavior

Next, we consider the extent to which the cues led to wider displays of non-compliance with state and local authorities in the form of arrests for crimes related to disorderly conduct and rebellion. As identified by the media and shown in our analysis of interactions with the messages on Twitter, calling for "liberation" has specific connotations and may inspire non-compliant and rebellious behavior against state and local authorities. We therefore expect that the cues had a short-lived but sharp increase in such behavior in the targeted states (Hypothesis 2).

To test the hypothesis, we follow the same research design as previous, with minor exceptions. First, we focus on arrests at the state-level rather than the county level. This is due to a lack of county-level arrest data in the FBI's National Incident-Based Reporting System (NIBRS) (FBI 2022). Second, we focus on arrests for four crimes related to civil disobedience and rebellion: Assault (simple and aggravated), Disorderly conduct, and Destruction/Damage/Vandalism of Property. We present descriptive statistics for these crimes in Appendix I. Third, we make April 18 the first day of the treatment period, given that the messages were sent in the evening on April 17.[10]

Following the same estimation strategy for the mobility data, we rely on matrix completion methods for inference (Athey et al. 2021; Liu, Wang, and Xu 2022). In the primary specification, we estimate the effects of the cues on the arrest rate of white Americans at the state level. In this specification, the control group includes the arrest rate in states that were under similar state-wide restrictions that were not explicitly targeted by the President.[11]

Table 3 presents the cumulative estimates with different transformations of the dependent variable. In each model, the dependent variable is the daily arrest rate (per million) of white Americans. The first three models use the arrest rate, a log transformation of the arrest rate, and an inverse hyperbolic sine transformation of the arrest rate, respectively. The fourth model uses the arrest rate and includes daily state temperature as a control variable, as weather has been shown to affect crime levels (Baryshnikova, Davidson, and Wesselbaum 2021).

The results in Table 3 indicate that the President's messages had a statistically measurable effect on the arrest rate of white Americans. Across each specification, the results demonstrate that white individuals in the states that were explicitly targeted by the President's calls for liberation were arrested at a higher rate than their counterparts in states that were not explicitly targeted by the President's messages. The results are robust to different transformations of the dependent variable and when conditioning on daily state temperature as a control variable.

We additionally considered the dynamic effect of the cues using the Model 4 specification in Figure 6. Similar to the dynamic estimates of mobility and stay-at-home compliance, Figure 6A

10. President Trump's messages were sent at approximately 4:21–4:25 PM EST. The results are similar and still significant when using April 17 as the first day of treatment. See Appendix O for that analysis.

11. In Appendix O, we additionally show that the same specification does not identify an increase in the arrest rate of white Americans for alternate crimes or when estimating the effects of the cues on the arrest rate of other racial groups (e.g. Black Americans and Asian Americans).

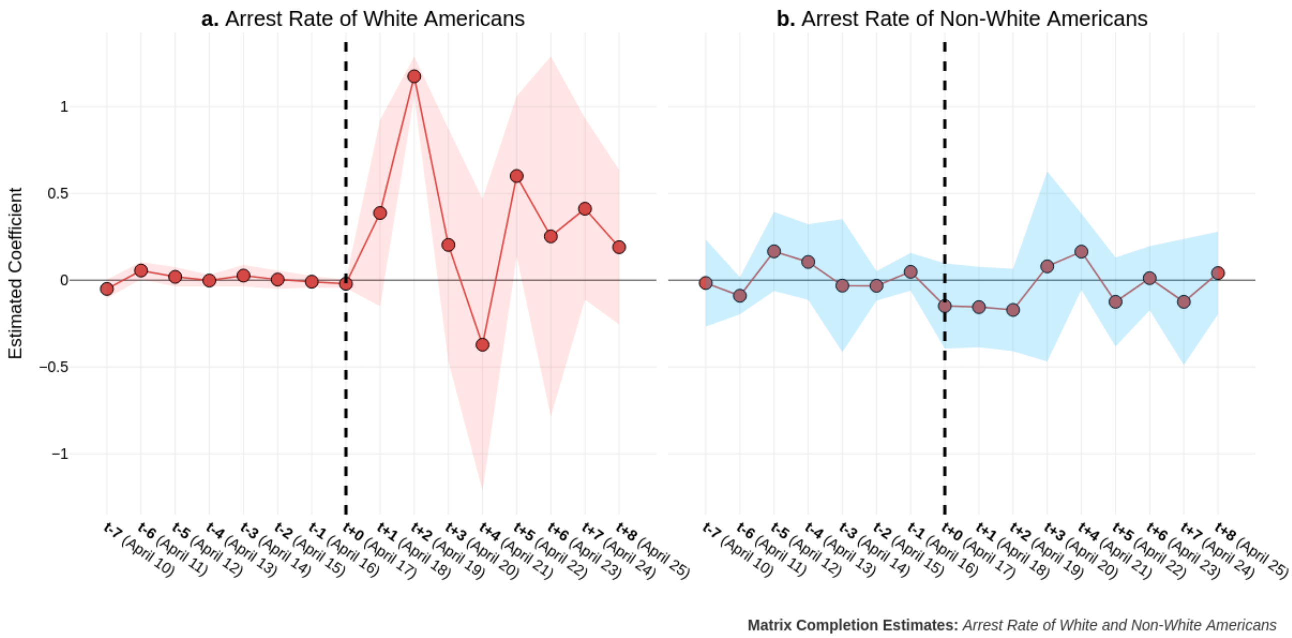
Table 3: Cumulative Conditional Effect of "Liberate" Cues on Arrest Rate of White Americans

	Arrests				
	Per million	Per million (IVHS)	Per million (w/Temp.)	Count	Count (w/Temp.)
Trump Cues (CATT)	0.359***	0.359***	0.345***	3.032*	2.969*
Standard error	0.108	0.106	0.100	1.235	1.215
CI lower (2.5%)	0.146	0.151	0.148	0.611	0.587
CI upper (97.5%)	0.571	0.566	0.542	5.453	5.352
P-value	0.001	0.001	0.001	0.014	0.015
Daily state temp.			✓		✓
State	✓	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓	✓
Racial group	✓	✓	✓	✓	✓
N obs.	3,600	3,600	3,600	3,600	3,600

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors presented in parentheses. All results presented use matrix completion and are estimated using the `Fect` library in R (Liu, Wang, and Xu 2022). Model 1 uses the arrest rate (per million). Model 2 uses an inverse hyperbolic sine transformation of the arrests rate (per million). Model 3 uses the arrest rate per million and conditions on daily state temperature. Model 4 uses the number of arrests and Model 5 using the arrest count and conditions on daily state temperature.

Figure 6: Conditional Effects of Trump Cues on Arrest rate of White Americans



Note: Matrix completion estimates for the effect of targeted cues on the arrest rate for white and non-white Americans for crimes related to assault, disorderly conduct and vandalism/destruction of property. Shaded area indicates 95% confidence intervals. Estimates include daily temperature at the state level. Full results are presented in Appendix N.

demonstrates that there was a sharp increase in the two-days following the messages. On April 18 and 19, the arrest rate of white Americans for crimes related to assault, disorderly conduct and vandalism increased in the targeted states. The arrest rate in the targeted states then returns to similar levels as the rest of the country on April 20 and 21, but appears to remain somewhat elevated over the following few days. In contrast, estimates for the arrest rate of non-white Americans (Figure 6B) suggests that these individuals were not as responsive to the President's message, which provide additional context. Taken in full, the estimates suggest a sharp but short-lived increase in arrest rate of white Americans, with only one of the days (April 19) clearly differentiable from zero.[12]

5.1 Alternative Explanations

Our analysis thus far demonstrates that Trump's messages led to an increase in movement, a decrease in compliance with stay-at-home orders and an increase in arrests for crimes related to civil disobedience and rebellion. In the following subsections, we consider alternative explanations that could challenge our results and present additional evidence supporting our primary findings.

5.1.1 Exogeneity of the Cues

One specific scenario that challenges our identifying assumptions is that President Trump was responding to events that were *already occurring* in the three states with his calls for liberation. For example, if the President was responding to increased criminal activity in Michigan, Virginia and Minnesota, these states may have an even greater propensity for crime than the rest of the country following Trump's cues.

We therefore "test" for different state-level observable characteristics by attempting to predict the states targeted by Trump using state-level characteristics the week before April 17. As predictors, we use state COVID-19 conditions (cases and deaths), daily state-wide protest activity (number of protests), arrests (violent crimes and crimes related to rebellion and civil disobedience), and mobility (movement and stay-at-home compliance). The results do not in-

12. In Appendix I and Appendix N, we provide the full results of the analysis and descriptive statistics for the arrests data. We also provide suggestive evidence that the increase in the arrest rate of white Americans appears to be statistically detectable due to an increase in the real arrest rate, rather than a decrease in the arrest rate in the control group (see Figure A8).

dicate that any of the state-level characteristics in the week prior to Trump's calls for liberation predict the three states in relation to the rest of the country. These results are presented in Appendix E.

5.1.2 Excludability of President Trump's other Online Messages

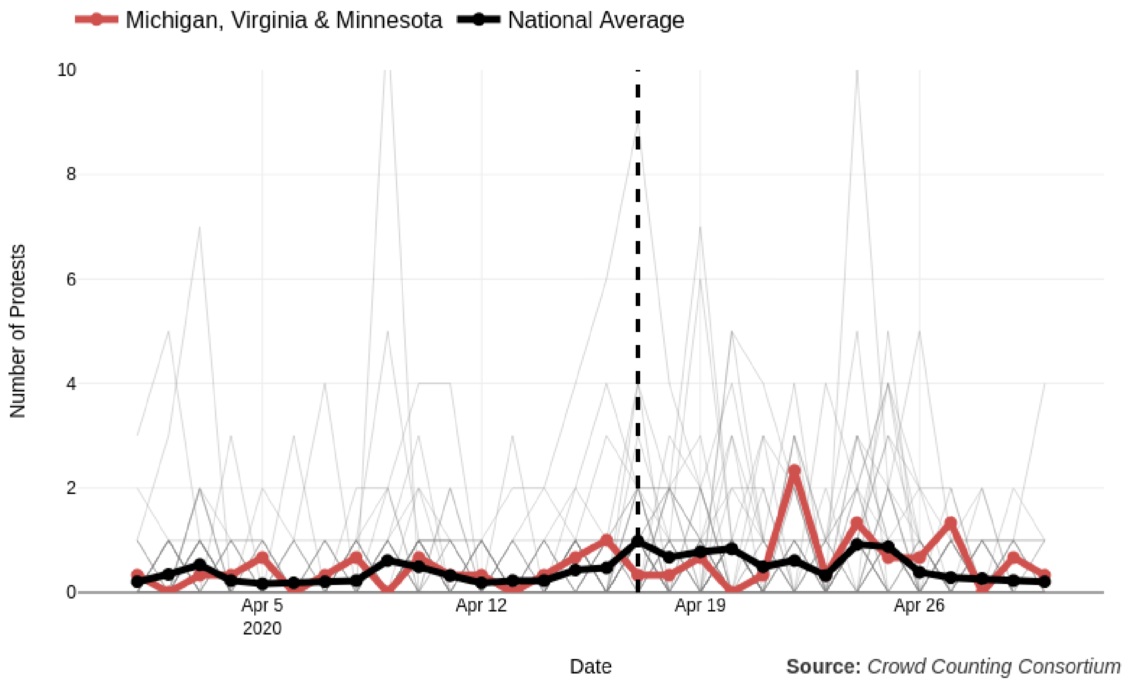
We additionally considered the extent to which the President's other Twitter messages could have caused the changes in mobility and crime. For confirmation that Trump did not target any of the three states in our analysis via social media messages, we systematically identified every Twitter messages sent by the President that explicitly mentioned a US state in the 20 days surrounding the *liberate* messages. In 52 of the messages, Trump explicitly mentioned a US state.[13] Messages that mentioned Virginia, Minnesota or Michigan were either campaign messages or messages that advertise the work of the federal government. The state-level search queries did not identify any messages that could be interpreted as calls to disobey local lockdown restrictions either broadly or location specific other than the *liberate* messages. We present the full list of Trump's messages that identify a US state in Appendix Q.

5.1.3 Independent Protest Activity

We also considered the possibility that protest activity planned independently of President Trump's messages could be driving the changes in mobility and crime that we observe. For instance, a protest planned on April 16th for two days later on April 18th would occur independent of Trump's cues and could cause an increase in both mobility and crime. To address this concern, we considered the universe of daily US protests in April (Pressman and Chenoweth 2022). We indeed observe an increase in the number of protests in the targeted states on April 22. However, our dynamic estimates for mobility (Figure 5) and arrests (Figure 6) suggest that the effects of the cues occur between the April 18 and April 21 in the outcomes we observe, indicating that it is unlikely that the changes we document in mobility and arrests are driven by the protests alone. We present the average daily number of protests for the three targeted states in relation to the national average in Figure 7.

13. We did not include Trump's messages that mention the *Washington* Post or *New York Times*.

Figure 7: Daily US protests in April 2020



Note: Daily number of US protests in April 2020. Light grey lines indicate individual states, while the red and black solid lines are averages for the targeted states and the nation (excluding the targeted states).

5.1.4 Alternative Data Sources

To check the robustness of our result, we used an alternative source of data for the mobility analysis – Google's Community Mobility Reports (Google 2020) – which measure daily mobility for US counties according to the type of mobility of the user. Focusing on mobility associated with retail and recreation as the outcome variable, as well as an aggregated measurement of mobility that combined all the available types of the mobility offered in the Google data, we replicated the primary analysis. Estimations using the same specifications but with Google mobility data confirm the substantive conclusions drawn in our primary analysis. Full details and results can be found in Appendix L.

5.1.5 Placebo Tests

We conducted a series of placebo tests for each of the two analyses. For mobility, we examine the extent to which Trump's targeting of other states on social media leads to an increase in movement. After identifying 49 instances in which Trump explicitly mentioned a US state on

Twitter in the month of April (2020), we estimate 49 regressions with counties in the targeted state as the treatment group and counties elsewhere around the country (under the same restrictions) as the control group. At random, we would expect the coefficient estimates to be normally distributed with a mean of zero and the p-values to be uniformly distributed, which is in large part what we observe. We present the full results of the placebo tests as a coefficient plot in Appendix M.

