Witnessing Political Protest on Civic Engagement*

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Abstract

How does physically witnessing a protest in a democratic society affect citizens in authoritarian societies? Existing data are unable to answer the question by failures to capture witnesses, to construct meaningful comparison groups and to obtain information on pre-protest political behaviors. Using a quasi-experiment design, we report a first causal estimation on impact of 13 protests in Hong Kong from 2012-14 on witnesses from mainland China. We used geocoded posts from Chinese social networking site to collect a panel of Chinese users who visited Hong Kong but at different timing: treated users were physically close to one of the protests when it occurred; control users already left Hong Kong before protests and could not witness protests. With the control group and users’ ex-ante posting history, difference-in-differences methods are used to estimate changes of intensities and issues of discussion of civic and political problems. Treated users discussed more civic and political problems by 40.39% (95% confidence interval: 3.62%, 75.48%) after protests, relative to the change of control

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users. The increase in intensity of civic engagement is robust under replication and placebo tests, and remains significant within three months after protest. Treated users discussed more about issues that are related to their daily lives such as pollution and food safety, and democratic protests in Hong Kong. Our result suggest that witnessing protests with democratic pursuits lead citizens from authoritarian regimes to be more involved in their civic life, but not necessarily lead to their support for electoral democracy.

Keywords: Natural Experiment; Hong Kong; China; Protest; Civic Engagement; Political Attitudes

1 Introduction

How does physical exposure to a political protest in a democratic society affect political behaviors of ordinary citizens from authoritarian regimes? In this paper, we offer a case study of the impact of 13 political protests in Hong Kong on witnesses from mainland China. These include a series of protests in 2012-13, and the recent “Umbrella Protest” in 2014 which received much domestic and international media attention. Number of participants from 1500 to over 100,000. All of them were organized around issues related to tensions between Hong Kong citizens and the Hong Kong government. Protestors sought to draw attention to their belief that the Hong Kong government has been acting under the influence of the Beijing government instead of pursuing the interest of their own citizens. Under the overarching mission, the protests demanded a wide spectrum of changes, including the freedom to nominate city mayor candidates; to oust the current city mayor whom they thought to be representing the interests of Chinese government; to reject proposed educational reforms that would replace previous civic education with a more nationalistic curriculum.

Existing research in social movements pay most attentions to the causes and policy consequences of protests, by studying participants (their organization and mobilization) and government (their policy reactions) and their interactions. We focus on witnesses instead by examining the spillover impacts of protests on witnesses. The shift to witnesses is important in both theory and its policy implications. Theoretically, interactions between activists and spectators are key to the success of protests, while micro-level studies on how protests influ-
ences witnesses’ political behaviors have been rare in social movement literature (Gamson, 2004; Wallace et al., 2014; Branton et al., 2015). The shift also have societal implications. We wish to study how protests influence political attitudes and behaviors of ordinary mainland Chinese people instead of political enthusiastic people or activists (O’Brien et al., 2006; O’Brien, 2009; Chen, 2011). However, opinions survey about political protests are hard to administer in authoritarian regimes. Even if scholars are able to carry out a survey about political attitudes, responses are often the artifact of the authoritarian government’s control over state-owned news media and censorship of social media. Witnesses nevertheless can get a more complete picture of the protests than they could get when they went back to China. Their changes of political behaviors hence are helpful to understand how ordinary Chinese citizens would react to the protests, if they were given more complete information.

Despite its importance, currently there is no research on how witnessing protests influences the political behaviors of individuals from authoritarian regimes. The only evidence comes from media reports. The New York Times and the NPR reported, as common perception may suggest, that exposures of protests shocked Chinese tourists; many of them supported the protests. However, other reports showed that attitudes towards these protests were predominantly negative in mainland cities (Gough and Ramzy, 2014; Kuhn, 2014; Jacobs, 2014).

The major obstacle for rigorous academic research thus far has been the lack of appropriate data. Current data collection efforts in the field of contentious politics draws exclusively on ethnographic interviews and surveys of participants of protests. However, by design they fail to capture witnesses who may happen to be physically passing by the scene of a protest but who do not actively participate or share the same political orientations of the protestors. Once the protest ends, it is extremely hard to find witnesses in a post hoc fashion (Verhulst and Walgrave, 2009; Walgrave and Verhulst, 2011). Even if one explicitly incorporates witnesses into future protest surveys, there remain two problems. First, there lacks a comparison group that are similar to witnesses in demographic characteristics, but did not witness the same protests. Without a comparison group, we cannot rule out the possibility that witnesses self-select into the democratic region such that they are systematically different from other fellow citizens who did not visit the democratic region. Secondly,
there lacks ex-ante information in most protest survey, since it is not easy for scholars to track participants/witnesses before the occurrence of protest. Without the ex-ante information, we cannot know whether observed attitudes or behavior after protest were already held by the individual even before protest. In short, current data collection procedures in social movement research are unable to find witnesses, to construct comparison groups and to collect ex-ante information on subjects. Without appropriate data, causal inference is extremely hard for the question we wish to answer.

There has been recent attempts to use social media to understand how social movements influence political behaviors. Most of these research relies on keyword filtering to construct study population: scholars filter posts or users who mentioned protest relevant keywords or hashtags in their posts (Tufekci, 2014). However, this approach cannot help us to identify causal impact of protests either, due to self-selection bias. In social media, users self-select to follow and discuss topics that they are interested in. Hence study population constructed by keyword-filtering method may heavily oversample users who were interested in events beforehand. Furthermore, in our specific case, keyword-filtering method will miss most data since Chinese internet censorship tools put more efforts into deleting posts that represent social mobilizations potentials regardless of content, such as posts which contain the word “protests”, than posts that directly show negative attitudes toward the government (King et al., 2013). Data collected through protest-related keywords/hashtags hence is vulnerable to self-selection and is biased due to censorship.

In this paper, we advance a novel method of using social media data which solves aforementioned difficulties with traditional ethnography/survey methods and keyword-filtering social media data collection methods. We use users’ spatial information from one of the largest Chinese social networking sites, Weibo, to construct a quasi-experiment in a post-hoc fashion. Akin to Twitter, geolocated posts from Weibo contain precise time and spatial information. With such information, we construct two groups of users that come from mainland China in the following principle:

- a treatment group that was physically near one of the 13 protests in Hong Kong when they occurred. We presume that they possibly witnessed one of the protests.
a control group that also visited Hong Kong but already left when protests occurred.

We presume that they did not witness the protests.

By using geolocation to find users that were exposed to protests, we were able to collect a sample of witnesses after protests, which is not easy for ad-hoc survey or ethnography methods. We also reduce the self-selection bias that would occur if one were use keyword-filtering method to filter potential witnesses. Furthermore, we collected these users’ posts before, during and after protests to assess potential changes within individuals over time. Therefore we are able to provide a rigorous difference-in-differences estimation procedure, by comparing changes of treated users before and after protests to changes of control users. Our design is able to capture witnesses in a post hoc fashion, to construct a meaningful control group, to collect their ex-ante information, and to reduce self-selection bias.

With the treatment and control group, we examine how online civic engagement patterns of users vary after protests. Two dimensions of civic engagement is analyzed: intensity (how often do social media users discuss civic and political issues), and content (what issues they discuss). The two dimensions are orthogonal to each other: there can be two individuals who discuss civic problems online as frequently as each other, while focus on different specific issues.

For the intensity of discussion of civic problems, while our treated users were not ex-ante politically engaged users (only 1.66% of their posts posts discussed civic and political problems), we observe marked increases in their intensity of civic engagement after having witnessed the protests. The difference-in-differences estimator shows that for every 100 tweets posted after protests, treated users had 0.669 more civilly- and politically-relevant posts than their pre-protest level, relative to the change of a set of matched control users. This means that treated users posted 0.669/1.66=40.39% (95% confidence interval: 3.62%, 75.48%) more civically- and politically-relevant posts compared to the control users. The increase in the intensity of discussion of civic and political problems is robust under two placebo tests and one replication test. It persisted in the first months after the protests, and decayed afterwards.

