Intensified Ideological Online Clashes with Group Political Bias*

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Abstract

In this paper, we collect the data from Hong Kong's major news media Facebook pages from 2019 to 2020 to examine the mechanism behind the intensified online clash between pro-democracy and pro-China parties. We show that compared to similar comments in Traditional Chinese, the increase of pro-police comments in Simplified Chinese induced a stronger reaction from the opposite side with more comments promoting anti-police and supporting Hong Kong independence. We attribute the intensification of ideological clashes to the longstanding inherent bias among netizens after the "Official Character Simplifications" reforms implemented by the People's Republic of China in the 1950s.

Keywords: social media, writing habit, political protests, ideological clashes;
JEL Codes: D71, L82, P48, P51

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1 Introduction

"It is not, then, the facts in themselves that strike the popular imagination, but the way in which they take place and are brought under notice."

— Le Bon (1897, The Crowd: A Study of the Popular Mind)

Online platforms provide a forum to communicate about various ideologies, which can also intensify ideological debates, leading to the polarization of opinions. Many social media platforms have gradually become battlefields for ideological clashes between different groups.[1] Despite the growing theoretical and empirical literature on online conflict and ideological polarization (e.g., Gentzkow and Shapiro (2011), Boxell, Gentzkow, and Shapiro (2017), Allcott and Gentzkow (2017), Stone (2020) and Iyer and Yoganarasimhan (2020)), two issues remain under-explored. First, the collision between Democracy and Authoritarian ideologies via the internet is important but rarely studied (Zhuravskaya, Petrova, and Enikolopov (2020)). Second, although the theoretical literature gives some basis for the online opinion polarization (e.g., Andreoni and Mylovanov (2012), Stone (2020), Iyer and Yoganarasimhan (2020) and Bowen, Dmitriev, and Galperti (2020)), it remains an open question from an empirical perspective to explore potential factors that intensify the polarization. This paper addresses both issues by using data from Hong Kong major news media's Facebook pages from April 2019 to April 2020.

Since 1997, Hong Kong has been one of the few places in the world where a "one country, two systems" policy is practiced.[2] Newspapers and magazines representing different political ideologies coexist and have the right to publicly express their opinions. Hong Kong citizens also use various channels to express their views. Because of this unique system, we can observe the open conflict between two political ideologies, post-authoritarianism and pro-democracy, which coexist in the region: the ruling pro-establishment camp leans

[1]For example: since 2020, the Trump administration has taken various policy countermeasures against the online ideological propaganda from Chinese social media apps (TikTok and WeChat). Source: https:// www.forbes.com/ sites/ alexcapri/ 2020/08/09/ us-action-against-tiktok-and-wechat-symbolizes-a-global-backlash-against-china-inc/#560e9c953e58.

[2]The Hong Kong Basic Law ensures that Hong Kong, as a special administrative region (SAR) of the People's Republic of China, retains its capitalist economic system, currency (the Hong Kong dollar), legal system, legislative system, and human rights and freedoms.

On June 30, 2020, China promulgated the Hong Kong National Security Law, which to some extent may affect the one country, two systems stipulation in the Basic Law of Hong Kong. However, for the period covered by our data (April 2019 to April 2020), Hong Kong's special status of one country, two systems applied and was widely recognized internationally.

more towards the Communist Party of China, while its rival, the Pro-democracy camp, leans more towards the Western democratic political system. The conflict between the two has never been greater, both online and offline, than it was in 2019 after the establishment party proposed the extradition bill.[3]

Several features of our setting enable this research. First, protests calling for Hong Kong's democratic autonomy were widespread in 2019. As the protests grew, there were inevitably many clashes between protestors and the police, leading to an increasing number of news reports on police attacks. Consequentially, attitudes towards the police became a focal point of ideological conflict: the pro-democracy party opposes police abuse, and the establishment party supports police policing. In particular, the more the police are supported, the more the protestors will face a police crackdown. This not only leads to more backlash from pro-democrats but also potentially increases the cost of protest. So the ideological clashes are conveniently captured by the attitudes toward police. Second, users' writing habits are directly observable and naturally divide them into two groups: Simplified Chinese users and other users. Because of language and cultural differences, people from mainland China typically comment using Simplified Chinese, whereas those growing up in Hong Kong generally use Traditional Chinese. There is no communication problem between the two writing systems, but using the different written habits signifies the writers' cultural background.[4]

In June 2019, Facebook recorded 6.46 million monthly active users in Hong Kong, or 96% of all internet users. [5] The raw dataset contains 140,838 daily news releases from 44 media outlets and 39,752,930 comments. We combine the raw dataset with information on the characteristics of the media Facebook pages as of May 2020, such as the number of followers and the number of "likes" and retweets by users.[6] The final dataset also contains the political tendency scores of the individual media outlets, using the results of a third-party questionnaire conducted two years before the period covered by our data. The unit of our analysis is per media and per day. We study the online interaction of ideology by analyzing the daily changes in comments in each media unit.

We use dynamic panel data regression models to provide a complete overview of the

[3]The Bill would allow Hong Kong suspects to be extradited to China, Macao, and Taiwan for trial, which opponents fear would undermine the territory's status as an independent jurisdiction under the "one country, two systems" principle. C.f., https://en.wikipedia.org/wiki/2019_Hong_Kong_extradition_bill.

[4]We provide in Appendix C a detailed description of the writing systems in mainland China and Hong Kong.

[5]In June 2019, Facebook recorded 6.46 million monthly active users in Hong Kong, or 96% of all internet users.

[6]In some platforms, "like" is interpreted as "thumb up".

ideological collisions online, analyze all of the comments and news reports, and study the interactions between different political camps. We then focus on the mechanism of how ideological clashes are intensified online by examining the influence of pro-establishment comments on democratic demands. As the government's use of police power is the focal point of the ideological contradiction, we examine the effect of pro-police comments on the usage frequency of anti-police comments and protest slogan. Our OLS results indicate that the support for the police greatly intensifies the pro-democracy camp's distrust of the police. Although the prevailing pro-police comments may encourage the government to rely on policy to crackdown protests, it also encourages netizens to express their appeals for democratic autonomy more frequently.

More interestingly, we find that when a pro-police comment is written in Simplified Chinese, it receives particularly strong opposite responses. Since the Simplified Chinese comments are typically pro-establishment, we further explore whether this tension arises from a political bias or the content of the comments. Further evidence indicates that the number of anti-police and pro-independence voices decreases if we remove pro-police comments from users who use Simplified Chinese only occasionally and Traditional Chinese most of the time. This means that users care more about how the comment is written than who the commenter is. The "Official Character Simplifications" reforms implemented by the People's Republic of China in the 1950s formed a longstanding inherent bias among netizens, which intensifies the current ideological clashes online.

To reinforce the findings, we use a set of instrumental variables to address the potential endogeneity issues. The IVs are based on the number of new and dead Simplified Chinese accounts per media per day. Our statistical test results show that the instrumental variables perform well in our sample. The regression results indicate that OLS underestimates the impact of pro-police comments on both pro-police comments and demands for the autonomy. We further explore the reason. We find that nearly half of the users comment in a similar way to a bot: they are active only for one day and then disappear from the platform. We construct new variables to measure the rate of pro-police comments from the "suspected bot" in all of the daily comments beneath each piece of media. The results show that provocative comments are likely to be diluted by the comments from suspected bots, which soften the debate's atmosphere.

Our paper makes the following contributions to the literature. First, our paper contributes to the growing body of literature on the online interactions of political groups (e.g., Gentzkow and Shapiro (2011), Halberstam and Knight (2016) and Greenstein, Gu, and Zhu

(2020)). Few studies have directly examined the online interactions of users from different political camps. We use rich, dynamic panel data combined with textual comments from readers across the political spectrum to explain how online ideological collisions intensify. Most recently, Greenstein, Gu, and Zhu (2020) use Wikipedia's publicly edited data to show that users on the left and right eventually converge in the middle by correcting each other in the long run. Our paper suggests the opposite, which is consistent with other theoretical studies related to opinion polarization. Theoretically, Iyer and Yoganarasimhan (2020) show that individuals may take online action that is more extreme than their true preferences, leading to polarization. And Stone (2020) first points out that the dynamic interaction between ideological opposites would be intensified and even mutual hatred due to some inherent biases. In our paper, we provide a new context of ideological clashes. We empirically show that seemingly negligible writing habits leads to more negative emotions and intensifies the conflicts. Our finding indicates that the reform of Chinese characters, which began in the 1950s, although greatly reduced the illiteracy rate in the mainland, also led to a long-standing cultural prejudice between the mainland and Hong Kong, Macao, and Taiwan.

We also contribute to the studies on the social media and its political impact. In addition, Enikolopov, Petrova, and Zhuravskaya (2011) reveal that watching independent television increases the number of votes for opposition parties in a study of Russian television usage data. Enikolopov, Makarin, and Petrova (2020) further provide evidence that the penetration of online social networks led to more protests in Russia in 2011. Durante, Pinotti, and Tesei (2019) show that individuals exposed to entertainment television as children are less cognitively sophisticated and civic-minded and are thus more susceptible to populist rhetoric. Many studies examine the effect of media bias on readers' offline political behavior.[7] Our paper focuses more on the interaction between media readers on the Internet and points out the underlying factors that lead to the intensification of online debates. In addition, the literature generally supports the assumption that online platforms provide many people with a low-cost form of free expression and generate more protests (Fergusson and

[7]Other examples include Larcinese, Puglisi, and Snyder Jr (2011) who provide evidence that American newspapers cater to their readers' partisan preferences when reporting budget deficits. Martin and Yurukoglu (2017) study the optimal editorial policy of cable channels that wish to maximize their viewership and electoral influence whereas, Levy (2019) conducts a field experiment on Facebook and finds no evidence that the political leanings of news outlets affect political opinions. Cagé (2019) uses data from the French newspaper industry from 1944 to 2014 and finds that competition led to a decline in content quality. Newspapers may be biased in their pursuit of profit, and readers are less likely to vote for their political recommendations for fear of being misled. In a recent study, Fowler et al. (2020) analyze data from U.S. gubernatorial elections and find that candidates who advertised on Facebook won more votes than those who advertised on television.

Molina (2019) and Enikolopov, Makarin, and Petrova (2020)). We find a significant correlation between offline protests and the frequency of democratic ideological expression. We also point out that online democratic ideological expression has not declined as support for the police has risen. The potential "chilling effect" is dominated by the intensification of the controversy.