For the arrests analysis, we conduct placebo tests by estimating the effects of the cues on arrests for 1) crimes related to civil disobedience for non-white Americans (Figure 6), 2) crimes related to civil disobedience by Black Americans; 3) crimes related to civil disobedience by Asian Americans; and 4) violent crimes (e.g. murder, rape etc.) by white Americans. Using the same matrix completion methods and various transformations of the dependent variable, we find no evidence of an increase in arrests for any of the different groups or crimes. The results of this analysis are presented in Appendix O.

5.1.6 Alternative Estimation Strategies

We also re-estimated our primary results using several alternative panel data estimators. These included Mahalanobis matching (Imai, Kim, and Wang 2023), trajectory balancing with kernel balancing weights (Hazlett and Xu 2018), interactive fixed effects, and an event series specification with two-way fixed effects. The results of these alternative estimators are presented in Appendix K and Appendix P and are substantively consistent with our primary analysis.

6 Discussion

During crises and times of uncertainty, elites play an important role in restoring calm and order and mobilizing support for policy responses. The literature has shown that elite cues can increase support for policies, especially among partisan supporters (Brader and Tucker 2012; Nicholson 2012; Anderson and Hobolt 2022; Jørgensen et al. 2021). In this article, we examine the effects of elite cues in a polarized environment during a crisis and ask whether political leaders can persuade their supporters to *disobey* the rules when personal costs are considerable.

Analyzing the effects of President Donald Trump's controversial tweets that called for the "liberation" of Minnesota, Virginia and Michigan from COVID-19 restrictions at the height of the pandemic, we show that there was considerable public interest in the tweets, especially in the targeted states. Furthermore, our analysis of the interactions with the tweets on social media reveal the violent and rebellious connotations associated with the President's calls for liberation. Leveraging the fact that Trump's messages exclusively referred to three specific states, our findings demonstrate that Trump's calls to action led to higher levels of non-compliant behavior in Republican counties in the targeted states in the days following the tweets: there was a marked increase in mobility in the Trump-targeted Republican counties when compared with Republican counties elsewhere around the country, despite the parallel trends in mobility in the days leading up to the messages. Expanding the focus to investigate the spill-over effects of the polarizing cues, we then show that Trump's calls for liberation resulted in an increase in arrests for crimes related to rebellion and civil disobedience. Notably, we document these effects exclusively among white Americans.

These results thus contribute to our understanding of elite cues by demonstrating the effects of elite messages on actual behavior, even behavior that can potentially come at a great personal risk. Going beyond recent findings of the effects of US politicians' social media messages on mobility (Grossman et al. 2020; Bisbee and Lee 2022), our study shows how polarizing elite messages can lead to more serious forms of disobedience among supporters. These results raise important questions about how divisive elite cues may encourage behavior that challenges the rule of law and the functioning of democratic institutions. While the specific actions of President Trump may be unique, the use of polarizing and incendiary rhetoric by political elites on social media is not. Indeed, the rise of populist leaders around the world has been associated with greater anti-establishment rhetoric and a decline in trust in liberal democratic institutions (Mudde and Rovira Kaltwasser 2018; De Vries and Hobolt 2020). The findings of this article therefore have broader implications for understanding how elite cues can undermine compliance with and respect for democratic institutions and the rule of law.

As with any study, there are limitations to our findings and the degree to which they generalize to other contexts. First, the capacity for elites to motivate non-compliant and/or criminal behavior is likely conditional on a number of other factors that are specific to the US context under President Trump and amidst a pandemic. Donald Trump is certainly a highly unique politician and communicator who has an unprecedented ability to reach a wide audience with his social media communication (Gadarian, Goodman, and Pepinsky 2022). Moreover, his calls for liberation occurred at a time when state governments had placed extraordinary restrictions on civil liberties, further polarizing the US electorate along political lines and likely enhancing Trump's persuasive powers to receptive Republican partisans.

Furthermore, while the effects of Trump's messages on increased mobility and crime are indeed robust, they were also relatively small and short-lived. Yet, this is unsurprising given that the intervention was a single set of tweets and that the counterfactual included individuals similarly exposed to the messages but not targeted directly. While the increase in non-compliant behavior in response to these tweets may not in and of itself be cause for concern, the great worry is that a sustained campaign by politicians, like Donald Trump, seeking to undermine respect for rules and norms can have even greater effects on non-compliant behavior among supporters and further fracture support for and trust in core democratic institutions. As an example, the continuing messaging to undermine trust in the outcome of the 2020 Presidential election has not only shifted attitudes among some Republican partisans, but also culminated in violent action on January 6, 2021. This study thus not only contributes to our understanding of the capacity of elites to mobilize supporters, it also highlights the potential dangers associated with elites who use their platforms to willingly encourage action against established rules, norms and institutions.

Declarations

Human Subjects

The authors affirm this research did not involve human participants.

Ethics & Conflict of Interest

The author declares no ethical issues or conflicts of interest in this research.

Funding

This research was funded by the Volkswagen Foundation (COVIDEU Project Grant: 9B051).

Data Transparency

Research documentation and/or data that support the findings of this study are openly available in the APSR Dataverse at [DOI].

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Part I
Appendix: Elite Cues and Non-Compliance

Table of Contents

A Software Utilized

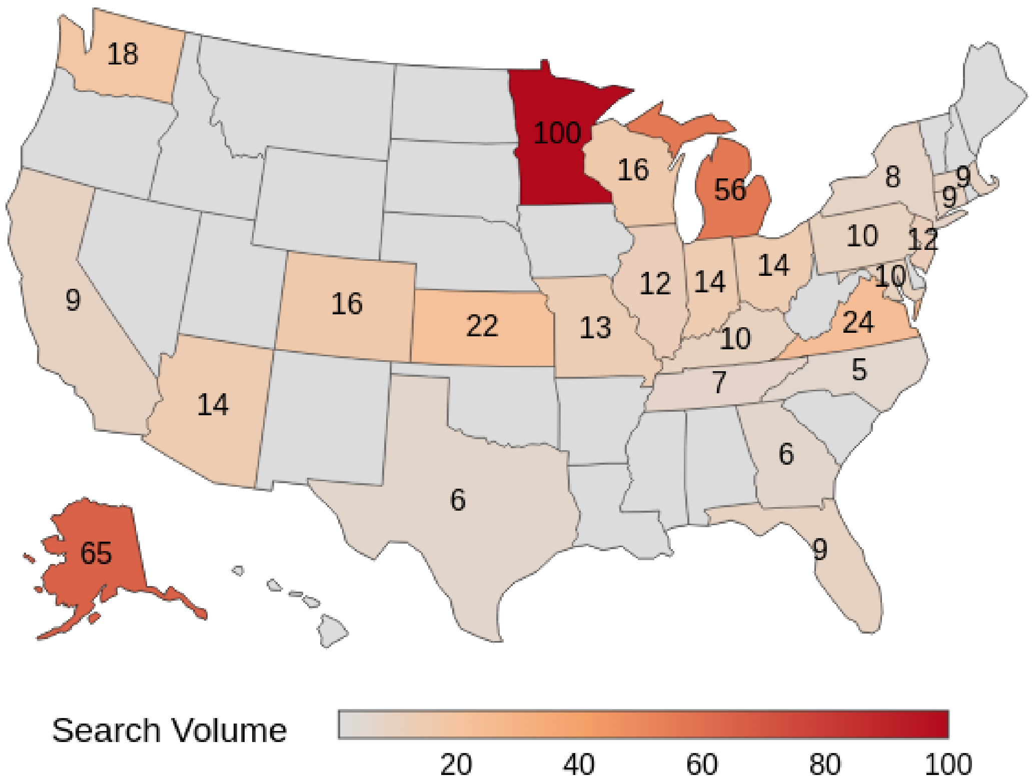
Software utilized but not referenced within the main text.

1. All figures in main text: `Plotly` (Plotly 2015)
2. Fixed effects estimations: `Fixest` (Berge, Krantz, and McDermott 2021)
3. Appendix figures: `ggplot2` (Wickham 2011) (Figure A11b, Figure A11a, Figure A10b, Figure A9b, Figure A10a, Figure A9a)

B Google Search Trends

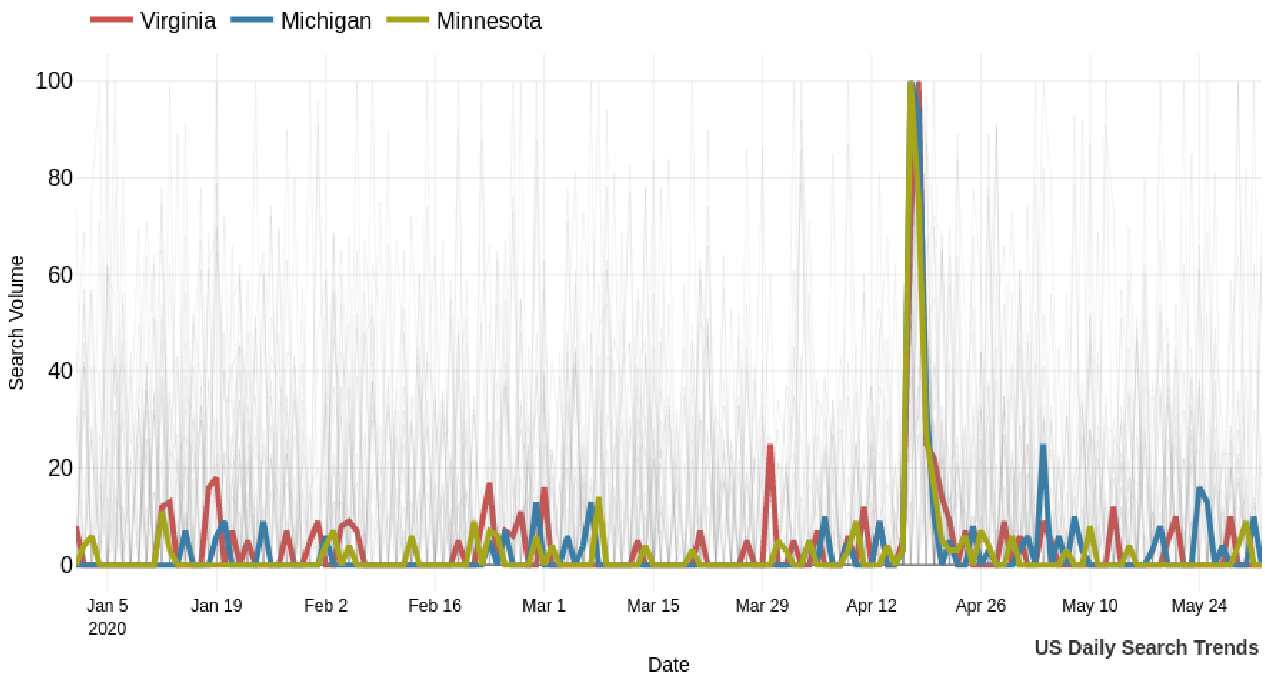
Figure A1 presents the between-state search trends for the word "liberate" in the United States on April 17.

Figure A1: Internet Search Trends for "Liberate" on April 17



Note: Google Search Trends for *liberate* on April 17. Google Trends data are normalized and scaled in order to represent the relative popularity of the search term on a range between 0 and 100 for all 50 states for a given time period. (Google 2020).

Figure A2: Daily Internet Search Trends for “Liberate”



Note: Google Search Trends for *liberate*. Google Trends data are normalized and scaled in order to represent the relative popularity of the search term on a range between 0 and 100 for each of the 50 states individually for a given time period (e.g. within the state). (Google 2020).

C Topic Models

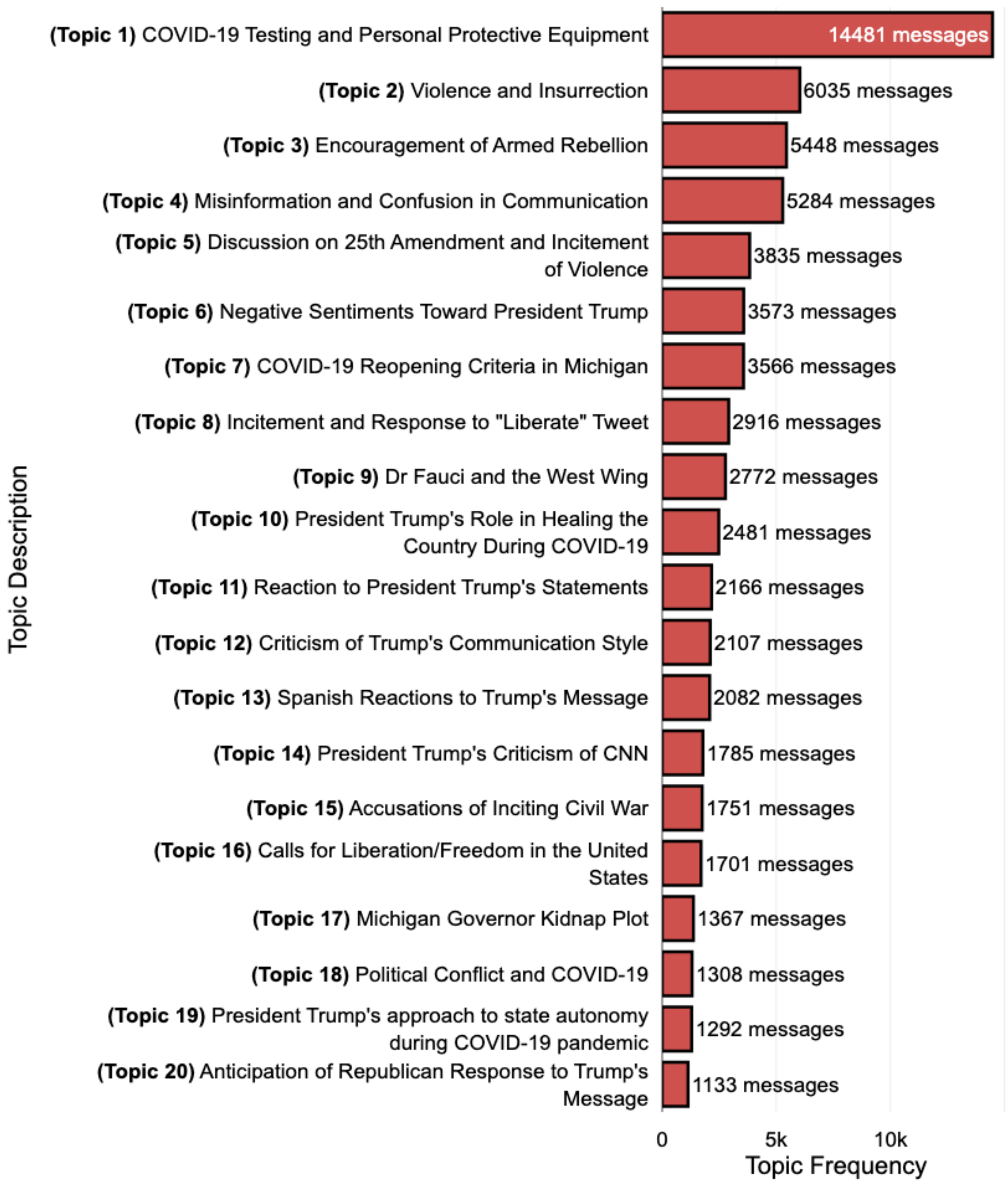
To give greater understanding of how the messages were interpreted, we collected all the available quote tweets using the Twitter V2 API (Twitter 2021). Our analysis focused on messages that quote-tweeted the original three messages, as well as the messages that then re-tweeted those messages as well. In total, we collected 143,171 quote tweets.