After knowing that treated users discuss civic and political problems more often, we further analyze the content of these discussions. For the social and political issues treated users
discussed after protests, the largest increase is about their daily lives, such as air pollution, food safety, legal problems and corruption. They also discuss more about their exposure to democracy in Hong Kong, and topics about nationalism. However, their discussion about democracy almost all occurred in the context of Hong Kong, but did not emerge as a single topic. In contrast, discussions of other topics, from daily lives to media and legal reform all occurred in the context of Chinese society, and Hong Kong rarely become a focal point of their discussion.

In sum, the 13 protests led to increases in overall intensity of the civic engagement of Chinese witnesses. A detailed analysis shows that witnesses expressed more concerns towards civic issues that are directly related to their daily lives and experiences. Yet such civic concerns however are yet to be translated into concerns toward political rights.

Our focus on witnesses from mainland China allows us to provide insights into how Chinese people might respond to political protests were they given more complete and uncensored information. In authoritarian states such as China, surveys about political attitudes toward protests are under government constraints. Till now there does not exist a nationally representative survey examining Chinese attitudes toward Hong Kong protests, and there is unlikely to be one in the near future. Moreover, even if there could be a representative survey on the general population, it possibly would only reflect opinions that are shaped through daily exposure to state-controlled media and censored information (King et al., 2013). However, witnesses who were physically at scene of protests can get more complete information of protests, which they might not easily get back in China. Hence their political behaviors after protests are indicative of the effect of protests if authoritarian governments were to allow information about the protests to be reported on freely.

2 Materials

2.1 Data

Weibo was the main data source for our study. Weibo is the biggest social networking site in China, with over 500 million registered users. The design of Weibo is very similar to
Twitter, which is blocked in China. Using publicly available Weibo API, we collected a list of 42,280 users who live in mainland China, and who checked in in Hong Kong during 2012-13 or between August to October in 2014 based on their geolocated posts. Users living in Hong Kong are excluded in the population since it is hard to distinguish whether they actively joined protests by self-selection, or witnessed it by chance. Users living outside mainland China such as Taiwan, Macau and all foreign countries are also excluded since they may witness political protests outside the mainland. Users who checked in in Hong Kong across multiple months were deleted from the population, since they might actually live there without declaring their residence. We exclude users who checked in in Hong Kong on the dates of more than one protest, since it indicates self-selection to participate in protests. Next we crawled the full historical records of all users to get their ex-ante information. The study is approved by the Institutional Review Board of the Princeton University.

2.2 Research Design

13 protests from 2012-14 in Hong Kong were selected as sources of exogenous variation; the latest one was the recent Umbrella Movement (Cheung, 2014; Davis, 2015; Chan, 2014). 12 of the 13 protests had over 1500 participants according to police estimates; 8 had over 10,000 participants. These protests reflect the pursuits of Hong Kong citizens for a full democracy. Hong Kong citizens enjoy many political rights such as freedom of speech, an effective legal system and partial voting rights. However, they do not enjoy a true universal suffrage system. Hong Kong citizens cannot freely nominate the Chief Executive (equivalent to city mayor). The candidates can only be nominated by the Election Committee, which is regarded as controlled by the pro-Beijing faction of politicians and business elites of Hong Kong (Chan, 2014). The mayor hence is regarded as representing the interests of the business elites and the pro-Beijing government, instead of the mass. Most protests are hence organized around issues about electoral reform towards a true universal suffrage, about government’s collusion with the business elites which strengthen the already high income inequality, and around government’s attempts to curtail civic education from high school curriculum. Detail claims of protests are listed in SI.

A crucial requirement for a valid quasi-experimental design is to ensure that protests are
real exogenous variations: users do not purposely join or avoid the protest. Four facts help to make this assumption. First, empirical check-in patterns show that there are no sudden bursts or declines of check-ins on the days of protests (see SI for details). Secondly, we found that protests caused by unexpected events had higher treatment effects than regular protests since the former is closer to an exogenous variation. Third, all protests happened in major business districts of Hong Kong which simultaneously attract more than 120,000 tourists per day not just protestors. Lastly, we read all posts of treated users which directly mentioned Hong Kong, and did not find evidence that they intentionally went to Hong Kong to join the protests.

We constructed treatment and control groups from the 42280 geolocated users, based on their spatial and temporal distance to protests. We used time of check-ins as the first criteria. Our potential treatment group is 1338 users among 42280 who checked in at the dates of Hong Kong protests. A naive choice of control group would be all other users whose check-in dates were not dates of protests. This choice however will wrongly assign users who were actually in Hong Kong during protests but did not check on the exact dates of protests into the control group. The potential control group in this paper hence includes users who checked in in Hong Kong within 6 days before one of the 13 protests. The choice of 6 is not arbitrary; it leverages the visa regulation of the Hong Kong government for Chinese visitors, who are allowed to stay up to 7 days. Hence deleting users who checked in before 1-6 days of the protest ensures that visitors already left Hong Kong after their check-in, as required under the law. Each control user was only paired with the closest protest in terms of check-in dates.

Second, distance to protest was used to decide who was physically “nearby” a protest. For any given distance threshold $x$, treatment and control group are users that satisfy the time constraints, and whose check-in records were within $x$ meters of the center point of the protest. Logically the increase of $x$ will lead to larger size of treatment and control group and hence more accurate estimates of causal effects, but result in lower reliability that treated users actually saw a protest. We use thresholds $x = 1500$ meters to balance the trade-off. One thing to note is that 1500 meters is an upper bound of real distance, since most protests have thousands of participants and span streets from central points. In the appendix, we
 vary thresholds $x$ and do empirically find that the larger the $x$, the smaller the treatment
effect and the larger the size of treatment group (Fig. SI 3 & 4).

After trimming our study population by time and distance to protests, we have a treat-
ment group with size 355 (denoted as $T$) and a treatment group with size 10169 (denoted
as $C_{raw}$). We finally created a matched sample of control users from $C_{raw}$ to minimize possible ex-ante differences between treated and control users. For each treated user, we select
2 control users from $C_{raw}$. The matching algorithm minimizes smallest average absolute
distance across all the matched pairs. We match users by their pre-treatment intensities
of political discussions, genders and check-in dates. Table 1 shows the descriptive statistics
of trimmed treatment and control groups, and the matched subset of the control group. $T$
and $C$ are the final treatment and matched control group. In the appendix, we show more
more detailed descriptive statistics of each group, as well as users’ pre-treatment level of
political discussions, tweets and check-in counts, and how matching improves balances on
these characteristics.

2.3 Automated Methods for Analyzing Posts

We next introduce methods we used to analyze changes of users’ civic engagements based
on their history of tweets. First, we classify posts as discussing civic- and political-issues or
not. A dictionary method was used (Grimmer and Stewart, 2013). We first constructed a
customized dictionary which contains frequent words used in political discussions on Weibo.
Then each post was classified as civilly- or politically-relevant if it contained more than two words in the political-discussion dictionary. The algorithm can achieve 90.3% accuracy by manually labeling randomly chosen 1000 posts.

We measure the intensity of each users’ civic engagement as the proportion of posts within a given time period that discuss civic or political issues. One feature of social media data is that users’ engagement in discussing certain topics varies dramatically by days. Hence we measure users’ discussion of civic political issues over months. For ex-ante intensity, we use six months as the time period and denote it as $y_{i0}$ where 0 means ex-post and $i$ is the index for user. For ex-post intensity, we use each month after protest as the time period. We denote it as $y_{it}$ where 1 is a dummy variable indicating ex-post and $t$ means each month after protest.

