Anger makes fake news viral online

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Fake news that manipulates political elections, strikes financial systems and even incites riots, is more viral than real news online, resulting unstable societies and buffeted democracy. It is found that the easier contagion of fake news online can be causally explained by more anger it carries. Offline questionnaires further reveal that anger leads to more incentivized audiences on anxiety management and information sharing and accordingly makes fake news more contagious than real news online. Our results suggest that the digital contagion of emotions, in particular the anger, should be comprehensively considered in profiling the online information spread. Cures like tagging anger in social media could be inspired to slowdown or prevent the contagion of fake news at the very beginning.

Fake news refers to information that is fabricated, misleading and veritably false (*1,2*). Most people popularly accept information instead of critically questioning its authenticity (*1*). In particular, with the boom of social media, on which individuals can be simultaneously producers and consumers of information, the ordinary could quite easily participate in the circulation and gain influence through posting (e.g., tweeting) and reposting (e.g., retweeting). The impact of fake news on social media can be consequently global and profound, especially in the political (*2–5*) and economic fields (*6*). In the first few months of the 2016 U.S. presidential election, each adult was exposed to more than one fake news on average, which was not only widely spread, but also deliberately biased (*4*). Even worse, fake news is more likely to appear in the high uncertainty of emergencies, such as disease epidemics and outbreaks (*7, 8*), accidents or conflicts (*9*), which makes spreading fake news a byproduct of the natural response that people have to disastrous events and social media can be fertile ground for this (*10*) online.

Fake news is more viral than real (true) news online (*2*). The mechanism underlying its fast spread, though critical, still remains unresolved. Unique structural features in the circulation of fake news, like long diameters in penetration, have been extensively revealed and also found to be platform independent (*11–14*). However, fake news is generally verified to be false after an explosive circulation (*15*) and thus in early spread it is essentially not thought to be fake, meaning the structural uniqueness is the manifestation of its fast spread, instead of a cause that can fundamentally explain its viral proliferation. Individuals, either human or bots (*16*), in posting and reposting fake news on social media can be an alternative cause, in particular the human which occupy the dominant partition (*17*). It has been found that spreading news is associated with friends and followers of the author. Nevertheless, user characteristics failed to explain the easy contagion of fake news sufficiently due to their greater effects on the dissemination of real news (*2*). The content of fake news, which was also found to be entangled with spread (*18*), could offer promising directions in probing the mechanism beyond its fast spread.

The content of news online not only delivers factual information, but also carries sophisticated emotional signals. Being embedded in information spread, the digital contagion of emotions, in which individuals experience the same feelings on social media, is also confirmed to be similar with the face-to-face emotion exchange offline (*19, 20*). Emotions further have impact on the spread of information (*21*), e.g., promoting the sharing or shaping the paths (*22*). When the relevance between content quality and popularity is not strong (*23*), the emotions involved and their influence on psychological arousals may be the key (*24–26*). Whats more, the spread of different emotions can be inherently distinguished (*26*), implying emotions conveyed by both fake and real news could offer a comparative proxy to examine mechanisms underlying their circulations. In fact, it has already been found that fake news will be preferentially injected with emotions like anger for political attack (*27*). However, differentiating fake news from the real one is rarely pictured on emotions delivered in content and incentives beyond reposting in extant efforts. At the meantime, though content on social media could be short, simplifying emotions it carries to one single emotion might miss the emotional richness (*28, 29*) and reluctantly lead to the deviation of emotion recognition and inconsistent results (*20, 25, 26, 30*).

In this study, by successfully combining digital traces on social media and offline questionnaires, we aim to unravel the mechanism underlying the fast spread of fake news through answering three key questions: What are the differences in the emotional distributions of real and fake news? Can these differences explain why fake news is more infectious than real news and how do they affect the incentives behind the news reposting?

We collected a large dataset of both fake news and real news from Weibo, the most popular Twitter-like service in China and it includes 10,000 true news posted by credibly verified users and 22,479 fake news endorsed by an official committee of Weibo after their wide dissemination (see SM S1 for more details). As expected, fake news on Weibo is more contagious (faster speed, lasts longer and gets more retweets) than real news (see SM S3), which is consistent with previous understandings on Twitter (*2*). Putting the number of followers on behalf of broadcasting potential of users and the number of retweets on behalf of spreading capability of news (*14*), we assemble both categories of news into groups of treatments and controls. For example, taking fake news of low numbers of followers (authors') and high volumes of retweets (LHF news) as treatment group, its controlled counterparts can be consisted by either fake news with high volumes of followers and low numbers of retweets (HLF news) or true news with high volumes of followers and low numbers of retweets (HLT news) (see SM S2 for details). By intentionally picking news lowly retweeted yet posted by highly followed authors, the possible effects from users could be excessively controlled to amplify clues of spread promotions from content in particular emotions it carries. Moreover, it is worth noting that fake news is statistically more contagious than real news, meaning not every fake news is necessarily more viral than any real news. For instance, the diffusion capability of highly retweeted true news is definitely more powerful than that of lowly circulated fake news. Therefore, we would compare LHF news with HLF news and HLT news first and then extended to a full spectrum of discrepancy between true (T) news and fake (F) news on emotions.

Emotional signals carried in either fake or real news can be sophisticated, i.e., a combination of elementary compounds rather than a single one (*29*). A distribution of five emotions that basically represent human feelings (*31*), including anger, disgust, joy, sadness and fear is inferred for each news in our data through a lexicon, which is manually labeled to cover 87.1% news with the remains as neutral (see SM S4). Emotions with high occupations in the distribution will be exactly the feelings that the sender of the news wishes the receivers to have (*32*). It is unexpected that the proportion of anger (Fig. 1A) in LHF news is significantly higher than that in both HLF and HLT news, while the joy is contrarily lower (Fig. 1E). The comparison is then extended to a full spectrum between all fake news and real news and consistent results, through with shrinking gaps for anger and joy as expected, are obtained (Figs. 1B, F). Even through a better resolution in which the distribution of emotions on keywords that precisely separate the treatment groups from control groups (see SM S6), the dominance of anger in fake news (especially the highly retweeted) and joy in real news (even the lowly retweeted) is further confirmed (see Fig. S7). These observations persistently suggest that fake news carries more anger yet less joy than real news and implies the possibility that anger might promote the fast spread of fake news online. And the divergence on anger and joy between fake news and real news is robust and independent to emotion inference models and emotion distribution measures (see SM S7). While the almost overlaps of disgust between different types of news (Fig. 1C, D), as that of sadness in true and fake news (Fig. 1H), and more dominant position in HLF news of fear (Fig. 1I) surprisingly indicate their less positive roles in virality of fake news (*21, 30, 33*), meaning significant gaps across news groups could also be independent to the circulation and well-controlled causal inference is accordingly necessary for anger and joy further.

In order to causally infer and qualify the promotion of anger and the prevention of joy in the spread of fake news, internal factors in content (*34*), user (*2*) and external shocks like disaster events (*7*) should be comprehensively controlled. Specifically, internal factors including Mention, Hashtag, Location, Date, URL, Length, Topic, Other Emotions, Follower (the number of followers), Friend (the number of reciprocal followers) and external shocks includes Emergency (a disaster event) compose control variables in the inference models of both logit and liner (see SM S8). The results of logit model (see SM S9) for lowly retweeted true (LT) news (control group) and highly retweeted fake (HF) news (treatment group) show that the coefficient of anger (Anger) is significantly positive and the coefficient of joy (Joy) is inversely negative, implying that anger causally promotes the fast spread of fake news online. Because of multicollinearity, other emotions (Others) are omitted (Table 1(1)) due to their trivial impact on the circulation. Moreover, for the logit model that estimated on all true and fake news, the anger is still positively associated with fake news, though with a shrunken coefficient yet a narrowed deviation as anticipated (Table 1(2)). Recall the gaps observed in emotion distributions across groups of news, all the results consistently suggest the positive promotion of anger in the circulation of fake news, in particular for those of highly retweeted. While the causally negative relationship between joy and fake news contrarily indicates its prevention in the dissemination. To further qualify the influence of both anger and joy in the spread of fake news, a linear regression model with the number of retweets being the dependent variable is established (see SM S9). It is congruously found, either on fake news or all news ignoring true and fake, the coefficients of anger are significantly positive while the coefficients of joy are negative (Table 1 (3), (4)), suggesting that anger can promote circulation while joy prevents the spread. Specifically, supposing other factors fixed, increasing the occupation of anger by 0.1 and reducing that of joy 0.1 in fake news will lead to 5.8 more retweets and 2.2 more retweets will be earned in like manner if increasing anger by 0.1 to replace other negative emotions but keep joy fixed. The above causal relationships between emotions and the circulations are also robust with alternative emotion detection approaches like competent machine learning models (see Table S15). For other significant factors, although Mention can promote the spread of news (Table 1(3,4)), it is not significant for LHF news (Table 1(1)) and even prevents the spread of fake news (Table 1(2)); Emergency is significantly positive in logit models (Table 1(1,2)), but its coefficients derived in linear models are inconsistently negative (see SM S8 for more details). Therefore, carrying more anger and less joy is exactly the mechanism beyond the fast spread of fake news, which makes it more viral than real news online.

Negative stimuli like anger inclines to elicit stronger and quicker emotional and even behavioral responses than the positive like joy (*35, 36*). The odds to be forwarded through e-mails is also found to be causally impacted by the physiological arousal caused by emotions articles carry and those evoking high-arousal positive or negative emotions could be more viral (*30*). In spread of fake news, the incentives beyond the action of reposting that reignites the circulation are therefore hypothetically associated with anger and joy the news carries. Taking LHF news as treatment group and HLF news and HLT news as control groups, the possible associations between reposting incentives and emotions are examined through offline questionnaires. By selecting 15 typical news with keywords marked from these groups (see SM S10), questionnaires are then implemented to investigate four motivations that well accepted underlying news reposting in social media (*37*), including anxiety management, information sharing, relationship management and self enhancement. Subjects of surveys are targeted as Weibo users and assure the confident overlapping between offline subjects and online users (see SM S11). Preliminary results indicate that the motivation of anxiety management in LHF news is significantly higher than that of controlled groups (Fig. 2A). Even more inspiring, as compared to HLT news, subjects are more intensively incentivized on information sharing when repost HLF news and LHF news (Fig. 2B). It can be accordingly derived that fake news can stimulate strong motivation of users on information sharing, in particular those of widely disseminated can also strengthen the motivation of anxiety management. There is no significant variation in the motivation of relationship management across news groups (Fig. 2C) and the motivation of self enhancement in HLT news is stronger than that in fake news (Fig. 2D). What's more interesting is that in questionnaires with keywords highlighted with marks, the unique stimuli on anxiety management of widely circulated fake news is further strengthened (see Fig. S19). And the incentive of information sharing is similarly enhanced for fake news (see SM S12.1). All these threads promisingly imply the possible responses to anger carried by fake news are sharing information and even managing anxiety. To validate this, the news in questionnaires are further split into anger dominated ones and joy dominated ones in terms of emotion occupations (see SM S12.2) to directly probe the impact caused by emotions. As compared with retweeting motivations of joy dominated news, anger dominated news stimulate stronger incentives of anxiety management (Fig. 2E) and information sharing (Fig. 2F) of subjects. While joy dominated news ultimately excites stronger self enhancement motivation (Fig. 2H) than that of the anger dominated. Meanwhile, there is no significant difference between anger and joy in relationship management motivation (Fig. 2G). Shuffling emotions randomly further testify the significance of these observations (see SM S12.2). Therefore, it is concluded that more anger delivered in fake news leads to more incentivized audiences on anxiety management and information sharing, resulting more likelihoods of retweets and thus more viral contagion.

Our findings emphasize the necessity of considering emotions particularly anger in understanding the spread of information online. On social media, the associations between information diffusion and emotions embedded have been noticed for a while, however, the profiles about roles of both positive and negative emotions are inconsistent and even contradictory across diverse contexts (*20*). Considering the heterogeneous influence on spread from negative emotions like anger and sadness (*21, 30, 33*), the causal impact to information diffusion should be examined in a manner of well-resolved negative emotions. Instead of simplifying emotions binarily into the positive and the negative, more elementary compounds of negative emotions are considered in this study and the distribution of five kinds of emotions are inferred to reflect the complete emotional spectrum of news online. Putting this spectrum under a magnifier, angers unique role of provoking strong incentives of anxiety management and information sharing is pinpointed, which in essence results in the virality of fake news online. From this perspective, emotions could be genes of fake news and like small mutations could make virus go viral, mutations of increasing anger or reducing joy in fake news will efficiently enhance its likelihood to be retweeted. Distinguishing structures in the circulation of fake news, which have been pervasively revealed in both Twitter (*2, 12*) and Weibo (*12*), could also be deciphered by anger it predominantly carries, since anger prefers weak ties in social networks (*38*) and may inherently forge the circulation structure of fake news. Meanwhile, the negative role of joy in preventing spread, especially in fake news further underlines the fundamentality of considering negative emotions of fine granularities to well control and deepen the extant understanding. It is thus anticipated that insights from emotions will upgrade extant understandings of online information spread.

Vigorous promotions from anger in circulation imply new weapons against fake news. Though structural signals can be sensed at early stage to target fake news (*12*), while in fact fake news spreads quite fast and reaches the peak of newly retweets in less than one hour (see Fig. S4), meaning the negative impact has been exposed to a large population of audiences before the identification. It even takes more than three days for a post to be rated as false by outside fact-checkers in Facebook (*39*). What's worse, like a cat-and-mouse game between the manipulation and detection, features derived from content or users that found to be helpful in machine learning on targeting fake news (*40*) can be easily converted to inspire future countermeasures of fabricating more sophisticated false news (*9*). In particular, fake news related to emergencies is widely disseminated because of its clever combination with anger, which may explain why efforts to counter misperceptions about diseases during epidemics and outbreaks are not always effective (*8*). Inefficient or ineffective efforts to detect fake news and debunk misinformation by correcting both call for new treatments and prevent the spread of anger could be a profound and promising direction. The early deviation in dissemination paths between fake news and real news suggests the quick effect of anger in shaping the retweeting (*22*). For example, platforms like Facebook, Twitter and Weibo should warn and discourage users as they try to retweet news that deliver too much anger at the very beginning and persuade them value the credibility of the information more critically. The trade-off between free speech and fake news prevention is the primed principle, however, a better balance would be achieved by tagging angry news (e.g., with the occupation of anger more than 20%, see SM S13 for more details) at the very beginning to make audiences and potential spreaders less emotional and more rational (*41*).

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Supplementary materials

Supplementary Text

Figs. S1 to S21

Tables S1 to S24

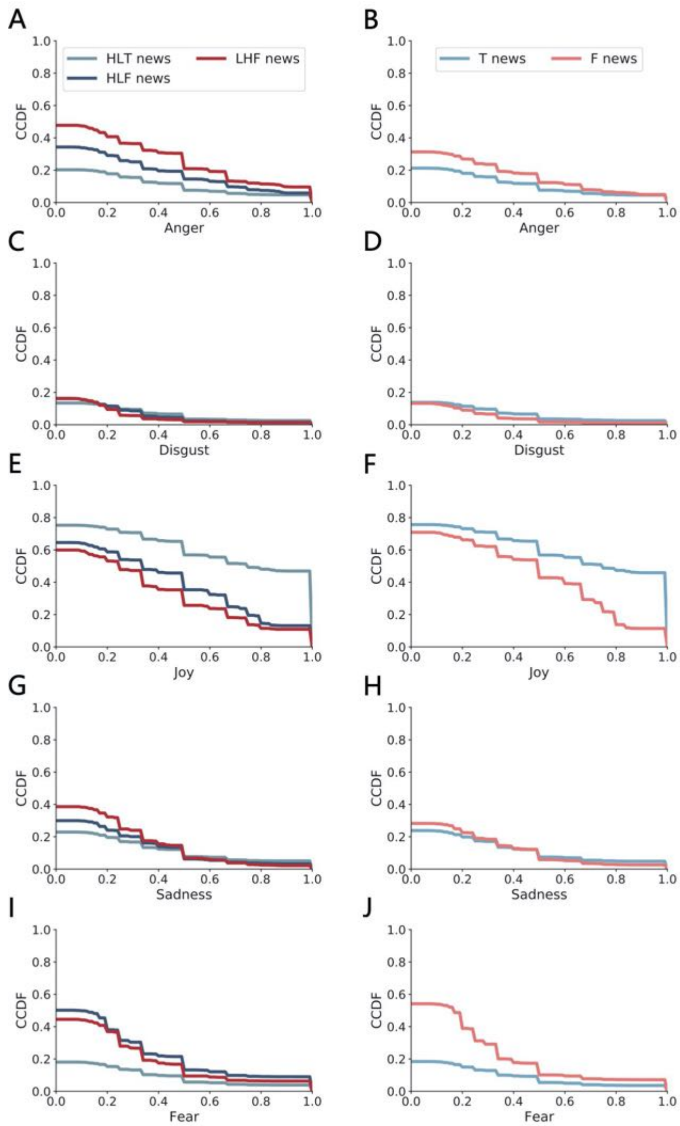

Fig. 1. Complementary cumulative distribution functions (CCDFs) of emotions. (A and B) The proportion of anger. The proportion of anger greater than 0.5 in LHF news is nearly 3 times as much as HLT news (A). (C and D) The proportion of disgust. (E and F) The proportion of joy. The proportion of joy in HLT news is more than 2 times as much as LHF news (E). (G and H) The proportion of sadness. (I and J) The proportion of fear. The results of K-S tests can be seen in SM S5 and the consistent results from other methods can be seen in SM S7.