Using the BERTopic library in Python (Grootendorst 2022), we created topic models with the quote tweets. Using default parameters, the model identified 219 topics. For each given topic, the model provides three examples of the most representative documents (tweets). These documents are then passed to the GPT-4 API (OpenAI 2023) to derive topic descriptions, which are presented below in Figure A4. Additionally, a word cloud of the top-20 most representative words from the quote tweets is presented in Figure A3.

Figure A3: Word Cloud of Top-20 Most Representative Words from Liberate Quote Tweets

Note: Most representative keywords derived from the top-20 topics of *liberate* quote tweets.

Figure A4: Top-20 Topics from LIBERATE Quote Tweets



Note: Topic Model of 143,171 quote tweets of the 'Liberate' tweets. The topic descriptions are created by interpreting the three most representatives documents from each identified topic. Each set of the three documents corresponding to each topic are then summarized using GPT-4 (OpenAI 2023) to create the latent topic descriptions.

D State COVID-19 Restrictions

Below in Figure A5, we present the various US State Restrictions during the first six months of 2020 according to the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al. 2021). The OxCGRT collects publicly available information on 17 indicators of government responses. The OxCGRT data is available for download at https://github.com/OxCGRT/covid-policy-dataset/tree/main

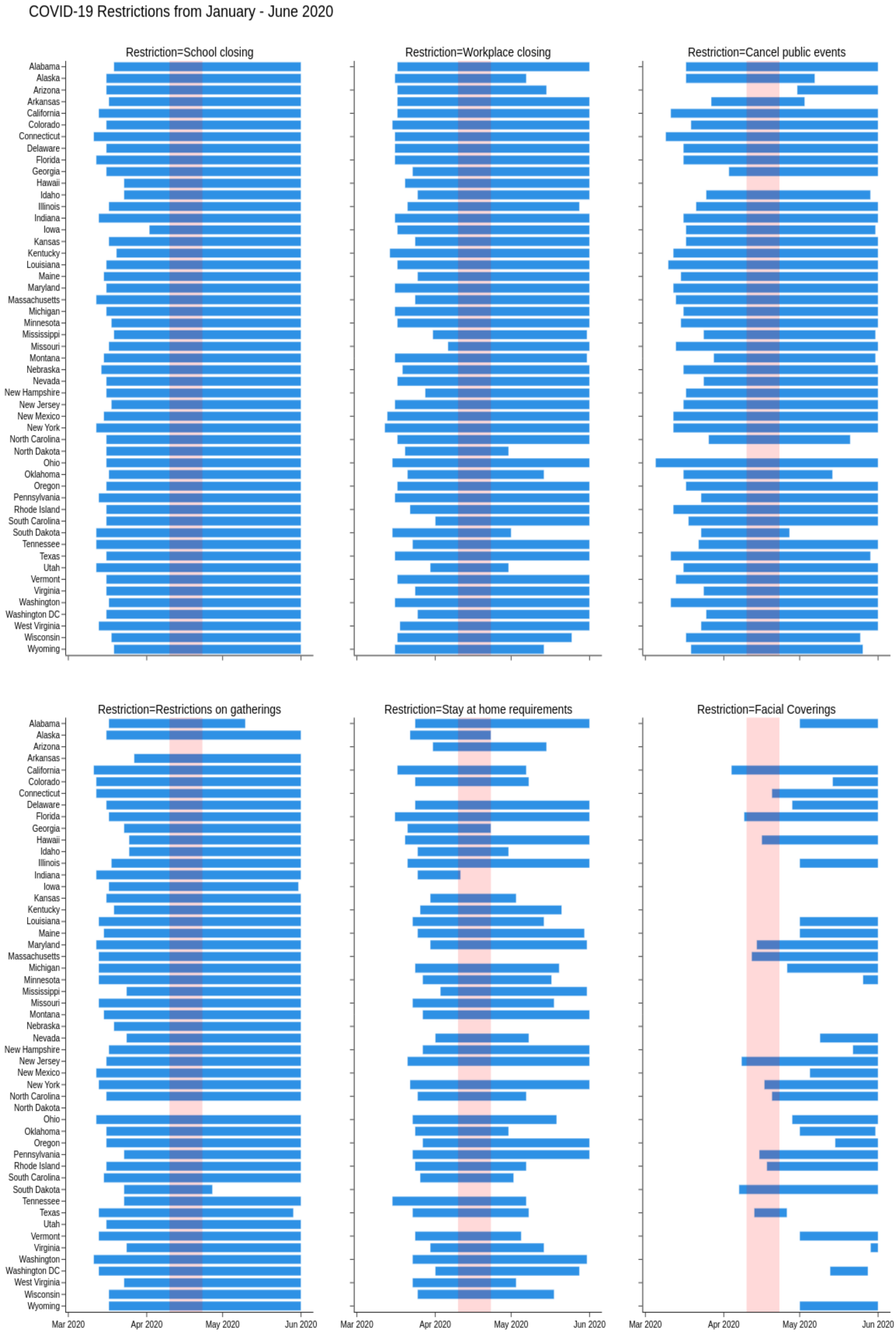
A careful view will reveal that there are several small discrepancies in the periods during which states were under stay-at-home orders according to Figure 4 in the main text and the periods reported in the Oxford data below. In the main text, we consider only states that have issued mandatory stay-at-home orders for the entire state (i.e. the state governor had issued a stay-at-home mandate). Some states had stay-at-home orders in place for only parts of the state, which were implemented by local jurisdictions, and were therefore recorded as states that had issued stay-at-home orders in the Oxford data but were not considered in the primary analysis (see Figure 4). These states include the following:

1. **Oklahoma:** State Governor Kevin Stitt encouraged that vulnerable people across Oklahoma to stay home but did not issue a mandatory order. However, mayors in major cities issued stay-at-home orders, including in Ardmore, Claremore, Edmond, Moore, Norman, Oklahoma City, Sallisaw, Stillwater and Tulsa (Mervosh, Lu, and Swales 2020). We do not include Oklahoma in the primary analysis because the stay-at-home orders were not issued by the state governor and were not mandatory across the entire state.

2. **Kentucky:** In Kentucky, Governor Andy Beshear encouraged residents to stay at home, but did not issue a statewide order (Mervosh, Lu, and Swales 2020). We do not include Kentucky in the primary analysis because the stay-at-home orders were not issued by the state governor and were not mandatory across the entire state.

Additionally, the Oxford data reports that Georgia ended its stay-at-home order on April 24. Governor Brian Kemp ordered Georgians to shelter in place on April 2, 2020. He then rescinded the order the next day on April 3, allowing individuals to go to beaches as long as they remained socially distanced. On April 10, Kemp changed course again and issued a statewide shelter in place order until the end of April. These Orders can be found at the following: Georgia Executive Orders 04.02.20.01, 04.03.20.01 and 04.03.20.02 https://gov.georgia.gov/, as well as https://gov.georgia.gov/). On April 20, Kemp then changed course again and said that certain businesses could re-open on April 24 (Executive Order 04.20.20.01 https://gov.georgia.gov/. There was confusion because shelter-in-place orders were in place until the end of April, but certain businesses were allowed to open on April 24 https://www.c-span.org/. We include Georgia in the primary analysis because the stay-at-home orders were issued by the state governor and were mandatory across the entire state for the duration of the time period analyzed.

Figure A5: US State Restrictions during the first six months of 2020



Source: Oxford COVID-19 Government Response Tracker (OxCGRT)
Highlighted period: April 10 - April 23, 2020

E Exogeneity of the Cues

We examine whether Trump was simply responding to increased protest activity in the three states he targeted by regressing a binary treatment indicator identifying the three states on several state level characteristics that could have feasibly influenced Trump to target the three states. These characteristics include the protests, violent crime, COVID-19 cases, COVID-19 deaths, and dependent variables we use in the analysis (mobility and arrests for crimes related to civil disobedience). We use the week before the cues (April 10-16) to measure each characteristic daily at the state level and estimate logit models.

Table A1: Predicting Targeted States with State Characteristics (logit)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Movement	0.000						
	(0.015)						
Stay-at-home compliance		0.000					
		(0.023)					
Arrests (violent crime)			0.000				
			(0.027)				
Arrests (civil disobedience)				0.000			
				(0.013)			
Statewide Protests					0.000		
					(0.220)		
COVID-19 deaths						0.000	
						(0.000)	
COVID-19 cases							0.000
							(0.000)
State	X	X	X	X	X	X	X
Time	X	X	X	X	X	X	X
Num.Obs.	273	273	245	245	273	273	273
AIC	82.0	82.0	74.0	74.0	82.0	82.0	82.0
BIC	230.0	230.0	203.5	203.5	230.0	230.0	230.0
Log.Lik.	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F	986.073	985.244			982.216	994.496	994.992
RMSE	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std.Errors	HC3	HC3	HC3	HC3	HC3	HC3	HC3

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors presented in parentheses. The dependent variable is a binary indicator for whether the state was targeted by Trump's tweets. The independent variables are measured at the state level and include the number of arrests for violent crime and civil disobedience, the number of statewide protests, the number of COVID-19 cases and deaths, and the dependent variables used in the analysis (movement and arrests for crimes related to civil disobedience).

F Data Limitations

There are several limitations to data used to measure both mobility and criminal behavior. In both cases, there is a potential for non-random missing data that could bias our estimates. When it comes to the mobility data, there are two limitations that are important to acknowledge. First, the data are only available for counties in which mobility is measured for more than 300 individuals in order to maintain user privacy (Meta 2022). Therefore, the data available from Meta include county-level data for 2,692 out of 3,244 county and county equivalents in the United States. Second, the data are only available for users who have location services enabled on their mobile devices. Location services are not enabled by default on mobile devices, and therefore the data are likely to be biased towards individuals who are more likely to enable location services on their mobile devices.

In both cases, we expect these limitations to work against our hypotheses. First, the counties with missing data are small and rural, and therefore are more likely to include Republican-leaning residents who are likely to be *more* susceptible to President Trump's cues (Gimpel et al. 2020). Second, individuals who are the most susceptible to President's Trump's cues are also probably the least likely to "opt-in" to enabling location services on their mobile devices in the first place. In other words, individuals who are more likely to enable location services on their mobile devices are likely to be more trusting of the government and less concerned about privacy, which is also likely to be associated with greater compliance with stay-at-home orders (Van Fossen et al. 2022; McLamore et al. 2022).

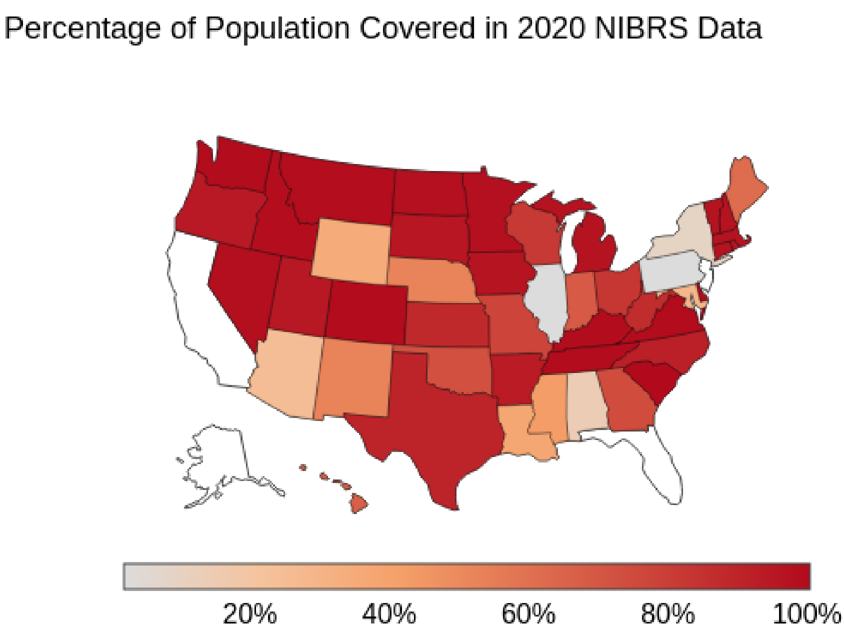
When it comes to the arrest data, there are two limitations that are important to acknowledge. First, local jurisdictions are not required to report crime data to the National Incident-Based Reporting System (NIBRS). In 2020, 9,880 law enforcement agencies reported data to the program, with coverage including approximately 177.5 million people (FBI 2022). The degree to which jurisdictions report data to NIBRS is at the discretion of local law enforcement agencies, and therefore missing data are likely to be non-random. Nonetheless the three targeted states are among the 25 US states that had over 90% population coverage in their reporting and 37 of the 50 states had at least 50% reporting in 2020. We present state coverage via the NIBRS data in **??**, and we add robustness to our results through a series of placebo tests in Appendix O.

