

A Different Story: How Conservative Narratives Diverge Between Twitter and Parler

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Abstract

Amidst a pandemic, a presidential election, and an insurrection – Parler became the social media platform of choice for Twitter users who felt politically censored. Because of Parler’s nascence, and an ever-evolving information environment, user behavior on unfettered platforms like Parler versus moderated platforms like Twitter has yet to be explored. This paper focuses on a select group of U.S. public political figures who occupy both Twitter and Parler. We compare this group’s behavior across the two platforms to observe how politically conservative narratives diverge. Leveraging scores from Media Bias/Fact Check, we find that media bias levels are higher for these users on Parler than the same users on Twitter, with notable exceptions at the individual level. Through citation networks, we also find that influential news sources are more politically varied on Parler. Finally, we observe initial evidence that moderated topics on Twitter diverge on Parler. Our findings offer an early insight into the new social media platform Parler.

1 Introduction

On January 6th, 2021, months of social and political tension culminated in an attack by insurrectionists on Capitol Hill. Mobs fueled by election fraud conspiracies, broke into the Congressional building, making their way as far as the Senate chamber and stopping just short of the House floor. New York representative Alexandria Ocasio Cortez, said in that moment, “I thought I was going to die.” [aoc21], and while no member of Congress faced injury, one Capitol Hill police officer and four rioters were killed in what has now become known as the Storming of the Capitol. But how did we reach this point?

There are a great many factors that may have contributed to the violence seen on January 5th and 6th, such as a chaotic information environment online wherein pandemic and election misinformation, not only flourished but was abetted by public figures [par21b]. Platforms attempted to combat misleading information through moderation practices like misinformation flags, added friction, and deplatforming [mis21]. These platform policies were considered by some to be forms of censorship [ted21]. With the perceived censorship and limitations on speech, users began to move to alternative platforms like Parler [ABB+21].

Parler was created in 2018 and marketed as a “Free speech” platform in which users did not have to fear moderation of their beliefs. It became a secondary platform for right-leaning online communities and major

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public figures like Tucker Carlson and Sean Hannity. In the wake of the election a larger exodus of users from Twitter signed on to Parler at the behest of such public figures [sig21], [ABB⁺21]. In some cases, if a user was completely banned from Twitter, Parler became one of their main platforms [par21c]. Because of Parler’s growing prominence as an alternative social media platform, we observe how the same group of users behave on Parler versus on Twitter, in the hopes of understanding how narratives may or may not diverge by platform.

The study of Twitter as a rich social network has previously been established [BM19], [FVD⁺16], but the nascence of Parler has rendered it, as of yet, unexplored territory. An early exploration has laid the foundation of describing the network’s characteristics at large [ABB⁺21] and comparison of topics in Parler and Twitter, and how organic the content is discussed in [HPG⁺21]. In this paper we present further means of exploration: a computational content analysis of the website links shared by a selected group of users, a network analysis of these links, and probabilistic topic models generated from user posts.

We focus on the links shared by users because news source selection, or selection bias, tends to be reflective of political affinities [IH09]. Previous research also suggests that race and partisanship may be reflected in online traffic patterns, resulting in the growing segregation of online communities [McI17], [FGR13], and [GS11]. In social media, this phenomenon is now more commonly known as the echo-chamber. Selecting our preferred news sites and curating our social media accounts potentially makes it easier to listen to groups or individuals who validate our own worldviews. As a result, we aim to characterize Parler through the news shared by and content written by users.

In order to measure media bias on Twitter versus Parler, we chose to subset the population to political figures that maintained accounts on both networks. The choice of public political figures was motivated by data availability and by previous literature on social media content analysis. One example comes from, William Brady and colleagues who tested what types of political messages on Twitter are more likely to be shared. Because Parler skews politically conservative, our sample users skews similarly and is also $N = 10$. We recognize that our results may not be generalizable due to this selection bias and small sample size.

