The Short-Run Consequences of January 6

Alberto Binetti

IGIER Reading Group

Introduction

- Large discussion on **democratic backsliding** even in established democracies such as the US
- Cultural and **partisan identity** has become more salient and polarizing in the past decades (Bonomi et al., 2021; Iyengar et al., 2019)
- *"Polarization of reality"* (Alesina et al., 2020) steadily increasing, as people perceive **the same reality very differently**

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$$\Downarrow$$

- Does this polarization start after **salient** and **interpretable** events?
- What are **politicians** and **voters'** reactions to political scandals?

Preview

- Study Republican and Democratic Members of Congress **communication strategies on Twitter**

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  - This effects depends on the **interpretation of the event**: justified protest vs. attack to democracy

Literature & contribution

- *6^{th} of January:*
  - Sonin et al. (2023) focus on the **drivers of participation**, Eady et al. (2021); Bhatt et al. (2023) describe **voter reaction** $\Rightarrow$ Focus on **both** supply and demand-side

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- *Strategic politicians*
  - **Strategic communication** strategies (Djourelova and Durante, 2022; Kaplan et al., 2019; Lewandowsky et al., 2020) , **narratives as political persuasion** (Aina, 2021; Eliaz and Spiegler, 2020; Bilotta and Manferdini, 2024) $\Rightarrow$ Quantify narratives with a text-as-data approach, link them with voters

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- *Economics of social media*
  - Causes and consequences of social media activity (Müller and Schwarz, 2023; D'Amico and Tabellini, 2022; Beknazar-Yuzbashev et al., 2022) $\Rightarrow$ Apply the production-consumption framework from Aridor et al. (2024) in an observational setting

Today

Background

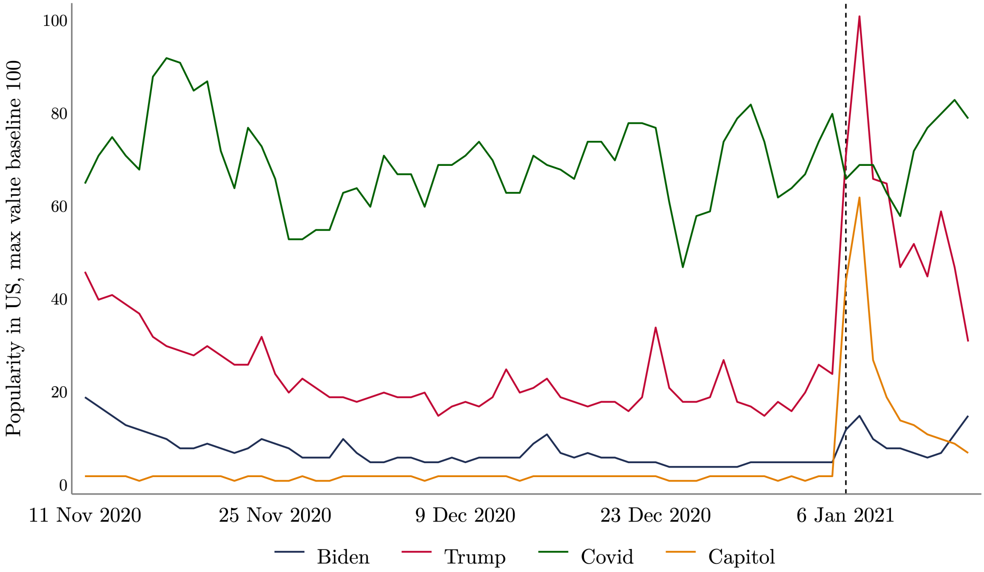
Data

Supply side

Demand side

January 6, 2021

How salient was it in the US? Google trends



Data

- *Twitter data*
  - **congresstweets:** $>$ 86,000 tweets from 414 Members of Congress (224 D, 190 R) from November 11, 2020 to February 1, 2021 $\Rightarrow$ **No engagement measures** ▸ Descriptives
    ▸ Summary statistics
  - **Twitter API:** $>$ 50,000 tweets from 323 Members of Congress (176 D, 145 R) $\Rightarrow$ **with engagement measures** ▸ Compare datasets
  - **ProPublica:** demographic and political characteristics of all Members of Congress (Propublica, API, 2023)

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- *Survey data*
  - **Nationscape survey:** nationally representative weekly public-opinion survey, use data from November 11, 2020 to February 3, 2021 ▸ Descriptives
  - **Civic capital:** combine different measures at the county level from Social Capital Project (2018) and Rupasingha et al. (2006)
  - **Congress district variables:** demographic data from Ruggles et al. (2023), electoral data from Daily Kos Elections (2020)

Supply side: politicians' communication strategy

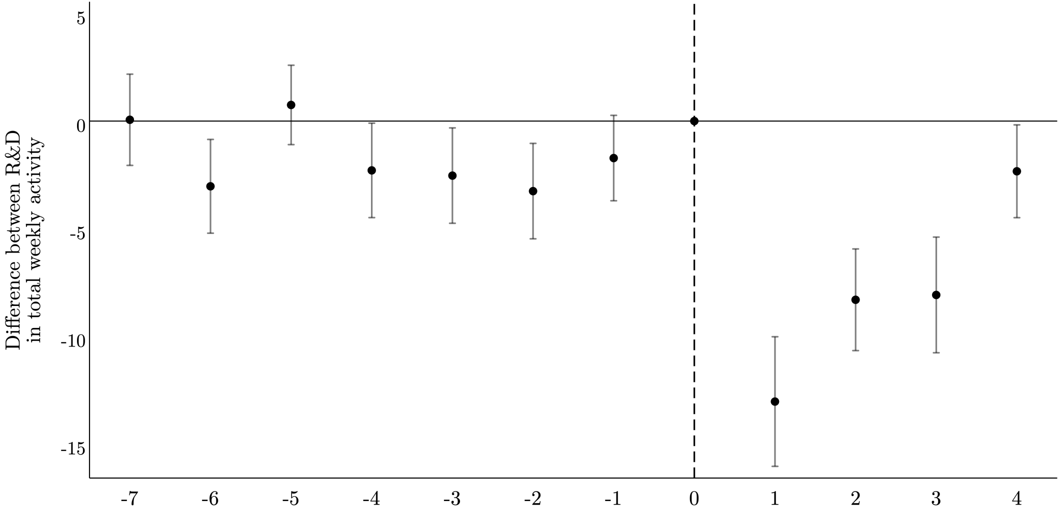
Activity specification

$$Y_{i,t} = \beta_0 + \alpha_i + \psi_t + \sum_{\substack{\tau=-7 \\ \tau\neq 0}}^{4} \mu_\tau \Big[\mathbb{1}(\text{Republican}_i) \times \mathbb{1}(\tau) \Big] + \varepsilon_{i,t} \tag{1}$$

