Collective Emotional Reaction to Societal Risks in China

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***Abstract*—Modern China is exposed to many societal risks. The risk perception induced emotion at the individual level but their relationship on a large scale is costly to assess, while some social emotional reactions such as anger may evoke collective actions. The seven societal risk perceptions including social stability, daily life, resource & environment, public moral, government management, national security and economic & finance were gotten on the basis of the public searching behavior on Baidu search engine. The five public moods including Happiness, Sadness, Fear, Anger and Disgust were obtained by analyzing the text content of daily Sina Weibo. The relationship between the societal risk perceptions and public moods using Granger causality analysis was that the societal risk perceptions are predictive of public moods but the effect of different kinds of societal risk perception is distinguishing. This research manifested that capturing public psychological characteristics on social media was feasible.**

Keywords–Baidu Hot Words; Micro-blog; Public Mood; Societal Risk Perception; China

I. INTRODUCTION

In the process of social transformation and globalization, the modern China is exposed to many kinds of societal risk such as intensive conflicts and disputes, structural poverty and unemployment. These all exert adverse effect on social stability and harmonious [1]. The collective risk perception, a critical component of the socio-political context, can fundamentally compel or constrain political, economic and social actions [2]. While the risk perception often induces emotional reaction at the individual level, their relationship on a large scale is costly to assess. But some public emotion may evoke collective actions to contribute to the constructive social change or social instability. For example, the increase in public anger preceded riots broken out [3] and many online collective actions were evoked by contagious anger in China [4]. Therefore, it is of great practical significance to study whether and how the social perceptions to Chinese societal risks affect people mood states.

The concern of risk perception first arose in mid 1960s, during which experts and lay people often disagreed on how risky various technologies were for producing clean and safe energy and natural hazards. Though technologically sophisticated risk assessments were applied to evaluate hazards, the majority of citizens relied on their intuition when it came to characterize and evaluate hazardous activities and technologies [5]. The psychometric paradigm of risk perception was to directly ask people the kinds of acceptable risks and to what extent the risks were acceptable, then gauge people's attitude in relate to a particular risk. The psychometric paradigm focused on the role of emotion in influencing the public risk perception and tried to identify the degree to which a risk is understood,

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the degree to which a risk evoke a feeling of dread, and the number of people exposed to the risk [6]. By asking subjects to assess 28 societal risk factors in a 10-point Likert scale on the basis of their dread feeling and occurring possibility, researchers found that the economic crisis and social unrest were the most concerned societal risks in China [7]. However, the predictive value of this methodology is restricted by the design, arrangement of questionnaire, as well as the statistical analysis methods which is difficult to reach consistent result. In addition, the public's risk perception is difficult to measure with limited resources such as time and manpower. To overcome the shortcomings of the traditional psychometric paradigm, some researchers constructed a new framework of societal risk indicators based on word association tests. They used the semantic network clustering analysis software CorMap and iView to group associated words into clusters and detected seven main categories of hazards. They were national security risk, economy & finance risk, public morals risk, daily life risk, social stability risk, government management risk and resources & environments risk, and thirty sub-categories in their societal risk indicators [8].

Nowadays, a number of user-oriented social media has emerged rapidly. Individuals are allowed to freely express themselves, which offered researchers opportunities to understand societal situations from a new perspective. Research showed that the searching frequency of word "recession" was correlated with unemployment rate and consumer confidence index (CCI) negatively, meaning that the public were pessimistic to economic or finance [9]. They searched or presented more negative words on Internet, they would judge the event to be more risky or uncertain.

Although public risk perception is highly dependent on intuition, experiential thinking, and emotions, it isn't purely emotional and cognitive analysis is also involved in interpreting complex societal risks [10]. Also, researchers considered the public risk perception to be multi-dimensional, resulting from a combination of cognitive, emotional, subconscious, socio-cultural and individual factors [11]. There are many controversies about the relationship between emotion and cognition, among which the cognitive appraisal of emotion model is widely acknowledged. The central tenet of the cognitive appraisal theories is that emotion is elicited and differentiated on the basis of a person's subjective evaluation of the personal significance to a situation, object, or event. On this view, it's the appraisal of a situation, not the situation per se, that determines the type and the intensity of an emotional response.