Second, biases in the NIBRS arrest data may occur at the level of the local jurisdictions and may reflect the tendency of local law enforcement agencies to target certain groups over others. Even beyond the widespread evidence of racial bias in policing practices (Knox, Lowe, and Mummolo 2020; Hoekstra and Sloan 2022), existing research suggests specifically that Trump's inflammatory rhetoric further perpetuates racially biased policing practices (Grosjean, Masera, and Yousaf 2023), which can lead to over-policing of minority communities. Therefore, we expect that the NIBRS data are likely to be biased towards arrests of non-white individuals.

While we are unable to develop strong expectations about the direction of bias we might expect from non-random missingness of data due to a lack of reporting, we do expect that the NIBRS data are likely to be biased toward arrests of non-white individuals due to over-policing and other documented racial biases in policing practices (Goncalves and Mello 2021). In this regard, such a bias would work against our hypotheses, as we expect that the effects of Trump's messages are likely to be concentrated among white individuals.

The following figure presents the percentage of each state population that is covered by NIBRS data in 2020. The data are from the FBI's NIBRS data collection (FBI 2022).

Figure A6: NIBRS Data Coverage in 2020



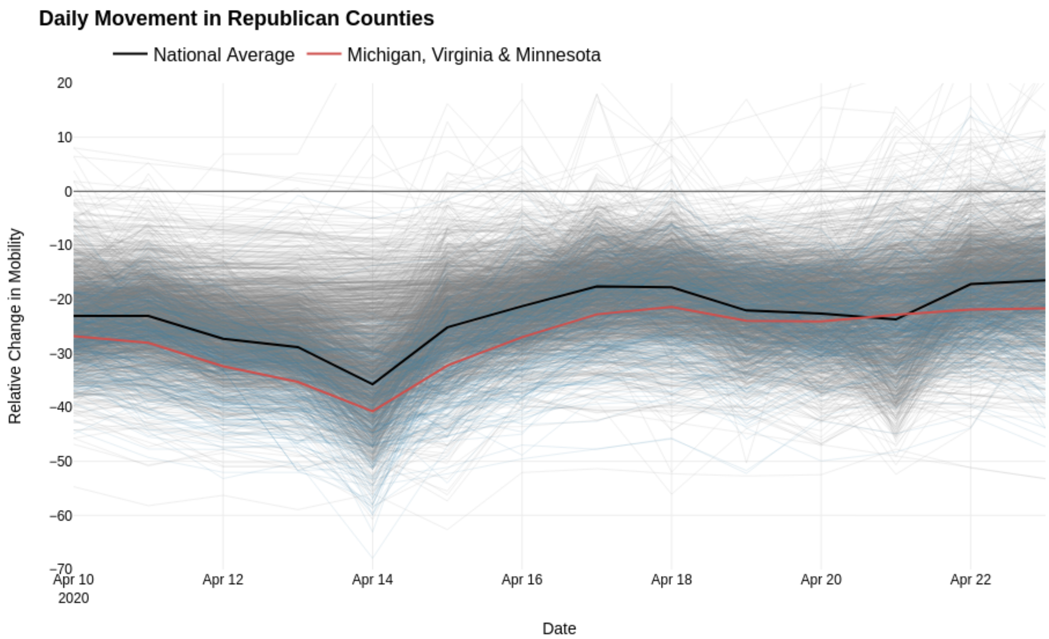
Note: The figure presents the percentage of each state population that is covered by NIBRS data in 2020. Data are from the FBI's NIBRS data collection (FBI 2022).

G Daily Movement Data

The following figure presents daily county-level movement data for Republican majority counties. In the figure, grey lines are control counties, while blue lines indicate Republican-majority counties in the targeted states. As these lines are hard to untangle, the solid black line represents the control group mean, while the solid red line represents the treatment group mean.

The figure provides suggestive evidence that Republican majority counties in the control group likely increased their movement around April 22, several days after the treatment group and Trump's tweets. This increase is then reflected as a return to the mean level of movement in the treatment group around April 22.

Figure A7: Daily Movement in Republican Majority Counties



H Predicted Outcomes - Mobility

Dynamic estimates of the effects of the cues on Stay-at-home compliance and mobility in Republican-majority counties.

Table A2: ATT estimates for Stay-at-home Compliance in Republican-majority counties

ATT	S.E.	CI.lower	CI.upper	p.value	Model	Time to treatment	Date
-0.917796	0.098487	-1.110828	-0.724764	0	Stay-at-home compliance	-6	2020-04-10
-0.196265	0.082378	-0.357723	-0.034807	0.017196	Stay-at-home compliance	-5	2020-04-11
-0.066725	0.113435	-0.289055	0.155604	0.556382	Stay-at-home compliance	-4	2020-04-12
0.531367	0.093539	0.348033	0.714701	0	Stay-at-home compliance	-3	2020-04-13
0.050902	0.111991	-0.168596	0.270401	0.649453	Stay-at-home compliance	-2	2020-04-14
0.470551	0.086914	0.300203	0.640898	0	Stay-at-home compliance	-1	2020-04-15
-0.026126	0.096734	-0.215722	0.163469	0.787095	Stay-at-home compliance	0	2020-04-16
-0.311240	0.137120	-0.579991	-0.042489	0.023218	Stay-at-home compliance	1	2020-04-17
-0.856404	0.132707	-1.116505	-0.596304	0	Stay-at-home compliance	2	2020-04-18
-1.887482	0.174732	-2.229950	-1.545014	0	Stay-at-home compliance	3	2020-04-19
-1.387395	0.188875	-1.757584	-1.017206	0	Stay-at-home compliance	4	2020-04-20
-2.128668	0.182029	-2.485438	-1.771898	0	Stay-at-home compliance	5	2020-04-21
-0.381090	0.200612	-0.774282	0.012102	0.057481	Stay-at-home compliance	6	2020-04-22
-0.038532	0.166884	-0.365618	0.288554	0.817399	Stay-at-home compliance	7	2020-04-23

Table A3: ATT estimates for movement in Republican-majority counties

ATT	S.E.	CI.lower	CI.upper	p.value	Model	Time to treatment	Date
0.445952	0.108230	0.233826	0.658079	0	Movement	-6	2020-04-10
0.074555	0.096438	-0.114461	0.263571	0.439473	Movement	-5	2020-04-11
0.118604	0.108647	-0.094339	0.331548	0.274986	Movement	-4	2020-04-12
-0.391451	0.106865	-0.600902	-0.181999	0.0249	Movement	-3	2020-04-13
0.157858	0.110892	-0.059486	0.375202	0.154582	Movement	-2	2020-04-14
-0.331526	0.1105	-0.547132	-0.115921	0.002580	Movement	-1	2020-04-15
-0.031811	0.106946	-0.241421	0.177799	0.766123	Movement	0	2020-04-16
0.032762	0.365186	-0.682989	0.748513	0.928516	Movement	1	2020-04-17
1.679983	0.351960	0.990154	2.369812	0	Movement	2	2020-04-18
3.642953	0.446124	2.768566	4.517341	0	Movement	3	2020-04-19
3.946769	0.453938	3.057067	4.836471	0	Movement	4	2020-04-20
5.971360	0.504566	4.982428	6.960292	0	Movement	5	2020-04-21
0.998064	0.507477	0.003428	1.992700	0.049216	Movement	6	2020-04-22
0.273045	0.421504	-0.553087	1.099177	0.517122	Movement	7	2020-04-23

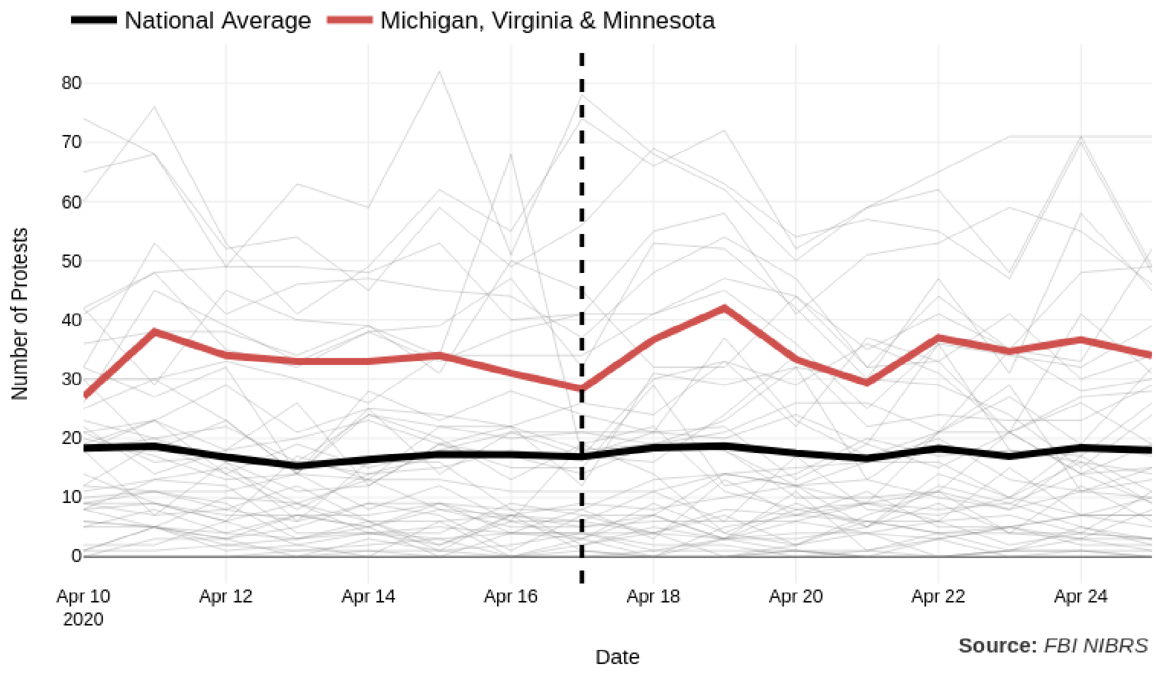
I Descriptive Statistics: Arrests

The following tables present descriptive statistics for the NIBRS arrests data (FBI 2022).

Table A4: Arrests for Crimes Related to Civil Disobedience by Racial Group

Racial Group	Arrests (mean)	Arrests (sum)	Arrests/million (mean)
American Indian or Alaska Native	0.53	297	0.22
Asian	0.38	213	0.09
Black or African American	10.19	5709	1.77
Multiple	0.00	0	0.00
Native Hawaiian or Other Pacific Islander	0.10	57	0.05
Unknown	0.51	283	0.11
White	19.66	11009	4.51

Figure A8: Daily Arrests for Crimes Related to Civil Disobedience



Note: Figure presents daily average arrests for assault (simple and aggravated), disorderly conduct, and destruction/damage/vandalism of property in the targeted states (red) and the national average (black). Gray background lines represent individual states. The horizontal line indicates the date at which President Trump called for the liberation of Michigan, Virginia and Minnesota.

Table A5: Arrests for Crimes Related to Civil Disobedience by State

State	Arrests (mean)	Arrests (sum)	Arrests/million (mean)
Alabama	0.84	81	0.17
Arizona	3.50	336	0.49
Colorado	11.57	1111	2.00
Connecticut	3.72	357	1.03
Delaware	2.41	231	2.43
Georgia	7.18	689	0.67
Hawaii	1.06	102	0.73
Idaho	1.91	183	1.04
Illinois	0.69	66	0.05
Indiana	4.10	394	0.60
Kansas	5.01	481	1.71
Louisiana	2.50	240	0.54
Maine	1.06	102	0.78
Maryland	0.75	72	0.12
Michigan	13.88	1332	1.38
Minnesota	2.84	273	0.50
Mississippi	1.47	141	0.50
Missouri	7.06	678	1.15
Montana	2.60	250	2.40
Nevada	1.44	138	0.46
New Hampshire	2.22	213	1.61
New Mexico	3.57	343	1.69
New York	1.08	104	0.05
North Carolina	12.53	1203	1.20
Ohio	12.35	1186	1.05
Oregon	7.57	727	1.79
Pennsylvania	0.07	7	0.01
Rhode Island	1.45	139	1.32
South Carolina	8.96	860	1.75
Tennessee	15.95	1531	2.31
Vermont	0.90	86	1.39
Virginia	12.84	1233	1.49
Washington	14.48	1390	1.88
West Virginia	1.80	173	1.00
Wisconsin	8.68	833	1.47

Note: Arrests for crimes related to rebellion: aggravated assault, simple assault, disorderly conduct, and destruction/damage/vandalism of property.

