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Elite Cues and Noncompliance

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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 noncompliant 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.

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 is 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 noncompliance 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 (Brader and Tucker 2012; Lupia 1994; Lupia and McCubbins 1998; Samuels and Zucco 2014). 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 (Anderson and Hobolt 2022; Jørgensen, Bor, and Petersen 2021; Jørgensen et al. 2021; Klüver et al. 2021). However, evidence from the United States (US) 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-19-related measures among Republicans and Democrats (Allcott et al. 2020; Bisbee and Lee 2022; Gadarian, Goodman, and Pepinsky 2022; Green et al. 2020; Grossman et al. 2020; Roberts and Utych 2021).

This raises the question of whether specific elite messages can change people's behavior and even encourage noncompliance 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 noncompliance 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 noncompliant 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

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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 noncompliant behavior. Using daily, county-level mobility data from Meta (Meta 2023) and Google (Google 2023), 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 noncompliant 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 noncompliant behavior resulting in criminal arrests. Relying on daily arrests data from the FBI's National Incident-Based Reporting System (US Federal Bureau of Investigation 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 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 (Druckman, Peterson, and Slothuus 2013; Slothuus and Bisgaard 2021; Tappin 2022). 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 noncompliant 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 microtargeting 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.

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, 273–4). 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 (Bisbee and Lee 2022; Grossman et al. 2020; Roberts and Utych 2021), reducing mask wearing (Hahn 2021), and undermining trust in science agencies (Gadarian, Goodman, and Pepinsky 2022; Hamilton and Safford 2021).

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-19-related restrictions on citizens' adherence to such restrictions and, in turn, on more radical instances of noncompliance.

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 (Brader and Tucker 2012; Nicholson 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; Mason 2018; Theodoridis 2017). 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 (Baekgaard et al. 2020; Bol et al. 2021; De Vries 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 (Anderson and Hobolt 2022; Barari et al. 2020; 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; Bisbee and Lee 2022; Roberts and Utych 2021). 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 (Gadarian, Goodman, and Pepinsky 2022; Van Green and Tyson 2020). Moreover, more Republican counties typically displayed lower levels of compliance with social distancing measures than Democratic counties, further highlighting a partisan disconnect (Bisbee and Lee 2022; Roberts and Utych 2021).

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-19-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' behavior. 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 nontargeted states. Our general expectation is that noncompliance 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 noncompliance 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 noncompliant 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 (Boman and Gallupe 2020; Stickle and Felson 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 noncompliant behavior to be concentrated only among individuals most receptive to Trump's messages—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.

