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Exploring the Participate Propensity in Cyberspace Collective Actions: The 5‰ Rule

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Highlights

It explores the participate propensity of individuals in online collective actions.

The whole participation spectrum of online collective actions contains 4 stages.

The participation propensity is stable and takes on the simple regularity of 5‰.

The participation propensity follows the lognormal distribution.

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Abstract

The Internet and Big data have become indispensable in people's daily life. The whole participation spectrum of cyberspace collective actions contains four stages, such as Access, Browse, Participate, and Offline. There exist three transition probabilities within four stages. This paper focuses on the ratio (second transition probability) between numbers of browse and participate, which is defined as the participate propensity P_{BP}. In the real world, amounts of browse (millions) and participation (tens of thousands) are huge, and they take on irregular distributions. However, it is discovered in this paper that this participate propensity is stable and takes on the regularity of 5‰, i.e. the participation propensity is slightly under 5‰ for most times, while sometimes it is slightly over 5‰. The empirical big data of 310 online collective actions are collected from a famous BBS (Tianya.cn) in China. This 5‰ rule not only holds true for the total 310 cases, but also for yearly, quarterly, and other subgroups. Furthermore, we check distributive traits of P_{BP}. It is not normally distributed as it has longer right tails. It is verified by the empirical big data that the propensity follows the lognormal distribution, which is relatively robust in the total and subgroups of 310 cyberspace collective actions. Given the distributive regularity of the participate propensity P_{BP}, its probability density function can be obtained. Combined with the known amount of browsers, big data prediction of participation would be possible.

Keywords: Big Data Prediction; Browse; 5‰ Rule; Cyberspace Collective Actions; Participate Propensity;

1. Introduction

In the Big Data Era, the Internet has become an indispensable element in people's daily life [1, 2, 3]. With the emergency of mobile Internet, the application of big data is exerting more and more influences on individuals. The big data prediction of individual behaviors and collective actions has become feasible, necessary and stable [1, 2, 3]. With cheaper costs of participation [3, 4, 5], launching or participating a collective action online has become quite convenient. As the cost is cheaper, the scale of participation is very huge, compared to traditional collective actions. For traditional collective action, the number of participants is from thousands to tens of thousands, but the number commonly is over millions for online collective actions.

As the amount of participation is huge, cyberspace collective actions have more power, impact, or influence than traditional actions [3, 5, 6], especially on the politics and public policy in China. Internet users launch collective actions to express their positions, and other individuals take part in it responding to them both positively and negatively. Cyberactivism is the extreme aspect of cyber collective actions; it forms contentious politics and shapes social movements [5, 6, 7]. The spirit of online collective actions is hacktivism or cyberactivism, while the spirit of traditional ones is linked to the concept of collective identity [8, 9, 10]. Online collective actions built the ideal public sphere for individuals [11], which break the more tightly controlled offline media and political space to facilitate people's participation and rights [11].

The parameters of individuals' online behaviors have been inspected [5, 8, 11, 12, 13]. Based on the online browse, we predict the participation [13, 14, 15, 16]. It seems that the numbers of browse (millions) and participation (tens of thousands) are huge with irregular distributions. However, it is discovered by this work that the ratio between them takes on the regularity of 5‰ approximately. The ratio is defined as the participation propensity of Internet users, which is a new research field. Sometimes the participation propensity is slightly under 5‰ while sometimes slightly beyond 5‰. Besides of the overall propensity, propensities of subgroups will be investigated. The distribution of the participation propensity is checked, and the probability density function is obtained, based on which big data prediction is feasible.

2. Methods

2.1 Spectrum of Cyberspace Collective Action

The process of online collective actions is dynamic and nonlinear [3, 5, 8, 11, 13], but the procedure of them can be decomposed into four stages, which forms the whole spectrum: (1) **Access**. Individuals get online via all kinds of tools, such as PC and smart phones, especially smart Apps or SNA [11, 13, 16]. This is the precondition for individuals to take part in collective actions online; (2) **Browse**. Individuals freely browses the information that is interesting, such as societal news, sports and events, entertainment and stars, gender issues, etc. [13, 17], according to the heterogeneous preferences of individuals [3, 18-20, 21, 22, 23]. The individuals that are browsing the same information (sharing the same interest) form the possible participation set; (3) **Participate**. In this stage, individuals in the participate set interact with each other online, which forms cyberspace collective actions. Cyberspace collective actions regularly happen on the BBS, Wechat groups, etc. Individuals response to others positively (support, like, or recommend), negatively (criticize, curse, or oppose), or neutrally [19, 24], which is common scenes of online collective actions; and (4) **Offline**. For some cyberspace collective actions, the online chatting or interaction may lead to further offline actions. In other words, there is a linkage probability for an online collective action to transform into an offline one [14, 15, 16].