Table A6: Arrests for Crimes Related to Civil Disobedience by Racial Group and Date

Racial Group	Date	Arrests (mean)	Arrests (sum)	Arrests/million (mean)
American Indian or Alaska Native	2020-04-10	0.66	23	0.27
American Indian or Alaska Native	2020-04-11	0.57	20	0.18
American Indian or Alaska Native	2020-04-12	0.57	20	0.21
American Indian or Alaska Native	2020-04-13	0.34	12	0.14
American Indian or Alaska Native	2020-04-14	0.77	27	0.26
American Indian or Alaska Native	2020-04-15	0.29	10	0.10
American Indian or Alaska Native	2020-04-16	0.66	23	0.28
American Indian or Alaska Native	2020-04-17	0.69	24	0.35
American Indian or Alaska Native	2020-04-18	0.40	14	0.22
American Indian or Alaska Native	2020-04-19	0.40	14	0.16
American Indian or Alaska Native	2020-04-20	0.43	15	0.16
American Indian or Alaska Native	2020-04-21	0.43	15	0.15
American Indian or Alaska Native	2020-04-22	0.57	20	0.23
American Indian or Alaska Native	2020-04-23	0.46	16	0.21
American Indian or Alaska Native	2020-04-24	0.66	23	0.30
American Indian or Alaska Native	2020-04-25	0.60	21	0.27
Asian	2020-04-10	0.49	17	0.15
Asian	2020-04-11	0.34	12	0.10
Asian	2020-04-12	0.46	16	0.08
Asian	2020-04-13	0.57	20	0.15
Asian	2020-04-14	0.31	11	0.04
Asian	2020-04-15	0.40	14	0.11
Asian	2020-04-16	0.17	6	0.05
Asian	2020-04-17	0.37	13	0.08
Asian	2020-04-18	0.34	12	0.07
Asian	2020-04-19	0.54	19	0.11
Asian	2020-04-20	0.31	11	0.07
Asian	2020-04-21	0.29	10	0.12
Asian	2020-04-22	0.37	13	0.10
Asian	2020-04-23	0.29	10	0.10
Asian	2020-04-24	0.49	17	0.12
Asian	2020-04-25	0.34	12	0.07
Black or African American	2020-04-10	10.37	363	1.91
Black or African American	2020-04-11	10.60	371	1.98
Black or African American	2020-04-12	10.31	361	1.90
Black or African American	2020-04-13	10.66	373	1.69
Black or African American	2020-04-14	9.31	326	1.57
Black or African American	2020-04-15	10.17	356	1.71
Black or African American	2020-04-16	9.66	338	1.68
Black or African American	2020-04-17	8.77	307	1.56
Black or African American	2020-04-18	10.29	360	1.78
Black or African American	2020-04-19	10.57	370	1.80
Black or African American	2020-04-20	9.63	337	1.78
Black or African American	2020-04-21	11.31	396	1.97
Black or African American	2020-04-22	10.57	370	1.83
Black or African American	2020-04-23	10.09	353	1.75
Black or African American	2020-04-24	9.86	345	1.63
Black or African American	2020-04-25	10.94	383	1.84

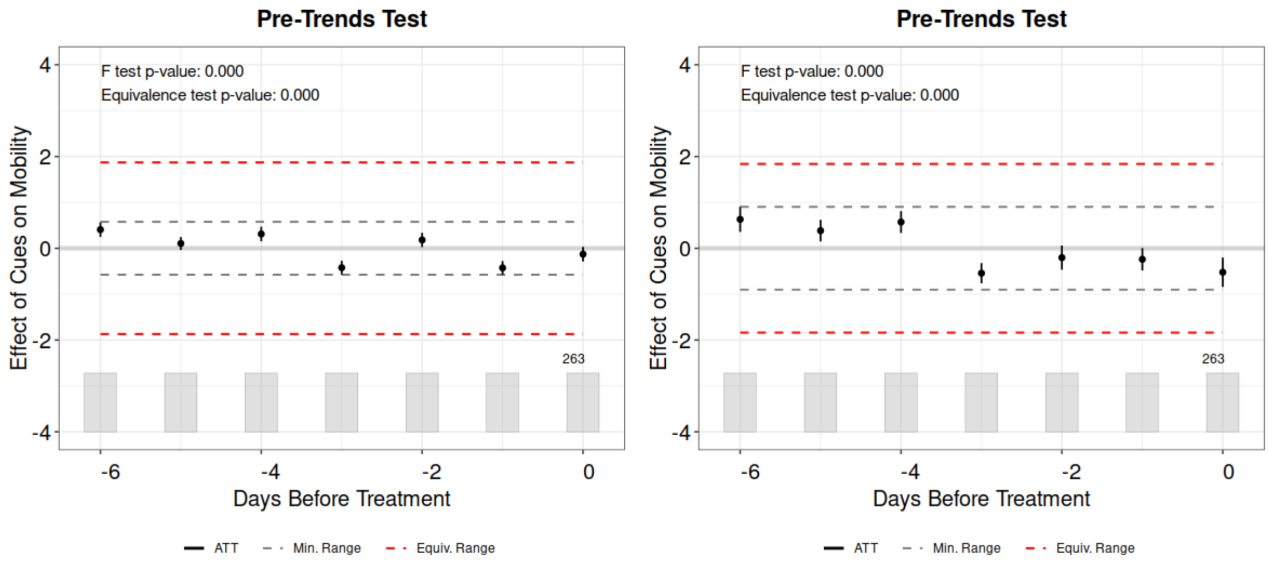
Table A7: Arrests for Crimes Related to Civil Disobedience by Racial Group and Date

Racial Group	Date	Arrests (mean)	Arrests (sum)	Arrests/million (mean)
Native Hawaiian or Other Pacific Islander	2020-04-10	0.03	1	0.02
Native Hawaiian or Other Pacific Islander	2020-04-11	0.06	2	0.02
Native Hawaiian or Other Pacific Islander	2020-04-12	0.09	3	0.05
Native Hawaiian or Other Pacific Islander	2020-04-13	0.09	3	0.06
Native Hawaiian or Other Pacific Islander	2020-04-14	0.09	3	0.03
Native Hawaiian or Other Pacific Islander	2020-04-15	0.06	2	0.04
Native Hawaiian or Other Pacific Islander	2020-04-16	0.17	6	0.12
Native Hawaiian or Other Pacific Islander	2020-04-17	0.11	4	0.08
Native Hawaiian or Other Pacific Islander	2020-04-18	0.20	7	0.06
Native Hawaiian or Other Pacific Islander	2020-04-19	0.06	2	0.02
Native Hawaiian or Other Pacific Islander	2020-04-20	0.09	3	0.03
Native Hawaiian or Other Pacific Islander	2020-04-21	0.11	4	0.06
Native Hawaiian or Other Pacific Islander	2020-04-22	0.09	3	0.04
Native Hawaiian or Other Pacific Islander	2020-04-23	0.14	5	0.02
Native Hawaiian or Other Pacific Islander	2020-04-24	0.09	3	0.03
Native Hawaiian or Other Pacific Islander	2020-04-25	0.17	6	0.10
Unknown	2020-04-10	0.69	24	0.21
Unknown	2020-04-11	0.66	23	0.16
Unknown	2020-04-12	0.43	15	0.08
Unknown	2020-04-13	0.37	13	0.08
Unknown	2020-04-14	0.49	17	0.13
Unknown	2020-04-15	0.54	19	0.09
Unknown	2020-04-16	0.51	18	0.11
Unknown	2020-04-17	0.66	23	0.15
Unknown	2020-04-18	0.71	25	0.17
Unknown	2020-04-19	0.23	8	0.05
Unknown	2020-04-20	0.51	18	0.16
Unknown	2020-04-21	0.43	15	0.07
Unknown	2020-04-22	0.54	19	0.13
Unknown	2020-04-23	0.31	11	0.09
Unknown	2020-04-24	0.57	20	0.11
Unknown	2020-04-25	0.43	15	0.07
White	2020-04-10	20.03	701	4.76
White	2020-04-11	21.31	746	4.77
White	2020-04-12	19.06	667	4.52
White	2020-04-13	17.74	621	4.48
White	2020-04-14	18.34	642	4.34
White	2020-04-15	19.91	697	4.63
White	2020-04-16	19.31	676	4.11
White	2020-04-17	18.74	656	4.16
White	2020-04-18	21.34	747	4.69
White	2020-04-19	21.54	754	4.61
White	2020-04-20	18.40	644	4.52
White	2020-04-21	18.46	646	4.13
White	2020-04-22	20.29	710	4.62
White	2020-04-23	18.94	663	4.42
White	2020-04-24	21.37	748	4.90
White	2020-04-25	19.74	691	4.44

J Tests for Pre-treatment trends

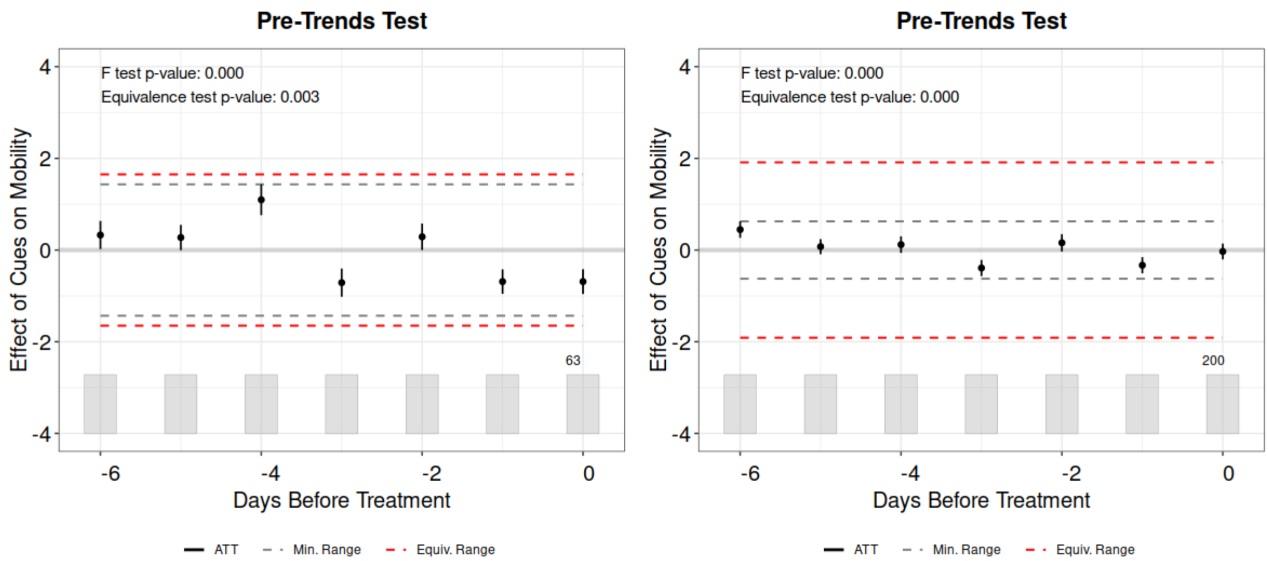
The following figures present tests for pre-trends in the mobility data. The tests are completed using the `Fect` library in R (Liu, Wang, and Xu 2022).

Figure A9: Pre-Trends Tests for Mobility



(a) Full State **(b)** Democrat Governor Only

Figure A10: Pre-Trends Tests for Mobility, cont'd



(a) Democratic Majority Counties **(b)** Republican Majority Counties

K Alternative Estimators (Mobility Data)

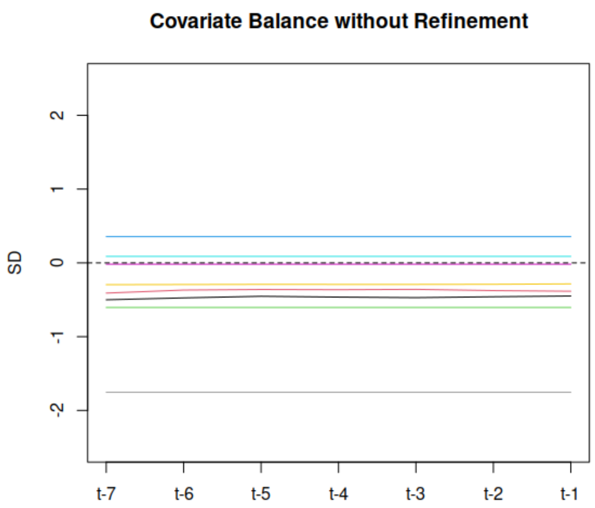
We replicated the mobility analysis using several different estimators. Specifically, we consider Mahalanobis matching, trajectory balancing with kernel balancing weights, and two-way fixed effects models. Our results are robust to these alternative estimators and are further detailed below.

K.1 Mahalanobis Matching

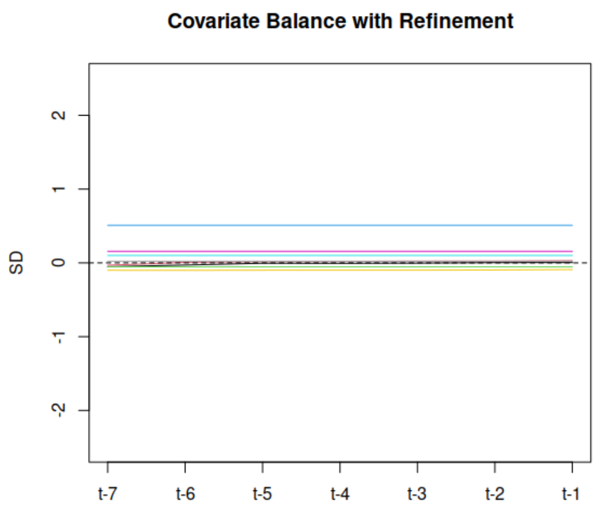
First, we replicated the analysis by matching counties in the targeted states to counties in the non-targeted states using Mahalanobis distance (Imai, Kim, and Wang 2023). This method allows us to match counties in the targeted states to counties in the non-targeted states based on a number of county-level characteristics relevant in the analysis, including COVID-19 conditions (COVID-19 cases and deaths) and past voting behavior (2016 US Presidential election). The method creates a matched set of counties that are similar in their pre-treatment characteristics up to a specified lagged time period, which allows for factoring in daily COVID-19 cases and deaths in the lead up to the President's messages. Matching on these characteristics improves the balance between the treated and control groups, reducing the potential for bias in the estimates.

Figure A11a and Figure A11b present the adjusted covariate balance plots for the mobility data before and after Mahalanobis refinement. The covariates are measured at the county level and include: (log) COVID-19 cases, (log) COVID-19 deaths, Republican county vote share (2016 election), (log) income, (log) unemployment, (log) black percentage, (log) county population, and (log) percent over 65.