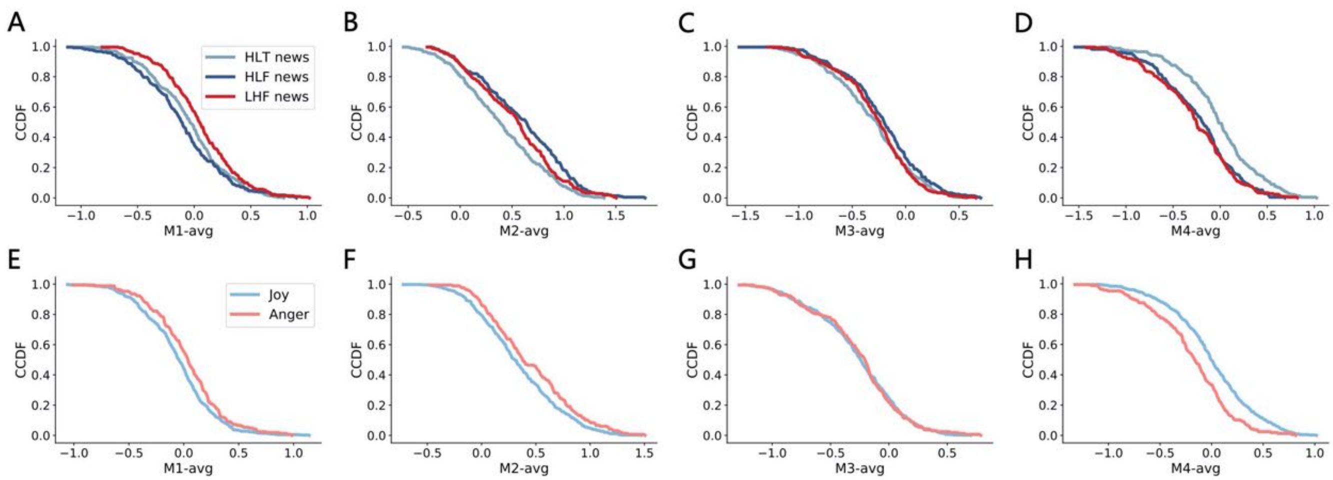

Fig. 2. The CCDFs of motivations. (A and E) Anxiety management (M1-avg). (B and F) Information sharing (M2-avg). (C and G) Relationship management (M3-avg). (D and F) Self enhancement (M4-avg). (A to D) The CCDFs of four motivations in HLT news, HLF news and LHF news. (E to H) The CCDFs of four motivations in the anger dominated news and joy dominated news. The results of K-S tests can be seen in SM S12.

Variables		Fake		Retweet	
		(1)	(2)	(3)	(4)
Anger		**0.889***** **(0.097)**	**0.385***** **(0.077)**	**23.959***** **(6.752)**	**22.278***** **(5.628)**
Joy		**-1.507***** **(0.074)**	**-1.279***** **(0.055)**	**-29.555***** **(5.452)**	**-35.978***** **(3.936)**
Other Emotions		0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)
Follower		-6.10e-08*** (1.04e-08)	-3.14e-07*** (1.70e-08)	0.00002*** (3.39e-06)	0.00001*** (7.08e-07)
Friend		0.001*** (0.00004)	-3.57e-06 (0.00003)	0.048*** (0.003)	0.040*** (0.003)
Mention		**0.104** **(0.067)**	**-0.201***** **(0.050)**	**23.998***** **(4.294)**	**17.067***** **(3.521)**
Hashtag		-1.264*** (0.072)	-1.631*** (0.052)	2.851 (6.268)	-3.350 (4.018)
Location		-0.066 (0.069)	-0.198*** (0.048)	-5.034* (3.011)	-4.438* (2.572)
Date		-0.542*** (0.056)	-1.217*** (0.040)	14.641*** (4.270)	0.424 (2.982)
URL		-2.205*** (0.062)	-1.592*** (0.040)	-20.438*** (2.664)	-24.866*** (2.263)
Length		-0.005*** (0.0007)	0.009*** (0.0005)	-0.281*** (0.054)	-0.197*** (0.036)
Emergency		**5.576***** **(0.722)**	**4.915***** **(0.585)**	**-33.522***** **(7.911)**	**-23.012***** **(6.545)**
Topic	Finance	-0.361*** (0.093)	0.153** (0.062)	-18.488** (8.130)	-19.635*** (5.065)
	International	-0.379** (0.153)	-0.547*** (0.118)	53.856** (22.359)	12.386 (12.479)
	Military	0.928*** (0.154)	0.879*** (0.122)	11.864 (14.884)	13.618 (11.159)
	Society	0.942*** (0.071)	1.513*** (0.053)	-21.502*** (6.915)	-15.074*** (4.401)
	Sports	-0.742*** (0.137)	-1.393*** (0.110)	110.648*** (29.290)	63.475*** (11.564)
	Technology	0.253** (0.104)	-0.143* (0.080)	-1.712 (11.131)	-6.322*** (6.508)
Cons		0.205** (0.098)	1.470*** (0.077)	81.871*** (10.733)	73.831*** (6.806)
R^2		0.353	0.359	0.084	0.134
N		10486	26831	20323	26831

Table 1. Results of logit and linear models in different groups. (1) The results of logit model in LT news and HF news. (2) The results of logit model in all true news and fake news. (3) The results of linear model in LF news and HF news (4). The results of linear model in lowly retweeted (L) news and highly retweeted (H) news (see SM S9 for more details). The values in brackets are the standard errors. $*P < 0.1, **P < 0.05, ***P < 0.01$

S1 Fake news and Real news

Both fake news and real news in this study were collected from Weibo, the most popular Twitter-like service in China, which possessed 200 million daily active users and generates over 100 million daily tweets (news) at the end of 2018[1]. The users of Weibo are dominated by young people and those with ages between 18 and 30 occupy 75% of all users. There is also a distinctive verification mechanism in Weibo, which could ensure the reliability of its user demographics. Specifically, all users have to provide their IDs in registration because the real-name certification regulation in China. In addition to this, influential users, including elites with a certain reputation and influence in specific domains, well-known enterprises and their executives, the mainstream media and government agencies such as public authorities, could be further manually verified through documentary evidence (*42*). Weibo even demonstrates red or blue badges on their online profiles. In the meantime, Weibo also officially organizes a committee, composed by experts outside Weibo, to tag fake news authoritatively and publicly.

Through the open API of Weibo, we collected fake news rated and exposed by the official committee. Considering the fact that fake news always drawn attention of the committee after being widely disseminated, hence the digital traces of their spread in Weibo can be completely traversed. Further probes on the time lines for all news will confirm this again in S3. Real news, also termed as true news in this study, refers to information that was not tagged as false by the committee and was posted by verified users like mainstream media, elites or public authorities with credibility. In total, we collected 22479 fakes posted by 20532 users and 10000 real news posted by 1527 users since 2011 to 2016. For each news in Weibo, we also collected its attributes of text, posting time, author profile (the number of followers, the number of reciprocally followers and etc.), retweeters and reposting time. A subset of both fake news and real news in this study has been already employed in our previous efforts on structural uniqueness of

[1] https://data.weibo.com/report/reportDetail?id=433

fake news in which equivalent results are derived from both Weibo and Twitter, implying the reliability and universality of our data. In addition, authentic tweets from credible by non-verified authors of Weibo further testified the representativeness of our data of real news (*12*).

We have also made the data of fake news and real news publicly available, which can be downloaded freely through https://doi.org/10.6084/m9.figshare.12163569.v1.

S2 News groups

The number of followers can intuitively represent the influence of users on social media, i.e., more followers mean the news will be broadcasted to more audiences and accordingly bring about more retweets, and the number of retweets can represent the spreading capability of a given news. Fake news might be widely retweeted because of the influence of its author; however, it has been found that the broadcasting penitential of authors do not sufficiently explain the fast spread of fake news (*2*), e.g., those posted by lowly followed authors might be massively retweeted. In order to examine the causal impact from emotions on the circulation of fake news, treatment groups and control groups have to be established to control variables and infer the significant roles of emotions underlying the spread. Considering the role of emotions in information spread might be subtle and easy to be interfered by other variables like the influence of authors, we aim to split news, either fake or real, into treatment group (e.g., those highly retweeted but posted by authors of low volume followers) and control group (e.g., those lowly retweeted but posted by authors of high volume of followers), through which the possible influence from authors will be excessively controlled and the clues of emotions will be thus sufficiently amplified. Intuitively, for highly retweeted news but posted by authors with low volume of followers, promotions from the content in particular the emotions carried would be more powerful and thus easier to be detected. In line with this, we group the news according to the number of its authors followers (x) and the number of retweets (y) (*14*). For example, based on the real news with high number of followers but low number of retweets and the fake news with low number of followers but high number of retweets, a division model of maximizing the difference between true and false news is defined to determine the splitting interface, which is specified as

$$D = \left(\frac{N_{lhf}}{N_f} - \frac{N_{lht}}{N_t}\right) + \left(\frac{N_{hlf}}{N_f} - \frac{N_{hlt}}{N_t}\right) - \left|\frac{N_{llf}}{N_f} - \frac{N_{llt}}{N_t}\right| - \left|\frac{N_{hhf}}{N_f} - \frac{N_{hht}}{N_t}\right|,$$

where

- N_t is the number of true (T) news.
- N_f is the number of fake (F) news.
- N_{llt} is the number of true news with low number of followers ($< x$) and low number of retweets ($< y$).
- N_{lht} is the number of true news with low number of followers ($< x$) and high number of retweets ($\geq y$).
- N_{hht} is the number of true news with high number of followers ($\geq x$) and high number of retweets ($\geq y$).
- N_{hlt} is the number of true news with high number of followers ($\geq x$) and low number of retweets ($< y$),
- N_{llf} is the number of fake news with low number of followers ($< x$) and low number of retweets ($< y$).
- N_{lhf} is the number of fake news with low number of followers ($< x$) and high number of retweets ($\geq y$).
- N_{hhf} is the number of fake news with high number of followers ($\geq x$) and high number of retweets ($\geq y$).
- N_{hlf} is the number of fake news with high number of followers ($\geq x$) and low number of retweets ($< y$).

True (T) news				Fake (F) news			
LT news		HT news		LF news		HF news	
LLT	HLT	LHT	HHT	LLF	HLF	LHF	HHF
388 (3.88%)	7867 (78.67%)	36 (0.36%)	1709 (17.09%)	12805 (56.96%)	3513 (15.63%)	1397 (6.21%)	4764 (21.19%)

Table S1: Numbers and proportions of all groups of both fake and real news.

We let the number of followers (from 10 to 10^4) and the number of retweets (from 10 to 10^8) grow exponentially with the step size of 1 to maximize the value of D and find the optimal partition line. As shown in Figure S1, the best tuple is $(x^*,\ y^*)$=$(10,\ 1000)$.

According to the tuple $(10,\ 1000)$, we divide the news into low volume of followers and lowly retweeted true (LLT) news, low volume of followers and highly retweeted true (LHT) news, high volume of followers and highly retweeted true (HHT) news, high volume of followers and lowly retweeted true (HLT) news, low volume of followers and lowly retweeted fake (LLF) news, low volume of followers and highly retweeted fake (LHF) news, high volume of followers and highly retweeted fake (HHF) news and high volume of followers and lowly retweeted fake (HLF) news (Figure S2). In particular, lowly retweeted true (LT) news is the news including LLT news and HLT news, highly retweeted true (HT) news is the news including LHT news and HHT news, lowly retweeted fake (LF) news is the news including LLF news and HLF news and highly retweeted fake (HF) news is the news including LHF news and HHF news. Additionally, in terms of neglecting the label of fake or true on news, those lowly retweeted will be grouped in to L news and the highly retweeted ones will be categorized to H news. Through pairing these groups, diverse assembles of treatments and controls could be accordingly established to examine the causal impact from emotions on circulation. Specifically, HLT news accounts for the largest proportion of true news and LLF news accounts for the largest proportion of fake news (Table S1).

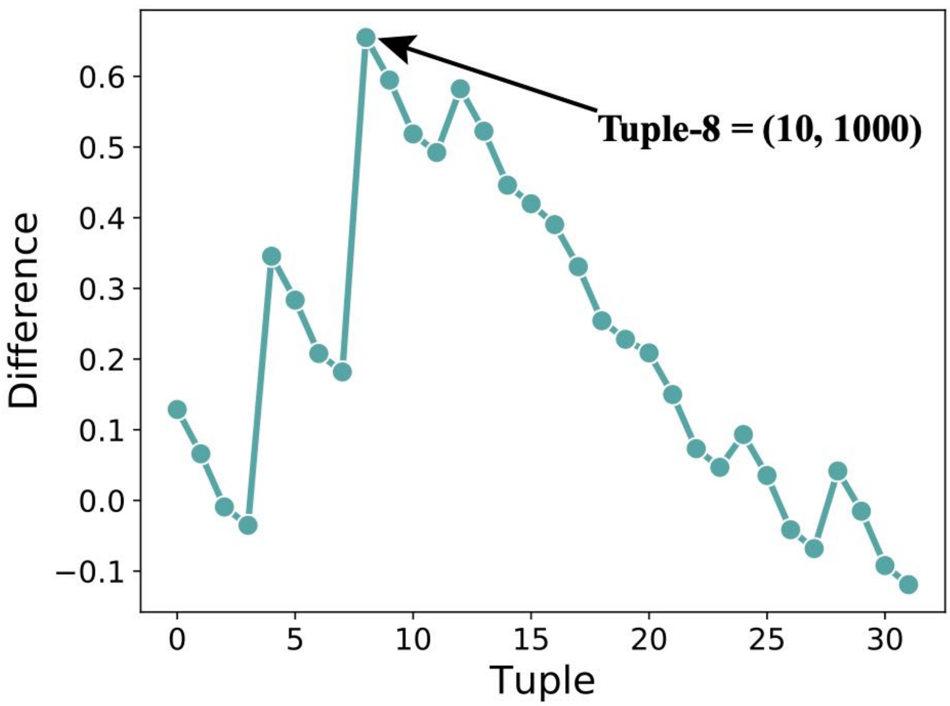

Figure S1: The difference (D) varies with the tuple (x, y), where $x = 10^i\ (i = 1, 2, 3, 4)$ and $y = 10^j\ (j = 1, 2, \cdots, 8)$.

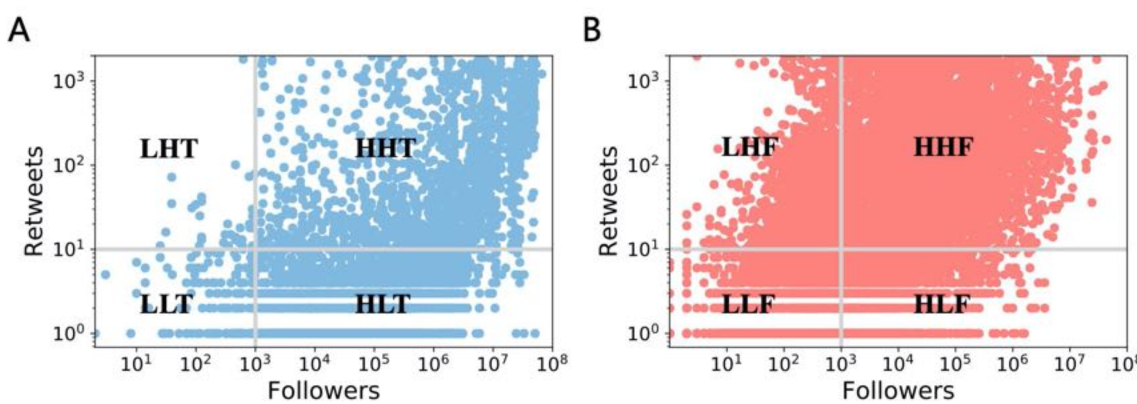

Figure S2: (A) The scatter plot of true news. (B) The scatter plot of fake news.