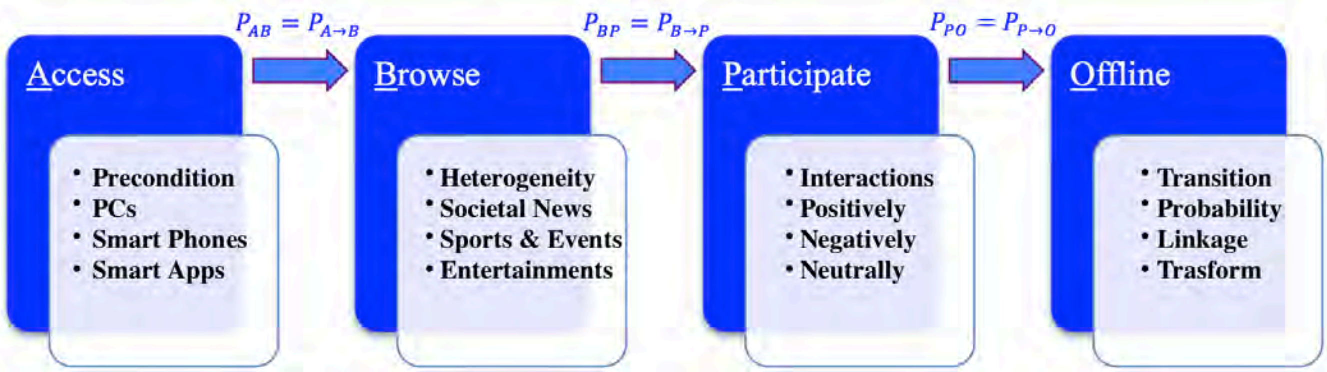

Figure 1. The Spectrum of Cyberspace Collective Action. It reflects the whole process of individuals' participation into online collective actions. First they should have access to the Internet, and then they browse the same or similar information with a probability P_{AB}. They participate the collective actions and interact with each other after they browse them with a probability P_{BP}. Eventually, there is a probability P_{PO} for online collective action to evolve as offline collective actions.

2.2 Variables and Measurement

The whole spectrum of online collective actions is shown in Figure 1. There exist three transition probabilities during the whole spectrum: (a) by June 2016, we have 668 million Internet users in China (CNNIC, 2016). The P_{AB} refers to the probability and percentage of how many browsers out of the total population with access to the Internet, and P_{AB} is calculated as equation (1) shows. For areas or countries with higher Internet penetration rates, online collective actions are more prevalence [11, 14, 19, 25]; (b) the P_{BP} in equation (2) refers to the percentage of how much participation in the total browsers. Not all browsers of Internet information launch or participate the cyberspace collective actions, and there should be a ratio to measure this probability or percentage; and (c) the transition probability for online collective actions to become offline collective actions has been investigated [14, 15, 16]. Therefore, we deem the transition probability from online to offline collective action as P_{PO}, i.e. from Participate (Online) stage to Offline stage.

$$P_{AB} = P_{A \to B} = P_{Access \to Browse} = \frac{\# Browse}{\# Access} \tag{1}$$

$$P_{BP} = P_{B \to P} = P_{Browse \to Participate} = \frac{\# Participation}{\# Browse} \tag{2}$$

$$P_{PO} = P_{P \to O} = P_{Participate \to Offline} = \frac{\# Online}{\# Offline} \tag{3}$$

2.3 Data of Participate Propensity

The transition probability P_{BP} is defined as the participate propensity. The key is to investigate and evaluate the propensity P_{BP}, which is directly related to the main processes of cyberspace collective actions. It determines and therefore helps to predict the total scale of participation. If the participate propensity P_{BP} has a stable level or takes on a regular distribution, the prediction of participation should be more robust. The data applied is from a famous BBS of China, which is Tianya.cn. The span of data is from April 2015 to August 2016. The monthly data of cyberspace collective actions are recorded, including the total participation ($\# Participation$) and total browse ($\# Browse$) of each case. The number of cases is 310, and they are all hot topics of that time. The total participate propensity P_{BP} and sub-group propensities $P_{BP}(.|type)$ will be explored and evaluated, based on which, the total participation of each collective action could be predicted given the number of people that have browse or witnessed the collective actions.

