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A Quantitative Analysis of the Relationship Between the Public and News Media Attentions to Hot Network Events in China

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ABSTRACT

With the popularity of new media, the relationship between the media and the public has changed considerably. A comprehensive and quantitative analysis of the relationship between the public and media can reveal the development of news media in China and help provide some constructive advice to improve their quality. Therefore, we establish vector autoregression (VAR) models between the media and the public on 160 network trending events from 2011 to 2018 based on the Baidu Index. In specific terms, we explore the causal relationship between them with the Granger causality test and analyze the dynamic effects using the impulse response function (IRF) analysis. Our findings suggest that there are satisfactory two-way interactions between the news media and the public in China (especially in the event categories directly related to people's livelihood, such as safety misadventure, natural disasters, food and drug safety, and entertainment) and that the public plays a leading role for most events. We also find that the news media lags behind users generally, which prompts us to propose the three-relay hypothesis to explain its dissemination mechanism. Also, the impulse responses of attention to negative events are generally more drastic than those to positive events. For hot network events in China, the time span and sample size of our research are large, increasing the results' reliability.

KEYWORDS

vector autoregression model; Granger causality test; impulse response function; hot network event; public attention; media attention

With the increasing popularity of new media, the scope of media has been expanding continuously. Thus, the relationship between the media and the public has changed profoundly. During times of traditional media, the relationship between the media and the public was relatively simple. The flow of information presented a single path from the media to the public, with the media as the disseminator and the public as the receiver. With the emergence of new media, such as social media and we-media, the relationship between the media and the public became complex and variable. The path of information flow was no longer unidirectional[1–3]. As a result of new media, opinions news received through social networks immediately lead to the formulation of opinions in the minds of the public. In turn, this phenomenon affects the media. In some news events, public attention may be ahead of media coverage.

Figure 1 depicts media classification. Unlike traditional media, online media leverages the Internet as its medium. Moreover, it comprises three typical media types, namely, the online official news media (i.e., news media in this paper), social media, and we-media (there are some intersections among them). Online official news media refers to the news coverage that many news organizations publish today. Compared with social media and we-media, news media is more formal and authoritative. However, the coverage of news media may lag behind the public, especially for some breaking news.

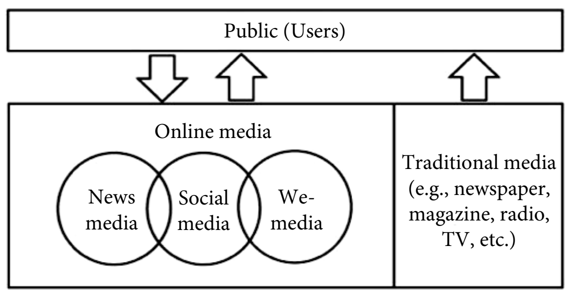

Fig. 1 Media categories and their interactions with the public.

1 Introduction

This paper aims to reveal the relationship between news media and the public in China and proposes some advice to improve the quality of the media. We obtain the search index and the media index as proxy variables of user attention (U) and media attention (M) based on the Baidu Index. Constituting 78.71% of China's market share, Baidu is the largest Chinese search engine in the country. Therefore, the Baidu Index can generally reflect the attention of users and the media. The Baidu search index is the weighted sum of search frequencies of a keyword of news, and the Baidu media index reflects the number of keyword-related news events that are included by Baidu News[4]. Note that the Baidu

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media index deals only with online official news media, which includes government websites and online news organizations. However, it does not deal with unofficial online media. Furthermore, due to the large number of news events being conducted every year, we have selected 160 top hot network events in China from 2011 to 2018 as our samples. These events are selected by the opinion channel of People's Daily Online, which is a leading authority in monitoring public opinion on the Internet in China.

Upon gathering a large volume of public and news media attention data, we establish the vector autoregression (VAR) models to analyze their causal relationship and dynamic effects. Based on the VAR models and using the Granger causality test, we explore the causal relationship between the news media and the public. Further, we leverage the impulse response function (IRF) analysis to reveal the dynamic effects of public and news media attention.

This paper has a theoretical and practical significance in the study of the relationship between online official media and users. With regard to the theoretical aspect, we focus on the relationship between the public and media in China, enriching the current research on the user-media interaction and the dissemination mechanism of hot network events. From a practical perspective, by revealing the status of the development of official online media in China, this study aims to improve the quality of the service of official online media and enhance user experience. Compared with previous studies, the main research contributions of this paper are as follows.

- We have conducted the first quantitative research and comprehensive analysis of the relationship between media users in China and the attention devoted to official online media from 2011 to 2018. Based on the user search index and media coverage index provided by the Baidu Index, this paper establishes the VAR model to analyze the relationship between the public and the media.
- We study the causal relationship between the media and users and the direction of the dissemination of information with the Granger causality test. Based on the analysis of four Granger causality situations, this research on the relationship between the media and users is more detailed and comprehensive than that of related works.
- We study the dynamic effect between online official media and users and the dissemination mechanism of network events with the IRF based on the VAR model. Previous studies have seldom focused on dynamic effects between the media and users at different periods. This paper leverages the IRF to simulate the response of online official media and users to the development of events, which is important for understanding the dynamic interaction between them. Further, this paper observes the dissemination of events pertaining to the interaction between online official media and users.
- Furthermore, we analyze the characteristics of the relationship between online official media and users in different years, event categories, and emotional polarities.

2 Related Work and Research Questions

2.1 Research on the impact of new media

With regard to official news media, the new media brings with its challenges as well as opportunities. In terms of challenges, the new media has gradually replaced official news media as the original disseminator of news information. Sayre et al.[5] (2010) compared the agenda-setting cues about "Proposition 8 in California" and found that the information flow was from new media (e.g., YouTube) to online official news media (e.g., Google News). Peng et al.[6] (2015) considered the example of a food safety incident called the "set-style yogurt and jelly event" and found that new media (e.g., Sina Weibo) was the original publisher of this food safety news. Wibowo and Karlinah[7] (2018) also revealed that new media (e.g., Twitter) could set the social media agenda to influence traditional media. Today, social media has a considerable influence on people's lives, even affecting politicians[8] and their attitudes on some pertinent social issues[9]. Typically, the public is already informed via social media about a piece of news before it is formally covered by the official news media. Consequently, the news media sometimes loses its leading role in the relationship between users and the media.