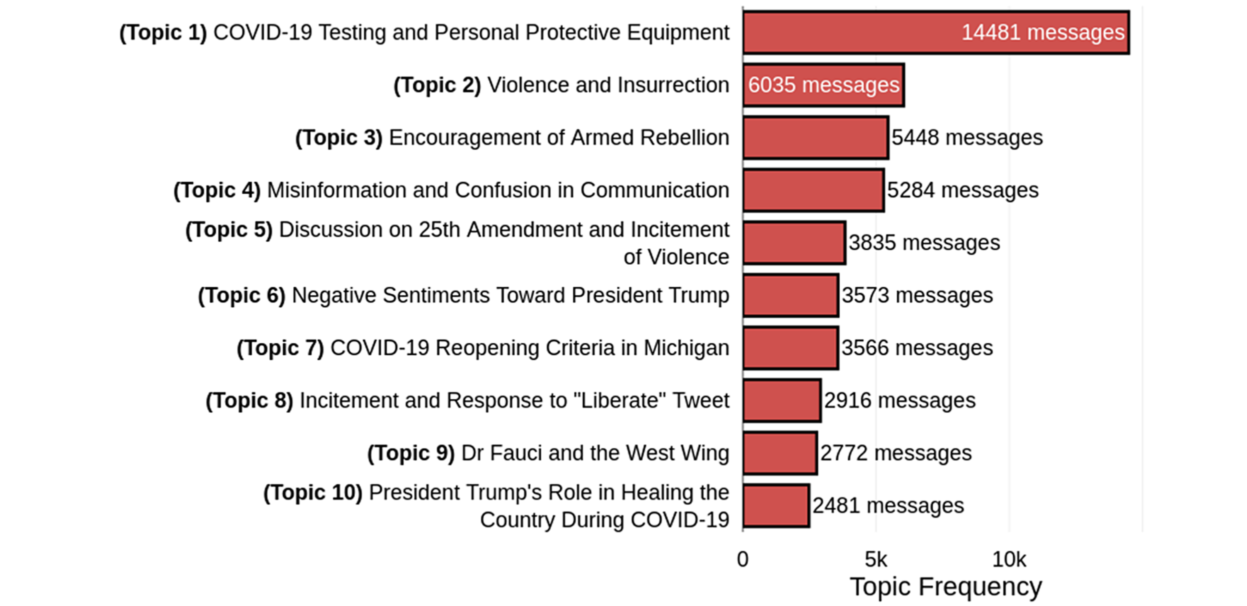
President Trump's Calls for Liberation

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 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

[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.
[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.

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 Supplementary Appendix C.

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 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 US. As shown in Figure 2, at no other point in the 20-year history that Google has tracked search data was the term *liberate* searched more frequently than in April 2020.

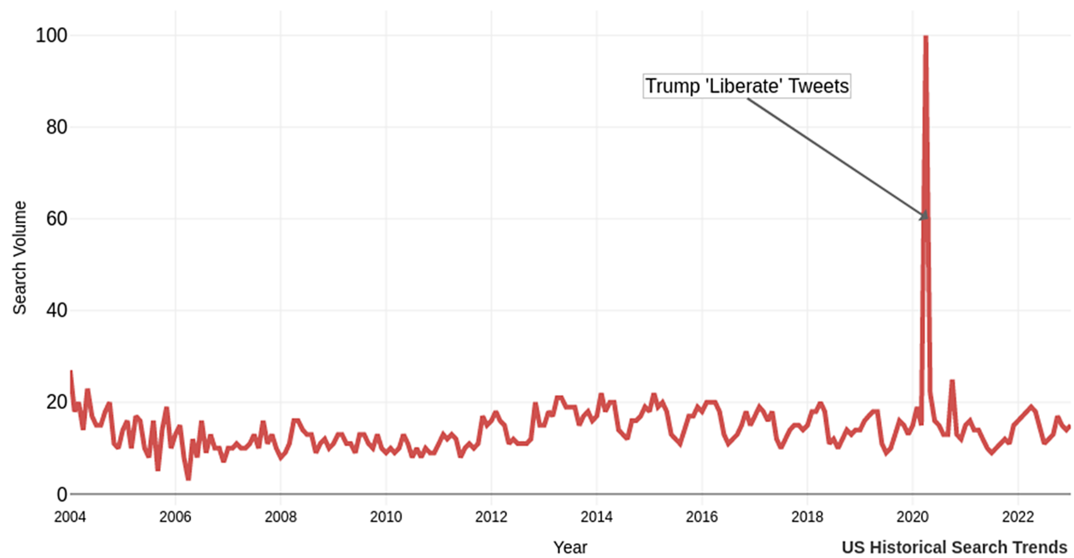
Although it is clear that the President's messages were widely seen and discussed, we further examined the spatial distribution of Internet search trends across the country. Focusing on the week following the President's messages, Figure 3 presents the spatial distribution of Internet searches for *liberate*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

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

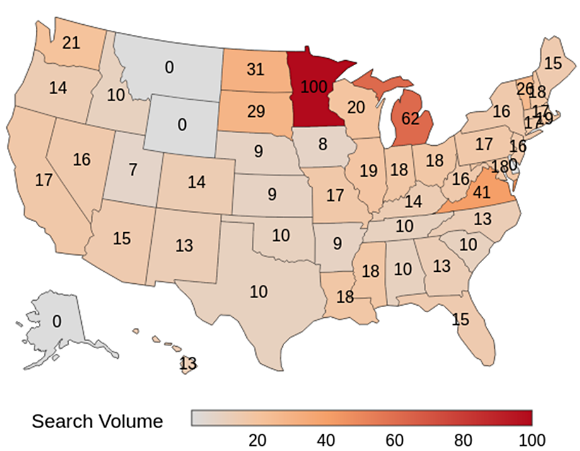
[6] The Google Trends data presented in Figure 3 constitute between-state comparisons which are normalized and scaled between 0 and 100 for the 50 states from April 17 to 23. Between-state comparisons can only be made with static Google Trends data, which means that the data are normalized/scaled over 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 2023).

