Supporting Information for:

Moral Contagion: How Emotion Shapes Diffusion of Moral Content in Social Networks

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Section 1: Materials and Methods

Data Collection and Preprocessing

Data collection periods ranged from 22-42 days depending on the specific topic (see Table S1). We chose political topics that are highly contentious in modern American politics and involve differing moral views. They were also issues that were recently at forefront of United States policy decisions at the time of collection, such as the Supreme Court decision to declare same-sex marriage bans unconstitutional on June 26, 2015. Topics were identified with a set of streaming keywords that were intended to optimize our signal-to-noise-ratio (SNR): maximally capturing discussion surrounding the topic of interest (i.e., signal) while minimizing extraneous or irrelevant conversation (i.e., noise). Using metadata from the Twitter API, we applied the following exclusion criteria: (1) only tweets composed in English were included and (2) user with "verified accounts" were excluded. These criteria were applied because our dictionary-based methods were only available in the English language. In addition, verified accounts are primarily used to distinguish valid accounts of various prestige (e.g., celebrities, news outlets) from imposter accounts. Pilot testing revealed that these verified users posed a relatively large statistical influence in our analyses since they were often linked to users with a disproportionately large base of followers and retweets (e.g., Justin Beiber). Tweets were further constrained to users whose ideology could be estimated (see "Measuring Ideology" below). To further boost our SNR, messages were only included if they contained at least one of our specific post-filter keywords (see Table S1).

One limitation of the Twitter API is that it does not account for "retweet chains", whereby a user can retweet a message that was also a retweet. Consider, for instance, if The President of the United States (i.e., @POTUS) composes an original message (Tweet A). Minutes later, CNN news company (i.e., @CNNNews) retweets this message (Tweet B). Now, if Jane Doe follows both of these verified users, she can retweet the US President (Tweet C) by either directly retweeting Tweet A or indirectly by retweeting Tweet B. In the latter case, the Twitter API will link Tweet B with Tweet C, even though the message originated from a different source (Tweet A). One potential consequence of this metadata scheme is that the *true* virality of a message can be diluted: the same exact originating message may be retweeted only a few times by a vast quantity of users. This is particularly important for our theoretical construct of moral contagion--a message that spreads across users (rather than solely the original source) should be *greater* evidence of contagion, even though such behavior would be penalized using the typical approach.

We addressed this limitation by inferring the original message source as a function of (1) the exact message text and (2) the user mentioned at the beginning of the tweet (e.g., @POTUS). We then re-associated each retweet with the original message source, rather than any intermediary retweeters (e.g., @CNNNews in the example above). Retweets were then identified as any tweet message beginning with "RT @". We then identified the tweet "author" (i.e., original composer of each retweeted message) by stripping the username immediately following this sequence of characters (e.g., "RT @POTUS:"). Retweets based on messages with (1) identical text and (2) identical authors were grouped together then collapsed into a single observation. As a caveat, this approach neglects unconventional retweets where users manually copy and paste the text and source of the original tweet. All preprocessing and analysis scripts are available at: https://osf.io/qyd48/wiki/home/. In addition, words used for the moral dictionary (26) are freely available at this link: https://osf.io/mvdut/. Words for the emotional dictionary must be purchased from the Linguistic Inquiry and Word Count (LIWC) website: https://store2.esellerate.net/store/checkout/CustomLayout.aspx?s=STR6622550055&pc=&page=OnePageCatalog.htm.

Our data collection resulted in a total of 563,312 observations across the three topics including both original messages and any retweets of those messages as observations. In order to organize the data into analyzable format, we collapsed and counted all retweets of a given message. Thus, we were left with a final analyzable data set that included 313,003 original messages and their corresponding retweet counts across all topics (48,394 for gun control, 29,061 for same-sex marriage, and 235,548 for climate change).

To ensure that our data collection procedures were accurate, we tested for the presence of errant tweets by randomly selecting 200 tweets from each data set to be coded by two trained research assistants. We created a set of practice tweets (N = 30, 10 per topic) to establish reliability in RAs' ratings. Using the following 7 point Likert scale: 1 (not relevant to [topic] at all) to 7 (very relevant to [topic]), they achieved high reliability (ICC (2,2) = .85). After establishing reliability, each RA rated a random sample of 300 total tweets (100 per topic) for relevance to the topic in question. Thus, there were 200 tweets rated per topic for a total N of 600. In training, RAs were instructed that the goal of the task was to "catch any errors" and to pay close attention to any off-topic tweets to help our data collection methods for the future. This instruction was designed to make our RAs use the ratings of high relevance carefully, thus making our test of errors in data collection more conservative. The error testing resulted in in the following error rates across data sets (percentages refer to how many tweets were not classified as at least "somewhat related to [topic]".

Topic	Percent Error
Gun Control	0.5%
Same-sex Marriage	6.0%
Climate Change	1.0%
Mean	2.5%

Thus, overall there were extremely few instances of data collection errors. We also investigated why the same-sex marriage data set had a higher error rate than the other data sets, and discovered that the hashtag "#lovewins" created the errant 6% tweets. To be thorough, we re-ran our main analysis on the same-sex marriage data set, dropping all observations with the #lovewins hashtag (including both errant observations and valid observations). This resulted in the removal of 10% of the total same-sex marriage data set, but the effects of moral-emotional language did change in direction nor significance (see Table S19).

Measures

Measuring moral-emotional language. We used Python v3.5 to "tokenize" each tweet into isolated words stripped of punctuation. As an example, the tweet, "Let's end #violent gun deaths now!" would be split into four words: "let's", "end", "violent", "gun", "deaths", and "now". Tokens that started with the "@" symbol were excluded, since they are used in Twitter to "mention" other users directly. In order to measure moral-emotional content, we used dictionaries related to morality (n = 411) (1,2) and emotion (n = 917) (3) to identify terms that overlapped with both dictionaries. For instance, the word "violent" would be deemed moral-emotional since it begins with the word-stem "violent*" in the emotion dictionary as well as "violen*" in the moral dictionary. After computing the number of moral-emotional terms for each tweet, this quantity from the total number of moral and emotional words to compute the number of *distinctly* moral and *distinctly* emotional words for each tweet. For instance, the tweet "Let's end #violent gun deaths now!" contains one moral-emotional word ("violent") and zero distinctly moral or emotional words. Using dictionaries related to positive emotion (n = 407) and negative emotion (n = 374) based on the LIWC categories (3), we used the same procedure to measure positive and negative moral-emotional language. The full word count script is freely available at the following OSF link: https://osf.io/59uyz/.