We ask the following research question, in what ways do narratives diverge on Twitter versus Parler for conservative public figures? Using a variety of proxies for narratives such as topics and media bias, we posit the following sub-questions: 1) Is the content from conservative public figures more or less biased on Twitter or Parler? 2) What websites are commonly shared and which of these sites are the most influential? Does this change by platform? 3) Within the sample group of conservative public figures, how similar or divergent are the topics across platforms? Our exploration finds evidence of more extreme media bias in one platform versus another. We also examine the networks of disseminated information across platforms and identify influential sources. Finally, we discover how moderated topics on Twitter diverge on Parler. In the following sections will discuss our data collection process, methods for analysis, results, and discuss future implications.

2 Data Collection

In brief, we have curated posts (i.e., *tweets* for Twitter, *parleys* / *parlers* for Parler) from users that have accounts in *both* Twitter and Parler. First, we have identified public figures (e.g., senators, journalists), who are active (posts at least once a day on average), have established presence (have been in the platforms for more than 6 months), and are verified in both platforms. Before Parler was shut down, we have identified 10 public figures, who were manually verified to have conservative ideology. Overall, we collected all posts of these users until December 22, 2021, which amounts to 28,754 tweets and 1860 parleys¹.

We have used Twitter’s tweet timeline API to retrieve most recent tweets of the users. None of the users have posted more than the API’s limitations hence we retrieved all of their tweets since they joined the platform. We have also developed a custom Parler scraper in Python using Selenium web automation to retrieve user parleys. The scraper was able to retrieve all parleys of users. It should also be noted that during the preparation of this write-up, a researcher claimed to have downloaded all Parler data [par21a] after Parler was shut down by AWS. While the ethical and legality concerns of using this data are debated, we chose not to use it. Major elements of data and metadata retrieved from both platforms include post texts, post URLs, posting date and time, number of likes / favorites / reposts, user screen names, user real names, whether the users are verified or not, and unique IDs of the posts.

¹Our efforts to find public figures, who have presence in Parler and are liberal or left-leaning, were unsuccessful therefore we restrict our comparative analysis to those who are conservative.

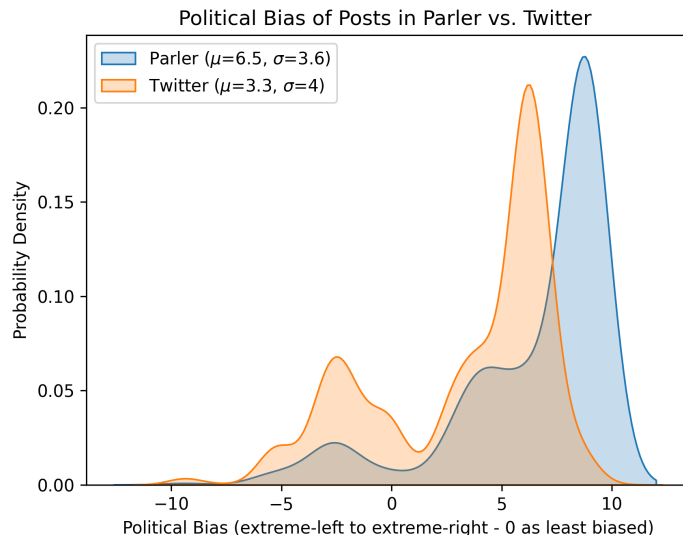


Figure 1: The political bias of posts in Parler vs. Twitter.