FIGURE 3. Internet Search Trends for "Liberate" from April 17 to 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 2023).

messages had an effect on the behavior of citizens—and specifically supporters—in the days following the messages, encouraging them to engage in noncompliant 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.

RESEARCH DESIGN

Data and Variables

To examine the extent to which President Trump's messages affected public behavior, we focus on three different outcomes of noncompliance, 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 2023). The movement range data track 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 measure 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

[7] More on the methodology of the mobility data is available directly from Meta Research https://research.facebook.com/blog/2020/06/protecting-privacy-in-facebook-mobility-data-during-the-covid-19-response/ (Meta 2023).

restrictions. Meta's mobility data are especially valuable for our analysis, because in combination they provide measures of both the extent to which individuals traveled as well as the percentage 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) (US Federal Bureau of Investigation 2022). Data are available at the arrest level and include information on the type of crime for which the arrest was made, as well as demographic characteristics of the offender. Forty-five 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 (Boman and Gallupe 2020; Stickle and Felson 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 Supplementary Appendix G.

In the cases of both the mobility and the arrest data, there are several limitations and the potential for nonrandom missing data. In Supplementary Appendix F, we provide a comprehensive discussion of the limitations of the data used in the analysis. To summarize, we expect nonrandom 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 three hundred 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 (Grosjean, Masera, and Yousaf 2023; Hoekstra and Sloan 2022; Knox, Lowe, and Mummolo 2020). We offer a further discussion of the limitations of the data in Supplementary Appendix F.

Identification Strategy

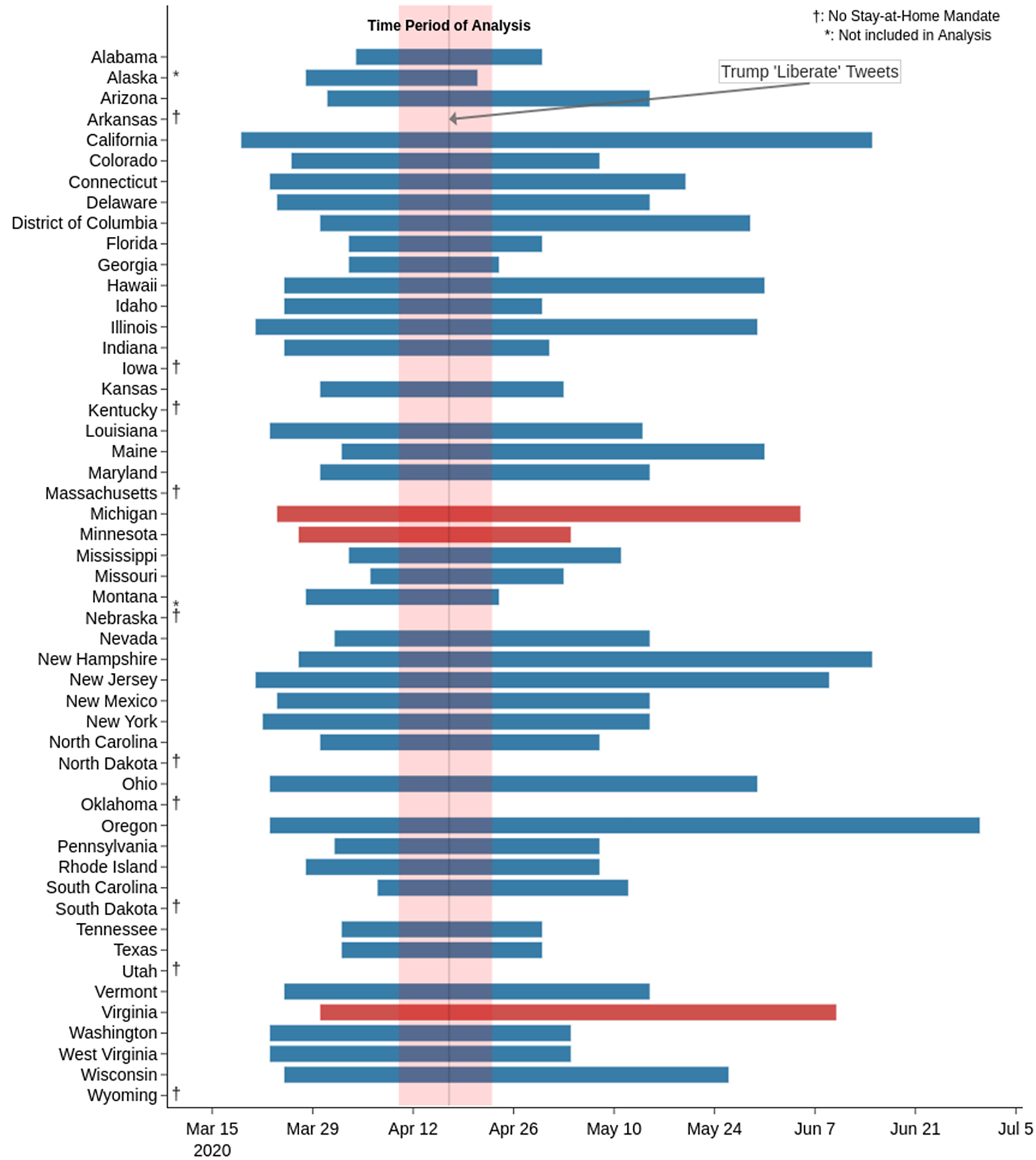
We adopt a generalized difference-in-differences design to estimate the effects of the cues on mobility and arrests related to civil disobedience following the President's messages. The focus of our analysis is on the extent to which President Trump's cues motivated noncompliant behavior in the areas 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 Figures 2 and 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 nontargeted 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 Supplementary 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 is 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.