Measuring covariates. We leveraged the Twitter API's meta-data to determine (A) whether a tweet included a URL, (B) whether a tweet included media (i.e., image, Vine, or gif), and (C) the number of other users actively following that user at the time of their message. Although we excluded users with "verified accounts" (e.g., celebrities, news outlets, politicians, etc.) from the original corpus (see above), there remained a portion of retweets that were based off messages originating from verifiers users before the data collection periods. In order to preserve data, we used effects codes to include these retweets in the model. However, none of our findings qualitatively changed when excluding these retweets altogether. Furthermore, several measures were computed after the retweet aggregation stage detailed in the preceding section: (A) the retweet count (i.e., the number of grouped observations prior to collapsing), (B) the average estimated ideologies of the retweeters (i.e., all users retweeting the original message), as well as (C) the standard deviation of these ideology estimates. All R scripts used in this procedure have been provided on the OSF: https://osf.io/59uyz /wiki/home/.

Measuring ideology. In order to estimate ideology, we used a previously validated computational model that leverages each Twitter user's social network (4,5). The model assumes that users will follower political actors that they perceive to be ideologically similar. In this way, ideology can be rendered as a position on a latent multidimensional dimension, whereby ideologically similar users are 'closer' in space. If we consider Twitter as a social networking site or as news media (6) then this assumption coheres with notions of ideological homophily (7) or selective exposure to politically congruent content (8). This approach is similar to other methods that rely on spatial voting assumptions (9,10).

Consider the following variables:

$i \in \{1, . . . , n\}$: each Twitter user
$j \in \{1, . . . , m\}$: each political actor with a Twitter account
g: social media network
$Y_{ij} \in \{0,1\}$: user i's decision to follow political actor j
θ_i: the ideological position (in latent space) of user i
θ_j: the ideological position (in latent space) of actor j
d_{ij}: distance in latent ideological space between user i and political actor j
α_i = random effect adjusting for different levels of user i's political interest ("out degree")
β_j = random effect adjusting for different levels of actor j's popularity ("in degree")

We can now formulate the probability that user i follows a political actor j with the following logit model:

$$Pr(Y_{ij} = 1|\alpha_i , \beta_j , d_{ij}) = Logit(\alpha_i + \beta_j - d_{ij}) \quad (1)$$

This model is then estimated using the R package "ca" (11) an implementation of correspondence analysis (12). Note that similar attempts with Markov-Chain Monte-Carlo methods are computationally intractable at this scale (4) and ultimately yield correlated estimates with the correspondence analysis (5). The estimation is conducted in two stages using singular value decomposition. In stage one, the model is constrained only to Twitter users who follow 10 or more political accounts with high ideological discriminability: legislators, president, candidates, media outlets, interest groups, etc. In stage two, popular (though not necessarily political) accounts among liberals and conservatives are identified and added to the latent subspace.

We used scores from an earlier study that accrued ideology estimates for over 9.6 million users (4) and then matched scores for each user in the present corpus. This procedure resulted in successful estimation for approximately 10% of tweets (see Table S2 for summary statistics and Fig. S1 for distributions across collections). The remaining 90% were excluded from all analyses. Within our 10% of tweets with estimable ideology, roughly 12% of the retweeted messages were originally composed by users whose ideology we were unable to estimate. Nevertheless, retweeted messages referencing these users were included in our primary analyses, though excluding them did not qualitatively alter the results.

Measuring in-group and out-group retweet networks. For every message, we considered the estimated political ideology of its author, and determined whether its retweeters were the same sign in ideology estimate (indicating an in-group member) or were the opposite sign (indicating an out-group member). For example, if a message was tweeted by a conservative author with an ideology estimate of 1.25, any retweeter with a positive ideology estimate (conservative) would be classified as in-group, while any retweeter with a negative ideology estimate would be classified as out-group. Thus, we formed two separate counts for each message: an in-group count and an out-group count. If the conservative tweet author in the above example was retweeted by 10 conservatives and 2 liberals, the in-group count would be 10 and the out-group count would be 2. This method created a nested data structure with in-group/out-group count nested within message.

Sensitivity analyses for the in-group / out-group analysis. As mentioned in the main text, one limitation of the above method is that we used an ideology score of 0 as a cutoff between liberal and conservative authors and therefore as a basis for determining in-group vs. out-group rates of diffusion. This method is imperfect when it comes to analyzing tweets sent by political moderates, whose ideological estimates are close to zero. For instance, the in-group network for an author with an ideology estimate of 0.01 will be classified as conservative, whereas the in-group network for an author with an ideology estimate of -0.01 will be classified as liberal, despite the fact that these authors are extremely close to one another with respect to ideology. To address this limitation, we conducted three robustness tests. The first test excluded all "verified" users (e.g., celebrities), to eliminate the possibility that a few well-known moderates could disproportionately sway the results. The second model excluded the middle 10% (in terms of ideological estimates, closest to zero) of authors in our data set. In other words, the 5% most moderate conservatives and 5% most moderate liberals were dropped from the data set. The third analysis was similar but excluded the middle 20% (in terms of ideological estimates, closest to zero). All three of these analyses yielded results that were highly similar to those reported in the main text, increasing our confidence that the methodological concerns discussed above did not substantially influence the findings reported here. For a full report of each of these sensitivity analyses, see Tables S12-S15.

Dictionary word pilot

In order to test the construct validity of our dictionary word category splits, we piloted a random 10% subset (*N* = 46) of moral words and a 5% subset (*N* = 45) of emotion words. We then separated the total word list created from the random subset (*N* = 91) into 3 categories: distinctly moral words (*n* = 40), distinctly emotional words (*n* = 42) and moral-emotional words (*n* = 9). Moral-emotional words were those words appearing in both moral and emotional subsets, while distinct words were those appearing exclusively in either the moral or emotion dictionary.

A group of 20 pilot participants recruited via Amazon Mechanical Turk (mTurK) viewed all 91 words in randomized order, and were asked, "To extent is each word or phrase related to the topic of morality?". Participants rated each word on a 1 (not related to morality at all) to 7 (very related to morality) Likert scale. In the instructions, participants were explained the difference between rating something as moral/immoral versus the goal of the experiment which was to determine if a word is generally related to the domain of morality—we were strictly interested in the latter case. Three participants were removed from the pilot for failing to an attention check that required participants to rate the moral relevance of the words 'abortion' and 'brick'. We set an *a priori* threshold of failing the attention check as any participant who rated the word 'abortion' as less than a 4 (somewhat related to morality) or rated 'brick' as more than 4 on the morality scale. The final sample consisted of 17 participants.