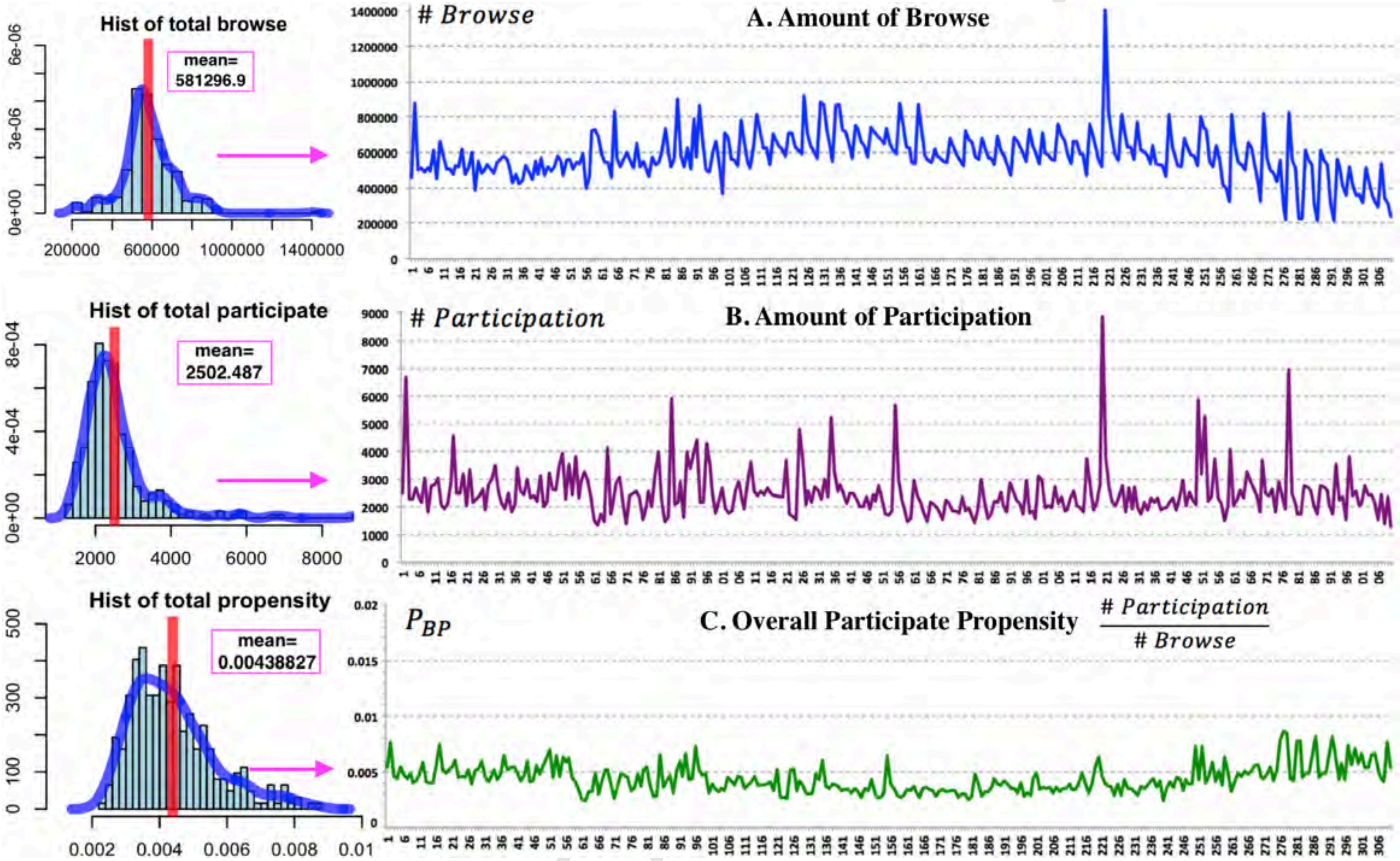

Figure 2. Empirical Big Data of Collective Actions Online. 2(A) visualizes the amount of information browse for each case with its histogram on the left. The y-axis is the number of browse, and x-axis refers to the ID of cases; 2(B) reflects the number of participation with the histogram on the left. Y-axis is the number of participation, and X-axis refers to ID of cases; 2(C) refers to the propensity for all 310 cases, and its distribution is on the left. Y-axis is the value, and X-axis refers to ID of cases.

3. Results

3.1 The 5‰ Rule of Participate Propensity

The total browse and total participation times are reflected by Figure 2: (1) Figure 2(A) refers to the fluctuation of total browse numbers ($\# \, Browse$) in 310 cases. The number of browse varies a great deal, and it ranges from 2,000,000 to 14,000,000 times. The distribution in the left part indicates that the central tendency is obvious and the mean is about 58-59 million; (2) Figure 2(B) shows the fluctuation of the amounts of participation numbers ($\# \, Participation$) for total 310 cases. The amount of participation times also varies a lot, ranging from 1,000 to 9,000. The distribution chart (left part) indicates that the long tail is obvious and the participation is skewed, not normally distributed. The average participation amount is approximately 2,500; (3) the overall participation propensity for 310 cases is about quite stable, although the two determinants are large and vary a great deal. It indicates that most propensities are close to 5‰. Some are slightly under 0.005, while others slightly beyond 0.005. Therefore, the 5‰ rule holds for the total cyberspace collective actions.