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.

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

[8] We use data from the 2016 Presidential Election to assess partisanship at the county level. Data from the 2020 Presidential Election were not used to avoid potential posttreatment bias.

(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 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 observe 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 pretreatment period using the methods described in Liu, Wang, and Xu (2024). 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 Supplementary Appendix H.

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 2024). 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 nontargeted 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 Supplementary Appendix I. In brief, the results of the alternative estimators are substantively 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) levels, inferences rely on the assumption that group behavior reflects the behavior of individuals within the said group (King 2013). In other words, we cannot avoid making 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 the "Alternative Explanations" section, as well as in Supplementary Appendices I and N.

MOBILITY RESULTS

We first examine the cumulative effects of the President's messages on mobility. Tables 1 and 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 modeling strategy articulated previously in the "Identification" section. 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 Tables 1 and 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-

TABLE 1. Cumulative Effect of "Liberate" Cues on Movement

	Movement			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump cues (ATT)	1.710***	−0.533	2.246***	1.619***
Standard error	0.257	0.400	0.285	0.239
CI lower	1.206	−1.317	1.687	1.150
CI upper	2.214	0.251	2.806	2.088
P-value	0.000	0.183	0.000	0.000
County	✓	✓	✓	✓
Time (day)	✓	✓	✓	✓
No. of obs.	29,064	5,516	23,548	13,902

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. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

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)	−0.787***	0.034	−0.968***	−0.754***
Standard error	0.102	0.225	0.121	0.112
CI lower	−0.986	−0.406	−1.206	−0.973
CI upper	−0.588	0.474	−0.731	−0.535
P-value	0.000	0.881	0.000	0.000
County	✓	✓	✓	✓
Time (day)	✓	✓	✓	✓
No. of obs.	29,064	5,516	23,548	13,902

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. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

majority counties, however, they are similarly detectable at the state level (model 1) and in the case that only counties in states with Democratic governors are considered as the control group (model 4).