A second group of 19 pilot participants recruited via Amazon Mechanical Turk (mTurK) viewed all 91 words in randomized order, and were asked, "To extent is each word or phrase emotional?" Participants rated each word on a 1 (not emotional at all) to 7 (very emotional) Likert scale. One participant was removed from the pilot for failing to an attention check that required participants to rate the emotionality of the words 'disgusting' and 'shovel'. We set an *a priori* threshold of failing the attention check as any participant who rated the word 'disgusting' as less than a 4 (somewhat emotional) or rated 'shovel' as more than 4 on the emotionality scale. The final sample consisted of 19 participants.

As a test of robustness, we also tested discriminant validity by having a larger group of pilot participants (*N* = 50) making discrete categorizations of random sets of words from each category. We recruited 60 participants via Amazon's mechanical turk. 10 participants failed a comprehension check of what the three different word categories represented, leaving a final sample of 50 participants. After explanation of the categories and the comprehension check, participants were shown 3 unlabeled sets of 10 randomly selected words corresponding to a dictionary. Thus, participants viewed a set of 10 moral words, a set of 10 emotional words, and a set of 10 moral-emotional words. Participants were then asked to choose the set of words that, "expressed both morality and emotion the most". To ensure that results were not driven by particular words, participants were also assigned to one of three conditions, where each condition had different random words in every set. No differences in results were found based on condition. Results revealed that 76% of participants choose the set with moral-emotional words which made that category significantly more likely to be chosen than the other category sets, $\chi^2(2) = 41.44$, $P < .001$.

Section 2: Statistical Models

Moral contagion effects

In order to estimate the effects of moral contagion, we fit a negative binomial model with maximum likelihood estimation (MLE) to account for overdispersion (13). Proc GENMOD in SAS 9.4 was used for all analyses and all syntax is available at: https://osf.io/qyd48/wiki/home/. For our main model, we entered our three main predictors (counts of distinctly moral language, distinctly emotional language, and moral-emotional language). We also adjusted for variables known to affect retweet rate independent of our three main predictors (14), which included whether a URL was attached to the tweet, whether media was attached to the tweet, whether the original author of the tweet was verified, and how many followers the original author had. All predictors were grand-mean centered, and all binary variables were effects coded. For a complete list of variables entered in the model and their coefficients, see Table S5.

We also examined a number of other models in order to explore the robustness of the effects found in the main model. First, we ran a simpler model without the predictors for distinctly moral and distinctly emotional words but we observed no qualitative change in the moral contagion effect (see Table S8). We also ran this model without any covariates (moral-emotional words as the sole predictor) and again observed no qualitative change in the results (see Table S7). Thus, the results of moral-emotions on diffusion were robust to a number of model specifications.

We also examined whether the moral contagion effect was additive (i.e., the addition of two moral-emotional word leads to greater diffusion than the addition of one moral-emotional) or was “all-or-none” (i.e., the presence of at least one moral-emotional word has significant effect on diffusion) in nature. We estimated a model where the moral-emotion language variable was dichotomous (had one or more moral-emotional word, or had none). This binary model demonstrated similar effects (in fact, somewhat stronger) of moral contagion (see Tables S9-S10).

Non-independence present in data

In our data, on average ~30% of message authors have more than one tweet, creating a source of non-independence for this portion the data. Table S16 shows that most of this 30% consist of users who have two messages in the data set, and users with 5 or more messages in the data set are uncommon. Furthermore, of the 30% of non-independent data, we also had highly heterogeneous cluster sizes (ranges of cluster size are shown in Table S16; gun control 1-384; same-sex marriage 1-291; climate change: 1-1498), and importantly we had an issue of “informative cluster size” (ICS).

ICS occurs when cluster size is associated with the outcome, conditional on the covariates, and under such conditions a standard multi-level model for handling clustering with count data–namely, Generalized Estimating Equations (GEE)–may produce inaccurate standard errors (15,16). Below we report the fixed effect of cluster size adjusting for all other fixed effects in the model:

Topic	Cluster Size Fixed Effect
Gun Control	-.003*
Same-Sex Marriage	-.01*
Climate Change	<.001

**p* < .05

These results show evidence of ICS for the datasets gun control and same-sex marriage, and thus complicates the use of GEE for handling clustering in those main models. ICS can be handled by improved variations of GEE–models which are not readily available on statistical software–but these improved models may be approximated by using within-cluster resampling methods (15,17). In this method, one observation from each cluster is randomly selected to form a new data set, and this process repeats (e.g., 1000 times) to form multiple new data sets for which effects can be estimated. This method allows one to form an effect size distribution for each fixed effect in question, demonstrating how much variability in each effect size occurs by sampling within each cluster.

In order to examine whether the results of our original models were biased due to the clustering, we opted to run a series of sensitivity analyses to examine the variation of our effects using multiple methods for handling the clustering. These analyses included (A) dropping all users with clustering and re-analyzing the data, (B) the within-cluster resampling method described above, and (C) a standard GEE model. Overall, the results of our original models were extremely robust to these different types of models, indicating that are results do not appear to be biased by the clustering. Each of these sensitivity analyses is described below.

In sensitivity analysis (A), we simply dropped all of the 30% of users who have multiple tweets, and re-ran our main models. Table S18 shows that coefficients and significance levels are highly consistent with our results which treat the entire data set as independent.

In sensitivity analysis (B), we drew on bootstrapping methods to randomly sample 1 tweet from every user that had multiple tweets, and then resampled 1000 times to form a distribution of effect sizes for each of our variables in our main model. In short, for every variable, this method provides the mean and 95% CI for the effect size when repeatedly (and randomly) sampling single tweets from all users. Figure S3 shows the effect size distributions for each data set and for each of our 3 main variables of interest. These data show coefficients that are consistent with the direction and significance of the coefficients of our model that treated all data independently. Also see summary table below (this section) for the exact estimates.

In sensitivity analysis (C), we ran a GEE model with an independent correlation structure. The variable "src_id" was entered as the subjects variable in the repeated statement for PROC GENMOD in SAS 9.4.

Below we summarize the effect size estimates (IRRs) for moral-emotional language across all data sets and sensitivity analyses. These coefficients refer to coefficients produced by a full model including distinctly moral language, distinctly emotional language and all covariates. Code for all sensitivity analyses is available at: https://osf.io/qyd48/wiki/home/.

Topic	Negative Binomial model with MLE (original)	NB w/ MLE, all users with clustering dropped	Within-Cluster Resampling via Bootstrapping	Generalized Estimating Equations (GEE)
Gun Control	1.19*	1.13*	1.17*	1.19*
Same-Sex Marriage	1.17*	1.46*	1.35*	1.17
Climate Change	1.25*	1.15*	1.19*	1.24*

*$p < .05$

Moral contagion and in-group and out-group networks.