In terms of opportunities, the new media has also promoted the development of official online media. On one hand, official news media and new media interact positively with one another. Guggenheim et al.[10] (2015) focused on mass shooting incidents and discovered a dynamic and reciprocal relationship between online news and social media (e.g., Twitter). On the other hand, official news media can leverage new media to improve communication with the public. As more institutions began settling formally into new media platforms (e.g., Twitter and YouTube), the official news media could easily meet people's need for information and gain their attention[11]. Furthermore, despite the impact of new media, official news media is still irreplaceable, especially the authoritative report of official events. As demonstrated by Groshek and Groshek[12] (2013), official media has primarily facilitated social media coverage of fixed focusing events such as political events. Moreover, on some issues such as academics[13], the influence of official media remains evident.

2.2 Research on the relationship between the media and the public

The study of the relationship between media and public attention can be traced back to the agenda-setting theory[14,15]. Agenda setting is the creation of public awareness and concern of salient issues by the media. On one hand, media coverage can draw public attention. Agenda setting occurs through a cognitive process known as "accessibility"[14], which means that the more attention there is from the news media, the more attention there is among the public[16,17]. On the other hand, public attention may also lead to media coverage. The agenda-building theory[18] suggests that the media agenda can be influenced by certain powerful groups between the mass media and society.

Due to the influence of new media, the relationship between media and the public has become complex and variable. Taking "the Gulf of Mexico oil spill in 2010" as an example, Ragas et al.[1] (2014) provided strong evidence of a two-way interaction between the media and search agendas. Neuman et al.[2] (2014) utilized the attention data of 29 political issues in 2012 and found that agenda setting for these issues is not a one-way pattern from traditional media to a mass audience; rather, it is a complex and dynamic interaction. Leveraging the time-series data of Twitter, Facebook, and onsite events at the Indignados, Occupy, and Brazilian Vinegar protests, Bastos et al.[3] (2015) found bidirectional Granger causality between online and onsite protests in the Occupy series. In the dissemination of news, there is a complex two-way interaction between the media and users as opposed to a simple one-way transmission. Furthermore, researchers carried out comparative studies of news events by different event categories and emotional polarities. The study by Uscinski[19] (2009) of news events based on different event categories unveiled the types of events that can affect the direction of influence between the public and media. For instance, in issues pertaining to energy and the environment, the attention of the public appeared to drive news media coverage. Ripberger[20] (2011) also expressed a similar view. He found that in some issues such as health care, public attention might precede media coverage, while in some issues such as terrorism or global warming, public attention seems to be parallel to or even lag behind the coverage of media. For different emotional polarities, Vosoughi et al.[21] (2018) found that false news runs faster, deeper, and wider than true news. Similar to the saying that goes, "Good things do not go out, bad news travels", negative news, including fake news, typically travels faster than positive news. Ghosh et al.[22] (2022) found that stories with close user attention, usually related to entertainment and accusing politicians, seemed to be by far the strongest driver of news media attention.

2.3 Research questions

Based on the theoretical foundation built by the agenda-setting theory and agenda-building theory, this work studies the public-media relationship of prominent hot network events in China. In particular, we ask the following questions. Q1 and Q2 are about the basic relationship, whereas Q3 and Q4 deal with its spatial and temporal dynamics.

- Q1: To what extent are public attention and media attention to China's hot network events two-way interactions?
- Q2: Are hot network events in China public or media driven?
- Q3: In what event categories are the interactions between the public and the media most active?
- Q4: Do positive or negative events get more attention?

3 Research Model

3.1 Data description

We leveraged the Baidu Index as the proxy for public and media attention. User queries were initially regarded as byproducts by the search engine industry to help improve indexing services. However, these queries were soon recognized as gold mines of data on user attention[23]. With the unprecedented popularity of search engines, people are increasingly accustomed to obtaining information by browsing through the Internet; therefore, the search index provided by search engines based on search volumes becomes a direct and timely proxy variable of attention. The most noticeable fields of Internet search queries are financial searches, and there are many relevant studies[24,25] using the Baidu Index or Google Trends as proxy variables of attention to study the influence of investor attention on financial markets or BitCoin returns.

A comparison of Google Trends and the Baidu Index[26] reveals that because of Google's smaller user base in China, the Baidu Index can provide more search volume data compared to Google Trends. As the largest Chinese language search engine, Baidu provides search and media indexes, which are practical choices for discovering user and media attention to Chinese hot network events. A keyword's search index is the weighted sum of search frequency based on Internet users' search volumes, and the media index reflects the number of pieces of keyword-related (i.e., news headlines contain the keyword) news covered by Baidu News. Note that Baidu's media index deals only with online editions of traditional media, coupled with official websites of government agencies and organizations—it does not cover unofficial new media.

In data processing, we take the first-order difference between user attention (U) and media attention (M). Economically, the first-order difference represents the increment of user attention (ΔU) and media attention (ΔM). Moreover, it is better to meet the stationary test, which facilitates further modeling. Moreover, the data range of the search index is much larger than the media index, as shown in Table 1. Therefore, we compute the Z-score for each event's ΔU_t and ΔM_t, and the resulting symbols are denoted by $\Delta\tilde{U}_t$ and $\Delta\tilde{M}_t$. The descriptive statistics are shown in Table 1.