Last, our paper contributes to the literature on the regulation of the Internet by authoritarian governments and its political effects. Gentzkow and Shapiro (2010) first constructed a political bias index of U.S. media by analyzing and comparing the language habits of U.S. daily newspapers and their similarities with the official statements of both parties (i.e., Republican and Democratic). Their empirical study suggests that a lack of media regulation can lead to biased media reports in pursuit of traffic. Similarly, Allcott and Gentzkow (2017) analyze news reports related to the U.S. presidential election, and find that fake news was widely disseminated and could influence voting decisions. Qin, Strömberg, and Wu (2017) use data from a Chinese microblogging platform, and show that low barriers to accessing social media make it easier to spread information that is critical of the government. Qin, Strömberg, and Wu (2018) note that the Chinese government intends to carry out ideological propaganda through the media (such as local party newspapers). Increased competition in the market can play a conciliatory role in reducing biased newspaper reports. Cantoni et al. (2019) examine protesters in Hong Kong in 2014.[8] They show that the protesters assessed their social ideology, the potential for repression, and the number of people marching together before deciding to take to the streets. Zhuravskaya, Petrova, and Enikolopov (2020) highlight that studying how the internet and social media shape politics in an autocracy and the autocracies are crucial today. To the best of our knowledge, our paper is the first to examine online conflicts between post-authoritarian and pro-democratic ideologies. We provide important reference for the policies relating to Internet governance. In particular, China's "Great Firewall" policy has long been criticized for not allowing users to freely browse foreign websites.[9] In our paper, we find the policy's positive aspects: First, although the policy prevents Chinese mainland netizens from visiting foreign websites, it also eases

[8]A political campaign for universal democratic suffrage was launched in Hong Kong on September 28, 2014. The campaign sought universal suffrage for the Chief Executive and the Legislative Council, which would ensure fair voting rights, by occupying the main thoroughfares of Central, Hong Kong's financial district.

[9]The role of The Great Firewall of China is to block access to selected foreign websites and to slow down cross-border internet traffic. The effect includes: limiting access to foreign information sources, blocking foreign internet tools (e.g. Google search, Facebook, Twitter, Wikipedia, and others) and mobile apps, and requiring foreign companies to adapt to domestic regulations. Source: https://en.wikipedia.org/wiki/Great_Firewall.

the online ideological clashes between China and the West. Second, even for those who have access to foreign websites, their ideology has not been significantly affected in the short term, and many of them are strongly pro-China. In addition, the paper also suggests that if an authoritarian government uses an "internet water army" to influence public opinion on social media platforms, aiming to ease social tension, the strategy will backfire.[10]

2 Background

2.1 2019~2020 Hong Kong Protests

On March 15, 2019, Hong Kong launched a large-scale Anti-Extradition Law Amendment Bill Movement. Hong Kong citizens organized through social media and protested against the Hong Kong government's Fugitive Offenders and Mutual Legal Assistance in Criminal Matters Legislation (Amendment) Bill 2019. From April 2019, demonstrators staged almost weekly protests, and what began as peaceful protests turned into violent clashes between the police and civilians. Later, the movement spread to all parts of Hong Kong, and clashes with the police intensified. As of May 27, 2020, the police arrested more than 9,000 people aged 11 to 84 in various protests, the highest number of arrests in Hong Kong history. Among them, at least 1,617 were prosecuted, including 595 charged with rioting.

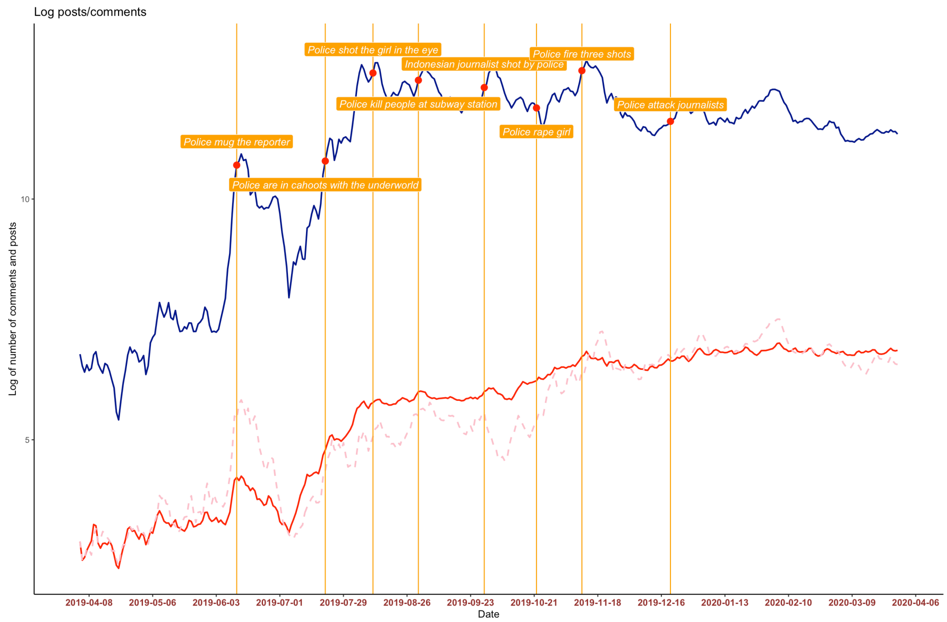
During the protests, Hong Kong police were repeatedly accused of the abuse of power. According to the report of the Independent Police Complaints Council (IPCC),[11] as of February 29, 2020, police enforcement actions in response to the protests resulted in 1,641 complaints, including 542 reporting complaints and 1,099 complaints related to guidance notes. For instance, on June 12, 2019, the police were accused of shooting protesters and journalists without raising a black flag.[12] On July 21, 2019, the police were accused of conspiring with white-clad gangsters to beat up citizens. These events caused widespread public concern at the time and were widely reported by the media. After these events, many incidents were referred to the courts and received a final decision, whereas other cases are still pending.

[10] Theoretically, Little (2016) states the driving force of social media for protests may mainly come from information and coordination channels.

[11] Independent Police Complaints Council (IPCC) is a statutory body in Hong Kong, and its members are appointed by the Chief Executive of the Hong Kong Special Administrative Region. The IPCC is responsible for monitoring and re-examining cases investigated by the Complaints and Internal Investigations Branch of the Hong Kong Police Force, but has no statutory investigative powers.

[12] There are four types of warning flags used by the Hong Kong police: yellow for "police cordon, do not cross," red for "stop advancing", or we will use force," black for "warning, tear gas will be fired," and orange for "retreat or we will fire."

For example, the July 21 news has already been dismissed as a rumor by the IPCC report.[13]



Note: The horizontal axis corresponds to the period covered by the data: 365 days from April 2, 2019 to March 31, 2020. The orange lines represent time points for major events related to the police. The ordinate represents the total number of daily posts (red line) and comments (blue line) received by all Hong Kong mainstream media on their Facebook pages based on the logarithm. The pink line is the median number of comments received daily by all media. All curves are smoothed by taking a 5-day moving average. Due to the data collection method, we obtain less data before June 2019 (historical data in some media cannot be traced), which is taken into account in our subsequent regression model analysis by controlling for time fixed effects and lagged variables.

Figure 1: Hong Kong news timeline

Figure 1 shows how the total number of posts and comments on all Hong Kong media Facebook pages before and after an event changes over time. It shows that for most incidents, the number of comments and posts increases after the incident, which means that these incidents raise public concern. In most cases, the increase in public opinion starts before the event, because clashes between the police and citizens often occur in the middle or at the end of a protest. At the start of a protest, many media and citizens are already discussing the related event. The occurrence of conflicts between the police and the population intensifies the discussion and makes it more focused.

[13]In Appendix A, we present a full list of major conflict incidents between the police and citizens in Hong Kong since June 2019.

2.2 Writing Habits

Facebook users in Hong Kong mainly come from three backgrounds: Hong Kong, mainland China, or overseas. Most Hong Kong people learn and use Traditional Chinese characters from childhood, whereas 95.25% of mainland Chinese people use Simplified Chinese characters. Only 0.92% of them use Traditional Chinese characters, and the rest use both. When typing, users need to switch languages in the same way as when switching between English and Chinese.[14] Therefore, although people can mostly understand each other, the usage is distinct, and the switch between the two is not costless.

Not every Chinese character has a simplified alternative. On October 10, 1949, the Chinese Character Reform Association was founded. Starting from the 1950s, the Soviet Union government proposed and offered to assist The Chinese government in carrying out literal reform. The Language Reform Research Committee of China first drafted the List of Frequently Used Simplification of Chinese Characters. On 31 January 1956, the People's Daily published in full about the Resolution Regarding the Promulgation of the "Chinese Character Simplification Scheme". The first list of the scheme was used nationwide on 1 February 1956, and the rest was put into use in batches later. The Simplified Character List promulgated by the National Language Work Committee in 1986 is the official scheme of current Simplified characters in mainland China. The character list contains 2,274 Simplified Chinese characters and 14 simplified components of Chinese characters, which account for less than half of the commonly used characters. In some cases, a sentence is the same whether written in Simplified or Traditional Chinese characters.[15]

2.3 Media's Political Tendencies

Most newspapers are politically partisan and the media in our dataset are no exception. Hong Kong's current spectrum is divided between the pro-establishment camp, which supports Beijing's policies,[16] and the pro-democracy camp, which demands greater autonomy. The pro-establishment media tend to publish more positive reports on police enforcement,

[14]These statistics are taken from Survey on Language Use in China (in Chinese). Zhang and Zhu (2011) also use Simplified Chinese to distinguish the contributions of users from mainland China to the Chinese Wikipedia.

[15]Source: https://en.wikipedia.org/wiki/Chinese_Character_Simplification_Scheme.

In Appendix C, we provide an additional introduction to the differences between Simplified and Traditional Chinese.

[16]The pro-establishment camp is also called the "pro-Beijing camp" or "pro-China camp." The pro-establishment camp evolved from Hong Kong's pro-Communist faction, often called the "leftists," which has a long history of following the directions of the Communist Party of China (CPC) for Hong Kong.

such as "supporting police enforcement and maintaining law and order in Hong Kong." For instance, they blamed the protesters for vandalizing property and confronting the police during the protests. In contrast, the pro-democracy media tend to portray the police as a tool to preserve political centralization in Beijing and undermine democracy and the rule of law. For the most part, they supported the protesting Hong Kong citizens.

In this paper, we score each media outlet for its political tendency based on the questionnaire results. The questionnaire is provided directly by the School of Journalism and Communication of the Chinese University of Hong Kong (CUHK).[17] It was conducted at the end of September 2016 by distributing questionnaires to CUHK students. One hundred and fifty-six students participated. Each media outlet was rated with a political preference score between +5 and -5, a positive score indicating the establishment camp and a negative score indicating the pro-democracy camp. To check the objectivity and impartiality of our scores, we compare them with Hong Kong news media's political tendency scores found in other sources. We report results in Appendix B. Our scores are generally consistent with other ratings, but are more refined.

3 Data Description

Our data is provided by a third party local IT solution provider,[18] which helped us collect all Hong Kong mainstream media news releases and comments on Facebook for the April 2, 2019 to March 31, 2020 period. Our raw dataset includes 140,838 reports from 44 media outlets and 39,752,930 comments. Figure 2 shows how we capture relevant information from online web pages.