- $Y_{i,t}$: number of tweets that individual i has made in window t or an indicator for the extensive margin of activity in that week
- α_i, ψ_t: individual FE, time-window FE
- $\mathbb{1}(\text{Republican}_i)$: 1 if i is a Republican
- $\mathbb{1}(\tau)$: 1 if we are in period τ

$\{\mu_\tau\}_\tau$: evolution of the difference between Republicans and Democrats' posting activity compared to the week right before January 6

Republicans are less active after the event



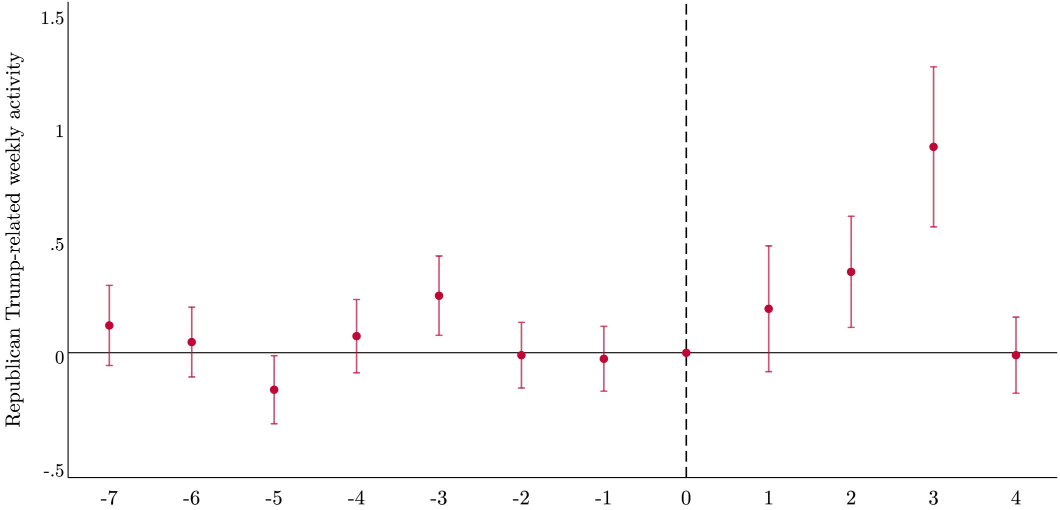
▸ Extensive margin ▸ Parallel trends violation ▸ Imputation estimator

Is it the Trump ban? Unlikely

Müller and Schwarz (2023) find that banning Trump decreases overall activity of his followers on Twitter. Unlikely to apply to politicians as well:

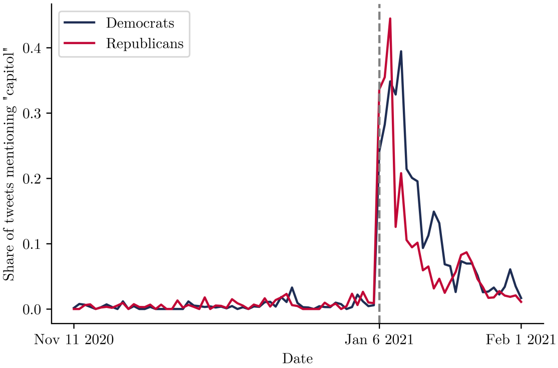
- **Cost of reducing activity** is higher for politicians than for average users
- Trump ban was first of its kind, unlikely to happen again

Republicans mention Trump more after

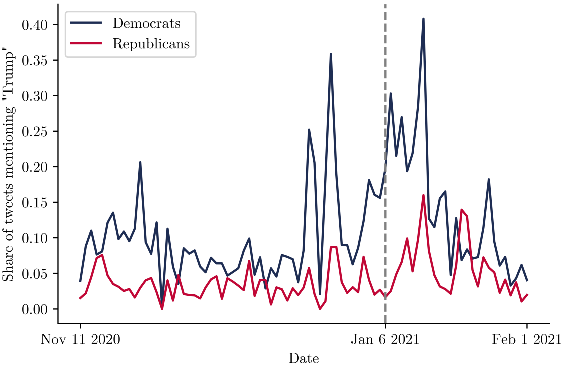


▸ Extended keywords

What do politicians talk about?



Share mentioning Capitol



Share mentioning Trump

Formalizing narratives

Narrative: an agent (who) does something (what) to a patient (whom)

- Same agent/patient but different verb imply completely different meaning $\Rightarrow$ capture the **nuance** of politicians' arguments

- Semi-supervised approach, advantages similar to LDA but **avoid post-hoc interpretation** Methodology

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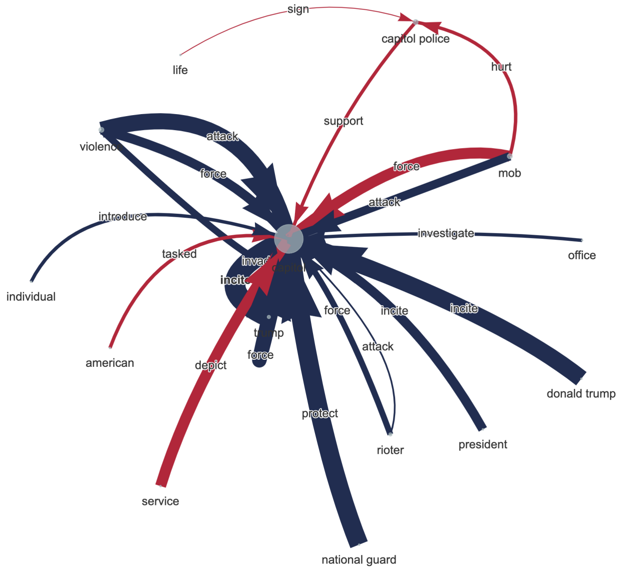
Apply the algorithm after January 6 and **estimate narratives both split by party and together**

Partisan narratives about capitol



Narratives by party after January 6

	Democratic Party		Republican Party	
Rank	Narrative	Frequency	Narrative	Frequency
1	penny invoke th amendment	72	open paycheckprotection program	40
2	fbi try washington dc	58	ustreasury announce paycheck protection program	22
3	trump incite capitol	50	hate attract hate	19
4	cabinet invoke th amendment	48	legislation stop legislation	18
5	individual incite violence	43	darkness attract darkness	18
6	senate convict donald trump	40	god sign america	18
7	senate support democracy	36	legislation break legislation	18
8	violence attack capitol	36	congress continue bill	17
9	trump incite violence	32	new radical left need change	17
10	president incite violence	32	colleague sign republican study	17

Double-the-blame vs. damage control?

$$
\begin{aligned}
Y_{t,i} = & \beta_0 + \beta_1 \mathbb{1}(\text{Democrat})_i + \beta_2 \mathbb{1}(\text{capitol} \in \text{tweet})_t + \\
& \beta_3 \mathbb{1}(\text{Democrat}) \times \mathbb{1}(\text{capitol} \in \text{tweet})_{t,i} + \delta_c + \alpha_i + \psi_d + \varepsilon_{t,i}
\end{aligned}
$$

