Supplementary Materials

Elite Cues and Non-compliance

American Political Science Review

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Contents

A Software Utilized

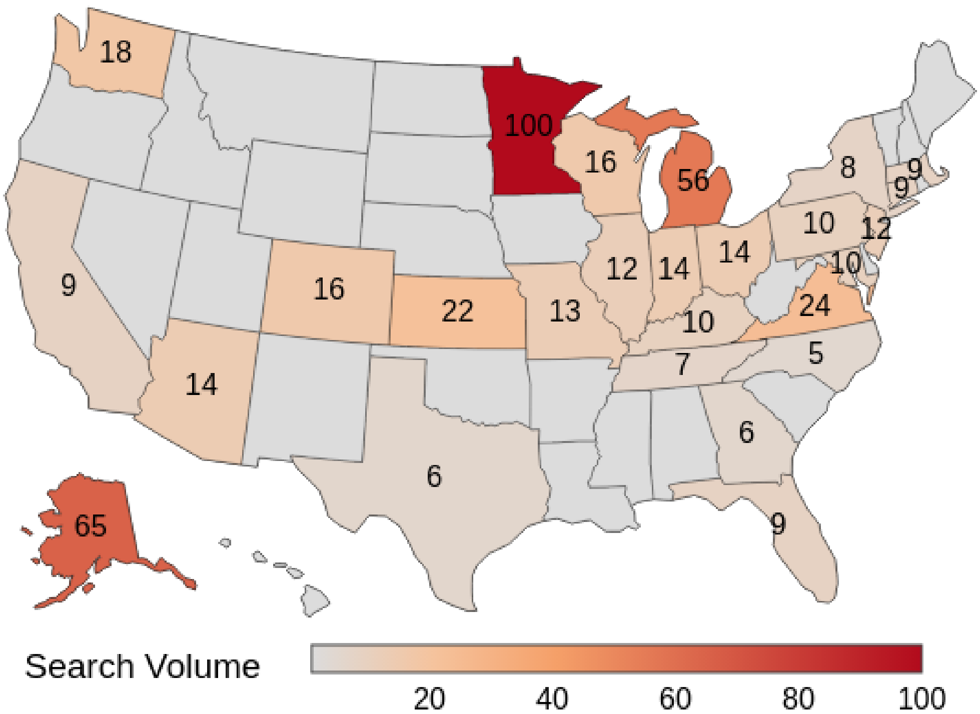
Software utilized but not referenced within the main text.

1. All figures in main text: `Plotly` (Plotly 2015)
2. Fixed effects estimations: `Fixest` (Berge, Krantz, and McDermott 2021)
3. Pre-trends figures: `ggplot2` (Wickham 2011)

B Google Search Trends

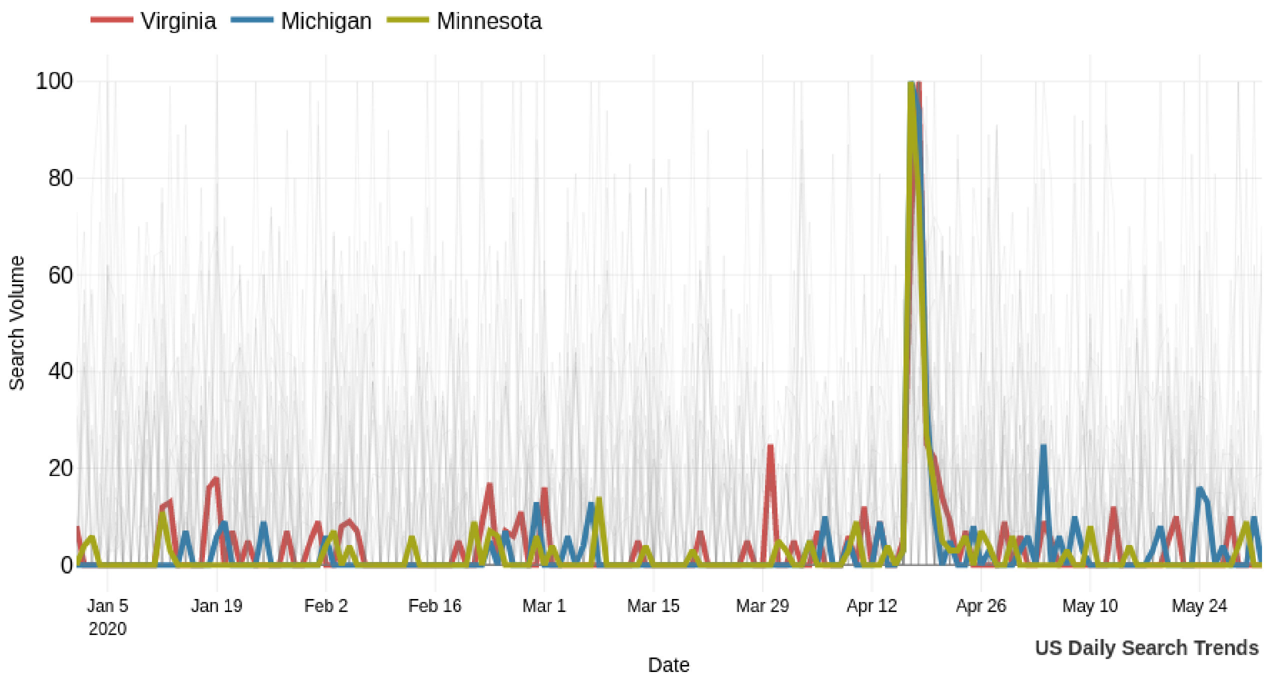
Figure 1 presents the between-state search trends for the word "liberate" in the United States on April 17.

Figure 1: 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 2: 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 4. Additionally, a word cloud of the top-20 most representative words from the quote tweets is presented in Figure 3.