3.2 Sample description

As mentioned before, we selected, as our samples, 160 network events in China from 2011 to 2018. These events were issued by People's Daily Online. We manually classified the sample events based on their contents. First, we classified these 160 events into four categories, i.e., political, economic, social, and cultural. This segregation was our first-level classification. However, this first-level classification entails imbalanced sample sizes among the different categories. Therefore, the first-level categories can be further classified into various categories, forming the second-level classification. For example, social events can be segregated into legal cases, safety misadventure, food and drug safety, group incidents, natural disasters, etc. After the second-level classification, if the number of events in a category is large (i.e., greater than or equal to 5), it is regarded as a second-level category for further analysis; if not, the category is discarded. There are nine categories in all, as shown in Table 2. These categories include anticorruption, food and drug safety, and natural disasters. These hot network events are typical with close user attention and close media attention; thus, the chosen events can fully represent each category.

Further, we classify the sample events into 46 positive events and 114 negative events based on the impact of the events on the emotions of the public.

3.3 VAR model

The VAR model is appropriate for circumstances where theory provides a weak rationale for modeling[27]. Thus, inspired by many influential works[20,24,28], we establish the VAR model to reflect the relationship between the media and the public. We set the VAR

Table 1 Descriptive statistics.

Data	Mean	StdDev	Q1	Q2	Q3	Skewness	Kurtosis
U	31 568.06	187 096.90	1135.50	3168.00	11 555.50	15.67	326.04
M	221.72	957.72	2.00	12.00	191.50	37.04	1993.05
ΔU	−17.01	140 226.50	−500.00	−45.00	138.00	2.44	1483.42
ΔM	0.60	1003.36	−12.00	0.00	7.00	5.21	2382.97
$\Delta\tilde{U}$	0.00	1.00	−0.06	0.00	0.02	2.59	61.37
$\Delta\tilde{M}$	0.00	1.00	−0.08	0.00	0.06	0.77	33.96

Table 2 Event categories.

Category	Number	Example
Anticorruption	6	Bo Xilai corruption case
Economic policy	10	Circuit breakers
Legal cases	20	Yao Jiaxin legal case
Safety misadventure	11	7.23 motor vehicle rear-end
Food and drug safety	11	Poison capsules and "leather shoes are busy"
Group incident	7	Hong Kong "occupy central" group incident
Natural disaster	6	Beijing torrential rain disaster
Entertainment	12	A bite of China
Sport	7	The London Olympics

model as follows:

$$\Delta\tilde{U}_t = \alpha_1 + \sum_{j=1}^{k} \beta_{1j}\Delta\tilde{U}_{t-j} + \sum_{j=1}^{k} \gamma_{1j}\Delta\tilde{M}_{t-j} + \varepsilon_{1t} \quad (1)$$

$$\Delta\tilde{M}_t = \alpha_2 + \sum_{j=1}^{k} \beta_{2j}\Delta\tilde{U}_{t-j} + \sum_{j=1}^{k} \gamma_{2j}\Delta\tilde{M}_{t-j} + \varepsilon_{2t} \quad (2)$$

In the model, $\Delta\tilde{U}_t$ and $\Delta\tilde{M}_t$ represent the standardized first-order difference of the public and media attention at time t, respectively※; k represents the optimal lag period‡, α represents the intercept term, β and γ represent the coefficients, respectively, and ε represents the disturbance term.

3.4 Granger causality test

The Granger causality test, first proposed by Granger (1969)§[29], is a statistical hypothesis test for determining whether one time series is useful for forecasting another. By using the Granger causality test, we can judge the causal relationship between the news media and the public. There are four types of the result of the test, as shown in Table 2¶:

(1) $M \to U$ type (unidirectional media-driven) is M Granger-causes U, indicating that media coverage leads ahead of public attention, but not vice versa.

(2) $U \to M$ type (unidirectional public-driven) is U Granger-causes M, indicating that public attention leads ahead of media coverage, but not vice versa.

(3) $M \leftrightarrow U$ type (bidirectional) is U Granger-causes M and M Granger-causes U, indicating that there is a two-way causal relationship between the media and the public, which is regarded as a good relationship between them.

(4) $M \not\leftrightarrow U$ type (no significant interaction) means that there is no causal Granger relationship between the media and the public, indicating a poor interaction.

3.5 Impulse response function

We study the dynamic effect between news media and the public with the IRF. For the VAR model, we usually analyze the dynamic effects on the system by using the IRF[30,31]. After applying a unit-positive impulse to public or media attention, we analyze the response to public and media attention for each period. Therefore, there are four IRFs in all:

(1) U to U IRF studies the response pertaining to public attention after applying a unit-positive impulse to the initial public attention.

(2) U to M IRF studies the response with regard to public attention after applying a unit-positive impulse to the initial media attention.

(3) M to U IRF studies the response to media attention after applying a unit-positive impulse to the initial public attention.

(4) M to M IRF studies the response pertaining to media attention after applying a unit-positive impulse to the initial media attention.

3.6 Model validation

Before formal modeling, it is necessary to test the stationarity of a time series; if not, the model may be characterized by spurious regression. We used a unit root test method called the Augmented Dickey-Fuller (ADF) test and found that the $\tilde{U}_t$ and $\tilde{M}_t$ series of all sample events reflect stationarity.

Furthermore, we had to choose the optimal lag order to establish the VAR model, which is an important parameter for modeling. Hence, we used the Akaike Information Criterion (AIC) to determine the appropriate lag length. For each event, the optimal lag order reflects the number of days of significant contribution to the prediction of current attention. The greater the optimal lag order is, the greater the number of historical days that the prediction of current attention depends on. This observation indicates that the development of this event is often more complicated.

After choosing the optimal lag order, we establish the VAR models and obtain the parameters to be estimated with ordinary least squares (OLS) regression. After establishing the VAR models, we conduct the Granger causality test and IRF analysis.