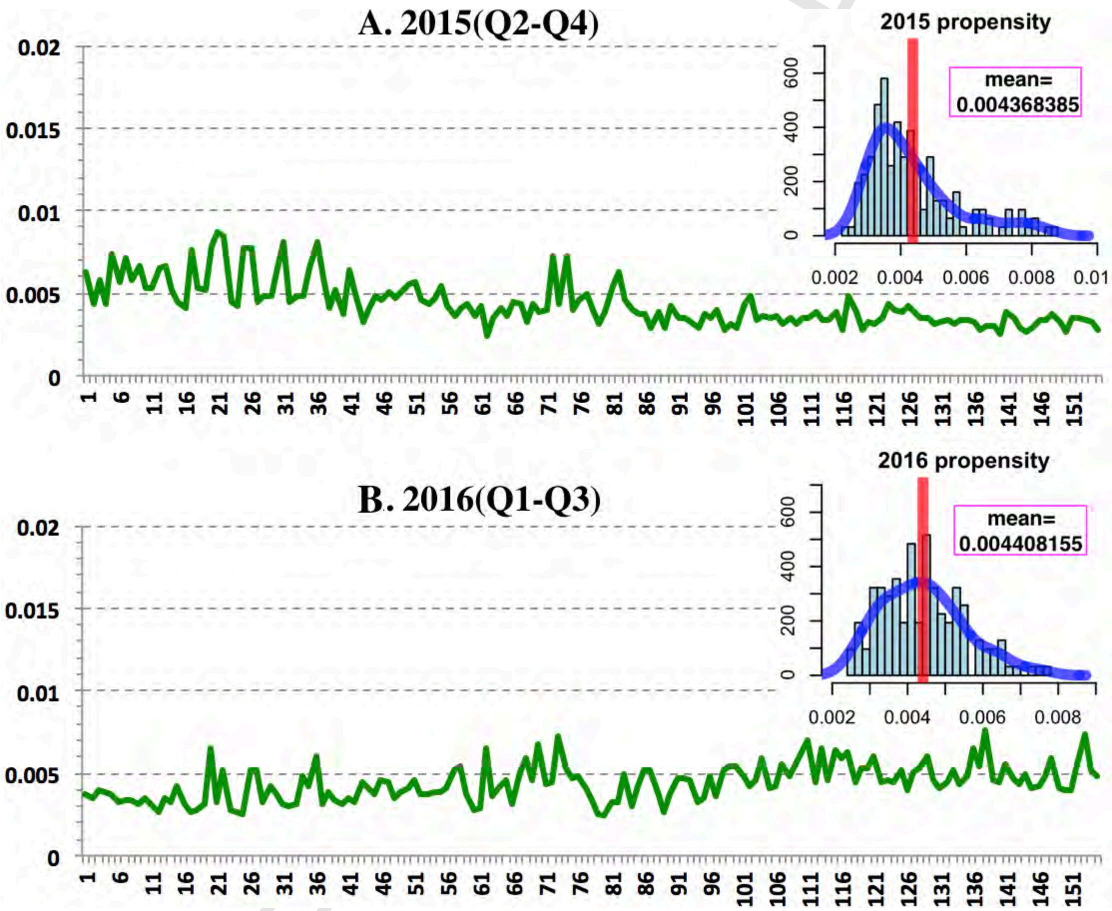

Figure 3. The Participate Propensity by Year. Y-axis represents the level, and x-axis is cases' ID. 3(A) visualizes the propensity in 2015, with its histogram on the right; 3(B) visualizes cases in 2015, with its histogram on the right corner.

3.2 Yearly Participate Propensity

As the data set is from 2015 to 2016, we divide 310 cases into two years, and visualize their participate propensities in Figure 3. For 2015 cases, the fluctuation is relatively dramatic, but the $P_{BP}(.|2015)$ still fluctuates around the 5‰, which is shown in Figure 3(A). The first half propensities in 2015 are higher than 0.005, and the second half are lower than 0.005. The distribution of $P_{BP}(.|2015)$ is skewed with longer right tails, and the average value is about 4.368‰; for 2016 cases, the fluctuation is not as fierce as 2015, and $P_{BP}(.|2015)$ fluctuates around 5‰ as well. The first half is lower than 5‰, and the second half larger than 5‰. The distribution of $P_{BP}(.|2016)$ is not normal distribution with the mean of 4.408‰.

