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Replication of the paper: Out-group animosity drives engagement on social media Rathje et al. (2021)

1. Motivation

Social media use in the United States of America has shown a steady upward trend over the last decade. In this context, as shown by a 2021 survey, Facebook is one of the most used platforms with a 69% share of usage among adults (Pew Research Center, 2021). Absolute worldwide numbers also indicate that Facebook is currently the sector leader with more than 2,900 million monthly active users (We Are Social & Meltwater, 2023).

Regarding social media usage reasons, “Reading news and stories” is one of the most widespread aims, with Facebook as the most employed platform to access news content (We Are Social & Meltwater, 2023). The implementation of social media as a news source conveys a drastic change in the way news are consumed in recent times compared to traditional newspapers or broadcasting (Thorson & Wells, 2016). In these platforms, news can be found incidentally while using online sources for other reasons (Boczkowski et al., 2018; Mitchelstein et al., 2020; Park & Kaye, 2021; Fletcher et al., 2023), making the study of its reach and diffusion dynamics relevant.

Users’ newsfeed in Facebook relies on what they “like” themselves, what their friends, content publishers (like media or politicians) and advertisers do and on the platform feed algorithm (Thorson et al., 2021). Between these influences a 2013 survey has shown that only 34% of Facebook news consumers “like” a “news organization or individual journalist or commentator” and that the remaining share found news “shared” by their friends’ network (Matsa & Mitchell, 2014).

Given the consequences that content publishers decisions and sharing actions have for posts visibility, this research aims to replicate previous work by Rathje et al. (2021) on the relationship of posts “share” actions and the verbal content in them on Facebook. Particularly, the population of interest were Facebook pages that correspond to media companies and congress members of the liberal and conservative ideological spectrum. Following previous studies, the focus was driven to political outgroup-ingroup mentions, positive and negative affect words and moral-emotional remarks (Brady et al., 2017; Rathje et al., 2021). The association of diffusion with this kind of language is also of interest to assess if social media platforms may incentivize speeches that are detrimental for social integration such as outgroup derogation (Rathje et al., 2021).

2. Background

Online sharing behaviors and the modelling of how information diffusion unfolds in social media has been of interest for more than a decade. Although terms like virality and (simple) contagion are usually used to explain these dynamics, it has been stated that viral epidemiology models widely overestimate the cascade size of information diffusion and this process can even depend on, between other variables, the topic at stake (Romero et al., 2011; Lerman, 2016). In addition, social media research in many cases cannot be directly deducted from previous social research due to the much larger scale of actors that are involved in comparison with usual face-to-face interactions. This has happened in the analysis of endorsement behaviors (i.e. digging, retweeting) as a function of friends that have done so, where the analyzed social media platform context should not be ignored (Lerman, 2016). Acknowledging the great number of variables that can have a role in online social sharing, in this research the focus has been given to political outgroup and ingroup terms, positive and negative affect language and moral-emotional language.

The concern about social media incentivizing polarizing content has turned researchers to the analysis of the effects of mentions of different political groups (Rathje et al., 2021). In the context of the USA, this divide has been mostly studied between Democrats and Republicans, who have shown increasing affective polarization (Iyengar et al., 2019). The reference article found that the mention of terms referring to the outgroup by partisan media or congress members was the strongest predictor of post shares in Facebook. Also, this dynamic was found to be even stronger for posts of conservative sources when the publication corresponded to a political leader rather than a media account. In the case of ingroup mentions, their effects for posts in the liberal spectrum were almost trivial, with odds very close to absence of effect. Conservative accounts, on the other hand, had a greater effect for ingroup references with odds surpassing estimates of 1.20. It should be noted that, while the original paper analyzed mostly data from a period when Republicans held the presidential office (January 2017 - January 2020), this replication mostly includes posts released during the running Democrat presidency (January 2020 - currently in office).

Sentiment analysis and the study of the connotative meaning of online messages have been widely studied by Computational Affective Science due to its multiple applications, for instance, in politics and marketing. This field, engaged with the computerized quantification of subjective states from text, comprehends the analysis of emotions, feelings and attitudes, between others. In the area of news outlets, it has been argued that there is a negativity bias in the psychophysiological reactions experimented while watching news (Soroka et al., 2019). Moreover, it has been found that negative affect language is related with increased shares in most news posts contexts, while positive affect language is related with decreased shares (Rathje et al., 2021; Schöne et al., 2021).

