Emotion shapes the diffusion of moralized content in social networks

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Political debate concerning moralized issues is increasingly common in online social networks. However, moral psychology has yet to incorporate the study of social networks to investigate processes by which some moral ideas spread more rapidly or broadly than others. Here, we show that the expression of moral emotion is key for the spread of moral and political ideas in online social networks, a process we call "moral contagion." Using a large sample of social media communications about three polarizing moral/political issues (*n* = 563,312), we observed that the presence of moral-emotional words in messages increased their diffusion by a factor of 20% for each additional word. Furthermore, we found that moral contagion was bounded by group membership; moral-emotional language increased diffusion more strongly within liberal and conservative networks, and less between them. Our results highlight the importance of emotion in the social transmission of moral ideas and also demonstrate the utility of social network methods for studying morality. These findings offer insights into how people are exposed to moral and political ideas through social networks, thus expanding models of social influence and group polarization as people become increasingly immersed in social media networks.

morality | emotion | politics | social networks | social media

Our sense of right and wrong shapes our daily interactions in a variety of domains such as political participation, consumer choices, and close relationships. What factors inform our intuitions about morality? Influential theories in psychology maintain that our moral sense is shaped by the social world (1), insofar as decades of research demonstrate that social communities influence moral development in children (2) and account for cross-cultural variation in moral beliefs (3). Furthermore, social information serves as input for cognitive and emotional processes in moral judgment and decision-making (4).

Despite a broad consensus that morality is influenced by attitudes and norms transmitted by our social world, remarkably little work has examined how social networks transmit moral attitudes and norms. Most existing research takes a dyadic perspective to study the social transmission of morality; typically, one person (such as a child) is exposed to another's ideas (e.g., parent) through behavior or communication (1, 2). In society, the transmission of morality goes well beyond the dyad. Our moods, thoughts, and actions are shaped by the entire network of individuals with whom we share direct and indirect relationships (5). Thus, we often develop similar ideas and intuitions as others because we are socially connected to them (6). This phenomenon is often deemed social "contagion" because it mimics the spread of disease. We use a social contagion perspective to illuminate how morally tinged messages about political issues are transmitted through social networks.

Research on the emotional underpinnings of morality provides a theoretical framework to understand the processes that may drive social contagion in the domain of morality. Emotions tend to be highly associated with moral judgments (3), amplify moral judgments (7), and may even serve to "moralize" actions that would otherwise be considered nonmoral (8). Furthermore, emotional expressions are often "caught" by close others in face-to-face interaction (9) and online social networks (10). If morality is deeply linked to emotion, then the social transmission of emotion likely plays a key role in the transmission of morality through social networks.

In the domain of morality, the expression of moral emotion in particular may drive social contagion. Compared with nonmoral emotions, moral emotions are those that are most often associated with evaluations of societal norms (11) and are elicited by interests that may go beyond self-interest [e.g., contempt in response to injustices committed in another country (12)]. Importantly, moral emotions may also be tied specifically to behavior that is relevant to morality and politics, including judgments of responsibility and voting (13, 14). Thus, emotions can be roughly divided into classes of "moral emotions" and "nonmoral emotions" that are associated with distinct appraisals, eliciting conditions, and functional outcomes. Because of the importance of emotions to the domain of morality and politics, we focused here on the role of moral emotion in social contagion.

To investigate the role of moral emotion in the transmission of morality in social networks, we used the context of online social networks. More and more, communications about morality and politics within social networks are computer-mediated (15), and contagion is often studied as information diffusion in online social networks. One important question is how people (or properties of their communications) with whom we interact regularly online affect the diffusion of information (16). We addressed this question in the specific context of morality, using large samples of real discussions on moralized topics with significant political implications. Rather than using artificial scenarios common in laboratory studies of morality (see ref. 17), we investigated how naturally formed

Significance

Twitter and other social media platforms are believed to have altered the course of numerous historical events, from the Arab Spring to the US presidential election. Online social networks have become a ubiquitous medium for discussing moral and political ideas. Nevertheless, the field of moral psychology has yet to investigate why some moral and political ideas spread more widely than others. Using a large sample of social media communications concerning polarizing issues in public policy debates (gun control, same-sex marriage, climate change), we found that the presence of moral-emotional language in political messages substantially increases their diffusion within (and less so between) ideological group boundaries. These findings offer insights into how moral ideas spread within networks during real political discussion.

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social networks and specific properties of messages affect the diffusion of moral ideas in online messages.

Bringing together research on morality, social networks, and emotion science, we examined whether the social transmission of moral emotion is a key process that determines how moral ideas diffuse through social networks—a phenomenon we call "moral contagion." In the context of online social networks, we proposed that moral and political messages with a stronger combination of moral and emotional contents would reach more people than messages with a weaker combination of moral and emotional contents. In short, we hypothesized that the presence of moral emotions would increase the likelihood that a given message would go "viral." Whereas previous work has investigated the general role of emotion in the diffusion of messages (18, 19), our research investigated social transmission specifically in the moral domain, focusing on the distinct role of moral emotions compared with nonmoral emotions.

We addressed several key questions about the process of moral contagion in social networks and its boundary conditions, including the following: (*i*) Is moral contagion simply driven by basic emotional contagion, or does it require a mix of moral appraisal and emotional expression (20)? (*ii*) Is moral contagion driven by a "negativity bias," as is the case with other psychological processes (21), or does it capture a more general process that applies to positive as well as negative emotions? (*iii*) Are there specific emotions that drive moral contagion (13)? (*iv*) Does moral contagion contribute to the diffusion of moral content within and between political group networks, or only within them (22)? These questions are central not only to understanding moral contagion but also to understanding phenomena such as political polarization and communication (23).