S3 News timelines

As mentioned in S1, both fake news and real news were collected before 2017 (the open API of Weibo was shut down in 2017) and news in our data set were posted since 2011 to 2016 (Figure S3). A lifecycle can be defined for each news, which starts from the posting time and ends when there were no longer retweets in the sampling period. The timeline of each true or fake news is analyzed by calculating the proportion of the number of newly retweets within each hour in its lifecycle. For both true and fake news, newly retweets reach the peak within one hour after the posting (Figure S4A and S4B), implying the quick circulation on social media and in particular the explosive spread in the very early stage. Furthermore, we count the number of retweets every ten minutes and calculate the cumulative distribution functions (CCDFs) for different types of news. It is found that fake (F) news demonstrates stronger vitality than true (T) news (K-S test ~ 0.140, P ~ 0.0) (Figure S4C). Specifically, fake news still obtains 26% retweets after 48 hours while that proportion for true news lowers to 20%. More importantly, the stronger vitality of fake news than true news is consistently observed on groups of LT news vs. LF news (K-S test ~ 0.114, P ~ 0.0) (Figure S4D) and HT news vs. HF news (K-S test ~ 0.138, P ~ 0.0) (Figure S4E). Besides, we compared the distribution of the number of retweets within 48 hours of the posting and found that the propagation speed of fake news is significantly higher than that of true news (K-S test ~ 0.195, P ~ 0.0) (Figure S4F). All these evidences suggest the similar finding in Twitter (*2*) that fake news is more viral than real news online. As compared to real news, its circulation lasts longer, demonstrates higher speed and ultimately gets more retweets.

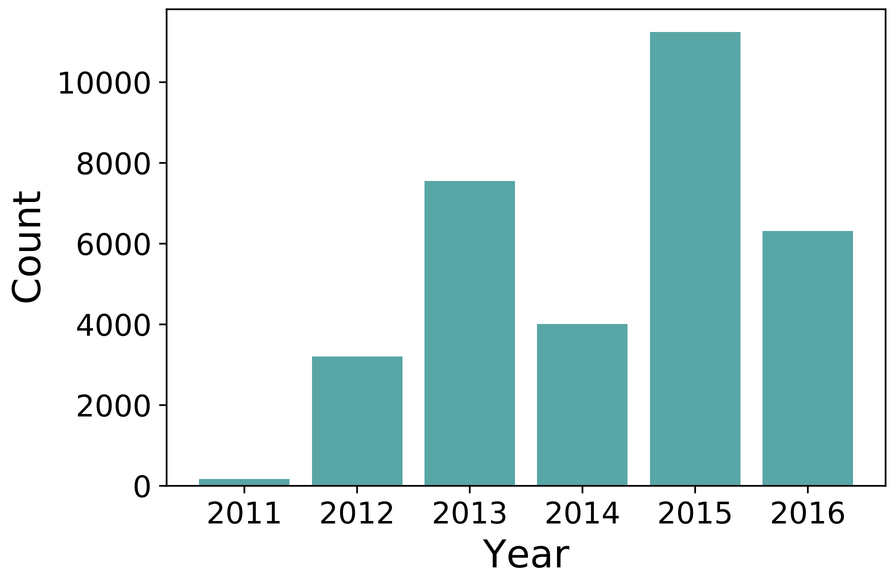

Figure S3: Yearly counts of news.

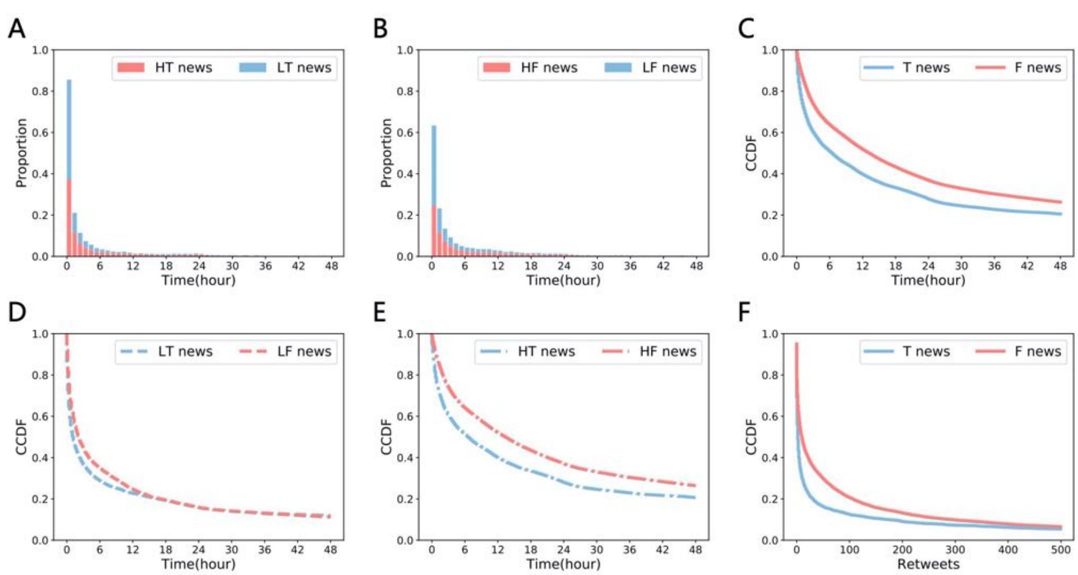

Figure S4: (A) The proportion of newly retweets of each hour for both HT and LT news. (B) The proportion of newly retweets of each hour for fake news. (C) CCDFs for retweeting time in true news and fake news. (D) CCDFs for retweeting time in LT news and LF news. (E) CCDFs for retweeting time in HT news and HF news. (F) CCDFs for the number of retweets within 48 hours in true news and fake news.

S4 Emotion lexicon

It is supposed in this study that emotional texts of news in social media, both the fake and the true, carries sophisticated signals that cannot be fully represented by binary values like the positive or the negative. Contrarily, emotions in particular the negative will be split into elementary compounds including anger, disgust, sadness and fear (*31, 43*). Then together with joy to reflect the positive, the distribution of five kinds of emotions here will be derived to fully represent the emotion spectrum of each news. In order to get the emotional distribution of the text in both fake and true news intuitively and accurately, an emotion lexicon needs to be established and then the occupation of a certain emotion can be simply calculated through the fraction of terms with this emotion in all emotional terms of the news text. We first segment all the texts in both fake and true news into terms, filter the part of speech and keep nouns, verbs, adverbs, gerunds, adjectives, adjectives directly used as adverbials and adjectives with noun function to compose a candidate set. As a result, 34227 preselected terms are obtained. Note that there might be also terms of non-emotion in the candidate set. We then hire human coders to manually label the terms in the candidate. And those without emotions will be marked as neutral. A WeChat applet, named Word Emotion (Figure S5), is accordingly built to make the labeling of terms convenient. The whole labeling task was completed by well-instructed 9 coders, who are active users in Weibo with ages in the range between 18 and 30, and each term is labelled three times by randomly selected coders. Finally, terms with more than two identical emotional labels are screened out to build the lexicon. Ultimately, there are 6155 emotional terms in total, including 1323 angry terms, 710 disgusted terms, 2066 joyful terms, 1243 sad terms and 813 fearful terms. The built emotion lexicon covers 87.1% texts in all fake and true news and the left are labelled as neutral, suggesting the news in social media is indeed emotional. The built emotion lexicon is publicly available, which can be downloaded freely

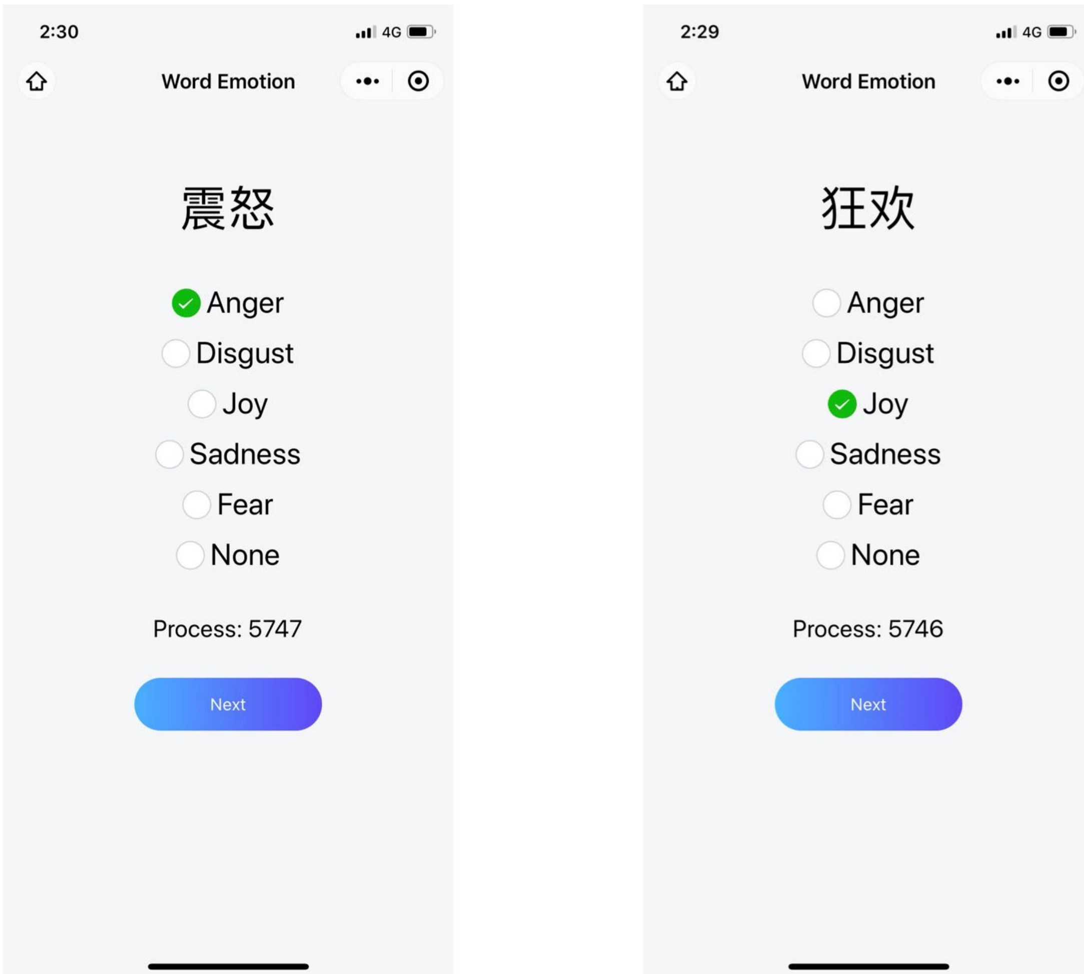

Figure S5: Main page of the WeChat applet named Word Emotion. The Chinese word in the left describes a very angry state. The Chinese word in the right describes rejoice with wild excitement.

through https://doi.org/10.6084/m9.figshare.12163569.v1.

S5 Emotion distributions

With the help of established emotion lexicon, the emotion distributions of news in the different groups can be accordingly derived. After the inference of emotion distributions, possible differences between treatment and control groups of news are comprehensively examined. It is anticipated that these differences will help reveal the mechanism underlying the circulation of fake news. In particular, in terms of splitting the negative emotion into elementary ones, more insights might be derived from these well-resolved emotions.

In the main text, we have discussed that the anger of fake news is significantly higher than that of true news, and the joy of true news is significantly higher than that of fake news. This phenomenon is more obvious in HLT news and LHF news after excluding the influence of news authors. At the same time, to further examine the difference between anger and joy and its possible association with the fast spread of fake news, we also compare the emotional differences between HLF news and LHF news. The results showed that the anger in LHF news is significantly higher than that in HLF news (Figure 1A in the main text), and the joy is significantly lower than that in HLF news (Figure 1E in the main text), which is also consistent with the comparison between L news and H news (Figure S6A, S6C), that is, the anger in the widely circulated news is significantly higher than that in the lowly retweeted news. The statistics of emotional distributions and the results of K-S tests are shown in Table S2-5. All these observations consistently suggest the association between anger and virality of fake news and inspire the later causal inference through regression models.

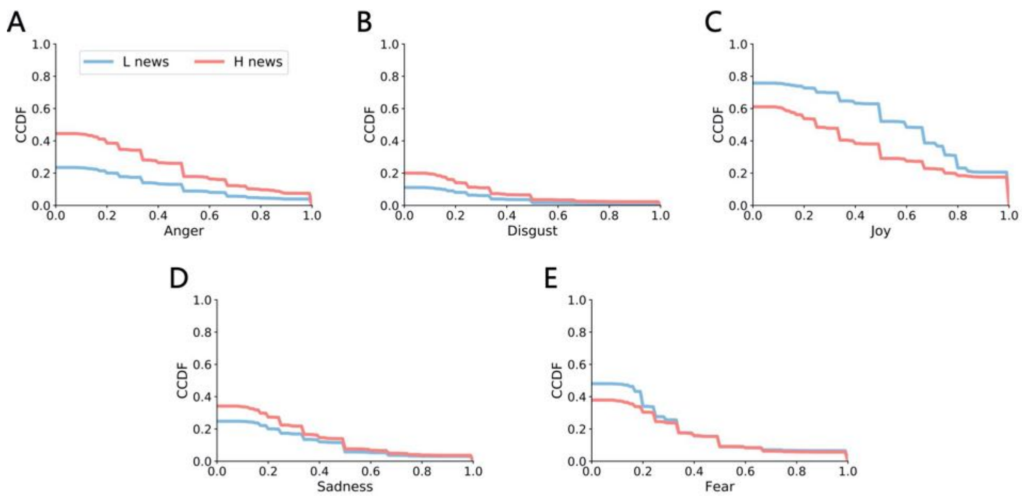

Figure S6: CCDFs of emotions in L news and H news. (A) Anger (B) Disgust (C) Joy (D) Sadness (E) Fear. The results of K-S tests can be seen in Table S5.

	Mean		Std		K-S test
	HLT (4862)	LHF (1238)	HLT	LHF	
Anger	**0.110781**	**0.266855**	**0.256383**	**0.343774**	**D ~ 0.275, p-value ~ 0**
Disgust	0.065549	0.052674	0.196524	0.154399	D ~ 0.039, p-value = 1.0
Joy	**0.610843**	**0.328504**	**0.42096**	**0.346331**	**D ~ 0.366, p-value ~ 0**
Sadness	0.119657	0.157584	0.260941	0.240621	D ~ 0.157, p-value ~ 0
Fear	0.09317	0.194382	0.23423	0.280941	D ~ 0.264, p-value ~ 0

Table S2: Statistics and K-S tests for HLT news and LHF news.

	Mean		Std		K-S test
	HLF (3132)	LHF (1238)	HLF	LHF	
Anger	**0.183563**	**0.266855**	**0.305268**	**0.343774**	**D ~ 0.135, p-value ~ 0**
Disgust	0.059838	0.052674	0.167523	0.154399	D ~ 0.033, p-value ~ 0.34
Joy	**0.391998**	**0.328504**	**0.36497**	**0.346331**	**D ~ 0.105, p-value ~ 0**
Sadness	0.133024	0.157584	0.244897	0.240621	D ~ 0.086, p-value ~ 0
Fear	0.231577	0.194382	0.309433	0.280941	D ~ 0.058, p-value ~ 0

Table S3: Statistics and K-S tests for HLF news and LHF news.

	Mean		Std		K-S test
	T (6550)	F (20352)	T	F	
Anger	**0.112438**	**0.165286**	**0.255438**	**0.290279**	**D ~ 0.101, p-value ~ 0**
Disgust	0.066563	0.047572	0.197113	0.149817	D ~ 0.031, p-value ~ 0
Joy	**0.609413**	**0.442912**	**0.418222**	**0.354057**	**D ~ 0.349, p-value ~ 0**
Sadness	0.120355	0.122562	0.258137	0.233947	D ~ 0.045, p-value ~ 0
Fear	0.09123	0.221667	0.229021	0.282974	D ~ 0.357, p-value ~ 0

Table S4: Statistics and K-S tests for true news and fake news.