Next we offer formulas for estimating treatment effects of intensity of civic engagement. First, we consider the treatment effect for each protest $j$ in the $t$’s month after protest, denoted as $ATT_{jt}$. Formally, denote $T_j$ as the treatment group and $C_j$ as the control group for protest $j$. Then $\bar{y}_{T1} = \sum_{i \in T_j} \frac{y_{it}}{|T_j|}$ is the mean ex-post intensity of civic engagement of treated users after the protest $j$ in month $t$. $\bar{y}_{T0}$ is the ex-ante mean intensity of civic engagement of control users. $\bar{y}_{T1} - \bar{y}_{T0}$ hence is the change of intensity of treated users in month $t$. Similarly, we measure mean ex-post and ex-ante intensity of control users as $\bar{y}_{C1}$ and $\bar{y}_{C0}$; their difference represent the change of intensity of civic engagement of control users. Finally the treatment effect $ATT_{jt}$ is calculated by comparing the change of treat users with the change of control users, as shown in the following equation.

$$ATT_{jt} = (\bar{y}_{T1} - \bar{y}_{T0}) - (\bar{y}_{C1} - \bar{y}_{C0})$$

$$= \left( \frac{\sum_{i \in T_j} y_{it}}{|T_j|} - \frac{\sum_{i \in T_j} y_{i0}}{|T_j|} \right) - \left( \frac{\sum_{i \in C_j} y_{it}}{|C_j|} - \frac{\sum_{i \in C_j} y_{i0}}{|C_j|} \right)$$

With the knowledge of treatment effect in each month for each protest, we further estimate pooled result for each month and for each protest. We used a Bayesian hierarchical model. Each protest may have different background and issues. The treatment effect for each protest hence may be different. We assume that there is a common treatment effect
\( \text{ATT}_j = \text{ATT}_j \) of protest \( j \), and variations of treatment effect in each month are sampled from this common effect. The pooled treatment effect for all protest, \( \text{ATT} \), are further obtained through a hierarchical model by assuming that treatment effect of each protests are sampled from the overall effect of all protests. Similarly, we also assume that there are common temporal patterns of impacts of protests. Hence the effect of protest \( j \) in month \( t \) can be regarded as sampled from the common time effect \( \text{ATT}_t \), which means the effect of all protests in the \( t \)’s month after protest. Details of the Bayesian hierarchical model are described in SI.

We used topic modelling to further explore the types of issues of users in their civically-relevant posts. Topic models are a suite of probabilistic statistical models developed by the computer science community. With a collection of documents as input, topic model produces a set of interpretable topics as output. Topics are defined as distributions over words used in documents, and each document can have multiple topics. (Blei et al., 2003; Steyvers et al., 2004; Blei, 2012). Words with high probabilities in a topic are those which occurs in documents more frequently than by chance. We use the most basic topic model Latent Dirichlet Allocation (LDA). One problem of directly applying LDA on raw tweets is that each post in Weibo is limited to 140 Chinese words—much shorter than typical documents. Thus performance of LDA deteriorate considerably (Zhao et al., 2011). Instead, for each user, we combine her socially- and politically- relevant posts before and after protests into two separate documents. Then we run LDA over the entire corpus. LDA infers topic distributions over documents: each document has a unique topic probability vector (length of the vector is the number of topics). An difference-of-difference estimator then compares the mean change of topic proportions of treated users before and after protest, to the change of control users. Details of running topic models are included in SI.
Figure 1: Average Treatment Effect (\(ATT_j\)) for each protest and its (2.5%, 97.5%) quantile. Number of treated users in each group is respectively 30,10,34,21,15,28,23,17,13,34,62,20,17,9,22.

3 Results

3.1 Intensity of Civic Engagement

Figure 1 depicts the treatment effect \(ATT_j\) for each protest \(j\). All protests increased the civic engagement of treated users after a protest compared with post-protest levels, relative to control users. Six protests have statistically significant treatment effects. Two of them (June 4th ones) were commemorations for the Tiananmen Square Protest of 1989. Two of them (June 29th and Sep. 9th, 2012) were protests against the Moral and National Education which is regarded by protesters as injecting nationalist ideologies into the school curriculum. Other two were marches which respectively supported and opposed the city mayor, who was believed to represent interests of Beijing government instead of Hong Kong citizens. Other seven protests all exhibited positive effects; those effects cannot be distinguished from zero at \(p < 0.05\) level.
y AT E (SD) Posterior quantile of ATE [2.5%, 97.5%]

| Study Type        | Location | y       | ATE (SD)       | ATE [2.5%, 97.5%] | ATE/y  
|-------------------|----------|---------|----------------|-------------------|--------
| Main Study        | Hong Kong| 0.01656 | 0.00669 (0.003) | [0.0006, 0.0125]  | 40.39% 
| Replication Study | Taiwan   | 0.01261 | 0.00587 (0.00710) | [-0.0082, 0.0197] | 46.55% 
| Placebo Test:     | Sport    | 0.01238 | -0.00169 (0.00213) | [-0.0059, 0.0024] | -13.76% 
| Placebo Test:     | Beijing  | 0.01942 | 0.00244 (0.00571) | [-0.0089, 0.0138] | 12.58% 
| Placebo Test:     | Shanghai | 0.0144  | 0.00087 (0.00132) | [-0.0017, 0.0035] | 6.03%  

Table 2: Average Treatment Effect for pooled sample. p-value is calculated by 1000 times bootstrap permutation test. y in the table is the average proportion of socially and politically-concerning posts among all posts.

The first row in Table 2 shows treatment effects for the entire pooled sample. \( ATT = 0.00589 \) means that for every every 1000 posts users wrote after her check-in at Hong Kong, witnesses of protests posted 5.89 more socially- and politically-relevant posts than non-witnesses from mainland China. This number may look small at first sight. However, the proportion of political relevant posts is itself small: the expectation was that only \( y = 16.56\% \) posts are relevant to social and political problems among every 1000 posts. The relative change \( ATT/y \) indicates that those who visited Hong Kong during political protests publish 40.39% more social- and political-relevant posts than her previous level. This reveal a strong causal effect of potentially witnessing a political protest on individuals’ civic engagement.

We use a regression difference-in-differences model to test whether adding covariates would change the result. SI table S4 finds that the larger a protest in terms of its size, the bigger the treatment effect. This makes sense since larger protests have more visibility. Protests caused by unexpected events also have a larger effect than planned events. Protests have bigger effects on male \( (p < 0.05) \).

For robustness checks, we did one replication test and two groups of placebo tests. Results are shown in the 2-5th rows of Table 2. To ensure that the result is not confined to our choice of Hong Kong, we replicate our study in the case of Taiwan. We used the same data collection and analysis methods to examine how Chinese witnesses reacted to five protests in Taiwan (see SI for descriptions of protests in Taiwan). The results shows that Chinese visitors who physically witnessed protests in Taiwan discussed 46.55% more social and political issues than a set of control users. The size of treatment effect is even bigger than that of Hong Kong witnesses. Second we ran two group of placebo tests to ensure that hypothesized
Figure 2: Treatment effect over time (2.5%, 97.5%) quantile of treatment effect are shaded. Number of treated users in each group is respectively 30,10,34,21,15,28,23,17,13,34,62,20,17,9,22.

effect of protest on political discussion does not occur where it is not expected to. We find that treated users remain the same in their level of discussion about sports, a topic that is unrelated to politics. There might be other politically relevant events happening in the same time of protests which might lead to an increase of online political discussions. To rule out this possibility, we examine Weibo users who had checked-in history at Beijing and Shanghai on same dates of protests, and do not find significant treatment effect.

Figure 2 shows the time trend $ATT_t$ of treatment effects. The treatment effect slightly increases at the first three months after a protest, indicating that the level of political discussion of treated users remained at high levels in the first three months after a protest. It decreases after three months, and drops to near zero after half a year, which suggests that influences of protests on witnesses withered away after six months. Still, witnessing protests seems to have a strong and enduring effect on witnesses at least for three months.
3.2 Issues of Civic Engagement

We then present the content change of users’ posts. Difference-in-differences estimation of topic changes are shown in SI Fig. S8. Topics with statistically significant treatment effect are listed in Table 3, according to descending sizes of their changes. The first row shows that users are more concerned with civic problems when they discussed social and political problems: among all political discussions, the topic about civic life increases its proportion by 15.8% for treated users after protests, relative to change of the same proportion by control users. Their discussion of civic problems, as revealed by top words in this topic, include the following issues: air and water pollution (such as carcinogenic effect of pollutions, and complaints about the Chinese government’s reluctance to publish air quality test information); medical system (the clashes between doctors/patients and health care system); food safety (such as genetically modified food and chemical additives in food). These issues are really about problems which influences their everyday lives.

The second row shows that treated users also discuss more issues that are directly related to the protests in Hong Kong. Treated users discuss about tourists in Hong Kong, and the relations between the Hong Kong and Chinese government. The topic also includes discussions political systems in Hong Kong (voters and the general election in Hong Kong and their the Election Committee system), and protests they witness (boycott, demonstrations) and their claims (freedom of speech democracy and democratization). Note that though democracy occurred as the topic word in this topics, it does not emerge as a separate topic but coalesce with the context of Hong Kong. It hence indicates that witnesses’ discussions about democracy were still organized around their experiences in Hong Kong, and their opinions towards protests. Such exposures have not been developed into concerns of political rights outside the context of Hong Kong.