Our data include the contents and total number of news stories published by each media outlet during the observation period and the contents of comments, and the number of their retweets, and emoticons received by each news story per day. For each media outlet, we collect its total number of followers and the date it started using Facebook. In addition, our data include all text information contained on their respective Facebook pages for our

[17]The School of Journalism and Communication of CUHK is Hong Kong's oldest academic institution. Since 1965, the school has been devoted to studying the political preferences and credibility of media organizations in Hong Kong, which is widely recognized by the community. Therefore, we believe that their ratings are fair and objective. The questionnaire was organized by Professor Clement Y. K. So and completed two years before our data collection, so we believe that the questionnaire results do not directly affect the number of news releases and comments two years later.

[18]TheAnswr provides us the data, it is a data analytics platform that collects and provides data by using AI engines.

Note: The image on the left shows the information that a Facebook user can get by clicking on the media page, and that on the right shows the basic information that a Facebook user can get when reading the related news provided by the media.

Figure 2: Example of a Facebook media page and news

natural language processing (NLP). It should be noted that all commenters are shown in our data as anonymous numeric codes which are uniquely dedicated to that person in the entire platform. We do not know their demographic details, such as their origin and personal page information, but we trace all their comments on the platform. We later analyze their writing habits to identify their background. At the same time, we track each user in the data to see when they first joined, and when they last joined the platform. This additional treatment, although cumbersome and time-consuming, provides crucial information for the identification.

We arrange the data at media-day level. Table 1 reports the descriptive statistics based on panel data. On average, each media outlet releases 16 posts per day and receives more than 4,500 comments. The content is shared approximately 2,777 times and receives over 16,000 emoticons (i.e., likes). Of all comments, only 4% are created in Simplified Chinese, which means that most comments are from Hong Kong residents. Comments from users with mainland China background represent only a small proportion. We also calculate the

Statistics	Observations	Mean	St. Dev.	Min	Max
Number of news releases	8,760	16.077	23.535	0	209
Number of comments	8,760	4,538.006	15,111.140	0	244,409
Simplified Chinese Comments (%)	8,760	4.297	7.301	0	100
Number of reactions	8,760	16,849.750	58,548.540	0	1,577,957
Number of shares	8,760	2,777.908	9,099.342	0	213,580
Total number of likes	8,760	629,809.900	661,576.400	4,921	2,553,029
Total number of followers	8,760	754,392.200	871,654.500	7,171	3,671,124
New users	8,760	384.011	1,271.460	0	44,889
Inactive users	8,760	367.033	904.200	0	17,675

Note: Simplified Chinese Comments is calculated by dividing the total number of Simplified Chinese comments per day by the total number of comments per day. Total number of likes and Total number of followers are captured directly from the media home page and do not change over time. Number of reactions and Number of shares are obtained by counting the total number of shares and emoticons received by each news story published on a given date. They do not represent the flow of the number of shares received by the media on that day. We use these two variables in our paper to capture the potential impact of each news story. Due to the data collection method, some data are missing before June 2019, so the number of news releases is 0. We reconsider this issue in the subsequent regression models. It is also worth mentioning that the variable Total number of likes refers to the total number of likes that a media home page receives, and the variable Number of reactions is the number of emoticon likes that a news story receives in the traditional sense.

Table 1: Descriptive statistics

number of new and inactive users per media outlet per day. The statistics show that overall, the number of new users is slightly higher than the number of inactive users, which further indicates that Facebook's overall activity in Hong Kong continues to increase. On average, for every user who leaves the platform, there are approximately 1.04 new users who join the platform.

3.1 Simplified and Traditional Chinese Comments

Among all collected comments in Chinese, 15.5% cannot be identified as Traditional or Simplified Chinese. Among all Chinese comments containing less than 10 characters (41.8%), the proportion of indistinguishable characters is 30.4%. [19] We calculate the number of comments in Simplified Chinese per day in the dataset. Most comments are from netizens with mainland background. In Appendix G, we report the word frequency analysis that

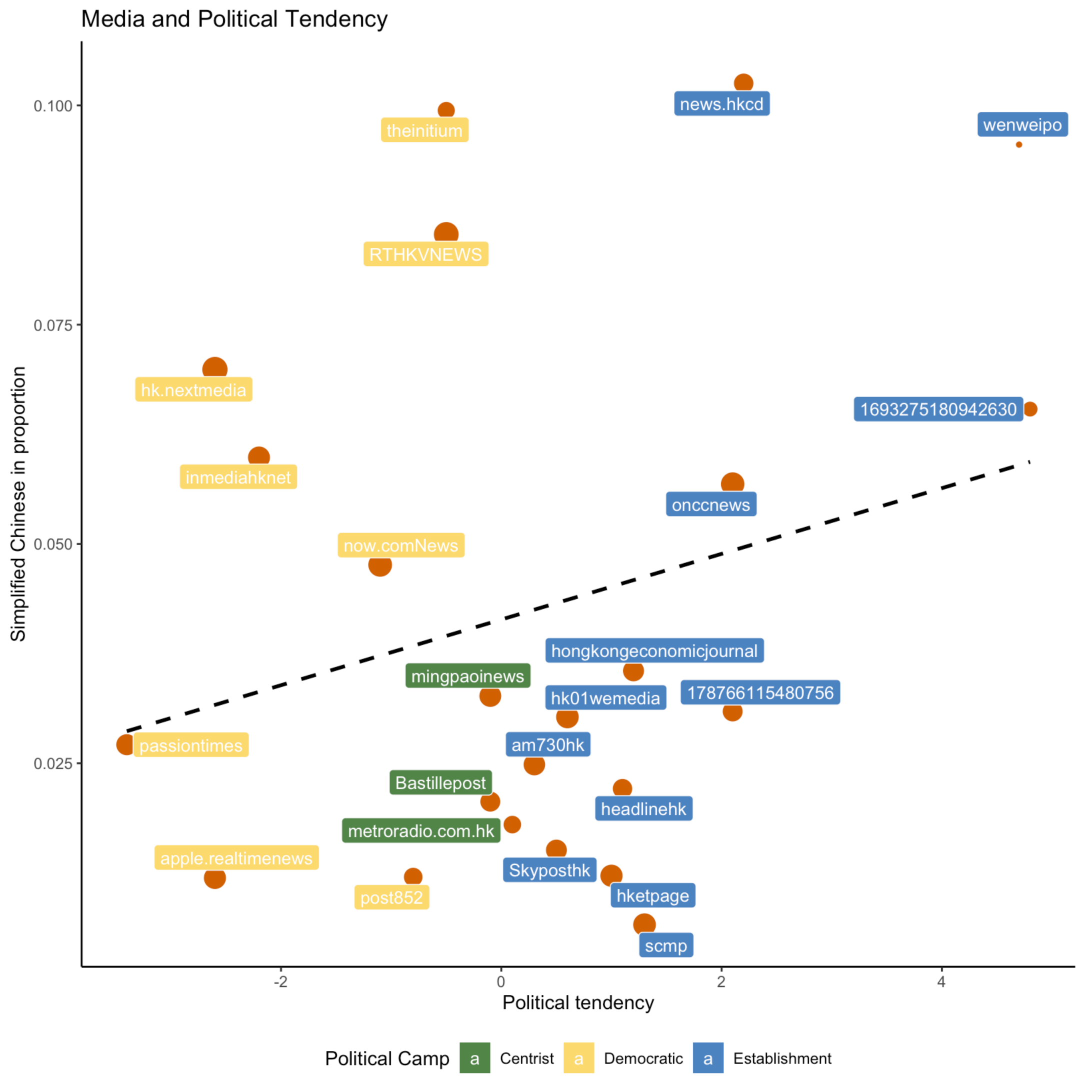
[19] In Appendix C, we provide an additional introduction to the differences between Simplified and Traditional Chinese. In Appendix G, we report the word frequency analysis that includes the 20 most frequently used words in both Simplified and Traditional Chinese.

includes the 20 most frequently used words. Compared with the whole sample, we find that the word frequency results change significantly after controlling for Simplified Chinese comments. Pro-establishment and pro-Beijing words appear more frequently in Simplified Chinese comments. For example, the term "decadent youth" is used by mainland media to describe young people participating in violent protests, to emphasize that they should be in school instead of protesting. The word ranks fifth in Simplified Chinese comments, but is not among the top 20 words in terms of overall word frequency ranking. Another classic example is the term "black cops." This term is widely used by pro-democracy media to describe police officers who collude with the establishment government and injure innocent demonstrators. We find that this term is the third most frequently used word in the overall comment ranking, but its ranking drops significantly in Simplified Chinese comments.

Figure 3 shows the political stance of the media in our data and the probability of Simplified Chinese comments appearing in the comments of a given media outlet. We find that Simplified Chinese comments generally appear in the pro-establishment media group. However, if we focus only on the leading media (i.e., those with the highest number of comments), the pro-democracy media group has a higher proportion of Simplified Chinese comments than the pro-establishment media group. This evidence indicates that if Simplified Chinese users can be considered as mainlanders and pro-establishment supporters, they often choose to leave comments on the media of their ideological camp, but are happy to join the discussions on the opposing media in an attempt to engage users on the opposite side of the ideological spectrum. It is always easier to spark discussions under news stories published by leading media by stating opposing positions. Figure 4 shows the word frequencies associated with the total number of comments and Simplified Chinese comments. We find that the figure on the right, which only includes comments from Simplified Chinese users, shows a clear pro-Beijing and pro-police tendency compared with the figure on the left.

The fact that Facebook users have a unique ID allows us to track each user's comments on different Facebook pages in more detail.[20] Surprisingly, we find that many identified Simplified Chinese users also post a significant amount of comments in Traditional Chinese. Overall, the total number of comments in Traditional Chinese is 10 times that of the comments in Simplified Chinese. This indicates that either some Traditional Chinese users may occasionally use some Simplified Chinese characters or some Simplified Chinese users may deliberately use Traditional Chinese characters to imitate Hong Kong netizens.

[20] This is different from Wikipedia (see Zhang and Zhu (2011)).



Note: Media's political tendencies. The horizontal axis represents the political tendency scores of each media outlet. The lower the score, the more pro-establishment the media. The vertical axis is the proportion of all comments in Simplified Chinese posted to the media. The political tendency scores are calculated from the results of a survey of Hong Kong Chinese university students. The blue media represent the pro-establishment camp that supports the police and Beijing's policies. The yellow media represent the pro-democracy camp that often opposes the police and seeks more autonomy. The green media are neutral, centrist media with no apparent political bias. The size of the red dots is based on the logarithm of the total number of comments under each media outlet.