In order to estimate the effects of moral contagion for in-groups and out-groups, we estimated a multi-level model using Generalized Estimating Equations with an exchangeable correlation structure. We entered the effects of distinctly moral, distinctly emotional, and moral-emotional words, with the addition of the in-group/out-group effects coded variable (and all interactions) predicting retweet counts. We report the interaction of moral-emotional language and cross-ideological communication adjusting for all other effects. As in our other models, we also adjust for covariates known to independently affect retweet counts as in the models above. For a complete list of variables entered into the model and their coefficients, see Tables S12-S15.

Moral contagion, in-group/out-group networks, and political ideology. In order to explore whether the in-group advantage for moral contagion existed for both liberal and conservative authors, we formed a three-way interaction that included the moral-emotional language variable, the in-group/out-group effects-coded variable, as well as "political party" effects coded variable that indicated whether the message author was liberal or conservative based on their ideology estimates. Distinctly moral and distinctly emotional language, all their higher order interactions as well as covariates were also entered into the model.

Section 3: Further Exploratory Analyses

As an exploratory analysis, we also looked beyond valence to specific discrete emotions and their impact on social transmission. We focused on the emotions of anger and disgust because of their association with morality, their theorized independent functions for communication, and their distinctive relationship to moral outcomes (18-20). We also included sadness, a low-arousal emotion, to compare its impact to the high-arousal emotions anger and disgust.

In order to measure the impact of anger, disgust, and sadness, we create formed new count variables that searched for the presence of the following words per category:

Anger		Disgust	Sadness	
fuming	maddest	disgust*	depress*	mourn*
furious*	maniac*	vile	gloom*	unhapp*
fury	bastard*	nast*	despair*	sorrow*
rage*	enrag*	gross*	grief	sob

raging	outrag*	ugl*	griev*	sobbed
tantrum*	spite*	stink*	sad	sobbing
agitat*	fiery	stank	sadde*	sobs
anger*	contempt*	sicken*	sadly	cried
angr*	piss*	rancid*	sadness	cries
mad	irrita*	perver*	miser*	cry
maddening	frustrat*	decay*	heartbreak*	crying
madder		appall*	heartbroke*	tears

The only consistent finding across all moral topics was that the low-arousal emotion sadness was associated with a *decrease* in social transmission (mean IRR = 0.73), replicating previous work investigating the impact of discrete emotions on social transmission of online messages (21). The effect of anger was context specific; it increased social transmission for the topic of climate change which was dominated by negative emotion, and it decreased social transmission in the topic of same-sex marriage which was dominated by positive emotion. We did not find significant effects for disgust. For a list of coefficients for all data sets see Table S17.

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Figure S1. Density plots of users' ideological point estimates across collections.

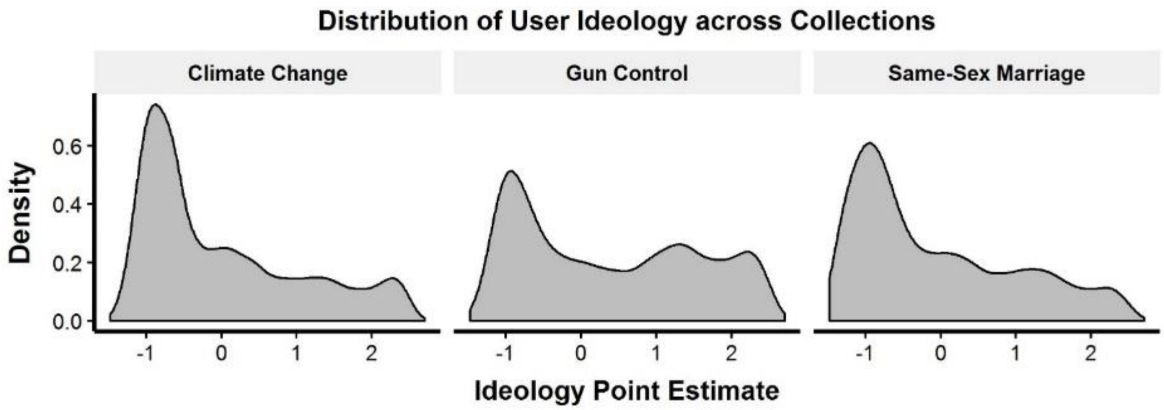

Figure S2. Predicted retweet count as a function of distinctly moral, distinctly emotional and moral-emotional language for the domain of (a) gun control, (b) same-sex marriage and (c) climate change. The x-axis represents the number of words from each respective dictionary found in the tweet. The y-axis represents predicted retweet count.