The third topic that users discuss more often about nationalism. Some posts express nationalistic ideas against Hong Kong due to cultural clashes between Hong Kong citizens and Chinese people, and against Japan due to the historical invasion of Japan during the WWII and recent disputes of sovereignty over the Diaoyu Island between China and Japan. However, the result should not be understood as evidence of heightened nationalistic sentiments.
Table 3: Top words of statistical significant changing topics.

<table>
<thead>
<tr>
<th>ATT(sd)</th>
<th>Topic</th>
<th>Top Words</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.158</td>
<td>Civic Life</td>
<td>Pollution, air, food, medical system, patients, exceed the set standard,</td>
</tr>
<tr>
<td>(0.079)</td>
<td></td>
<td>food safety, genetically modified, chemical additive, toxic, society,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>health care, water quality, carcinogen, quality testing, doctors, nurses,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ministry of Health</td>
</tr>
<tr>
<td>0.136</td>
<td>China-Hong Kong</td>
<td>mainland, state, revolution, tourists, democracy, Ma Ying-jeou, general</td>
</tr>
<tr>
<td>(0.061)</td>
<td></td>
<td>election, Hong Kong, voters, freedom of speech, demonstrations, boycott,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>protests, the Election Committee, democratization, legal system</td>
</tr>
<tr>
<td>0.119</td>
<td>Nationalism</td>
<td>Diaoyu Island, patriotic, State, Anti-Japanese War, fellow citizen,</td>
</tr>
<tr>
<td>(0.061)</td>
<td></td>
<td>Anti-Japanese, boycott, territory, sovereignty, protest, war, wealth,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>infringe, oppose, demonstration</td>
</tr>
<tr>
<td>-</td>
<td>Police and Media</td>
<td>Police, the Celestial Empire, media, police department, CCTV, expose,</td>
</tr>
<tr>
<td>0.121</td>
<td></td>
<td>Chengguan, ordinary people, society, the deceased, mainland</td>
</tr>
<tr>
<td>(0.025)</td>
<td></td>
<td></td>
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</table>

Many posts under this topic are critical about the nationalism. These posts heavily criticized the unconscious behaviors by some Chinese citizens such as the smashing of Japanese cars. Hence the increase in the nationalism topic really indicates the heated debates about issues related to nationalism, which include both support for and disapproval against nationalism.

There is one topic that decreases its proportion. It include discussions of media exposures of police activities (police department). The Celestial Empire is often used by Chinese netizens to sarcastically refer to China under the current government. Chengguan is the government agency that enforce urban management of the city. It is interesting to see that treated users become less engaged with discussions of the enforcement of law by police and the Chengguan. One possible explanation is that polices and Cheng-guan are often criticized for their physical abuse of physical power against street vendors. Our treated users, who were able to afford travels to Hong Kong, often have better socioeconomic status and belongs to the middle and upper classes. It is possible that protests trigger treated users to use more
energy to civic issues that have direct relevance to themselves, and hence spend relative less
time in expressing empathy towards people in lower economic status that are more distant
away from treated users’ lives.

The rest of the topics whose changes are not statistically significant are listed in SI Table
S3. They respectively discuss economic policy, media and the freedom of speech, the state,
animal rights, famous social critics, and famous trials.

In sum, topic model results show that witnesses of the protest did not significantly discuss
more about democracy as might be expected. Witnesses discussed more about Hong Kong
where they experienced protests, more expressions of nationalism which may be a reaction to
the separatists claims of some Hong Kong protesters, and more about their living conditions.

4 Discussion

There are three major contributions of this paper. It address shortcomings in two different
fields. For the field of contentious politics, this paper resonates with recent attempts to
study spatial impact of protests and the temporal unfolding of protests(Wallace et al., 2014;
Branton et al., 2015). It specifically focuses on witnesses, and hence reveals how micro-level
interactions between protestors and witnesses shape the latter’s attitudes toward protests.
For the research of authoritarian politics, results of this paper– witnesses from mainland
China increase their intensity of online civic engagements, and become engaged in discussions
of civic issues, after witnessing protests in a democracy Hong Kong–have implication for civic
consciousness in authoritarian regimes, especially in the age of globalization.

The paper also has important societal implications. The protests in Hong Kong attracted
both domestic and international attention in 2014. Common wisdom suggests that exposures
of citizens of authoritarian states to democratic ideas, such as access to Western news media,
often lead to increasing affinity towards Western democracy. Recently, another approach
challenges the view by pointing out that correlations between exposures to western media
and critical attitudes toward authoritarian regimes are subject to self-selection bias: people
who access Western news media are already different from those who do not attempt to in
authoritarian regimes(Kern and Hainmueller, 2009; Tai, 2015) News media observed cases
supporting both directions but not provide rigorous evidences. Our results suggest that protests promote frequencies of civic discussion on Chinese social media websites. Result further suggest that witness become more engaged in civic issues that are directly relevant to their daily life, such as pollution, food safety and medical system. Their discussions of democracy also increase, but mostly within context of Hong Kong. The result suggests that population flows among regions with different political systems may indeed lead to the rise of civic consciousness among citizens from authoritarian regimes.

Methodologically, the paper illustrates how to use social media data to construct a panel of users that can allow scholars to achieve rigorous causal estimate of the impacts of protests. Previous research in contentious politics often relies on ethnographic and survey methods. By focusing on active participants, they fail to draw comparisons with non-participants and are unable to collect pre-protest information on political behaviors. Recent scholarship which use social media to study protests rely on hashtags or mentions of certain protest to collect study population. This approach however is subject to selection bias because it only focuses on users who actively engaged in discussion of protests, but fails to consider the majority of social media users who did not participate. Our method uses check-in records in social media to construct a stable panel of users in a post-hoc fashion, and distinguish treatment and control groups from the panel. Our design is able to find witnesses in a post-hoc fashion, to construct a meaningful control group, to collect their ex-ante information, and to reduce self-selection bias. These advantages address shortcomings with traditional methods. The design can be extended to general studies of impacts of events on individual behaviors with social media data: 1) construct a panel of users who were possibly influenced by the event, based on their geographic and time proximity to the event; 2) try to identify treatment and control group from the panel and 3) compare changes of outcome variables–civic engagement in this paper–to the changes of control users. The design suggests that careful research design with social media data can allow scholars to examine problems in social movement research that cannot be easily done with traditional methods.
References


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1 Background and Related Work

1.1 Background

Hong Kong citizens enjoyed much political rights such as freedom of speech, fruitful legal system and partial election rights. Hong Kong has also been constantly ranked as the most free economy by the Economic Freedom of the World.\(^1\) Yet under the “One Country, Two Systems” rule of China, Hong Kong is not an independent democracy. Its citizens cannot freely nominate the Chief Executive, which is equivalent to the city mayor who have administrative authorities. The candidates of Chief Executive are nominated (with support from more than one eighth of members), and elected (the simple majority rule) by the Election Committee. The current Election Committee is divided into 38 sub-sectors with 1200 members. Most of the sub-sectors represent a special group of professions, such as finance, industry, industrial, real estates, education, etc. Three fourths of the members of the committee are elected within respective professional sub-sectors by eligible voters that work in the sub-sector. In many sub-sectors, such as finance, corporate voters (legal representatives of corporations) have disproportionately high voting rights over individual voters who worked in the sub-sectors. A non trivial proportion of sub-sectors—11 out of 38, have uncontested candidates. The rest one fourth of the committee are members of the local district councils, the Legislative Council of Hong Kong, as well as uncontested members assigned by the Beijing government. Given the relative advantages of corporate voters in the committed, it is believed that the Election Committee has the potential to screen out politicians that were unfavored by the Beijing government as candidates for the city mayor. In return, government has been pausing reforms of wealth redistribution, which made Hong Kong as the most unequal society of the developed regions (Gini coefficient of 0.537 in 2012). The collusion between the business and the government delayed the democracy and increased wealth inequality. Boix (2003).