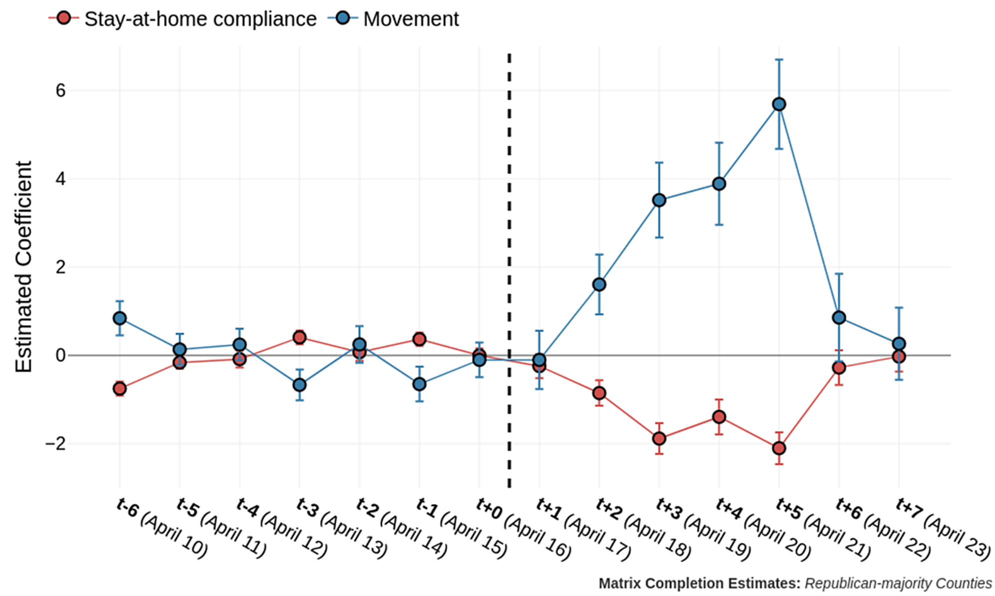
In the specification that includes only Democrat-majority counties, the estimates are not statistically distinguishable from zero at conventional levels. This suggests that the President's messages did not have significant effects on movement or stay-at-home compliance in Democrat-majority counties.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

The Dynamic Effects of the President's Messages

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 pretreatment trends in the targeted states.[9]

[9] Several estimates are statistically distinguishable from zero in the time leading up to the messages. One 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 posttreatment ATT estimates by the worst-case (maximum) pretreatment parallel trends violation, a statistically meaningful effect is still reliably identifiable for both outcomes (Manski and Pepper 2018; Rambachan and Roth 2023). Additionally, we provide further evidence to empirically support a lack of trends in the outcome variable, as well as event study estimates from two-way fixed effects regressions in Supplementary Appendices H and I.

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 Tables 1 and 2). The counterfactual 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.

However, the estimates 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 4 days, peaking on April 21 before returning to similar levels as other Republican majority counties on April 22 and 23. The compliance estimates indicate a similar pattern but in reverse, with compliance decreasing—though not as sharply as movement increased—in the following 5 days before returning to similar levels as other Republican-majority counties on April 22 and 23.

While the dynamic effects of the cues are 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 Supplementary Appendix E, we provide suggestive 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 not 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.

CRIMINAL BEHAVIOR

Next, we consider the extent to which the cues led to wider displays of noncompliance 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 noncompliant 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) (US Federal Bureau of Investigation 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 Supplementary Appendix G. 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 2024). 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

[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 Supplementary Appendix M for that analysis.

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)	0.324**	0.324**	0.325**	3.146**	3.006*
Standard error	0.123	0.123	0.119	1.194	1.183
CI lower (2.5%)	0.083	0.083	0.092	0.805	0.686
CI upper (97.5%)	0.566	0.566	0.558	5.487	5.325
P-value	0.009	0.009	0.006	0.008	0.011
Daily state temp.			✓		✓
State	✓	✓	✓	✓	✓
Time (day)	✓	✓	✓	✓	✓
Racial group	✓	✓	✓	✓	✓
No. of obs.	3,600	3,600	3,600	3,600	3,600

Note: All results presented use matrix completion to estimate the effect of the targeted messages on the arrest rate of white Americans. 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 uses the number of arrests when conditioning on daily state temperature. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

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 the first three models, the dependent variable is the daily arrest rate (per million) of white Americans. Models 4 and 5 use the total number of arrests of white Americans. Additionally, models 3 and 5 condition on daily state temperature as a control variable, given that 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 3 specification in Figure 6. Similar to the dynamic estimates of mobility and stay-at-home compliance, Figure 6a demonstrates that there was a sharp increase in the 2 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) suggest that these individuals were not as responsive to the President's message, which provides additional context. Taken in full, the estimates suggest a sharp but short-lived increase in the arrest rate of white Americans, with only one of the days (April 19) clearly differentiable from zero.[12]

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.