4 Result

4.1 Overall Granger causality results

According to the results of the Granger causality test, we count the proportion of the four types. Also, we define the media-driven proportion as the total percentage of the $M \to U$ type and $M \leftrightarrow U$ type and the public-driven proportion as the total percentage of the $U \to M$ type and $M \leftrightarrow U$ type.

$M \leftrightarrow U$ type accounts for 45.63% of the total number of events, ranking first, which reflects the overall quite good two-way interactions between the news media and the public. The $U \to M$ type accounts for 33.75%, ranking second, and the $M \not\leftrightarrow U$ and $M \to U$ types account for 13.75% and 6.88%, respectively.

The public-driven proportion is 79.38%, and the media-driven proportion is 52.50%. This finding reflects that the public plays an integral role in the dissemination of information, and the leadership of news media on the public must be improved for hot network events.

4.2 Granger causality results by years

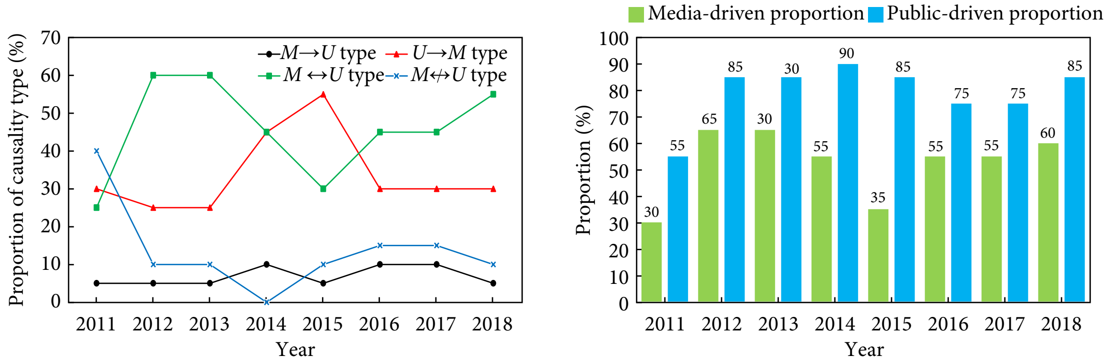
We have demonstrated the percentages of events of different causality types in each year in Fig. 2a and the media-driven and public-driven proportions in Fig. 2b.

※ Strictly speaking, they are first-order incremental time series, and the tilde (~) above the symbols means that they are after standardization.

‡ Because the lag order of different endogenous variables of the VAR model can only be set to the same value in EViews, the lag order of U and M has the same k value.

§ Although the Granger causality test is not true causality test, analyzing and interpreting the results still reveal something about causality[20]. Besides, considering many events we experienced in China that people's attention makes media respond, and media coverage arouses people's more attention, we think there exists true causality between media coverage and user attention.

¶ Readers should note that the types are defined in the sense of statistical significance.



(a) Causality types (b) Media driven and public driven proportions

Fig. 2 Granger causality results by each year.

4.3 Granger causality by event categories and emotional polarities

We have indicated the proportion of the four causality types in different event categories in Table 3. The top three event categories in each type have been depicted in bold. The top four categories of $M \leftrightarrow U$ are food and drug safety (81.82%), natural disasters (66.67%), entertainment (50.00%), and legal cases (50.00%). The top three categories of $U \rightarrow M$ are economic policy (70.00%), safety misadventure (54.55%), and anticorruption (50.00%). The interactions between the media and the public, as well as the leading role of the public in the media, are quite good in most of the people's livelihood-related categories.

Moreover, in Fig. 3a, we count the media-driven and public-driven proportions for each category. Except for the group incidents category, the public-driven proportion is usually larger than the media-driven proportion, reflecting the dominant public-driven relationship in hot network events. The four categories with the highest public-driven proportion are safety misadventure (100%), natural disasters (100%), entertainment (92%), and food and drug safety (91%), which are vital to people's livelihood.

4.4 Overall IRF results

The impulse response analysis is complementary to the Granger causality analysis because it can further demonstrate the quantitative degree to which the changes in one variable impact the other variable. We average the results of the IRFs of U to U, U to M, M to U, and M to M for 160 sample events. To avoid the repercussions of extreme values, we winsorize outliers at 5% and 95% of the response.

The IRF analysis is done for the first-order differentiation of attention (i.e., $\tilde{U}$ and $\tilde{M}$); we depict the corresponding attention (i.e., U and M) by accumulation in figures. Furthermore, we treat each event as equal by unifying its data range with the Z-score normalization, and one unit denotes one standard deviation.

In the IRF analysis of the U to U response, following the application of a unit-positive impulse to the public attention increment (Fig. 4a), public attention (U-1) first rose when the public began paying more attention to the event. Thereafter, public attention declined (U-2). Finally, public attention was in the long tail period (U-4), when it depicted a steady state with little fluctuation. There is no U-3 in this case.