The pan-democracy camp—the major opposition political fractions, as well as the mass in Hong Kong have been struggling for a “true universal suffrage” for years to make sure that their choices of mayor are not prevented from being nominated as candidates even before election. The Chinese government promised in 1997 that Hong Kong would gradually transformed to a universal suffrage system before 2017. Hence the struggle for a more representative Election Committee, or nomination by citizens, has been heated after 2012. In our research, goals of the protests that occurred on 04/01, 07/01, 12/30 in 2012 and 01/01/2013 include a electoral reform plan for universal suffrage, and a plan to prevent business-government collusion.

However, the Chinese government do not want to abandon their control over the candidate selection process through corporate voters. On September 1st, 2014, the Chinese government officials announced that for the 2017 Chief Executive election, candidates still need to be chosen

by a nominee committed mirroring the current Election Committee. Furthermore, this decision even tighten up the control by raising the threshold for nomination from one eight of support to at least one half of support from the committee. The Umbrella Movement in our study occurred since September 26th, 2014 was the direct backlash reaction to the decision of the Chinese government.

Besides issues around electoral reforms, other issues of the protests in this paper are cultural clashes between Chinese tourists and the Hong Kong citizens. Chinese and Hong Kong government agreed to encourage Chinese people to visit Hong Kong in 2003, in order to promote local tourism which is heavily deteriorated due to the SARS break. Since then, Chinese tourists quickly increased: around 30 million Chinese people visited Hong Kong in 2014. Tourism boomed the economic growth. Yet many Hong Kong citizens believe that they did not enjoy the economic benefits, while simultaneously the flood of tourists interfere in their lives. Some Chinese visitors were actually day-trippers who just went to Hong Kong for tax-free goods such as clothes, make-ups and jewelers, and resell those back to China for profits. Hong Kong residents complaint that local business shift their strategies to cater to needs of Chinese visitors, which lead to decline of life quality of local people. The willingness of the wealthy Chinese to invest in real estates also lead to another round of increase in the already unaffordable housing prices for local citizens. There are also cases that Chinese tourists are unaware of or do not respect the local rules and customs. Such in-group conflicts sometimes lead to hostile attitudes, and even violent attacks and language insults toward Chinese tourists\(^2\). For instance, the protest on 2012-02-19 in our study was an attempt to prevent Chinese tourists drive their own car to travel in Hong Kong.

1.2 Description of Protests

Table S1 lists political protests in Hong Kong used in our study.

There are 14 districts in total in Hong Kong. All protests occurred in three districts of Hong Kong, the Wan Chai District, the Central and the Western District. Protests occurred in these places since 1) they contain buildings that have that have symbolic meanings, such as The Central Government Offices and the PLA’s Hong Kong Forces Hong Kong building and 2) they are also the major business, finance and shopping area in Hong Kong. Protestors wish to get attentions by holding protests in the economic and political center districts of the Hong Kong. These three districts coincidences with the places where Chinese tourists are most likely to visit–shopping centers and landmark buildings and parks. The intersection between the sites of protests, and the destination places of Chinese tourists, increase the chance that tourists saw protests during their visits.

In the main text we note that we did a robustness check to see whether witnesses from mainland China also have similar outcomes when seeing protests in Taiwan. Table ?? listed details of protests in Taiwan that we used. Some protests in Taiwan occurred in several cities. To simplify data collection procedures, we only collect geolocated posts from Chinese Weibo users near protests in Taipei.

2 Text Analysis Algorithms

2.1 Classification Algorithm

The following procedures are used to classify each post into two category: either discussing social or political problems or not.

\(^2\)http://www.cnn.com/2015/03/03/china/hong-kong-china-conflict/
<table>
<thead>
<tr>
<th>Date</th>
<th>Description</th>
<th>Size</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012/02/19</td>
<td>March to protest the open of self-drive travel from mainland China to Hong Kong. protesters think that there is already too many tourists from China currently (over 30 million in 2013), and the new opening will further interfere their life.</td>
<td>1500</td>
<td>From Causeway Bay to Central Plaza</td>
</tr>
<tr>
<td>2012/04/01</td>
<td>Protest the interference of Chinese government on election affairs of Hong Kong</td>
<td>5000</td>
<td>Victoria Park to The Westpoint</td>
</tr>
<tr>
<td>2012/05/13</td>
<td>Protest against the Moral and National Education, which is thought to be biased toward Communist Party, and replace the old civic education. protesters concerned that it transmit the communist and nationalist ideology of Chinese government, and give biased portrait of democracy.</td>
<td>300</td>
<td>From Causeway Bay to Central Plaza</td>
</tr>
<tr>
<td>2012/06/04</td>
<td>The annual commemorations of the Tiananmen Square Protest 1989</td>
<td>85000</td>
<td>Victoria Park</td>
</tr>
<tr>
<td>2012/06/10</td>
<td>Demonstration of the suspicious death of Li Wangyang in Chinese prison, who is jailed for 22 years in aggregation for supporting Tiananmen Square Protest, and later organizing labor rights protests.</td>
<td>25000</td>
<td>Central Plaza</td>
</tr>
<tr>
<td>2012/07/01</td>
<td>Annual 1 July Marches. Theme of this year includes: protest against the city mayor who is believed to be pro-Beijing; against widening gap between rich and the poor; against the Moral and National Education</td>
<td>63000</td>
<td>From Victoria Park to Central Government Offices</td>
</tr>
<tr>
<td>2012/07/29</td>
<td>protest against the Moral and National Education (similar to 05/13)</td>
<td>19000-32000</td>
<td>Victoria Park</td>
</tr>
<tr>
<td>2012/09/01</td>
<td>protest against the Moral and National Education (similar to 05/13)</td>
<td>8100</td>
<td>Central Government Offices</td>
</tr>
<tr>
<td>2012/09/07</td>
<td>protest against the Moral and National Education (similar to 05/13)</td>
<td>36000</td>
<td>Central Government Offices</td>
</tr>
<tr>
<td>2012/12/30</td>
<td>Organized by &quot;Caring Hong Kong Power&quot; which is a pro-JPX organization. March to support the city mayor, and against pro-Democracy camp.</td>
<td>2800</td>
<td>Victoria Park</td>
</tr>
<tr>
<td>2013/01/01</td>
<td>The Annual New Year’s March. Several protests occurred; some of them support the city mayor and others protest against him.</td>
<td>40000</td>
<td>Victoria Park; Central Government Offices; Central Plaza</td>
</tr>
<tr>
<td>2013/06/04</td>
<td>The annual commemorations of the Tiananmen Square Protest 1989</td>
<td>54000</td>
<td>Victoria Park</td>
</tr>
<tr>
<td>2014/09/20</td>
<td>Civil Disobedience against the Standing Committee of the National People's Congress (NPCSC) of the China’s decision on proposed reforms to the Hong Kong electoral system. The decision is regarded as restrictive since only members of the the Election Committee can select the Chief Executive (CE, equivalent to City Mayor), and the members in the Committed is thought to present the interests of business, and are pro of Chinese government. Chan (2014)</td>
<td>Over 100,000</td>
<td>Admiralty;Causeway Bay</td>
</tr>
<tr>
<td>Date</td>
<td>Description</td>
<td>Size</td>
<td>Location</td>
</tr>
<tr>
<td>----------</td>
<td>------------------------------------------------------------------------------------------------</td>
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<td>-----------------------------------</td>
</tr>
<tr>
<td>2013/03/09</td>
<td>Anti Nuclear-Power movement. The protest occurred in the eve of two year anniversary of Fukushima. protesters claim to stop the nuclear power plant in Taiwan since similar accident can happen, and Taiwan is geographically small so most regions will be affected.</td>
<td>120000</td>
<td>Ketagalan Boulevard, Taipei</td>
</tr>
<tr>
<td>2013/07/20</td>
<td>Ask for Openness of Military Protests. The cause is the sudden death of Hong Zhongqiu, a Military Non-commissioned officer. The armed force is regarded to cover the death, and not protect human rights of soliders.</td>
<td>30000</td>
<td>Ministry of National Defense (Taiwan)</td>
</tr>
<tr>
<td>2013/08/03</td>
<td>Ask for Openness of Military Protests. The cause is the sudden death of Hong Zhongqiu, a Military Non-commissioned officer. The armed force is regarded to cover the death, and not protect human rights of soliders.</td>
<td>100000</td>
<td>Ketagalan Boulevard</td>
</tr>
<tr>
<td>2014/03/18-19</td>
<td>Sunflower Student Movement</td>
<td>10000</td>
<td>The Legislative Yuan</td>
</tr>
</tbody>
</table>

1. Construct a customized dictionary that were related to discussions of social and political problems within Weibo.
   (a) First run topic model, and select top words (30 words for each topic) from social and political-concern topics from the topic model results.
   (b) Expand top words by finding similar words with those top words, using the state-of-art tool called word2vec. (Mikolov et al., 2013).
   (c) Hand-craft the dictionary by adding common homophones and puns used by Chinese netizens. The final keyword sets include 1829 words.