The last variable of interest in the present research is moral-emotional language. This variable is particularly relevant to politics due to its tie with societal norms (Brady et al., 2017). Previous research has found that moral-emotional language, but not solely moral or emotional terms, had been associated with increased expressions of endorsement in social media. This significant effect has also been present in the replicated article where the sharing behavior showed an increase of 5 to 17% when moral-emotional language was present.

3. Data

3.1. Data collection and filtering

As in the original paper, news media pages were extracted from the updated “Media Bias Chart” published by AllSides (AllSides, 2023). This table classifies media organizations according to a left (liberal) or right (conservative) leaning bias rating. The chart used and the differences to the chart in the original paper are shown in Appendix 1.

Facebook posts of the media and current congress members were collected through CrowdTangle, a tool owned by Meta that allows real time visualization of the platform content and posts information download. For the creation of liberal and conservative leaning media lists in CrowdTangle, two “txt” documents were written with the Facebook URLs of the media sources consolidated by AllSides. These can be found in the “media_acounts” folder of the GitHub repository under the names “left_media.txt” (30 total pages) and “right_media.txt” (24 total pages). Posts written by Facebook pages from congress members of the Democratic and Republican parties were obtained through lists consolidated by CrowdTangle (i.e., US House Democrats, US House Republicans, US Senate Democrats and US Senate Republicans).

All data was retrieved on the 8th of August of 2023 and it was set to reach posts up to the previous day to avoid the collection of very recent posts that had not reached most of its sharing behaviors. The last 300,000 posts for each media list were downloaded (for greater insights on the posts dates see Appendix 2). Posts from congress members of both parties were retrieved from the last date of the original paper, 1st of July, up to the 7th of August. 351,106 posts were retrieved from Democrat members and 286,552 from Republican members. Although unbalanced sample sizes can be inaccurate for statistical tests comparison, the size of the smaller sample was assessed as big enough for correct performance of the statistical tests and the difference was smaller than in the benchmark article.

From all retrieved data, the only implemented filter was eliminating posts with missing values in the “Likes at Posting” control variable. These accounted for 65 posts from the Democrat congress members (15 pages affected) and 190 posts of the Republican congress members (36 pages affected). Lists of the names of the affected pages can be found in the provided script under the names “NaN_democrat_congress” and “NaN_republican_congress”.

3.2. Variable operationalizations

3.2.1. Dependent variable

Shares (log). The count of shares for the posts was obtained from the CrowdTangle datasets “Shares” columns. This variable was log-transformed to mitigate its skewed behavior. To avoid errors related to the logarithm of zero, one was added to all “Shares” instances before transformation.

3.2.2. Independent variables

Building of variables dictionaries

Democrat and Republican dictionaries. Dictionaries to detect references to the democratic and republican parties and members were created. Like in the article by Rathje et al. (2020), these were consolidated by accounting for its congress members, famous politicians and general identity terms.

Current congress members were scrapped from the Ballotpedia page[1] using the Python modules "requests (2.28.1)" and "bs4 (4.11.1)". For congress members with middle names an additional entry without the initial was added since it is usually absent when they are mentioned. As the data extraction started from the final date of the original paper (July 2020) and congress elections took place in 2020 and 2022, the congress members list of the original article was also considered.

The most famous Democrat and Republican politicians were extracted from YouGov as in the original paper. The list shared in their OSF was manually updated with the new entries name and Facebook account. The intent to collect them through scrapping was not successful due to their implementation of a JavaScript dynamic table. Identity terms (e.g., "repubs", "libs") were kept as in the original paper.

When the mentioned terms lists were consolidated, duplicates (e.g., famous congress members) and holonyms were erased for faster processing. A total of 564 Democrat and 547 Republican terms were obtained. For easier comprehension and comparison of the analyses of both political sides and in correspondence with the research question, democratic and republican terms count variables were accordingly renamed as "ingroup" and "outgroup" in all analyzed datasets.

