Replication Report:
"Out-group animosity drives engagement on social media", Rathje et al. (2021)

By Minh Quach

Similarities and Differences:

Before discussing the results, it is important to at least mention a few meaningful differences between the original study and this replication effort.

In terms of the input data, the study analyzed over 2.7 million posts from news media accounts (2018 to 2020) and the accounts of U.S. Congressional members (2016 to 2020) on Facebook and Twitter. For the replication, I had 1.2 million tweets from every Congressperson, from the year of 2008 to 2017.

In terms of the tool used, the original study used a range of author-custom dictionaries, as well as several of those from the Linguistic Inquiry and Word Count (LIWC) dictionaries. Meanwhile, this replication relied on a smaller subset of the original custom dictionaries that are publicly available, in addition to the dictionary included in the Valence Aware Dictionary and sEntiment Reasoner (VADER) toolkit.

These preliminary factors alone set the replication exercise to be more hyper-specific than the original study (looking at one single platform – Twitter, and from one highly exclusive author group – Congresspeople). Meanwhile, the time dimension is significantly broader here, spanning 10 years of tweets from the very early days, compared to the 2-4 years of data (Trump presidency exclusive) in the original study. This in turn makes the replication exercise less time-specific, and the consequent findings more chronologically sweeping.

Comparing the results, I observed a general theme of agreement, especially with the key points of arguments. Beyond that, there are minor disagreements with potential extensions to follow.

Regarding the central hypothesis, both the replication results and the original positively show that political out-group words were the strongest predictors of retweet from both Liberal and Conservative Congressional member accounts on Twitter. Similarly, albeit weaker, negative affect was also a positive indicator of retweet possibility (Appendix A2) (Fig 1).

In both, removing the control variables also does not change our conclusions above, with out-group language and negative affect remaining top predictors of retweet (Appendix A2, A3).

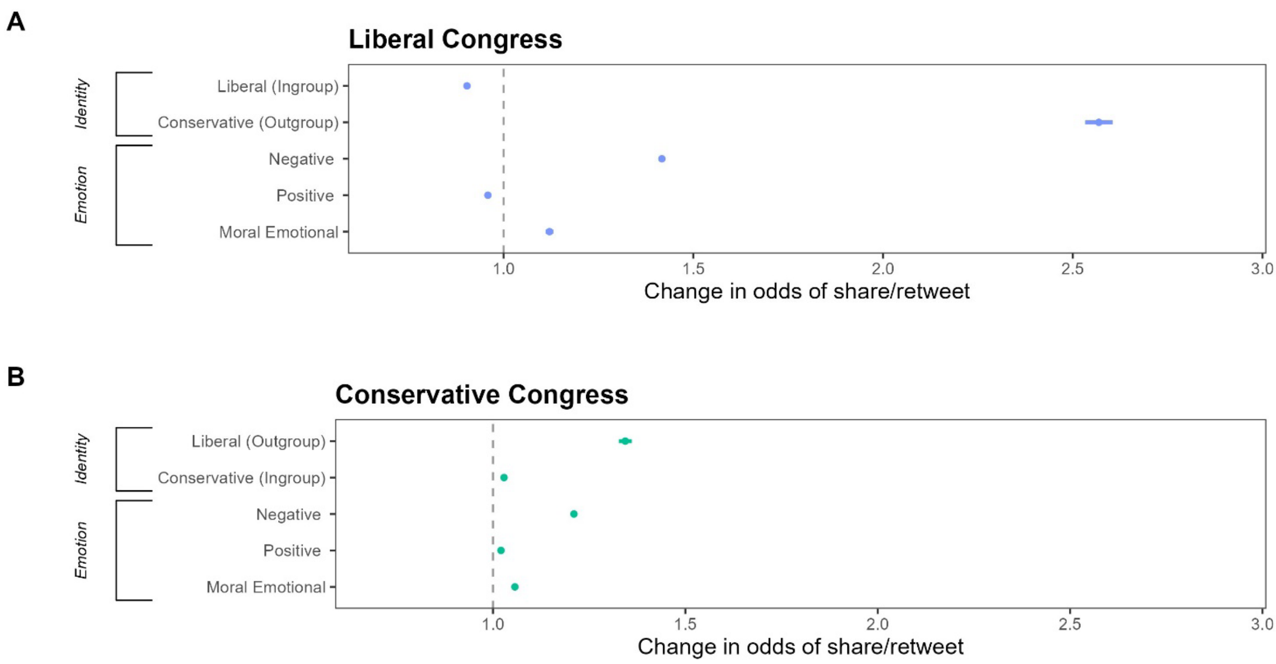

Fig 1. Change in odds of share/retweet if a tweet's language belong to a certain identity or emotion, by party.