Researchers extended the appraisal theory to the intergroup context and developed a model of intergroup emotion to explain the group-level emotion [12]. When social identity is salient, individuals may experience the same emotion as group members do even if they aren't necessarily personally concerned [13]. Overall, researches have consistently showed that the subjective judgment of risk would induce different emotions at the group level [14, 15]. By integrating the basic principles of social identity theory and intergroup emotion theory, Gao and Chen constructed the identity emotion model of online collective actions to analyze the emotion evaluation combination and the evaluation indicators, and derived five appraisal criteria to differentiate collective emotion, namely, consistency, irrational, agency, controllable and deviation [16]. When the risk is perceived to be injustice and high controllable, and the risk deviates people anticipation seriously and been caused by the power estate mainly, it is tending to induce anger. By contrast, when the risk is perceived to be low controllable and been caused by natural force, it may elicit sadness or helpless. Therefore, will the public perception to the societal risks have profound effect on their mood states as well? Can we identify the collective emotional reactions according to the appraisal dimensions of the seven different societal risk perceptions mentioned above?

But how to measure the public mood states? There are two major theoretical approaches to understand the emotional structure. One is the emotional categorical approach. It proposed that there are a small set of basic emotions and complex emotions that are consisted of basic emotions or emotion and cognition [17]. The most widely accepted five kinds of basic emotion are Happiness, Sadness, Fear, Anger and Disgust [18]. The other approach is the dimensional approach, according to which the basic emotions are interrelated in a highly systematic fashion and can be represented by a spatial model rather than being independent with each other [19]. Based on the above two approaches, the traditional way to measure the individual emotion is through self-reporting or opinion-polling using emotional scale or affective adjective checklist. These methods are generally expensive and time-consuming, and not suitable for measuring emotion of large-scale population. Some researchers proposed other indicators that may be associated with public emotion such as games [20] and weather condition [21]. However, these indirect indexes were actually having low degree of correlations with the public mood. Recently, the reliable, scalable and early assessments of the public mood are emerged with the big data on Internet and the advancement of sentiment analysis techniques. Significant progress has been made in extracting indicators of the public mood directly from social media and correlating with the meaningful index, such as box office [22] and market prediction [23], disease infection [24] and information dissemination [25], macroeconomic [26] or stock market prediction [27, 28].

In this research, we are concerned how the public perception to different Chinese societal risks affects people mood states. The public risk perception obtained from Baidu search engine based on the hot words including social stability, daily life, resource & environment, public moral, government management, national security and economic & finance. While the public mood time series were gotten by analyzing the text content of daily Sina Weibo using the Weibo Five Basic Mood Lexicon (Weibo-5BML) and sentiment analysis technique, which included Happiness, Sadness, Fear, Anger and Disgust. Then we applied the Granger causality analysis from econometrics to study the predictive effect of the societal risk perception on the five public mood time series of 365 days, and investigated the different collective emotional reaction evoked by the seven societal risk perceptions based on the appraisal theories of emotion.