Mentions count of positive and negative affect. Computational Affective Science has developed a variety of methods for measuring message connotative meaning. In this research, positive and negative affect will be accounted for separately by adding the amount of positive and negative words instead of calculating a global score of message valence. This is implemented through dictionaries retrieved from the OSF site of the article by Brady et al. (2017).

Mentions count of moral-emotional language. This variable is also measured through a dictionary retrieved from the OSF site of the article by Brady et al. (2017).

Control variables

As in the replicated research variables that tend to increase sharing behaviors were inserted in the model to avoid systematic errors.

Presence of media content. Dichotomous variable of a value of one when the post had a photo or video as indicated by the "Type" variable of the post given by CrowdTangle.

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[1] https://ballotpedia.org/List_of_current_members_of_the_U.S._Congress

Presence of an external link. Dichotomous variable of a value of one when the post had a link as indicated by the "Type" variable of the post given by CrowdTangle.

Page 'Likes at Posting'. Count variable obtained from the column of the same name exported in the CrowdTangle data retrieval. This variable was mean centered.

Dictionaries implementation

A string variable was created for each of the five dictionaries. The regex module "re (2.2.1)" was implemented to count the occurrences of the different term families in each retrieved post. This approach was chosen over text tokenization since Democrat and Republican politicians' names would account for more than one token. As in the original article, all count variables were mean centered, which can be helpful for the interpretation of the intercept of regression models.

Dictionary methods: strengths and pitfalls

Dictionary methods are unsupervised procedures that do not require labeled data for its set up thanks to the use of expert knowledge. Specialists in the area of interest determine which are the relevant words to quantify variables in diverse fields like emotions or mentions of social groups.

The implementation of dictionaries through the consolidation of lists of words and stems related with the measured topic is simple and usually has a satisfactory recall. However, precision can be low due to the presence of homonyms and its "bag of words" assumption which does not account for the relationship between words and, for instance, does not recognize negation. In addition, these methods do not take into account for the presence of stronger or weaker statements due to words like "republicans" vs. "far-right", exclamation marks or capitalization.

4. Methods

Linear regression models with ordinary least squares (OLS) as fitting method were built for each of the described datasets (i.e., liberal media, conservative media, liberal congress members and conservative congress members). In these, the log-transformed "shares" variable was regressed on the abovementioned independent variables. No interaction terms were inserted since effects were assumed to be additive. The regressions structural model is as detailed in Equation 1. Since the main interest was is in the behavior of the "Shares" count variable, thr exponentiated beta values are informed in the results.

Equation 1. Regression models structural equation

$$\ln(Shares) = \beta_0 + \beta_1\, Outgroup + \beta_2\, Ingroup + \beta_3\, NegativeAffect + \beta_4\, PositiveAffect + \beta_5\, MoralEmotional + \beta_6\, hasMedia + \beta_7\, hasURL + \beta_8\, 'Likes\ at\ Posting' + \varepsilon$$

The collected data was assumed to be representative, therefore, the construction of robust confidence intervals through bootstrapping was possible. To calculate the confidence intervals for the model parameters 10,000 samples with replacement where the model was fitted were created. Afterwards, as the significance level (α) was set at 5%, 2.5% and 97.5% percentiles were calculated to get the confidence intervals lower and upper bounds respectively. This way, the pitfalls of parametric estimation of CI 95% were avoided, getting more trustworthy intervals to draw inferences from the models. It should be noted that the bootstrap samples were of size 150,000 instead of the size of the total samples to reduce processing time.

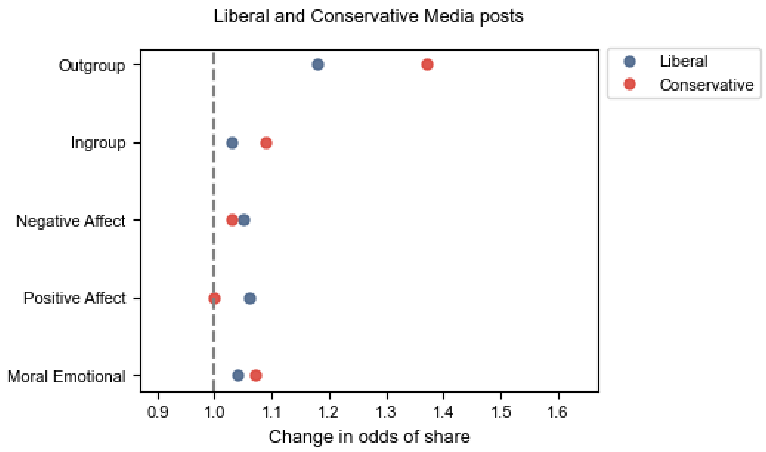
As indicators of goodness of fit for the models R^2 and Akaike and Bayes information criteria are communicated. The R^2 indicator or coefficient of determination calculates the fraction of variance of the dependent variable that is explained by the model's independent variables. As a fractional number, it is a value between 0 and 1, being 0 no variance explained and 1 perfect prediction.