3 Main Results

3.1 Is Shared Content More Biased on Twitter or Parler?

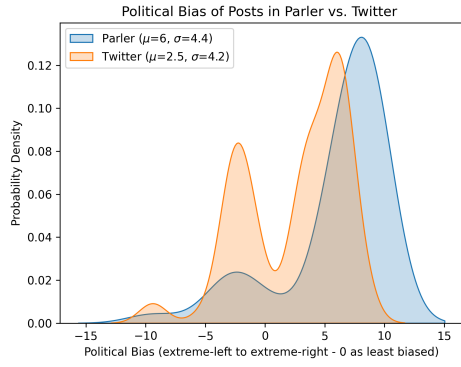
To quantify the political bias of a post, we first extract the URL from the post and assign it a bias rating obtained from the Media Bias Fact Check (MBFC) [MBF21]. While there is not any true scientific formula that is 100% objective, MBFC uses a methodology, which has been vetted and is used, for example, to compute the *Iffy Quotient* [iff21] or predicting the factuality of news sources [BKA⁺18]. Naturally, there are objective measures that can be calculated, but ultimately there will be some degree of subjective judgment to determine these. When calculating bias MBFC evaluates not only the political bias, but also how factual the information is and if they provide links to credible, verifiable sources. It is important to note that the bias scale is based on the USA political scale, which may differ from other countries. For example, the Democratic Party is considered centrist or even right-center in many countries around the world, however in the USA they are considered Left-Center. Numerically, media bias score is positive for right-leaning and negative for left-leaning sources. Least biased sources have a score of 0-2, left/right center is between 2 and 5, left/right bias is between 5 and 8, and extreme bias is 8 and above.

As shown in Fig. 1, the distribution of media bias scores skews more right for Parler than Twitter, indicating that on average websites shared on Parler are more extreme-right in their political leanings. This aligns with the current characterization of Parler as a haven for more far-right speech. The characterization, however, does not hold true for every political public figure.

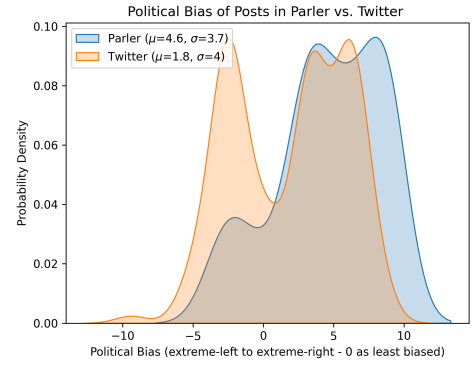
An analysis of media bias score distributions by users as shown in Fig. 2 illustrates that users behavior can diverge and converge across platforms. For example, Sen. Ted Cruz and Sen. Rand Paul are more likely to post extreme-right content on Parler. On Twitter, Rand Paul’s media bias distribution is bi-modal. It seems, he tweets both moderate-left and moderate-right leaning content. In a deeper dive into Rand Paul’s posts, we found that he posted nytimes.com (a left-leaning media source) at a ratio of 10:2 on Twitter versus Parler. The parleys containing nytimes.com links had the same language as two tweets, but it is not clear why he shares links from the same source at different rates.

Surprisingly, South Dakota governor Kirsti Noem showed very divergent post behavior on Twitter versus Parler. While Noem’s Parler presence skews right, her Twitter account shows extreme-left. One possible explanation could be that Noem is more likely to respond to liberal media and left-leaning content on Twitter because the platform has more diversity in its political communities.

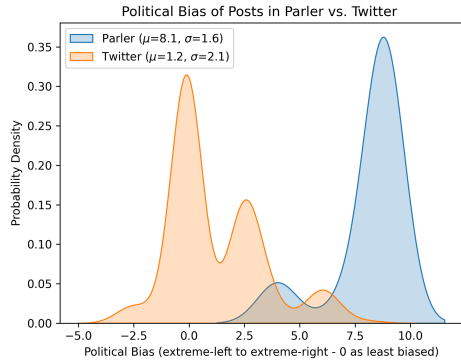
Meanwhile, Sean Hannity’s Twitter and Parler accounts are almost perfectly aligned in their bias distribution. Likely this is due to both accounts only sharing content from hannity.com and few other sources.