2. Classify whether a discuss talks about social and political contents, based on the dictionary.
   We currently use the following criteria: for a post, if it contains more than 2 words in the dictionary, it is treated as a social and political-concern tweet.

As discussed in the main text, the algorithm achieves 91.67% precision. One concern is that the algorithm may sacrifice recall in sake of improving precision. Recall in natural language process means the fraction of politics-relevant posts found by our classifier. For instance, the post such as "we support democracy" will be missed by our methods since only one word "democracy" is in the dictionary, while the classification criteria requires two words. Manually tagging results based on 1000 posts shows that recall is 70.9%, which is acceptable.

Moreover, the difference-in-difference estimator we used help to minimize the biases caused by classification algorithm, based on the assumption that classification errors were similar for the treatment and the control group. Comparison between two groups will thus cancel out the classification error. We examined the empirical validity of this assumption and did not significant differences between the classification accuracy rates of two groups. This fact ensured that potential error caused by classification algorithms will be minimized by comparison between treatment and control group.

### 2.2 Topic Model

We used topic model to explore content changes of users. Topic model is a general category of mixed membership models developed in machine learning and natural language processing com-
communities in the recent decade. (Blei et al., 2003) It seeks to find latent topics from a given set of documents. In this paper we use Latent Dirichlet Allocation (LDA) model; further models in the family are mostly built upon LDA.

LDA assumes that there are given number of topics in the corpus. Topics are formally defined as a distribution over a vocabulary which contains all words in the corpus; they are latent variables to be estimated. Hence, words have varying probabilities to belong to different topics: “democracy” have higher probability to be in a topic discussing politics instead of a topic about sports. Words which have high probabilities in a topic are those which usually co-occurs within a single document than by chance. (DiMaggio et al., 2013)

Intuitively, LDA takes a generative process which is a common approach in machine learning: For a given document in our corpus, LDA assumes that the document is generated from the following process:

1. First, randomly generated a distribution over topics, and assumes that the document is a mixture of topics according to the distribution. For instance, if there are three topics in total and the randomly drawn proportions are [0.2, 0.3, 0.4] respectively, then the observed document are comprised of 0.2 of topic 1, 0.3 of topic 2, and 0.4 of topic 3.

2. For each word in document, assume that it is generated as the following process:
   
   (a) Randomly sample a topic from the topic distributions defined in step 1. Assume that the words are generated from this topic in next step.
   
   (b) Randomly sample a word from the corresponding distribution over vocabulary of that topic.

The formal generative model can be found in the original papers and reviews. (Blei et al., 2003; Blei, 2012) LDA is a Bayesian generative model; common algorithms for estimation include Gibbs sampling, and variational methods.

Topic models have the following advantages compared with a simple classification algorithms. The LDA captures polysemy. Each word can have different meanings in different topics (as shown by different probability in each topic categories). Topic models are also able to capture heteroglossia, in the sense that each document can belong to a mixture of topics instead of a single topic DiMaggio et al. (2013). There are also limitations of topic model. When used for exploratory analysis, scholars often estimate the probability distribution of words for each topic, and show top n words with highest probabilities. Scholars need to interpret the meaning of topics. Another common problem is that there lacks common statistical way to find optimal number of topics. Despite those challenges, topic model is suggested to be used as a lens for understanding large corpus which cannot be handle by manually reading, which offers unique advantages over existing methods, especially with big data (Blei et al., 2003).

One problem of directly applying LDA on raw tweets is that each post in Weibo is limited to 140 Chinese words—much shorter than typical documents. Thus performance of LDA deteriorate considerably Zhao et al. (2011). As a solution, for each users, we generate two documents, one as the combination of her socially and politically relevant posts before her check-in at Hong Kong, and the other document as the combination of ex-post posts. Hence for n users, we have 2n documents in total. We run the LDA algorithm on these documents McCallum (2002).

LDA will assign each document a topic per document distribution, that is, each document have different proportions of topics. By averaging over documents, we can have a mean topic proportion. For each user i, x_{1k} is the topic proportion of the k'th topic in all her posts after protest, and x_{0k} is the topic proportion of the topic k before protest. \( x_{1k} = \frac{1}{|N|} \sum_{i=1}^{N} x_{d1k} \) is the mean topic proportion.
for topic $k$ across all documents. Then the difference-in-difference estimation of topic proportion change of treated users after protest, relative to control users, is defined as the difference of treated users’ mean topic proportion change after/before protests, minus such difference for control users. Formally, the difference-in-difference estimator uses the following equation:

$$AT_{T}^{\text{topic } k} = \frac{1}{T} \left( \sum_{i \in T} x_{i1k} - \sum_{i \in T} x_{i0k} \right) - \frac{1}{C} \left( \sum_{i \in C} x_{i1k} - \sum_{i \in C} x_{i0k} \right)$$

(1)

The confidence interval users in Figure 5 in main text are estimated through bootstrap methods. For each topic, we randomly sample the the per-document topic distribution. In this way we estimate the standard deviation of our $AT_{T}^{\text{topic } k}$ estimation by comparing the real topic model results, with the bootstrapped difference-in-difference estimator for each topic changes.

### 3 Details of Experimental Design and Analysis

#### 3.1 Related Work

Scholars use social media for social movement research in two ways. (Weber et al., 2013a; Budak and Watts, 2015) One approach focuses on the strategic use of social media for mobilization by activists during social movements. (González-Bailón et al., 2011; Tufekci and Wilson, 2012; Yang, 2013; Huang and Sun, 2014) Another approach uses social media as a data source to understand impacts of contentious politics (Hanna, 2013; Weber et al., 2013b). We take the second approach by using social media as the data sources.

Social media data are generally regarded as non-representative compared with probability-based population survey. However, scholars in contentious politics still regard it is a valuable resource with low time and monetary costs. The early use of social media, especially with Twitter and Twitter-alike platforms (such as Weibo), often take an keyword-centric approach. Scholars select keywords/hashtags that were relevant to protests, and collect tweets that contain these keywords/hashtags. (Lotan et al. (2011); Conover et al. (2013) These tweets are used to track development of protests, to trace mobilization processes, as well as to examine user characteristics that contribute to their participation.

However, we argue that the keyword-centric methods are problematic since users selected through this approach exhibit strong selection bias. Users who tweeted more tweets on certain event are most users that were already interested in event even before its occurrences. (Zhang et al. (2015). In the social movement setting, it is likely that users who tweet about certain protests are either participant, sympathizers or people that are already interested in discussing politics before events. Hence if we observed that users talked about a protest more often afterwards, such effect is confounded by the fact that their ex-ante tendency to discuss politics is already high.

Our approach has two advantages. First, by using geolocated to filter users who were exposed to events, instead of tweeting about events by themselves, we were able to reduce the selection bias by design caused by the keyword-centric methods. The geolocation-centric methods allow us to select ordinary Chinese users, instead of special group of users who were more likely to discuss the topic even before event. Secondly, we were able to further differentiate treatment and control group in a post-hoc way. Yet it is tough to construct a comparison group with the keyword-centric data collection methods, since users who all self-selected into the event and it is not straightforward who were not influence by the event. One can surely compare the users who discussed protests, and a random set of users, but they will be further different on other unobservable characteristics.
3.2 Data collection and research ethics

The data is collected through the public API of Weibo. There are two sources of data. Weibo has a geolocation search API (application program interface). Given a pair of latitude/longitude points, the geolocation search API in Weibo returns users whose check-in records is around that point. For the Umbrella Movement in 2014, we use this geolocation search API to find users who had geolocated posts (checked-in) within 5 kilometers of the protest. Yet due to the restriction of the Weibo company, the API can only track back to users who has checked-in history within last six months prior to the date of data crawling. When we began the research in 2014, it is not feasible for us to collect data of users who were around protests back in 2012-13. Hence our data of users who has checked in around protests in 2012-13 are filtered from an existing dataset(Yuan et al., 2013). The authors collected a large random collection of posts through the stream of Weibo from 2009-13. There are totally 25,269,196 users in their data set, and a total of 1,304,091,243 tweets. Among those, 6,472,914 has check-in records, and we filtered users who have checked in at Hong Kong during 2012-13 from them.