	Mean		Std		K-S test
	L (20066)	H (6836)	L	H	
Anger	**0.122546**	**0.240105**	**0.259731**	**0.327235**	**D ~ 0.210, p-value ~ 0**
Disgust	0.043108	0.078873	0.148363	0.196844	D ~ 0.089, p-value ~ 0
Joy	**0.524593**	**0.362686**	**0.368586**	**0.377564**	**D ~ 0.249, p-value ~ 0**
Sadness	0.113074	0.148299	0.234553	0.253735	D ~ 0.094, p-value ~ 0
Fear	0.196679	0.170037	0.276485	0.275805	D ~ 0.108, p-value ~ 0

Table S5: Statistics and K-S tests for L news and H news.

S6 Keywords in separating news groups

The existing of tweets that posted by authors with low volume of followers but highly retweeted in both fake news and real news implies the potential of content in the circulation. In addition, emotions are literally carried by words in text of news. The distinguishing distributions of emotions in particular anger and joy between fake news and real news further inspire us to pinpoint keywords that could in essence split news groups decently. And even more inspiring, these keywords could also help in later offline questionnaires to strengthen the stimuli of anger and joy the news carries on reposting incentives of audiences (see S12).

Specifically, for groups of LHF news, HLT news and HLF news, we respectively train an SVM (*44*) and a Logistic Regression model to evaluate the separability of text and extract keywords that influential in the separation, which is pervasively employed to weigh words in tasks of text mining. These groups of news are further split into two corpuses to learn binary classification models, i.e., one corpus is composed by LHF news (positive class) and HLT news (negative class) and another corpus is composed by LHF news (positive class) and HLF news (negative class). Using words as text features, TF-IDF matrix (*45*) is calculated for the classification. After 5 folds cross validations, the average accuracy scores are 0.94 (SVM) and 0.98 (Logistic Regression) in the corpus of LHF-HLT and the average accuracy scores in the corpus of LHF-HLF are 0.75 (SVM) and 0.81 (Logistic Regression), implying that with words being features can excellently separate LHF news from HLT news and HLF news, respectively. It also indicates the content that carries emotions like anger and joy could be influential driver beyond the news circulation. In particular, the better separability between LHF news and HLT news further suggests the feasibility of keywords in strengthening the divergence of different news in reposting stimuli. On this basis, we combine Chi Square test, Mutual Information, AdaBoost and Extra-Trees for feature selection (*46*)[2] and 150 influential keywords that weigh most in the

[2]These methods are implemented based on scikit-learn package in Python.

classification are selected from each group of news (Figure S7A, C, and E). By analyzing the emotional distributions of keywords in each group of news, we found that emotional keywords in HLT news are all joyful (Figure S7B) and the ones in HLF news are mainly joy (Figure S7F), followed by fear. However, negative emotions dominate keywords in LHF news, especially anger (Figure S7D). These observations solidly support the assumption in the beginning that emotions carried by news, in particular the dominate ones of anger and joy can be concentratedly reflected by keywords that effectively separate different groups of news and therefore these keywords will help in enhancement of incentives underlying retweets. Meanwhile, the exactly same difference in emotion distribution at the keyword level further confirm the consistence and robustness of emotional divergency between fake news and true news revealed in the collective level (see S7).

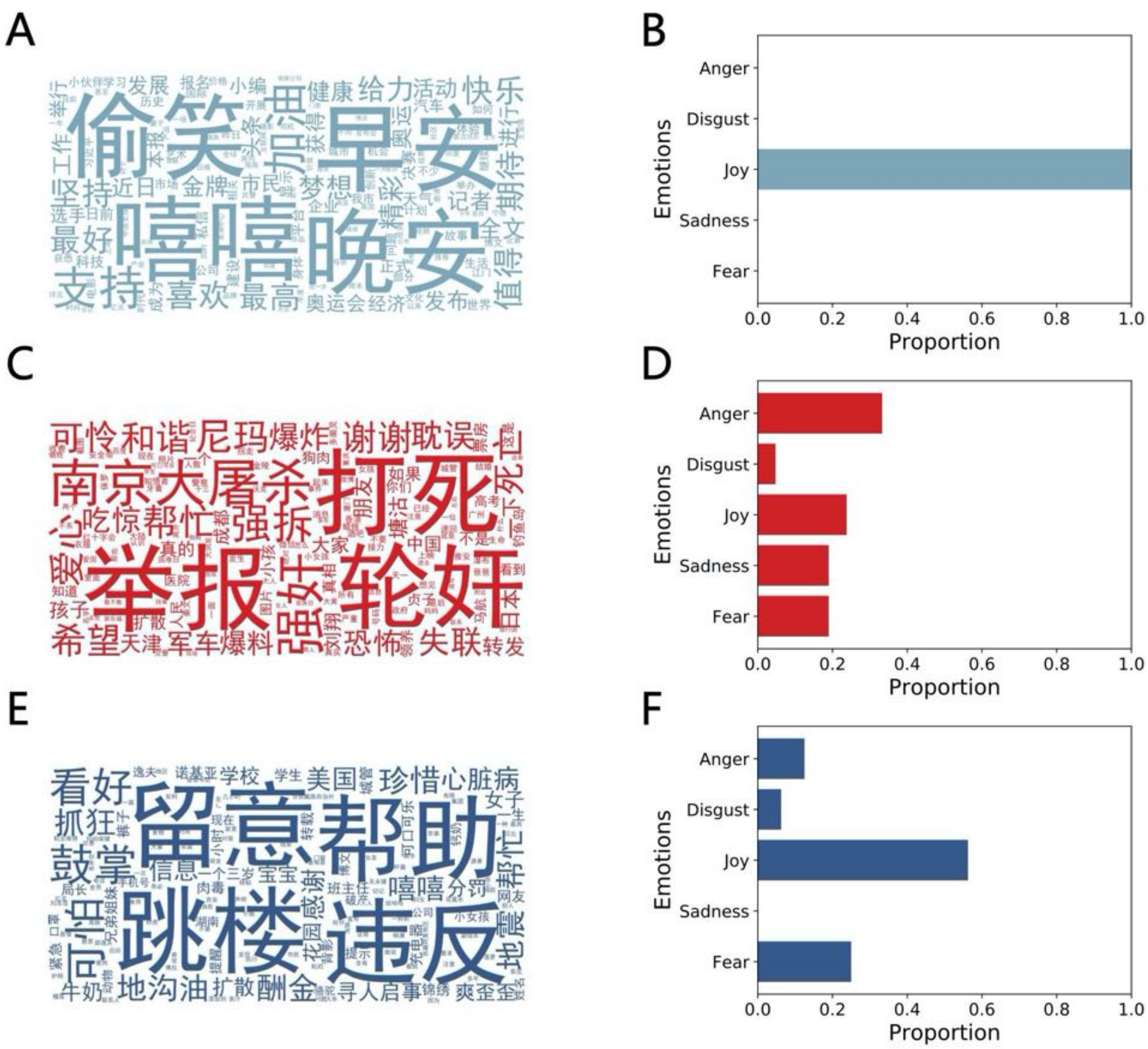

Figure S7: (A) Word cloud of keywords in HLT news. (B) Emotional distribution of keywords in HLT news. (C) Word cloud of keywords in LHF news. (D) Emotional distribution of keywords. in LHF news. (E) Word cloud of keywords in HLF news. (F) Emotional distribution of keywords in HLF news. All the keywords demonstrated in the word cloud are translated into English, which can be found in the data set publicly available through https://doi.org/10.6084/m9.figshare.12163569.v1.

S7 Additional tests for emotion inference and divergency

S7.1 Alternative approaches of emotion inference

Except the emotion lexicon, which offers intuitive measures of emotion occupations, machine learning models in particular the state-of-the-art solutions like deep neural networks could also be alternative models to infer the emotion distributions of both fake and true news. In this study, to ensure the consistency and accuracy of our results on emotion distributions, we also considered classical machine learning and deep learning models. Specifically, two classifiers that built for emotion detection in Chinese tweets from Weibo are employed to perform the additional tests, including the Nave Bayesian classifier (termed as Bayes and its accuracy is 0.64) (*47*) and Back-propagation Neural Network based on an emotional dictionary (termed as BP1 and its accuracy is 0.69) [3] , to calculate the emotion distributions of the texts in terms of probabilities belonging to certain emotions. Then the occupations of different emotions are further compared across different groups and the results are shown in Table S6-11. All of them consistently support our conclusions obtained from the emotion lexicon, in particular the difference on emotion distributions between anger and joy, suggesting the robustness of our understandings on emotion divergence between fake news and real news.

S7.2 Alternative measure of emotion distribution

In previous analysis and the addition test on emotion divergence, the emotion distribution of each news is inferred exclusively by one method, i.e., lexicon-based, Bayes or BP1 and is simply represented by the occupations of emotions in each text. However, it is possible that different methods result in different inferences on the same text, which might undermine the consistency of emotion divergency we previously observed in the level of text. In order to further test the robustness of our above conclusions on different occupations of anger and joy

[3] BP1 was built with Keras.

	Mean		Std		K-S test
	HLT (6797)	LHF (1326)	HLT	LHF	
Anger	**0.260271**	**0.321154**	**0.125017**	**0.10956**	**D ~ 0.294, p-value ~ 0**
Disgust	0.208931	0.150072	0.094848	0.086206	D ~ 0.355, p-value ~ 0
Joy	**0.253518**	**0.149253**	**0.137519**	**0.110704**	**D ~ 0.403, p-value ~ 0**
Sadness	0.216766	0.315336	0.122535	0.127497	D ~ 0.367, p-value ~ 0
Fear	0.060514	0.064185	0.126408	0.114596	D ~ 0.053, p-value ~ 0.004

Table S6: Statistics and K-S tests for HLT news and LHF news based on Bayes.

	Mean		Std		K-S test
	T (8836)	F (22065)	T	F	
Anger	**0.257017**	**0.32336**	**0.124972**	**0.101632**	**D ~ 0.334, p-value ~ 0**
Disgust	0.206955	0.16109	0.095054	0.081381	D ~ 0.315, p-value ~ 0
Joy	**0.25383**	**0.163993**	**0.13615**	**0.103545**	**D ~ 0.389, p-value ~ 0**
Sadness	0.222754	0.304678	0.122226	0.128804	D ~ 0.368, p-value ~ 0
Fear	0.059445	0.046879	0.125032	0.103895	D ~ 0.034, p-value ~ 0

Table S7: Statistics and K-S tests for T news and F news based on Bayes.

	Mean		Std		K-S test
	L (23215)	H (7686)	L	H	
Anger	**0.302948**	**0.308743**	**0.107285**	**0.12818**	**D ~ 0.095, p-value ~ 0**
Disgust	0.174278	0.173983	0.085508	0.095092	D ~ 0.058, p-value ~ 0
Joy	**0.194394**	**0.175448**	**0.118335**	**0.127085**	**D ~ 0.112, p-value ~ 0**
Sadness	0.283035	0.275866	0.131581	0.134087	D ~ 0.111, p-value ~ 0
Fear	0.045345	0.065959	0.10502	0.124328	D ~ 0.093, p-value ~ 0

Table S8: Statistics and K-S tests for L news and H news based on Bayes.

	Mean		Std		K-S test
	HLT (2607)	LHF (893)	HLT	LHF	
Anger	**0.061185**	**0.296197**	**0.154826**	**0.350258**	**D ~ 0.436, p-value ~ 0**
Disgust	0.095284	0.104351	0.164124	0.10821	D ~ 0.288, p-value ~ 0
Joy	**0.552737**	**0.209983**	**0.414815**	**0.301277**	**D ~ 0.399, p-value ~ 0**
Sadness	0.178144	0.226401	0.299973	0.312545	D ~ 0.131, p-value ~ 0
Fear	0.112649	0.163068	0.256806	0.266463	D ~ 0.216, p-value ~ 0

Table S9: Statistics and K-S tests for HLT news and LHF news based on BP1.

	Mean		Std		K-S test
	T (3692)	F (15000)	T	F	
Anger	**0.060797**	**0.142411**	**0.153548**	**0.262294**	**D ~ 0.262, p-value ~ 0**
Disgust	0.092621	0.079041	0.161604	0.102752	D ~ 0.189, p-value ~ 0
Joy	**0.559246**	**0.343842**	**0.413631**	**0.339062**	**D ~ 0.367, p-value ~ 0**
Sadness	0.176255	0.214104	0.299774	0.303651	D ~ 0.124, p-value ~ 0
Fear	0.111082	0.220601	0.25587	0.292651	D ~ 0.359, p-value ~ 0

Table S10: Statistics and K-S tests for T news and F news based on BP1.

	Mean		Std		K-S test
	L (14098)	H (4594)	L	H	
Anger	**0.098229**	**0.212406**	**0.217867**	**0.303962**	**D ~ 0.260, p-value ~ 0**
Disgust	0.073238	0.107763	0.107646	0.138275	D ~ 0.190, p-value ~ 0
Joy	**0.417254**	**0.291668**	**0.360852**	**0.36234**	**D ~ 0.238, p-value ~ 0**
Sadness	0.196246	0.238491	0.293552	0.329259	D ~ 0.069, p-value ~ 0
Fear	0.215033	0.149672	0.29317	0.27021	D ~ 0.225, p-value ~ 0

Table S11: Statistics and K-S tests for L news and H news based on BP1.

between fake news and true news, a new measure in the level of text is presented to represent the emotion distribution through ranks. Specifically, for each text of news, a batch of models will be employed separately to infer the probabilities belonging to five emotions and according to these probabilities all five emotions can be ranked, in which lower ranking values stand for higher probabilities of texts belonging to the corresponding emotions. Note that for emotions with the same probability will be ranked randomly. By aggregating ranks of a certain emotion over all models, a distribution of rank can be obtained for the emotion in each text. Then for each group of news, the distributions of five emotions can be obtained by averaging rank distributions of corresponding emotions in all texts.

First, through a word2vec (*48*) model that inferred on over 560 million tweets of Weibo, each term will be embedded into a vector of 200 dimensions. Then a text of news can be further converted into a vector of 200 dimensions in terms of averaging embeddings of all terms in the text. In order to increase the number of inference models of emotions, another six emotion classifiers are further constructed on the emotion lexicon, including AdaBoost, Decision Tree, Logistic Regression, Ridge Classifier, SVM, and Back-propagation Neural Network (BP2) [4]. To be specific, terms with emotional labels in the emotion lexicon are embedded first to train these models then emotions of a text of news in the same embedding space can be accordingly inferred. The accuracies of these newly trained models in 5 folds cross validations are successively 0.67, 0.73, 0.79, 0.76, 0.75 and 0.86. From the results of rank distributions, ranks of anger in LHF news, F news and H news are significantly lower than that in HLT news, T news and L news (Figure S8A, B, C), while the ranks of joy are on the contrary (Figure S8G, H, I). Note that lower ranks mean higher probabilities belonging to the corresponding emotions. This is consistent with all the previous results, indicating that the divergence on anger and joy between fake news and real news is robust and independent to emotion inference models and emotion

[4]The models of classical machine learning are built with scikit-learn and BP2 was built with PyTorch.

	Mean		Std		K-S test
	HLT (2436)	LHF (879)	HLT	LHF	
Anger	**3.460226**	**2.574137**	**0.678131**	**0.79142**	**D ~ 0.499, p-value ~ 0**
Disgust	3.877445	2.574137	0.540155	0.649136	D ~ 0.106, p-value ~ 0
Joy	**2.567116**	**3.489314**	**1.113701**	**1.035653**	**D ~ 0.400, p-value ~ 0**
Sadness	2.776523	2.931249	0.516753	0.701081	D ~ 0.201, p-value ~ 0
Fear	3.727724	3.612004	0.915611	1.06055	D ~ 0.108, p-value ~ 0

Table S12: Statistics and K-S tests for the rank distributions of HLT news and LHF news.

distribution measures. However, the differences of other negative emotions across news groups, though significant, are inconsistent and vary confusedly. The ranks of sadness in LHF news, F news and H news are significantly higher than that in HLT news, T news and L news (Figure S8J, K, L), which is inconsistent with the previous results about sadness from the occupations (see Figure 1in the main text). The ranks of disgust fluctuate inconsistently across different assembles of news groups. Though the rank of fear in LHF news is significantly lower than that in HLT news as the rank is smaller than 4, it conversely becomes higher than that of HLT as the rank is 5. (Figure S8M). Because of this, in the following causal inference of impact from emotions on circulation, other negative emptions will no longer be separately considered.