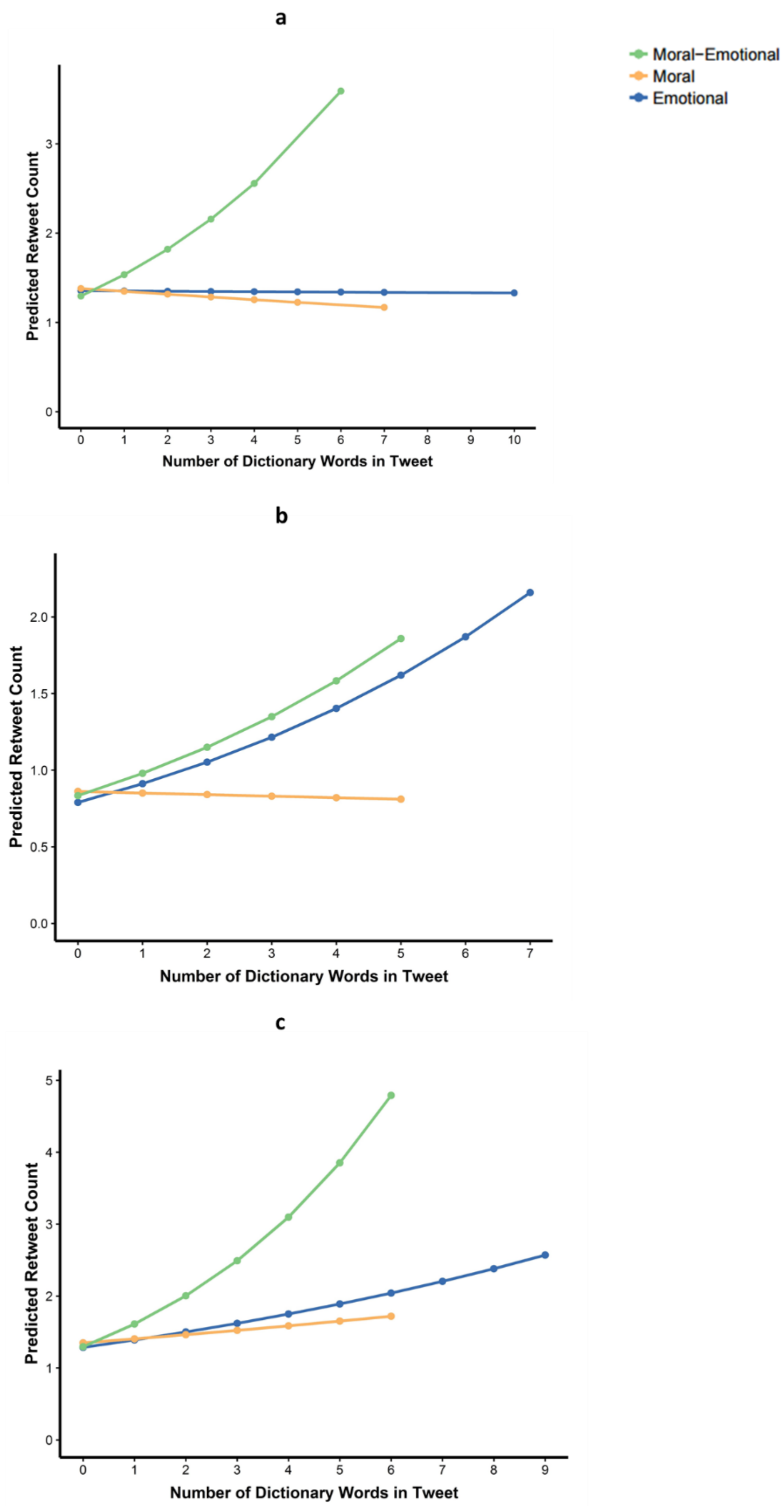

Figure S3. Results of repeated random sampling with bootstrapping. One tweet was randomly selected from each user with multiple tweets to form a data set. This processes was repeated 1000 times to form a distribution of effect sizes for each variable and each data set. The mean coefficients are represented by the blue dotted line. 95% Cis are represented by the red dotted line. The mean coefficients are consistent (in the same direction) with our original models that treat the full data set independently.

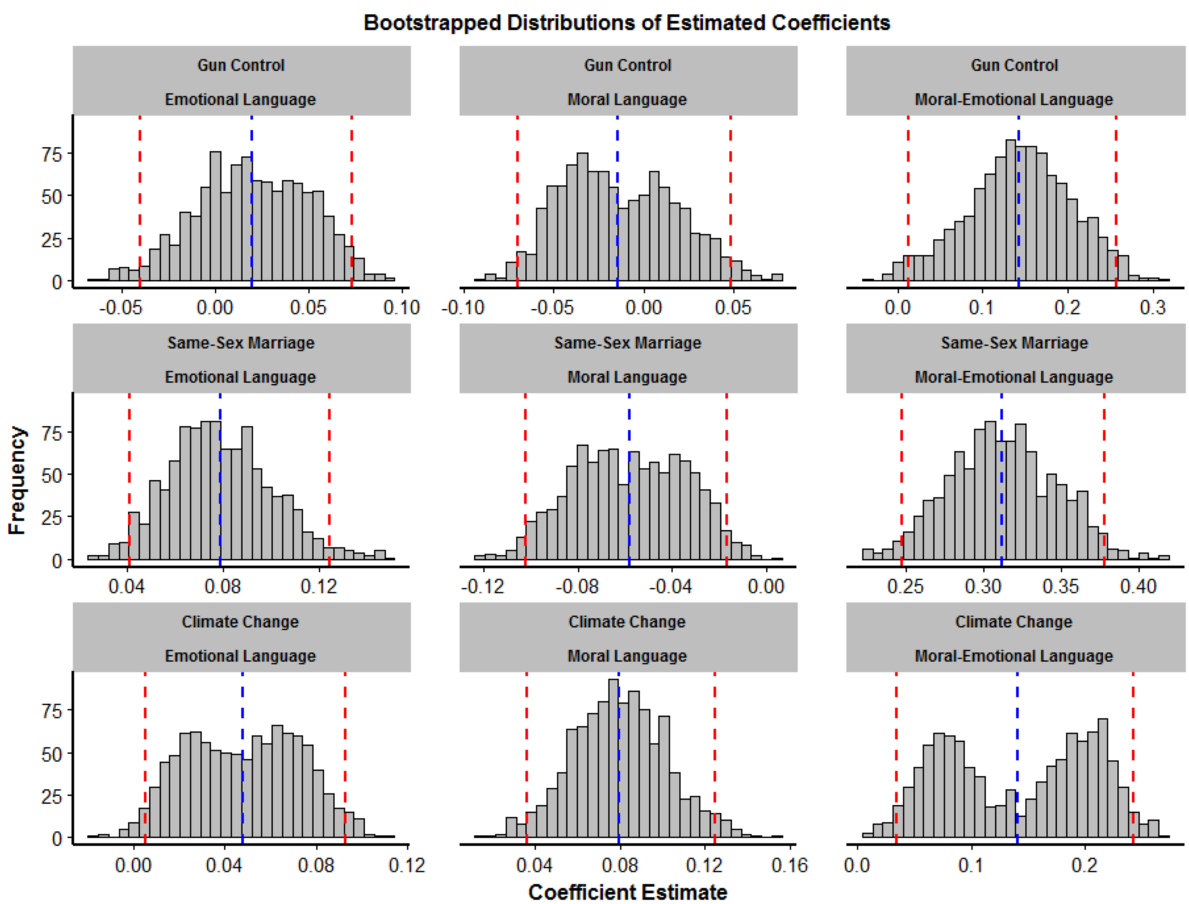

Table S1. Keywords used for data collection. Stream keywords indicate words used to pull Tweets from Twitter's API to form initial data collection. Keyword post-filters indicate filters applied after collection to increase precision in collecting specifically moral topics.