Results

To investigate these questions, we analyzed a large (n = 563,312) corpus of tweets from Twitter. We selected three politically polarizing topics: gun control (study 1), same-sex marriage (study 2), and climate change (study 3; see *SI Appendix*, section 1, for more details). These topics are highly contentious in American politics and have been at the forefront of major public policy debates (24). Because language is one direct way in which people communicate emotion, we coded the language in Twitter messages to quantify morality and emotion. Specifically, we used (and pilot tested) previously validated dictionaries (25, 26) to count the frequency of moral and emotional words in each tweet. [Moral words are those appearing only in the moral dictionary, emotional words appear only in the emotional dictionary, and moral-emotional words (e.g., hate) are those that appear in both dictionaries (for more details, see *Methods*, as well as *SI Appendix*, section 1).] "Contagion" was indexed as the number of times each message was retweeted by a user for each moral/political topic (see *SI Appendix*, section 1, for more details). A retweet occurs when one user shares another user's message with his or her own social network, and represents a key form of information diffusion on Twitter (27).

In study 1, we investigated whether moral and emotional language contained in messages predicted contagion on the topic of gun control (n = 102,328). We measured the distinctly moral language, distinctly emotional language, and moral-emotional language for each message and fit a regression model predicting retweet rate (30% of messages were retweeted at least once). The analysis yielded no main effect of distinctly moral language [incident rate ratio (IRR) = 0.98, P = 0.086, 95% CI = 0.95, 1.00], nor did it yield a main effect of distinctly emotional language (IRR = 1.00, P = 0.896, 95% CI = 0.97, 1.03). Importantly, there was a significant main effect of moral-emotional language (IRR = 1.19, P < 0.001, 95% CI = 1.14, 1.23); adding a single moral-emotional word to a given tweet increased its expected retweet rate by 19% (Fig. 1). [The main effect of moral-emotional words remained significant after distinctly moral and distinctly emotional words were removed from the model (*SI Appendix*, Tables S5–S7).]

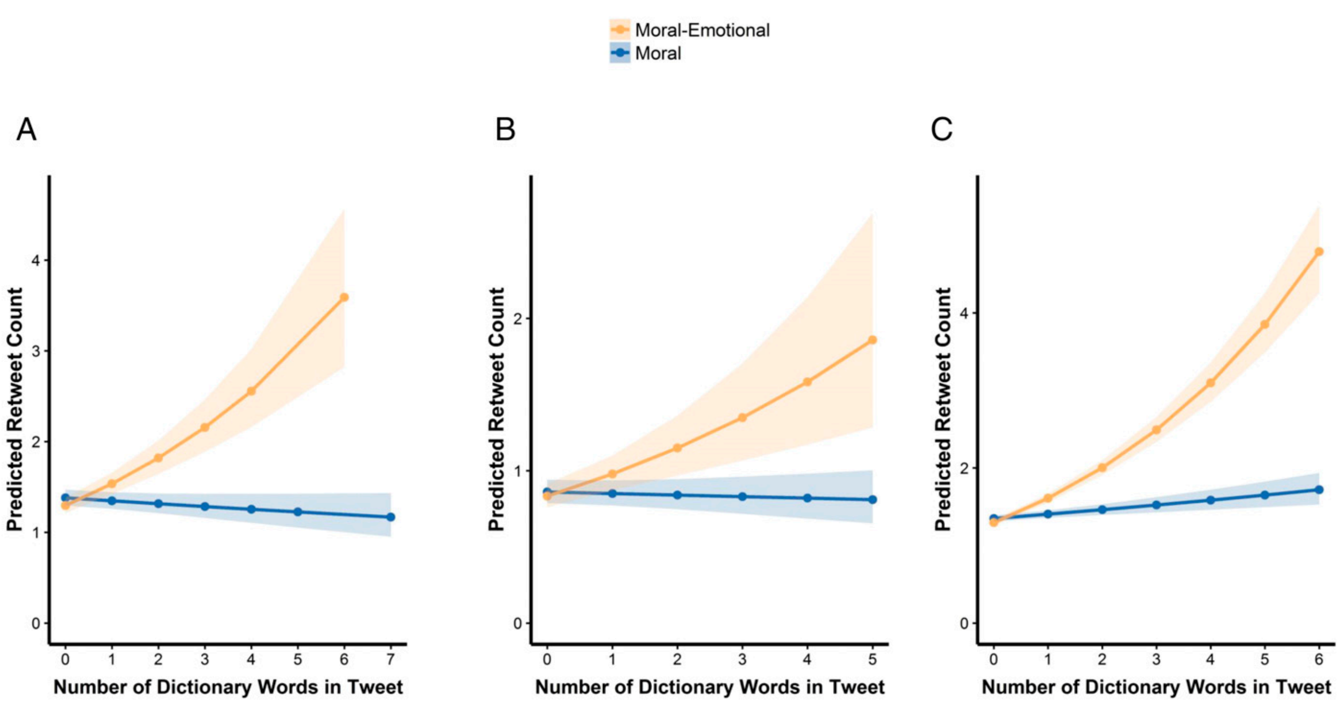

Fig. 1. Moral-emotional language predicts the greatest number of retweets. The graph depicts the number of retweets, at the mean level of continuous and effects-coded covariates, predicted for a given tweet as a function of moral and moral-emotional language present in the tweet. Bands reflect 95% CIs. An increase in moral-emotional language predicted large increases in retweet counts in the domain of (*A*) gun control, (*B*) same-sex marriage, and (*C*) climate change after adjusting for the effects of distinctly moral and distinctly emotional language and covariates.