Exogeneity of the Cues

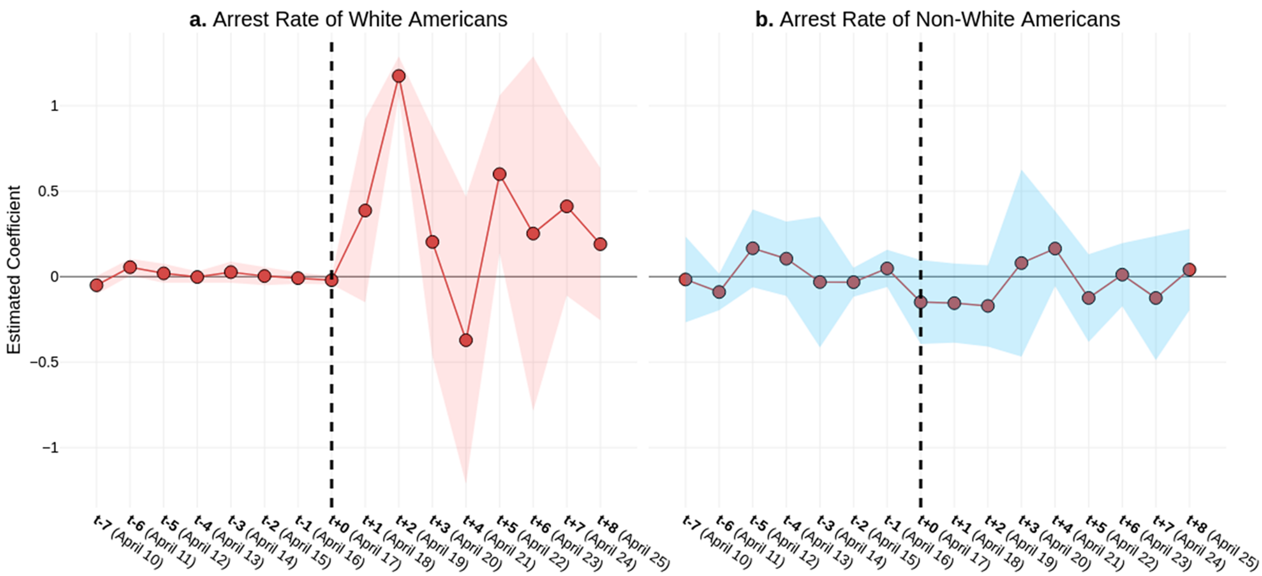
One specific scenario that challenges our identifying assumptions is that President Trump was responding to events that were *already occurring* in the three states with his calls for liberation. For example, if the President was responding to increased criminal activity in Michigan, Virginia, and Minnesota, 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

[11] In Supplementary Appendix M, 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).

[12] In Supplementary Appendices G and L, 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 6 in Supplementary Appendix G).

FIGURE 6. Conditional Effects of Trump Cues on Arrest Rate



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 Supplementary Appendix L. Matrix completion estimates: Arrest rate of white and non-white americans.

week before April 17. As predictors, we use state COVID-19 conditions (cases and deaths), daily statewide 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 indicate 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 Supplementary Appendix K.

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 Supplementary Appendix Q.

