Emotion shapes the diffusion of moralized content in social networks

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Edited by Susan T. Fiske, Princeton University, Princeton, NJ, and approved May 23, 2017 (received for review November 15, 2016)

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.

Author contributions: W.J.B., J.A.W., J.T.J., J.A.T., and J.J.V.B. designed research; W.J.B. and J.A.W. performed research; W.J.B., J.A.W., J.T.J., J.A.T., and J.J.V.B. planned analyses; W.J.B. and J.A.W. analyzed data; and W.J.B. wrote the paper and all authors contributed to revisions.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

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This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1618923114/-/DCSupplemental.

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).]

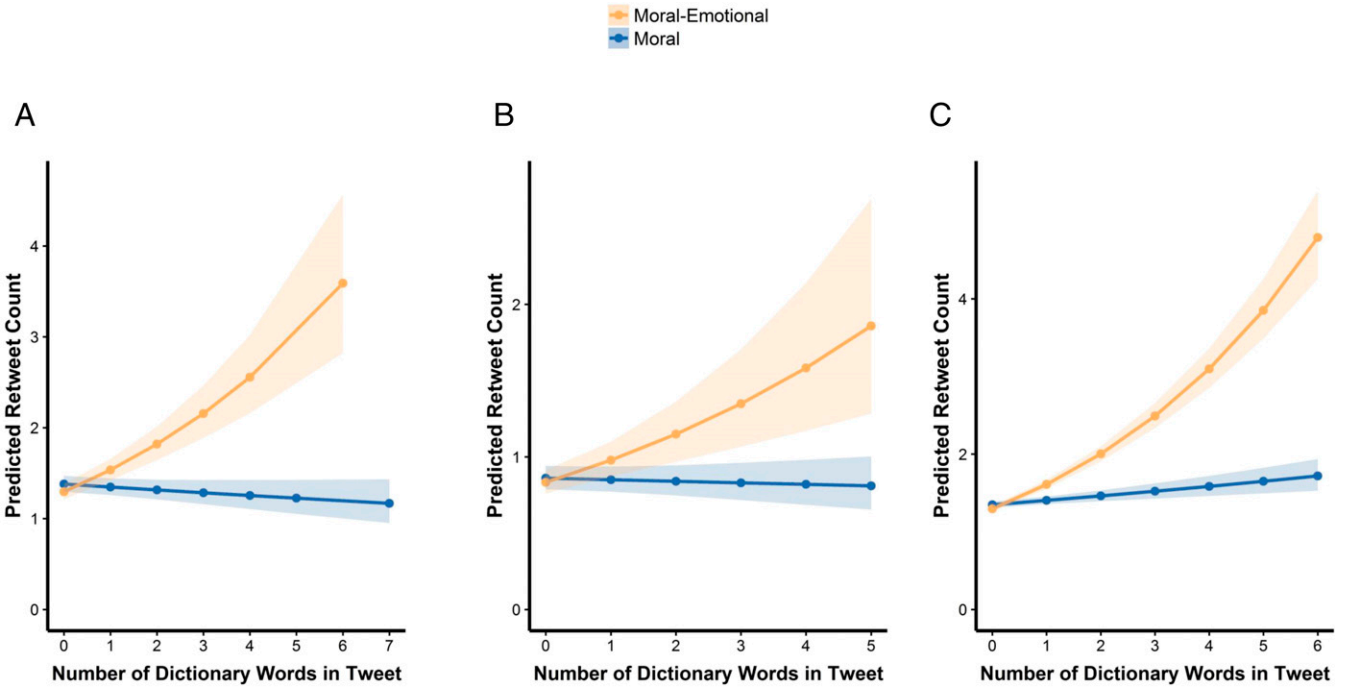

Fig. 1. Moral-emotional language predicts the greatest number of retweets. The graph depicts the number of retweets, at the mean level of continuous and effects-coded covariates, predicted for a given tweet as a function of moral and moral-emotional language present in the tweet. Bands reflect 95% CIs. 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

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.