Figure 3: Media's political tendencies

We design a new variable for each identifiable Simplified Chinese user, $SRatio_j$:

$$SRatio_j = \frac{\sum_{t=1}^{T} SimCom_{j,t}}{\sum_{t=1}^{T} TraCom_{j,t}},$$

Note: The figure on the left shows the word frequency cloud associated with all comments, and the figure on the right shows the word frequency cloud associated with all Simplified Chinese comments. The Chinese words in the figures are presented in Traditional Chinese.

Figure 4: Word frequencies

where $SimCom_{j,t}$ is the number of comments in Simplified Chinese that user j posts at time at time t and $TraCom_{j,t}$ is the number of comments in Traditional Chinese that user j have posted at time t. In Appendix 18, we report the number of users and the number of comments from different subsamples filtered by different levels of $SRatio$. For example, for the subsample of "$SRatio \geq 1$," all users post at least 1 Simplified Chinese comment for every 100 Traditional Chinese comments.

The distribution of $SRatio$ is highly skewed. After filtering out all users with an $SRatio$ less than 1%, the total number of users drops by 99% and the total number of Traditional Chinese comments by 45%. Meanwhile, the number of Simplified Chinese comments drops by only 2%. This finding suggests that users with an $SRatio$ less than 1% are typical Traditional Chinese users. They occasionally use Simplified Chinese characters to post comments for some reason. As the $SRatio$ threshold increases, the number of users decreases significantly. Most of the remaining users in the subsample are users who generally comment in Simplified Chinese. An $SRatio$ greater than 100% indicates that most users in this subsample have mainland China background and post comments in Simplified Chinese. Overall, we find that 123,029 users post 1,557,524 Simplified Chinese comments and 184,590 Traditional Chinese comments in the subsample of $SRatio \geq 1$.

4 A General Picture

In this section, we focus on the effect of comments under the media at the opposite end of the ideological spectrum on the comments of the focal media. We evaluate the dynamic interactions of comments and news reports from the Facebook pages of Hong Kong media of different ideologies using econometric models. We identify two stylized facts: (1) an increase in the number of comments under the media at the opposite end of the ideological spectrum significantly reduces the number of comments under the focal media; (2) this effect disappears after the occurrence of certain major events due to the effects of "mass edits". Commenters from different ideological camps tend to fight across the platform on both sides after major events.

4.1 Dynamics of Comments

Unlike the traditional literature in which the ratings/reviews directly reveal information about product quality, user comments on Facebook are often not motivated by the content itself, but by their desire to express their opinions or to convince users who disagree with them. We start by evaluating the dynamics of the comments with the following regression model:

$$\begin{aligned}\log Comments_{i,t} =& \beta_c \log Comments_{i,t-1} + \beta_o Opposite_{i,t-1} + \\ & \beta_n News_{i,t} + \beta_m' Media_{i,t} + \mu_i + \nu_t + \eta_{i,t},\end{aligned}$$

where $Comments_{i,t}$ is the total number of comments that media i receives at date $t-1$; $News_{i,t}$ is the total number of news stories published by media i at time t; $Media_{i,t}$ is a vector of media-specific characteristics that includes both time-varying and time-invariant variables. The time-invariant variables contain the political tendency and the total number of followers of media i. The time-varying variables include the potential impact of news releases and the total number of users who comment at time t; We calculate the potential impact of news releases at time t with the total number of retweets and likes from daily media posts observed in May 2020. The political tendency and the total number of followers are collected only once on the home page of the different media in May 2020, which are time-invariant. We have $Media_{i,t} = (Tendency_i, \log Followers_i, \log Retweets_{i,t}, \log Likes_{i,t}, \log Users_{i,t})'$ where $Tendency_i$ is the political tendency score of media, $\log Followers_i$ is the log of the total number of followers, $\log Retweets_{i,t}$ and $\log Likes_{i,t}$ are the log of the total number of retweets and likes, respectively, and $\log Users_{i,t}$ is the total number of users who post comments. β_m is a vector comprising the corresponding parameters. More specifically, we have $\beta_m = (\beta_t, \beta_f, \beta_r, \beta_l, \beta_u)'$. Finally, μ_i and ν_t are two components of media and time fixed effects and $\eta_{i,t}$ is the unobserved error term.

Construction of $Opposite_{i,t-1}$ A key variable in the model is $Opposite_{i,t-1}$, which indicates the number of comments in the media at the opposite end of the ideological spectrum. As we observe directly the political tendency score of each media outlet, we can build the political distance between media outlets. We denote $d_{i,j}$ the political distance between media i and j, and $Tendency_i$ the political tendency score of media i. We define:

$$d_{i,j} = |Tendency_i - Tendency_j|.$$

Based on the political distance scores, we further construct $Opposite_{i,t-1}$ as the weighted sum of the log of the comments under each media outlet at $t-1$; that is:

$$Opposite_{i,t-1} = \sum_{j \neq i} \omega_{i,j} \times \log Comments_{j,t-1},$$
$$\omega_{i,j} = \frac{d_{i,j}}{\sum_k d_{i,k}} \; and \; \omega_{i,i} = 0.$$

We take $Opposite_{i,t-1}$ as a combination of two effects: political effect and size effect. For the political effect, a media outlet will get a higher weight if its political tendency is very different from that of media i. For the size effect, famous media always get more readers and publish more content every day. So if the number of comments on a media outlet is very large, it should have more influence on media i.

Empirical Results Table 2 reports the results. Before controlling for media characteristics (i.e., columns (1), (2), and (3)), both the number of received comments at $t-1$ and the number of news releases at time t show a significant correlation with the number of comments at time t. We then include media information which vary over time and by media. and control for fixed effects to alleviate the endogeneity problem. In columns (4) and (5), in which both media characteristics and fixed effects are controlled for, the results show more comments appeared in the pro-establishment media. This is driven by the news published by pro-establishment media. We conduct further empirical analysis in the next section. We also find that the number of comments increases with the number of participants, but the potential impact of the news has a significant negative effect on the number of comments. The reason is that the potential influence of news stories is a proxy for their quality and recognition: if most people agree with a given news story, it will trigger less discussion.

Dependent variable: $\log Comments_{i,t}$					
	(1)	(2)	(3)	(4)	(5)
News and comments					
$News_{i,t}$	0.014***	0.014***	0.022***	−0.0004***	−0.0002
	(0.001)	(0.001)	(0.001)	(0.0002)	(0.0002)
$\log Comments_{i,t-1}$	0.892***	0.880***	0.779***	0.003	−0.010***
	(0.004)	(0.005)	(0.007)	(0.002)	(0.002)
$Opposite_{i,t-1}$		0.039***	−0.067	−0.017***	−0.033***
		(0.005)	(0.045)	(0.002)	(0.009)
Media characteristics					
$Tendency_i$				0.001	0.021**
				(0.002)	(0.009)
$\log Followers_i$				−0.020***	0.016
				(0.002)	(0.013)
$\log Retweets_{i,t}$				−0.008**	0.001
				(0.004)	(0.004)
$\log Likes_{i,t}$				−0.018***	−0.016***
				(0.003)	(0.003)
$\log Users_{i,t}$				1.120***	1.122***
				(0.004)	(0.003)
Time FE			YES		YES
Media FE			YES		YES
Observations	8,760	8,760	8,760	8,760	8,760
R^2	0.935	0.935	0.949	0.996	0.997
Adjusted R^2	0.935	0.935	0.947	0.996	0.997

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where $x = 0$, and $\log(x)$ does not exist.

Table 2: A regression model for news comments

We find that the estimation bias of $\log Comments_{i,t-1}$ and $News_{i,t}$is largely corrected after controlling for fixed effects and media characteristics: the number of new posts is no longer significant, and the number of comments received the day before has a significant negative effect on the number of comments received today. Our findings capture the additional effect that a heated discussion the day before will lead users to feel tired the next day and opt for a "truce." Similarly, after controlling for the quality of the potential impact of news releases and their content, the results suggest that the number of media output on the same day no longer has any predictive power on the overall number of comments. In Appendix I, we provide further estimates of dynamics of news release.

4.2 Effect of "Mass Edits"

Table 2 indicates that an increase in the number of comments at the opposite end of the ideological spectrum significantly reduces the number of comments under the focal media (columns (3), (4), and (5)). After controlling for news quality, media influence, and time fixed effects, we find that the main factor determining the number of comments under the focal media is the intensity of discussions in the media with the opposing ideology. This finding reveals that people tend to debate under the media belonging to one side of competing ideologies. This result is intuitive. With a limited amount of time online each day for each individual, if user groups of different ideologies come together under the media affiliated with one political camp, they tend not to go to the opposing media to comment again on the same day.[21]

However, this effect disappears after the occurrence of certain major events. We select subsamples with a time span of 3, 5, and 7 days after a conflict between the police and civilians (including the day of the incident) and re-estimate the regression model. We focus on these types of conflicts for two reasons. First, conflicts between the police and civilians are exogenous to the media and commenters.[22] Protests against Beijing took place frequently in Hong Kong during the year covered by our data (April 2019 to April 2020). These protests were organized and planned, usually online by their sponsors a few weeks in advance. However, not all protests are accompanied by violent conflict between the police and civilians, which means that such events are exogenous shocks. Therefore, changes in the comments were not planned in advance. Second, these conflicts have been the most discussed topic on the Internet over the past year, apart from protests. In Appendix G, we analyze the 2,389 most frequently used Chinese words in Hong Kong media comments. For each media outlet, we calculate the number of comments in which each word appears. The results show that

[21] In Appendix E, we provide further statistical evidence that validates the distraction effect. The estimation results show that if other media publish high-quality or influential news the day before, it will have a significant negative effect on the comments in today's media.

[22] In Greenstein, Gu, and Zhu (2020), they used the "mass edits" (i.e., when online articles are attracting an unusually high number of contributions in a given period due to a sudden social event or breaking news about the topic) to establish causality.

"police" and its associated words are among the most frequently used words.

Dependent variable: $\log Comments_{i,t}$				
	(1)	(2)	(3)	(4)
	Full	Subsample (3 days)	Subsample (5 days)	Subsample (7 days)
News and comments				
$News_{i,t}$	−0.0002	−0.0005	−0.0001	−0.0001
	(0.0002)	(0.001)	(0.001)	(0.0005)
$\log Comments_{i,t-1}$	−0.010***	−0.010	−0.011	−0.016***
	(0.002)	(0.009)	(0.007)	(0.006)
$Opposite_{i,t-1}$	−0.033***	0.028	0.037	0.032
	(0.009)	(0.039)	(0.031)	(0.027)
Media characteristics				
$Tendency_i$	0.021**	0.030	−0.001	0.012
	(0.009)	(0.039)	(0.030)	(0.025)
$\log Followers_i$	0.016	0.043	0.012	0.037
	(0.013)	(0.057)	(0.045)	(0.038)
$\log Retweets_{i,t}$	0.001	0.010	0.003	0.003
	(0.004)	(0.015)	(0.012)	(0.010)
$\log Likes_{i,t}$	−0.016***	−0.015	−0.021**	−0.016**
	(0.003)	(0.012)	(0.010)	(0.008)
$\log Users_{i,t}$	1.120***	1.113***	1.129***	1.127***
	(0.003)	(0.013)	(0.010)	(0.009)
Time FE	YES	YES	YES	YES
Media FE	YES	YES	YES	YES
Observations	8,760	576	960	1,344
R^2	0.997	0.997	0.997	0.997
Adjusted R^2	0.997	0.997	0.996	0.996

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where $x = 0$, and $\log(x)$ does not exist. In columns (2), (3), and (4), we select subsamples for 3, 5, and 7 days after the occurrence of a police – civilian conflict (including the day of the incident). The periods are set according to the table provided in Appendix A.