Messages with the greatest amount of moral-emotional language had the highest expected retweet rate in the sample, even after adjusting for the effects of distinctly moral and distinctly emotional words. These results suggest that emotion is a key component for the diffusion of moral content through social networks but that the social transmission of morality is distinct from basic emotional contagion.

In study 2, we replicated these results in the domain of same-sex marriage ($n = 47{,}373$). Again, we measured distinctly moral language, distinctly emotional language, and moral-emotional language and fit a regression model predicting retweet rate (23% of messages were retweeted). We observed no main effect of distinctly moral language (IRR = 0.99, $P = 0.540$, 95% CI = 0.95, 1.03), but we did observe a main effect of distinctly emotional language (IRR = 1.15, $P < 0.001$, 95% CI = 1.11, 1.20), demonstrating basic emotional contagion (28). Adjusting for these effects, there was again a significant effect of moral-emotional language (IRR = 1.17, $P < 0.001$, 95% CI = 1.09, 1.26). Adding a single moral-emotional word to a given tweet increased its expected retweet rate by 17%. Tweets with the greatest amount of moral-emotional language had the highest expected retweet rates (Fig. 1).

In study 3, we obtained parallel results with respect to communications about climate change ($n = 413{,}611$). We used the same methods as in the previous studies (29% of messages were retweeted). This time, we observed a main effect of distinctly moral language (IRR = 1.04, $P < 0.001$, 95% CI = 1.02, 1.06), indicating a moral contagion effect in the absence of emotional language, as well as a significant main effect of distinctly emotional language (IRR = 1.08, $P < 0.001$, 95% CI = 1.07, 1.09), demonstrating basic emotional contagion. As in studies 1 and 2, we also observed a significant main effect of moral-emotional language (IRR = 1.24, $P < 0.001$, 95% CI = 1.22, 1.27); adding a single moral-emotional word to a given tweet increased its expected retweet rate by 24% (Fig. 1).

Across three contentious political topics, moral-emotional language produced substantial moral contagion effects (mean IRR = 1.20, or a 20% increase in retweet rate per moral-emotional word added), even after adjusting for the effects of distinctly moral and distinctly emotional language, as well as other covariates known to affect retweet rate. [We note that there were interactions such that the presence of media lead to a relative increase in moral contagion effect (climate change), and the presence of a URL led to a relative decrease in moral contagion (climate change, same-sex marriage).] These results shed light on the types of linguistic content that can amplify messages in social networks (for a list of specific emotional and moral-emotional words that were most impactful across topics, as well as sample tweets for each word, see *SI Appendix*, Tables S3 and S4).

Next, we examined whether contagion was driven by a general negativity bias or applied to positive valence as well. To measure emotional valence, we split our emotion and moral-emotion dictionaries into "positive" and "negative" emotions (25). In the case of messages related to gun control, we observed that negative moral-emotional language (IRR = 1.19, $P < 0.001$, 95% CI = 1.13, 1.25) and positive moral-emotional language (IRR = 1.09, $P = 0.053$, 95% CI = 1.00, 1.18) both contributed to contagion effects. In the case of same-sex marriage, positive moral-emotional language predicted contagion (IRR = 1.92, $P < 0.001$, 95% CI = 1.68, 2.20), whereas negative moral-emotional language was a negative predictor of contagion (IRR = 0.87, $P = 0.008$, 95% CI = 0.79, 0.96). It is worth noting, however, that at the time of our data collection, attitudes expressed online about same-sex marriage were predominantly positive (such as those communicated with the hashtag "#lovewins"). [The phrase #lovewins led to ∼6% error in data collection for our same-sex marriage dataset due to seemingly arbitrary use of the hashtag. Removal of all tweets with #lovewins does not change results (*SI Appendix*, section 1 and Table S19).] People were less likely to retweet messages about same-sex marriage that contained negative moral-emotional language (e.g., "hate"). In the case of climate change, negative moral-emotional language predicted moral contagion (IRR = 1.31, $P < 0.001$, 95% CI = 1.28, 1.35), whereas positive moral-emotional language did not (IRR = 1.03, $P = 0.178$, 95% CI = 0.99, 1.07). In contrast to the pattern found for same-sex marriage, when discussing climate change people were more likely to retweet negatively valenced messages, such as those referring to environmental harms caused by climate change. Thus, overall, the effects of valence on moral-emotional contagion were specific to the topic in question. See *SI Appendix*, Table S11, for further model details and coefficients.

In an exploratory analysis, we also considered specific discrete emotions and their effects on social transmission. We focused on the emotions of anger and disgust because of their prominent role in communication, association with moral judgment, and distinctive relationship to moral outcomes (29–31). We also included sadness, a low-arousal emotion, to compare its impact to the high-arousal emotions of anger and disgust. The only consistent finding across all moral topics was that the low-arousal emotion of sadness was associated with a decrease in social transmission (mean IRR = 0.73). This pattern replicated previous work investigating the impact of discrete emotions on social transmission of online news articles (18). The effect of anger was context-specific; it was associated with increased social transmission for the topic of climate change, which was dominated by negative emotion, but was associated with decreased social transmission for the topic of same-sex marriage, which was dominated by positive emotion. We observed no significant effects for disgust (*SI Appendix*, section 3).