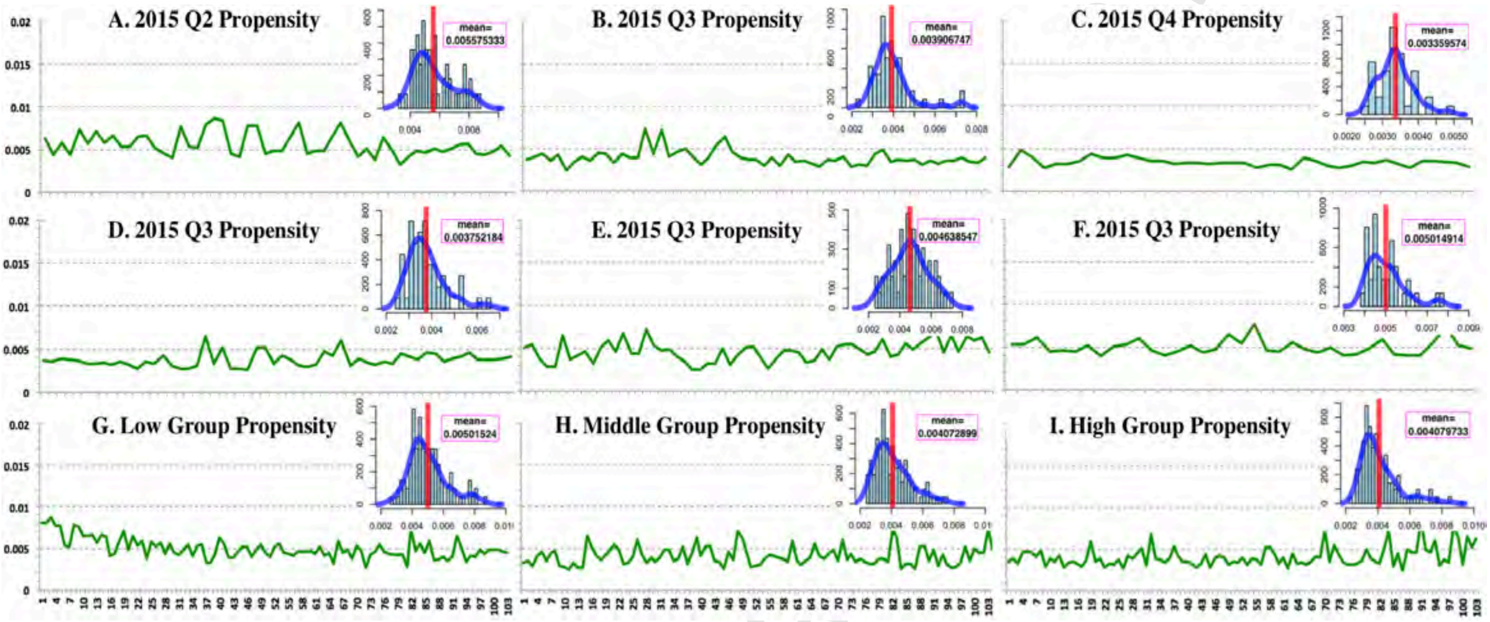

Figure 4. Subgroup Propensities. For all subfigures, the y-axis represents the level or value, and x-axis represents cases' ID. Figure 4(A)-(F) visualizes the quarterly propensities form Q2 in 2015 to Q3 in 2016, with the histogram on the right. Figure 4(G)-(I) visualize the propensity in low, middle, and high-browse groups.

3.3 Quarterly Participate Propensity

To explore possible differences within quarters, the overall 310 cases can be divided into six quarters. The year of 2015 has three quarters of Q2, Q3, and Q4, and the year of 2016 has three quarters of Q1, Q2, and Q3. It indicates that most of them is not normally distributed, and Figure 4 shows the fluctuations and distribution of their six propensities from Figure 4(A) to 4(F): (a) For the second quarter (Q2) of 2015 in Figure 4(A), the propensity $P_{BP}(.|2015Q2)$ is slightly beyond 5‰ for most cases, and the mean is about 5.558‰. The distribution is not normal distribution; (b) for Q3 of 2015, the propensity $P_{BP}(.|2015Q3)$ is slightly below 5‰ for most of them, and the distribution is not normal distribution with a mean of 3.908‰; (c) for Q4 in 2015, the propensity $P_{BP}(.|2015Q4)$ is under 5‰ as well for all cases, and the mean is 3.360‰; (d) in Q1 of 2016, $P_{BP}(.|2016Q1)$ is under 5‰ for most of them, and the mean is about 3.752‰, the distribution is not normal distribution with longer tails; (e) in the Q2 of 2016, the distribution of $P_{BP}(.|2016Q2)$ is quite close to the normal distribution, as the central tendency is obvious, with the mean of 4.639‰; (f) for Q3 of 2016, $P_{BP}(.|2016Q3)$ is skewed distributed and most of them is close to 5‰. The mean is about 5.015‰.