Figure 3: Word Cloud of Top-20 Most Representative Words from Liberate Quote Tweets

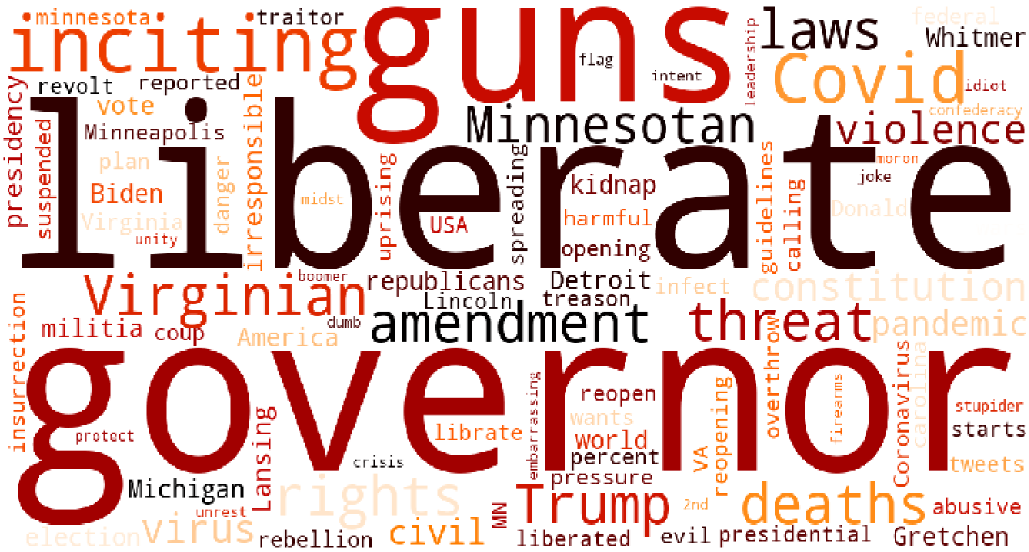
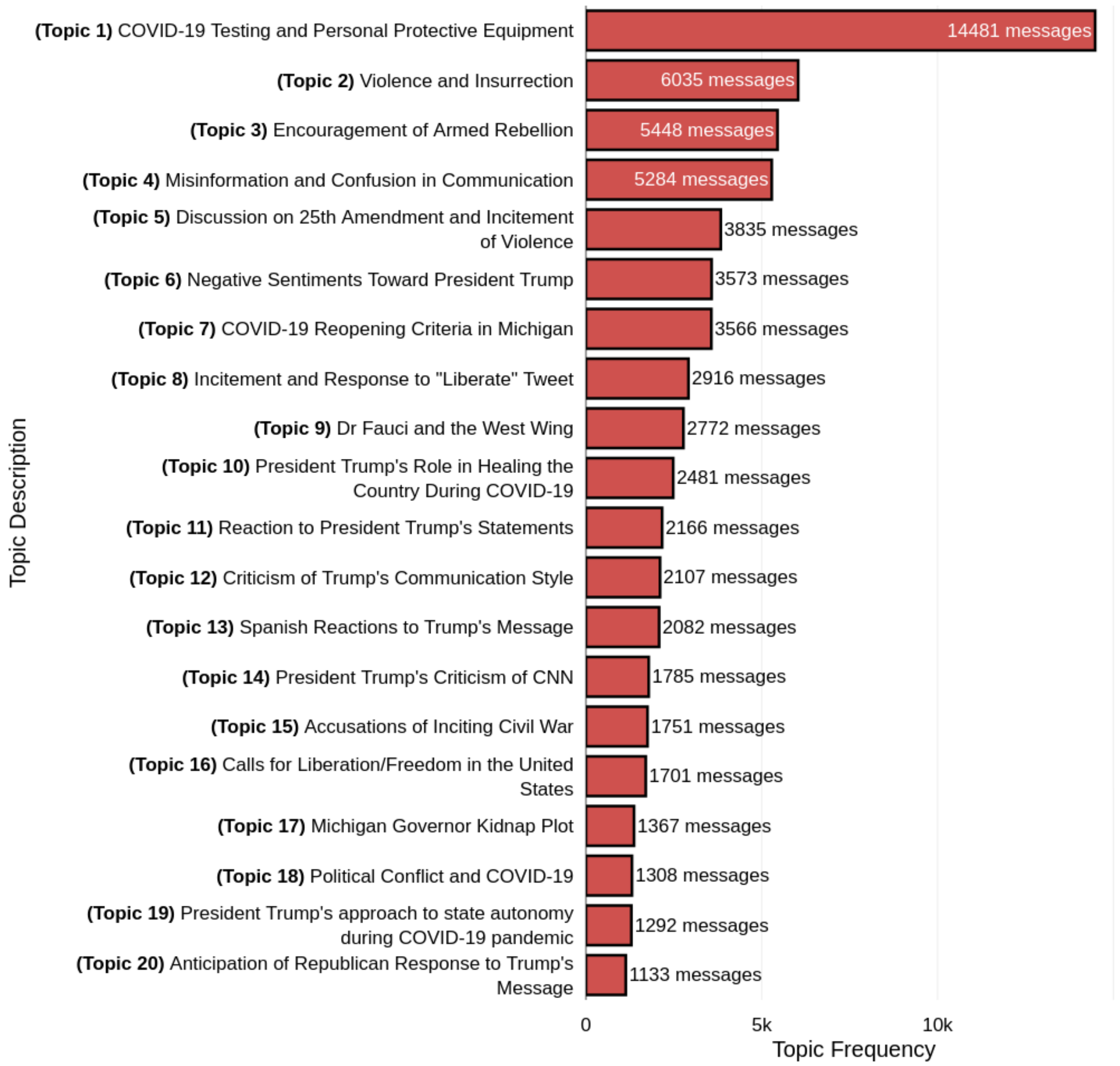