We also investigated the extent to which messages containing moral-emotional language transcended ideological group boundaries, as opposed to spreading largely within those boundaries. Specifically, we compared diffusion rates in retweet networks that either did or did not share the ideological orientation of the original author. We started by estimating each user's political ideology as a continuous value using a previously validated algorithm based on follower networks (32). For each message, we computed a retweet count based on retweeters who possessed the same ideological classification as the original author (in-group members) and a separate count based on retweeters who possessed a different ideological classification than the original author (out-group members). [One feature of this approach 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 by (*i*) excluding all "verified" users (e.g., celebrities), to eliminate the possibility that a few well-known moderates could disproportionately sway the results; (*ii*) excluding the middle 10% (in terms of ideological estimates, closest to zero) of authors in our dataset; and (*iii*) excluding the middle 20% (in terms of ideological estimates, closest to zero) of authors. 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.] We then estimated a multilevel model to test whether moral-emotional contagion was stronger within the in-group retweet network than the out-group retweet network, to assess the tendency for moral-emotional messages to diffuse more widely within ideological boundaries than between them. In this model, we interacted the moral-emotional language count variable with an effects-coded classification variable indicating the in-group (as opposed to out-group). To the extent that moral-emotional language plays a larger role spreading information within in-group

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networks as opposed to out-group networks, we would expect to find a positive interaction coefficient (see *SI Appendix*, section 2, for details).

With respect to messages about gun control, moral-emotional language did have a larger impact on retweet rates within in-group networks than out-group networks. The interaction was statistically significant (IRR = 1.20, $P = 0.049$, 95% CI = 1.00, 1.45), with an estimated 20% higher diffusion rate of moral-emotional language for in-group (vs. out-group) networks (Fig. 2). Very similar results were obtained with respect to messages about climate change (IRR = 1.34, $P = 0.001$, 95% CI = 1.12, 1.60). For same-sex marriage, however, the interaction did not approach statistical significance, although the effect remained in the same direction (IRR = 1.10, $P = 0.746$, 95% CI = 0.61, 1.98). These findings indicate there may be an in-group advantage (22, 33) for moral contagion; that is, moral-emotional language may spread more widely within in-group networks than out-group networks (for a visualization of the retweet network for messages containing moral and emotional language, see Fig. 3). The in-group advantage was also observed more consistently for moral-emotional language than nonmoral-emotional language (*SI Appendix*, Table S12). To the extent that moral contagion is greater for in-group (vs. out-group) networks, it may help to explain why online discussions of moral and political topics often occur within polarized "echo chambers."

Given past research suggesting that political conservatives may possess more homophilous online social networks than liberals (32, 34), we also explored whether the in-group advantage for moral-emotional language would be greater in conservative (vs. liberal) social networks. Thus, we estimated a model that included a three-way interaction term involving the original author's ideological classification, the moral-emotional language variable, and the binary in-group/out-group classification variable. Moral-emotional language increased retweets within conservative in-groups significantly more than liberal in-groups for the issue of climate change (IRR = 1.78, $P < 0.001$, 95% CI = 1.35, 2.34). The three-way interaction was in the same direction for gun control and same-sex marriage, but it did not reach statistical significance for those two issues. See *SI Appendix*, section 1, for more details.

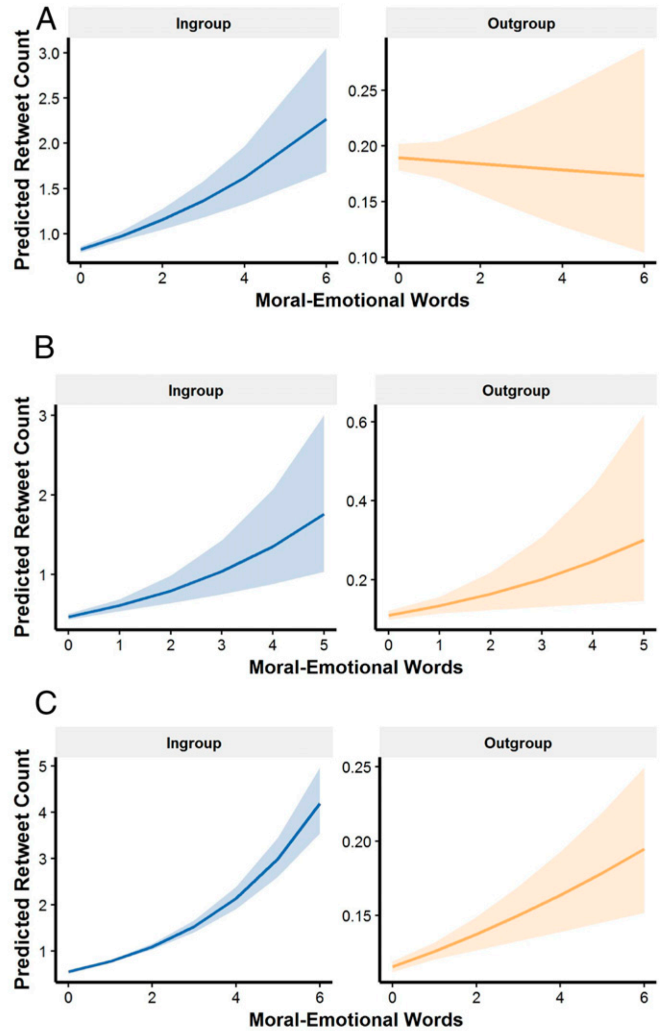

Fig. 2. The effect of moral contagion is greatest within political in-groups compared with political out-groups. The graph depicts expected retweet count as a function in-group/out-group network and moral-emotional content. Bands reflect 95% CIs. Moral-emotional language was associated with a significantly larger retweet rate for the political in-group for the topics of (*A*) gun control and (*C*) climate change. For the topic of (*B*) same-sex marriage, the result was not significant, although in a consistent direction.