- $Y_{t,i}$: sentiment of tweet t made by individual i
- $\mathbb{1}$(Democrat): 1 if individual is Democrat, 0 if Republican
- $\mathbb{1}$(capitol $\in$ tweet): 1 if word capitol is in the tweet, 0 otherwise
- δ_c, α_i, ψ_d: chamber, individual, day FE
- Errors are **heteorskedasticity** robust, tweets are weighted by the **square root of total non-stop words** (Enke, 2020)

▸ Descriptives

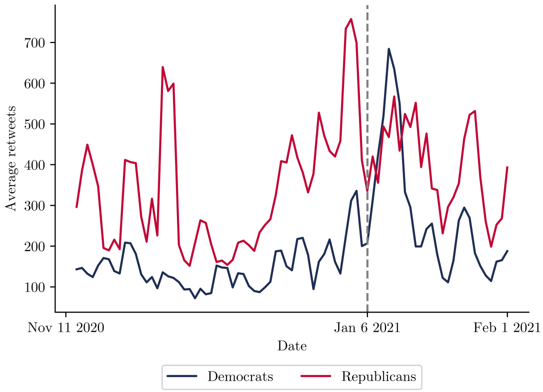
Double-the-blame vs. damage control!

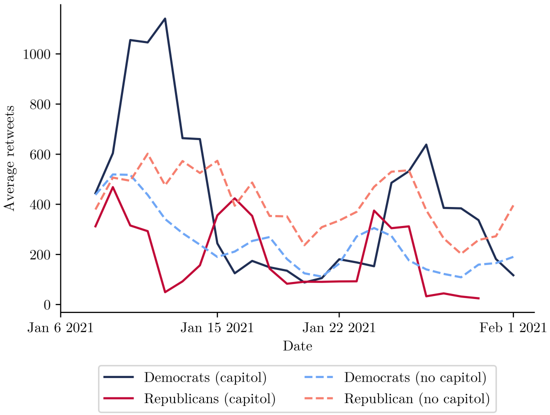
	Dependent variable: xlm compound score			
	(1)	(2)	(3)	(4)
Democrat	0.094***	0.104***		
	(0.033)	(0.033)		
$\mathbf{1}$(capitol $\in$ tweet)	0.084**	0.089**	0.052	0.188***
	(0.040)	(0.039)	(0.034)	(0.031)
Democrat $\times$ $\mathbf{1}$(capitol $\in$ tweet)	-0.496***	-0.497***	-0.421***	-0.421***
	(0.045)	(0.045)	(0.039)	(0.035)
Chamber FE		✓		
Individual FE			✓	✓
Day FE				✓
Observations	32278	32278	32275	32275
$\mathbb{E}$(Dependent variable)	0.036	0.036	0.036	0.036
Dependent variable std. dev.	0.679	0.679	0.679	0.679

▸ capitol before Capitol ▸ Extreme Republicans ▸ Extreme Democrats

Demand side: voters' reaction from Twitter

Engagement on Twitter: Retweets





▸ Likes

Who's more popular when talking about capitol?

$$
\begin{aligned}
Y_{t,i} =& \beta_0 + \beta_1 \mathbb{1}(\text{capitol} \in \text{tweet})_t + \beta_2 \mathbb{1}(\text{Republican}) \times \mathbb{1}(\text{capitol} \in \text{tweet}) \\
& + \delta \mathbb{1}(\text{Negative sentiment})_{t,i} + \alpha_i + \psi_d + \gamma_h + \varepsilon_{t,i}
\end{aligned}
$$

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- $\mathbb{1}$(Democrat): 1 if individual is Democrat, 0 if Republican
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- α_i, ψ_d, γ_h: individual, day, hour of day FE
- Errors are **heteorskedasticity** robust, tweets are weighted by the **square root of total non-stop words** (Enke, 2020)

Democrats are more popular when tweeting about capitol!

	Likes		Retweets	
	(1)	(2)	(3)	(4)
$\mathbf{1}(\text{capitol} \in \text{tweet})$	942.925**	431.941	189.492**	111.274
	(473.761)	(481.979)	(89.489)	(89.941)
Republican $\times$ $\mathbf{1}(\text{capitol} \in \text{tweet})$	-865.553	-796.243	-222.604**	-200.177**
	(533.696)	(492.561)	(105.197)	(97.129)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	19208	19208	19208	19208
Adj. R^2	0.182	0.182	0.175	0.179
$\mathbb{E}$(Dependent variable)	1619.524	1619.524	287.024	287.024
Dependent variable std. dev.	9771.391	9771.391	1686.288	1686.288

▸ capitol before Capitol

Consumption on social media: discussion

- Effect on retweets **stronger** than on likes: image concerns?
- **No overall pre-post effect on engagement** ▸ Overall engagement ▸ No capitol engagement
- Suggestive evidence that being negative about capitol pays off for Democrats but not for Republicans ▸ Democrats ▸ Republicans
- Twitter (active users) are very self-selected, hard to detect any **“accountability effects”**

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$$\Downarrow$$

Turn to **representative** survey data on attitudes!

Demand side: voters' reaction from survey data

Changes in attitudes towards Trump after January 6

$$Y_{i,t} = \alpha + \sum_{\substack{\tau=-6 \\ \tau \neq 0}}^{2} \beta_\tau \mathbb{1}(i,\tau) + \gamma X_{i,t} + \varepsilon_{i,t}$$

- $Y_{i,t}$: attitude of individual i in wave t
- $\mathbb{1}(i,\tau)$: 1 if individual is in wave τ
- $X_{i,t}$: individual level controls
- Errors clustered at the Congress District level
- Estimated **separately** for Democrats and Republicans
- Estimated on 9 different waves, each with $\approx 1.5k$ respondents for each political affiliation

Threats to identification

- Something else happens in that same period:
  - Trump's ban on January 8 $\Rightarrow$ a **consequence** of January 6!
  - Biden's inauguration on January 20 $\Rightarrow$ can check changes in **attitude towards Biden**