Figure 4: Top-20 Topics from LIBERATE Quote Tweets



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 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 1: Predicting Targeted States with State Characteristics (logit)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Movement	0.00000						
	(0.01537)						
Stay-at-home compliance		0.00000					
		(0.02266)					
Arrests (violent crime)			0.00000				
			(0.02662)				
Arrests (civil disobedience)				0.00000			
				(0.01275)			
Statewide Protests					0.00000		
					(0.22012)		
COVID-19 deaths						0.00000	
						(0.00032)	
COVID-19 cases							0.00000
							(0.00003)
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	1140.041	1139.074			1135.573	1149.779	1150.353
RMSE	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std.Errors	HC3	HC3	HC3	HC3	HC3	HC3	HC3

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

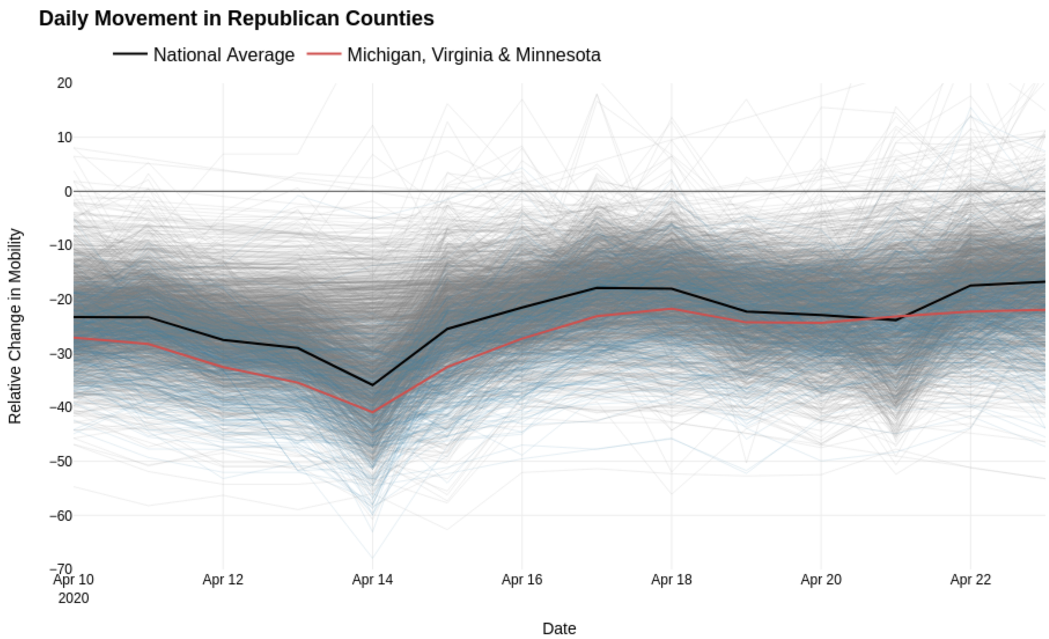
Note: Standard errors presented in parentheses. The dependent variable is a binary indicator for whether the state was targeted by Trump's tweets. The independent variables are measured at the state level and include the number of arrests for violent crime and civil disobedience, the number of statewide 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).

E 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 5: Daily Movement in Republican Majority Counties



F Predicted Outcomes - Mobility

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

Table 2: 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
-0.752156	0.080295	-0.909532	-0.594780	0.000000	Stay-at-home compliance	-6	April 10 2020
-0.160707	0.070539	-0.298960	-0.022453	0.022710	Stay-at-home compliance	-5	April 11 2020
-0.085360	0.095095	-0.271744	0.101023	0.369385	Stay-at-home compliance	-4	April 12 2020
0.408854	0.079490	0.253058	0.564651	0.000000	Stay-at-home compliance	-3	April 13 2020
0.071414	0.098551	-0.121742	0.264569	0.468672	Stay-at-home compliance	-2	April 14 2020
0.366453	0.076585	0.216349	0.516556	0.000002	Stay-at-home compliance	-1	April 15 2020
-0.000836	0.081447	-0.160469	0.158797	0.991811	Stay-at-home compliance	0	April 16 2020
-0.242033	0.138809	-0.514094	0.030028	0.081223	Stay-at-home compliance	1	April 17 2020
-0.853810	0.145917	-1.139802	-0.567817	0.000000	Stay-at-home compliance	2	April 18 2020
-1.884782	0.176285	-2.230294	-1.539271	0.000000	Stay-at-home compliance	3	April 19 2020
-1.393435	0.200702	-1.786804	-1.000067	0.000000	Stay-at-home compliance	4	April 20 2020
-2.102872	0.182610	-2.460780	-1.744964	0.000000	Stay-at-home compliance	5	April 21 2020
-0.276091	0.198204	-0.664565	0.112382	0.163631	Stay-at-home compliance	6	April 22 2020
-0.026232	0.171859	-0.363069	0.310604	0.878684	Stay-at-home compliance	7	April 23 2020

Table 3: ATT estimates for movement in Republican-majority counties

ATT	S.E.	CI.lower	CI.upper	p.value	Model	Time to treatment	Date
0.841593	0.196437	0.456583	1.226603	0.000018	Movement	-6	April 10 2020
0.133869	0.179258	-0.217470	0.485208	0.455186	Movement	-5	April 11 2020
0.244528	0.181619	-0.111439	0.600495	0.178181	Movement	-4	April 12 2020
-0.668040	0.177857	-1.016634	-0.319446	0.000173	Movement	-3	April 13 2020
0.249611	0.210880	-0.163705	0.662928	0.236545	Movement	-2	April 14 2020
-0.650828	0.199265	-1.041380	-0.260275	0.001090	Movement	-1	April 15 2020
-0.101818	0.198285	-0.490449	0.286814	0.607607	Movement	0	April 16 2020
-0.102418	0.334083	-0.757209	0.552373	0.759175	Movement	1	April 17 2020
1.606979	0.343196	0.934327	2.279630	0.000003	Movement	2	April 18 2020
3.517375	0.429761	2.675059	4.359690	0.000000	Movement	3	April 19 2020
3.888736	0.471646	2.964328	4.813145	0.000000	Movement	4	April 20 2020
5.693456	0.514000	4.686034	6.700878	0.000000	Movement	5	April 21 2020
0.856582	0.502866	-0.129017	1.842181	0.088493	Movement	6	April 22 2020
0.263041	0.414106	-0.548591	1.074673	0.525296	Movement	7	April 23 2020