Table 3: News comments during periods of hot social issues

Table 3 reports the estimation results for the subsamples. For comparison, we report the results of the full sample in the first column. In general, the significance of the estimated coefficients decreases due to the smaller sample size. However, the signs and the magnitude of most coefficients are consistent with those of the full sample. The only exceptions are the coefficients of $Tendency$ and $Opposite$, which are no longer significant. For comments from the opposing media, not only is the coefficient no longer significant, but the sign also changes. This effect of "mass edits" indicates that users no longer argue under one side of the media after the occurrence of conflicts between the police and civilians. Discussions under one side of the media may fuel those under the other side. As a result, the "fights" heat up under the media of the two competing ideologies on the platform.

5 Ideological Clashes and its Intensification

In this section, we focus on describe how online ideological clashes are intensified. In our context, we are able to identify the background and ideological tendency of commenters based on their writing habits by differentiating between their use of Simplified Chinese and Traditional Chinese. For the parsimony of reasoning, we focus on the Simplified Chinese comments, which represent a very small group in the overall sample. Most Simplified Chinese users have a mainland Chinese background: they have long been exposed to post-authoritarian propaganda and are generally more pro-establishment. In particular, in a place where most people use Traditional Chinese for communication, using Simplified Chinese to express ideology may cause bias: the Simplified Chinese commenters may lack a basic understanding of democracy because of their cultural background. We use $SimCom_{i,t-1}$ to denote the number of Simplified Chinese comments under media i at date $t-1$, and try to evaluate its impact.

Table 4 reports the estimation results. Columns (1) and (2) are based on the full sample. In columns (3) and (4), we use subsamples according to the ideological tendencies of different media group. We find that the effect of comments in Simplified Chinese is consistent across all samples and model specifications: it has a significant positive effect on the total number of comments under the focal media. A 10% increase in the number of identifiable comments in Simplified Chinese results in a 1% increase in the total number of comments. Furthermore, the interaction term between $SimCom$ and $Tendency$ indicates the number of comments in Simplified Chinese has an even stronger positive effect when the political tendency of the media becomes extreme right. The other regression results are consistent with those in Tables 2 and 3. Since the increase in the number of comments in Simplified Chinese represents an overall increase in pro-establishment views and an increase in external voices (non-Hong Kong netizens), it also makes the whole discussion more intense. In the following sections, we take will a close look at those comments and provide more in-depth semantic analysis.[23]

[23]In Appendix F, we provide a robustness check by replacing the number of Simplified Chinese comments

Dependent variable: $\log Comments_{i,t}$				
	(1)	(2)	(3)	(4)
	Full	Full	Pro-democracy	Establishment
News and comments				
$News_{i,t}$	-0.0002	-0.002^{***}	-0.001^{***}	-0.003^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
$\log Comments_{i,t-1}$	-0.010^{***}	-0.016^{***}	-0.005^{*}	-0.018^{***}
	(0.002)	(0.002)	(0.003)	(0.003)
$Opposite_{i,t-1}$	-0.033^{***}	-0.015^{*}	-0.089^{***}	-0.031^{**}
	(0.009)	(0.008)	(0.024)	(0.014)
$\log SimCom_{i,t-1}$		0.108^{***}	0.103^{***}	0.091^{***}
		(0.003)	(0.005)	(0.005)
$Tendency_i \times \log SimCom_{i,t-1}$			-0.002	0.015^{***}
			(0.001)	(0.001)
Media characteristics	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Media FE	YES	YES	YES	YES
Observations	8,760	8,760	3,285	4,380
R^2	0.997	0.998	0.998	0.998
Adjusted R^2	0.997	0.997	0.998	0.998

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where $x = 0$, and $\log(x)$ does not exist. In column (3), we select the pro-democracy media subsample and their political tendency scores are all negative. In column (4), we select the pro-establishment media and their political tendency scores are all positive. The period is set according to the table provided in Appendix A.

Table 4: Impact of the use of Simplified Chinese on the number of comments

5.1 In-Depth Semantic Analysis

Our data do not directly measure the political tendency of each commenter using the survey method as in previous studies (e.g., Levy (2019)). However, by exploring the semantics in their comments, we reveal the political preference of the users and evaluate how the fighting between the two camps is dynamically driving the online ideological expressions of Facebook users. This section aims to understand how pro-democracy netizens deal with attacks from pro-establishment netizens by analyzing the meaning of words. We conduct an in-depth analysis of two dimensions: ideological expressions and negative emotions. According to the word frequency table in Appendix G, we select the following words for further analysis.

with the number of Simplified Chinese users, and find that the regression results are almost the same.

For the pro-democracy camp

- Liberate Hong Kong (光復香港): "Liberate Hong Kong" is a clear indicator of a pro-democracy political tendency in the 2019 – 2020 period. It means reviving Hong Kong and restoring the old system. "Liberate Hong Kong, the revolution of our times" is a slogan often used in social movements in Hong Kong.[24] From 2019, Hong Kong's pro-democracy activists started using this slogan during marches to protest Hong Kong's Extradition Law. For this reason, we use the frequency of "Liberate Hong Kong" in all comments as a proxy for netizens expression of their pro-democracy political preference, although the word "Liberate" does not appear in the word frequency table. We use $LHK_{i,t}$ to denote the number of times "Liberate Hong Kong" appears in all comments under media i at time t. Only 4.74% of the comments containing "Liberate Hong Kong" are Simplified Chinese comments. Therefore, the users of this term are netizens who support pro-democracy ideology.

- Black Cops (黑警): This word ranks third in the overall word frequency ranking. The conduct of the Hong Kong Police Force has been the subject of controversy during the 2019 – 2020 Hong Kong protests. While many pro-establishment activists supported police efforts to maintain order, many pro-democracy campaigners felt that the police used excessive force and arbitrarily detained democratic protestors.[25] The phrase "Black Cops" is used to mock police misconduct, as a symbol of people expressing their dissatisfaction with the government's post-authoritarian bias.We use $BC_{i,t}$ to denote the number of times "Black Cops" appears in all comments under media i at time t.

For the pro-establishment camp

- Support Police (撐警): "Support" and "Police" are both high frequency words. The co-occurrence of the two terms is a clear sign of pro-Beijing support for the actions of the Hong Kong police. We use $SP_{i,t}$ to denote the number of times "Support Police" appears in all comments under media i at time t, and $SSP_{i,t}$ to denote the number of times "Support Police" appears in all comments with $SRatio \geq 1$ under media i at time t. We use the $SSP_{i,t}$ better understand whether supportive comments from Simplified Chinese users will exacerbate the conflict.

[24]Source: https://en.wikipedia.org/wiki/Liberate_Hong_Kong,_revolution_of_our_times.

[25]Source:
https://en.wikipedia.org/wiki/Police_misconduct_allegations_during_the_2019%E2%80%9320_Hong_Kong_protests.

- Roaches (曱甴): This word is used to describe a sinister and vicious person. During the Hong Kong events, it was often used to mock protestors dressed in black and wearing masks. Most protesters were pro-democracy activists, who covered their faces with masks for fear of being arrested. Therefore, we consider this word as online abuse of the pro-democratic party by pro-establishment netizens. We use $RO_{i,t}$ to denote the number of times "Roaches" appears in all comments under media i at time t;

Abusive language

- Planking (仆街): This word appears in the word frequency table as the representative word for swearing in Hong Kong. The word comes from Cantonese and is widely used in Cantonese-speaking regions. It means "throw yourself in the street." It also means being mean and letting people step on you. The term is often used online as a curse, meaning "go to die" or "damn it." We use this word as a measure of negative sentiment among Hong Kong netizens. We use $PL_{i,t}$ to denote the number of times "Planking" appears in all comments under media i at time t.

Words	Pro-democracy		Abusive Language	Pro-establishment	
	(1)	(2)	(3)	(4)	(5)
	Liberate Hong Kong	Black Cops	Planking	Roaches	Support Police
Total number of comments	84965	1575007	625636	727006	438755
Simplified Chinese comments	4011 (4.72%)	34484 (2.19%)	11427 (1.82%)	68410 (9.41%)	47400 (10.80%)
Unidentified comments	0 (0.00%)	338991 (21.52%)	134765 (21.54%)	110797 (15.24%)	134586 (30.67%)
Total number of users	31914	189908	128237	72652	95486
Simplified Chinese users	1723 (5.39%)	13399 (7.06%)	5962 (4.65%)	10750 (14.80%)	13253 (13.88%)

Note: The proportion of specific comments to overall comments is reported in brackets. Unidentified comments are comments in which Simplified Chinese and Traditional Chinese characters are written in the same way.

Table 5: Lexical analysis

Table 5 presents the summary statistics for the above words. The statistical results show that Traditional Chinese users make most of the comments. However, the words representing pro-establishment ideology involve more Simplified Chinese users. To analyze the impact of opinion expression by pro-establishment supporters, we use the following models:

$$ProDemo_{i,t} = \gamma_d ProDemo_{i,t-1} + \gamma_r RO_{i,t-1} + \gamma_s SP_{i,t-1} + \gamma_o Opposite_{i,t-1}^{ProDemo} +$$

$$\gamma_c \log Comments_{i,t} + \gamma_n News_{i,t} + \gamma_m' Media_{i,t} + \mu_i + \nu_t + \zeta_{i,t}, \quad (1)$$

and

$$\begin{aligned} AL_{i,t} = & \gamma_a AL_{i,t-1} + \gamma_r RO_{i,t-1} + \gamma_s SP_{i,t-1} + \gamma_o Opposite^{AL}_{i,t-1} + \\ & \gamma_c \log Comments_{i,t} + \gamma_n News_{i,t} + \gamma_m' Media_{i,t} + \mu_i + \nu_t + \zeta_{i,t}; \end{aligned} \quad (2)$$

where $ProDemo_{i,t} \in \{LHK_{i,t}, BC_{i,t}\}$ represents the number of occurrences of words associated with pro-democracy ideology, which can be either $LHK_{i,t}$ or $BC_{i,t}$. $AL_{i,t}$ represents the use of abusive language (i.e., $PL_{i,t}$). $Opposite^{ProDemo}_{i,t-1}$ and $Opposite^{AL}_{i,t-1}$ are constructed as above, and they measure responses to ideological expressions and negative emotions in the media with the opposite ideology. μ_i and ν_t are two components of media and time fixed effects and $\zeta_{i,t}$ is the unobserved error term.