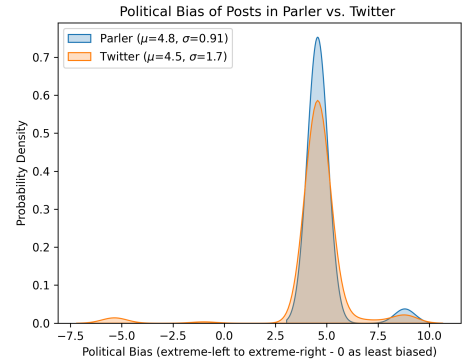
(a) Ted Cruz



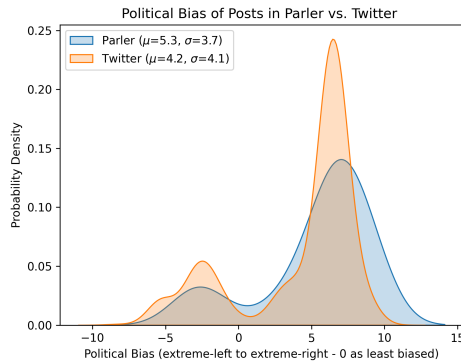
(b) Rand Paul



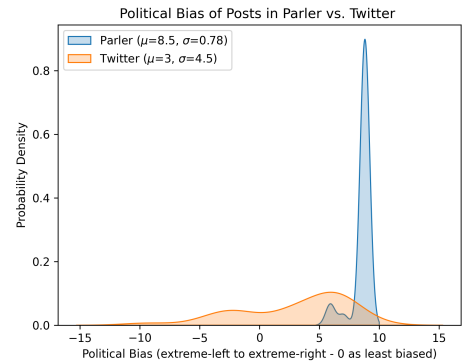
(c) Gov. Kirsti Noem



(d) Sean Hannity



(e) Mark Levin



(f) Allen West

Figure 2: Individual political bias of selected users in Parler vs. Twitter.

3.2 What Sources Are Influential on Twitter vs. on Parler?

In order to analyze the information dissemination patterns of users, citation networks were generated for each data set. We defined an edge as a link shared by a user so that each node was either a website domain or a political public figure. The Twitter graph had over 643 nodes and 899 edges, while the Parler graph, due to the smaller dataset had 125 nodes and 168 edges. We then filtered the networks to “core” networks, wherein a link was shared more than one user (degree >1). We present the graphs in Fig. 3.

We employed the PageRank algorithm [BP98] to identify the most influential sources across the selected political users, by platform. As it was originally designed as a method to rank websites, PageRank was especially well suited to the task. PageRank was calculated based on incoming connections to a node with respect to edge weight and our findings can be seen in Fig. 4.

On Twitter the sites with the highest PageRank scores included hannity.com, Allen West’s personal blog