II. METHOD

A. Measurement of societal risk perception

Researchers from Chinese Academy of Sciences corresponded the searching behavior on search engine to societal risk perception for the first time. They extracted the social risk perception daily time series from November 1, 2011 to October 30, 2012 by corresponding the social searching behavior on Baidu search engine to societal risk perception. Baidu is the biggest Chinese search engine worldwide, whose news portal site presents 10-20 hottest query words (Baidu Hot Words) of news automatically updated every 5 minutes. Tang automatically discerned the Baidu Hot Words into 7 risk categories including national security risk, economy & finance risk, social morals risk, daily life risk, social stability risk, government management risk and resources & environments risk mentioned above and improved the accuracy further manually. She assigned different scores from 20 to 1 according to the word's hourly rank by crawling the hottest search words hourly and got a daily list of hot words normally around 30-70, together with their frequencies and accumulated hot scores. The societal risk perception indicators are validated ecologically by corresponding to significant influences of the major social events on Chinese people during the past several years. For instance, the risk perception dropped during the London Olympic Games as most hot words were about sports but not relevant to risks, which manifests the societal risk perception indicators are the excellent thermometer of Chinese society [29].

B. Generating five public mood time series

We generated the five basic public mood indicators including happiness, sadness, anger, fear and disgust based on the Sina Weibo's user generated content (UGC) in three phases. In the first phase, we created the Weibo Five Basic Mood Lexicon (Weibo-5BML) on the basis of emotional categorical approach in psychology. First, we got 448 terms by asking five psychological graduated students to search the synonyms of emotional terms among the basic emotional psychological scales. Then we combined the 1500 emotional terms from Chinese affective words system [30], as well as the Internet folk terminology from micro-blog, such as "屌丝", "你妹", "吐槽", "有木有", which were searched by research team members for several days. All of these emotional terms were collected as the initial and raw source of micro-blog emotional lexicon. Then, these terms were simply filtered by removing the ambiguity and overlapping expression. Next, we removed the low frequency emotional terms using the searching engine function of Sina Weibo. At last, we got the initial mood lexicon pool of 2,242 terms. Second, we asked three psychological graduated students to judge discretely to which kind of basic emotions every emotional term belongs in the sight of the emotional categorical approach of psychology. Then we got 942 terms according to their consistent judgment and deleted the last 10% low frequency terms of each kind. Finally, we got the formal version of the Weibo-5BML with a total of 818 emotional terms, in which Happiness has 306 terms, Sadness has 205 terms, Fear has 72 terms, Disgust has 142 terms, and Anger has 93 terms.

In the second phase, we generated five public mood time series on the basis of Weibo-5BML. We crawled and analyzed minute texts of approximate 1.22 million of Weibo active users using a transparent approach named term-based matching technique, which matches the emotional terms used in each tweet against the emotional lexicon [31]. The Weibo-5BML could capture a variety of naturally occurring emotional words in Weibo tweets and map them to respective basic mood dimensions. First, we computed the score of each term that matched the Weibo-5BML as the fraction of tweets containing it each day. Then we averaged the quantity over all words linked to that particular emotion which means that the higher frequency of a word will have a larger impact on the mean value of each emotion. At last, we obtained five basic public mood daily series from November 1, 2011 to October 30, 2012.

In the third phase, we validated the public mood time series by comparing the mood time series to fluctuations recorded and labeled by the vital social events and the traditional festivals in China. This method was widely used in sentiment analysis [32]. For example, the conflict of Diaoyu Islands between China and Japan was dramatically at the critical moment in 2012. On September 10, Japan government announced to buy the Diaoyu's southern and northern islands to implement so-called nationalization, and would finish the relevant procedures the next day, which seriously violated the territorial sovereignty of China. The Chinese government and people opposed the behavior, marched throughout the country, and launched anti-Japanese activities including some aggressive and radical behaviors. In the present analysis, we found anger emotion was rising from September 10 and spiked on September 16, which the suspects were surrendered who had smashed the Japanese car in Xi'an, and September 18 of "9.18 Incident" anniversary in 2012. The happiness wasn't high from September 10 until the mid-Autumn day of September 30. But during the period of Golden Week from October 1 to 7, people were not happy as been thought, even a little sad, fearful and disgusted due to the congestion, chaos, and unpredictable accidents.