Table 6 reports the results of this semantic analysis. After controlling for fixed effects and media characteristics, the regression results show that the appearance of ideological expressions (support police) and abusive language (planking) in the comments significantly strengthen the voices of pro-democracy netizens in their demand for Hong Kong's independence and autonomy. We find no significant evidence (column (2)) that pro-police rhetoric leads to more anti-police rhetoric. However, additional evidence (column (5)) suggests that if the voices supporting the police come from Simplified Chinese users, the effect becomes significantly positive, which indicates that pro-police comments from users in Simplified Chinese might be treated with prejudice by other netizens. We also find that the mockery of pro-democracy netizens leads to more negative emotions and ideological expressions in all cases. This finding indicates that ideological expressions contribute to the generation of negative emotions. When users on one side of the ideological divide voice their opinions, it always involves abuse. Such expressions and attacks will trigger abusive statements and responses from the opposite side, which will eventually intensify the conflict and make the ideological expressions on both sides more extreme. Our results suggest that if the authoritarian government wants to hire people to support their ideology online to alleviate tension between the two groups, they should be cautious since the result may backfire.

We find that Simplified Chinese comments have a greater catalytic effect on the intensity of the debate. The comments from Simplified Chinese users not only stimulated the expression of democratic, but also worsen the discussion environment. For each comment in Simplified Chinese that supports the police, there are 0.37 anti-police comments and 0.16 insults added. Almost every 25 comments in Simplified Chinese supporting the police elicit

Dependent variable:	$ProDemo_{i,t}$		$AL_{i,t}$	$ProDemo_{i,t}$		$AL_{i,t}$
	$LHK_{i,t}$	$BC_{i,t}$	$PL_{i,t}$	$LHK_{i,t}$	$BC_{i,t}$	$PL_{i,t}$
	Liberate Hong Kong	Black Cops	Planking	Liberate Hong Kong	Black Cops	Planking
	(1)	(2)	(3)	(4)	(5)	(6)
Words						
$SP_{i,t-1}$	0.011***	0.044	0.042**			
	(0.004)	(0.067)	(0.017)			
$SSP_{i,t-1}$				0.038***	0.379**	0.166***
				(0.012)	(0.191)	(0.050)
$RO_{i,t-1}$	0.007**	0.161***	0.083***	0.010***	0.147***	0.088***
	(0.003)	(0.049)	(0.013)	(0.003)	(0.041)	(0.011)
$ProDemo_{i,t-1}/AL_{i,t-1}$	0.335***	0.461***	0.430***	0.334***	0.459***	0.431***
	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
$Opposite_{i,t-1}^{ProDemo}/Opposite_{i,t-1}^{AL}$	−0.090	−0.105**	−0.163***	−0.088	−0.097**	−0.153***
	(0.055)	(0.046)	(0.046)	(0.055)	(0.046)	(0.046)
News and comments						
$News_{i,t}$	0.698***	14.282***	3.954***	0.701***	14.321***	3.962***
	(0.028)	(0.438)	(0.117)	(0.028)	(0.438)	(0.117)
$\log Comments_{i,t}$	8.856***	241.392***	55.872***	8.950***	241.938***	56.246***
	(1.568)	(24.380)	(6.476)	(1.568)	(24.372)	(6.472)
Media characteristics						
$Tendency_i$	−0.430	−19.150	−4.401	−0.436	−19.540	−4.497
	(1.235)	(19.201)	(5.101)	(1.235)	(19.197)	(5.100)
$\log Followers_i$	−1.048	−30.966	−8.152	−1.054	−31.159	−8.180
	(1.870)	(29.066)	(7.720)	(1.869)	(29.060)	(7.718)
$\log Retweets_{i,t}$	−0.070	2.308	−0.606	−0.076	2.407	−0.608
	(0.503)	(7.828)	(2.078)	(0.503)	(7.826)	(2.078)
$\log Likes_{i,t}$	−0.211	−18.311***	−5.308***	−0.221	−18.396***	−5.340***
	(0.405)	(6.303)	(1.674)	(0.405)	(6.301)	(1.674)
$\log Users_{i,t}$	−10.280***	−268.486***	−60.131***	−10.362***	−269.420***	−60.532***
	(1.770)	(27.522)	(7.308)	(1.770)	(27.520)	(7.307)
Time FE	YES	YES	YES	YES	YES	YES
Media FE	YES	YES	YES	YES	YES	YES
Observations	8,760	8,760	8,760	8,760	8,760	8,760
R^2	0.555	0.698	0.736	0.555	0.698	0.736
Adjusted R^2	0.534	0.684	0.724	0.534	0.684	0.724

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where $x = 0$, and $\log(x)$ does not exist. We control for all pro-police comments in columns (1), (2), and (3). In columns (4), (5), and (6), we control for all pro-police comments in Simplified Chinese provided by users with $SRatio \geq 1$.

Table 6: Semantic analysis

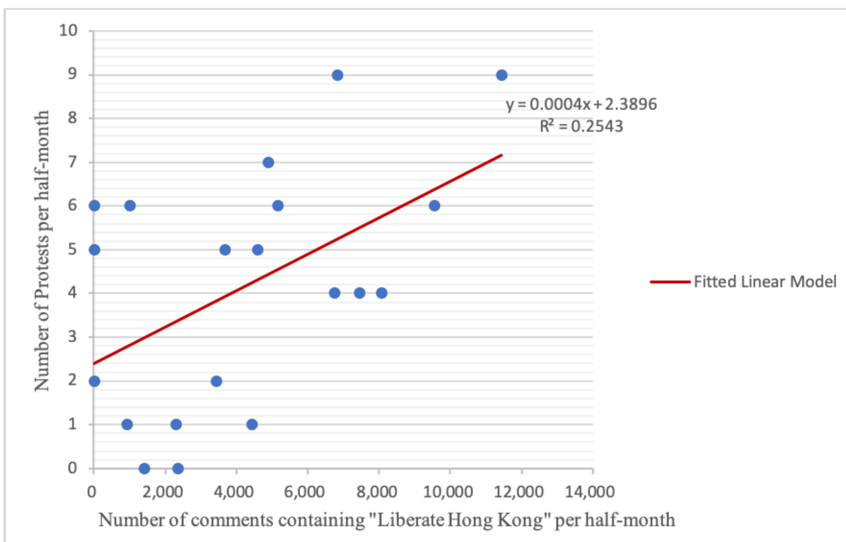
an expression of pro-democracy netizens' demand for democratic independence. When we take all comments, most of the effects remain significant but diminish in magnitude. Our findings are consistent with predictions in the theoretical literature of recent years (e.g., Iyer and Yoganarasimhan (2020), Stone (2020)). Pro-police comments from Simplified Chinese can make other users biased in their reading of the content. Many might consider such comments from a mainland background to be thoughtless or even sarcastic. Such prejudice breeds resentment and an even stronger pro-democracy feedback.

Dependent variable:	$ProDemo_{i,t}$		$AL_{i,t}$	$ProDemo_{i,t}$		$AL_{i,t}$
	$LHK_{i,t}$	$BC_{i,t}$	$PL_{i,t}$	$LHK_{i,t}$	$BC_{i,t}$	$PL_{i,t}$
	Liberate Hong Kong	Black Cops	Planking	Liberate Hong Kong	Black Cops	Planking
	All Simplified Chinese Comments			Comments with $SRatio \geq 1$		
	(1)	(2)	(3)	(4)	(5)	(6)
Words						
$SP_{i,t-1}$	0.062***	0.674**	0.176**			
	(0.017)	(0.272)	(0.072)			
$SSP_{i,t-1}$				0.038***	0.379**	0.166***
				(0.012)	(0.191)	(0.050)
$RO_{i,t-1}$	0.010***	0.141***	0.094***	0.010***	0.147***	0.088***
	(0.002)	(0.040)	(0.011)	(0.003)	(0.041)	(0.011)
$ProDemo_{i,t-1}/AL_{i,t-1}$	0.334***	0.459***	0.432***	0.334***	0.459***	0.431***
	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
$Opposite^{ProDemo}_{i,t-1}/Opposite^{AL}_{i,t-1}$	−0.090	−0.105**	−0.163***	−0.088	−0.097**	−0.153***
	(0.055)	(0.046)	(0.046)	(0.055)	(0.046)	(0.046)
News and comments	YES	YES	YES	YES	YES	YES
Media characteristics	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Media FE	YES	YES	YES	YES	YES	YES
Observations	8,760	8,760	8,760	8,760	8,760	8,760
R^2	0.556	0.698	0.736	0.555	0.698	0.736
Adjusted R^2	0.534	0.684	0.724	0.534	0.684	0.724

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where $x = 0$, and $\log(x)$ does not exist. We control for all pro-police Simplified Chinese comments in columns (1), (2), and (3). In columns (4), (5), and (6), we control for all pro-police comments in Simplified Chinese provided by users with $SRatio \geq 1$.

Table 7: Semantic analysis (additional table)

Biases against Simplified Chinese comments In Table 7, we provide some further evidence of the inherent bias against the Simplified Chinese user base. The only difference from Table 6 is that we consider the impact of all comments in Simplified Chinese supporting police in Table 7. As we noticed earlier, a large percentage of all Simplified Chinese comments are actually made from Traditional Chinese users who just happen to use Simplified Chinese occasionally. If users from mainland backgrounds were more hateful and irrational than other users, comments with higher $SRatio$ would provoke stronger backlashes. Instead, we find that estimation results based on all Simplified Chinese comments are similar and even slightly higher. These results indicate that users care more about how the comment is written than who the commenter is. There exists a bias against Simplified Chinese criticism. The change in writing habits does not affect the ideological expression and the reason behind it, but the bias significantly intensifies the clashes between the two sides.



Note: Data for offline protests come from Wikipedia. The vertical axis shows the number of offline protests organized per half-month, and the horizontal axis shows the number of online comments containing the words "Liberate Hong Kong." The red line represents the fitted linear model. The zero comment point comes from the fact that some of our Facebook media data are not traceable before June 2019 and are missing.

Figure 5: Online expression and offline demonstrations

Online supports and offline protests Finally, we link the comments on Facebook to offline protests. Admittedly, online ideological expressions may not be a complete substitute for willingness to participate in offline protests, but the literature shows a relationship between the two (e.g., Qin, Strömberg, and Wu (2017), Enikolopov, Makarin, and Petrova (2020), Zhuravskaya, Petrova, and Enikolopov (2020)). In Figure 5, we compare the relationship between the number of comments that include “Liberate Hong Kong” and the frequency of offline demonstrations. The simple regression results show that they are significantly and positively correlated at 10%.