Discussion

Using naturally occurring social networks on Twitter, we identified a critical role for emotion when it comes to the diffusion of moral ideas in real, online social networks. Using a large sample of tweets concerning three polarizing issues ($n = 563{,}312$), the presence of moral-emotional words in messages increased their transmission by approximately 20% per word. The effect of moral-emotional language was observed over and above distinctly moral and distinctly emotional language as well as other factors that are known to increase online diffusion of messages. This work is consistent with accounts of moral psychology that highlight the social and emotional nature of moral discourse. It also extends current theories by identifying a social transmission process of information diffusion. In doing so, this work fosters questions pertaining to the role of social influence in the domain of morality such as how online messages can affect moral attitudes. These issues are more important than ever, given the growing use of social media for political purposes (35).

In recent years, Twitter and other social media have changed the course of numerous political events, from the Arab Spring to the US presidential election. Online social networks have become ubiquitous for discussing—and influencing—political events. In his first interview after winning the 2016 US presidential election, Donald Trump claimed that Twitter helped him "win all of those races" where his political opponent was spending much more money. Several commentators agreed that Trump's unique style of language fueled his primary win and later his election to the presidency, allowing him to connect directly with voters in his own voice. (See, for example, the following: www.independent.co.uk/news/world/americas/donald-trump-twitter-account-election-victory-president-elect-david-robinson-statistical-analysis-a7443071.html; www.vanityfair.com/news/2016/12/twitter-helped-trump-win-board-member-says; and thehill.com/blogs/pundits-blog/technology/306175-trump-won-thanks-to-social-media.) Our analysis of the moral and emotional language used on Twitter may help to explain why certain political messages "go viral" on social media. It seems likely that politicians, community leaders, and organizers of social movements express moral emotions—of either positive or negative valence—in an effort to increase message exposure and to influence perceived norms within social networks. Our work suggests that such efforts might pay off.

The results of our studies also clarify how moral emotions contribute to moral contagion. One key finding was that morally framed emotional expressions explained statistical variance in diffusion of moral and political ideas over and above nonmoral-emotional expression. This finding highlights the need for an analysis of how specific emotions are functionally linked to moral outcomes, especially when it comes to the transmission of moral ideas. We have distinguished broadly between moral and nonmoral

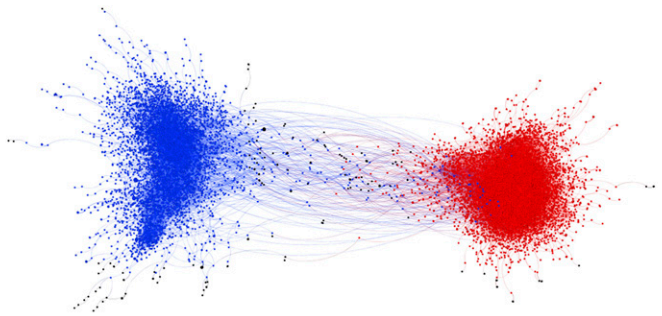

Fig. 3. Network graph of moral contagion shaded by political ideology. The graph represents a depiction of messages containing moral and emotional language, and their retweet activity, across all political topics (gun control, same-sex marriage, climate change). Nodes represent a user who sent a message, and edges (lines) represent a user retweeting another user. The two large communities were shaded based on the mean ideology of each respective community (blue represents a liberal mean, red represents a conservative mean).

emotions, but it is likely that moral emotions can be broken down into more fine-grained subcategories [such as moral emotions that are self-conscious vs. other-condemning (12)] that may have distinct effects on social transmission. We also observed that nonmoral emotions had a unique impact on social transmission for two out of three topics, replicating prior work demonstrating the impact of emotion on online diffusion (18, 19). Future work should clarify how the class of moral emotions motivates individuals to share and discuss their ideas and the conditions under which moral emotions yield greater power than nonmoral emotions.

Another key finding was that the expression of moral emotion aids diffusion within political in-group networks more than out-group networks. With respect to politics, this result highlights one process that may partly explain increasing polarization between liberals and conservatives (24). To the extent that the spread of online messages infused with moral-emotional contents is circumscribed by group boundaries, communications about morality are more likely to resemble echo chambers and may exacerbate ideological polarization. Our results also speak to recent controversies over the role of social media in creating a biased informational environment (36). For example, the use of negative messages about rival political candidates containing strongly worded moral-emotional terms may spread more easily within (but not necessarily between) liberal or conservative social networks.

Finally, our approach illustrates the utility of bringing a social network approach to bear on questions of moral psychology. In comparison with laboratory-based studies, the social network approach offers much greater ecological validity. We were able to investigate moral discourse about contentious political topics with significant policy ramifications and to track users in complex, naturally formed social environments rather than isolated, artificial settings. Furthermore, we investigated the diffusion of ideas in digital online environments, which are becoming increasingly prominent when it comes to promoting moral and political discourse. As of 2017, Twitter is estimated to have 317 million active monthly users, and Facebook is estimated to have 1.87 billion (37). Data collection from social media platforms can pose challenges when it comes to precisely measuring psychological constructs of interest, and the analysis of such data can be computationally intensive. For example, the effect size estimate for the issue of same-sex marriage, although robust in direction, was the most variable in size across all sensitivity analyses. This may have been due to small errors in data collection (*SI Appendix*, section 1), or to the statistical clustering we described in *SI Appendix*, section 2. Despite these challenges, we believe that the benefits of studying moral and political discourse in real time in naturally occurring social networks outweigh potential limitations. Future work should seek to corroborate our conclusions with more carefully controlled laboratory experiments. In particular, it is important to test the causal influence of exposure to moral-emotional language on attitudes and behavior.