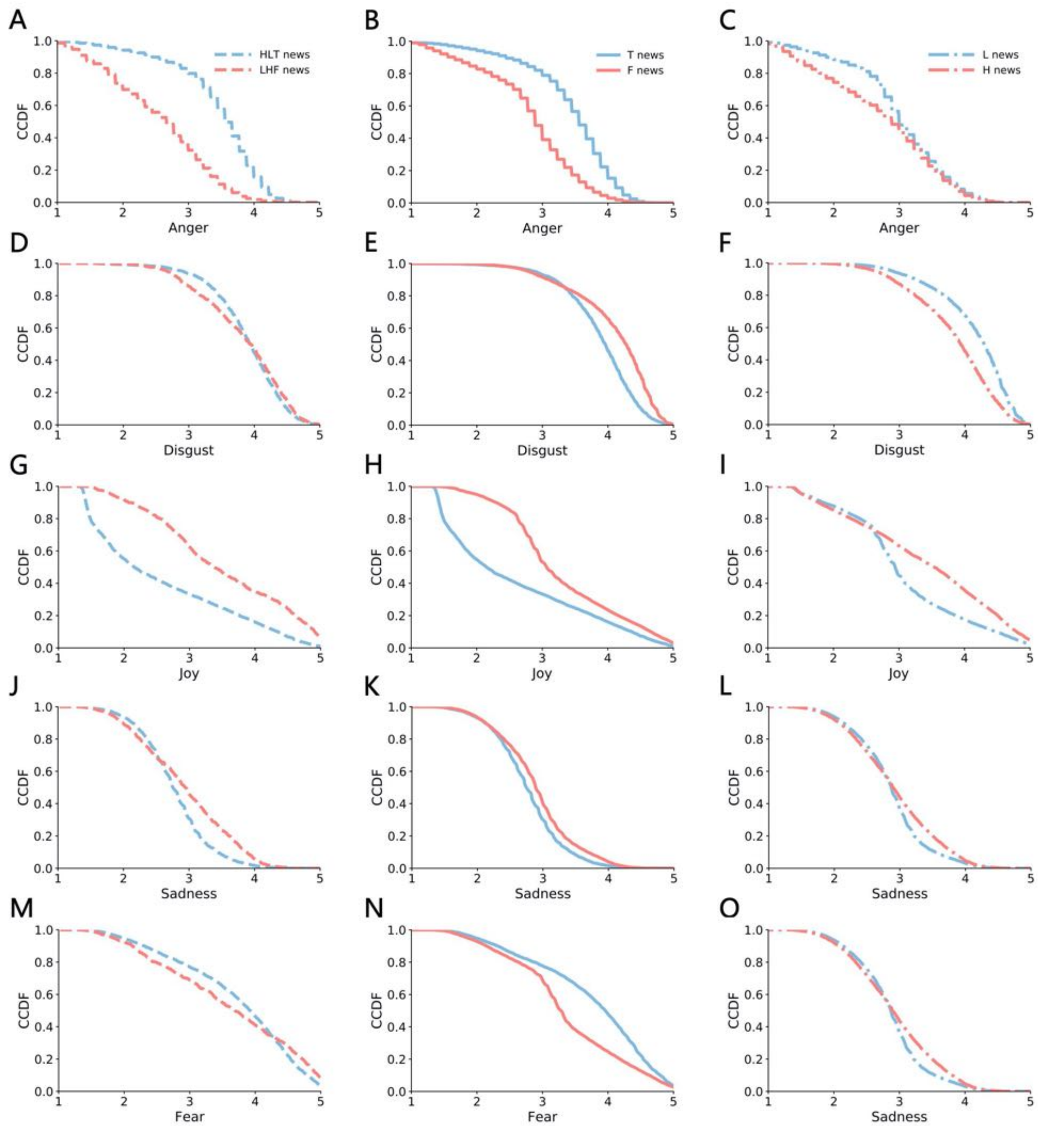

Figure S8: CCDFs of emotional ranks in HLT news and LHF news, T news and F news, L news and H news. (A, B, C) Anger (D, E, F) Disgust (G, H, I) Joy (J, K, L) Sadness (M, N, O) Fear. The results of K-S tests for them are shown in Table 12-14.

	Mean		Std		K-S test
	T (3476)	F (14589)	T	F	
Anger	**3.442622**	**2.82039**	**0.685257**	**0.746122**	**D ~ 0.429, p-value ~ 0**
Disgust	3.883473	4.087925	0.547386	0.630079	D ~ 0.260, p-value ~ 0
Joy	**2.567956**	**3.296035**	**1.12176**	**0.87241**	**D ~ 0.442, p-value ~ 0**
Sadness	2.765095	2.893998	0.520543	0.579022	D ~ 0.142, p-value ~ 0
Fear	3.747426	3.357023	0.911518	0.874507	D ~ 0.285, p-value ~ 0

Table S13: Statistics and K-S tests for the rank distributions of T news and F news.

	Mean		Std		K-S test
	L (13597)	H (4468)	L	H	
Anger	**3.00335**	**2.747687**	**0.724269**	**0.883641**	**D ~ 0.181, p-value ~ 0**
Disgust	4.124329	3.818081	0.593661	0.642307	D ~ 0.246, p-value ~ 0
Joy	**3.072798**	**3.408962**	**0.908621**	**1.095298**	**D ~ 0.237, p-value ~ 0**
Sadness	2.853962	2.915554	0.542974	0.644931	D ~ 0.122, p-value ~ 0
Fear	3.396054	3.54197	0.858397	0.990407	D ~ 0.157, p-value ~ 0

Table S14: Statistics and K-S tests for the rank distributions of L news and H news.

S8 Control variables

Carrying more anger but less joy is significantly associated with the fast spread of fake news. To further examine the causal impact of anger and joy on the circulation of news online, variables that might be correlated with the spread should be comprehensively considered and controlled. Except emotions inferred from texts, other factors from content (*34*), user profiles (*2*) and external shocks like disaster events (*7*) that could also be sensed from the content will be considered and controlled in this study. Note that considering the fast spread of fake news (see S3) and in particular most people do not critically question its credibility (*1*), only variables that can be derived at the very beginning of the posting are considered, while those related to spread structures that usually employed in detection of fake news (*12*) will not be considered due to the ex post facto inference. In addition to variables derived from content, we also introduce the number of followers and the number of friends, i.e., reciprocally followed in Weibo as control variables to further consider the possible impact from user profiles. It should be noted that ages of authors are missed in the user profiles returned by Weibos open API. However, evidence from previous efforts of ages impact on spread is inconsistent (*2, 49*). In the meantime, according to the annual report [5], most of Weibo user ages are concentrated in a narrow range between 18 and 30, meaning impact from ages could be trivial because of context-dependence and thus they can be omitted without significant disturbs to the results.

In total, the following variables will be derived and controlled:

- Mention: Whether the text contains @.
- Hashtag: Whether the text contains hashtag.
- Location: Whether the text contains location information.

[5] https://data.weibo.com/report/index

- Date: Whether the text contains date information.
- URL: Whether the text contains URL.
- Length: The length of the text.
- Emergency: Whether the text content is related to the disaster events. The emergency event in this study refers to the Explosion accident in Tianjin Binhai New Area on August 12, 2015 within the sampling period.
- Topic: The topic discussed in the text.
- Follower: The number of followers of the author.
- Friend: The number of friends of the author.

S8.1 Analysis of binary factors

Table S15 shows the statistics of binary factors including Mention, Hashtag, Location, Date, URL and Emergency. From the perspective of the proportions of all binary factors, Mention and Emergency have impressively high proportions in LHF news followed by H news, suggesting both of them may promote the spread of fake news. Hashtag, Date and URL have higher proportions in true news than that in fake news, implying they may contribute little in the spread of fake news. Meanwhile, although the proportion of Location is relatively high in fake news, it is mainly concentrated in L news, meaning its impact on spread might be trivial. These preliminary analyses could offer directions in examining the causal impact on spread of these factors.

		HLT	HLF	LHF	T	F	L	H	All
Mention	Yes	941	510	293	1388	3346	3276	1458	4734
	No	5856	2942	1033	7448	18719	19939	6228	26167
	P (%)	**13.84**	**14.77**	**22.10**	**15.71**	**15.16**	**14.11**	**18.97**	**15.32**
Hashtag	Yes	1675	353	252	2369	1833	2827	1375	4202
	No	5122	3099	1074	6467	20232	20388	6311	26699
	P (%)	**24.64**	**10.23**	**19.00**	**26.81**	**8.31**	**12.18**	**17.89**	**13.60**
Location	Yes	1249	794	270	1524	4614	4917	1221	6138
	No	5548	2658	1056	7312	17451	18298	6465	24763
	P (%)	**18.38**	**23.00**	**20.36**	**17.25**	**20.91**	**21.18**	**15.89**	**19.86**
Date	Yes	3670	1085	504	4661	5791	7215	3237	10452
	No	3127	2367	822	4175	16274	16000	4449	20449
	P (%)	**53.99**	**31.43**	**38.01**	**52.75**	**26.25**	**31.08**	**42.12**	**33.82**
URL	Yes	3744	853	212	4693	5364	8353	1704	10057
	No	3053	2599	1114	4143	16701	14862	5982	20844
	P (%)	**55.08**	**24.71**	**15.99**	**53.11**	**24.31**	**35.98**	**22.17**	**32.55**
Emergency	Yes	2	82	180	3	663	404	262	666
	No	6795	3370	1146	8833	21402	22811	7424	30235
	P (%)	**0.03**	**2.38**	**13.57**	**0.03**	**3.00**	**1.74**	**3.41**	**2.16**
Total		6797	3452	1326	8836	22065	23215	7686	30901

Table S15: Statistics of binary factors.

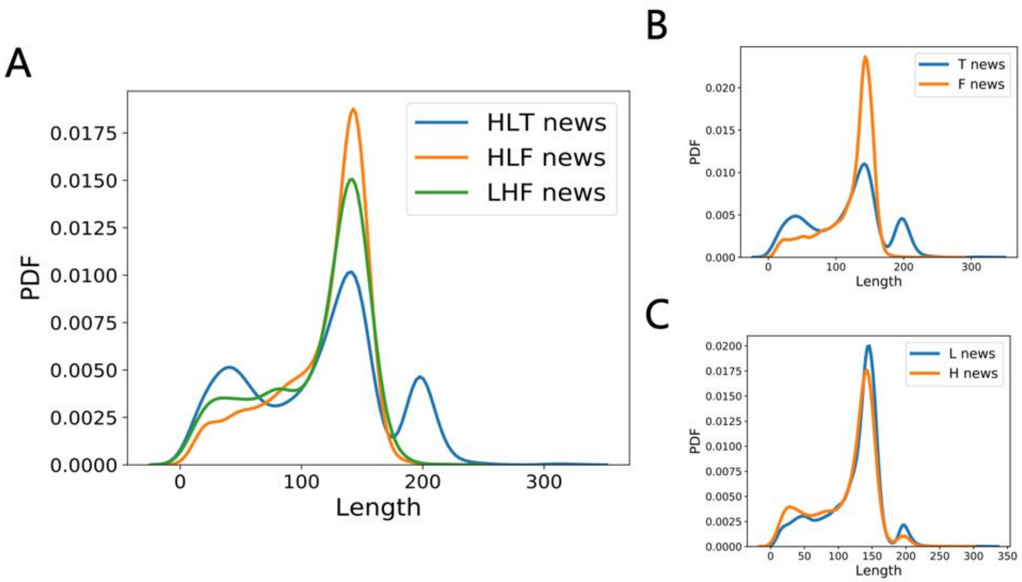

Figure S9: Probability distribution functions (PDFs) of Length.

S8.2 Analysis of Length

We calculated the length distribution of the text, in which the length refers to the number of characters and letters. It is found that the length of LHF news is more concentratedly distributed than that of HLT news (K-S test ~ 0.145, p-value ~ 0) (Figure S9A), which is also significant in fake news and true news (K-S test ~ 0.134, p-value ~ 0) (Figure S9B). Therefore, fake news may be more deliberate and planned in the linguistic organization, while real news is more casually narrated. However, the text length is more concentrated in HLF news (compared with LHF news, K-S test ~ 0.073, p-value ~ 0) (Figure S9A) and L news (compared with H news, K-S test ~ 0.095, p-value ~ 0) (Figure S9C), indicating that this factor might function little in promoting the spread of false news.

S8.3 Analysis of Topic

The topics discussed in the news are also important features of the text. We used the topic classifier (*50*) based on Nave Bayesian to analyze the topic distributions of different types of news. The classifier was trained on more than 410,000 Weibo tweets and group them into seven categories that fit well with the news taxonomy of Weibo, including entertainment, finance, international, military, society, sports and technology. Both of its accuracy and F-measure are more than 0.84, assuring its competent performance in topic classifications. Besides, incremental training in this classifier can also help solve the problem of new words. The news cant be split into above seven categories is omitted in related analysis. As shown in Figure S10, there are also significant differences in the distribution of topics among different groups of news. Specifically, the topic of Society accounts for the largest proportion in HLF news, LHF news and F news. suggesting that fake news mainly focuses on social issues closely related to peoples daily lives. Hot social topics would make fake news more likely to breed, but this does not necessarily make fake news widely spread, because H news proportion of Society topic is lower than that of L news.

Through the analysis of above 8 variables derived from content, the differences between true and fake news on these factors are primarily examined, but many of them may not promote the spread of fake news. There are two factors, Mention and Emergency, which may play promoting roles in the spread of fake news, however, they only occupy small proportions in all news, which might undermine their effect on the fast circulation.

S8.4 Analysis of variables from authors

We also examine the variables from author profiles preliminarily. It is interesting that whether true or fake, the news with more retweets were posted by authors with more followers (Figure S11) and friends (Figure S12). However, more followers and friends in true news (compared with fake news) suggest that both factors might be not the key factors making fake news more viral than the true online. By controlling all these variables, we will establish logit and linear models further to examine the causal impact of anger and joy on the spread of fake news.

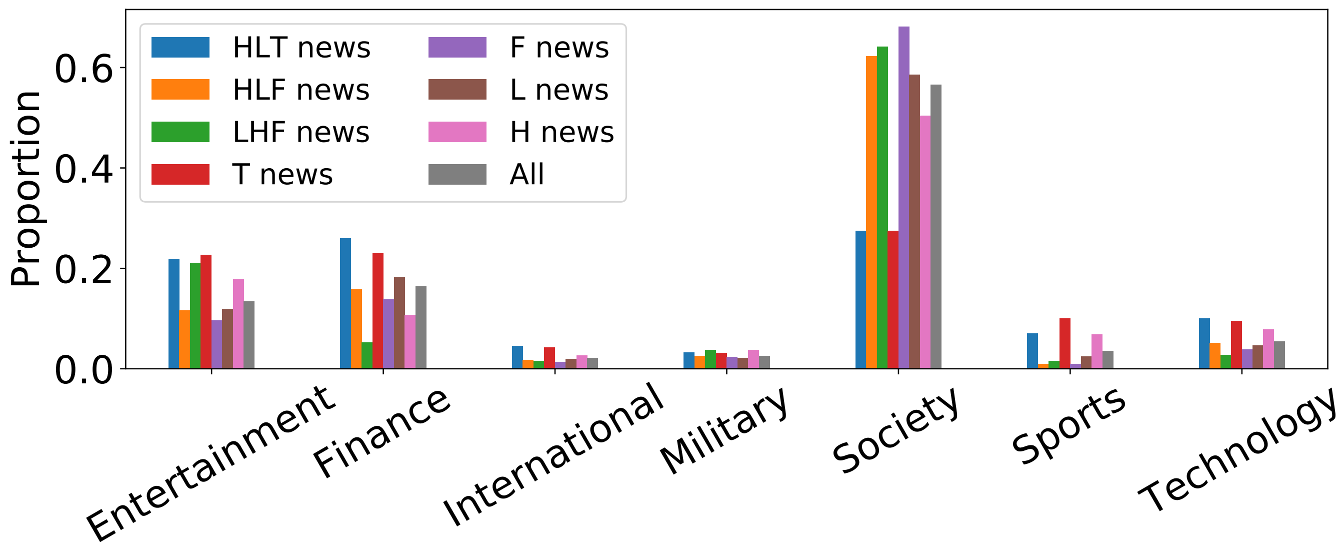

Figure S10: Topic distributions of different groups of news.