However, when it comes to coefficient size, there are some discrepancies. In the original study, Conservative congresspeople are found to be 180% more likely to retweet because of out-group language, while their Liberal counterparts are 113% more likely to retweet under the same influence (Appendix A1). In contrast, the replication shows that it is 34% and 157%, for Conservatives and Liberals, respectively (Appendix A2). This can be attributed to the parameter differences discussed in the beginning.

As I combined both sides of the aisle into one analysis, ignoring the party-specific effect, I also observed that out-group language continues to be the strongest predictor of tweet engagements, and again followed by the measure of negative sentiment (Fig. 2). The study also arrived at similar results.

Furthermore, both the original study and the replication found that the out-group language motivates the Congressperson to retweet more than to favorite, while in-group language brings the oppositive motivational effects, if at all (Fig. 3). If we consider retweeting to be an indicator of the user's "intention to propagate", and favoriting an indicator of "approval", that might explain the perverse (though totally expected) rationale behind the Congresspeople's Twitter activity: A tweet that calls out the out-group needs to be propagated; a tweet that supports the in-group ought to be approved.

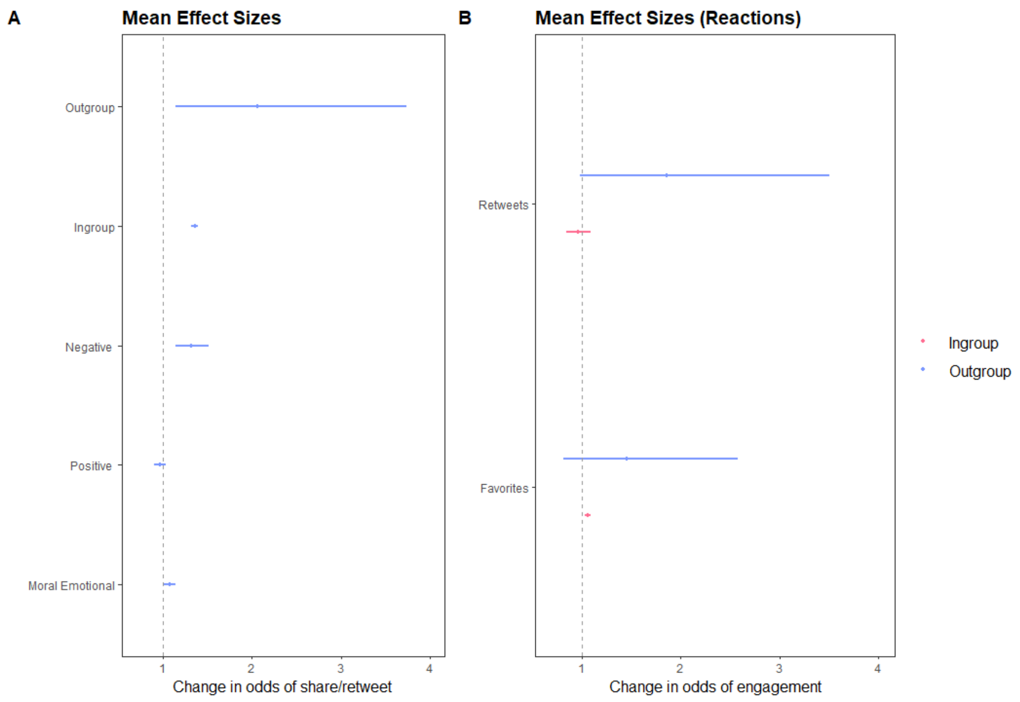

Fig 2. Change in odds of favorite/retweet if a tweet's language belong to a certain identity or emotion, both sides combined.