AIC and BIC information criteria are mostly useful to compare goodness of fit for models fitted on different dependent variables but the same data. This is because the coefficient of determination and the likelihood of models always increase when additional variables are inserted. On the other hand, information criteria values are corrected by the number of parameters and sample size. Although the assessment of the model variables is not an aim of this research, these criteria are communicated as in the original article.

5. Results

Interpretations for coefficients where the output variable was log-transformed can be less intuitive, therefore here they are presented exponentiated and understood as explained in the replicated article and other internet reliable sources (UCLA, 2021). Results of the regression exponential coefficients for the Media posts are shown in Graph 1. Outgroup language was the strongest predictor of “shares” for liberal (exp(β) = 1.18, CI 95% [1.17, 1.20]) and conservative (exp(β) = 1.37, CI 95% [1.35, 1.39]) Media. Confidence intervals for the parameters would indicate that this relationship was even stronger in the case of conservative media.

Graph 1. Exponential coefficients for the regression done for the “shares” of Media posts [exp(β)]



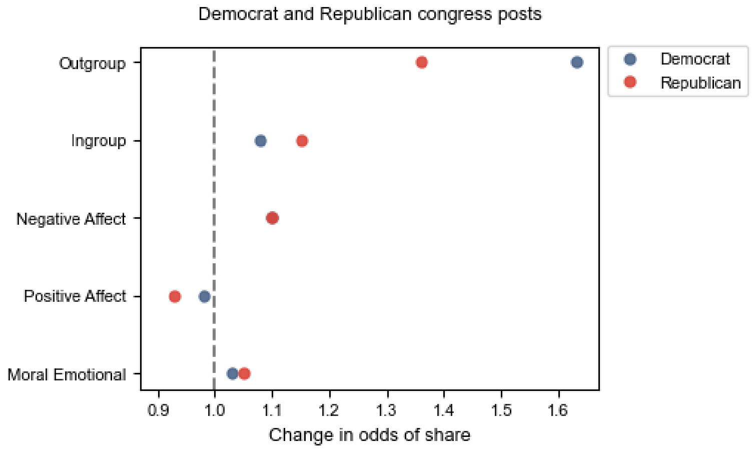
Note. Liberal N = 300,000. Conservative N = 300,000.

All other coefficients for the language variables were significant but lower, remaining beneath values of 1.11. The only exception was Positive Affect for Conservative Media, which was non-significant, with a CI 95% passing through the no effect value. Further details of the descriptive statistics, regression coefficients and goodness of fit values can be found in the Appendix 3.

In Graph 2 the same information is shown but for data from posts of congress members. Outgroup language was again the variable with the highest estimators for Democrats (exp(β) = 1.63, CI 95% [1.54, 1.69]) and Republicans (exp(β) = 1.36, CI 95% [1.35, 1.38]). However, in this case the members of the liberal leaning group were the ones that showed a greater effect.

Other differential behavior compared to media outlets results is the significantly negative relationship of Positive Affect with "shares" for both parties' members (Democrats: exp(β) = 0.98, CI 95% [0.98, 0.98], Republicans: exp(β) = 0.93, CI 95% [0.93, 0.93]).

Graph 2. Exponential coefficients for the regression done for the "shares" of congress posts [exp(β)]



Note. Democrat *N* = 351,041. Republican *N* = 286,362.

6. Discussion

Most of the results obtained through this replication agree with those of the Rathje et al. (2021) studies. Again, in what refers to group boundaries related to political identities, intergroup language raises as the best predictor for greater number of shares in posts. Although formal moderation tests between the different ideologies and pages type were not ran, this effect had a greater value for posts from congress members that are ideologically related with the party in the presidential office. Contrarily, opponent parties show similar effect sizes for both page types.