Another contribution of the social network approach is that it generates a number of exciting questions for interpersonal accounts of moral judgment and behavior. Although our research program was focused on the contents of social media messages, adopting a social network approach also raises important questions about source effects and social network structure. For example, why do some communicators have more influence than others when it comes to the diffusion of moral ideas? Do more densely connected social networks spread moral ideas faster than networks with fewer ties between individuals? Our findings thus far have addressed only a sliver of important questions that can be addressed by applying a social network approach to the study of morality.

Methods

All research was conducted in accordance with the New York University (NYU) University Committee on Activities Involving Human Subjects (IRB no. 12-9058). Data collection was ruled "exempt" due to our use of public tweets only. A public tweet is a message that the user consents to be publicly available rather than only to a collection of approved followers.

To determine the presence of morality and emotion in language, we split the total corpus of words from the two dictionaries into three categories: distinctly moral (e.g., "duty"; n = 329), distinctly emotional (e.g., "fear"; n = 819), and moral-emotional (e.g., "hate"; n = 159; *SI Appendix*, section 1). Distinctly

Table 1. Sample tweets from each political topic, separated by ideology

Topic	Mean ideology of retweeters	Twitter message
Gun control	Conservative	America needs to Arm itself. Stand and **Fight** for Your Second Amendment Rights. We are literally in a **War** Zone. Carry and get Trained.
	Liberal	Thanks to **greed**, the republication leadership & the #NRA – No one is **safe** #SanBernadino #gunsense #guns #morningjoe
Same-sex marriage	Conservative	Gay marriage is a diabolical, **evil** lie aimed at **destroying** our nation #o4a #news #marriage
	Liberal	New Mormon Policy Bans Children Of Same-Sex Parents-this church wants to **punish** children? Are you kidding me?!? **Shame**
Climate change	Conservative	Leftists take 'global warming' based on **bad** science as **faith** and act on it, but proven voter fraud is just racism #tcot #teaparty
	Liberal	**Fighting** #climatechange is **fighting** hunger. Put your #eyesonParis for a fair climate deal.

Examples of tweets containing at least one moral-emotional word that were retweeted largely by liberals or conservatives. Moral-emotional words are in bold.

moral and emotional words were those that appeared only in one of the two dictionaries, whereas moral-emotional words appeared in both moral and emotion dictionaries (see Table 1 for examples).

Pilot participants confirmed the discriminant validity of our word categories by rating each word on continuous dimensions of morality and emotion. One group of participants ($n = 17$) rated a random 10% subset ($n = 40$) of distinctly moral words from our dictionary as more "moral" than the distinctly emotional words ($n = 42$) [$t_{(16)} = 9.19$, $P < 0.001$, Cohen's $d = 2.23$], and they rated a random subset of moral-emotional words ($n = 9$) as more moral than distinctly emotional words [$t_{(16)} = 9.88$, $P < 0.001$, $d = 2.40$]. A second group of pilot participants ($n = 19$) rated the subset of distinctly emotion words as more "emotional" than the distinctly moral words [$t_{(18)} = 3.19$, $P = 0.005$, $d = 0.73$], and they rated moral-emotional words as more emotional than distinctly moral words [$t_{(18)} = 8.95$, $P < 0.001$, $d = 2.05$].

As a test of robustness, we also investigated discriminant validity by asking a larger group of pilot participants ($n = 50$) to make discrete categorizations of random sets of words from each category. When they were presented with unlabeled random sets of words from each (moral, emotional, moral-emotional) category and asked which word set best expressed a combination of morality and emotion, 76% of participants choose the moral-emotional set, which made that category significantly more likely to be chosen than the other category sets [$\chi^2_{(2)} = 41.44$, $P < 0.001$]. For more details, see *SI Appendix*, section 1.

To form our main predictor variables, we computed the frequency of distinctly moral, distinctly emotional, and moral-emotional words present in each tweet to determine how these factors predicted contagion as measured by retweet count (*SI Appendix*, section 2). We fit a negative-binomial model with maximum likelihood estimation to account for overdispersion (38). The majority of our data were independent (70% of users had only one message in our dataset), but there were some sources of nonindependence due to the 30% of users with more than one message in the dataset. Accounting for these sources of nonindependence revealed that the results from models that treat all data as independent are robust. For instance, dropping all sources with nonindependence produced nearly identical results to the full dataset as did within-cluster resampling via bootstrapping and the use of multilevel models. For a detailed examination of nonindependence and robustness, see *SI Appendix*, section 2. Proc GENMOD in SAS 9.4 was used for all analyses and all syntax is available at https://osf.io/59uyz/wiki/home/.

For each study, our statistical models included our three main predictor variables, as well as covariates known to affect retweet rate independent of message content (27), including number of Twitter followers the original message author had, whether media or a URL was attached to the message, and whether the message author was a "verified" Twitter user. 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 *SI Appendix*, Table S5. For specific details of each model and further tests of robustness for each effect, see *SI Appendix*, section 2. For all studies, the effect of moral-emotional words was almost exactly the same when covariates were included or omitted from the model (*SI Appendix*, Tables S5–S10).

For our models estimating differences in the effect of moral contagion for in-group and out-group networks, we estimated a multilevel model using generalized estimating equations (39) with an exchangeable correlation structure. See *SI Appendix*, section 2, for more details.