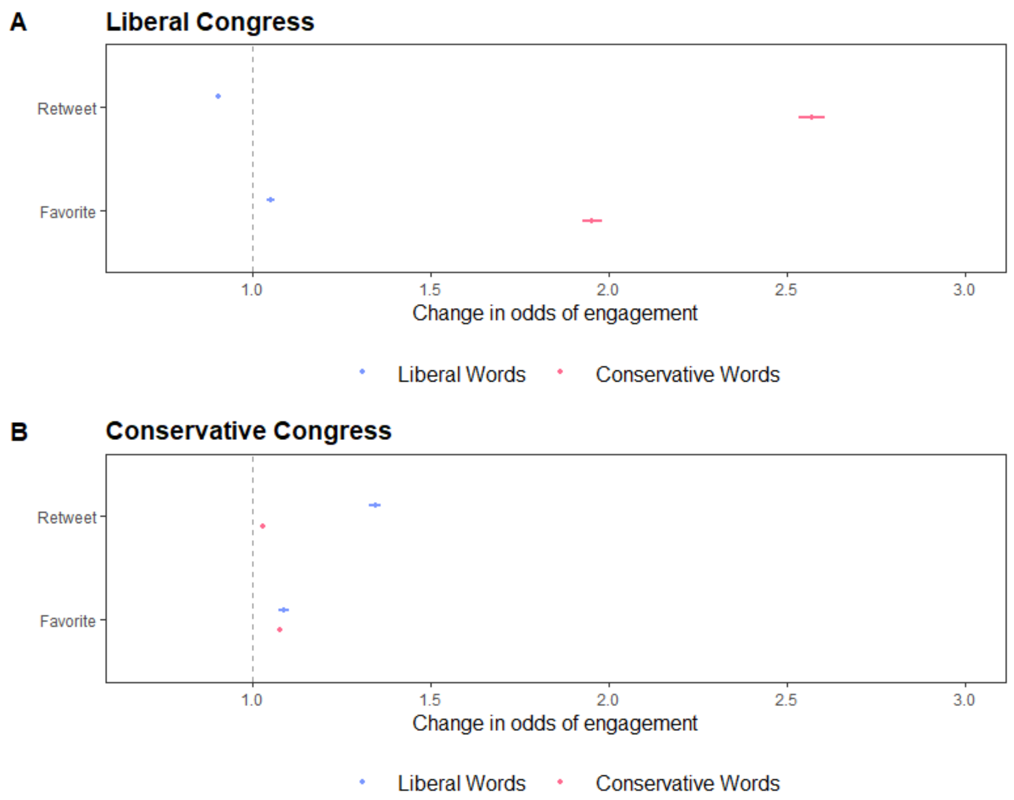

Fig 3. Change in odds of favorite/retweet if a tweet's language belong to a political identity, by party.

On the other hand, so far, the replication shows greater retweet probability coefficients for Liberal Congresspeople than their Conservative counterparts. The study, meanwhile, points to the opposite direction, showing a contrasting dynamic of ‘political sensitivity’.

Autopsy:

Initially, lack of available data was a problem until a public source was successfully identified. The reason was due to Twitter’s radically changed data and API access after the company’s recent overhaul in 2022. The Facebook data was also not available due to the authors acquiring them from a paid intermediary, which prevents sharing with public readers. The replication ended up looking at 2 of the 8 proposed datasets.

Even then, the publicly sourced data still needs to be cleaned and processed again:

- The relevant metadata (e.g. URL, Media, Retweet) was either missing or faulty, requiring additional scanning and deciphering through text and author analysis.
- The profile information, especially followers count and political affiliation, was not available, thus requiring additional work to gather this information.

The LIWC dictionaries were also proprietary, forcing us to use another dictionary (VADER) with a smaller scope of sentiment analysis. More specifically, LIWC has dictionaries for more nuanced sentiments such as anger and anxiety, while VADER only deals with the negative/positive dichotomy.

Last but not least, the initial readin of the main json file was run on R, the original authors’ programming language of choice. After several iterations, I found that the same process, implemented and run on Python, shows to be approximately 60 times faster.

Extension:

Firstly, an expanded set of data that comprehensively covers every year including the latest tweets would be an immense improvement. Furthermore, the data should be better verified with the correct metadata and attachment information.

Secondly, we can improve the choices of dictionaries, especially the custom dictionaries that can be updated to more recent times, and with more recent political colloquial to better reflect the discourse.

Thirdly, looking at the broader theme of political polarization, sensationalism and negativity bias, one can say that a lot has changed over the years. Thus, it is worth looking into changes over time, especially the before/after pictures of those more contextually significant years such as presidential election years, the pandemic years, or the year when Twitter or Facebook made major change to its content policy, audience base, and algorithms, which are all significant factors to our central research question.