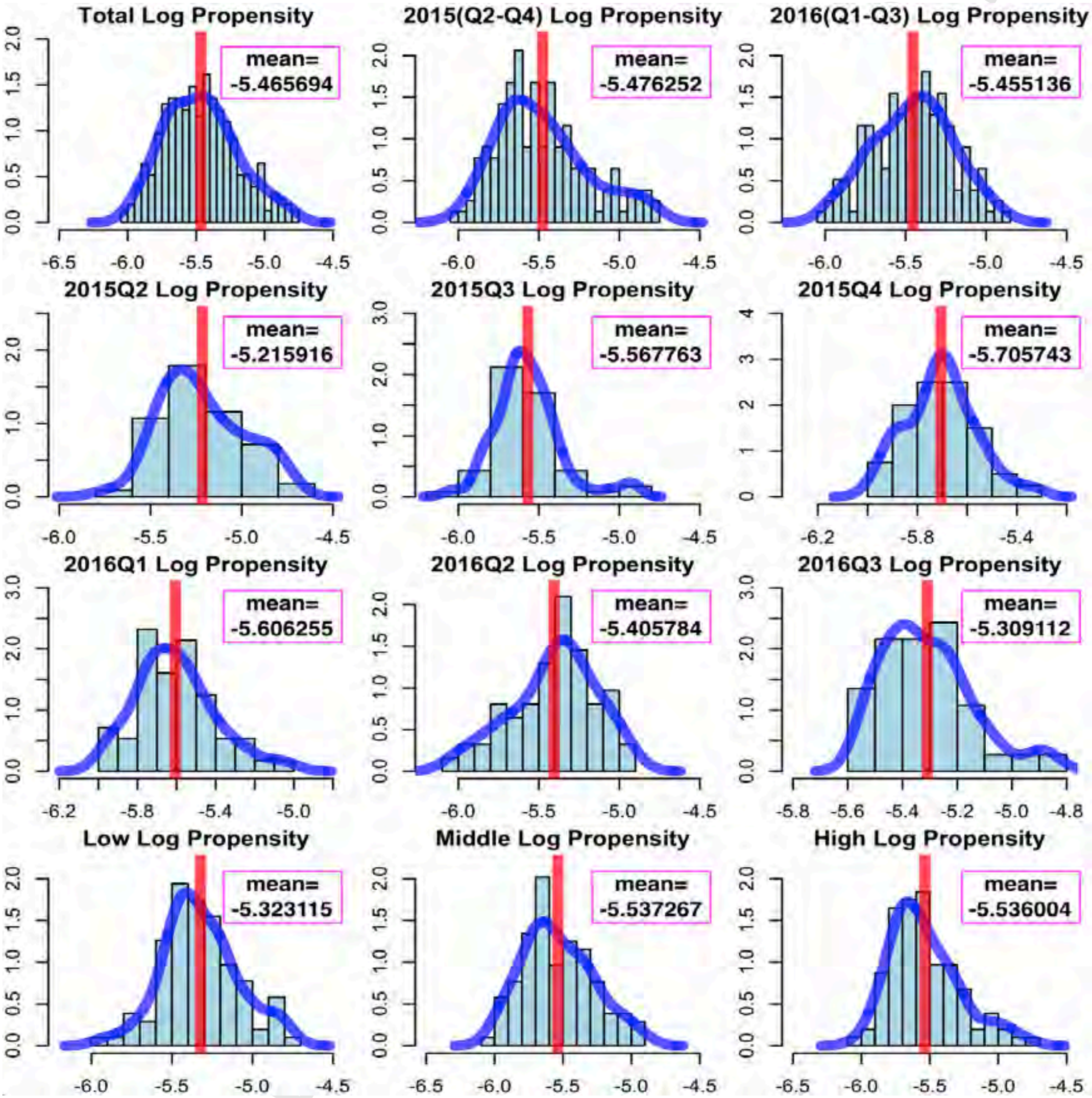

Figure 5. Histograms of $\boldsymbol{p}$. It reflects distributions of p in all figures. The blue curve refers to the probability density of p and the red line refers to the mean of p. The total as well as the yearly p is normally distributed; most quarterly distributions are quite close to the normal distribution. For small, middle, and high-browse groups, distributions of p are close to the normal distribution as well.

3.4 Low-Middle-High Participate Propensity

To investigate whether the scale of information browsers have influence on the propensity or not, we explore the propensities within low, middle, and high–browse groups. According to the amount of browse ($\# Browse$), the overall 310 cases are divided three groups that have even numbers of cases. For the low-browse group in Figure 4(G), the propensity $P_{BP}(.|low)$ is vibrating around the 5‰. The mean of $P_{BP}(.|low)$ is about 5.015‰, which is quite close to 5‰. The distribution has longer tails; for middle group cases, $P_{BP}(.|middle)$ is under 5‰ for most cases. Therefore, the mean of $P_{BP}(.|middle)$ is about 4.073‰; and for high group cases, most $P_{BP}(.|middle)$ is under 5‰. Likely, the mean of $P_{BP}(.|middle)$ is about 4.080‰.

It seems in Figure 5 that the participate propensity of most online collective action is around a stable level of 0.005, which holds true for total, yearly, quarterly, and other sub-groups of online collective actions. The stable participate propensity indicates that the action probability of Internet users is stable, i.e. there are roughly 5 actors out of 1000 witnesses. The possible reason or mechanism is that the output energy or impact in online collective action is constant: there seems to be a certain proportion of people interested in online collective actions; there seems to be a certain proportion of attention that the individual could pay to (online) collective actions.

4. The Lognormal distribution of Propensity

For most cases in total cases and the sub-groups of online collective actions in Figure 2(C), Figure 3, and Figure 4, the participate propensity is not normally distributed with longer tails. Therefore, the distribution of propensity seems to be the lognormal distribution. We take the logarithm of P_{BP} and it indicates that the logged propensity is well normal distributed. As in equation (4), p is the logarithm of P_{BP}.

$$p = ln(P_{BP}) = ln\left(\frac{\#\ Participation}{\#\ Browse}\right) \tag{4}$$

For the total and yearly propensities of 2015 and 2016, the distribution of P_{BP} is quite close to the normal distribution and symmetric to the mean value. For the total propensity, the mean is about -5.466, and the yearly means of 2015 and 2016 are -5.476 and -5.455. For six quarterly logged propensities, they are closer to the normal distribution and more symmetric to their mean values. For low, middle, and high group propensities, the distributions of logged propensity p are close to the normal distribution as well. Figure 5 merely provides the visualization of p, but we need more established tools to check whether the p is normally distributed or not. Hence, the Q-Q plot is applied to check the normal distribution of p for the total and subgroup cyberspace collective actions.