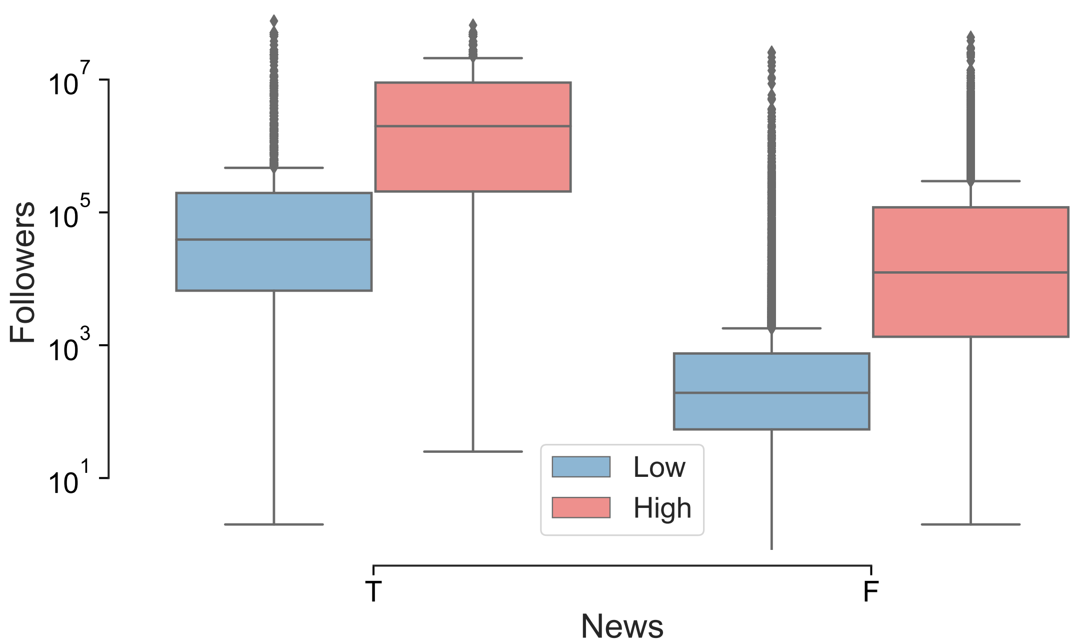

Figure S11: The boxplots of followers in true (LT and HT) news and fake (LF and HF) news.

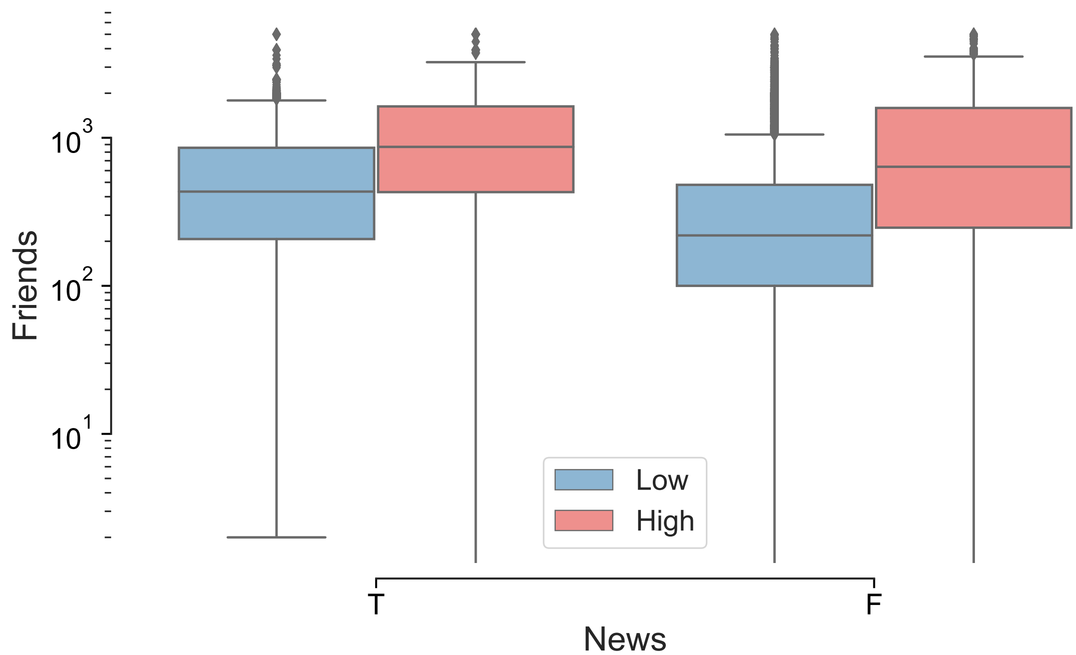

Figure S12: The boxplots of friends in true (LT and HT) news and fake (LF and HF) news.

S9 Logit and linear regression models

In order to causally examine the impact from anger and joy on the spread of fake news, regression models of logit and linear are established. Note that for variables of emotions, with combining the other emotions into Other Emotions, we primarily focused on anger and joy. Note that there is a linear relationship between emotion related variables because the ratios of the five emotions sum to be 1. And all the control variables from content, user profiles and the external shock as presented above will be comprehensively introduced into both models. The logit model is defined as

$$logit\,(p_{fake}) = \beta_0 + \beta_1 v_1 + \beta_2 v_2 + \beta_3 v_3 + \beta_4 v_4 + \beta_5 v_5 + \beta_6 v_6 + \beta_7 v_7 + \beta_8 v_8 + \beta_9 v_9 + \beta_{10} v_{10} + \beta_{11} v_{11} + \beta_{12} v_{12} + \beta_{13} v_{13},$$

where

- p_{fake} is the probability of fake news.
- β_0 is the intercept.
- $\beta_1,\ \beta_2,\ ...,\ \beta_{13}$ are the coefficients of variables.
- $v_1,\ v_2,\ ...,\ v_{13}$ represent Anger, Joy, Other Emotions, Follower, Friend, Mention, Hashtag, Location, Date, URL, Length, Emergency and Topic.
- Mention, Hashtag, Location, Date, URL, Emergency and Topic are virtual variable.

Emotion variables that derived from emotion distributions in logit model are calculated respectively on all methods including emotion lexicon, Bayes and BP1. The results of the model based on the emotion lexicon are shown in Table 1 of the main text. We hereby supplement the estimation results for the remaining two methods (Table S16). From all results, the coefficients of anger are uniformly and significantly positive after controlling all other variables, indicating that the anger is causally associated with fake news, in particular those of highly retweeted. While the significance of negative coefficients of joy in all results, especially on groups of HF news and H news, surprisingly indicates its prevention on the spread, in particular that of fake news. The coefficients of Emergency and Military and the topic of Society are significantly positive, while the coefficients of Mention are positive but insignificant (Table 1 in the main text and Table S16), which is consistent with our analysis in S8.

Then a linear regression model is established to further qualify the influence from anger and joy on the spread of fake news. The model is defined as

$reg\left(Num_{retweet}\right) = \beta_0 + \beta_1 v_1 + \beta_2 v_2 + \beta_3 v_3 + \beta_4 v_4 + \beta_5 v_5 + \beta_6 v_6 + \beta_7 v_7 + \beta_8 v_8 + \beta_9 v_9 + \beta_{10} v_{10} + \beta_{11} v_{11} + \beta_{12} v_{12} + \beta_{13} v_{13}$,

where

- The dependent variable $Num_{retweet}$ is the number of retweets within 48 hours of news release. Note that over 70% retweets of fake news and 80% retweets of real news were obtained within 48 hours after the posting (see S3). And other settings, e.g., longer than 48 hours do not influence the results.

- The independent variables are consistent with the explanatory variables of the logit model.

We first estimate the linear model on false news and then for all news neglecting labels of true or fake, the results can be found in Table 1 (3, 4) of the main text, in which the emotion distributions are inferred through the method based on the emotion lexicon. we also apply the linear model on emotion distributions from other two methods and the consistent results can be found in Table S16 (3, 6). Specifically, the positive coefficient of Anger causally indicates its promotions on the spread, while the negative coefficients suggest joys preventions on the circulation of fake news. It is also interesting that coefficients of Emergency, Military topic and Social topic are significantly positive, implying their boosting roles in information spread.

Variables		Bayes			BP1		
		Fake		Retweet	Fake		Retweet
		(1)	(2)	(3)	(4)	(5)	(6)
Anger		**2.809***** **(0.230)**	**2.834***** **(0.176)**	**36.203***** **(13.766)**	**2.450***** **(0.175)**	**1.933***** **(0.144)**	**27.283***** **(7.364)**
Joy		**-4.678***** **(0.235)**	**-4.266***** **(0.174)**	**-103.948***** **(12.597)**	**-1.306***** **(0.098)**	**-1.245***** **(0.071)**	**-31.191***** **(3.906)**
Others		0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)
Follower		-5.84e-08*** (9.25e-09)	-3.07e-07*** (1.60e-08)	0.00001*** (6.57e-07)	-8.63e-08*** (1.58e-08)	-3.78e-07*** (2.31e-08)	0.00001*** (8.68e-07)
Friend		0.0008*** (0.00003)	0.00005* (0.00003)	0.041*** (0.002)	0.0007*** (0.00005)	-0.00008** (0.00003)	0.045** (0.003)
Mention		0.069 (0.061)	-0.161*** (0.046)	18.374*** (3.390)	-0.023 (0.091)	-0.431*** (0.069)	22.585*** (4.690)
Hashtag		-1.240*** (0.067)	-1.560*** (0.048)	-2.510 (3.610)	-1.161*** (0.096)	-1.622*** (0.069)	-0.821 (5.086)
Location		-0.397*** (0.063)	-0.433*** (0.044)	-8.549*** (2.504)	-0.312*** (0.093)	-0.563*** (0.065)	0.859 (3.550)
Date		-0.661*** (0.051)	-1.324*** (0.036)	2.310 (2.611)	-0.647*** (0.074)	-1.326*** (0.054)	3.529 (3.741)
URL		-2.272*** (0.057)	-1.580*** (0.035)	-26.224*** (2.076)	-2.035*** (0.084)	-1.563*** (0.055)	-15.181*** (2.787)
Length		-0.007*** (0.0005)	0.009*** (0.0004)	-0.195*** (0.029)	0.006*** (0.001)	0.010*** (0.0007)	-0.282*** (0.049)
Emergency		5.418*** (0.721)	4.793*** (0.584)	-25.962*** (6.470)	5.169*** (0.733)	4.536*** (0.592)	-24.301*** (7.287)
Topic	Finance	-1.129*** (0.084)	-0.475*** (0.056)	-27.532*** (4.395)	-0.249* (0.132)	0.607*** (0.085)	-13.402** (5.840)
	International	-0.952*** (0.142)	-1.012*** (0.110)	-1.902 (10.466)	0.205 (0.209)	-0.179 (0.164)	32.082* (17.156)
	Military	0.252* (0.134)	0.263** (0.104)	13.958 (10.264)	1.550*** (0.203)	1.228*** (0.163)	40.708*** (14.566)
	Society	0.242*** (0.069)	0.726*** (0.051)	-26.640*** (4.160)	1.307*** (0.097)	1.821*** (0.071)	-2.845 (5.237)
	Sports	-0.855*** (0.121)	-1.422*** (0.099)	52.292*** (10.198)	-0.926*** (0.190)	-1.503*** (0.150)	55.398*** (13.741)
	Technology	0.106 (0.091)	-0.198*** (0.070)	-7.469 (5.745)	0.568 (0.139)	0.205* (0.109)	-10.068 (7.304)
Cons		0.065 (0.120)	1.278*** (0.091)	75.999*** (7.639)	-0.294** (0.139)	1.091*** (0.106)	62.778*** (8.469)
R^2		0.353	0.360	0.123	0.395	0.410	0.135
N		13063	30816	30816	6382	18654	18654

Table S16: (1,4) The logit model for LT news and HF news. (2,5) The logit model for T news and F news. (3,6) The linear model for L news and H news. $*P < 0.1, **P < 0.05, ***P < 0.01$.

S10 Selecting typical news for questionnaires

Emotions of high arousal like anger and joy are found to be profoundly associated with information diffusion in particular information sharing (*21*). In order to further investigate how anger and joy that carried in news influence incentives underlying the retweeting, which reignites the circulation of news on social media, offline questionnaires are conducted further to bind the emotion divergence between fake news and real news with retweeting incentives beyond their disseminations in this study. Due to the consuming and intensive labor costs, it is indeed challenging for the questionnaires to cover all the fake news and true news in our data. Therefore, five typical news from groups of HLT news, LHF news and HLF news are respectively selected to perform the surveys. Similarly, in terms of news in these groups, the possible stimuli from emotions like anger and joy to the retweeting incentives is hoped to be amplified to ease the following detection. In order to guarantee the selection of news samples from each group is representative, each group of news is clustered into clusters before the sampling. Firstly, we use the word2vec model to convert words in each news into vectors of 200 dimensions and take the mean of these word vectors to represent the news, i.e., the news is similarly embedded to a space of 200 dimensions. Then K-Means is employed to cluster each group of news into five clusters. Next, with the principle trying to include keywords with high importance in each news (see S6), as well as intrinsic factors such as Mention and Hashtag in each group (S8), representative texts are sampled from those near the cluster centers. Note that we do not deliberately consider emotion distributions in the selection to avoid the impact of subjective bias on subsequent incentive stimuli and ensure the objectivity of the results. Finally, we select 15 typical news (Table 17-20) and their positions in the group can be found in Figure S13, as can be seen, sampled texts and keywords in these texts distribute evenly in the embedding space of different groups of news, suggesting they are indeed typical and representative. It should be noted that

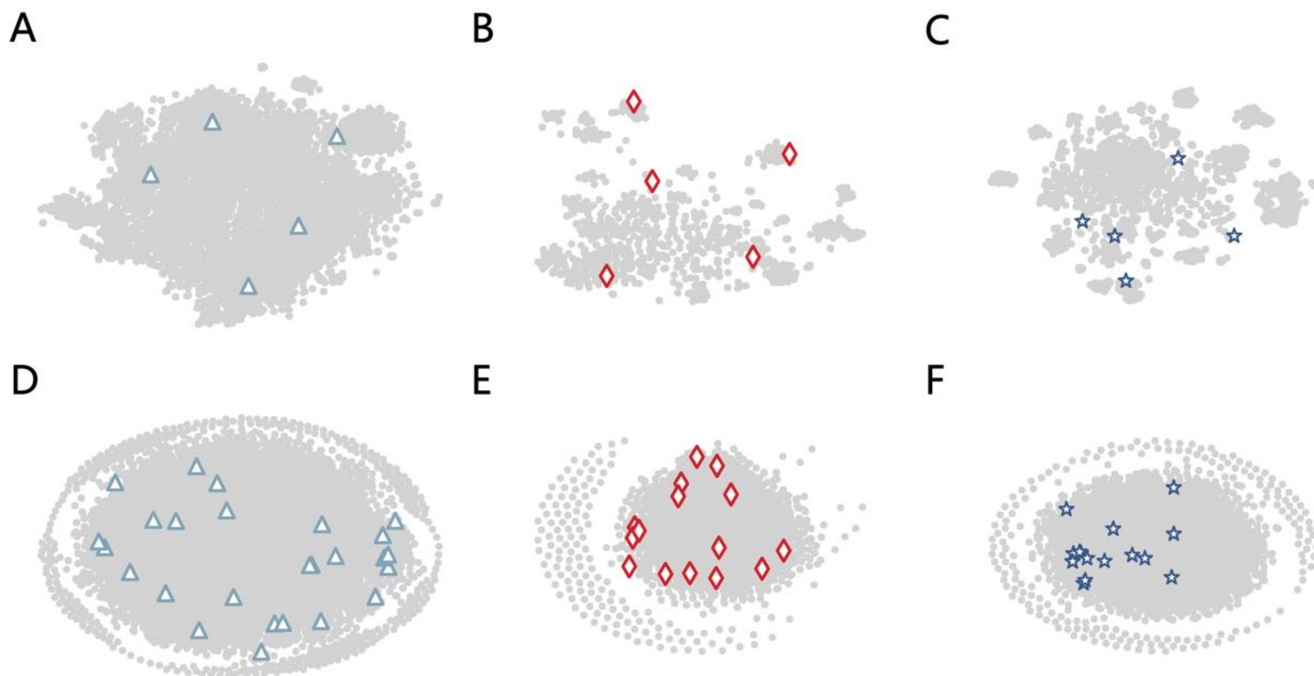

Figure S13: Positions of sampled texts and keywords in the embedding space. (A) Text in HLT news. (B) Text in LHF news. (C) Text in HLF news. (D) Keywords in HLT news. (E) Keywords in LHF news. (F) Keywords in HLF news.

selected keywords that help well separate the groups of news in sampling the texts are anticipated to help strengthen the stimuli on reposting incentives, which would further enhance the impact from anger and joy.