C. Methods

In the present study, we are concerned with the question whether the variations of the societal risk perception have significant effect on the ups and downs of the public mood states. To answer the question, we apply the econometric technique of Granger causality analysis to the level of seven kinds of societal risk perception based on Baidu Hot Words versus the five public mood time series produced by Weibo-5BML from November 1, 2011 to October 30, 2012. The Granger causality analysis rests on the assumption that if a variable X causes Y then changes in X will systematically occur before changes in Y. We will thus find the lagged values of X will exhibit a statistically significant correlation with Y. Correlation however does not prove causation but one time series has predictive information about the other or not. We test the unit root of five public moods and the seven societal risk perceptions and found all of them are integrative which are suitable for Granger causality analysis directly.

III. Results

A. Prediction of social stability risk perception on five public moods

Based on the results of our Granger causality in table I, we found that the social stability risk perception does not predict the five public mood time series because the p-values of the Granger causality correlation are statistically insignificance.

TABLE I. GRANGER CAUSALITY CORRELATION OF THE SOCIAL STABILITY RISK PERCEPTION AND 5 DIFFERENT PUBLIC MOODS.

	1day	2days	3days	4days	5days
social stability risk → sadness	0.939	0.461	0.823	0.898	0.850
social stability risk → happiness	0.125	0.240	0.259	0.324	0.162
social stability risk → fear	0.671	0.798	0.819	0.954	0.869
social stability risk → disgust	0.291	0.623	0.173	0.291	0.541
social stability risk → anger	0.817	0.208	0.320	0.426	0.276

The statistical values are the p-values of the bivariate Ganger causality correlation between the lagged values of 5 basic public moods from 1 to 5 days and the different societal risk perceptions.

B. Prediction of daily life risk perception on five public moods

We observed that the daily life risk perception doesn't have causal relation with all kinds of public moods from the Granger causality analysis in table II.

TABLE II. GRANGER CAUSALITY CORRELATION OF THE DAILY LIFE RISK PERCEPTION AND 5 DIFFERENT PUBLIC MOODS.

	1day	2days	3days	4days	5days
daily life risk → sadness	0.720	0.933	0.883	0.584	0.618
daily life risk → happiness	0.258	0.408	0.386	0.409	0.275
daily life risk → fear	0.182	0.354	0.224	0.269	0.352
daily life risk → disgust	0.212	0.528	0.792	0.902	0.926
daily life risk → anger	0.655	0.891	0.963	0.987	0.989

C. Prediction of national security risk perception on five public moods

According to the results of the Granger causality analysis in table III, we observed that the national security risk perception is not the Granger causality of all five public moods.

TABLE III. GRANGER CAUSALITY CORRELATION OF THE NATIONAL SECURITY RISK PERCEPTION AND 5 DIFFERENT PUBLIC MOODS.

	1day	2days	3days	4days	5days
national security risk → sadness	0.961	0.778	0.900	0.929	0.897
national security risk → happiness	0.700	0.851	0.951	0.982	0.799
national security risk → fear	0.916	0.893	0.812	0.773	0.827
national security risk → disgust	0.558	0.586	0.719	0.855	0.914
national security risk → anger	0.239	0.458	0.565	0.579	0.553

D. Prediction of economy & finance risk perception on five public moods

From the table IV of the results of our Granger causality analysis, we rejected the null hypothesis that the economy & finance risk perception does not predict the five public moods. The economy & finance risk perception has the Granger causality relation with happiness for lags ranging from 1 to 3 days, while it is the Granger causality of fear only lagging from 3 to 5 days and of anger lagging 1 and 2 days.

TABLE IV. GRANGER CAUSALITY CORRELATION OF THE ECONOMY & FINANCE RISK PERCEPTION AND 5 DIFFERENT PUBLIC MOODS.