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  - Changes in attitudes towards Trump (improvements) lead to the protest of January 6 and then kept improving from there (think about social protests and the salience of their underlying topic)
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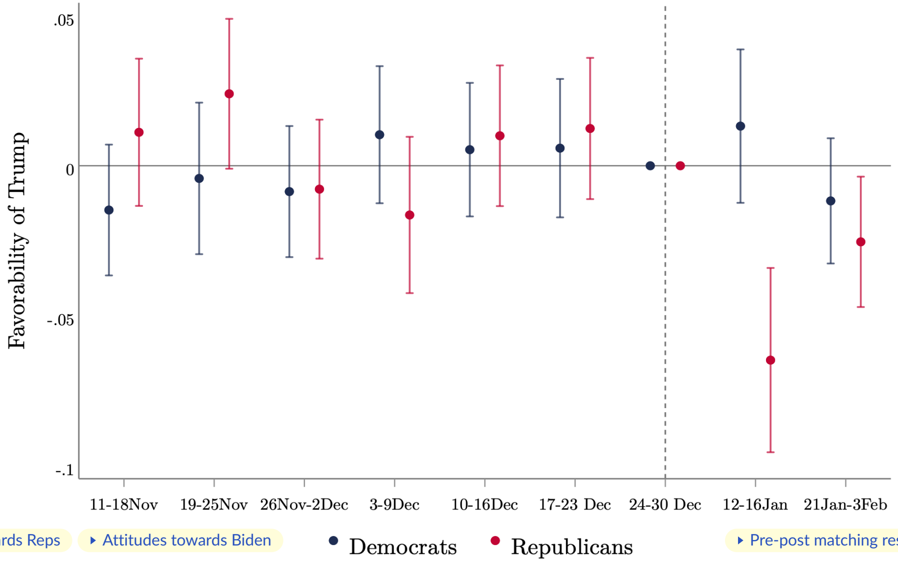
- Survey is cross-sectional:
  - Results are driven by inherent differences between the control group (those interviewed right before January 6) and the rest of the sample
  - Within political affiliation, **cross-section** across waves **is very similar** for demographics and ideology ▸ Descriptives

Attitudes towards Trump worsened for Republicans

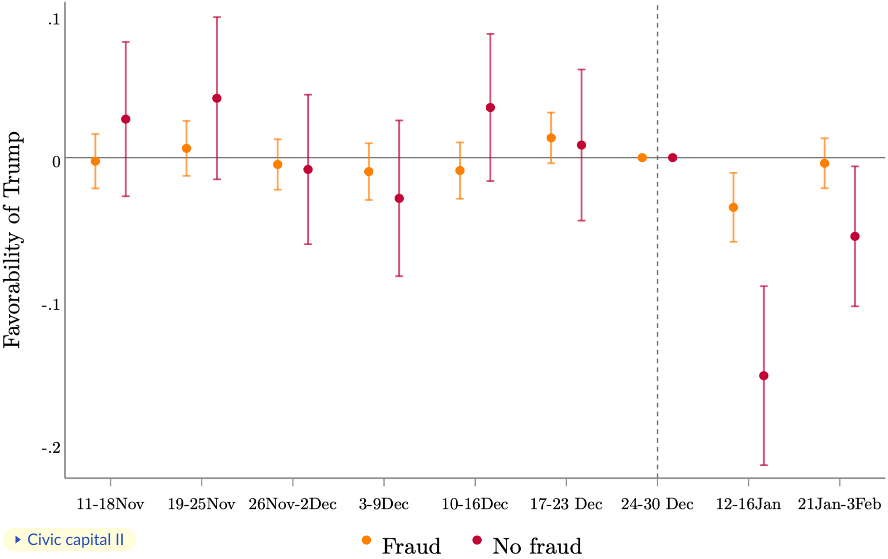


▸ Attitudes towards Reps
▸ Attitudes towards Biden
▸ Pre-post matching results
▸ Matching results

What explains these results?

- **Belief about election:**
  - If you think Biden **did not win the election**, you may interpret January 6 as a justified protest
  - The (negative) effect should be **stronger** for Republicans believing Biden won the election
- **Civic capital:**
  - Higher levels of civic capital are associated with higher levels of political accountability (Nannicini et al., 2013)
  - The (negative) effect should be stronger for Republicans coming from Districts with higher levels of civic capital

The effect is (much) stronger for those believing Biden won the election



▸ Civic capital I ▸ Civic capital II

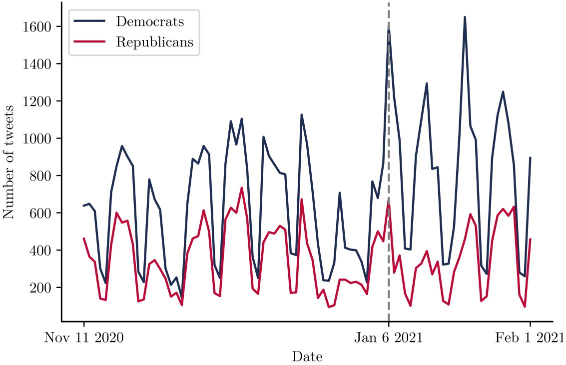
Conclusion

- Study **both sides of the political equilibrium** in the immediate aftermath of a major scandal
- Politicians have incentives to adjust their communication strategies along several margins and **offer competing narratives**
- Find both a **behavioral** (avoiding capitol) and **accountability** (worsening attitudes towards Trump) channel of voters' reaction

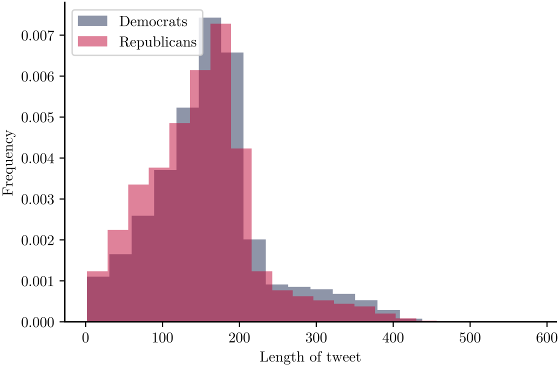
Thank you for your attention!

Appendix

Twitter Descriptives



Number of tweets by party



Length of tweets by party

Back

Twitter Summary Statistics

	N	Mean	SD	Min	Max
Democratic users	224				
Tweets per Democratic user		256.089	186.006	9.000	1459.000
Republican users	190				
Tweets per Republican user		153.289	185.767	1.000	1771.000
Number of words in tweet	86745	19.244	8.713	1.000	80.000
Share after January 5		0.375			
Share mentioning capitol		0.043			
Sentiment	86745	0.098	0.680	-0.943	0.986
Sentiment in capitol tweets	86745	-0.006	0.148	-0.930	0.980

Back

Twitter: comparing the two datasets

	N	Mean	SD	Min	Max
Panel A: Only *congresstweets*					
Democratic users	224				
Tweets per Democratic user		101.683	134.617	1.000	978.000
Republican users	185				
Tweets per Republican user		68.114	126.436	1.000	1271.000
Number of words in tweet	35378	21.220	9.932	1.000	80.000
Share after January 5		0.377			
Share mentioning capitol		0.046			
Sentiment	35378	0.062	0.669	-0.942	0.986
Sentiment in capitol tweets	35378	-0.009	0.149	-0.930	0.980
Panel B: Consumption sample					
Democratic users	174				
Tweets per Democratic user		197.972	111.465	5.000	500.000
Republican users	145				
Tweets per Republican user		113.959	104.213	1.000	500.000
Number of words in tweet	51367	17.884	7.464	1.000	51.000
Share after January 5		0.374			
Share mentioning capitol		0.042			
Sentiment	51367	0.122	0.687	-0.943	0.986
Sentiment in capitol tweets	51367	-0.005	0.148	-0.925	0.980