After we get a list of users that have check-in history in 2012-13 and the September of 2014, we then collected their all posts without limited to geolocated posts. The data collection procedure is approved by the the Princeton University Institutional Review Board (IRB), under protocol 0000006998.

3.3 Balance between treatment and control group, and difference between study population and general Weibo users

Since we use geolocated posts to construct our study population, the users in our population at least have one geolocated posts. This clearly differs from the general Weibo users since many of them have never used check-in functions. Next we show why our geolocated users can still be used as a valid sources. Our argument is that our study population are more active on posting and checking-in compared with random users. However, our study population is not significantly different from random users in the level of political discussions. Hence their differences in Weibo usage does not necessarily influence their changes of political behaviors.

We empirically validate our result. We first collected a random set of 10000 users that have at least one post in 2014 (as group Random). Then we collected a random set of 10000 users that have at least one check-in record in 2014 (as group Check-in). These group are used as reference groups. Then we compared how our treatment group, control group before and after matching to see how they differ from the two comparison groups (denoted as group Treated, Control:full and Control:matched respectively).

Figure S1 shows the probability density distribution of number of check-ins of our users. A non-trivial proportion (40.52%) of the random sample of users do not have check-in records. Furthermore, comparing with a random sample of users who have at least one check-in record (the group “Check-in” in the figure), our treatment and control group who all have check-in records at Hong Kong have significantly more check-ins. This suggest that our population in the study were more active users compared to the random sets of users in their check-in patterns. Moreover, the check-in probability density of our control group after matching resemble the density of the treatment group, more than that of the control group before matching.

Figure S2 tells a similar story that our population posted more than random users. The random users with at least one post and random users with at least one check-in record looks similar in

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7http://open.weibo.com/
8http://open.weibo.com/wiki/2/place/nearby/users
Figure S1: Density plot of number of check-ins in Weibo. Note that 4052 users in the “Random” group does not have check-in records, and one cannot calculate log value for 0. In order to draw the log density plot, we add 0.01 to counts.
their probability to post. It suggests that despite random users with at least one check-in checked-in more often than the random users with at least one post, their likelihood to post is similar. Our study population however posted significantly more posts than the two groups of random users. They posted more often than random users. However, the internal differences between treated and control users are not as salient as their difference to random users.

![Kernel density of tweets counts](image)

**Figure S2:** Density plot of number of total posts in Weibo of users in our population.

Figure S1 and S2 show that our population are more active Weibo users in terms of check-in counts and post counts, compared to a random sample. However, are our study population more politically engaged than random users? Figure S3 suggests no. Figure S3 plots the probability density of the level of civic engagement before protests for different groups. The figure shows that despite our study population posted and checked-in more often, they did not discuss more politics compared with random users. This provides evidence that our population is not political activists, but rather ordinary Chinese users who may not be very politically enthusiastic. Furthermore, matching improves balance between the treatment and the control group.

In summary, our population is users who have checked-in at Hong Kong during 2012-13 and September of 2014. Our users are essentially Weibo users who are more actively engaged in posting, and more likely to check-in than regular users. However, they did not discuss politics more frequently than random users before events. Empirical results show that we did not oversample politically enthusiastic users, or otherwise our result will be confounded by their ex-ante engagement in political discussions.
Kernel density of pre-treatment level of civic engagement

Figure S3: Density plot of users’ pre-treatment level of civic engagement in Weibo.
Figure S4: Treatment effect and 95% confidence interval by different threshold of determining treated and control users. For instance, if distance equals 1000, users who are with 1000 meters to the center of the protest will be selected as potential treated and control users.

The second observation from Figure ??, S3 is that matching improves balance between treatment and control groups. The probability density are more similar between the treatment group and the control group after matching than between the treatment group the control group before matching.

3.4 Selection of treatment and control groups

Figure S4 shows the treatment effect by varying thresholds of maximum distance requirement of treated and control users. For instance, if the distance is set to 500 meters, then only potential treatment and control group users, who satisfy the time eligibility and are within 500 meters of the protest are considered in the calculation. Theoretically, the closer one was to the protest, the more likely he saw the protest and hence the higher likelihood that he was influenced by the protest. Figure S4 exactly reveal this trend.

If we decrease the threshold of the maximum distance that one is regarded as close enough to protest, we have higher confidence that treated users selected witness the protest, but we have less amount of users. Figure S5 shows that as the maximum distance to the center of protest increases, the size of treatment group increases. To balance the trade off between larger treatment size and high credibility that treated users actually saw protests, we limit treatment and control group to users who have been within 1500 meters of protests in most of the analysis in the main text.
3.5 Experimental evaluations: bayesian hierarchical model

As discussed in the main text, we first calculate the $ATT_{jt}$, which is the effect of protest $j$ in $t$'th month after protests. Then treatment effect for each protest $ATT_j$, and average effect for all protests $ATT$ are estimated from observed effect $ATT_{jt}$ through a bayesian hierarchical model:

- $ATT_{jt} | \theta_{jt} \sim N(\theta_{jt}, \sigma_{jt}^2)$
- $\theta_{jt} \sim N(ATT_j, \sigma_j)$, for $t = 1 \cdots 6$ and $j = 1 \cdots 13$.
- $\theta_j \sim N(ATT, \sigma^2)$, for $j = 1 \cdots 13$.
- $\sigma_{jt}^2$ are known variance from data
- hyperparameters $\sigma_j$ and $\sigma$ are drawn from noninformative uniform distribution, instead of conjugate inverse-gamma distribution, as suggested by Gelman since the conjugate prior is sensitive to the choice of prior values. (Gelman, 2006) Prior of $\theta$ are drawn from an noninformative uniform distribution.

In other words, $ATT_{jt}$ is the treatment effect for protest $j$ in time period $t$. It is drawn from its own mean parameter $\theta_{jt}$. For the protest $j$, treatment effects across time are regarded as sharing the same impact $ATT_j$ from the same protest. Finally, all protests are seen as drawn from the common effect, and protest-level effect $ATT_j$ are drawn from pooled parameter $ATT$. $ATT_j$ is interpreted as treatment effect for protest $j$, and $ATT$ is treatment effect for all protests.

We also estimated $ATT_t$, which is the average treatment in month $t$ after protests across all protests. $ATT_t$ is estimated from a similar bayesian model.

- $ATT_{jt} | \theta_{jt} \sim N(\theta_{jt}, \sigma_{jt}^2)$
- $\theta_{jt} \sim N(ATT_t, \sigma_t)$, for $j = 1 \cdots 13$.
- hyperparameters $\sigma_t$ and $\sigma$ are drawn from noninformative uniform distribution.
4 Supplementary Results

4.1 Further Descriptive Statistics

Figure S6 shows the geographic origins of our study population. Large cities, i.e. Shanghai and Beijing, and economically most prosperous provinces such as Guangdong and Jiangsu contribute most Hong Kong visitors. The further west a province is at China, typically the more economic disadvantaged it is, and the less amount of users from the province. Geographic distribution of our study population is similar to the distribution of the entire Weibo.

![Figure S6: Origins of users in our sample.](image)

4.2 Further Result

In this section we first show the more refined measures of treatment effects for each protests across time. Then

Figure S7 shows $ATT_{jt}$ for each protest $j$ across months $t$. The last protests only have data for 50 days after protests, since we originally crawled the data in the end of 2014. Hence the last protests are not included when estimating treatment effect $ATT_t$ for each month.

Figure S8 visualizes treatment effect for topics. Table S3 shows the words with highest occurrences probability in each topic. Topics whose effects are statistically significant are in bold. There are four topics whose changes can be statistically distinguished from zero. These four are listed in the main text. For the other six topics, three of them still have positive changes but cannot be distinguished from zero. These are about discussion of lawyers and trials that have raised societal
Figure S7: Time trends for ATT. (2.5%, 97.5%) quantile of treatment effect are shaded. Number of treated users in each group is respectively 30,10,34,21,15,28,23,17,13,34,62,20,17,9,22.
Figure S8: Difference-in-difference estimation of topic proportion changes, and 95% confidence intervals. ATE is the topic proportion change of treated users after/before the protest, net of change of control group users. Only 129,795 posts which discuss social and political problems are used, 26,566 for treated users and 123,229 for control group.
attentions [topic 10]; such political institutions (democracy, constitution), economic stand (capitalism vs. socialism) [topic 4]. Protests have non-significant negative effects on users’ proportion of discussion on how media report police activities, economic policy, animal rights.