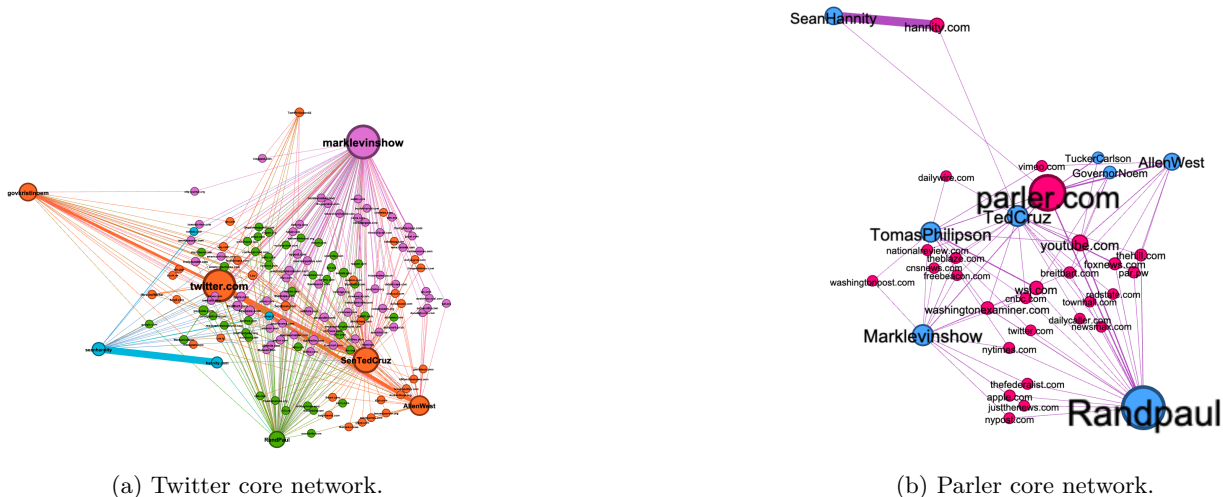


Figure 3: Core networks where degree > 1 .

theoldschoolpatriot.com, foxnews.com, and Breitbart.com (Fig. 4a). The same sites also scored within the top twenty PageRank scores on Parler, but it was surprising to find a greater diversity of sources as well. Meanwhile, Parler’s PageRank list (Fig. 4b) included politically center sources like Newsweek, and more left sources like the New York Times and CNBC, as well. PageRank is often used as a measure of influence. In this case, we can see that the most commonly shared links and influential sources on Parler include both politically right and politically left sources. On the other hand, no left-leaning sources were in the top twenty most influential sources on Twitter.

We have also clustered the citation networks using Girvan–Newman community detection algorithm [MJ02]. We have identified 4 distinct communities with graph sizes 534, 63, 42, and 4. Analyzing the top two communities of this graph, namely the communities with sizes 534 and 63, we have found out the average media bias to be 3.07 and 1.16, respectively. This result demonstrates how subgroups in a larger community can exhibit varying degrees of conservative bias and sheds insights on inter-group information dissemination patterns.

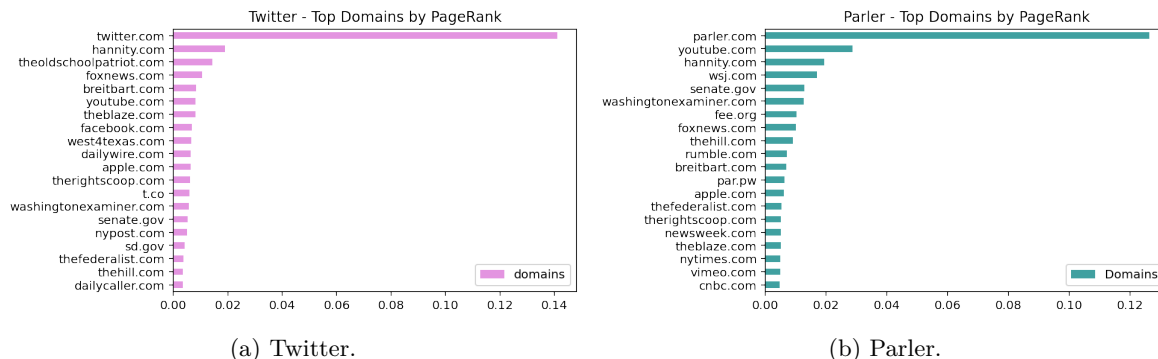


Figure 4: Influence scores of shared links.

Our project represents very early work into Parler as a platform, but we conjecture that the reason for the greater political diversity in Parler’s influential sources is due to its demographics. Because Twitter has variety of political communities, conservative public figures on Twitter may feel compelled to evangelize conservative content at a higher rate. Another interpretation is that liberal content is less likely to receive engagement on Parler. We hope future will be able to disambiguate the relationship between the two.