▸ Back

Nationscape Demographic Characteristics: Republican

	Wave								
	11-18Nov	19-25Nov	26Nov-2Dec	3-9Dec	10-16Dec	17-23Dec	23-30Dec	12-15Jan	21Jan-3Feb
Demographics									
Male	0.585	0.563	0.529	0.532	0.605	0.521	0.491	0.555	0.509
Employed	0.547	0.575	0.577	0.523	0.524	0.530	0.576	0.494	0.510
Age	46.354	47.667	46.998	49.979	49.213	51.115	49.110	51.270	50.286
White	0.877	0.875	0.909	0.904	0.887	0.899	0.884	0.893	0.879
Black	0.034	0.044	0.029	0.028	0.040	0.041	0.044	0.035	0.040
Income $<$ 25 K	0.293	0.247	0.263	0.242	0.263	0.250	0.236	0.237	0.253
Income $\leq$ 25K $<$ 75K	0.373	0.418	0.402	0.414	0.410	0.431	0.418	0.415	0.416
Income $\geq$ 75K	0.333	0.335	0.336	0.343	0.327	0.319	0.346	0.349	0.331
College	0.634	0.653	0.640	0.679	0.670	0.658	0.658	0.687	0.572
Ideology									
Liberal	0.088	0.108	0.086	0.081	0.094	0.071	0.076	0.067	0.074
Moderate	0.280	0.268	0.273	0.257	0.240	0.241	0.244	0.250	0.240
Conservative	0.656	0.642	0.665	0.678	0.684	0.701	0.694	0.692	0.702
Believes in election fraud	0.640	0.658	0.640	0.635	0.657	0.641	0.641	0.666	0.640
Seen the NYT last week	0.275	0.278	0.253	0.257	0.242	0.241	0.259	0.217	0.227
Seen Fox News last week	0.622	0.580	0.576	0.563	0.550	0.522	0.557	0.554	0.536
N	1838	1458	2232	1734	1861	1942	1919	1224	3049

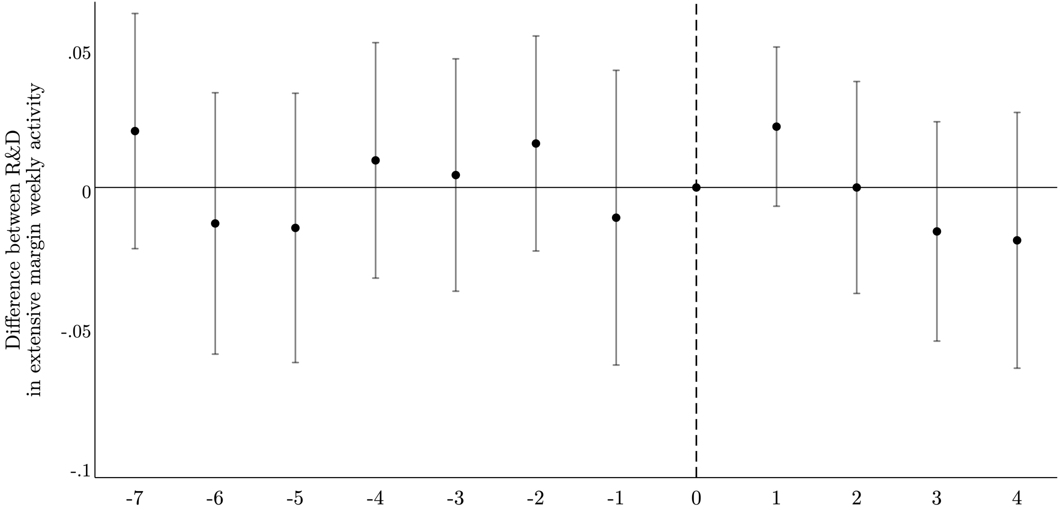
▸ Back ▸ Back to specification

Nationscape Demographic Characteristics: Democrats

	Wave								
	11-18Nov	19-25Nov	26Nov-2Dec	3-9Dec	10-16Dec	17-23Dec	23-30Dec	12-15Jan	21Jan-3Feb
Demographics									
Male	0.628	0.595	0.597	0.624	0.639	0.596	0.615	0.635	0.576
Employed	0.583	0.598	0.596	0.560	0.559	0.562	0.589	0.560	0.555
Age	42.645	42.957	43.785	44.620	45.149	45.676	44.187	46.286	45.366
White	0.660	0.675	0.688	0.680	0.674	0.657	0.667	0.665	0.644
Black	0.195	0.199	0.194	0.187	0.204	0.204	0.189	0.213	0.205
Income $<$ 25 K	0.332	0.302	0.299	0.295	0.307	0.281	0.271	0.311	0.306
Income $\leq$ 25K $<$ 75K	0.353	0.352	0.367	0.371	0.359	0.379	0.387	0.369	0.353
Income $\geq$ 75K	0.315	0.346	0.335	0.334	0.334	0.340	0.342	0.320	0.341
College	0.667	0.694	0.698	0.686	0.716	0.717	0.714	0.707	0.621
Ideology									
Liberal	0.551	0.565	0.550	0.552	0.547	0.538	0.569	0.533	0.549
Moderate	0.360	0.337	0.355	0.354	0.340	0.364	0.351	0.357	0.357
Conservative	0.143	0.155	0.148	0.135	0.163	0.141	0.120	0.143	0.136
Believes in election fraud	0.046	0.045	0.042	0.048	0.053	0.045	0.049	0.047	0.058
Seen the NYT last week	0.435	0.467	0.433	0.415	0.418	0.424	0.427	0.371	0.393
Seen Fox News last week	0.469	0.445	0.392	0.371	0.383	0.362	0.362	0.371	0.374
N	2253	1956	2608	2124	2473	2481	2583	1654	3752