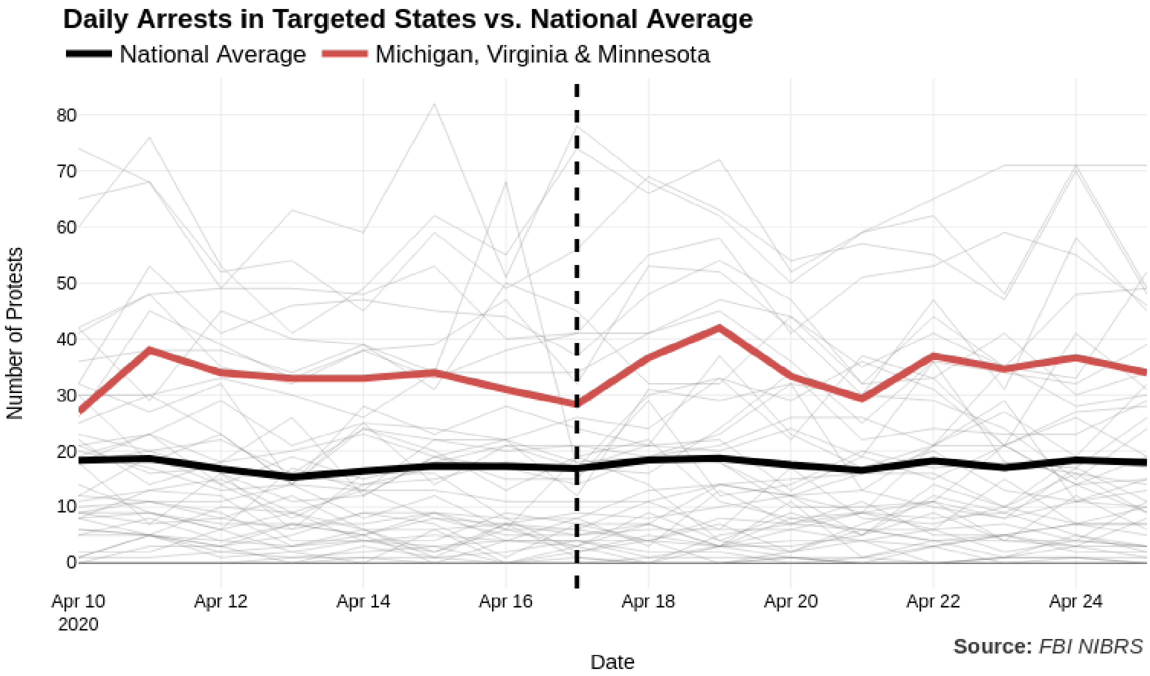
G Descriptive Statistics: Arrests

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

Table 4: 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 6: 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 5: 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 6: 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

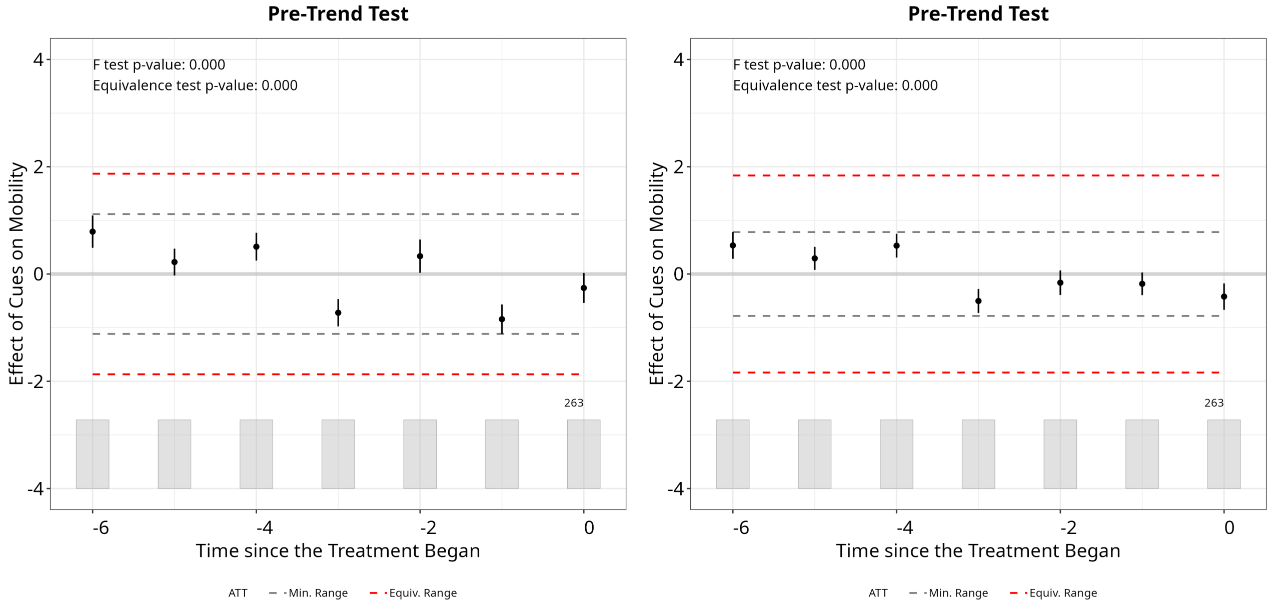
Table 7: Arrests for Crimes Related to Civil Disobedience by Racial Group and Date

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

H 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).