Ingroup language also had consistently shown an association with greater number of shares, although it was at a lower extent. In this case, this relation had also place for accounts from liberal media. It is remarkable that both studies found an even greater bond between ingroup language and shares in conservative pages.

These results would again support the hypotheses that, in the context of ideologically biased media and politicians' pages, publications that get greater diffusion and endorsement through "share" behaviors are those that refer directly to the other side of the political spectrum.

Regarding the negative and positive affective variables, most of the results were also in the same direction of the replicated paper. Negative affect has consistently shown a positive association with shares, except from Rathje et al. (2021) conservative media subgroup, and this was even stronger for congress pages results. Positive affect, contrarily, was mostly an indicator for reduced shares. The exceptions were the results for the media companies in this study, which were null for the conservative pages and positive for the liberal pages.
It is difficult to derive conclusions on the matters of affect and their possible outcomes for political polarization since none of the research designs directly assessed outgroup-animosity or ingroup-favoritism. Negative affect expressions may occur towards non-political events like natural disasters and positive affect expressions may take place for non-partisan sportive or festive reasons. For this reason, to specifically address the diffusion of polarized messages may be of use to filter analyzed posts with political content or fine-tune more robust large language models to assess both variables, group and affect language, at the same time. Nevertheless, looking at both results independently, the associations shown in both studies would indicate that messages about the outgroup that are accompanied with negative affect terms would have the greatest odds to get disseminated.

The fact that these associations were stronger for congress members pages would also be interesting to be further studied. One possible hypothesis is that these elicit greater credibility than media, being shares of these accounts less risky for the users' reputation (Van Bavel et al., 2021). An alternative hypothesis would be that it is easier for users to empathise with human rather than company pages.

Finally, moral-emotional language was consistently related with more post's shares in all the political spectrum and all page types. Even if it has always remained lower than for other variables, it remarks the relevance of the union between social norms and emotions in the political field.

Some additional limitations for both studies design should be noted. Even if by looking at the variable operationalization results and their related messages most extracted words seemed to be "true positives", problems with precision were noted (e.g. taking "Supreme" referring to the "Supreme Court" or the word "Diving" for "divin*" as positive). Despite these problems, the trial of the VADER tool (Hutto & Gilbert, 2014), which accounts for language rules and other written text non-word related subtleties, was even less satisfactory.

Other future improvements in the research in this field could be accounting for the text from the images and links shared in the posts, which is provided by CrowdTangle. Introducing in the model the extent to which a media outlet is biased (as published by AllSides) could also be of interest to examine if more biased outlets are associated with a greater amount of shares.

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Appendix 1: Media companies classification

Figure 1. Chart used to extract the USA media companies and associate them to the liberal or conservative spectrum

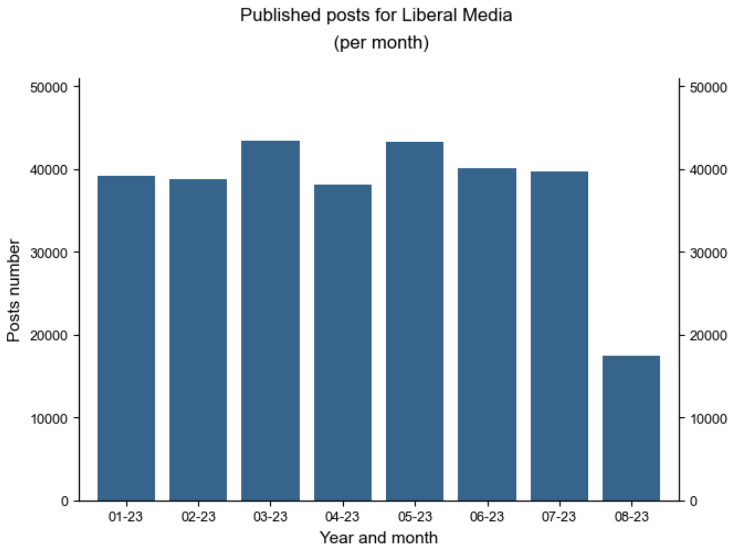
Table 1. Differences detected to the media chart from the replicated paper