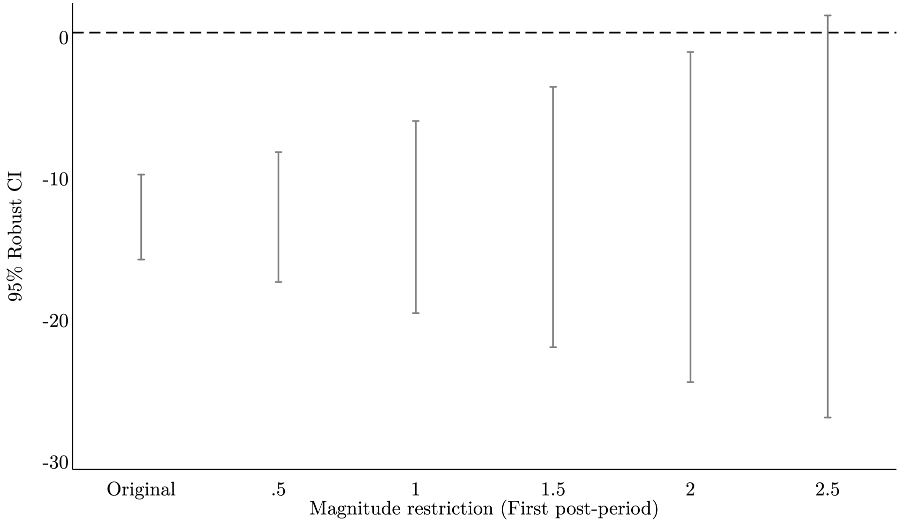
Back   Back to specification

Supply side: Activity Results, Extensive Margin

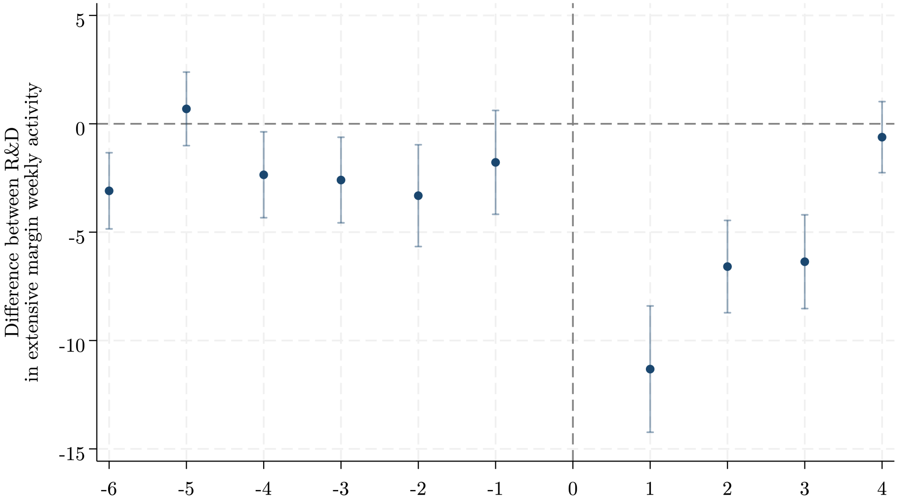


Back

Robust to 2.5 times maximum violation of parallel trends!

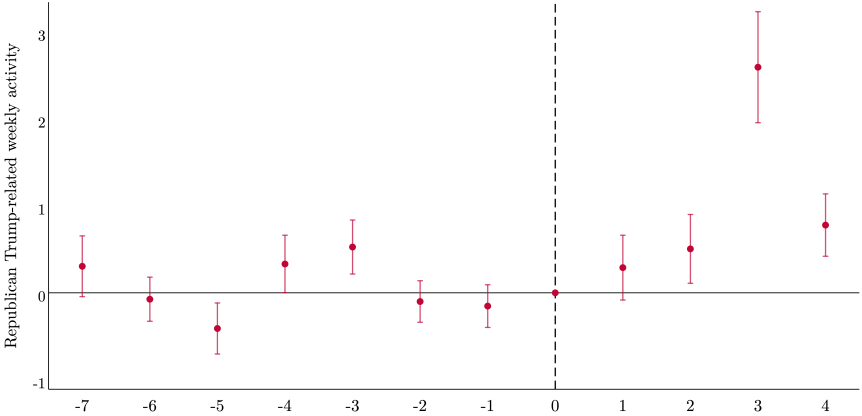


Robust to imputation estimator



▸ Back

Republicans mention Trump more after: extended keywords



▸ Back

The RELATIO package

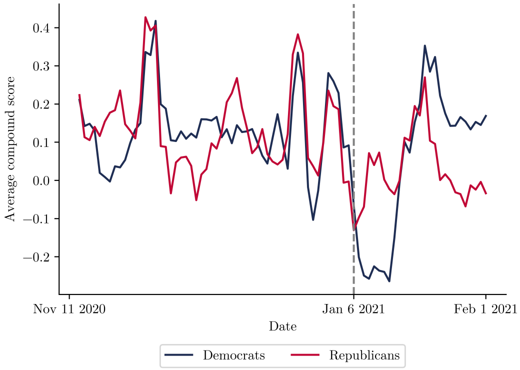
- **Pre-processing:** break down the corpus in sentences and apply SRL to assign role of agent, patient, and verb.

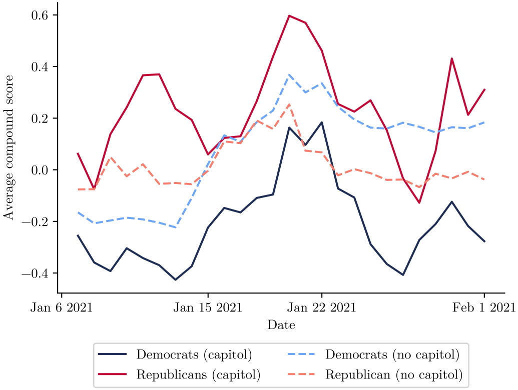
- **Dimensionality reduction:**
  - $\mathcal{A}_0$ is the set of agents, $\mathcal{V}$ is the set of verbs, $\mathcal{A}_1$ is the set of the sets of agents, verbs, and patients respectively
  - Extract latent entities $E \leq |\mathcal{A}_0 \cup \mathcal{A}_1|$ through **named entity recognition** and **K-means algorithm** with 100 clusters
  - Normalize the set of verbs $\mathcal{V}$ and add the prefix “not” to negated verbs

$$\text{AGENT ENTITY} \xrightarrow{\text{(NEGATED) VERB}} \text{PATIENT ENTITY} \in E \times \mathcal{V} \times E = \mathcal{N}$$

▸ Back

Evolution of sentiment





Over the whole period

capitol and non-capitol

Back

Is capitol used differently by the two parties?

	Dependent variable: xlm compound score			
	(1)	(2)	(3)	(4)
Democrat	-0.013	-0.008		
	(0.041)	(0.041)		
$\mathbf{1}(\text{capitol} \in \text{tweet})$	0.146*	0.149**	0.155**	0.147**
	(0.075)	(0.074)	(0.061)	(0.064)
Democrat $\times$ $\mathbf{1}(\text{capitol} \in \text{tweet})$	0.072	0.071	0.073	0.084
	(0.093)	(0.093)	(0.078)	(0.081)
Chamber FE		✓		
Individual FE			✓	✓
Day FE				✓
Observations	54050	54050	54047	54047
$\mathbb{E}$(Dependent variable)	0.124	0.124	0.124	0.124
Dependent variable std. dev.	0.684	0.684	0.684	0.684

Back

Extreme Republicans are more positive about capitol...