Independent Protest Activity

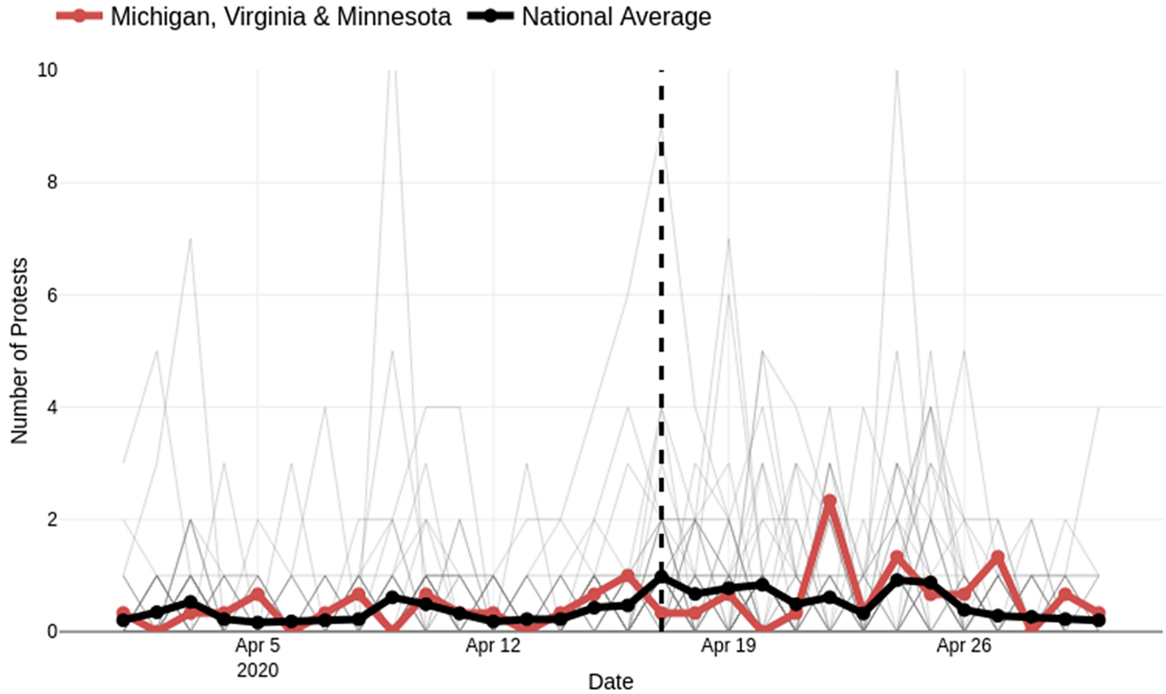
We also considered the possibility that protest activity planned independently of President Trump's messages could be driving the changes in mobility and crime that we observe. For instance, a protest planned on April 16 for 2 days later on April 18 would occur independent of Trump's cues and could cause 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 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.

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 2023)—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

[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 gray lines indicate individual states, while the red and black solid lines are averages for the targeted states and the nation (excluding the targeted states). Source: Crowd counting consortium.

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 Supplementary Appendix J.

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 Supplementary Appendix K.

For the arrests analysis, we conduct placebo tests by estimating the effects of the cues on arrests for crimes related to civil disobedience for non-white Americans (Figure 6), crimes related to civil disobedience by Black Americans, crimes related to civil disobedience by Asian Americans, and violent crimes (e.g., murder and rape) 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 Supplementary Appendix M.

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 Supplementary Appendices I and N and are substantively consistent with our primary analysis.

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 (Anderson and

Hobolt 2022; Brader and Tucker 2012; Jørgensen, Bor, and Petersen 2021; Nicholson 2012). 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 reveals 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 noncompliant 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 spillover 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 (Bisbee and Lee 2022; Grossman et al. 2020), 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 antiestablishment rhetoric and a decline in trust in liberal democratic institutions (De Vries and Hobolt 2020; Mudde and Rovira Kaltwasser 2018). 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 of elites to motivate noncompliant 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 noncompliant 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 noncompliant 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.

SUPPLEMENTARY MATERIAL

To view supplementary material for this article, please visit https://doi.org/10.1017/S0003055424000741.

DATA AVAILABILITY STATEMENT

Research documentation and data that support the findings of this study are openly available at the American Political Science Review Dataverse: https://doi.org/10.7910/DVN/IYN1YN.

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CONFLICT OF INTEREST

The authors declare no ethical issues or conflicts of interest in this research.

ETHICAL STANDARDS

The authors affirm this research did not involve human participants.

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