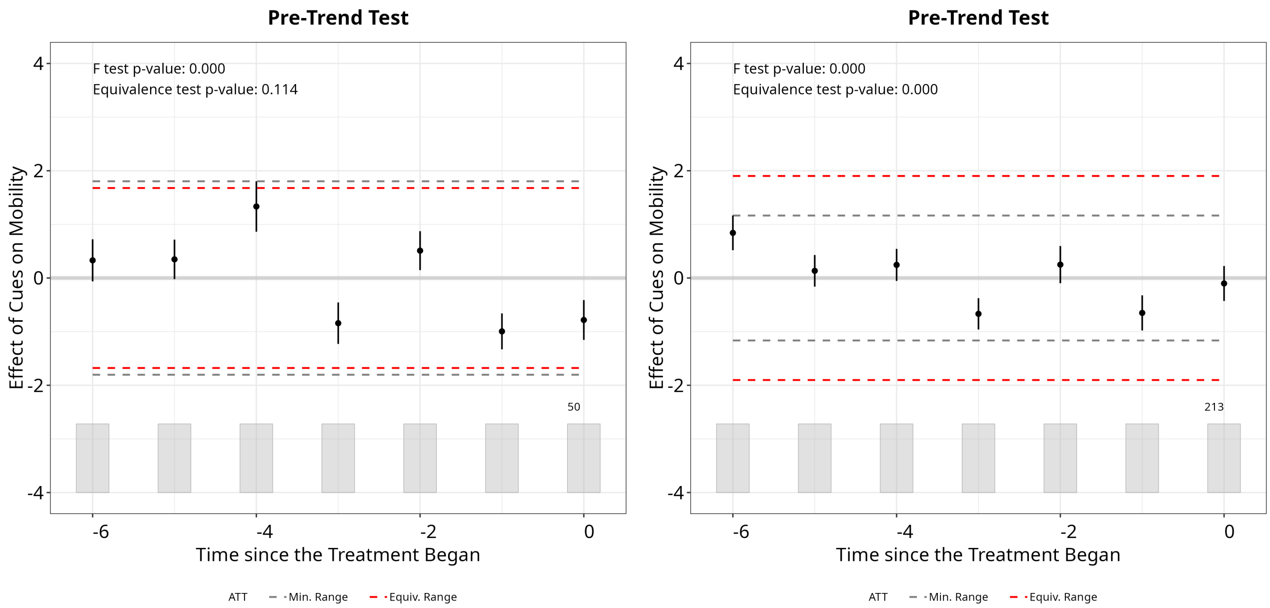
Figure 7: Pre-Trends Tests for Mobility



(a) Full State

(b) Democrat Governor Only

Figure 8: Pre-Trends Tests for Mobility, cont'd



(a) Democratic Majority Counties

(b) Republican Majority Counties

I 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.

I.A 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 9 presents 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 9: Pre-treatment Covariate Balance before and after Matching with Mahalanobis Distance

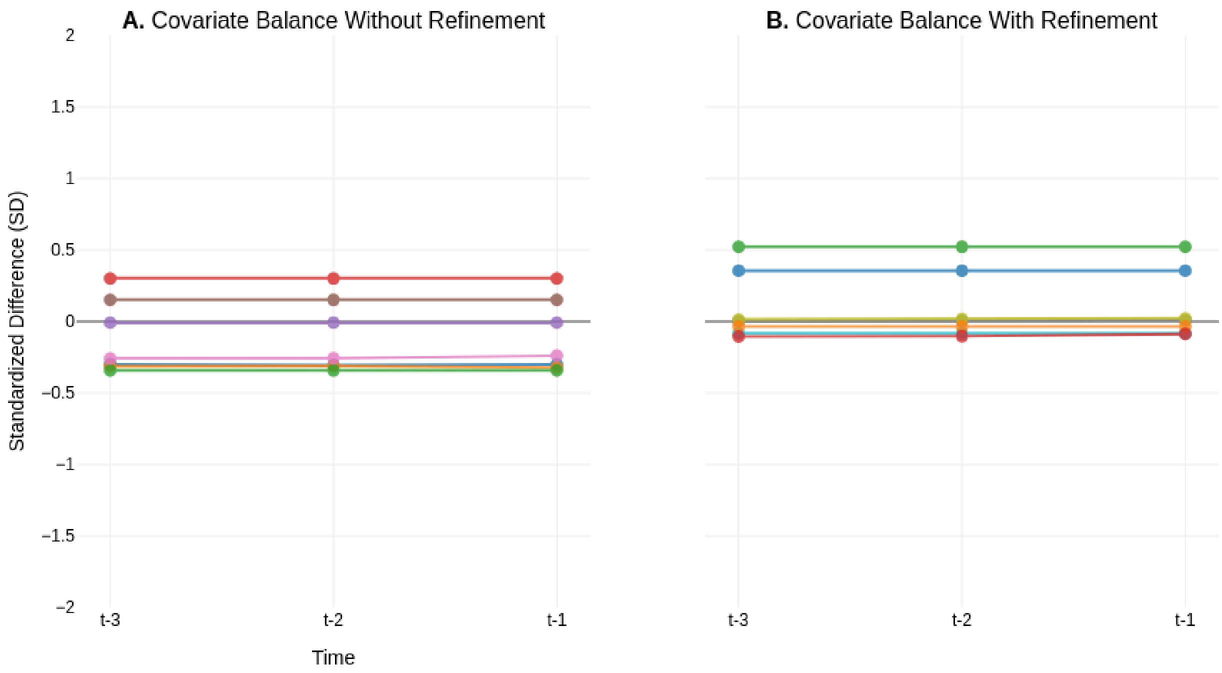


Table 8: Cumulative Effect of "Liberate" Cues on Movement (Mahalanobis Matching)

	Movement			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	2.144***	1.324	2.388***	1.364***
Standard error	0.437	0.877	0.516	0.425
P-value	0.000	0.131	0.000	0.001
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	5,516	23,548	13,902

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

Note: 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 9: 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)	-0.809***	-0.891*	-0.857***	-0.669***
Standard error	0.196	0.393	0.226	0.187
P-value	0.000	0.024	0.000	0.000
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	5,516	23,548	13,902

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

Note: 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.

I.B 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 10 and Table 11.