Figure A11: Pre-treatment Covariate Balance before and after Matching with Mahalanobis Distance



(a) Balance Before Refinement



(b) Balance After Refinement

Table A8: Cumulative Effect of "Liberate" Cues on Movement (Mahalanobis Matching)

	Movement			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	2.838***	1.575*	3.056***	2.735***
Standard error	(0.455)	(0.694)	(0.540)	(0.453)
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	6,132	22,932	13,902

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors presented in parentheses. All results presented use Mahalanobis matching and are estimated using the `panelMatch` library in R (Imai, Kim, and Wang 2023). Models 1 estimates the effect of the cues on movement in all counties within the targeted states. Model 2 uses only democrat-majority counties in the targeted states as the treatment group and democratic-majority counties elsewhere around the country under the same stay-at-home orders as the control groups. Model 3 follows the same partisan format with only republican-majority counties for the treated and control groups. Model 4 uses only counties in states with democratic governors as the control group and all counties in the targeted states as the treatment group.

Table A9: Cumulative Effect of "Liberate" Cues on Stay-at-home Compliance (Mahalanobis Matching)

	Stay-at-home compliance			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	-1.269***	-0.724*	-1.349***	-1.377***
Standard error	(0.165)	(0.276)	(0.195)	(0.176)
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	6,132	22,932	13,902

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors presented in parentheses. All results presented use Mahalanobis matching and are estimated using the `panelMatch` library in R (Imai, Kim, and Wang 2023). Models 1 estimates the effect of the cues on movement in all counties within the targeted states. Model 2 uses only democrat-majority counties in the targeted states as the treatment group and democratic-majority counties elsewhere around the country under the same stay-at-home orders as the control groups. Model 3 follows the same partisan format with only republican-majority counties for the treated and control groups. Model 4 uses only counties in states with democratic governors as the control group and all counties in the targeted states as the treatment group.

K.2 Trajectory Balancing with Kernel Balancing Weights

We also used a trajectory balancing approach that uses kernel balancing to weight the control units in order to achieve balance on the pre-treatment trajectory of the outcome variable (Hazlett and Xu 2018). The method finds a linear combination of pre-treatment, time-invariant confounders that best predict the outcome variable and then weights the control units to match the treated units.

Below, we present the results from the trajectory balancing approach. The results are similar to the results from the main analysis, with the President's messages leading to a significant increase in mobility in the targeted states. The results are presented in Table A10 and Table A11.

Table A10: Cumulative Effect of "Liberate" Cues on Movement

	Movement			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	2.231***	0.636	2.879***	1.595***
Standard error	(0.221)	(0.359)	(0.264)	(0.188)
CI lower (2.5%)	1.798	-0.068	2.362	1.227
CI upper (97.5%)	2.664	1.34	3.396	1.963
P-value	0	0.077	0	0
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	6,132	22,932	13,902

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors presented in parentheses. All results presented use trajectory balancing with kernel balancing weights and are estimated using the `tbal` library in R (Hazlett and Xu 2018). Models 1 estimates the effect of the cues on movement in all counties within the targeted states. Model 2 uses only democrat-majority counties in the targeted states as the treatment group and democratic-majority counties elsewhere around the country under the same stay-at-home orders as the control groups. Model 3 follows the same partisan format with only republican-majority counties for the treated and control groups. Model 4 uses only counties in states with democratic governors as the control group and all counties in the targeted states as the treatment group.

Table A11: Cumulative Effect of "Liberate" Cues on Stay-at-home Compliance

	Stay-at-home compliance			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	-0.176*	-0.225	-0.276*	-0.255*
Standard error	(0.082)	(0.193)	(0.104)	(0.086)
CI lower (2.5%)	-0.336	-0.604	-0.48	-0.424
CI upper (97.5%)	-0.016	0.154	-0.071	-0.085
P-value	0.031	0.244	0.008	0.003
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	6,132	22,932	13,902

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors presented in parentheses. All results presented use trajectory balancing with kernel balancing weights and are estimated using the `tbal` library in R (Hazlett and Xu 2018). Models 1 estimates the effect of the cues on movement in all counties within the targeted states. Model 2 uses only democrat-majority counties in the targeted states as the treatment group and democratic-majority counties elsewhere around the country under the same stay-at-home orders as the control groups. Model 3 follows the same partisan format with only republican-majority counties for the treated and control groups. Model 4 uses only counties in states with democratic governors as the control group and all counties in the targeted states as the treatment group.

K.3 Interactive Fixed-effects Models

We also estimated the cumulative effects of the targeted cues at the county level using interactive fixed effects regressions. We select hyper-parameters based on mean squared prediction errors using the `Fect` library in R (Liu, Wang, and Xu 2022).

Table A12: Cumulative Effect of "Liberate" Cues on Movement (Interactive Fixed Effects)

	Movement			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	1.746***	-0.283	2.416***	1.72***
Standard error	(0.26)	(0.412)	(0.29)	(0.281)
CI lower (2.5)	1.236	-1.09	1.848	1.169
CI upper (97.5)	2.256	0.524	2.983	2.27
P-value	0	0.492	0	0
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	6,132	22,932	13,902

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors presented in parentheses. All results presented use interactive fixed effects and are estimated using the `Fect` library in R (Liu, Wang, and Xu 2022). Models 1 estimates the effect of the cues on movement in all counties within the targeted states. Model 2 uses only democrat-majority counties in the targeted states as the treatment group and democratic-majority counties elsewhere around the country under the same stay-at-home orders as the control groups. Model 3 follows the same partisan format with only republican-majority counties for the treated and control groups. Model 4 uses only counties in states with democratic governors as the control group and all counties in the targeted states as the treatment group.

Table A13: Cumulative Effect of "Liberate" Cues on Stay-at-home Compliance (Interactive Fixed Effects)

	Stay-at-home Compliance			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	-0.868***	-0.018	-1.135***	-0.802***
Standard error	(0.113)	(0.215)	(0.133)	(0.131)
CI lower (2.5)	-1.09	-0.439	-1.395	-1.058
CI upper (97.5)	-0.645	0.403	-0.875	-0.546
P-value	0	0.932	0	0
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	6,132	22,932	13,902

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors presented in parentheses. All results presented use interactive fixed effects and are estimated using the `Fect` library in R (Liu, Wang, and Xu 2022). Models 1 estimates the effect of the cues on movement in all counties within the targeted states. Model 2 uses only democrat-majority counties in the targeted states as the treatment group and democratic-majority counties elsewhere around the country under the same stay-at-home orders as the control groups. Model 3 follows the same partisan format with only republican-majority counties for the treated and control groups. Model 4 uses only counties in states with democratic governors as the control group and all counties in the targeted states as the treatment group.

K.3.1 Event Study

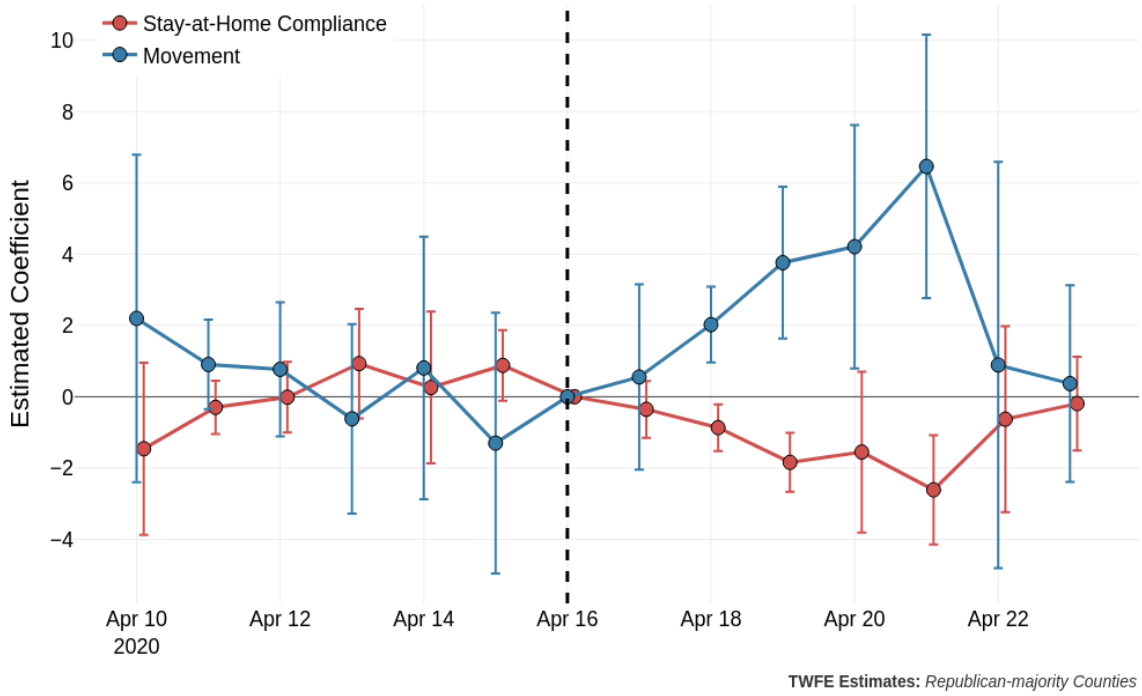
We also conducted our analysis using an event study specification. Our event study model can be formalized as follows:

$$Y_{i,j,t} = \sum_{\tau=-7}^{7} \theta_\tau Targeted_{j,t} + \delta_t + \zeta_i + X_{i,j,t} + \epsilon_{i,j,t} \tag{1}$$

where Y is mobility in county i in state j at time t. τ indicates the leads and lags of the treatment period. In the case that τ is greater than zero, the model captures the dynamic treatment effect of the cues. Whereas when τ is less than zero, the results allow for inspection of a pre-treatment trends between the treated and control counties. In the models, the omitted reference period is $\tau = 0$ (the day before the messages were sent).

Figure A12 presents the daily effects of the cues on mobility and on stay-at-home compliance in the seven days before and after treatment in Republican majority counties. Reassuringly, both outcomes meet the parallel trends assumption in the time leading up to Trump's messages. Following the cues, mobility increases in near-linear fashion for the following few days, peaking on April 21 before returning to similar levels as other Republican majority counties on the 22nd and 23rd. The compliance estimates indicate a similar pattern but in reverse, with compliance sharply decreasing in the following five days before decreasing on April 22nd and 23rd.

Figure A12: Dynamic Effect of Cues on Mobility in Republican Counties



Note: Event study results include estimates of mobility and stay-at-home compliance in Republican counties only. In both models, Republican counties elsewhere are the counterfactual. Time 0 is April 16th, the day before Trump sent the liberate tweets, and is the "holdout period" in our event study specification. Time 1 indicates the day the messages were sent (April 17, 2020). Standard errors were clustered by state and time. Estimation procedures explained in subsubsection K.3.1.

L Alternative Data Source – Google Mobility

We replicated the primary analysis using data from Google's Community Mobility Reports (Aktay et al. 2020). The Google Community Mobility Reports data consist of aggregated and anonymized daily mobility data. These data were similarly created with the aim of aiding public health officials in combating COVID-19. Mobility data were calculated daily for each US county using the median daily value from the respective location's five-week period in January 2020 (January 3 – February 6). Daily county values are then provided as the percentage change in mobility from the respective area's median value. These data are especially informative given that mobility for various activities are available. For each US county, daily data are available for human mobility resulting from retail and recreation, grocery and pharmacy, transit and transportation, workplace mobility and residential mobility.

Following the same format as the primary analysis, we use matrix completion to estimate the effect of the cues over the following days. We estimate the effect of the cues on the entire state (Model 1), on Democratic counties (Model 2), on Republican counties (Model 3) and on counties with Democratic governors only (Model 4). Table A14 presents the results for the effect of the cues on retail and recreational mobility. Table A15 presents the results for the effect of the cues on aggregate mobility.

In both tables that follow: Standard errors presented in parentheses. All results presented use matrix completion methods and are estimated using the `Fect` library in R (Liu, Wang, and Xu 2022). Model 1 estimates the effect of the cues on movement in all counties within the targeted states. Model 2 uses only Democratic-majority counties in the targeted states as the treatment group and Democratic-majority counties elsewhere around the country under the same stay-at-home orders as the control groups. Model 3 follows the same partisan format with only Republican-majority counties for the treated and control groups. Model 4 uses only counties in states with Democratic governors as the control group and all counties in the targeted states as the treatment group.