5.2 Robustness check: Instrumental variables Regression

Although we control for a rich set of control variables in the regression of Table 6, the ideological expression of the pro-establishment and the pro-democracy netizens may still be correlated with some unobserved factors, which bias the results of estimation (Manski (1999)). For example, some users' over-expression and ineffective communication may make other users from the opposite side feel tired and give up persuasion. Some debates that arise during certain events, such as coronavirus, may affect both sides' enthusiasm for ideological expression. To reinforce our previous findings, the following two instrumental variables are provided to tackle the possible endogeneity issues.

Number of new Simplified Chinese users ($NewSimUsers$) and Number of inactive Simplified Chinese users ($InactiveSimUsers$) For each media i at each date t, we calculate the number of Simplified Chinese users who, for the first time, post a comment in our data. Let $\mathcal{U}_{i,t}$ be a set of users who leave at lease one comment under media i at time t and $\mathcal{M}$ is a set of media names. We have:

$$NewSimUsers_{i,t} = \sum_{j \in \mathcal{U}_{i,t}} \left(\prod_{\tau < t,\, i \in \mathcal{M}} 1\{j \neq \mathcal{U}_{i,\tau}\} \right).$$

Analogously, we can also obtain the number of Simplified Chinese users who, after the period t, are no longer active:

$$InactiveSimUsers_{i,t} = \sum_{j \in \mathcal{U}_{i,t}} \left(\prod_{\tau > t,\, i \in \mathcal{M}} 1\{j \neq \mathcal{U}_{i,\tau}\} \right).$$

As we mentioned earlier, Simplified Chinese users tend to have a relatively strong pro-establishment and pro-police bias. We believe that the addition of new Simplified Chinese users and the departure of old Simplified Chinese users at current time period do not directly affect the enthusiasm of the pro-democracy users for their democratic demands and anti-police expressions of previous period. At the same time, in our data, the number of identifiable simplified Chinese comments per medium accounts for only 5% of the total number of comments. There is little concern or discretion to determine whether the simplified Chinese characters in the comments are joining the platform for the first time or leaving (i.e., they do not go to other media pages to confirm the information as we do.). Therefore, both $NewSimUsers$ and $InactiveSimUsers$ are unlikely to be related to the error term after controlling for other variables, which satisfies the exclusion restriction. They do not go to other media pages to confirm the information as we do. Simultaneously, the entry and leave of Simplified Chinese users directly influence the number of pro-democracy and pro-police comments, which makes our instrumental variables to meet the relevant condition. After controlling for other variables, the test results show that the IV we chose work well at least in our sample.

Table 8 reports the results from instrumental variable regressions. We focus on measuring the impact of comments that support police ($SP_{i,t-1}$ and $SSP_{i,t-1}$) on the number of demands for democracy ($LHK_{i,t}$) and anti-police rhetoric ($BC_{i,t}$). Our instrumental results consistently show that pro-police comments significantly increase the demands for democracy and anti-police statements. Furthermore, we find that Simplified Chinese users' comments had a far greater impact than the comments from all users. In terms of the magnitude of the effect, our Wu-Hausman test results further revealed the possible existence of endogeneity. Such findings indicate that the results we show in Table 6 are lower limits of these effects. The OLS estimator would underestimate the true effect engendered by pro-police comments. Results from test of weak instruments and Sargan test also jointly show that the instrumental variables statistically satisfy the exclusion restriction and relevance conditions.

We further provide the results from first stage regression, and these result are shown in Table 9. The results show that both the entry and leave of Simplified Chinese users are positively correlated to the number of pro-police comments. The results show that both the entry and leave of Simplified Chinese users are positively correlated to the number of pro-police comments. The addition of users means more support for the police. The leave of users occurs after the end of the day, so we suspect that many users may have left after making aggressive comments, which makes the number of users leaving and the number of supporting police being positively correlated.

Dependent variable:	$ProDemo_{i,t}$		$ProDemo_{i,t}$	
	$LHK_{i,t}$	$BC_{i,t}$	$LHK_{i,t}$	$BC_{i,t}$
	Liberate Hong Kong	Black Cops	Liberate Hong Kong	Black Cops
	(1)	(2)	(3)	(4)
$SP_{i,t-1}$	0.087***	1.307***		
	(0.014)	(0.000)		
$SSP_{i,t-1}$			0.409***	6.111***
			(0.067)	(1.228)
Lag and Opposite	YES	YES	YES	YES
News and Comments	YES	YES	YES	YES
Media Characteristics	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Media FE	YES	YES	YES	YES
Diagnostics (p-value)				
Weak instrument	2e-16***	2e-16***	2e-16***	2e-16***
Wu-Hausman	9.16e-08***	2.9e-06***	2.77e-08***	2.33e-06***
Sargan	0.476	0.810	0.132	0.298
Observations	8,760	8,760	8,760	8,760
R^2	0.521	0.680	0.492	0.661
Adjusted R^2	0.499	0.665	0.469	0.645

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where $x = 0$, and $\log(x)$ does not exist. We control for all pro-police comments in columns (1) and (2). In columns (3) and (4), we control for all pro-police comments in Simplified Chinese provided by users with $SRatio \geq 1$. In the table of IV Diagnostics, we report the p-values of weak instrument, Wu-Hausman and Sargan tests. Compared with Table 6, we removed the variable RO from the regression model since we are mainly concerned with the impact of comments supporting the police (i.e., SP and SSP), which also allows as to do the Sargan tests. All other variables remain unchanged.

Table 8: IV regression results for semantic analysis

Dependent variable:	$SP_{i,t-1}$		$SSP_{i,t-1}$	
	(1)	(2)	(3)	(4)
log $NewSimUsers_{i,t-1}$	7.457	9.139**	4.123***	4.532***
	(5.008)	(4.366)	(1.354)	(1.258)
log $InactiveSimUsers_{i,t-1}$	33.813***	25.615***	4.550***	2.823**
	(4.952)	(4.317)	(1.339)	(1.244)
Lag and Opposite	YES	YES	YES	YES
News and Comments	YES	YES	YES	YES
Media Characteristics	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Media FE	YES	YES	YES	YES
Observations	8,760	8,760	8,760	8,760
R^2	0.532	0.644	0.406	0.487
Adjusted R^2	0.510	0.628	0.378	0.463

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where $x = 0$, and $\log(x)$ does not exist.

Table 9: IV regression results for semantic analysis (first stage)

5.3 Detecting Water Armies and Bots

An alternative way to check our results is to detect potential water armies and bots in our data.[26] On the Internet in China, an Internet Water Army is a group of Internet ghostwriters paid to post online comments with particular content. It has been developed into an industry in which a company specializing in internet water army can earn 7.6 million RMB within three months and has made over 2500 transactions. And many empirical evidence show that the Chinese Communist Party has the incentive of hiring water army or bots to disseminate online propaganda.[27]

The challenge is that we are hard to see directly from the data which netizens are water soldiers or robots. To evaluate impact of comments provided by water armies and bots, we further define those users who have only been active on the platform for one day or left only one comment as potential web bots. We classify users according to Table 10. We find that close to 50% of users have only commented in one day. Of these, 41.56% have only commented once, and 7.90% had not commented at all after multiple comments in one day.

[26] An Internet Water Army is a group of Internet ghostwriters paid to post online comments with certain content. These paid posters can post news, comments, gossip, disinformation on the online social platforms. Source: https://en.wikipedia.org/wiki/Internet_Water_Army.

[27] See, https://en.wikipedia.org/wiki/Internet_Water_Army for more detailed descriptions.

Type	Number of users	Number of users (%)	Comments per user	Comments per day
One comment	840325	41.56%	1	1
activity $\leq$ 1 day (more comments)	159643	7.90%	3.85	3.85
1 day $<$ activity $\leq$ 3 days	25266	1.25%	5.51	2.10
3 days $<$ activity $\leq$ 5 days	17072	0.84%	5.75	0.84
5 days $<$ activity $\leq$ 7 days	15738	0.78%	6.09	0.53
7 days $<$ activity	963967	47.67%	45.76	0.11

Note: If a user adds at least one comment during the period from 12:00 a.m. to 12:00 a.m. the next day, we treat that user as an active user of the given date. In total, our data contains more than 2 million users, and the second column is the proportion of these users in each group. The fourth column is the ratio of users in each group whose $SRatio$ is greater than 1.

Table 10: Bot and Water Army detection

There is no significant increase in the number of users active for more than one day and less than seven days, and they account for less than 3% of the total users. Therefore, we mainly focus on those users who have only been active for one day.

We further divide them into two groups. The first group includes 41.56% of users who have commented only once on their only active day. They only gave one comment and did not seem to be very active, whether they were real robots or mercenaries or not. They only gave one comment and did not seem to be very active, whether they were real robots or mercenaries or not. Because they only gave one comment, and they do not interact with other users, we call call them naive groups of robots, and use $\mathcal{N}$ to denote the group. The other group (users in the second raw of Table 10) seems to be more interactive in their behavior. Although they were only active one day, they left an average of 4 comments per user on that day, which is significantly higher than users in other groups: those regular users who have been active for more than seven days only leave an average of 0.11 comments per day. We call them interactive groups of robots, and use $\mathcal{I}$ to denote the group.

With the help of $\mathcal{N}$ and $\mathcal{I}$, we define two following new variables:

$$NSP_{i,t} = \frac{\sum_{j \in \mathcal{U}_{i,t}} 1\left\{j \in \mathcal{N}\right\} SP_{i,j,t}}{Comment_{i,t}}\%, \ and \ ISP_{i,t} = \frac{\sum_{j \in \mathcal{U}_{i,t}} 1\left\{j \in \mathcal{I}\right\} SP_{i,j,t}}{Comment_{i,t}}\%,$$

where $SP_{i,j,t}$ is the number of comments including the words "support police" that a user j leaves under media i at time t; $NSP_{i,t}$ is the proportion of comments including the words "support police" left my users in group $\mathcal{N}$ under media i at time t, $ISP_{i,t}$ is the proportion of comments including the words "support police" left my users in group $\mathcal{I}$ under media i at time t. The difference between a naive boot and an interactive boots is that the latter is harder to be recognized, since it is more like a real person communicating with others.