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

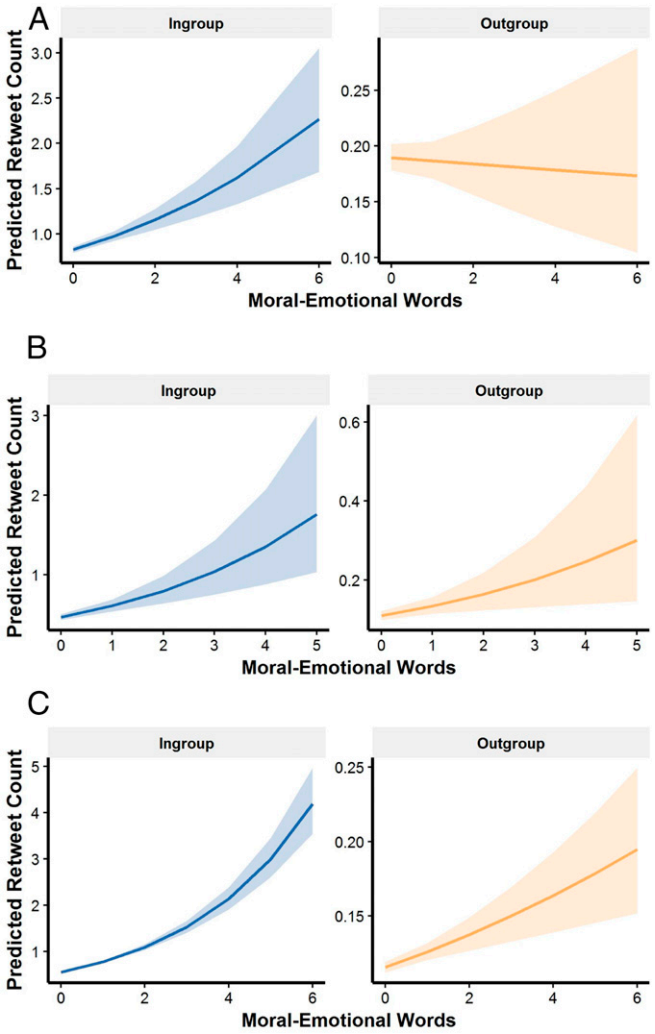

Fig. 2. The effect of moral contagion is greatest within political in-groups compared with political out-groups. The graph depicts expected retweet count as a function in-group/out-group network and moral-emotional content. Bands reflect 95% CIs. Moral-emotional language was associated with a significantly 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.

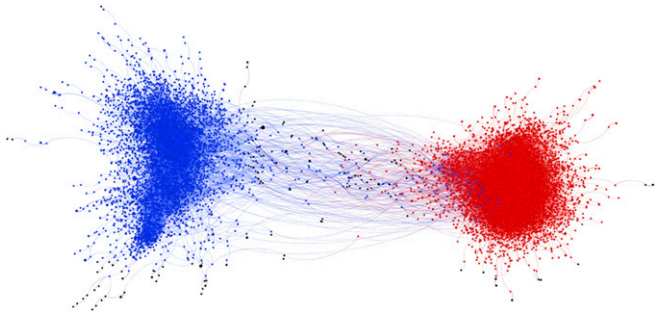

Fig. 3. Network graph of moral contagion shaded by political ideology. The graph represents a depiction of messages containing moral and emotional language, and their retweet activity, across all political topics (gun control, same-sex marriage, climate change). Nodes represent a user who sent a message, 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 outgroup 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.

ACKNOWLEDGMENTS. We are grateful for the extremely helpful feedback we received from Stanley Feldman, James L. Gibson, Leonie Huddy, Kevin Lanning, George Marcus, Diana Mutz, Russell Neuman, and others. We are also grateful to members of the NYU Social Perception and Evaluation Lab (@vanbavellab) for their comments and suggestions. We also thank Yvan Scher, Jonathen Ronen, and Dominic Burkart for aid in data collection and programming. The data were collected by the NYU Social Media and Political Participation Laboratory (https://wp.nyu.edu/smapp/), where J.T.J. and J.A.T. are principal investigators along with Richard Bonneau and Jonathan Nagler. This research was presented by W.J.B. at the 2016 Society for Personality and Social Psychology Annual Convention and by W.J.B., J.T.J., and J.V.B. at the Fall 2016 Meeting of the New York Area Political Psychology (NYAPP) group, which was sponsored by the Center for Social and Political Behavior at NYU. This research was supported by grants from the NSF (Awards 1349089, SES-1248077, and SES-1248077-001) as well as NYU's Global Institute for Advanced Study (GIAS) and Dean Thomas Carew's Research Investment Fund (RIF).

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