3.3 Do Topics Diverge by Social Platform?

After examining the media bias and networks of shared links, the next step was to explore the text of the tweets and parleys to give some context for the user behavior seen in previous sections. Using the python packages Gensim and NLTK, we preprocessed the text to generate corpora and dictionaries for each dataset (including the

Table 1: Twitter Topics

Topic0	Topic1	Topic2	Topic3	Topic4
south_dakota	election	police	biden	georgia
one	trump	report	say	cuomo
state	tonight	mayor	trump	election
facebook	join	thanksgiving	pennsylvania	fraud
shutdown	sentedcruz	city	attack	hunter_biden
america	watch	covid	twitter	state
need	vaccine	lawsuit	mentorship	update
year	life_liberty_amp_levin	urge	right	obama
investigate	destroy	owner	demand	show
family	democrat	target	would	please
help	confirm	democrat	caught	michigan
school	interview	hell	go	china
proud	claim	violence	president_trump	trump
come	dem	new	story	et
together	tune	violent	scandal	u
Topic5	Topic6	Topic7	Topic8	Topic9
joe_biden	democrat	voter	state	lie
medium	supreme_court	nyc	people	voting
democrat	election	medium	texas	reporter
say	vote	judge	aoc	say
president	senate	democrat_party	pelosi	justice
get	cnn	america	rule	day
well	court	democrat	help	job
time	ballot	rt_texasgop	thank	evidence
want	scotus	honor	hunter	covid
tax	dems	serve	american	message
family	say	constitution	need	refuse
nothing	president	today	south_dakota	news
take	job	change	keep	show
year	republican	support	continue	today
case	china	senate	today	poll

hashtags within each post). We chose to use the probabilistic topic model, Latent Dirichlet Allocation (LDA) and identified the optimal number of topics per model through coherence score calculations. For each dataset we generated models that ranged in number of topics from one to 50 per model, at intervals of five for a total of twenty LDA models. As seen in figure 5, for both the Twitter and Parler topic models, there was a precipitous drop off in coherence values initially, followed by a slight increase in coherence around the n = 10 topics. In order to optimize for coherence and human interpret ability, ten topics per model were deemed optimal.

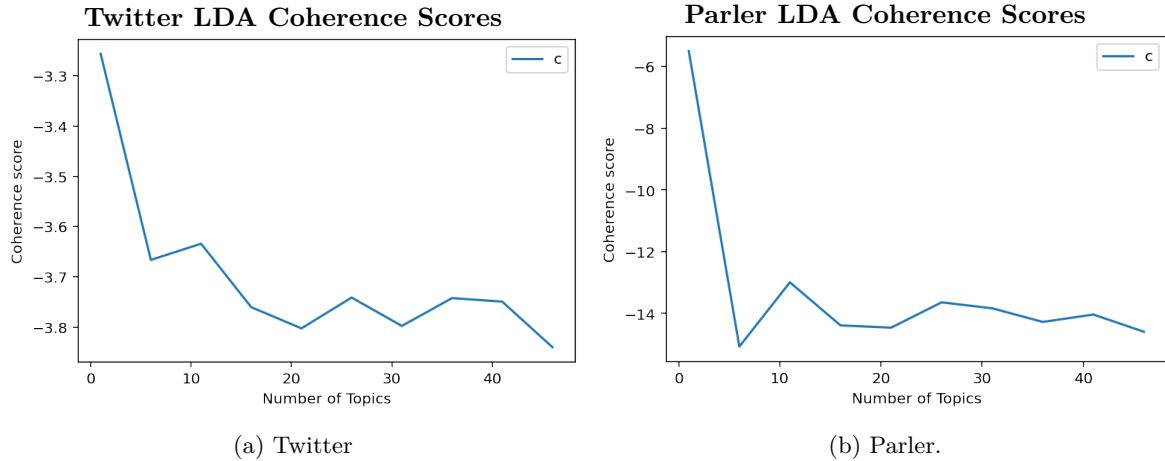


Figure 5: Model coherence generally trends downwards as number of topics increase.