Change type	Rathje et al. (2021)	Replication
Bias rating	The Atlantic (L)	The Atlantic (LL)
Bias rating	AP (C)	AP (L)
Bias rating	Bloomberg (C)	Bloomberg (L)
Bias rating	USA Today (C)	USA Today (L)
Media consolidation	CNN opinion (LL) & CNN online news only (L)	CNN (L)
Media consolidation	NPR opinion (L) & NPR online news only (C)	NPR (L)
No Facebook page found		New York Times (opinion) (LL)
No Facebook page found		New York Post (opinion) (RR)
Eliminated from chart	BuzzFeedNEWS (L)	
Eliminated from chart	The Economist (L)	
Eliminated from chart	FOX online news only (R)	
New in chart (L)	AXIOS, INSIDER, ProPublica, Yahoo! News	
New in chart (R)	The Dispatch, The Epoch Times, FOX Business, New York Post NEWS, The Post Millennial	
New in chart (RR)	The American Conservative, Independent Journal Review, The Washington Free Beacon, One America News Network OAN	
Name change	The Huffington Post (LL)	Huffpost (LL)
Name change	ABC (L)	ABC NEWS (L)
Name change	CBS (L)	CBS NEWS (L)
Name change	NBC (L)	NBC NEWS (L)
Name change	FOX NEWS (RR)	FOX NEWS opinion (RR)

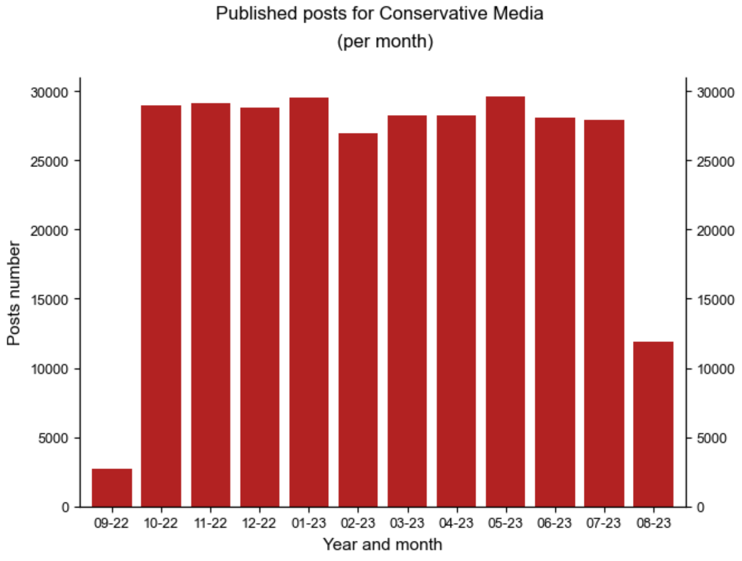
Note. (L): left bias, (LL): high left bias, (C): center, (R): right bias, (RR): high right bias.