	1day	2days	3days	4days	5days
economy & finance risk → sadness	0.587	0.657	0.184	0.407	0.456
economy & finance risk → happiness	0.037**	0.078*	0.096*	0.182	0.096*
economy & finance risk → fear	0.404	0.994	0.019**	0.056*	0.084*
economy & finance risk → disgust	0.775	0.796	0.055*	0.117	0.146
economy & finance risk → anger	0.019**	0.064*	0.106	0.206	0.422

* p–value < 0.10; ** p–value < 0.05

E. Prediction of resource & environments risk perception on five public moods

From the table V of the Granger causality analysis, we found that the resource & environments risk perception is only the Granger causality of sadness lagging from 2 to 5 days which is marginally significant ($p<0.10$).

TABLE V. GRANGER CAUSALITY CORRELATION OF THE RESOURCE & ENVIRONMENTS RISK PERCEPTION AND 5 DIFFERENT PUBLIC MOODS.

	1day	2days	3days	4days	5days
resource & environments risk → sadness	0.136	0.083*	0.085*	0.051*	0.071*
resource & environments risk → happiness	0.874	0.782	0.947	0.950	0.983
resource & environments risk → fear	0.333	0.658	0.783	0.877	0.831
resource & environments risk → disgust	0.363	0.785	0.138	0.137	0.155
resource & environments risk → anger	0.197	0.450	0.663	0.785	0.713

* p–value < 0.10

F. Prediction of public morals risk perception on five public moods

Applying the Granger causality analysis, we found that the public morals risk perception does not predict the five public moods except for disgust of lagging 5 days in table VI.

TABLE VI. GRANGER CAUSALITY CORRELATION OF THE PUBLIC MORALS RISK PERCEPTION AND 5 DIFFERENT PUBLIC MOODS.

	1day	2days	3days	4days	5days
public morals risk → sadness	0.638	0.883	0.791	0.872	0.864
public morals risk→ happiness	0.804	0.979	0.970	0.990	0.506
public morals risk → fear	0.676	0.780	0.855	0.912	0.402
public morals risk → disgust	0.125	0.229	0.448	0.323	0.090*
public morals risk → anger	0.345	0.399	0.601	0.752	0.824

* p–value < 0.10

G. *Prediction of government management risk perception on five public moods*

Based on the results of our Granger causality analysis in table VII, we observed that the government management risk perception has the Granger causality relation with anger lagging 1 and 2 days which is significant ($p<0.05$), with sadness lagging 2 days which is marginally significant ($p<0.10$), and is the Granger causality of fear only lagging 5 days.

TABLE VII. GRANGER CAUSALITY CORRELATION OF THE GOVERNMENT MANAGEMENT RISK PERCEPTION AND 5 DIFFERENT PUBLIC MOODS.

	1day	2days	3days	4days	5days
government management risk → sadness	0.460	0.083*	0.160	0.343	0.051*
government management risk → happiness	0.173	0.197	0.126	0.164	0.198
government management risk → fear	0.410	0.501	0.700	0.446	0.028**
government management risk → disgust	0.659	0.797	0.752	0.707	0.106
government management risk → anger	0.017**	0.056*	0.103	0.179	0.236

* p–value < 0.10; ** p–value < 0.05

Based on the above results, we find that the societal risk perception has predictive effect on public moods, and different categories of societal risk perception can predict different kinds of public moods. We describe the most important societal risk perception to every kind of public moods and map the relation of societal risk perception with public moods in Fig 1. We can see that the government management risk perception can predict anger. The economy & finance risk perception has great effect on happiness and anger one day later, and fear three days later. The resource & environments risk perception can predict sadness after two to five days. However, the other four societal risks have no prediction power on the five public moods.