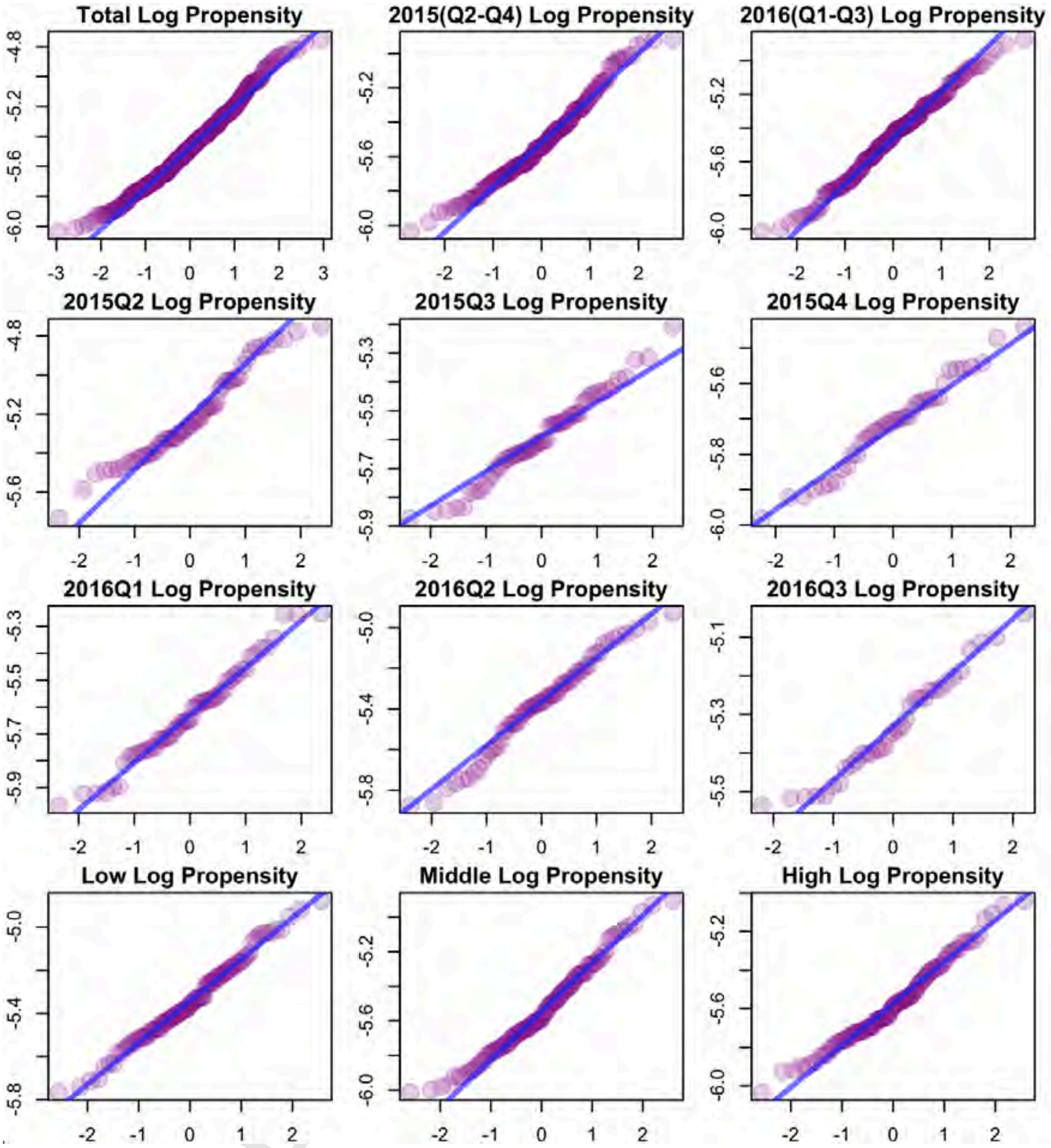

Figure 6. The Normal Distributions of $\boldsymbol{p}$**.** It checks the normal distribution of p (logged participate propensity) under all scenarios. For total and yearly situations, p is normally distributed in subfigures (the first row); for quarterly cases, p is quasi-normally distributed in the middle range (the second and third rows); for low, middle, and high-browse groups, p is normally distributed as well (the forth row).

As is indicated by Figure 6, almost all the data points in purple are exactly located on or close to the Q-Q normal line in blue: (a) for the distribution of the total p, almost all the data points are located on the Q-Q line, except for some extreme values; (b) for 2015 and 2016, p follows the normal distribution, it is closer to the normal distribution in 2016 than in 2015; (c) p follows the normal distribution in three quarters (Q2, Q3, and Q4) of 2015, and p in Q4 is the closest to the normal distribution; (d) for three quarters (Q1, Q2, and Q3) in 2016, p in all of them is well normally distributed; (e) for the low-browse group, p perfectly follows the normal distribution as most data points are on the Q-Q line; for the middle-browse group, p follows the normal distribution quite well except for some smaller values; p also follows the normal distribution in the high-browse group.

Therefore, it is verified in Figure 5 that the p follows the normal distribution (the participate propensity P_{BP} follows the lognormal distribution) by 310 cases, and it is highly possible that its big data distribution still follows the normal distribution. The normal distribution is a quite ideal distribution of variables. The reason why p follows the normal distribution is that most online collective actions have the mean level of participate propensity and merely a small percentage of online collective actions take on extremely high or low propensities. In others words, the distribution of participate propensity P_{BP} has a longer right tail.