The topic model for Twitter demonstrated a wider range of subjects than Parler’s model. Twitter topics include Covid-19, the election, accusations of censorship, to foreign policy, 11. The topic models for Parler were more focused on the election, though both Parler and Twitter LDA models contained topics associated with Hunter Biden (Twitter Topic 4 and Parler Topic 0). Parler corpus is smaller than Twitter’s, but a few topic stood out as focused on Topic 0 with "usb_handoff" and "pull suitcase", both details of the Hunter Biden story, 12. Topic4 on Twitter mentions Hunter Biden more explicitly.

As LDA models are probability distributions of words, we leverage set theory and the Jaccard distance to measure the differences between the two models in a pairwise fashion. Most of the topics fall between the .82-1.00 in topic decorrelation, suggesting topics on Twitter are not similar to topics on Parler.

Through manual inspection we found that though Topic 4 from Parler and Topic 0 from Twitter were both related to Hunter Biden, they were strongly decorrelated at a .98 index. This decorrelation of across platform topics may indicate that though users on Twitter post about Hunter Biden, the conversation diverges radically on Parler. Such dissimilarity could be due to the moderation practices of Twitter. Twitter began removing

Table 2: Parler Topics

Topic0	Topic1	Topic2	Topic3	Topic4
right happen_open gbi_need time_country need_truth wound find_mail heal_never ballot_prison investigation_people usb_handoff leader_stand someone_georgia pull_suitcase table_secretly	year doubter_shock people_trust smackdown_many block_lay government let_georgian gabriel_sterling well_gov truth_integrity remember_calm brad_raffensprerger signature_verification show_fight restore_trust	special_session counting_vote else_go expose_call henhouse_wonder bleeding_stop say_fox senator_georgia america_great biden georgia_one do_dark get_truth one_love sure_vote	heals_truth stop_president job_unless democrat_republican story_america want_truth quit_want texas election_even get care_people thousand_people voter_fraud listen_hundred swing_state	win_stay together_trump2020 covid american new election georgia say people make government democrat president show family
Topic5	Topic6	Topic7	Topic8	Topic9
school one parler state end many year join trump war open help follow get take	government america_great economy covid obama trump case say year biden people democrat report efficacy fight_keep	stood_stage attention_gop president_spoken senator_representative rally_benefit realdonaldtrump_stopthsteal state say one people medium make could government would	democracy_america need_leader local_judge spit_constitution scotus_step law_order violate_must civil_right stop_state problem_country uncivilized_america keep_faith right_wrong u_electoral paid_play	faith trump2020_keep time join government election u people year state problem away america liberty cnn

content and posts related to the NYPost story on Hunter Biden. It is difficult to measure the difference between narratives when one is actively moderated on a platform, but with this limited data set we see some potential signals of narrative divergence related to moderation.

4 Conclusion

Our results suggest that on average these conservative political figures share content on Parler that leans extreme-right, which aligns with current characterizations of the platform as a haven for conservative right groups. However, liberal sources are more likely to be ranked as influential on Parler than on Twitter. Our topic model analysis indicates that moderation may be one driver of divergent behavior. Are users more likely to share left-leaning content on Twitter because of the diversity of political communities on Twitter or is it because right-leaning content tends to be moderated? Does Parler content lean extreme-right because the platform is unmoderated, or more because such content drives user engagement? We recommend that future work explore such questions to test the potential unintended consequences of moderation as a driver of partisanship.

There are, of course, limitations to our presented study. The sample size is small and the population is hand-selected. Our results are therefore non-generalizable to a larger population and should instead be considered exploratory work. Our work is also U.S. centric and the paradigms of the political spectrum are unique. But the focus on high-profile political figures does offer some advantages. One advantage is ethical, we do not need to trespass the privacy of individuals that did not consent to be a part of public discourse.

