Negativity Spreads More than Positivity on Twitter after both Positive and Negative Political Situations (Supplementary Material)

Emotional language intensity predicting likes in Studies 1 and 2

We assessed the degree to which positive and negative emotion scores predicted the spread of content as measured by the number of likes. For both studies, we conducted linear mixed model analysis predicting the number of likes by both the positive emotion score and the negative emotion score for each tweet as well as their interaction. The number of likes was log+1 transformed as the distribution was positively skewed and contained zero-values. We again added a random intercept of user id to the model to deal with the issue of multiple tweets from the same users. We also included the user's number of followers as a covariate, because users with more followers generally have more likes regardless of the emotional content of their tweets.

Election loss

Table 1S. Linear mixed model with four factors (positive language, negative language, number of followers, positive language x negative language) and number of likes (log+1) as the dependent variable.

	Fixed Effects				
	Estimate	SE	95% CI	t	p
Intercept	0.68	0.0027	0.68 – 0.69	246.44	.000
Positive Language	0.021	0.0026	0.016 – 0.025	8.02	.000
Negative Language	0.028	0.0014	0.026 – 0.031	19.71	.003
Number of followers	0.094	0.0019	0.088 – 0.097	47.31	.026
Positive Language x Negative Language	-0.0013	0.0017	-0.0054 – 0.0017	-0.78	.43
	Random Effects				
			Variance	SD	

Participant (Intercept)		0.45	0.67
Residual		0.42	0.65
Model fit			
	R^2	Marginal	Conditional
		0.011	0.52
Model equation: Likes (log + 1) ~ Positive * Negative + centered (Followers) + (1 | User)			

Notes. Model fit was calculated using the R package MuMIn (Barton, 2018) based on the paper of Nakagawa et al. (2017).

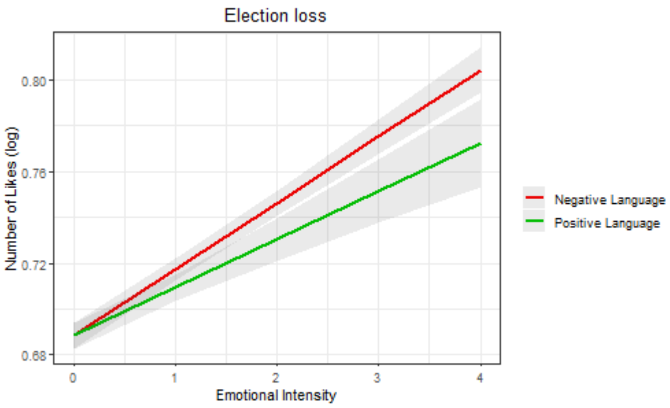

Figure 1S. Results of emotional language intensity (negative and positive) predicting number of likes (log+1 transformed) for the tweets mourning Hillary Clinton's election loss. We found that an increase in negative language intensity was associated with an increase in the number of likes. Positive language intensity was also associated with an increase in likes.

Election win

Table 2S. Linear mixed model with four factors (positive language, negative language, number of followers, positive language x negative language) and number of likes (log+1) as the dependent variable.

Fixed Effects					
	Estimate	SE	95% CI	t	p

Intercept	0.59	0.0029	49.25 – 52.16	203.73	.000
Positive Language	0.017	0.0020	4.14 – 4.66	8.90	.000
Negative Language	-0.0044	0.0017	0.03 – 0.13	-2.56	.010
Number of followers	0.10	0.0026	0.01 – 0.11	41.93	.000
Positive Language x Negative Language	-0.00026	0.0017	-0.01 – 0.01	-0.15	.879
Random Effects					
			Variance	SD	
Participant (Intercept)			0.47	0.68	
Residual			0.29	0.54	
Model fit					
R^2			Marginal	Conditional	
			0.015	0.62	
Model equation: Likes (log + 1) ~ Positive * Negative + centered (Followers) + (1 | User)					

Notes. Model fit was calculated using the R package MuMIn (Barton, 2018) based on the paper of Nakagawa et al. (2017).