Table 10: Cumulative Effect of "Liberate" Cues on Movement

	Movement			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	1.789***	0.312	2.093***	1.528***
Standard error	0.193	0.342	0.217	0.177
CI lower (2.5)	1.411	-0.359	1.669	1.181
CI upper (97.5)	2.167	0.983	2.518	1.874
P-value	0.000	0.362	0.000	0.000
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	6,132	22,932	13,902

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

Note: 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 11: 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)	-0.315	-0.173	-0.329	-0.373
Standard error	0.070	0.137	0.083	0.068
CI lower (2.5)	-0.452	-0.442	-0.491	-0.507
CI upper (97.5)	-0.178	0.095	-0.167	-0.239
P-value	0.000	0.205	0.000	0.000
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	6,132	22,932	13,902

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

Note: 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.

I.C 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 12: 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***	-0.660	2.311***	1.720***
Standard error	0.265	0.380	0.286	0.281
CI lower (2.5)	1.226	-1.405	1.750	1.169
CI upper (97.5)	2.266	0.086	2.873	2.270
P-value	0.000	0.083	0.000	0.000
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	5,516	23,548	13,902

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

Note: 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 13: 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)	-0.166	0.199	-0.300**	-0.375**
Standard error	0.089	0.247	0.107	0.113
CI lower (2.5)	-0.340	-0.284	-0.511	-0.597
CI upper (97.5)	0.009	0.683	-0.090	-0.153
P-value	0.062	0.419	0.005	0.001
County	✓	✓	✓	✓
Time	✓	✓	✓	✓
N obs.	29,064	6,132	22,932	13,902

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

Note: 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.

I.D Event Study

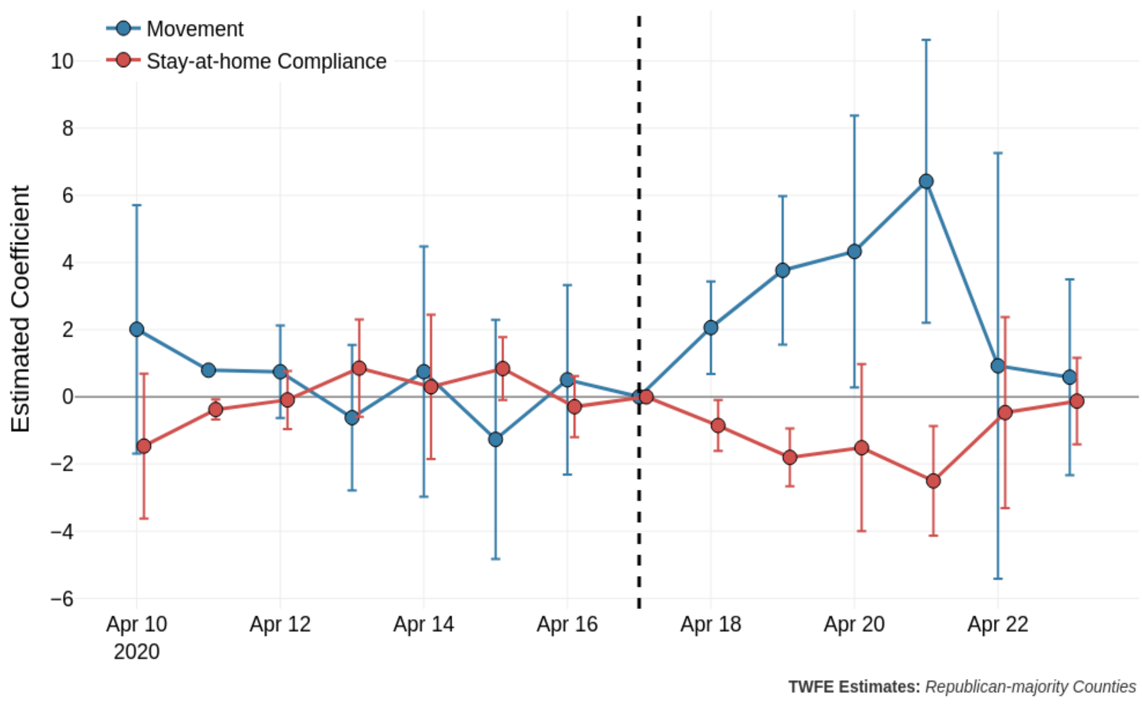
We also conducted our analysis using an event study specification. Our event study model can be formalized as follows:

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

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 10 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 10: 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 subsection I.D.

J 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 14 presents the results for the effect of the cues on retail and recreational mobility. Table 15 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 14: 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)	1.546***	1.250**	1.873***	1.797***
Standard error	0.288	0.390	0.346	0.294
CI lower (2.5)	0.981	0.485	1.194	1.221
CI upper (97.5)	2.111	2.015	2.551	2.373
p.value	0.000	0.001	0.000	0.000
County	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
N Obs.	14,631	4,002	10,278	7,793

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

Table 15: Cumulative Effect of "Liberate" Cues on Aggregate Mobility

	Aggregate Mobility			
	Entire state	Dem. counties	Rep. counties	Dem. governor only
Trump Cues (ATT)	6.273**	10.539*	4.980**	7.319***
Standard error	1.904	4.411	1.914	1.959
CI lower (2.5)	2.541	1.894	1.228	3.478
CI upper (97.5)	10.005	19.184	8.731	11.159
P-value	0.001	0.017	0.009	0.000
County	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓
N Obs.	14,631	4,002	10,278	7,793