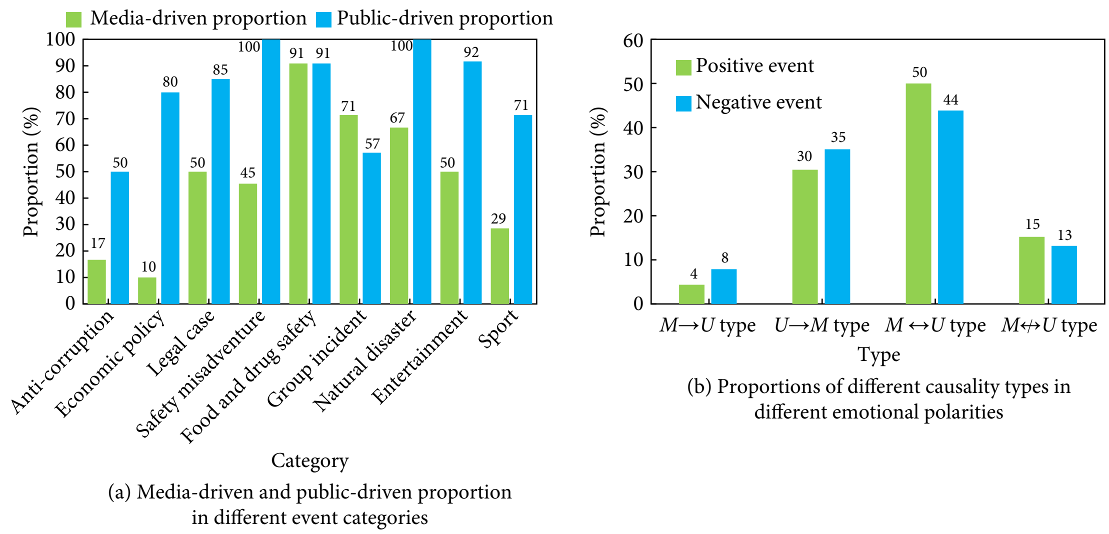
In the IRF analysis of the U to M response after applying a unit-positive impulse to the media attention increment (Fig. 4b), first, public attention descends when media attention increases by one unit-positive impulse, which reflects the lag effect of news media coverage. Namely, public attention is already in decline (U-2) when news media coverage starts to increase. It is interesting but not surprising because, overall, the public-driven proportion (79.38%) is significantly greater than the media-driven proportion (52.5%). Then, public attention goes into the recovery period (U-3), affected by the rising media attention. Finally, public attention can be compartmentalized into the long tail period (U-4).

In the IRF analysis of the M to U response after applying a unit-positive impulse to the public attention increment (Fig. 4c), media attention first increases when more people begin paying attention (M-1); it then descends (M-2) and finally becomes steady in the long tail period (M-4). Hence, there is no M-3 in this case.

In the IRF of the M to M response after the application of a unit-positive impulse to the media attention increment (Fig. 4d), the media attention rises first (M-1), then descends (M-2), then rises again (M-3), and finally becomes steady in the long tail period (M-4).

Table 3 Proportion of different causality types in different event categories (the top three event categories in each type are depicted in bold).

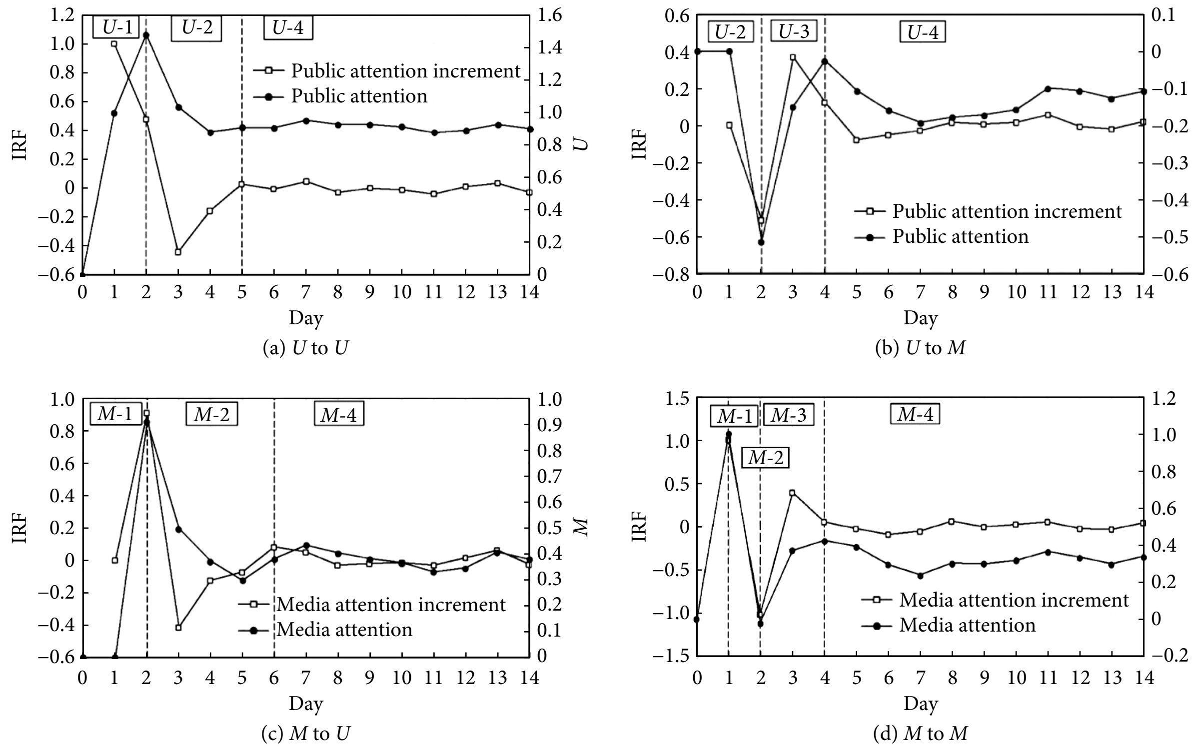
Event category\ Causality type	Proportion of different causality types (%)			
	$M \rightarrow U$ type	$U \rightarrow M$ type	$M \leftrightarrow U$ type	$M \not\leftrightarrow U$ type
Anti-corruption	**16.67**	**50.00**	0.00	**33.33**
Economic policy	0.00	**70.00**	10.00	**20.00**
Legal case	0.00	35.00	**50.00**	15.00
Safety misadventure	0.00	**54.55**	45.45	0.00
Food and drug safety	**9.09**	9.09	**81.82**	0.00
Group incident	**28.57**	14.29	42.86	14.29
Natural disaster	0.00	33.33	**66.67**	0.00
Entertainment	0.00	41.67	**50.00**	8.33
Sport	0.00	42.86	28.57	**28.57**



(a) Media-driven and public-driven proportion in different event categories

(b) Proportions of different causality types in different emotional polarities

Fig. 3 Granger causality results by event categories and polarities.