5. Conclusions and Discussions

In equation (5), given the primary normal distribution of p under 310 cases, we are able to inference or estimate the normal distribution of p with more and more data (Big Data), using the observed parameter values such as the mean ($mean$) and standard deviation (sd) of p. Once the normal distribution is known, the probability density function f p can be obtained, which paves the way for big data prediction of participant in online collective actions [5, 8, 11, 13, 14, 15, 18]. The key application of p's normal distribution is to predict the amount of participation, based on the number of browse for specific types of online collective actions.

$$p_{type} \sim N(u_p, \sigma_p) \cong N(\hat{u}_p, \hat{\sigma}_p) = N(mean, sd) \tag{5}$$

$$ln(\widehat{Participation}_{type}) = p_{type} + ln(\#Browse_{type}) \tag{6}$$

$$\widehat{Participation}_{type} = e^{p_{type}} \cdot \#Browse_{i,type} \tag{7}$$

For each type, the normal distribution of p is estimated by the mean and standard deviation in type's sample in equation (5), and then we get the probability density function of p_{type} for a certain type of online collective actions. The term $\# Participation$ and $\# Browse$ refers to the observed amounts of participation and browse in equation (4), while $\widehat{Participation}_{type}$ refers to the predicted amount of participation for a specific type of online collective actions. Based on equation (4) and (6), the participation can be predicted as $\widehat{Participation}_{type}$ in equation (7). We take the prediction of total participation as an example. The mean and standard deviation of the total p are plunged into equation (7), and we use R to simulate this process repeatedly for 1000 times with 1000 random seeds.

```
p=log(data$propensity);hist(p);mean(p)
pm=matrix(0,1000,length(p));dim(pm)
for (i in 1:1000){
    set.seed(i);
    pm[i,]=exp(rnorm(length(p),mean(p),sd(p)))*data$browse}
p_hat=apply(pm,2,mean)
```

Figure 7 visualizes the simulation and prediction of participation person times for the total collective actions online based on 310 collected online cases. It indicates in Figure 7 that the predicted amount of participation is quite close to the observed participation amount, considering that the participation is over thousands. Therefore, based on the lognormal distribution of the ratio between amounts of participate and browse, the prediction of participate person-times for certain cyberspace collective actions are feasible and practical.

As well, there exists a simple regularity of 5‰ for the participate propensity, with a mean of 0.00438827. If the propensity's mean and browse amounts are applied, we get the same participation's prediction. Key factors of predicting online participate have been investigated already [15, 17, 18, 19, 22, 24], such as social identification [17], psychosocial predictors [19], thresholds [15, 22], network and spatial games [26, 27, 28], etc. However, this work believes that these factors are not necessarily needed, because we can predict the participation given the participation propensity and amount of browse. As the data points gets denser, it is highly possible that big data prediction of participation will be more and accurate. Dynamic monitoring and prediction of online collective action could be realized based on the distribution regularity of participate propensity. Besides, the linkage between online and offline collective actions is an important research field [14, 15, 16]. Given the browse propensity and participation propensity, we are able to predict the total participation and how possible that certain online collective actions are turned into offline collective actions.

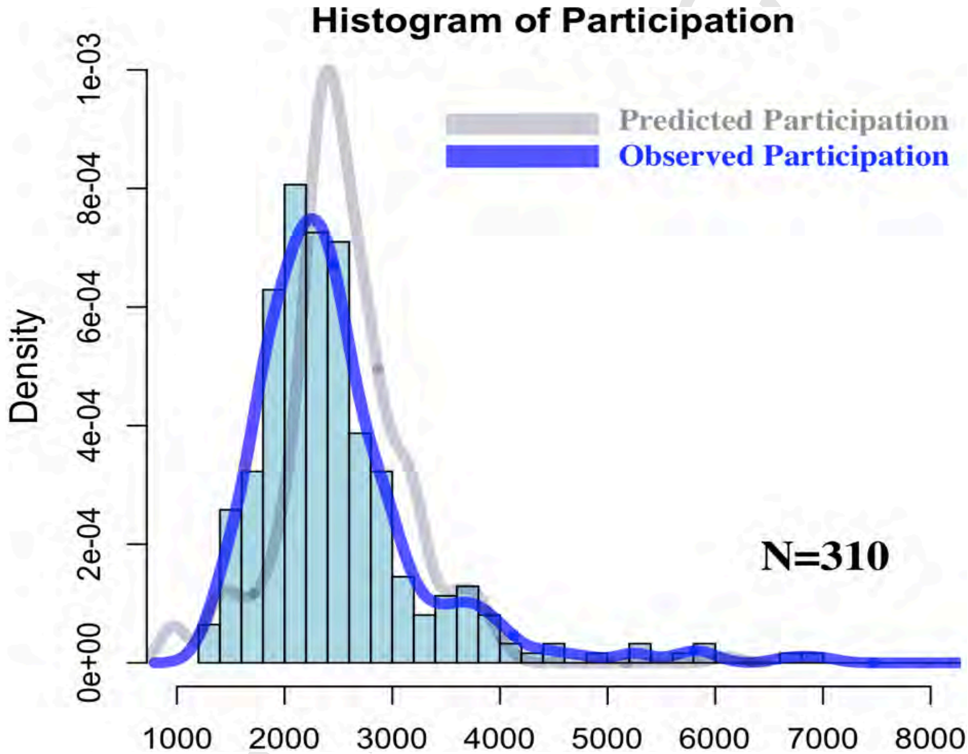

Figure 7. Observed & Predicted Participation of Online Collective Aciton. It compares the observed distribution (with the histogram and the blue density line) and predicted or simulated distribution (with the gray density line) of participation.

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