Appendix 2: Monthly amount of posts composition

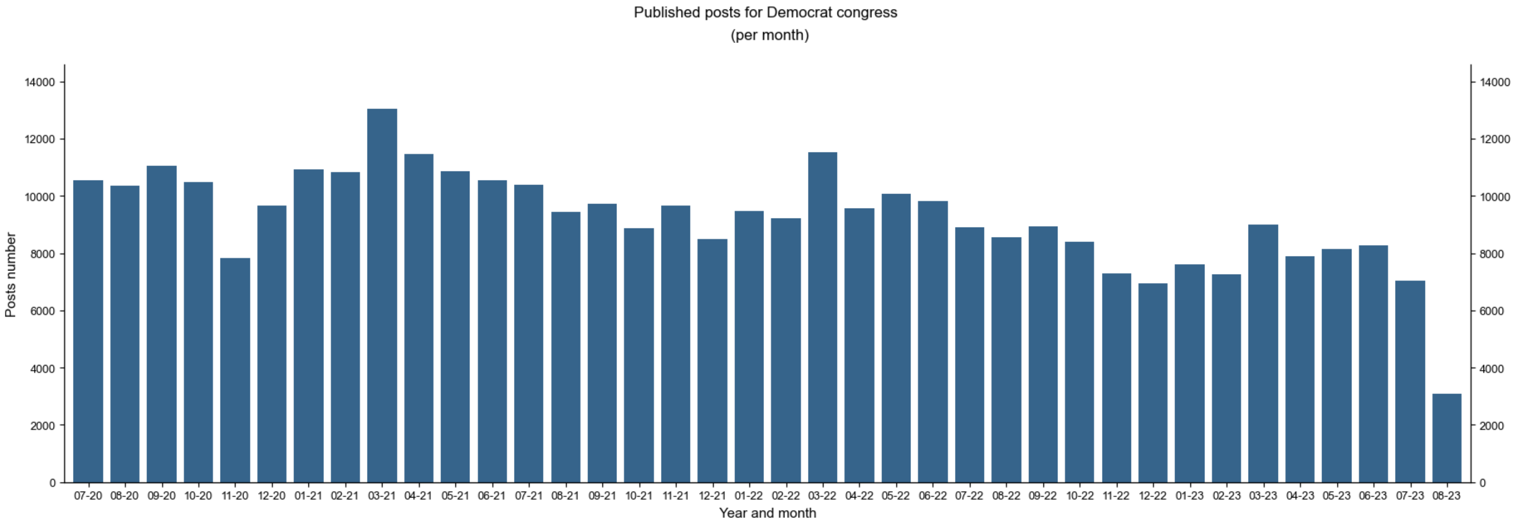
Graph 3. Monthly amount of Liberal Media posts in data



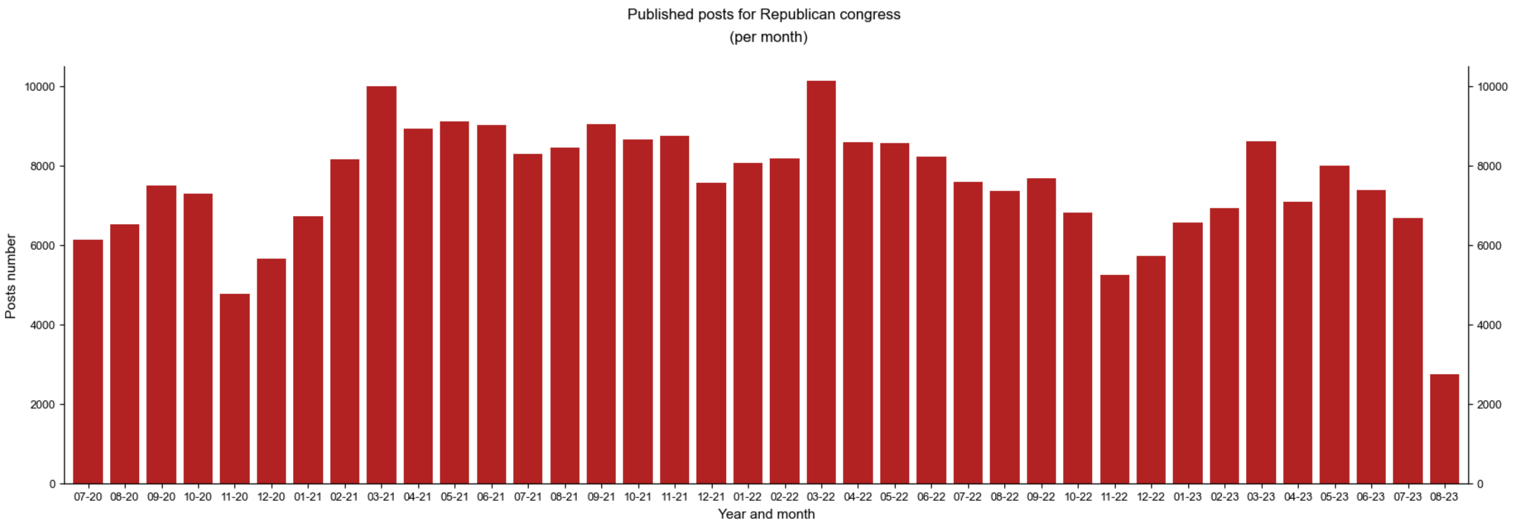
Graph 4. Monthly amount of Conservative Media posts in data