	Gun Control	*Same-sex Marriage*	*Climate Change*
Stream Keywords	*pistol, shooting range, shootingrange, rifle, gun, guns, firearm, NRA, second amendment, 2nd amendment, 2A, gunsafety, gunviolence, endgunviolence, guncontrol, gunlaws, gunsense, rangeday*	*gaymarriage, gaywedding, gay-marriage, gay-wedding, wedding, marriage, same sex, bride, groom, lovewins, gayrights, MarRef, samesex*	*weather report, climate policy, inclement weather, global warming, globalwarming, climate change, climatechange, climate science*
Keyword Post-Filters	*guncontrol, gunviolence, endgunviolence, second amendment, 2nd amendment, gunlaws, gunsense, gunsafety, 2A, gun culture, gun murders, gun threat, gun offenses, gun crisis, gun reform, gun owner, gun owners, gun ownership, gun crime, gun ban, gun smuggling, gun confiscation, gun tights, gun deaths, gun violence, gun safety, gun laws, gun control*	*gaymarriage, gay-marriage, gaywedding, gay-wedding, same same, samesex, lovewins, gayrights, marref, gay marriage, same sex, gay wedding, gay rights*	*climate, climate change, climatechange, global warming, global warming*

Table S2. Characteristics and descriptive statistics for each data set. Date format is mm/dd/yy. Proportion of retweets refers to the percentage of tweets in the collection that were retweets. Bolded values refer to means, and values in parenthesis refer to standard deviations. Means and standard deviations of word types show how many words of that type appear in the average tweet. Percentages of verified users, media, url, and show what percentage of tweets fell into each category. Both Media and URL were binary variables

Variable		*Gun Control*	*Marriage*	*Climate Change*
1.	Dates Collected	11/03/15 – 12/15/15	11/02/15 – 11/24/15	10/30/15 – 11/24/15
2.	Number of Tweets	101,549	44,132	409,132
3.	Proportion Retweets	60.62%	49.26%	59.14%
4.	Retweet Count Range	0-1388	0-732	0-989
5.	Moral Words	**0.818**(*0.767*)	**0.606***(0.802)*	**0.230***(0.498)*
6.	Emotion Words	**0.543***(0.787)*	**0.553***(0.790)*	**0.733***(0.854)*
7.	Moral-Emotion Words	**0.258***(0.544)*	**0.155***(0.417)*	**0.223***(0.490)*
8.	Positive Moral-Emotion Words	**0.063***(0.257)*	**0.045***(0.219)*	**0.059***(0.243)*
9.	Negative Moral-Emotion Words	**0.193***(0.466)*	**0.089***(0.315)*	**0.126***(0.361)*
10.	Average Ideology	**0.549***(1.069)*	**-0.092***(1.003)*	**0.175***(1.054)*
11.	Followers	**33,406***(684,308)*	**55,773***(995,580)*	**39,056***(737,226)*
12.	Verified Users	3.5%	4.5%	4.1%
13.	Media	15.5%	11.6%	12.9%
14.	URL	62.8%	71.3%	71.4%
14.	User Ideology Estimates	**0.384**(*1.18*)	**-0.056**(*1.08*)	**0.101**(*1.10*)

Table S3. The top 15 most impactful words on retweet count from the *moral-emotion* category, adjusting for the base-rate of the word frequency within the data sets. These words are only those that appeared to be impactful in at least 2/3 data sets, as opposed to context-specific words that only appeared impactful in one data set. Words are bolded in the example tweets.

Word	Example Tweet
attack	We truly regret that Gay Marriage **attacks** the sanctity of your fourth marriage #StopRush
bad	Weather Channel founder @JohnColemanMRWX says there is no man-made global warming - it's "science gone **bad**" https://...
blame	@POTUS tried to **blame** #SanBernardino on gun control when it was caused by a hate-filled heart intent on killing infidels in name of Islam
care	Funny that people who didn't **care** what the Bible said about gay marriage are very concerned with its stance on immigration
destroy	@tedcruz **destroys** the myth of #GlobalWarming & correctly identifies #BigGovernment control #CruzToVictory
fight	"If we are silent, we lose our children": The moms **fighting** gun violence https://...
hate	This is just UGLY, **hateful**, and awful. The LDS (Mormon) Church says children of same-sex couples cannot be members
kill	While Obama gears up to lead the world in his war against climate change, Islam gears up to **kill** innocents everywhere.
murder	Guns are made for Killing. **Murder**. Death. End of story. #gunsense #2a #gunviolence #guncontrol #nra
peace	Sending love, light and strength to #Paris. Stand together for **#Peace**. #LoveWins
safe	World leaders must act swiftly to secure the **safety** of our planet. https://t.co/1zvw3f2cwF #ClimateChange #OYW
shame	**Shameful** - The Mormon Church has just decreed babies of same-sex couples cannot be baptized. https://...
terrorism	Let's pass more gun laws to stop **terrorism**! Clueless celebrities coming after your guns: https://... #2A
war	While Obama gears up to lead the world in his **war** against climate change, Islam gears up to kill innocents everywhere. #WWIII

wrong	A good answer on same-sex marriage is: Much of America had this **wrong** until 2015. I'm sorry for any role I played in that.

Table S4. The top 15 most impactful words on retweet count from the *non-moral emotion* category, adjusting for the base-rate of the word frequency within the data sets. These words are only those that appeared to be impactful in at least 2/3 data sets, as opposed to context-specific words that only appeared impactful in one data set. Words are bolded in the example tweets.

Word	Example Tweet
agree	Here's a good refugee screening question: will you **agree** to bake a cake for a gay wedding?
amazing	**Amazing** how saying "restrict immigration" is now the equal of fascism, but regulations on speech, property rights, and gun ownership aren’t
challenge	No, Mrs. Clinton, no, President Obama: climate change is not our most pressing national security **challenge**.
dear	**Dear** poor oppressed Christians, #Starbucks supports Gay Marriage and Planned Parenthood. Thanks for your donation #merica
free	Firearms = **Freedom** | The Tide Is Turning Against Democrats in the Debate Over Gun Control https://...
lost	30 percent of the polar bears could be **lost** by 2050 because of climate change, study finds. https://...
lose	Kim Davis **loses** latest gay marriage appeal https://...
love	Gay rights are #HumanRights . **Love**, #marriage and acceptance are human rights not heterosexual privilege .#equality
risk	The N.Y. attorney general is investigating whether Exxon Mobil lied to the public about the **risks** of climate change http://...
support	Retweet if you **support** American leadership on climate change. #ActOnClimate
terror	"...an incident of gun violence." White House is back to not calling the California attacks **terror** https://...
threat	Can't wait to watch POTUS tell everyone climate change is the #1 **threat** to humanity at the Climate Change Summit...
truth	**Truth** is, states w/ most gun laws had 42% LOWER gun death rate than states w/ fewer laws https://...
worry	Maybe Republicans will **worry** about gun violence after they solve the problem of too many people having health insurance.

worst	"If we want to prevent the **worst** effects of climate change before it's too late, the time to act is now." -President Obama