4.3 Treatment effect by user characteristics

Table S4 shows how users’ covariates influence the treatment effect. It can be observed that male are more likely to be influenced; older people has larger effect but such effect is not significant; number of check-ins and number of posts has a marginal effect.

Figure S9 and S10 shows how treatment effect varies by size of protests, and whether protests is planned before. It is reasonable to argue that larger protest 1) influence more people and 2) cause more emotion effervescence compared with smaller ones. It is indeed true in our data. Except for one outlier which has large negative treatment, sizes of other protests is positively correlated with treatment effect. Sudden events are more like real exogenous variations. Figure S10 compares size of sudden protests, with those protests which has been planned years before. It is indeed that sudden events has a larger effect on witnesses.

![Figure S9: Treatment Effect by Size of Protests](image_url)
<table>
<thead>
<tr>
<th>Topic Number</th>
<th>Topic</th>
<th>ATT(SD)</th>
<th>Top Words</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Economic Policy</td>
<td>-0.035(0.053)</td>
<td>policy, state, reform, media, society, institution, regulation, officials, interests, people, state-owned company, China Securities Regulatory Commission (CSRC), stock market, monopoly, debt (policy, state, reform, media, society, institution, regulation, officials, interests, people, state-owned company, China Securities Regulatory Commission (CSRC), stock market, monopoly, debt)</td>
</tr>
<tr>
<td>2</td>
<td>Nationalism</td>
<td>0.119 (0.061)</td>
<td>Diaoyu Island, patriotic, State, Anti-Japanese War, fellow citizen, Anti-Japanese, boycott, territory, sovereignty, protest, war, wealth, infringe, oppose, demonstration (钓鱼岛, 爱国, 国家, 抗日战争, 同胞, 反日, 抵制, 领土, 主权, 抗议, 站长, 财富, 侵犯, 反对, 游行)</td>
</tr>
<tr>
<td>3</td>
<td>Media on Ideology</td>
<td>0.017(0.035)</td>
<td>society, media, moral, politics, value system, political institution, social security, medical, democracy, freedom of speech, religion, capitalism, human rights (社会, 媒体, 道德, 政治, 价值观, 政治制度, 社会安全, 医疗, 民主, 言论自由, 宗教, 资本主义, 人权)</td>
</tr>
<tr>
<td>4</td>
<td>State</td>
<td>0.050(0.042)</td>
<td>state, people, democracy, politics, North Korea, ordinary people, socialism, corruption, reform, capitalism, communist party, cadre, Mao Zedong, regime, the Soviet Union, the KMT, constitution (国家, 民主, 政治, 朝鲜, 老百姓, 社会主义, 政府, 改革, 资本主义, 共产党, 干部, 毛泽东, 政权, 苏联, 国民党, 宪法)</td>
</tr>
<tr>
<td>5</td>
<td>Animal Rights</td>
<td>-0.017(0.082)</td>
<td>animal, protect, boycott, dog meat, legislation, abuse, police, slaughter, conscience, exposure, bear's ball, humanitarian, food safety, the Ministry of Agriculture, apologize (动物, 保护, 抵制, 狗肉, 立法, 虐待, 警察, 虐杀, 良知, 曝光, 熊胆, 人道, 食品安全, 农业部, 道歉)</td>
</tr>
<tr>
<td>6</td>
<td>Media on Police</td>
<td>-0.121(0.025)</td>
<td>Police, the Celestial Empire, media, police department, CCTV, expose, Chengguan, ordinary people, society, the deceased, mainland (警察, 天朝, 媒体, 警察局, 中央电视台, 曝光, 城管, 百姓, 社会, 死者, 大陆)</td>
</tr>
<tr>
<td>7</td>
<td>Civic Life</td>
<td>0.158(0.079)</td>
<td>Pollution, air, food, medical system, patients, exceed the set standard, food safety, genetically modified, chemical additive, toxic, society, health care, water quality, carcinogen, quality testing, doctors, nurses, Ministry of Health (污染, 空气, 视频, 卫生系统, 病人, 超标, 食品安全, 转基因, 化学添加剂, 有毒, 社会, 医保, 水质, 致癌物, 检测, 医生, 护士, 卫生部)</td>
</tr>
<tr>
<td>8</td>
<td>Social Critics</td>
<td>0.015(0.082)</td>
<td>people, lawyer, officials, Xue Manzi, Xu Xiaoping, Yuan Li, Li Chengpeng, Chen Zhiwu, Yuan Tengfei, presidents, tax payer, monopoly, power, institutions, pollution, the Cultural Revolution, rule of law (人民, 律师, 官员, 薛蛮子, 徐小平, 袁莉, 李承鹏, 任志强, 陈志武, 袁腾飞, 总统, 纳税人, 独裁, 权力, 组织, 污染, 文革, 法治)</td>
</tr>
<tr>
<td>9</td>
<td>China-Hong Kong</td>
<td>0.136(0.061)</td>
<td>mainland, state, revolution, tourists, democracy, Ma Ying-jeou, general election, Hong Kong, votes, freedom of speech, demonstrations, boycott, protests, the election Committee, democratization, legal system (大陆, 国家, 革命, 游客, 民主, 马英九, 选举, 香港, 选民, 言论自由, 游行, 抵制, 抗议, 立法会, 民主化, 法律体系)</td>
</tr>
<tr>
<td>10</td>
<td>Lawyers and Trials</td>
<td>0.089(0.048)</td>
<td>lawyer, law, Chengguan, police, media, court, judge, rule of law, life sentence, judicial, illegal, rights, pronounce sentences, according to the law, prosecute (律师, 法律, 城管, 警察, 媒体, 法官, 法治, 死刑, 司法, 违法, 宣判, 依法, 执行)</td>
</tr>
</tbody>
</table>
Table S4: Regression difference-in-difference result. The table shows the effect of covariates on treatment effects. Regression is performed on post-level.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>iscivic2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>after</td>
<td>0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>treated</td>
<td>−0.001</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>after:treated</td>
<td>0.003***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>gender=male</td>
<td>0.013***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>age&gt;=25</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>number of checkins</td>
<td>−0.00001***</td>
</tr>
<tr>
<td></td>
<td>(0.00000)</td>
</tr>
<tr>
<td>number of posts</td>
<td>0.00000***</td>
</tr>
<tr>
<td></td>
<td>(0.00000)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.014***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

Observations 827,612 761,412 234,544 234,544
Log Likelihood 291,060.200 263,970.200 92,495.120 92,480.240
Akaike Inf. Crit. −582,106.300 −527,922.400 −184,972.200 −184,938.500
Bayesian Inf. Crit. −582,029.600 −527,824.600 −184,885.200 −184,832.100

Note: *p<0.1; **p<0.05; ***p<0.01
Figure S10: Treatment Effect by whether planned ex-ante.

4.4 Further robustness check

Some concerns is that posts which discusses protests will be deleted due to censorship. We cannot have direct evidences about how many posts are already deleted before we crawl them. The reason is that most sensitive posts are deleted within a very short time period. As King et al. show, the vast majority of deleted blog posts is being censored with 24 hours of posts (King et al., 2013). Ex-post web crawler cannot find such data.

We show instead to show in Figure S11 that in 2012, there is no significant increase in the tendency of censorship for the entire Weibo site (Fu et al., 2013). The data is from Weiboscope project (Fu et al., 2013). The authors focus on a sample of Weibo users with more than 1000 followers, and track whether their posts are deleted at hours level. They release the data in 2012 so that we can see whether dates of protests in Hong Kong increase censorship. Figure S11 shows the results. It can be seen that censorship tendency mostly varies along with seasonal variations; dates of protests do not increases the likelihood of being censored.

We wish to emphasize that even if there is censorship incurred by protests, it brings less threat to our results since our experimental design will minimize the differences.
Figure S11: Deleted posts per day

References