(a) *U* to *U*

(b) *U* to *M*

(c) *M* to *U*

(d) *M* to *M*

Fig. 4 Average attention responses of all sample events.

4.5 IRF results by event categories and emotional polarities

We show the attention responses of each event category in Fig. 5 and compare them in descending order of the sum of response attention values in the first 14 days. The first three categories are marked by solid lines, the middle three categories are marked by dashed lines, and the last three categories are marked by dotted lines.

Also, we average the attention from the IRF results in two emotional polarities, as shown in Fig. 6. As the Fig. 6 shows, the impulse responses of attention to negative events are generally more drastic than those to positive events. The average attention response of *U* to *U* of negative events is larger than that of positive events on Day 2. The average attention response of *U* to *M* of negative events is far lower than that of positive events on Day 2, showing the significant lag effect of news media for negative events. The average attention response of *M* to *U* of negative events is significantly higher than that of positive events on Days 2–4. The attention responses of *M* to *M* of negative events are also higher than those of positive events on most days except Days 2 and 3.

5 Discussion and Implication

5.1 Overall public-media interaction

As described by the agenda-setting theory[12], the news media have the ability to influence the importance placed on the topics of the public agenda. As the theory[17] maintains, media and user attention are associated positively and significantly. In most events, the trends of attention clearly track one another.

Both theoretically and practically, the media attention and user

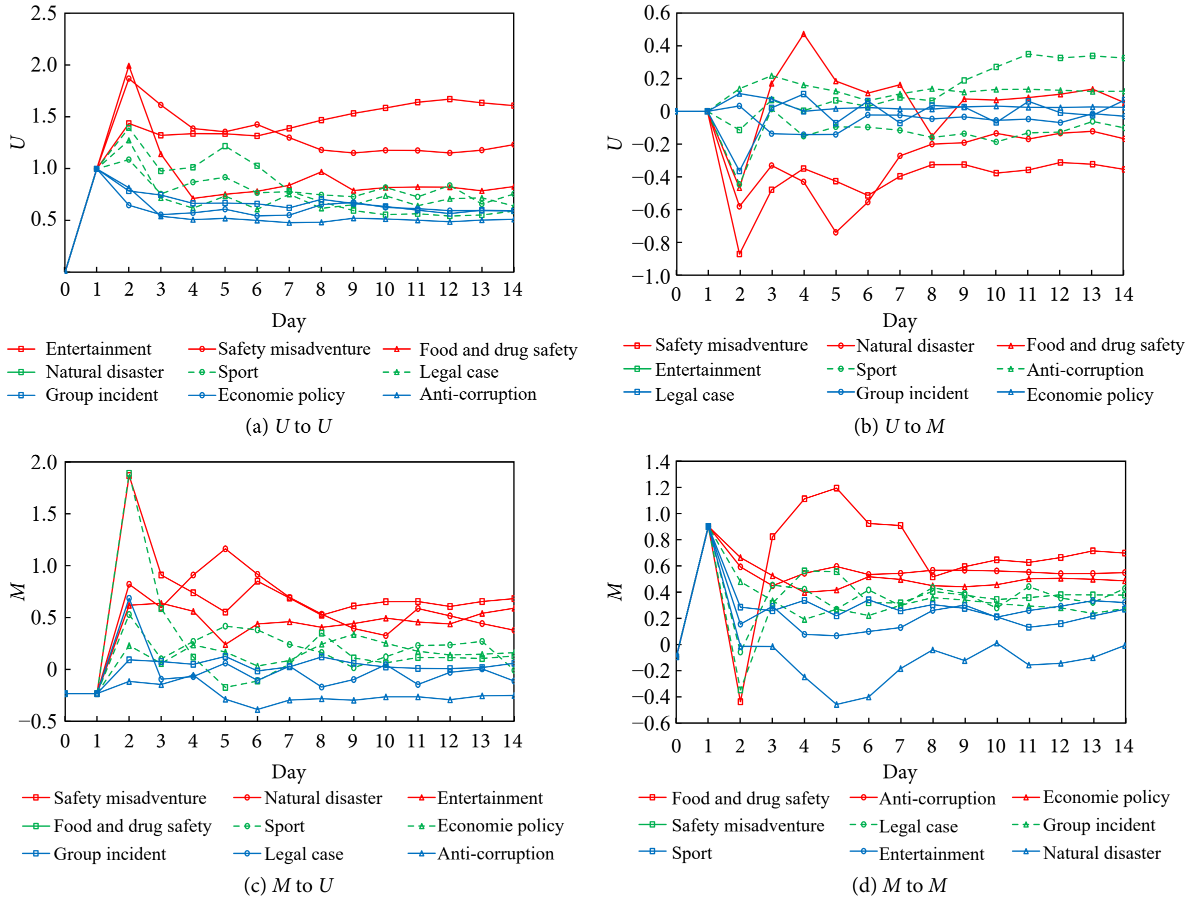


Fig. 5 Attention responses in different categories.