Table S5. Retweet count as a function of distinctly moral content, distinctly emotional content, moral-emotional content, and covariates. Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Distinctly emotional language	1.00 (0.01)	1.15* (0.02)	1.08* (0.01)
Distinctly moral language	0.98 (0.01)	0.99 (0.02)	1.04* (0.01)
Moral-emotional language	1.19* (0.02)	1.17* (0.04)	1.24* (0.01)
Followers	1.00* (<.001)	1.00* (<.001)	1.00* (<.001)
Verified	9.17* (0.06)	8.01* (0.07)	8.25* (0.02)
Media	4.93* (0.03)	3.33* (0.04)	3.02* (0.01)
URL	0.80* (0.02)	0.57* (0.03)	0.72* (0.01)
Constant	0.64* (0.02)	0.57* (0.03)	0.67* (0.01)
Observations (original messages)	48,394	29,061	235,548

† $p<.10$; *$p<.05$

Table S6. Retweet count as a function of distinctly moral content, distinctly emotional content, moral-emotional content only. Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Distinctly emotional language	0.95* (0.02)	1.11* (0.02)	1.04* (0.01)
Distinctly moral language	0.87* (0.02)	1.05* (0.02)	1.07* (0.01)
Moral-emotional language	1.36* (0.02)	$1.08^{\dagger}$ (0.04)	1.15* (0.01)
Constant	1.24* (0.01)	0.74* (0.02)	1.02* (0.01)
Observations (original messages)	48,394	29,061	235,548

† p<.10; *p<.05

Table S7. Retweet count as a function of moral-emotional language only. Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Moral-emotional language	1.37* (0.02)	1.09* (0.04)	1.15* (0.01)
Constant	1.25* (0.01)	0.75* (0.02)	1.02* (0.01)
Observations (original messages)	48,394	29,061	235,548

† p<.10; *p<.05

Table S8. Retweet count as a function of moral-emotional language only and covariates. Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Moral-emotional language	1.19* (0.02)	1.18* (0.04)	1.25* (0.01)
Followers	1.00* (<.001)	1.00* (<.001)	1.00* (<.001)
Verified	9.18* (0.06)	7.94* (0.07)	8.24* (0.02)
Media	4.97* (0.03)	3.33* (0.04)	2.98* (0.01)
URL	0.80* (0.02)	0.54* (0.03)	0.70* (0.01)
Constant	0.64* (0.02)	0.60* (0.03)	0.69* (0.01)
Observations (original messages)	48,394	29,061	235,548

† p<.10; *p<.05

Table S9. Retweet count as a function of moral-emotional language (binary) only. Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Moral-emotional language (binary)	1.44* (0.03)	1.16* (0.05)	1.16* (0.01)
Constant	1.40* (0.02)	0.79* (0.03)	1.07* (0.01)
Observations (original messages)	48,394	29,061	235,548

† p<.10; *p<.05

Table S10. Retweet count as a function of moral-emotional language (binary) and covariates. Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Moral-emotional language (binary)	1.26* (0.03)	1.27* (0.04)	1.30* (0.01)
Followers	1.00* (<.001)	1.00* (<.001)	1.00* (<.001)
Verified	9.25* (0.06)	7.97* (0.07)	8.25* (0.02)
Media	4.96* (0.03)	3.32* (0.04)	2.98* (0.01)
URL	0.80* (0.02)	0.54* (0.03)	0.70* (0.01)
Constant	0.68* (0.02)	0.65* (0.03)	0.75* (0.01)
Observations (original messages)	48,394	29,061	235,548

† p<.10; *p<.05

Table S11. Retweet count as a function of distinctly moral content, positive and negative emotional content, positive and negative moral-emotional content, and covariates. Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Distinctly moral language	0.98† (0.01)	1.01 (0.02)	1.05* (0.01)
Distinctly positive emotional language	0.98 (0.02)	1.06* (0.02)	1.01 (0.01)
Distinctly negative emotional language	1.02 (0.02)	1.45* (0.04)	1.20* (0.01)
Positive moral-emotional language	1.09* (0.04)	1.92* (0.07)	1.03 (0.02)
Negative moral-emotional language	1.19* (0.03)	0.87* (0.05)	1.31* (0.01)
URL	0.79* (0.02)	0.59* (0.04)	0.71* (0.01)
Media	4.88* (0.03)	3.31* (0.04)	2.99* (0.01)
Verified	9.18* (0.06)	8.17* (0.07)	8.25* (0.02)
Followers	1.00* (<.001)	1.00* (<.001)	1.00* (<.001)
Constant	0.65* (0.02)	0.55* (0.03)	0.68* (0.01)
Observations (original messages)	48,394	29,061	235,548

† *p*<.10; **p*<.05

Table S12. Retweet count as a function of distinctly moral content, distinctly emotional content, moral-emotional content, covariates, and in-group/out-group classification. Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Distinctly moral language	0.75* (0.05)	1.12 (0.07)	1.14† (0.07)
Distinctly emotional language	1.01 (0.10)	1.20† (0.10)	0.88* (0.04)
Moral-emotional language	0.98 (0.08)	1.21 (0.14)	1.05 (0.09)
In-group/out-group	5.22* (0.06)	3.73* (0.10)	5.11* (0.04)
Distinctly moral * in-group/out-group	1.39* (0.07)	0.86† (0.09)	0.93 (0.07)
Distinctly emotional *in-group/out-group	0.97 (0.11)	1.00 (0.11)	1.32* (0.04)
Moral-emotional *in-group/out-group	1.20* (0.09)	1.10 (0.30)	1.34* (0.09)
URL	0.82* (0.08)	0.63* (0.17)	0.71* (0.05)
Media	6.57* (0.07)	3.67* (0.13)	3.53* (0.04)
Verified	14.59* (0.10)	11.95* (0.09)	15.44* (0.04)
Followers	1.00* (<.001)	1.00* (<.001)	1.00* (<.001)
Constant	0.08* (0.10)	0.08* (0.18)	0.07* (0.06)