	Dependent variable: xlm compound score			
	(1)	(2)	(3)	(4)
$\mathbf{1}(\text{capitol} \in \text{tweet})$	-0.039	-0.042	-0.043	0.002
	(0.080)	(0.069)	(0.063)	(0.056)
$\mathbf{1}(\text{capitol} \in \text{tweet}) \times \mathbf{1}(\text{Nominate} > 0.5)$	0.235**	0.241***	0.199**	0.213***
	(0.099)	(0.090)	(0.077)	(0.071)
Chamber FE		✓		
Individual FE			✓	✓
Day FE				✓
Observations	7904	7904	7901	7901
$\mathbb{E}$(Dependent variable)	0.009	0.009	0.009	0.009
Dependent variable std. dev.	0.682	0.682	0.682	0.682

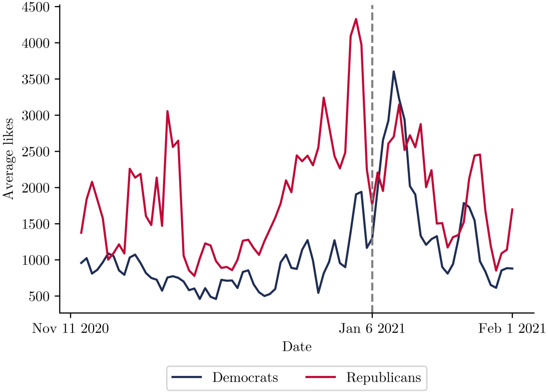
Back

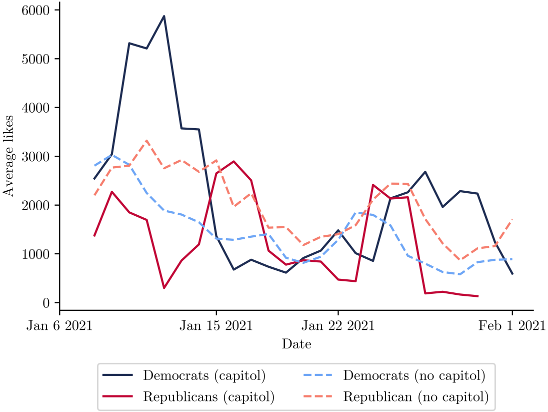
While extreme Democrats are more negative about capitol

	Dependent variable: xlm compound score			
	(1)	(2)	(3)	(4)
$\mathbf{1}(\text{capitol} \in \text{tweet})$	-0.425***	-0.416***	-0.371***	-0.208***
	(0.023)	(0.022)	(0.022)	(0.020)
$\mathbf{1}(\text{capitol} \in \text{tweet}) \times \mathbf{1}(\text{Nominate} < -0.5)$	-0.098	-0.098	-0.124**	-0.087*
	(0.060)	(0.061)	(0.054)	(0.047)
Chamber FE		✓		
Individual FE			✓	✓
Day FE				✓
Observations	18523	18523	18523	18523
$\mathbb{E}$(Dependent variable)	0.028	0.028	0.028	0.028
Dependent variable std. dev.	0.681	0.681	0.681	0.681

Back

Engagement on Twitter: likes





Back

Democrats were not more popular when tweeting about capitol before Jan 6

	Likes		Retweets	
	(1)	(2)	(3)	(4)
$\mathbf{1}(\text{capitol} \in \text{tweet})$	-821.814	-953.690	-148.119	-171.798
	(531.224)	(644.849)	(107.687)	(106.747)
Republican $\times$ $\mathbf{1}(\text{capitol} \in \text{tweet})$	551.416	644.127	99.904	115.692
	(913.266)	(714.692)	(122.293)	(121.842)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	32154	32154	32154	32154
Adj. R^2	0.273	0.273	0.228	0.232
$\mathbb{E}$(Dependent variable)	1045.511	1045.511	184.036	184.036
Dependent variable std. dev.	6196.444	6196.444	1125.166	1125.166

▸ Back

No overall differences in engagement

	Likes		Retweets	
	(1)	(2)	(3)	(4)
Democrat $\times$ After January 6	272.946	175.633	-8.374	-24.909
	(318.034)	(320.165)	(62.994)	(63.755)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	51365	51365	51365	51365
Adj. R^2	0.203	0.203	0.182	0.187
$\mathbb{E}$(Dependent variable)	1261.123	1261.123	222.692	222.692
Dependent variable std. dev.	7736.383	7736.383	1363.457	1363.457

▸ Back

No overall differences in engagement, even excluding capitol tweets

	Likes		Retweets	
	(1)	(2)	(3)	(4)
Democrat $\times$ After January 6	95.989	9.235	-50.161	-63.065
	(308.906)	(312.516)	(63.856)	(64.932)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	49226	49226	49226	49226
Adj. R^2	0.214	0.214	0.200	0.205
$\mathbb{E}$(Dependent variable)	1217.317	1217.317	214.314	214.314
Dependent variable std. dev.	7471.128	7471.128	1292.816	1292.816

Back

Negativity about capitol seems to pay off for Democrats...

	Likes		Retweets	
	(1)	(2)	(3)	(4)
$\mathbf{1}$(capitol $\in$ tweet)	597.073*	-125.471	58.774	-57.574
	(304.215)	(378.157)	(42.021)	(56.917)
Negative sentiment	1099.928***	847.249***	229.277***	189.095***
	(224.571)	(199.156)	(42.594)	(37.304)
Negative sentiment $\times$ $\mathbf{1}$(capitol $\in$ tweet)	495.560	681.594	202.980	233.016*
	(598.378)	(593.967)	(125.120)	(124.939)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	13622	13622	13622	13622
Adj. R^2	0.155	0.155	0.138	0.143
$\mathbb{E}$(Dependent variable)	1551.751	1551.751	254.394	254.394
Dependent variable std. dev.	1.0e+04	1.0e+04	1691.367	1691.367