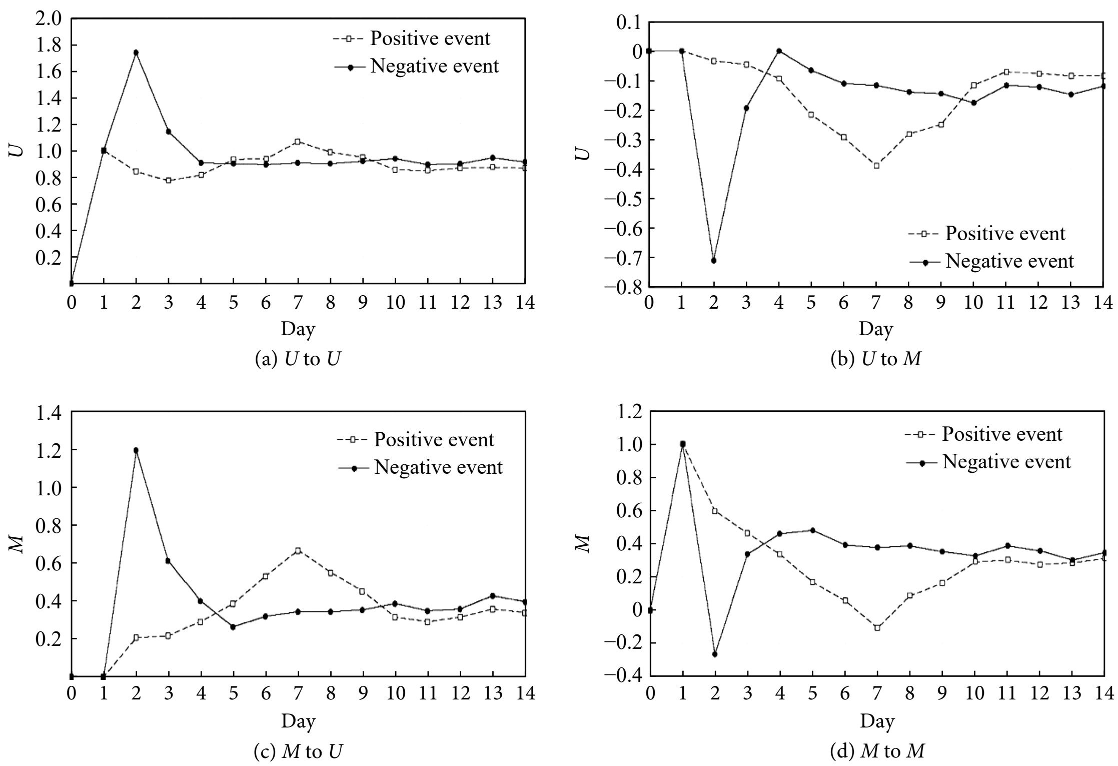


Fig. 6 Attention responses in different emotional polarities.

attention are positively and significantly.

Collating the above information, we find a three-relay pattern for the overall public-media dynamic relationship depicted in Fig. 7. The rising attention of the public, who takes the lead in obtaining information, promotes the coverage of online media, which responds sensitively. This phenomenon is the

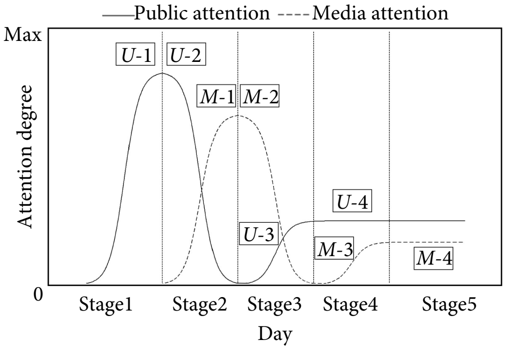


Fig. 7 Schematic diagram of the three-relay pattern of the interactions of media attention and public attention.

first relay. The rising coverage of the media promotes the attention of the public—this tendency is the second relay. The rising attention of the public further promotes the coverage of the media, forming the third relay.

5.2 Discussion on different years

As shown in Fig. 2, in 2011, the $M \nleftrightarrow U$ type accounted for 40% of all events, which is higher than that of the succeeding years. The $M \leftrightarrow U$ type accounted for 25%, which is the lowest from 2011 to 2018. Moreover, the proportions of media-driven and public-driven are at the lowest level. In the early stage of online media development, the interaction between news media and the public was poor.

In 2012 and 2013, the $M \leftrightarrow U$ type accounted for 60%, and the $U \to M$ type accounted for 25%. Moreover, the media-driven proportion was the highest in the period 2011–2018, and the public-driven proportion also increased considerably, i.e., to 85%. With the appearance and popularity of WeChat and WeChat official accounts in this period, the interaction between news media and the public improved considerably.

In 2014 and 2015, the percentage of the $U \to M$ type rose continuously and surpassed that of the $M \leftrightarrow U$ type. Moreover, the media-driven proportion decreased significantly, whereas the public-driven proportion remained at a high level, indicating that the attention of the public was ahead of the coverage of the media. In 2015, the monthly active users (MAU) of Sina Weibo and WeChat reached 212 million and 549 million, respectively, increasing greatly from 2014. As indicated by the results, the public tended to receive, spread, and publish information through new media rapidly, and the news media then followed to report.

In 2016 and 2017, the proportion of the $M \leftrightarrow U$ type rose to 45%, while the proportion of the $U \to M$ type dropped to 30%. Moreover, the public-driven proportion declined a bit compared with the previous two years. As indicated by the result, the coverage of news media promoted its interaction with the public.

In 2018, the proportion of the $M \leftrightarrow U$ type continued to rise to 55%. Both public-driven and media-driven proportions increased marginally compared with the previous two years, and the user-driven phenomenon was still predominant.

5.3 Discussion on different event categories and emotional polarities

As shown in Fig. 3, we examine each category in detail.

In the anticorruption category, the proportion of the $M \to U$ type is 16.67%, whereas the proportion of the $U \to M$ type is 50%. However, there is no $M \leftrightarrow U$ type, while the $M \nleftrightarrow U$ type is 33.33%, which ranks first among all categories. Moreover, the public-driven proportion is higher than the media-driven proportion by 33%. We should enhance the two-way interactions of this category.

In the economic policy category, the proportion of the $U \to M$ type is 70%, which is far higher than the average level and ranks first among all categories. The $M \nleftrightarrow U$ type accounts for 20%. Moreover, the public-driven proportion is higher than the media-driven proportion by 70%. This is the biggest gap between the public-driven proportion and the media-driven proportion among all categories, which suggests that the media should drive the agendas more actively.

In the legal cases category, the $M \leftrightarrow U$ type accounts for 50%, followed by the $U \to M$ type at 35%. Moreover, the public-driven proportion is higher than the media-driven proportion by 35%.