News1	CN	#西部资源重组媒体说明会#【阙文彬回答媒体提问：**继续**加大稀贵金属**投资**】针对媒体关于**公司**主业方面的提问，西部资源实际控制人阙文彬说，从新能源到**文化**转到稀贵金属，我个人认为新的董事会或者新的经营班子接上后，应该在 2 亿-5 亿的利润差不多，在这个基础上将现有的一些**企业**通过一种合法的途径出售，...**全文**： http://m.weibo.cn/1315587597/4010238174942685
	EN	# Western Resources Reorganization Media Briefing # [Wenbin Que Answers Media Questions: **Continue** to Increase **Investment** in Rare and Precious Metals] In response to media questions about the **company's** main business, Wenbin Que, the actual controller of Western Resources, said that from new energy to **culture** to rare and precious metals, I personally think that after the new board or new management team is connected, it should have a profit of about 200 million to 500 million. On this basis, some existing **enterprises** will be sold through a legal way, ... **Full text**: http://m.weibo.cn/1315587597/4010238174942685
News2	CN	#聚焦赣州#【[心]爸妈在哪里？崇义文昌塔旁**发现**的小男孩至今还在福利院】8 月 17 日，一则“崇义县横水派出所**民警**在文昌塔附近一脐橙园树下，**发现**一名哭泣的小男孩至今无人认领”的消息，在微信朋友圈广泛**转发**，文章中还附有几张小男孩的照片。当日下午，**记者**了解到，**目前**小男孩经医院检查无碍后已被送往...**全文**： http://m.weibo.cn/1970239225/4009774025014136
	EN	# Focus Ganzhou # [[heart] Where are the parents? The little boy **found** next to Wenchang Pagoda in Chongyi is still in the welfare home] On August 17th, a **policeman** from the Hengshui Police Station in Chongyi County **found** a crying little boy under a navel orange tree near Wenchang Pagoda. The "claim" message was widely **reposted** in WeChat Moments, and there are several pictures of the little boy in the article. In the afternoon of the same day, the **reporter** learned that the little boy was sent to the hospital after being checked by the hospital ... **Full text**: http://m.weibo.cn/1970239225/4009774025014136
News3	CN	#鹤壁身边事# 【淇滨区兰苑**社区**刘振强：带爸妈旅行，**收获**满满的**幸福**】“我父亲一直想出门走走，特别想去北京看一看。我以前没有在意，感觉父母还年轻，以后有的是**机会**。直到父亲生了**一场**大病，需要借助轮椅出行，我才感到了**后悔**，**幸好**还来得及**补救**。”8 月 16 日，淇滨区兰苑**社区**的刘振强告诉**记者**，最近他...**全文**：http://m.weibo.cn/2514256341/4009491428875467
	EN	# Things around Hebi # [Zhenqiang Liu, Lanyuan Community, Qibin **District**: Take my parents to travel and **reap** the full **happiness**] "My father always wanted to go out for a walk, especially to go to Beijing to take a look. I didn't care before, I feel my parents are still young, There will be **opportunities** in the future. It was not until my father had a serious illness that I needed to use a wheelchair to travel. I **regretted** it. **Fortunately**, I had time to **remedy** it. "On August 16, Zhenqiang Liu of Lanyuan Community in Qibin **District** told **reporters** that he recently ... **Full text**: http://m.weibo.cn/2514256341/4009491428875467

Table S17: HLT-News1-3 selected in HLT news. Keywords are highlighted in red.

News4	CN	#里约**奥运会**# 【“不懂球的胖纸”辛苦啦[威武]】那位中国乒乓天团背后的胖子[偷笑]，对！刘国梁，绝对是个全能多面手。**魔鬼**训练队员，提供呐喊、**助威**、唤醒**服务**，送水送毛巾，**么么哒**队员[亲亲]，还得亲自煮面**犒赏**三军......于是中国连续三届**奥运**拿下乒乓全部**金牌**[奥运金牌]。有网友说：“又当爹又当妈...全文： http://m.weibo.cn/1891503444/4009944795388322
	EN	# Rio **Olympics** # ["Fat paper that doesn't know the ball" is hard [powerful]] The fat man behind the Chinese table tennis team [sneers], yes! Guoliang Liu is definitely an all-rounder. The **devil** trains the team members, provides shouting, **cheering**, wake-up **services**, water and towels, **kiss** the team members [kiss] and have to cook the noodles to **reward** the three troops ... So China won all the **gold medals** in table tennis for the third consecutive **Olympic** Games [Olympic gold medal]. Some netizens said: "Being a father and being a mother ... full text: http://m.weibo.cn/1891503444/4009944795388322
News5	CN	7 月 12 日**本报**二版为您**呈现**：中国文物保护基金会召开专项基金**工作**座谈会、安徽铜陵全力抢险凤凰山铜矿金牛洞古采矿遗址、国博**举办**《四部医典》曼唐长卷——娘本唐卡**艺术**传承成果展、湖北实施“三级联审”模式，加快推进文物普查数据审核、新疆**举办**第一次全国可移动文物普查培训班、《南海诸岛地理志略》...**全文**： http://m.weibo.cn/1250227403/3997198805156773
	EN	On July 12, the second edition of **the newspaper presented** to you: China Cultural Relics Conservation Foundation held a special fund **work** symposium, Tongling in Anhui made an emergency rescue of the ancient mining site of Jinniu Cave at Fenghuangshan Copper Mine, and Guobo **held** the "Four Medical Books". Ben Thangka Art Inheritance Achievement Exhibition, Hubei implemented a "three-level joint review" model, accelerated the promotion of cultural relics census data review, Xinjiang **held** the first national mobile cultural relics census training class, "South China Sea Geography Strategy" ... **Full text** : http://m.weibo.cn/1250227403/3997198805156773

Table S18: HLT-News4-5 selected in HLT news. Keywords are highlighted in red.

News1	CN	5 月 12 日不要去电影院。请大家一定别进影院，大家一起为**贞子票房**为零，做努力！ 中国人拍的《金陵十三钗》在日本小鬼子**票房**为零。小日本拍的**贞子** 3D 将于 5 月 12 日在中国大陆上映。而 5 月 12 日既是**南京大屠杀**纪念日，又是**国难日**。**勿忘国耻**！作为中国人，敢不敢让贞子 3D 5 月 12 日票房为零。**朋友**们，必须**转起转起**
	EN	Don't go to the cinema on May 12. Please don’t enter the theater. Let’s work hard for Sadako’s box office. The Chinese filmed "Jinling Thirteen Hairpins" at the box office in Japan is zero. Sadako 3D filmed by Little Japan will be released in mainland China on May 12. And May 12 is both the anniversary of the Nanjing Massacre and the national disaster day. Don't forget the national shame! As a Chinese, dare not to make Zhenzi 3D box office zero on May 12. Friends, you must repost repost
News2	CN	#**天津塘沽**大**爆炸**#我不确定文字真实 我只知道我很**感动** 我只知道几批消防队员没有生还 他们奔赴爆炸现场的时候那种无畏 可他们为了人民 真的很伟大 没错我做不了什么 我只能给予他们最真诚的**感谢**[祈祷] 我只是一个刚刚成年的学生 看法自然稚嫩 我只希望人们可以做好自己该做的事 不要被利益地位冲昏头脑
	EN	# Tianjin Tanggu Big Bang # I am not sure the text is true. I only know that I am very moved. I only know that a few batches of firefighters did not survive when they went to the scene of the explosion. They are so fearless. I can give them the most sincere thanks [prayer] I am just a student who has just grown up. The views are natural and immature. I only hope that people can do what they should do and not be blinded by their interests.
News3	CN	**朋友**捡到一个准考证，有认识的通知**一下**：姓名：白娅倩、考点：一中、考场：013、座号：11、准考证号：204101311。联系电话：15935078941。别耽误孩子高考。**帮助**别人手留余香！**谢谢**！@开心消消乐 @Happy 张江 @上海浦东川沙派出所 @互动川沙
	EN	A friend picked up an admission ticket and informed me about it: name: Bai Yaqian, examination center: No. 1 middle school, examination room: 013, seat number: 11, admission ticket number: 204101311. Contact number: 15935078941. Don't delay your child's college entrance examination. Gifts of roses, hand a fragrance! Thank you! @ Happy Xiao-Xiao-Le @Happy Zhang-Jiang @ Shanghai Pudong Chuansha Police Station @ Interactive Chuansha
News4	CN	**爱心**接力：胡云星，女，四岁半，运城人。救救她，她患有罕见的“布加氏综合征”对激素已经产生抗体，体重不断上升，每天不停地重复一句话：妈妈，疼!希望大家帮帮她，多一个人**转发**多一份力量，@韩红**爱心**慈善基金会 @365 儿童救助**爱心**基金
	EN	Love Relay: Yunxing Hu, female, 4 and a half years old, from Yuncheng. Save her, she suffers from a rare "Bugat's syndrome" that has produced antibodies to hormones, and her weight continues to rise. She repeats a sentence every day: Mom, hurt! I hope everyone can help her, one more person forwards more power. @Han Hong Caring Charity Foundation @365 Child Rescue Caring Fund
News5	CN	今天下午六点开始，全市高清探头全部启用，副驾驶不系安全带相同处罚，开车时打电话**罚款** 50 元，闯黄闪**罚款** 200，越线停车**罚款** 100，今天起晚六点至深夜 2 点，为期 60 天的全国交警集中查处酒驾，一经查获，一律拘役六个月，五年内不得考证。请相互**转告**至有车的本人、**朋友**及亲属，避免罚款
	EN	Starting at 6 o'clock this afternoon, the city's high-definition probes were all activated. The co-pilot did not wear seat belts and the same penalties. When driving, he was fined 50 yuan for calling, 200 for yellow flashes, and 100 for parking over the line. The 60-day national traffic police centrally investigates and deals with drunk driving. Once seized, they will be detained for six months in total, and no testimony is allowed within five years. Please tell each other to the car owner, friends and relatives to avoid fines

Table S19: LHF-News1-5 selected in LHF news. Keywords are highlighted in red.

News1	CN	**紧急**通知： 妇幼保健院通知、：现在得白血病的小孩越来越多，妇幼保健院提示您，请不要给宝宝喝**爽歪歪**和有**添加剂**的**牛奶**饮料，告诉家里有小孩的朋友，**旺仔**牛奶、可口可乐、**爽歪歪**、**娃哈哈** AD **钙奶**、未来星、Q 星、美汁源果粒**奶优**的。都含有**肉毒杆菌**。现在紧急**召回**。有孩子的都转下！！！ 没娃转转！！！
	EN	**Urgent** notice: The Maternal and Child Health Hospital notices: There are more and more children with leukemia. The Maternal and Child Health Hospital reminds you, please don't give your baby **Shuang Wai Wai** and **milk** drinks with **additives**. **Wang Zai** milk, Coca-Cola, **Shuang Wai Wai**, **Wahaha** AD **Calcium Milk**, Future Star, Q Star, Mei Ju Yuan **Fruit Milk**. Both contain **botulinum**. Now an emergency **recall**. Anyone with a child turns down ! ! ! People without baby repost ! ! !
News2	CN	看，**安利**老板死了！才 56 岁，吃了 27 年的纽崔莱，好讽刺啊。再看！**安利**成冠 3S 系统创始人陈观田因肝癌 56 岁去世，干了 27 年安利，27 年纽崔莱，为美国人赚了 27 年钱。请再看，**安利**大师超凡创办人王慈官《远离贫穷》的作者，在福州逝世. 天天吃安利保健品享年 61 岁。
	EN	See, **Amway** boss is dead! Just 56 years old, eating Nutrilite for 27 years, so ironic. Look again! **Amway** Chengguan, the founder of the 3S system, Guantian Chen, died of liver cancer at the age of 56 and worked for 27 years in Amway and 27 years in Nutrilite, making 27 years of money for Americans. Please look again, the author of "Away from Poverty", the founder of **Amway** Master Ciguan Wang, died in Fuzhou. He eats Amway health care products every day at the age of 61.
News3	CN	在宁波已发现中国国内第一起埃博拉，此疾病基本死亡率 90%。流入中国时间比专家预估时间早十天。大家务必提醒孩子和家人随时肥皂洗手，不吃街边摊和露天食物，买回家的成品食物务必煮开食用，防范在先！切记此次埃博拉极可能发展为比 SARS 更可怕的**瘟疫**。大家注意卫生，保重！[脸红]
	EN	The first Ebola in China has been discovered in Ningbo, with a basic mortality rate of 90%. The time of inflow into China is ten days earlier than the time estimated by experts. Everyone must remind children and their families to wash their hands with soap at any time, do not eat street stalls and open-air food, and buy the finished food home to boil and eat, precautions! Remember this time Ebola is likely to develop into a more terrible **plague** than SARS. Pay attention to hygiene and take care! [blush]
News4	CN	**小女孩**死于用完没有收好的手机**充电器**，她将**充电器**的一端放进嘴里，触电身亡，女孩父母悔恨不已，主动站起来**警示**大家！请不要让**悲剧**重复！
	EN	The **little girl** died after using up the uncharged mobile phone **charger**. She put one end of the **charger** into her mouth and was electrocuted. The girl 's parents regretted it and stood up to **warn** everyone! Please don't let the **tragedy** repeat!
News5	CN	【可恶！**骆驼**被砍四肢当街行乞】**骆驼**一般只在**动物**园才能见到，但近日，人们却在福州街头见到一只乞讨的**骆驼**。**骆驼**身旁有两位衣衫褴褛的人跪在地上磕头乞讨。民警发现，**骆驼**的四肢均有不同程度的损伤，四肢均无蹄子，据伤口观测有很大可能是人为造成。警方已协调相关部门处理
	EN	[hateful! **Camels** were cut off and limbs were beg on the street] **Camels** are generally only seen in **zoos**, but recently, people have seen a begging **camel** on the streets of Fuzhou. There were two rags beside the **camel** kneeling on the ground and begging. The police found that the **camel's** limbs were all injured to varying degrees, and all limbs had no hooves. According to the wound observation, it is likely to be caused by man. The police have coordinated with relevant departments

Table S20: HLF-News1-5 selected news from HLF news. Keywords are highlighted in red.

S11 Questionnaires

We employ a carefully designed questionnaire that pervasively used for the rumor sharing motivations survey on social media (*37*), which comprehensively measures four motivations of the subjects, including anxiety management, information sharing, relationship management and self enhancement. Among them, there are 6 items for anxiety management (Figure S14), 6 items for information sharing (Figure S15), 5 items for relationship management (Figure S16) and 4 items for self enhancement (Figure S17). Each item is measured on a four-point scale (1-strongly disagree, 2-disagree, 3-agree, 4-strongly agree). There are 6 questionnaires in total. For each group of news, we implement two online questionnaires, one showing the original text and one showing the text with keywords marked in terms of a red squares (Figure S18). Meanwhile, five news of each group appear in each questionnaire randomly. Except for the news presented, all other circumstances in the questionnaires, e.g., author profile, posting time, posting source and etc., are carefully controlled to be consistent. Specifically, the difference in stimuli to the incentives of subjects will only come from the news itself. As for the presentation of the text, we tried our best to simulate the real Weibo interface through adding the background of the mobile version of Weibo App to each news (Figure S18). For those who fill in the questionnaires, we required them to be Weibo users and aged between 18 and 30 (according to the 2018 Weibo user development report, this age group accounts for 75%)[6], matching users in online data as much as possible. Note that here subjects are not specifically targeted due to occupations or income-levels, because we anticipate to probe the general effect from emotion divergency on the retweeting incentives on the majority of Weibo users. More importantly, considering the wide spread of global impact of fake news online, revealing the mechanism that independent to user demographics would be powerful in inspiring new cures.

[6] https://data.weibo.com/report/index

Figure S14: Anxiety Management Motivation (M1).

Figure S15: Information Sharing Motivation (M2).

Figure S16: Relationship Management Motivation (M3).

Figure S17: Self Enhancement Motivation (M4).