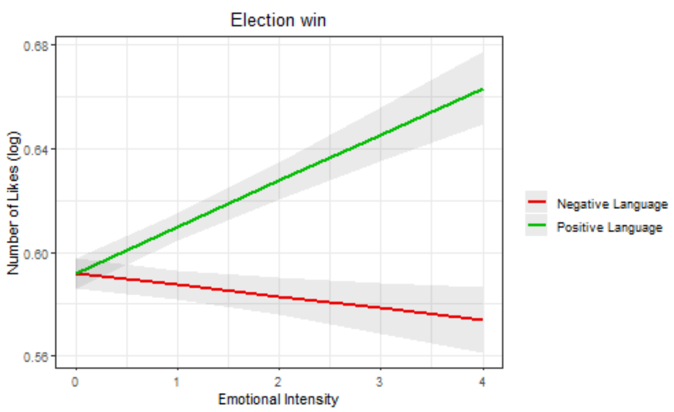

Figure 2S. Results of emotional language intensity (negative and positive) predicting number of likes (log+1 transformed) expressed in the tweets celebrating Donald Trump's victory. We found that an increase in negative language intensity was associated with a decrease in the number of retweets (only example where negative language was a negative predictor), while an increase in positive language was associated with an increase in retweets. This result highlights the difference between likes and retweets as negative language was consistently a positive predictor for an increase in number of retweets, while we saw a decrease in the number of likes in this particular event.

Ferguson Unrest

Table 3S. Linear mixed model with four factors (positive language, negative language, number of followers, positive language x negative language) and number of likes (log+1) as the dependent variable.

Fixed Effects					
	Estimate	SE	95% CI	t	p
Intercept	0.32	0.0017	0.32 – 0.33	190.71	.000
Positive Language	0.029	0.0017	0.024 – 0.033	16.28	.000
Negative Language	0.021	0.00091	0.019 – 0.023	23.59	.000
Number of followers	0.11	0.0014	0.11 – 0.12	80.27	.000
Positive Language x Negative Language	-0.0027	0.0012	-0.0053 – 0.00010	-2.15	.031
Random Effects					
			Variance	SD	
Participant (Intercept)			0.15	0.38	
Residual			0.31	0.56	
Model fit					
R^2			Marginal	Conditional	

		0.029		0. 34

Model equation: Likes (log + 1) ~ Positive * Negative + centered (Followers) + (1 | User)

Notes. Model fit was calculated using the R package MuMIn (Barton, 2018) based on the paper of Nakagawa et al. (2017).

Figure 3S. Results of emotional language intensity (negative and positive) predicting number of likes (log+1 transformed) expressed in the Ferguson unrest tweets. We found that an increase in negative language intensity was associated with an increase in the number of likes.

Supreme Court Ruling for Same – Sex Marriage

Table 4S. Linear mixed model with four factors (positive language, negative language, number of followers, positive language x negative language) and number of likes (log+1) as the dependent variable.

	Fixed Effects				
	Estimate	SE	95% CI	t	p
Intercept	0.32	0.0017	0.32 – 0.32	190.71	.000
Positive Language	0.029	0.0017	0.024 – 0.033	16.28	.000
Negative Language	0.021	0.00091	0.019 – 0.023	23.59	.000
Number of followers	0.11	0.0014	0.10 – 0.12	80.27	.000
Positive Language x Negative Language	-0.0027	0.0012	-0.0053 – 0.00010	-2.15	.031

Random Effects		
	Variance	SD
Participant (Intercept)	0.15	0.38
Residual	0.31	0.56
Model fit		
R^2	Marginal	Conditional
	0.029	0.34
Model equation: Likes (log + 1) ~ Positive * Negative + centered (Followers) + (1 | User)		

Notes. Model fit was calculated using the R package MuMIn (Barton, 2018) based on the paper of Nakagawa et al. (2017).

Figure 4S. Results of emotional language intensity (negative and positive) predicting number of likes (log+1 transformed) expressed in the same-sex marriage tweets. We found that an increase in negative language intensity was associated with an increase in the number of likes. Positive language intensity was also associated with an increase in likes.

Emotional language intensity predicting retweets in subsets for positive situations. We repeated the main analysis of the manuscript that assessed the spread of content for both positive situations in each study (Study 1: Election win, Study 2: Same-sex marriage) with a subsample that only contained users that belonged to the political group that supported the event as estimated by our political affiliation estimation. This analysis addressed the concern that the effect of negative language on spreadibility of content was caused by an opposing political group expressing their negative language content.

Trump election win (Subset 22,642 tweets from conservatives)

Table 5S. Linear mixed model with four factors (positive language, negative language, number of followers, positive language x negative language) and number of retweets (log+1) as the dependent variable.