In the safety misadventure category, the proportion of the $U \to M$ type is 54.55%, whereas the remaining 45.45% of the events are of the $M \leftrightarrow U$ type. Moreover, the public-driven proportion is higher than the media-driven proportion by 54.55%. The development of these events easily creates widespread public attention through social networks in a short time and arouses media attention thereafter.

In the food and drug safety category, the proportion of the $M \leftrightarrow U$ type is 81.82%, which ranks first among all categories. The rest of the events are of the $U \to M$ type (9.09%) and the $M \to U$ type (9.09%). Moreover, the media-driven and public-driven proportions are large (91%). There is pretty good interaction between news media and the public in this category. These events are related closely to people's lives and are valued by the news media.

In the group incidents category, the proportion of the $M \to U$ type is 28.57%, and the $M \leftrightarrow U$ type accounts for 42.86%. Moreover, the media-driven proportion is 14% higher than the public-driven proportion, and it is the only category wherein the media-driven proportion is higher than the public-driven proportion.

In the natural disasters category, the proportion of the $M \leftrightarrow U$ type is 66.67%, which is the second largest after the food and drug safety category. The remainder of the events is of the $U \to M$ type. Moreover, the public-driven proportion is higher than the media-driven proportion by 33.33%. When natural disasters occur, the media usually devotes a great deal of effort to front-line reporting. As a result of the humanitarian spirit, when disaster strikes, help comes from all sides—the public also tends to display a high degree of attention and participation. News media and the public are actively concerned about the development of these events.

In the entertainment category, the $M \leftrightarrow U$ type accounts for 50%, followed by the $U \to M$ type at 41.67%. Moreover, the public-driven proportion is higher than the media-driven proportion by 42%.

In the sports category, the $U \to M$ type accounts for 42.86%, which is higher than the $M \leftrightarrow U$ type (i.e., at 28.57%). Moreover, the public-driven proportion is higher than the media-driven proportion by 42%. The leading role of the public is prominent.

We also calculate the proportion of different causality types in positive and negative emotional polarities and obtain the statistical results in Fig. 3b. The percentages of positive events and negative events of the four causality types are generally similar. Moreover, their media-driven and public-driven proportions are also similar, which reflects that the causal relationship between news media and the public is not affected by emotional polarities.

Moreover, we have demonstrated the attention responses of each event category in Fig. 5, comparing them in descending order of the total responses of attention values in the first 14 days.

IRF of U to U: The attention responses of the entertainment category, the food and drug safety category, and the safety misadventure category are significantly higher than others, indicating that the public attention aroused by other users is significant in these categories. Public attention to the categories of group incidents, anti-corruption, and economic policy is below 1 (the unit response) from Day 2, which reflects that the public is not aroused enthusiastically by the other users in these categories.

IRF of U to M: Except for the categories of group incidents, anti-corruption, and economic policy, the responses of U to M depict a lag effect, which reflects quantitatively that the changes in public attention are significantly ahead of those pertaining to media attention. The negative attention response of the safety misadventure category is the lowest among all categories, reflecting the great leading role of public attention to media attention. The natural disaster category and the food and drug safety category rank second and third, respectively. Additionally, the attention response of the food and drug safety category is significantly higher than the average level on Day 4, which reflects that the second rise of public attention is very high because of media coverage.

IRF of M to U: The attention response of the safety misadventure category is the highest among all the categories on Day 2, which reflects that media response to the public is great in terms of speed and volume. The food and drug safety category ranks second on Day 2. However, the positive attention responses in the group incidents, anticorruption, and economic policy categories are significantly lower than the average level on Day 2, which reflects that the media is not very active in responding to the public in these categories.

IRF of M to M: The attention response of the food and drug safety category is more persistent than that of the other categories from Day 3, which reflects that the interactions between media are quite good. In the group incidents, anticorruption, and economic policy categories, the positive attention response is lower than the average level, which reflects that the responses among news media are not very good.

Also, as depicted in Fig. 6, the impulse responses of attention to negative events are generally more drastic than those to positive events. The average attention response of U to U for negative events is larger than that for positive events on Day 2. The average attention response of U to M for negative events is far lower than that for positive events on Day 2, which shows the significant lag effect of the news media for negative events. The average attention response of M to U for negative events is significantly higher than that for positive events on Days 2–4. The attention responses of M to M for negative events are also higher than those for positive events on most days except Days 2 and 3.

6 Conclusion

In this work, we explore the relationship between public attention and news media attention on Chinese hot network events from 2011 to 2018 with the Granger causality test and the IRF.

Conclusions about research questions Q1 & Q2: According to the Granger causality test, there are considerably positive two-way interactions between the news media and the public (the $M \leftrightarrow U$ type accounts for 45.63% of all events). The public plays a leading role ahead of the media for most hot network events (the overall public-driven percentage is 79.38%). Using the IRF analysis, we find that there is a lag effect in the U to M response. This reflects that public attention is already in decline when news media coverage starts to increase, which also indicates the leading role of the public ahead of the media. We also observe a three-relay pattern of the interactions between media attention and public attention.

Conclusion about research question Q3: We examine the Granger causality results and IRFs and propose some suggestions to enhance the public–media relationship for each event category. Event categories directly related to people's livelihood, such as safety misadventure, natural disasters, food and drug safety, and entertainment have good public–media interactions, i.e., the percentage of the $M \leftrightarrow U$ type is generally relatively high in such categories, their public-driven proportions are generally very high, and their impulse responses are generally more drastic than those of the other event categories. However, the Granger test shows that the media-driven proportion of economic policy and anti-corruption is below 20%, which suggests that the media should be more active in leading the public here.

Conclusion about research question Q4: Although the percentages of positive events and negative events of the four causality types are generally similar, the impulse responses of attention to negative events are generally more drastic than those for positive events.

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