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

K Placebo Tests: Mobility

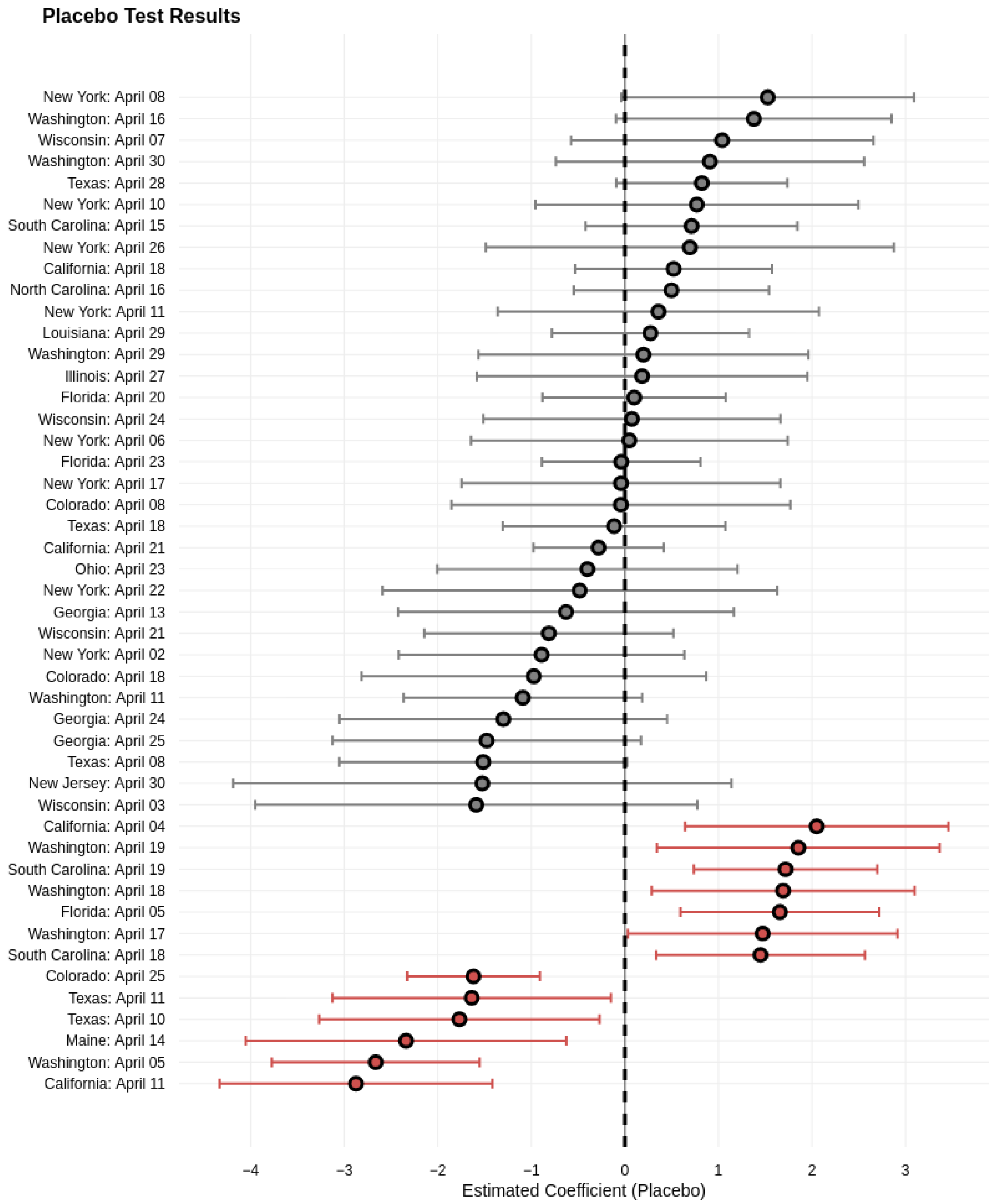
We conduct placebo tests by estimating the (placebo) effect of Trump's mentioning of a particular state on mobility (movement) in that state in the following week. We use two-way fixed effects regressions with county and date (day) fixed effects. Standard errors are clustered by county and day. Only 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 16 and Figure 11. In Table 16, 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 16: 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 11: 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 section K.

L Full Results from Crime Analysis

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

Table 17: Cumulative CATT: Arrest Rate of White Americans

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.32	0.12	0.08	0.53	0.009

Table 18: Dynamic CATT Estimates for the Effect of the Cues on the Arrest Rate of White Americans

Time	Date	ATT	S.E.	CI upper	CI lower	p-value
-7	2020-04-10	-0.05	0.03	0.00	-0.10	0.07
-6	2020-04-11	0.06	0.03	0.10	0.01	0.03
-5	2020-04-12	0.02	0.03	0.07	-0.04	0.50
-4	2020-04-13	-0.00	0.02	0.03	-0.03	0.90
-3	2020-04-14	0.03	0.03	0.09	-0.03	0.40
-2	2020-04-15	0.00	0.03	0.06	-0.05	0.89
-1	2020-04-16	-0.01	0.02	0.02	-0.04	0.61
0	2020-04-17	-0.02	0.01	0.00	-0.04	0.09
1	2020-04-18	0.39	0.27	0.92	-0.15	0.16
2	2020-04-19	1.17	0.06	1.29	1.06	0.00
3	2020-04-20	0.20	0.34	0.87	-0.47	0.55
4	2020-04-21	-0.37	0.43	0.47	-1.21	0.39
5	2020-04-22	0.60	0.23	1.06	0.14	0.01
6	2020-04-23	0.25	0.53	1.29	-0.78	0.63
7	2020-04-24	0.41	0.27	0.93	-0.11	0.12
8	2020-04-25	0.19	0.23	0.64	-0.26	0.40

Table 19: Dynamic CATT Estimates for the Effects of the Cues on the Arrest Rate of **Non-White** Americans

Time	Date	ATT	S.E.	CI upper	CI lower	p-value
-7	2020-04-10	-0.02	0.13	0.23	-0.27	0.90
-6	2020-04-11	-0.09	0.05	0.02	-0.20	0.10
-5	2020-04-12	0.17	0.12	0.39	-0.06	0.15
-4	2020-04-13	0.11	0.11	0.32	-0.11	0.34
-3	2020-04-14	-0.03	0.20	0.35	-0.41	0.87
-2	2020-04-15	-0.03	0.04	0.05	-0.12	0.45
-1	2020-04-16	0.05	0.06	0.16	-0.06	0.38
0	2020-04-17	-0.15	0.13	0.10	-0.39	0.23
1	2020-04-18	-0.15	0.12	0.08	-0.39	0.19
2	2020-04-19	-0.17	0.12	0.07	-0.41	0.16
3	2020-04-20	0.08	0.28	0.63	-0.47	0.78
4	2020-04-21	0.16	0.11	0.38	-0.06	0.14
5	2020-04-22	-0.12	0.13	0.13	-0.38	0.34
6	2020-04-23	0.01	0.09	0.20	-0.17	0.90
7	2020-04-24	-0.12	0.18	0.24	-0.49	0.50
8	2020-04-25	0.04	0.12	0.28	-0.20	0.74

M 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.