Observations (original messages)	48,394	29,061	235,548

[†] $p<.10$; * $p<.05$

Table S13. Retweet count as a function of distinctly moral content, distinctly emotional content, moral-emotional content, covariates, and in-group/out-group classification (*verified users dropped*). Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Distinctly moral language	0.69*	1.25*	1.18*
	(0.06)	(0.07)	(0.06)
Distinctly emotional language	0.88*	1.16†	0.90*
	(0.05)	(0.09)	(0.03)
Moral-emotional language	0.98	1.20	1.01
	(0.07)	(0.16)	(0.07)
In-group/out-group	5.26*	3.93*	5.66*
	(0.04)	(0.09)	(0.03)
Distinctly moral * in-group/out-group	1.40*	0.82*	0.90
	(0.07)	(0.07)	(0.06)
Distinctly emotional *in-group/out-group	1.13*	0.97	1.23*
	(0.05)	(0.09)	(0.03)
Moral-emotional *in-group/out-group	1.17*	0.82	1.29*
	(0.07)	(0.16)	(0.07)
URL	0.85*	0.70*	0.75*
	(0.05)	(0.13)	(0.03)
Media	6.61*	3.38*	3.01*
	(0.05)	(0.13)	(0.03)
Followers	1.00*	1.00*	0.06*
	(<.001)	(<.001)	(<.001)
Constant	0.06*	0.06*	0.00
	(0.05)	(0.16)	(0.00)
Observations (original messages)	42,457	25,237	197,885

† *p*<.10; **p*<.05

Table S14. Retweet count as a function of distinctly moral content, distinctly emotional content, moral-emotional content, covariates, and in-group/out-group classification (*10% of most moderate users dropped*). Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Distinctly moral language	0.80* (0.06)	1.11 (0.08)	1.09 (0.08)
Distinctly emotional language	1.10 (0.12)	1.35* (0.09)	0.88* (0.05)
Moral-emotional language	0.95 (0.09)	1.24 (0.15)	1.08 (0.10)
In-group/out-group	7.61* (0.07)	4.26* (0.10)	6.31* (0.04)
Distinctly moral * in-group/out-group	1.30* (0.08)	0.83† (0.10)	0.95 (0.08)
Distinctly emotional *in-group/out-group	0.88 (0.13)	0.94 (0.11)	1.31* (0.05)
Moral-emotional *in-group/out-group	1.20† (0.11)	1.12 (0.31)	1.31* (0.11)
URL	0.72* (0.08)	0.71* (0.17)	0.70* (0.05)
Media	5.39* (0.07)	3.89* (0.13)	3.58* (0.04)
Verified	17.76* (0.10)	10.04* (0.09)	15.76* (0.04)
Followers	1.00* (<.001)	1.00* (<.001)	1.00* (<.001)
Constant	0.06* (0.12)	0.06* (0.18)	0.06* (0.07)

Observations (original messages)	39,562	23,587	184,222

† *p*<.10; **p*<.05

Table S15. Retweet count as a function of distinctly moral content, distinctly emotional content, moral-emotional content, covariates, and in-group/out-group classification (*20% of most moderate users dropped*). Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Distinctly moral language	0.78* (0.06)	1.14 (0.10)	1.20† (0.10)
Distinctly emotional language	0.86* 0.05)	1.38* (0.10)	0.89* (0.03)
Moral-emotional language	1.06 (0.08)	1.23 (0.18)	0.95 (0.06)
In-group/out-group	12.98* (0.05)	4.89* (0.11)	9.20* (0.03)
Distinctly moral * in-group/out-group	1.37* (0.07)	0.82† (0.11)	0.86 (0.10)
Distinctly emotional *in-group/out-group	1.12+ (0.06)	0.92 (0.12)	1.31* (0.04)
Moral-emotional *in-group/out-group	1.09 (0.10)	1.13 (0.32)	1.49* (0.07)
URL	0.84* (0.08)	0.68* (0.18)	0.75* (0.04)
Media	5.79* (0.07)	3.84* (0.15)	4.06* (0.04)
Verified	15.82* (0.12)	10.24* (0.09)	19.01* (0.05)
Followers	1.00 (<.001)	1.00* (<.001)	1.00* (<.001)
Constant	0.03* (0.08)	0.06* (0.19)	0.04* (0.04)

Observations (original messages)	35,182	20,995	163,979

† p<.10; *p<.05

Table S16. Percentages of users with only 1 tweet appearing in the data set, more than 1, more than 2, and so on. Of users with more than 1 tweet, ~50% of them have only two messages appearing in the data sets.

		Topic		
Number of tweets appearing in data set	Gun Control	Same-sex Marriage	Climate Change	*Mean*
1	69.01	73.60	61.50	68.04
>1	30.99	26.40	38.50	31.96
>2	16.10	12.77	22.60	17.16
>3	10.32	7.86	15.66	11.28
>4	7.29	5.26	11.63	8.06
>5	5.57	3.93	9.15	6.22
Range	1-384	1-291	1-1498	

Table S17. Coefficients for models estimating the effect of discrete emotional language of anger, disgust and sadness predicting retweet count.

	Topic		
Emotion	Gun Control	Same-sex Marriage	Climate Change
Sadness	0.76*	0.66†	0.78*
Anger	1.09	0.68†	1.28*
Disgust	0.67†	0.87	0.78

† p<.10, *p<.05

Table S18. Retweet count as a function of distinctly moral content, distinctly emotional content, moral-emotional content, covariates, *when all users with multiple tweets are removed from the data sets*. Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count		
	Gun Control	Same-Sex Marriage	Climate Change
Distinctly emotional language	0.99 (0.02)	1.08* (0.02)	1.01 (0.01)
Distinctly moral language	0.95* (0.03)	0.90* (0.03)	1.09* (0.02)
Moral-emotional language	1.13* (0.02)	1.47* (0.06)	1.16* (0.04)
Followers	1.00 (<.001)	1.00* (<.001)	1.00* (0.02)
Verified	9.33* (0.09)	6.89* (0.10)	7.04* (0.05)
Media	4.93* (0.06)	2.38* (0.05)	2.74* (0.03)
URL	0.73* (0.05)	0.61* (0.03)	0.77* (0.02)
Constant	0.50* (0.04)	0.57* (0.05)	0.51* (0.02)

† p<.10, *p<.05

Table S19. Retweet count as a function of distinctly moral content, distinctly emotional content, moral-emotional content, covariates, when the hashtag "lovewins" is removed from the data set. Coefficients refer to incident rate ratios; parenthesis refer to standard errors.

	Retweet Count	
	Same-Sex Marriage (#lovewins dropped)	Same-Sex Marriage (full dataset)
Distinctly emotional language	1.20* (0.02)	1.00 (0.01)
Distinctly moral language	0.97† (0.02)	0.98† (0.01)
Moral-emotional language	1.21* (0.04)	1.17* (0.04)
Followers	1.00* (<.001)	1.00* (0.02)
Verified	7.32* (0.07)	9.17* (0.06)
Media	1.93* (0.03)	4.93* (0.03)
URL	0.72* (0.03)	0.80* (0.02)
Constant	0.48* (0.02)	0.64* (0.02)

† *p*<.10, **p*<.05