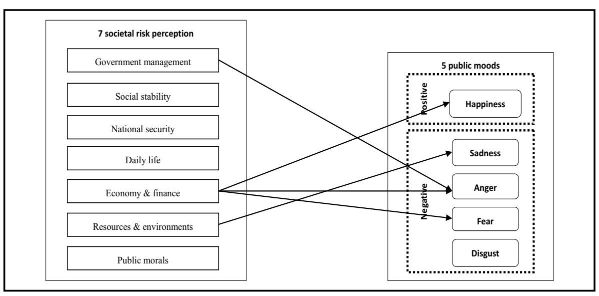

Figure 1. The predictive effects of seven Chinese societal risk perceptions on five public moods

IV. DISCUSSION

As we enter the Web 2.0 era, new media such as micro-blogging sites brings about life and cultural changes. It offers people opportunities to publicly express opinions, and has attracted many researchers to get images of societal situations by making use of those free expressions. This paper made an attempt to understand how public emotion can be induced by risk perception among the public using an interdisciplinary approach. The five public mood time series were obtained by using the Sina tweets directly on the emotional structure theories of psychology and sentiment analysis technique from information science. The seven societal risk perceptions were gotten by making using of the public searching behavior from Baidu search engine on the basis of system science. Then we employed the Granger causality analysis from econometrics and found that different kinds of societal risk perception could induce different collective reaction of emotion which could be explained by the cognitive appraisal theory and identity emotion model.

In this paper, the subcategory of government management risk includes corruption and degeneration, governance ability, legal system, social security and social welfare, which are implemented and controlled by government officials mainly. Therefore, the appraisal of government management risk is the power estate taking all responsibility, the situation may be changed after denounce and accountability (high controllable), all of which tend to induce anger and call for further changes and reforms. However, when the call from citizens can't solve the problem or have no practical effect, the public may be sadness or worried some days later. By contrast, the most concerned resources and environments risk is haze during 2012, the appraisal of which is everyone taking responsibility for the situation, and low controllable and lack of effective solution nowadays inducing sadness or helpless more likely.

Our research has important theoretical and practical value. First, we present a reliable, scalable and early assessment of the public mood, having some offset for large survey which is expensive and time consuming to conduct or other indicators which can't measure public mood directly. Second, we argue that sentiment analysis of minute text corpora (such as Weibo) is efficiently obtained via a term-based approach that requires no training or machine learning, and providing a useful micro-blog mood lexicon. Third, we study the psychological attitude from searching behavior while the traditional research only speculated them based on sample with the limitation of manpower, material and resources. Fourth, we can study the psychological characteristics directly based on the massive information from Internet or social network and text analysis technique, while traditional research mainly relied on one-time, self-reported data which isn't so real because of social desirability and other subjective effects. In addition, we explore a new way for social science research. The Internet develops so rapid and accumulates a mass of information expressed in text, picture, video and other forms which can be complied into comprehensive pictures of both individual and group behavior making up for the defect of traditional research in many areas, with the potential to transform our understanding of lives, organizations and societies.

Of course, there are many limitations in our paper and doesn't acknowledge a lot of important factors which need further research. First, although the popularity of Sina Weibo increased rapidly, mainstream micro-blog users in China are still the highly educated and young people. To what extent these users are representative of the general public of China is still debatable. Second, the data of public moods and societal risk perception are extracted from different network platforms. The users of those two website are not entirely identical which may influence the accuracy and validity of research. Third, we don't examine other factors influencing public moods, so the relationship between public moods and societal risk perception isn't causal but correlational indeed. Whatever, the societal risk is so complex that it's difficult to evaluate according to the appraisal criteria. Such as, the sub category of resources & environments risk includes natural disaster and environment pollution which focus on different evaluation, inducing different emotions too. Whereas the societal risk may induce some more complex moral or ethical emotions, we only identified the five basic emotional reactions including happiness, anger, sadness, fear and disgust because of the difficult to measure public complex emotion using sentiment analysis technique. However, the basic public mood is relevant to ethic too because of the high correlation with social event such as the Diaoyu Island conflict.

V. CONCLUSION

This paper related the public moods to societal risk perception and applied Granger causality analysis to reveal that the societal risk perception has predictive effect on public moods, but different categories of societal risk perception can predict different kinds of public moods on the basis of cognitive appraisal theories.

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