Fixed Effects					
	Estimate	SE	95% CI	t	p
Intercept	0.66	0.013	0.63 – 0.68	49.90	.000
Positive Language	-0.016	0.0065	-0.029 – -0049	-2.42	.015
Negative Language	0.053	0.0052	0.043 – 0.065	10.33	.000
Number of followers	0.22	0.011	0.20 – 0.24	19.69	.000
Positive Language x Negative Language	0.013	0.0052	0.0025 – 0.024	2.48	.013
Random Effects					
			Variance	SD	
Participant (Intercept)			0.40	0.63	
Residual			0.29	0.54	
Model fit					
R^2			Marginal	Conditional	
			0.071	0.60	
Model equation: Retweets (log + 1) ~ Positive * Negative + centered (Followers) + (1 | User)					

Notes. Model fit was calculated using the R package MuMIn (Barton, 2018) based on the paper of Nakagawa et al. (2017).

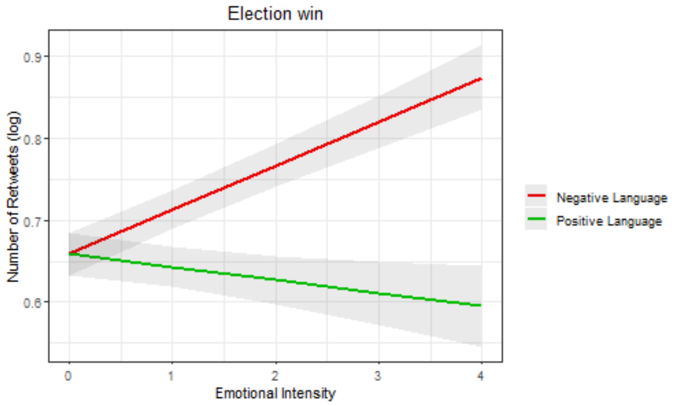

Figure 5S. Results of emotional language intensity (negative and positive) predicting number of retweets (log+1 transformed) expressed in the tweets celebrating Donald Trump's victory (subsample of estimated conservatives). We found that an increase in negative language intensity was associated with an increase in the number of retweets, while an increase in positive language was negatively correlated with the number of retweets.

Same-Sex Marriage (Subset 7.661 tweets from liberals)

Table 6S. Linear mixed model with four factors (positive language, negative language, number of followers, positive language x negative language) and number of retweets (log+1) as the dependent variable.

	Fixed Effects				
	Estimate	SE	95% CI	t	p
Intercept	0.85	0.031	0.78 – 0.91	32.01	.000
Positive Language	0.017	0.017	-0.017 – 0.053	1.00	.317
Negative Language	0.086	0.017	0.052 – 0.12	5.00	.000

Number of followers	0.25	0.018	0.21 – 0.28	13.96	.000
Positive Language x Negative Language	0.007	0.013	-0.017 – 0.033	0.59	.551
		Random Effects			
			Variance	SD	
Participant (Intercept)			0.48	0.70	
Residual			0.44	0.66	
		Model fit			
R^2			Marginal	Conditional	
			0.070	0.57	
Model equation: Retweets (log + 1) ~ Positive * Negative + centered (Followers) + (1 | User)					

Notes. Model fit was calculated using the R package MuMIn (Barton, 2018) based on the paper of Nakagawa et al. (2017).

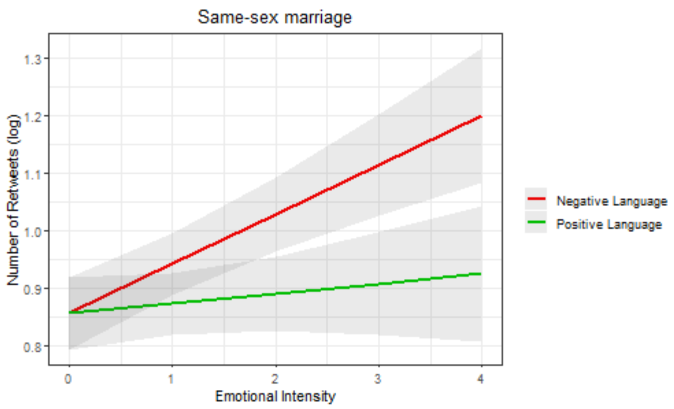

Figure 6S. Results of emotional language intensity (negative and positive) predicting number of retweets (log+1 transformed) expressed in the same-sex marriage tweets (subsample of estimated liberals). We found that an increase in negative language intensity is associated with an increase in the number of retweets, while an increase in positive language was not correlated with number of retweets.