References:

Dataset:

https://www.kaggle.com/datasets/oscaryezfeijo/us-congressional-tweets-dataset/data

Original Paper:

Rathje, S., Van Bavel, J. J., & van der Linden, S. (2021). Out-group animosity drives engagement on social media. Proceedings of the National Academy of Sciences, 118(26), e2024292118. https://doi.org/10.1073/pnas.2024292118

Appendix:

A1 – Original regression table with control variables (the relevant area of comparison is within the yellow rectangle)

Table S11. Study 2 Regression Models

	Facebook		Twitter	
	Liberal	Conservative	Liberal	Conservative
(Intercept)	8.79 ***	7.83 ***	9.70 ***	6.25 ***
	[8.65, 8.94]	[7.71, 7.95]	[9.63, 9.78]	[6.20, 6.30]
Democrat	1.02 ***	1.65 ***	0.75 ***	2.80 ***
	[1.01, 1.03]	[1.64, 1.67]	[0.75, 0.75]	[2.77, 2.84]
Republican	1.58 ***	1.20 ***	2.13 ***	0.85 ***
	[1.57, 1.59]	[1.19, 1.20]	[2.11, 2.15]	[0.84, 0.85]
NegativeAffect	1.14 ***	1.12 ***	1.33 ***	1.45 ***
	[1.13, 1.14]	[1.11, 1.12]	[1.33, 1.34]	[1.44, 1.45]
PositiveAffect	0.96 ***	0.98 ***	0.95 ***	1.04 ***
	[0.95, 0.96]	[0.97, 0.98]	[0.95, 0.95]	[1.04, 1.05]
MoralEmotional	1.06 ***	1.05 ***	1.10 ***	1.06 ***
	[1.05, 1.06]	[1.04, 1.05]	[1.10, 1.11]	[1.05, 1.07]
has_URLTRUE	1.24 ***	1.00	0.95 ***	0.83 ***
	[1.21, 1.26]	[0.98, 1.01]	[0.94, 0.96]	[0.82, 0.83]
has_mediaTRUE	1.09 ***	0.92 ***	1.08 ***	1.22 ***
	[1.08, 1.11]	[0.91, 0.94]	[1.07, 1.09]	[1.20, 1.23]
`Likes at Posting`	1.00 ***	1.00 ***		
	[1.00, 1.00]	[1.00, 1.00]		
followers_count			1.00 ***	1.00 ***
			[1.00, 1.00]	[1.00, 1.00]
is_retweetTRUE			5.10 ***	5.36 ***
			[5.04, 5.16]	[5.30, 5.42]
N	354814	410313	747675	611292
AIC	1253213.12	1474731.77	2861220.18	2343833.57
BIC	1253320.92	1474841.02	2861346.95	2343958.13
Pseudo R2	0.33	0.13	0.30	0.33

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

A2 – Replication regression table with control variables

	Liberal Congress Twitter	Conservative Congress Twitter
(Intercept)	6.79 ***	3.89 ***
	[6.74, 6.84]	[3.87, 3.91]
Democrat	0.90 ***	1.34 ***
	[0.90, 0.91]	[1.33, 1.36]
Republican	2.57 ***	1.03 ***
	[2.53, 2.61]	[1.02, 1.04]
Negative	1.42 ***	1.21 ***
	[1.41, 1.42]	[1.21, 1.22]
Positive	0.96 ***	1.02 ***
	[0.95, 0.96]	[1.02, 1.02]
MoralEmotional	1.12 ***	1.06 ***
	[1.11, 1.13]	[1.05, 1.06]
has_URLTRUE	0.93 ***	1.14 ***
	[0.93, 0.94]	[1.13, 1.14]
followers_count	1.00 ***	1.00 ***
	[1.00, 1.00]	[1.00, 1.00]
is_retweetTRUE	2.97 ***	2.36 ***
	[2.94, 3.00]	[2.34, 2.38]
N	563010	669889
AIC	2087227.66	2186166.74
BIC	2087340.07	2186280.89
Pseudo R2	0.19	0.24

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

A3 – Replication regression table with no control variable

	Liberal Congress Twitter	Conservative Congress Twitter
(Intercept)	8.26 ***	5.02 ***
	[8.22, 8.29]	[5.01, 5.04]
Democrat	1.34 ***	1.53 ***
	[1.33, 1.35]	[1.51, 1.55]
Republican	2.80 ***	1.38 ***
	[2.76, 2.84]	[1.37, 1.39]
Negative	1.41 ***	1.22 ***
	[1.40, 1.42]	[1.21, 1.23]
Positive	0.93 ***	1.00
	[0.93, 0.93]	[1.00, 1.00]
MoralEmotional	1.11 ***	1.04 ***
	[1.10, 1.12]	[1.03, 1.05]
N	563010	669889
AIC	2155788.23	2347778.26
BIC	2155866.92	2347858.16
Pseudo R2	0.08	0.03

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.