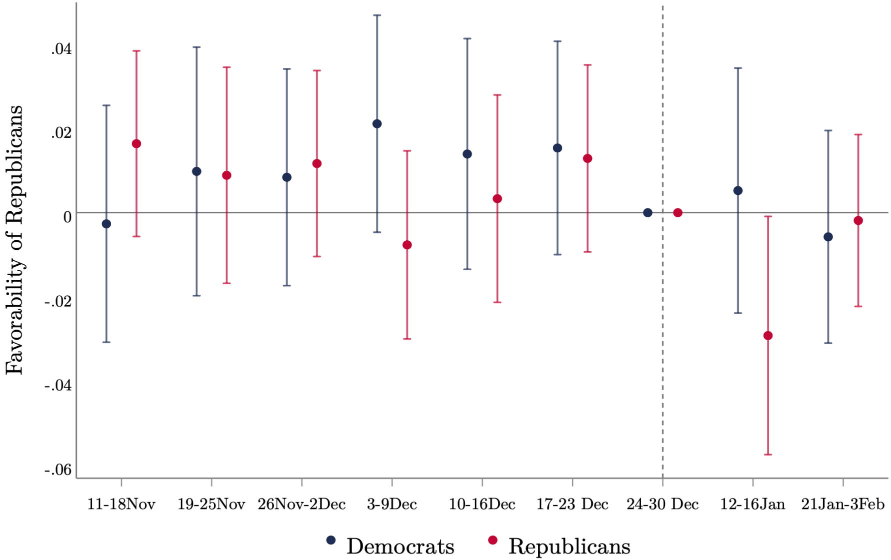
Back

...but not so much for Republicans

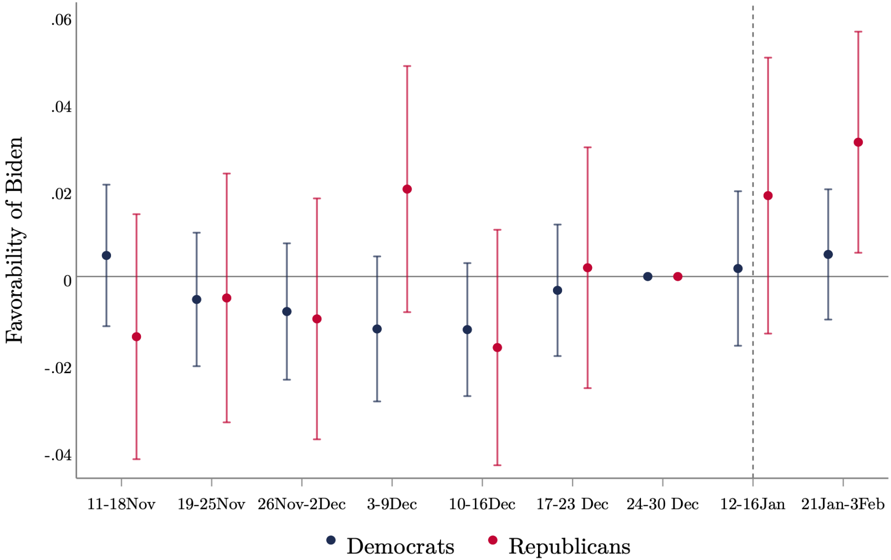
	Likes		Retweets	
	(1)	(2)	(3)	(4)
$\mathbf{1}(\text{capitol} \in \text{tweet})$	336.533	250.891	16.746	6.656
	(235.716)	(268.095)	(34.236)	(44.677)
Negative sentiment	867.220***	803.063***	265.572***	255.898***
	(182.501)	(178.177)	(52.293)	(49.776)
Negative sentiment $\times$ $\mathbf{1}(\text{capitol} \in \text{tweet})$	-596.852	-527.791	-127.449	-99.735
	(450.837)	(436.927)	(111.422)	(96.407)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	5586	5586	5586	5586
Adj. R^2	0.294	0.294	0.271	0.274
$\mathbb{E}$(Dependent variable)	1784.793	1784.793	366.596	366.596
Dependent variable std. dev.	8228.140	8228.140	1671.322	1671.322

▸ Back

Attitudes towards Republicans worsened for Republicans

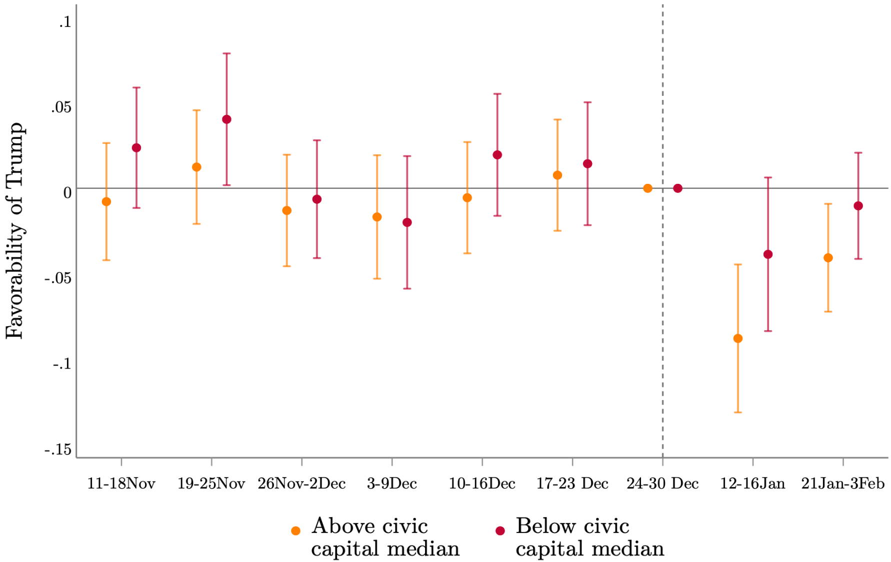


Attitudes towards Biden (slightly) improved for Republicans



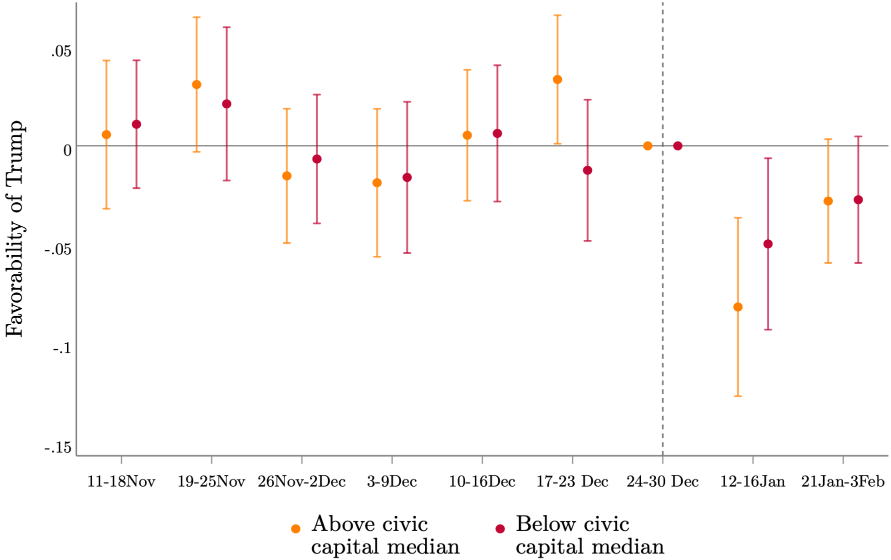
Back

Civic capital and attitudes towards Trump: I



Back

Civic capital and attitudes towards Trump: II



Back

ATE matching each wave with the baseline wave using demographic and ideological predictors

	Dependent variable: Favorability of Trump							
Wave	11-18Nov	19-25Nov	26Nov-2Dec	3-9Dec	10-16Dec	17-23 Dec	12-16Jan	21Jan-3Feb
Not in wave before January 6	0.018	0.027**	-0.012	-0.002	0.013	0.034***	-0.063***	-0.017
	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.016)	(0.012)
Observations	3489	3152	3876	3398	3513	3606	2945	4211

Back

ATE pre-post matching with different predictors

	Dependent variable: Favorability of Trump		
After January 6	-0.042***	-0.034***	-0.026***
	(0.008)	(0.007)	(0.008)
Observations	16070	16205	15562
Predictors	Demographic	Ideological	Demographic + Ideological

Back

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