Below, each table in this section presents results in the same format. The results in Table 20 replicate the primary analysis using arrests for the same crimes but include arrests from Black Americans instead of white individuals.

The results in Table 21 replicate the primary analysis using arrests of white Americans for violent crimes (Aggravated Assault, Homicide, Rape, and Robbery).

The results in Table 22 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 23 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 24 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 20: Placebo Test: Cumulative Conditional Effect of "Liberate" Cues on Arrest Rate of **Black Americans**

	Per million	Per million (IVHS)	Per million (w/Temp)	Count (IVHS)	Count (w/Temp)
Trump Cues (CATT)	0.048	0.048	0.048	0.083	0.083
Standard error	0.090	0.090	0.086	0.831	0.834
CI lower (2.5)	-0.128	-0.128	-0.120	-1.545	-1.551
CI upper (97.5)	0.225	0.225	0.216	1.712	1.718
P-value	0.591	0.591	0.575	0.920	0.920
Daily state temp.			✓		✓
State	✓	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓	✓
Racial group	✓	✓	✓	✓	✓
N obs.	3,920	3,920	3,920	3,920	3,920

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

Table 21: Placebo Test: Cumulative Conditional Effect of "Liberate" Cues on Arrest Rate of White Individuals for Violent Crimes

	Per million	Per million (IVHS)	Per million (w/Temp)	Count (IVHS)	Count (w/Temp)
Trump Cues (CATT)	-0.002	-0.002	-0.001	0.007	0.006
Standard error	0.072	0.072	0.077	0.582	0.598
CI lower (2.5)	-0.144	-0.144	-0.152	-1.134	-1.167
CI upper (97.5)	0.140	0.140	0.149	1.148	1.179
P-value	0.977	0.977	0.986	0.990	0.992
Daily state temp.			✓		✓
State	✓	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓	✓
Racial group	✓	✓	✓	✓	✓
N obs.	3,920	3,920	3,920	3,920	3,920

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

Table 22: 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)

	Per million	Per million (IVHS)	Per million (w/Temp)	Count (IVHS)	Count (w/Temp)
Trump Cues (CATT)	-0.045	-0.045	-0.045	-0.354	-0.354
Standard error	0.044	0.044	0.049	0.414	0.433
CI lower (2.5)	-0.133	-0.133	-0.141	-1.165	-1.202
CI upper (97.5)	0.042	0.042	0.050	0.457	0.494
P-value	0.307	0.307	0.351	0.392	0.413
Daily state temp.			✓		✓
State	✓	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓	✓
Racial group	✓	✓	✓	✓	✓
N obs.	3,920	3,920	3,920	3,920	3,920

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

Table 23: Cumulative Unconditional Effect of "Liberate" Cues on Arrest Rate (Aggravated Assault, Disorderly Conduct, Simple Assault, and Damage/Vandalism/Destruction of Property)

	Per million	Per million (IVHS)	Per million (w/Temp)	Count (IVHS)	Count (w/Temp)
Trump Cues (CATT)	0.053*	0.053*	0.040*	2.514**	2.125*
Standard error	0.021	0.021	0.018	0.897	1.021
CI lower (2.5)	0.011	0.011	0.005	0.757	0.124
CI upper (97.5)	0.095	0.095	0.075	4.272	4.126
P-value	0.013	0.013	0.024	0.005	0.037
Daily state temp.			✓		✓
State	✓	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓	✓
N obs.	530	530	530	530	530

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

Note: Unconditional effects are estimated using Interactive Fixed Effects as an estimator to allow for jackknife bootstrap inference to account for the limited number of treated units.

Table 24: Cumulative Effect of "Liberate" Cues on Arrests of White Americans with April 17 as first treatment day

	Per million	Per million (IVHS)	Per million (w/Temp)	Count (IVHS)	Count (w/Temp)
Trump Cues (CATT)	0.234	0.234	0.234	1.997	1.997
Standard error	0.158	0.158	0.149	1.562	1.546
CI lower (2.5)	-0.076	-0.076	-0.057	-1.064	-1.033
CI upper (97.5)	0.544	0.544	0.526	5.058	5.028
P-value	0.139	0.139	0.116	0.201	0.196
State	✓	✓	✓	✓	
Time (Day)	✓	✓	✓	✓	
N obs.	3,920	3,920	3,920	3,920	3,920

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

N 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 25. The results are consistent with the main text.

Table 25: Cumulative Conditional Effect of "Liberate" Cues on Arrest Rate of White Individuals (Interactive Fixed Effects)

	Per million	Per million (IVHS)	Per million (w/Temp)	Count (IVHS)	Count (w/Temp)
Trump Cues (CATT)	0.234*	0.234*	0.234*	1.997*	1.997*
standard error	0.099	0.099	0.093	0.978	0.970
CI lower	0.040	0.040	0.052	0.080	0.096
CI upper	0.428	0.428	0.416	3.915	3.899
P-value	0.018	0.018	0.012	0.041	0.040
Daily state temp.			✓		✓
State	✓	✓	✓	✓	✓
Time (Day)	✓	✓	✓	✓	✓
N obs.	3,920	3,920	3,920	3,920	3,920

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

Note: 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.

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