Table A14: Cumulative Effect of "Liberate" Cues on Retail and Recreational Mobility

	Retail and Recreational Mobility			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	1.527***	0.895**	2.396***	1.841***
Standard error	(0.287)	(0.314)	(0.338)	(0.322)
CI lower (2.5)	0.964	0.279	1.733	1.209
CI upper (97.5)	2.09	1.511	3.059	2.472
P-value	0	0.004	0	0
County	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
N Obs.	14,911	6,241	8,670	7,793

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A15: Cumulative Effect of "Liberate" Cues on Aggregate Mobility

	Aggregate Mobility			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	6.485***	6.751*	6.57**	7.323***
Standard error	1.843	3.289	2.075	1.872
CI lower (2.5)	2.873	0.304	2.504	3.654
CI upper (97.5)	10.097	13.197	10.637	10.992
P-value	0	0.04	0.002	0
County	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
N Obs.	14,911	6,241	8,670	7,793

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

M Placebo Tests: Mobility

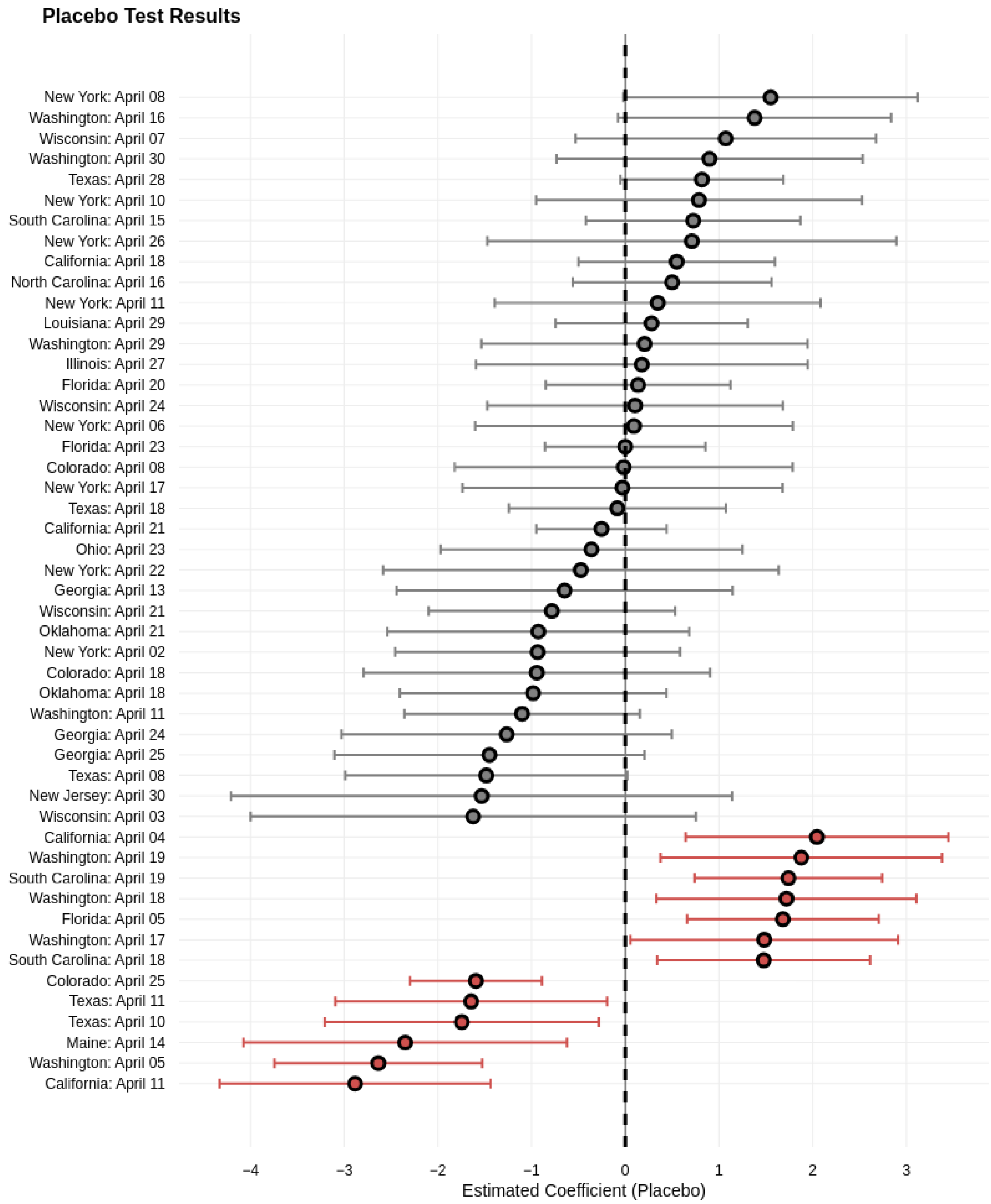
We conduct placebo tests by estimating the (placebo) effect of Trump's mentioning of a particular state on mobility (movement) in that state in the following week. We use two-way fixed effects regressions with county and date (day) fixed effects. Standard errors are clustered by county and day. Only states that were under similar lockdown orders as the targeted states are included in the placebo tests. Additionally, we do not include the targeted states (Minnesota, Michigan, and Virginia) in the placebo tests.

We present the results of the placebo tests in Table A16 and Figure A13. In Table A16, each row presents the abbreviated results from a single model, with the parameter of interest labelled `Coefficient` and the standard error labelled `Std. error`.

Table A16: Placebo Tests: Effect of Trump Mentioning a State on Mobility in that State

State	Date	Coefficient	P-val	Std. error	N observations
California	April 11, 2020	-2.883	0.000	0.734	30567
Washington	April 05, 2020	-2.635	0.000	0.563	30567
Maine	April 14, 2020	-2.348	0.007	0.876	30557
Texas	April 10, 2020	-1.744	0.019	0.743	30572
Texas	April 11, 2020	-1.645	0.025	0.736	30567
Wisconsin	April 03, 2020	-1.623	0.178	1.206	30557
Colorado	April 25, 2020	-1.594	0.000	0.358	30487
New Jersey	April 30, 2020	-1.533	0.259	1.357	30462
Texas	April 08, 2020	-1.483	0.052	0.764	30577
Georgia	April 25, 2020	-1.449	0.084	0.840	30487
Georgia	April 24, 2020	-1.266	0.157	0.894	30493
Washington	April 11, 2020	-1.102	0.084	0.637	30567
Oklahoma	April 18, 2020	-0.983	0.173	0.722	30536
Colorado	April 18, 2020	-0.944	0.314	0.938	30536
New York	April 02, 2020	-0.935	0.226	0.772	30560
Oklahoma	April 21, 2020	-0.929	0.256	0.818	30511
Wisconsin	April 21, 2020	-0.784	0.240	0.668	30511
Georgia	April 13, 2020	-0.648	0.476	0.910	30559
New York	April 22, 2020	-0.474	0.658	1.071	30510
Ohio	April 23, 2020	-0.361	0.659	0.817	30504
California	April 21, 2020	-0.254	0.472	0.353	30511
Texas	April 18, 2020	-0.084	0.886	0.588	30536
New York	April 17, 2020	-0.030	0.972	0.867	30543
Colorado	April 08, 2020	-0.017	0.985	0.915	30577
Florida	April 23, 2020	-0.000	1.000	0.435	30504
New York	April 06, 2020	0.092	0.914	0.860	30571
Wisconsin	April 24, 2020	0.104	0.896	0.801	30493
Florida	April 20, 2020	0.137	0.785	0.501	30516
Illinois	April 27, 2020	0.176	0.844	0.899	30479
Washington	April 29, 2020	0.205	0.816	0.883	30467
Louisiana	April 29, 2020	0.281	0.589	0.520	30467
New York	April 11, 2020	0.346	0.695	0.883	30567
North Carolina	April 16, 2020	0.500	0.353	0.539	30543
California	April 18, 2020	0.549	0.302	0.532	30536
New York	April 26, 2020	0.710	0.522	1.108	30481
South Carolina	April 15, 2020	0.725	0.212	0.581	30547
New York	April 10, 2020	0.787	0.373	0.883	30572
Texas	April 28, 2020	0.818	0.064	0.441	30471
Washington	April 30, 2020	0.899	0.278	0.829	30462
Wisconsin	April 07, 2020	1.072	0.188	0.814	30573
Washington	April 16, 2020	1.380	0.062	0.740	30543
South Carolina	April 18, 2020	1.477	0.010	0.576	30536
Washington	April 17, 2020	1.482	0.041	0.725	30543
New York	April 08, 2020	1.551	0.052	0.797	30577
Florida	April 05, 2020	1.682	0.001	0.519	30567
Washington	April 18, 2020	1.719	0.015	0.705	30536
South Carolina	April 19, 2020	1.741	0.001	0.508	30524
Washington	April 19, 2020	1.878	0.014	0.762	30524
California	April 04, 2020	2.045	0.004	0.712	30562

Figure A13: Placebo Tests: Effect of Trump Mentioning a State on Mobility in that State



Note: Each horizontal line represents the placebo estimate and 95% confidence intervals for a particular state/date combination in a separate model. All estimates in which the confidence interval does not include zero are marked in red. Full details of estimation provided in Appendix M.

N Full Results from Crime Analysis

The following includes full results from matrix completion estimation of the primary arrests analysis presented in the article.

Table A17: Cumulative CATT: Arrest Rate of White Americans

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.35	0.11	0.14	0.56	0.001

Table A18: Dynamic CATT Estimates for the Effect of the Cues on the Arrest Rate of White Americans

Date	Day	ATT	S.E.	CI.lower	CI.upper	p.value
2020-04-09	-8	0.015	0.077	-0.135	0.165	0.847
2020-04-10	-7	-0.161	0.071	-0.301	-0.022	0.024
2020-04-11	-6	0.106	0.064	-0.019	0.232	0.095
2020-04-12	-5	0.030	0.080	-0.127	0.186	0.711
2020-04-13	-4	-0.004	0.051	-0.104	0.096	0.936
2020-04-14	-3	0.105	0.079	-0.050	0.259	0.186
2020-04-15	-2	0.014	0.064	-0.112	0.140	0.827
2020-04-16	-1	-0.010	0.038	-0.085	0.065	0.802
2020-04-17	0	-0.037	0.041	-0.118	0.044	0.373
2020-04-18	1	0.222	0.371	-0.506	0.950	0.551
2020-04-19	2	1.057	0.197	0.671	1.443	0.000
2020-04-20	3	0.108	0.351	-0.580	0.797	0.758
2020-04-21	4	-0.302	0.514	-1.309	0.705	0.557
2020-04-22	5	0.448	0.284	-0.110	1.005	0.115
2020-04-23	6	0.194	0.601	-0.983	1.371	0.747
2020-04-24	7	0.229	0.379	-0.515	0.972	0.546
2020-04-25	8	0.073	0.306	-0.527	0.674	0.811

Table A19: Dynamic CATT Estimates for the Effects of the Cues on the Arrest Rate of **Non-White** Americans

Date	Day	ATT	S.E.	CI.lower	CI.upper	p.value
2020-04-09	-8	0.028	0.048	-0.066	0.122	0.556
2020-04-10	-7	-0.054	0.076	-0.202	0.095	0.480
2020-04-11	-6	-0.103	0.045	-0.191	-0.014	0.023
2020-04-12	-5	0.089	0.076	-0.060	0.238	0.241
2020-04-13	-4	0.044	0.071	-0.094	0.183	0.532
2020-04-14	-3	0.016	0.106	-0.191	0.223	0.881
2020-04-15	-2	0.005	0.050	-0.094	0.103	0.926
2020-04-16	-1	0.027	0.049	-0.068	0.122	0.577
2020-04-17	0	-0.053	0.079	-0.208	0.102	0.503
2020-04-18	1	-0.095	0.072	-0.236	0.047	0.190
2020-04-19	2	-0.111	0.073	-0.254	0.032	0.128
2020-04-20	3	0.043	0.150	-0.252	0.338	0.775
2020-04-21	4	0.140	0.072	0.000	0.281	0.050
2020-04-22	5	-0.074	0.067	-0.205	0.058	0.272
2020-04-23	6	0.014	0.058	-0.099	0.127	0.812
2020-04-24	7	-0.080	0.110	-0.296	0.136	0.467
2020-04-25	8	0.002	0.072	-0.139	0.142	0.983

O Alternative Racial Groups/Crimes

The following results include placebo tests in which we examine the effect of the "Liberate" cues on the arrest rate of Black Americans, the arrest rate of Asian Americans, and the arrest rate of white Americans for violent crimes. We additionally present unconditional estimates of the effect of the "Liberate" cues on the arrest rate of all Americans (in the targeted states, regardless of race) for the crimes examined in the primary analysis.

Each table in this section presents results in the same format: Standard errors are presented in parentheses. All results presented use matrix completion and are estimated using the `Fect` library in R (Liu, Wang, and Xu 2022). Model 1 uses the natural arrests rate (per million). Model 2 includes a log transformation of the arrest rate. Model 3 uses an inverse hyperbolic sine transformation of the arrests rate. Model 4 uses the natural arrest rate and includes daily state temperature as a control variable.

The results in Table A20 replicate the primary analysis using arrests for the same crimes but include arrests from Black Americans instead of white individuals.

The results in Table A21 replicate the primary analysis using arrests of white Americans for violent crimes (Aggravated Assault, Homicide, Rape, and Robbery).

The results in Table A22 estimate the effects of the cues on the arrest rate of Asian Americans using the same crimes as the primary analysis (Simple Assault, Damage/ Vandalism/ Destruction of property, Aggravated Assault and Disorderly conduct).

The results in Table A23 estimate the unconditional effect of the cues on state-wide arrests for the crimes examined in the primary analysis (Simple Assault, Damage/ Vandalism/ Destruction of property, Aggravated Assault and Disorderly conduct).

The results in Table A24 present estimates for state-wide arrests for the crimes examined in the primary analysis (Simple Assault, Damage/ Vandalism/ Destruction of property, Aggravated Assault and Disorderly conduct) using April 17 as the first day of the treated period. President Trump's messages were sent at approximately 4:21–4:25 PM EST on April 17.