Graph 5. Monthly amount of Democrat congress posts in data



Graph 6. Monthly amount of Republican congress posts in data



Appendix 3: Descriptive statistics, regression results and VIFs values

Table 2. Descriptive statistics for all datasets

	Liberal media		Conservative media		Democrat congress		Republican congress	
Variable	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Outgroup	0.14	0.51	0.17	0.53	0.13	0.50	0.41	0.87
Ingroup	0.07	0.36	0.16	0.53	0.21	0.61	0.17	0.60
Negative Affect	0.39	0.74	0.30	0.62	0.54	1.06	0.55	1.11
Positive Affect	0.66	1.09	0.47	0.86	2.15	2.23	2.11	2.64
Moral Emotional	0.23	0.55	0.18	0.48	0.71	1.11	0.59	1.07
Likes at Posting	7,963,808.25	7,489,472.02	6,318,159.67	6,025,753.32	119,570.08	627,304.93	103,456.88	525,918.05

Note. Means and standard deviations for each of the language categories and likes at posting in each dataset.

Table 3. Results of regression for media companies' datasets with logarithm of "Shares" as output variable

	Liberal media		Conservative media	
	exp(β)	CI 95%	exp(β)	CI 95%
(Intercept)	4.56	[3.23, 6.62]	17.13	[15.33, 19.15]
Outgroup	1.18	[1.01, 1.05]	1.37	[1.08, 1.11]
Ingroup	1.03	[1.17, 1.20]	1.09	[1.35, 1.39]
Negative Affect	1.05	[1.04, 1.06]	1.03	[1.02, 1.04]
Positive Affect	1.06	[1.05, 1.07]	1.00	[0.99, 1.01]
Moral Emotional	1.04	[1.02, 1.05]	1.07	[1.05, 1.09]
has_mediaTRUE	3.76	[2.59, 5.32]	1.30	[1.16, 1.45]
has_URLTRUE	1.59	[1.10, 2.24]	0.64	[0.57, 0.72]
Likes at Posting	1.00	[1.00, 1.00]	1.00	[1.00, 1.00]
N	300,000		300,000	
R^2	0.18		0.14	
AIC	1,050,620.46		1,090,668.62	
BIC	1,050,715.96		1,090,764.13	

Note. The CI 95% were built through bootstrapping.

Table 4. Results of regression for congress members datasets with logarithm of "Shares" as output variable

	Democrat congress		Republican congress	
	exp(β)	CI 95%	exp(β)	CI 95%
(Intercept)	7.15	[7.02, 7.29]	17.48	[17.04, 17.92]
Outgroup	1.63	[1.54, 1.69]	1.36	[1.35, 1.38]
Ingroup	1.08	[1.06, 1.09]	1.15	[1.13, 1.16]
Negative Affect	1.10	[1.09, 1.11]	1.10	[1.09, 1.11]
Positive Affect	0.98	[0.98, 0.98]	0.93	[0.93, 0.93]
Moral Emotional	1.03	[1.02, 1.04]	1.05	[1.04, 1.06]
has_mediaTRUE	0.92	[0.90, 0.94]	0.63	[0.61, 0.65]
has_URLTRUE	0.71	[0.69, 0.73]	0.36	[0.35, 0.37]
Likes at Posting	1.00	[1.00, 1.00]	1.00	[1.00, 1.00]
N	351,041		286,362	
R^2	0.17		0.12	
AIC	1,227,564.80		1,127,261.84	
BIC	1,227,661.71		1,127,356.93	

Note. The CI 95% were built through bootstrapping.

Table 5. Variance inflation factors (VIF) for regression variables for all datasets

	Liberal media	Conservative media	Democrat congress	Republican congress
Variable	VIF	VIF	VIF	VIF
Outgroup	1.04	1.06	1.05	1.13
Ingroup	1.04	1.06	1.04	1.04
Negative Affect	1.28	1.24	1.35	1.46
Positive Affect	1.08	1.10	1.40	1.47
Moral Emotional	1.34	1.31	1.72	1.79
has_mediaTRUE	1.01	1.13	1.01	1.02
has_URLTRUE	1.00	1.05	1.00	1.01
Likes at Posting	1.00	1.21	1.00	1.00