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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:

$i \in \{1, \ldots, n\}$: each Twitter user
$j \in \{1, \ldots, m\}$: 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.

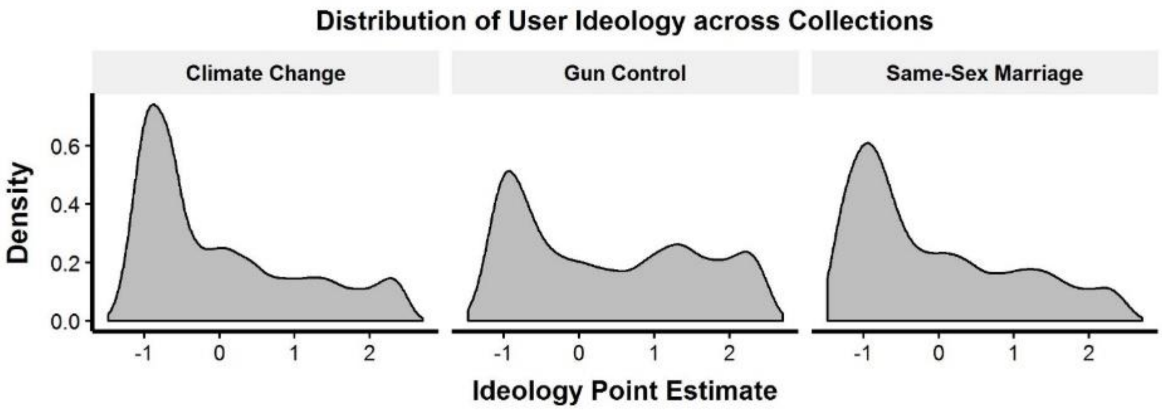

Figure S2. Predicted retweet count as a function of distinctly moral, distinctly emotional and moral-emotional language for the domain of (a) gun control, (b) same-sex marriage and (c) climate change. The x-axis represents the number of words from each respective dictionary found in the tweet. The y-axis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

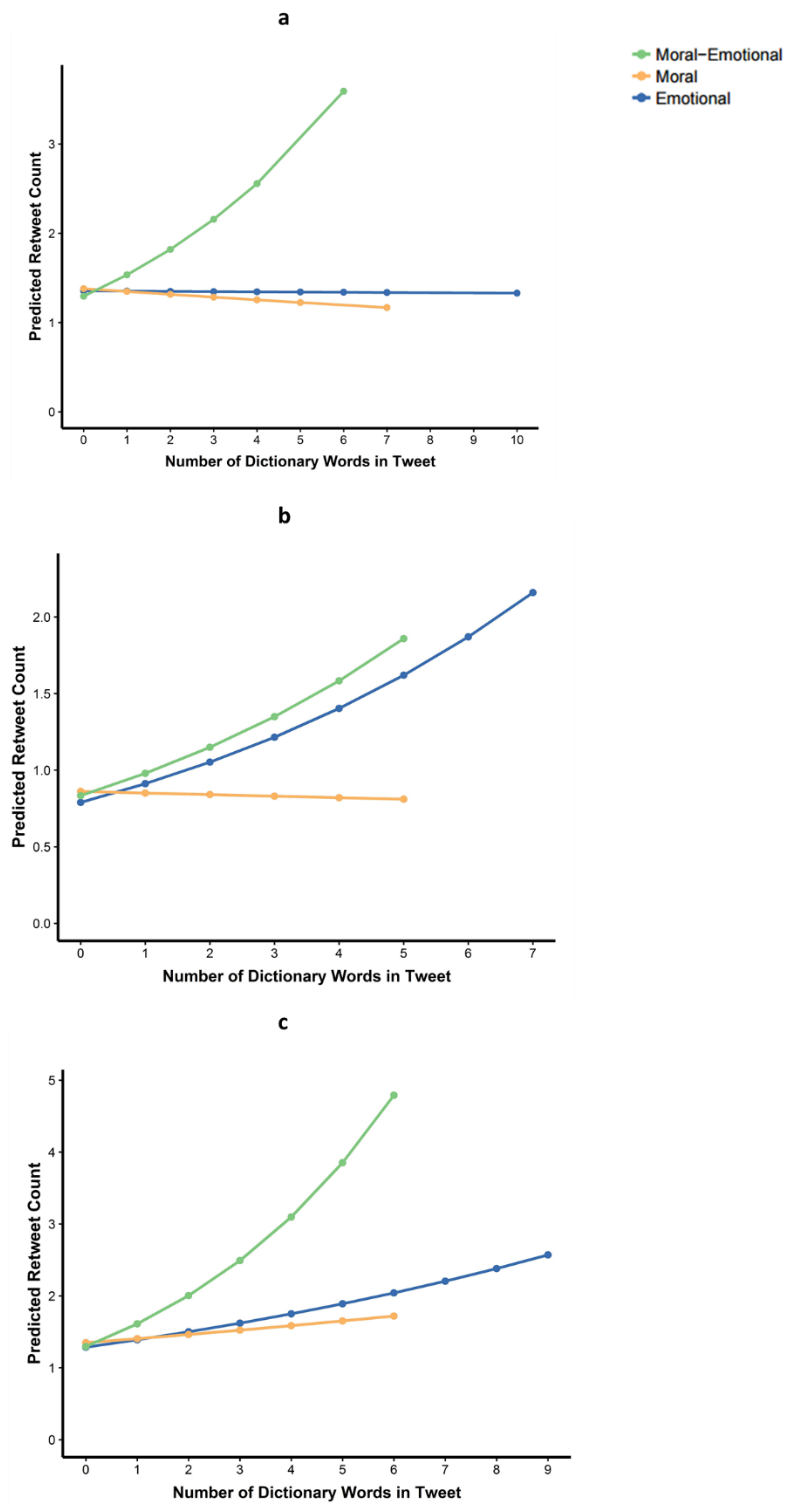

Figure S3. Results of repeated random sampling with bootstrapping. One tweet was randomly selected from each user with multiple tweets to form a data set. This processes was repeated 1000 times to form a distribution of effect sizes for each variable and each data set. The mean coefficients are represented 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.