Table A20: Placebo Test: Cumulative Conditional Effect of "Liberate" Cues on Arrest Rate of **Black Americans**

	Arrest rate (per million)			
	Arrests	Arrests (log)	Arrests (IVHS)	Arrests (w/Temp.)
Trump Cues (CATT)	0.094	0.081	0.081	0.068
Standard error	(0.095)	(0.093)	(0.095)	(0.091)
CI lower (2.5%)	-0.093	-0.100	-0.105	-0.111
CI upper (97.5%)	0.281	0.263	0.268	0.247
P-value	0.324	0.380	0.392	0.456
Daily state temp.				✓
State	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
Racial group	✓	✓	✓	✓
N obs.	3,600	3,600	3,600	3,600

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A21: Placebo Test: Cumulative Conditional Effect of "Liberate" Cues on Arrest Rate of White Individuals for **Violent** Crimes

	Arrest rate (per million)			
	Arrests	Arrests (log)	Arrests (IVHS)	Arrests (w/Temp.)
Trump Cues (CATT)	0.009	0.009	0.009	-0.001
Standard error	(0.063)	(0.063)	(0.060)	(0.067)
CI lower (2.5%)	-0.115	-0.115	-0.110	-0.132
CI upper (97.5%)	0.133	0.133	0.128	0.130
P-value	0.887	0.887	0.882	0.988
Daily state temp.				✓
State	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
Racial group	✓	✓	✓	✓
N obs.	3,600	3,600	3,600	3,600

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A22: Placebo Test: Cumulative Conditional Effect of "Liberate" Cues on Arrest Rate of **Asian Americans** (Aggravated Assault, Disorderly Conduct, Simple Assault, and Damage/Vandalism/Destruction of Property)

	Arrest rate (per million)			
	Arrests	Arrests (log)	Arrests (IVHS)	Arrests (w/Temp.)
Trump Cues (CATT)	0.002	0.002	0.002	-0.012
Standard error	(0.024)	(0.024)	(0.022)	(0.035)
CI lower (2.5%)	-0.045	-0.044	-0.041	-0.080
CI upper (97.5%)	0.049	0.048	0.045	0.056
P-value	0.933	0.932	0.927	0.739
Daily state temp.				✓
State	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
Racial group	✓	✓	✓	✓
N obs.	3,600	3,600	3,600	3,600

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A23: Cumulative Unconditional Effect of “Liberate” Cues on Arrest Rate (Aggravated Assault, Disorderly Conduct, Simple Assault, and Damage/Vandalism/Destruction of Property)

	Arrest rate (per million)			
	Arrests	Arrests (log)	Arrests (IVHS)	Arrests (w/Temp.)
Trump Cues (ATT)	0.056**	0.043*	0.061**	0.046
Standard error	(0.019)	(0.020)	(0.019)	(0.024)
CI lower (2.5%)	0.019	0.003	0.024	-0.001
CI upper (97.5%)	0.093	0.082	0.097	0.093
P-value	0.003	0.034	0.001	0.057
Daily state temp.				✓
State	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
N obs.	3,600	3,600	3,600	3,600

* p < 0.05, ** p < 0.01, *** p < 0.001

Table A24: Cumulative Effect of “Liberate” Cues on Arrests of White Americans with April 17 as first treatment day

	Arrest rate (per million)			
	Arrests	Arrests (log)	Arrests (IVHS)	Arrests (w/Temp.)
Trump Cues (ATT)	0.220*	0.220*	0.220*	0.208*
Standard error	(0.108)	(0.105)	(0.107)	(0.103)
CI lower (2.5)	0.008	0.015	0.010	0.006
CI upper (97.5)	0.432	0.426	0.431	0.410
P-value	0.041	0.036	0.040	0.043
State	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
N obs.	3,600	3,600	3,600	3,600

* p < 0.05, ** p < 0.01, *** p < 0.001

P Alternative Estimators: Arrests

In this section, we present estimates of the effect of the cues on the arrest rate of white Americans using interactive fixed effects. We select hyperparameters for the model using mean squared error using 15-fold cross validation. We use the `Fect` library in R (Liu, Wang, and Xu 2022). We use the same covariates as in the main text. We present the results in Table A25. The results are consistent with the main text.

Table A25: Cumulative Conditional Effect of "Liberate" Cues on Arrest Rate of White Individuals (Interactive Fixed Effects)

	Arrest rate (per million)			
	Arrests	Arrests (log)	Arrests (IVHS)	Arrests (w/Temp.)
Trump Cues (CATT)	0.359***	0.359***	0.359**	0.345**
Standard error	(0.099)	(0.102)	(0.108)	(0.100)
CI lower (2.5%)	0.164	0.159	0.147	0.149
CI upper (97.5%)	0.553	0.558	0.570	0.542
P-value	0.000	0.000	0.001	0.001
Daily state temp.				✓
State	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
Racial group	✓	✓	✓	✓
N obs.	3,600	3,600	3,600	3,600

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors are presented in parentheses. All results presented use interactive fixed effects and are estimated using the `Fect` library in R (Liu, Wang, and Xu 2022). Model 1 uses the natural arrests rate (per million). Model 2 includes a log transformation of the arrest rate. Model 3 uses an inverse hyperbolic sine transformation of the arrests rate. Model 4 uses the natural arrest rate and includes daily state temperature as a control variable.

Q Trump tweets mentioning US states

President Trump's tweets that explicitly mention a US state one week before and after the "LIBERATE" Tweets. Each item includes the date and the state that is mentioned in the tweet at the end in parentheses.

1. April 10: RT @USACE_NY: The New York District, in conjunction with state, federal and local partners, is constructing an alternate care facility for... (New York)
2. April 10: RT @realDonaldTrump: This morning, 450,000 protective suits landed in Dallas, Texas. This was made possible because of the partnership of t... (Texas)
3. April 11: "Trump did a deal with Japan. A lot of our product goes to Japan, and we are booming in North Dakota." Jim on C Span, Washington Journal. Our Trade Deals will be having a big impact on our Country as they kick in! (North Dakota)
4. April 11: Wishing all a safe and blessed Easter Sunday. I will be tuning into Pastor @robertjeffress at https... Church in Dallas, Texas tomorrow morning at 10:20 AM Eastern. (Texas)
5. April 11: "The President and the Federal Government are doing an excellent job. When they say the death toll isn't going to be as high as reported, they (the opposition) act like they're sad because it's lower. I think they are (Press Conferences) wonderful." West Virginia Resident, C Span (West Virginia)
6. April 11: Governor @GavinNewsom of California has been very nice & highly supportive about the great job we have done, working together, for California. That is the good news, but this is the bad. He is unfairly under attack by the Radical Left Dems, MSDNC etc. He is strong! Will he fold? (California)
7. April 13: RT @ScottPresler: Georgia's 6th District is flippable. This one's for you, Cobb, Fulton, & Dekalb Counties. https... #GA... (Georgia)
8. April 13: RT @ScottPresler: Here's an example of what I'm working on: Virginia's 2nd Congressional District is flippable. (Virginia)

9. April 14: RT @WhiteHouse: Over the weekend, the number of daily new infections remained flat. Thanks to the efforts of every American, our strategie. . . (Maine)

10. April 15: Our GREAT Senator from South Carolina, @SenatorTimScott just released a fantastic new book, "OPPORTUNITY KNOCKS: How Hard Work, Community, and Business Can Improve Lives and End Poverty." Get your copy today! https... (South Carolina)

11. April 16: .@OANN Poll "Gives President Trump a 52% Approval Rating in North Carolina, and a seven point lead over (Sleepy) Joe Biden. The President also helps other Republican Candidates, including @SenThomTillis, who has a 4% lead over his Democrat rival." (North Carolina)

12. April 16: Crazy "Nancy Pelosi, you are a weak person. You are a poor leader. You are the reason America hates career politicians, like yourself." @seanhannity She is totally incompetent & controlled by the Radical Left, a weak and pathetic puppet. Come back to Washington and do your job! (Washington)

13. April 17: Today people started losing their jobs because of Crazy Nancy Pelosi, Cryin' Chuck Schumer, and the Radical Left, Do Nothing Democrats, who should immediately come back to Washington and approve legislation to help families in America. End your ENDLESS VACATION! (Washington)

14. April 17: LIBERATE MINNESOTA! (Minnesota)

15. April 17: LIBERATE MICHIGAN! (Michigan)

16. April 17: LIBERATE VIRGINIA, and save your great 2nd Amendment. It is under siege! (Virginia)

17. April 17: ....testing that you should be doing. We have given New York far more money, help and equipment than any other state, by far, & these great men & women who did the job never hear you say thanks. Your numbers are not good. Less talk and more action! (New York)

18. April 18: RT @charliekirk11: Facts: California's Motor Voter law resulted in AT LEAST 1,500 people, including non-citizens, being registered to vote. . . (California)

19. April 18: An incompetent political hack! Come back to Washington & take care of our great American workers. https... (Washington)

20. April 18: RT @SenatorTimScott: Through yesterday, the PPP approved 22,933 loans for more than $3.8b in South Carolina. $3.8b to ensure workers get th. . . (South Carolina)

21. April 18: RT @SenateGOP: The #PaycheckProtectionProgram is WORKING in Colorado! (Colorado)

22. April 18: RT @SenatorLankford: Small businesses in Oklahoma received more than $4 billion dollars from the #PaycheckProtectionProgram to help them &. . . (Oklahoma)

23. April 18: RT @JimInhofe: BREAKING – Funds have officially run out for the #PaycheckProtectionProgram. This program has helped so many in Oklahoma and. . . (Oklahoma)

24. April 18: John James will be a GREAT Senator for Michigan! (Michigan)

25. April 18: Will be online tomorrow morning at 10:30am (Eastern) watching @jackngraham from @Prestonwood Baptist in Dallas, Texas. You can join us at (Texas)

26. April 19: Great new book out by @realKTMcFarland, "Revolution: Trump, Washington, and We the People". Get your copy today! https...(Washington)

27. April 19: RT @realDonaldTrump: Our GREAT Senator from South Carolina, @SenatorTimScott just released a fantastic new book, "OPPORTUNITY KNOCKS: How H. . . (South Carolina)

28. April 20: Congratulations to all of my many friends at The Villages in Florida on having done so well, and with such great spirit, during these rather unusual times. So proud of everyone! Mark Morse & Gary Lester have really stepped up to the plate. Hope to see everyone soon. (Florida)

29. April 20: Received a very nice call from @GovTimWalz of Minnesota. We are working closely on getting him all he needs, and fast. Good things happening! (Minnesota)

30. April 21: Tom Tiffany (@TomTiffanyWI) is a Great Advocate for the incredible people of Wisconsin (WI07). We need Tom in Congress to help us Make America Great Again! He will Fight for Small Business, supports our Incredible Farmers, Loves our Military and our Vets.... (Wisconsin)

31. April 21: ....He is Strong on Crime, the Border, and Second Amendment. Tom has deep roots in Wisconsin, is a big Tax Cutter, and will help me DRAIN THE SWAMP! Tom has my Complete and Total Endorsement. Vote for Tom Tiffany! https... (Wisconsin)

32. April 21: .@MikeGarcia2020 will be a tremendous fighter for the U.S. and the State of California. An Annapolis graduate, he served our Country as a highly decorated Navy Fighter Pilot and will be a great Congressman (#CA25). Loves our Military, and Vets... (California)

33. April 21: RT @JimInhofe: Our farmers and ranchers are instrumental to Oklahoma's economy and they've been hit hard by #COVID19. This funding will bri. . . (Oklahoma)

34. April 21: RT @realDonaldTrump: ....He is Strong on Crime, the Border, and Second Amendment. Tom has deep roots in Wisconsin, is a big Tax Cutter, and... (Wisconsin)

35. April 21: RT @realDonaldTrump: Tom Tiffany (@TomTiffanyWI) is a Great Advocate for the incredible people of Wisconsin (WI07). We need Tom in Congress... (Wisconsin)

36. April 21: RT @realDonaldTrump: .@MikeGarcia2020 will be a tremendous fighter for the U.S. and the State of California. An Annapolis graduate, he serv... (California)

37. April 22: RT @WhiteHouse: "The New York Metropolitan area has been the epicenter of the outbreak here in America and the Federal government has spare... (New York)

38. April 23: Congressman Bill Johnson (@JohnsonLeads) is an incredible fighter for the Great State of Ohio! He's a proud Veteran and a hard worker who Cares for our Veterans, Supports Small Business, and is Strong on the Border and Second Amendment.... (Ohio)

39. April 23: Congressman Warren Davidson (@Vote_Davidson) is working very hard for the people of Ohio! He's a strong supporter of our Military, Vets, Second Amendment, and #MAGA Agenda. Warren has my Complete and Total Endorsement! https... (Ohio)

40. April 23: Congressman Chris Stewart (@StewartforUtah) is a tremendous fighter for Utah. He served our Country in the U.S. Air Force, and has been a strong supporter of our #MAGA Agenda.... (Utah)

41. April 23: Congressman John Curtis (@CurtisUT) gets things done for Utah! John fights for Small Businesses, will Lower your Taxes, and will protect your Second Amendment. He has my Complete and Total Endorsement! (Utah)

42. April 23: Utah Attorney General Sean Reyes (@SeanReyesUT) is a fighter and hard worker for the Great State of Utah. He is a big supporter of our #MAGA Agenda – Strong on Crime, the Second Amendment, and Loves our Law Enforcement.... (Utah)

43. April 23: ....My co-chair in Utah and a really great guy. Sean has my Complete and Total Endorsement! (Utah)

44. April 23: Congressman @BradWenstrup is doing a tremendous job for the People of Ohio! He's a proud Veteran and is Strong on the Border, Tough on Crime, the Second Amendment, and Supports Small Business. Brad has my Complete and Total Endorsement! https... (Ohio)

45. April 23: Congressman @DaveJoyceOH14 is a tremendous fighter for the Great State of Ohio! He is Tough on Crime, our Border, Second Amendment, and helps us Combat Illegal Drugs! David has my Complete and Total Endorsement! https... (Ohio)

46. April 23: Congressman @Troy_Balderson is doing a GREAT job for the People of Ohio! He will always Protect your #2A, Defend our Borders, and Support Small Business – a great supporter of the #MAGA Agenda. Troy has my Complete and Total Endorsement! https... (Ohio)

47. April 23: Congressman @MikeTurnerOH is a strong supporter and fighter for the People of Ohio! He will help us #MAGA! He's Strong on the Border, Tough on Crime, will Protect our Vets, and our GREAT Second Amendment. Mike has my Complete and Total Endorsement! (Ohio)

48. April 23: Congressman Bill Posey is a tremendous fighter for the Great State of Florida. He is a big supporter of our #MAGA Agenda – Strong on Crime, the Second Amendment, and Loves our Veterans and Law Enforcement. Bill has my Complete and Total Endorsement! (Florida)

49. April 23: Congressman @SteveStivers is doing a terrific job for the People of Ohio! He defends our Borders, Supports our Veterans, Strong on Crime, and the Second Amendment. Steve has my Complete and Total Endorsement! (Ohio)

50. April 23: Governor @JimJusticeWV is a tremendous fighter for the incredible people of West Virginia. Big Jim is strong on Life, the Second Amendment, and Building the Wall! With Governors like Jim, America will recover and get back to business. Jim has my Complete and Total Endorsement! (West Virginia)

51. April 24: RT @Mike_Pence: Yesterday, I had the privilege of visiting @GEHealthcare in Wisconsin to see American industry and American workers at their... (Wisconsin)

52. April 24: I (or @VP) never gave Governor Brian Kemp an OK on those few businesses outside of the Guidelines. FAKE NEWS! Spas, beauty salons, tattoo parlors, & barber shops should take a little slower path, but I told the Governor to do what is right for the great people of Georgia (USA)! (Georgia)

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