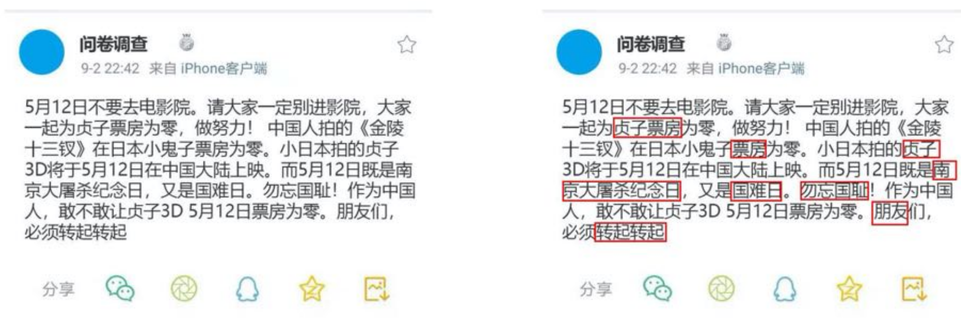

Figure S18: Questionnaire examples of original text (left) and text with marked keywords (right).

	M1	M2	M3	M4	N
LHF-Q1	0.775	0.718	0.771	0.768	210
LHF-Q2	0.774	0.682	0.794	0.732	212
HLF-Q1	0.787	0.706	0.799	0.721	211
HLF-Q2	0.759	0.714	0.773	0.768	210
HLT-Q1	0.702	0.562	0.714	0.695	224
HLT-Q2	0.744	0.642	0.777	0.724	214

Table S21: The values of Cronbach's alpha in different questionnaires.

S12 Questionnaire results

Through hiring a well-reputed company in online surveys , we collected in total 1291 valid responses from 1316 subjects within China. Specifically, we obtained 224 responses to the unmarked HLT news questionnaire (HLT-Q1), 214 responses to the marked HLT news questionnaire (HLT-Q2), 210 responses to the unmarked LHF news questionnaire (LHF-Q1), 212 responses to the marked LHF newss questionnaire (LHF-Q2), 211 responses to the unmarked HLF news questionnaire (HLF-Q1) and 210 responses to the marked HLF news questionnaire (HLF-Q2). All the responses are carefully validated and the values of Cronbachs alpha can be found in Table S1. The responses we collected can also be publicly available through https://doi.org/10.6084/m9.figshare.12163569.v1. The values of Cronbach's alpha are shown in Table S21. Since there may be subjective bias, that is, the response degree might vary across different subjects, the following method is accordingly adopted to eliminate the subjective bias:

$$Mi - avg \ = m_i - \frac{m_1 + m_2 + m_3 + m_4}{4}, \ i = 1, 2, 3, 4$$

where m_i is the average score of all the items in motivation Mi and$Mi - avg$ is the debiased average score for Mi.

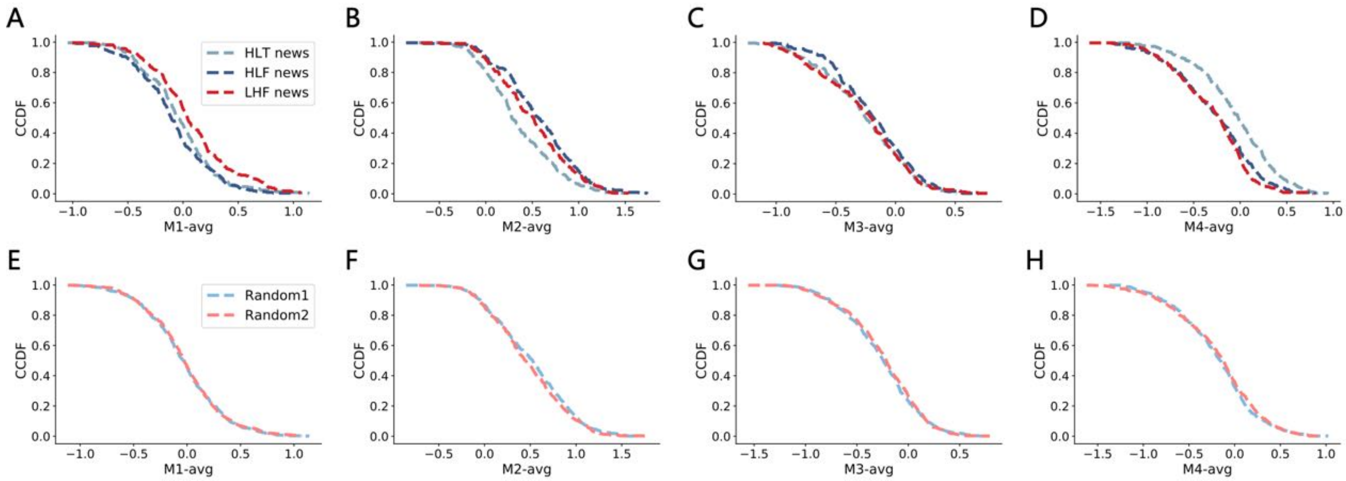

Figure S19: (A to D) CCDFs for the motivations in different groups of news with marked keywords. (E to F) CCDFs for the motivations in the two groups separated randomly.

S12.1 Differences in motivations between different groups of news

It has been shown in the main text that the motivation of information sharing of false news is stronger than that of real news, and the motivation of anxiety management of LHF news is significantly stronger than that of news in both HLF and HLT. For responses with keywords outlined, these differences are still significant and even augmented, and interestingly, the differences between LHF news and the other two groups of news are more significant in M1 (Figure S19A), implying audiences of highly retweeted fake news will be more incentivized on anxiety management. The statistics and K-S tests are shown in Table S22 and Table S23.

S12.2 Differences in motivations between anger and joy

Next, we divide the news in the questionnaires according to emotions it carries with the largest occupations. News1 and News5 in LHF news are dominated by anger. Joy dominates News2 in LHF news, News1, 3, 4, 5 in HLT news. The rest news is dominated by other emotions. From the analysis in S12.1, we found that the marked keywords play a role in widening differences. Hence here we directly combine the responses without keywords and those with keywords

	M1-avg		M2-avg		M3-avg		M4-avg	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
LHF-Q1	0.051052	0.321949	0.520893	0.403365	-0.288472	0.354567	-0.283472	0.436567
LHF-Q2	0.073487	0.380414	0.498801	0.40541	-0.264092	0.384499	-0.308196	0.409732
HLF-Q1	-0.115521	0.378259	0.58906	0.43338	-0.228476	0.382048	-0.245063	0.42301
HLF-Q2	-0.097599	0.347347	0.565893	0.421701	-0.188552	0.333062	-0.279742	0.447777
HLT-Q1	-0.05692	0.345747	0.390253	0.414137	-0.317336	0.382803	-0.015997	0.416897
HLT-Q2	-0.037578	0.337936	0.353388	0.395185	-0.264213	0.360444	-0.051597	0.425809

Table S22: The statistics of each motivation in each questionnaire.

	LHF-HLF-Q1	LHF-HLT-Q1	HLF-HLT-Q1	LHF-HLF-Q2	LHF-HLT-Q2	HLF-HLT-Q2
M1-avg	D ~ 0.235, p-value ~ 0	D ~ 0.144, p-value ~ 0.019	D ~ 0.117, p-value ~ 0.091	D ~ 0.242, p-value ~ 0	D ~ 0.153, p-value ~ 0.012	D ~ 0.107, p-value ~ 0.158
M2-avg	D=0.127, p-value=0.056	D ~ 0.167, p-value ~ 0.004	D ~ 0.212, p-value ~ 0	D ~ 0.094, p-value ~ 0.282	D ~ 0.187, p-value ~ 0.001	D ~ 0.266, p-value ~ 0
M3-avg	D=0.103, p-value=0.193	D ~ 0.100, p-value ~ 0.207	D ~ 0.130, p-value ~ 0.044	D ~ 0.136, p-value ~ 0.034	D ~ 0.058, p-value ~ 0.834	D ~ 0.106, p-value ~ 0.171
M4-avg	D=0.087, p-value=0.359	D ~ 0.284, p-value ~ 0	D ~ 0.230, p-value ~ 0	D ~ 0.096, p-value ~ 0.261	D ~ 0.274, p-value ~ 0	D ~ 0.214, p-value ~ 0

Table S23: The results of K-S tests

	Mean		Std		K-S test
	Anger (168)	Joy (437)	Anger	Joy	
M1-avg	**0.027232**	**-0.057122**	**0.324823**	**0.323216**	**D ~ 0.134, p-value ~ 0.023**
M2-avg	**0.443899**	**0.334945**	**0.392053**	**0.383744**	**D ~ 0.125, p-value ~ 0.042**
M3-avg	-0.269196	-0.272378	0.378696	0.373137	D ~ 0.056, p-value ~ 0.822
M4-avg	-0.201935	-0.005444	0.393358	0.400885	D ~ 0.202, p-value ~ 0

Table S24: The statistics and K-S tests for anger and joy.

according to their dominant emotions to further examine the emotions stimuli on retweeting motivations. The results have been analyzed in the main text, and the results of K-S tests are shown in Table S24. At the meantime, in terms of neglecting emotion dominance, all the data of questionnaires are divided into two groups randomly to analyze the difference in the motivations. Surprisingly, there is no significant difference in the four motivations (Figure S19E-H) (anxiety management: K-S test $\sim$ 0.040, P $\sim$ 0.673; information sharing: K-S test $\sim$ 0.062, P $\sim$ 0.168; relationship management: K-S test $\sim$ 0.053, P $\sim$ 0.317; self enhancement: K-S test $\sim$ 0.059, P $\sim$ 0.200.) It suggests the significance of the different incentives provoked by anger and joy.

S13 The cure against fake news through tagging and warning anger

Carrying more anger makes fake news more viral than the real on line. According to this conclusion, instead of figuring out new features in fake news detection, new cues of tagging anger on social media can be a promising approach to restrain the spread of fake news at the very beginning. Considering the intervene on anger can be implemented immediately after the posting, there will be no lag in the fight against fake news. More importantly, the principle of guaranteeing the freedom of speech will be sufficiently respected and a better trade-off between free sharing and fake news prevention could be achieved. By alerting angry tweets, audiences are persuaded to value them more critically before the emotional retweeting, consequently leading to less emotional and more rational retweeters. Specifically, for tweets (news) that deliver too much anger, e.g., the occupations of anger surpass a predetermined threshold (θ), a retweeting could be warned in the platforms like Twitter, Facebook and Weibo. To determine the value of θ, we focus on the news with high volumes of retweets (HT news and HF news in our data) and define a measure to optimize θ, i.e., preventing more fake news that will be highly retweeted but less real news that will be quite popular. The measure is denoted as β and defined as

$$\beta = \frac{HF\,(\geq \theta)}{HF} - \frac{HT\,(\geq \theta)}{HT},$$

where

- N_{HF} is the number of HF news.
- $N_{HF(\geq\theta)}$ is the number of HF news with the occupation of anger more than θ.
- N_{HT} is the number of HT news.
- $N_{HT(\geq\theta)}$ is the number of HT news with the occupation anger more than θ.

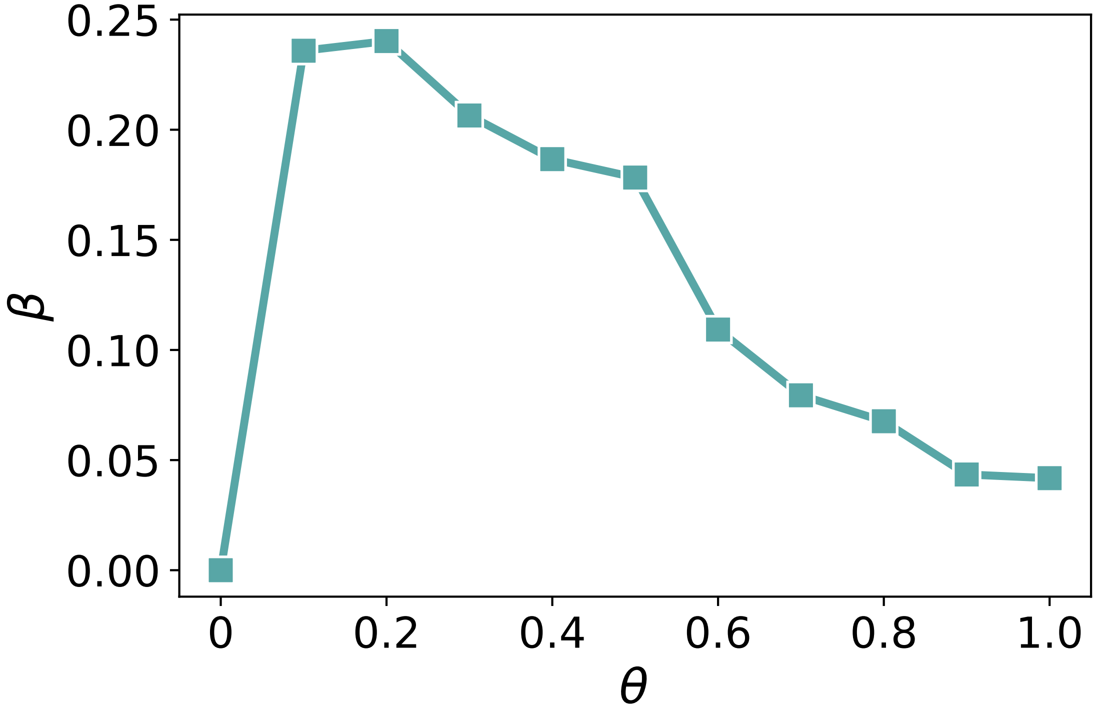

Figure S20: The value of β with θ growing by 0.1.

By respectively setting the step size of θ as 0.1 and 0.05, the values of β are shown in Figure S20 and Figure S21, which reach a peak when θ=0.2 consistently. In our dataset from Weibo, warning news in which anger occupies more than 20% will efficiently and effectively prevent 46% fake news of highly retweeted and only influence the circulation of 22% popular real news. Hence, its well worth trying to prevent the spread of fake news online through this new weapon.

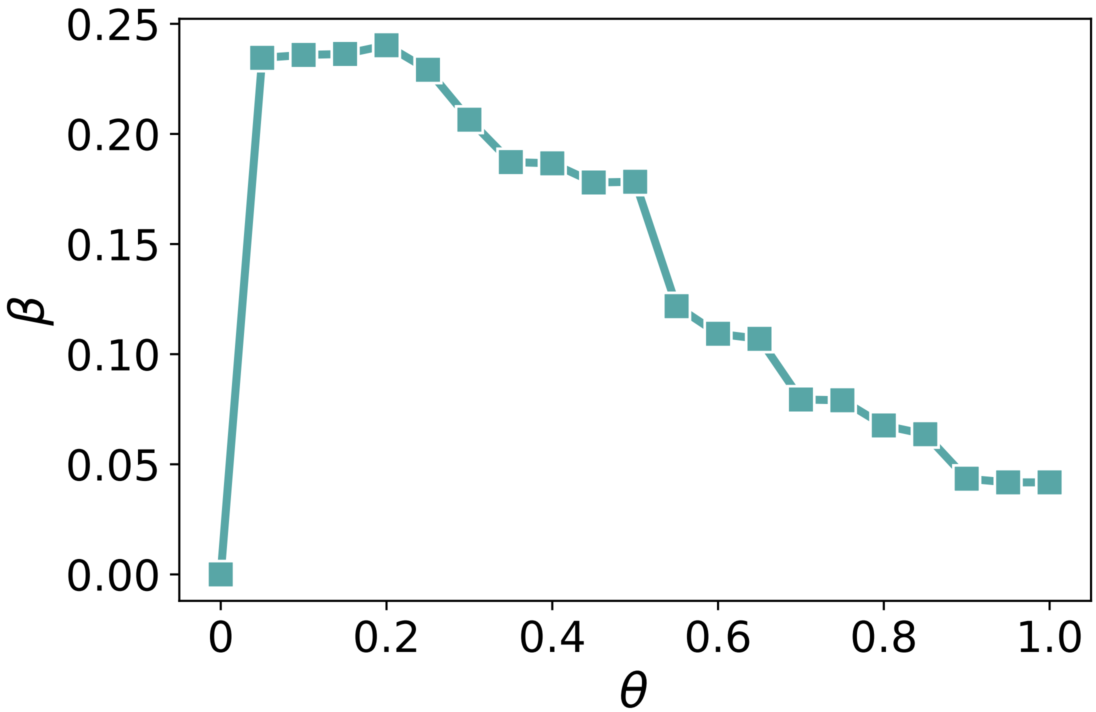

Figure S21: The value of β with θ growing by 0.05.