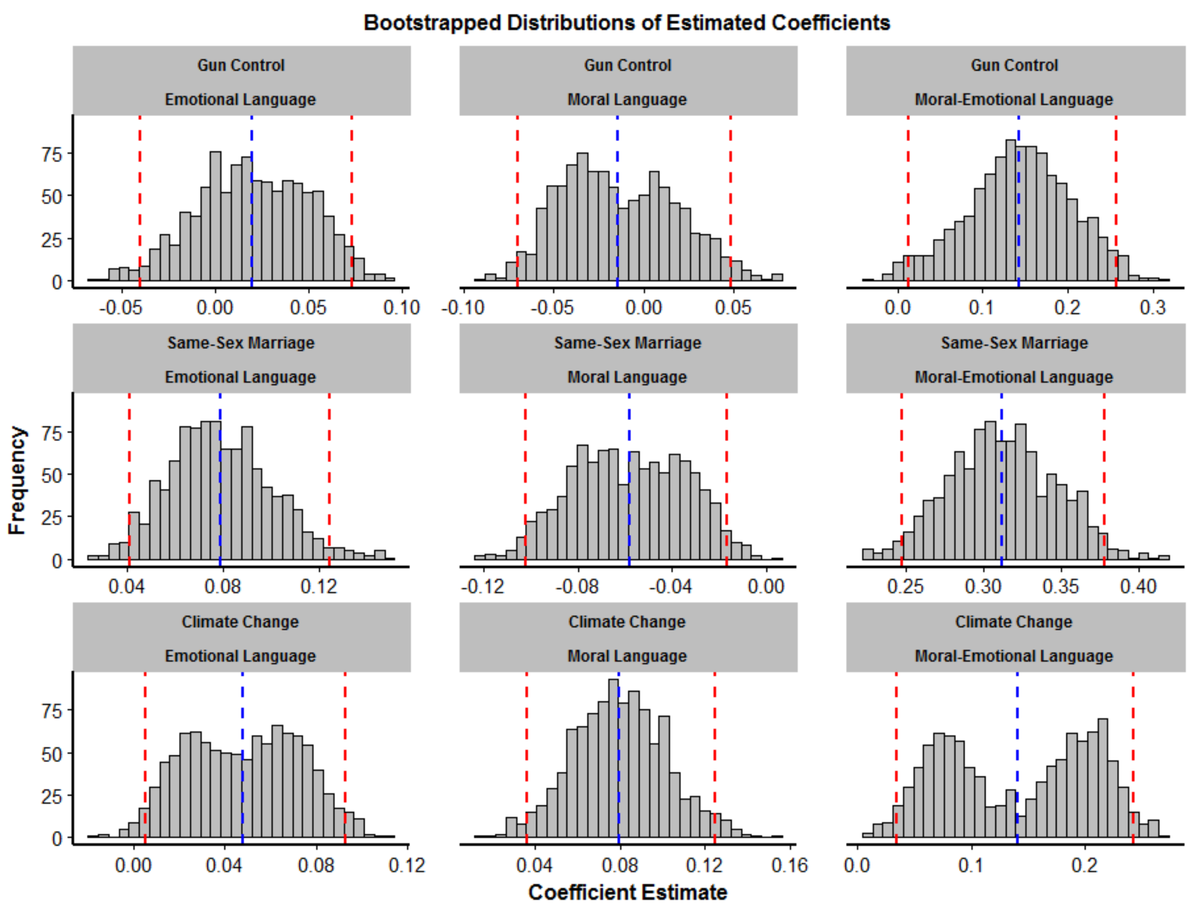

Table S1. Keywords used for data collection. Stream keywords indicate words used to pull Tweets from Twitter's API to form initial data collection. Keyword post-filters indicate filters applied after collection to increase precision in collecting specifically moral topics.

	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† (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* (0.06)	1.25* (0.07)	1.18* (0.06)
Distinctly emotional language	0.88* (0.05)	1.16† (0.09)	0.90* (0.03)
Moral-emotional language	0.98 (0.07)	1.20 (0.16)	1.01 (0.07)
In-group/out-group	5.26* (0.04)	3.93* (0.09)	5.66* (0.03)
Distinctly moral * in-group/out-group	1.40* (0.07)	0.82* (0.07)	0.90 (0.06)
Distinctly emotional *in-group/out-group	1.13* (0.05)	0.97 (0.09)	1.23* (0.03)
Moral-emotional *in-group/out-group	1.17* (0.07)	0.82 (0.16)	1.29* (0.07)
URL	0.85* (0.05)	0.70* (0.13)	0.75* (0.03)
Media	6.61* (0.05)	3.38* (0.13)	3.01* (0.03)
Followers	1.00* (<.001)	1.00* (<.001)	0.06* (<.001)
Constant	0.06* (0.05)	0.06* (0.16)	0.00 (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)

† $p<.10$, *$p<.05$