References

- [ABB⁺21] Max Aliapoulos, Emmi Bevensee, Jeremy Blackburn, Emiliano De Cristofaro, Gianluca Stringhini, and Savvas Zannettou. An early look at the parler online social network, 2021.
- [aoc21] “I thought I was going to die” - AOC at Capitol. <https://news.yahoo.com/thought-going-die-aoc-capitol-092608485.html>, 2021. [Online; accessed January 18, 2021].
- [BKA⁺18] Ramy Baly, Georgi Karadzhov, Dimitar Alexandrov, James Glass, and Preslav Nakov. Predicting Factuality of Reporting and Bias of News Media Sources. *arXiv e-prints*, page arXiv:1810.01765, October 2018.
- [BM19] Alexandre Bovet and Hernán A Makse. Influence of fake news in twitter during the 2016 us presidential election. *Nature communications*, 10(1):1–14, 2019.
- [BP98] S. Brin and L. Page. The anatomy of a large-scale hypertextual web search engine,. *Computer Networks and ISDN Systems*, 30:107–117, 1998.

- [FGR13] Seth Flaxman, Sharad Goel, and Justin M. Rao. Ideological segregation and the effects of social media on news consumption. SSRN, 2013.
- [FVD⁺16] Emilio Ferrara, Onur Varol, Clayton Davis, Filippo Menczer, and Alessandro Flammini. The rise of social bots. *Commun. ACM*, 59(7):96–104, June 2016.
- [GS11] Matthew Gentzkow and Jesse M. Shapiro. Ideological Segregation Online and Offline. *The Quarterly Journal of Economics*, 126(4):1799–1839, 11 2011.
- [HPG⁺21] Hitkul, Avinash Prabhu, Dipanwita Guhathakurta, Jivitesh jain, Mallika Subramanian, Manwith Reddy, Shradha Sehgal, Tanvi Karandikar, Amogh Gulati, Udit Arora, Rajiv Ratn Shah, and Pon-nurangam Kumaraguru. Capitol (pat)riots: A comparative study of twitter and parler, 2021.
- [iff21] The Iffy Quotient. <https://csmr.umich.edu/projects/iffy-quotient/>, 2021. [Online; accessed February 4, 2021].
- [IH09] Shanto Iyengar and Kyu S Hahn. Red media, blue media: Evidence of ideological selectivity in media use. *Journal of communication*, 59(1):19–39, 2009.
- [MBF21] Media Bias Fact Check (MBFC). <https://mediabiasfactcheck.com/>, 2021. [Online; accessed January 22, 2021].
- [McI17] Charlton McIlwain. Racial formation, inequality and the political economy of web traffic. *Information, Communication & Society*, 20(7):1073–1089, 2017.
- [mis21] “Misinformation dropped dramatically the week after Twitter banned Trump and some allies”. <https://www.washingtonpost.com/technology/2021/01/16/misinformation-trump-twitter/>, 2021. [Online; accessed January 18, 2021].
- [MJ02] Girvan M. and Newman M. E. J. Community structure in social and biological networks,. *Proc. Natl. Acad. Sci.*, 99:7821–7826, 2002.
- [par21a] Every Deleted Parler Post, Many With Users’ Location Data, Has Been Archived. <https://gizmodo.com/every-deleted-parler-post-many-with-users-location-dat-1846032466>, 2021. [Online; accessed January 18, 2021].
- [par21b] “How Parler, a Chosen App of Trump Fans, Became a Test of Free Speech”. <https://www.nytimes.com/2021/01/10/technology/parler-app-trump-free-speech.html>, 2021. [Online; accessed January 18, 2021].
- [par21c] Parler - Wikipedia. <https://en.wikipedia.org/wiki/Parler>, 2021. [Online; accessed January 18, 2021].
- [sig21] “Parler Games: Inside the Right’s Favorite ‘Free Speech’ App”. <https://www.wired.com/story/parler-app-free-speech-influencers/>, 2021. [Online; accessed January 18, 2021].
- [ted21] “Ted Cruz: Facebook, Twitter, Google collectively pose ‘single greatest threat’ to free speech in America”. <https://fxn.ws/31IJ7Jy>, 2021. [Online; accessed January 18, 2021].