In this case, we take $NSP_{i,t-1}$ and $ISP_{i,t-1}$ as exogenous given after controlling for fixed effects and other variables. They only reflect the proportion of comments that may be mixed with those from the water army or bots and are not directly affected by the next day's pro-democracy comments. We consider the following regression model:

$$\begin{aligned} ProDemo_{i,t} =& \gamma_d ProDemo_{i,t-1} + \gamma_N NSP_{i,t} + \gamma_s SP_{i,t-1} + \gamma_{NS} NSP_{i,t} \times SP_{i,t-1} + \\ & \gamma_c' Controls_{i,t} + \mu_i + \nu_t + \zeta_{i,t}; \\ ProDemo_{i,t} =& \gamma_d ProDemo_{i,t-1} + \gamma_I ISP_{i,t} + \gamma_s SP_{i,t-1} + \gamma_{IS} ISP_{i,t} \times SP_{i,t-1} + \\ & \gamma_c' Controls_{i,t} + \mu_i + \nu_t + \zeta_{i,t}, \end{aligned}$$

where the variable $Controls_{i,t}$ includes all the remaining control variables as we show in Equation 1. γ_{NS} and γ_{IS} capture the heterogenous impact of pro-police comments related to the proportion of potential bots.

Table 11 reports the results of estimation. We use the IVs to correct the variables $SP_{i,t-1}$, $NSP_{i,t} \times SP_{i,t-1}$ and $ISP_{i,t} \times SP_{i,t-1}$. Both Wu-Hansman and Sargan test results indicate that the IVs correct the potential endogeneity and are valid in our sample. We find that the impact of $SP_{i,t-1}$, on $ProDemo_{i,t}$ is consistent with the previous results in Table 8. In addition, the results indicate that if many comments were delivered from potential bots or water armies, impact of $SP_{i,t-1}$ would be reduced. Comparing the influence of changes in different groups, we find that the influence from group $\mathcal{N}$ is greater than that from group $\mathcal{I}$.

Our results echo what we have found before. One the political preference is observed, even the comments are from bots, they will also intensify the collision. The results also provide potential explanation of why OLS regression underestimates the potential impact of $SP_{i,t-1}$. In our data, nearly half of the users are very low on activity, having been active for only one day. Their comments are considered inattentive and unresponsive by the other half of active users. When such comments flood discussion boards, they dilute the "loaded" comments that provoke conflict. This is like buying a product on an e-commerce platform: if the goods are covered in fake reviews left by bots, real consumers may also be less interested in making any constructive comments. We find that when the suspected bot account has more comments on the same day (i.e., interaction with other users), they look less like bots. It still significantly reduces the opposing camp's ideological expression, but the negative effect is almost negligible.

Dependent variable:	$LHK_{i,t}$	$BC_{i,t}$	$LHK_{i,t}$	$BC_{i,t}$	$LHK_{i,t}$	$BC_{i,t}$	$LHK_{i,t}$	$BC_{i,t}$
	Liberate Hong Kong	Black Cops	Liberate Hong Kong	Black Cops	Liberate Hong Kong	Black Cops	Liberate Hong Kong	Black Cops
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SP_{i,t-1}$	0.021***	0.247***	0.024***	0.265***	0.091***	1.381***	0.091***	1.431***
	(0.003)	(0.052)	(0.003)	(0.057)	(0.014)	(0.260)	(0.014)	(0.270)
$NSP_{i,t-1}$	−0.399	−19.009			2.614	29.155		
	(2.580)	(40.140)			(2.904)	(44.977)		
$ISP_{i,t-1}$			2.435	81.421			1.571	50.035
			(4.652)	(72.384)			(4.959)	(76.881)
$SP_{i,t-1} \times NSP_{i,t-1}$	−0.013***	−0.171***			−0.067***	−1.076***		
	(0.004)	(0.066)			(0.012)	(0.212)		
$SP_{i,t-1} \times ISP_{i,t-1}$			−0.028***	−0.303***			−0.099***	−1.446***
			(0.007)	(0.116)			(0.018)	(0.335)
Lag and Opposite	YES	YES	YES	YES	YES	YES	YES	YES
News and Comments	YES	YES	YES	YES	YES	YES	YES	YES
Media Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Media FE	YES	YES	YES	YES	YES	YES	YES	YES
Diagnostics (p-value)								
Wu-Hausman					4.37e-07***	9.06e-06***	9.95e-08***	7.25e-08***
Sargan					0.812	0.834	0.627	0.963
Observations	8,760	8,760	8,760	8,760	8,760	8,760	8,760	8,760
R^2	0.556	0.698	0.556	0.698	0.523	0.680	0.530	0.683
Adjusted R^2	0.534	0.684	0.535	0.684	0.500	0.664	0.507	0.668

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where $x = 0$, and $\log(x)$ does not exist. In the table of IV Diagnostics, we report the p-values of Wu-Hausman and Sargan tests. Compared with Table 6, we removed the variable RO from the regression model since we are mainly concerned with the impact of comments supporting the police, which also allows as to do the Sargan tests. All other variables remain unchanged.

Table 11: IV estimation of the impact of Water Armies and Bots

6 Concluding Remarks and Discussion

The development of online platforms and computer programming has widened the frontiers of research of social scientists. Taking a platform as a natural laboratory, researchers analyze the online behaviors of many users from multiple dimensions and study the online interactions between people and their influence.[28] Our paper is the first attempt to study how pro-democratic and post-authoritarian ideologies interact dynamically on one online platform by analyzing all news releases and comments on the Facebook pages of Hong Kong news media since 2019.

In a dynamic environment, we show that an increasing number of comments under news stories will hurt future reports and comments. However, this negative effect will disappear during periods of mass edits (clashes between the police and civilians) because users are more persistent in their discussions. In particular, we find that the ideological online war between pro-democracy and post-authoritarian regimes is getting more intense, which further generates more negative emotions hurting the online environment. Our empirical results point out that the conflicts may get intensified, especially with the coexistence of two different writing habits.

Our paper has strong practical significance today. With the reinforcement of conflicts due to the support from one side, hiring "internet water army" to influence online opinion would backfire. In addition, China's widely used Great Firewall policy adds to the cost of Internet users browsing international websites.[29] Based on our results, we suggest that China's Great Firewall policy, although restricting the information received by Chinese netizens from the democratic world, alleviates tensions between people of different ideologies.

To conclude, our paper suggests that policymakers should be cautious when using online and offline regulation to balance the political climate.[30] When people offline experience are experiencing more political stress, the government can implement more restrictive online regulations to to alleviate the tension. In contrast, it should consider relaxing online regulations to make people use platforms as a tranquilizer of negative emotions at normal

[28]See Ledford (2020), a news article published in Nature for further discussion.

[29]The role of China's "Great Firewall of China is to block access to selected foreign websites and to slow down cross-border Internet traffic. The effect includes: limiting access to foreign information sources, blocking foreign Internet tools (e.g. Google search, Facebook, Twitter, Wikipedia, and others) and mobile apps, and requiring foreign companies to adapt to domestic regulations.Source: https://en.wikipedia.org/wiki/Great_Firewall.

[30]Tirole (2019) highlights the potential pros and cons of governments using big data to strengthen regulation. Han, Li, and Wang (2020) also demonstrate that stricter platform regulation will enhance the chilling effect and make users afraid to express their opinions freely.

times.

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Appendix For Online Publication

A Major Conflict Incidents since 2019

Table 12 shows the main conflict incidents between the police and citizens in Hong Kong that have been widely followed and reported since June 2019. According to the Rule of Law Index 2020 released by the World Justice Project,[31] Hong Kong's score of 0.76 out of 1 remains unchanged from last year, ranking 5th in East Asia and the Pacific and 16th in the world. Therefore, we reasonably believe that the rule of law in Hong Kong retains a very high level of autonomy and justice, at least until the end of May 2020, when the Hong Kong National Security Law was passed at the National People's Congress in Beijing. In other words, the IPCC's final report on police complaints should be objective.

Date	Event
2019-06-12	Police opened fire on demonstrators and journalists without raising a black flag.
2019-07-21	Police collaborated with the white-clad gangsters in Yuen Long to beat up the public.
2019-08-11	A woman was shot in the face by the police during a protest, injuring her right eye to pop.
2019-08-31	Police killed people in public at Prince Street subway station.
2019-09-29	An Indonesian journalist who was shot in the right eye by a police officer, she may have lost her sight.
2019-10-22	A girl reported being raped by the police. She then left Hong Kong on November 9.
2019-11-11	Traffic police fired at least three shots at Sai Wan Ho. One of the residents was shot and is in critical condition.
2019-12-20	A masked police officer without a badge had attacked a reporter with a baton and lunged at the reporter's mobile phone.

Note: The table only shows events that the authors consider to be relatively important and of great concern. It does not contain all events. For example, on December 20, 2019, it was reported that at the Shatin Hilton Centre, large numbers of riot police continued to break into private areas at gunpoint, prevented by security guards from the mall. We do not include this event in the table because it did not have a broad social impact.

Table 12: Police incidents in Hong Kong

[31] c.f., https://worldjusticeproject.org/our-work/research-and-data/wjp-rule-law-index-2020

B Objectivity and Impartiality of our Political Tendency Scores

We report in Table 13 a verification of our political tendency scores. Our data are provided directly by the Department of Media of The Chinese University of Hong Kong (CUHK) based on the results of a survey questionnaire they organized. To verify that the questionnaire results are fair and objective, we interactively compare our results with external data from Wikipedia. The results show that our media political tendency scores are generally consistent with the Wikipedia results, but are more detailed.

Media ID (Facebook)	Chinese Name	CUHK	Wikipedia (Chinese background)	Wikipedia (Media pro-CCP ranking)
1693275180942630	大公报	4.8	mainland's official mouthpiece	2
wenweipo	文汇报	4.7	mainland's official mouthpiece	1
tvbnewshk	无线电视	3.3		
news.hkcd	香港商报	2.2	mainland's official mouthpiece	3
178766115480756	星岛日报	2.1	pro-establishment and pro-Beijing	4
onccnews	东方日报	2.1		8
scmp	南华早报	1.3	pro-establishment and pro-Beijing	
hongkongeconomicjournal	信报	1.2	establishment centrist	
headlinehk	头条日报	1.1		
hketpage	经济日报	1	pro-establishment and pro-Beijing	
hk01wemedia	HK01	0.6	establishment centrist	
Skyposthk	晴报	0.5	pro-establishment and pro-Beijing	
am730hk	am730	0.3		
metroradio.com.hk	新城电台	0.1		
mingpaoinews	明报	-0.1	establishment centrist	9
Bastillepost	巴士的报	-0.1		
881903com	商业电台	-0.2		
theinitium	端传媒	-0.5		
RTHKVNEWS	香港电台	-0.5		
icablenews	有线电视	-0.7		
post852	852__	-0.8		
now.comNews	Now/ViuTV	-1.1		
standnewshk	立场新闻	-1.9		
inmediahknet	香港独立媒体	-2.2		
hk.nextmediaapple.realtimenews	苹果日报	-2.6		Mainstream pro-democracy media
passiontimes	热血时报	-3.4		

Note: Column (1) in the table contains all of the media for which we can identify political tendencies. Column (3) is the political tendency scores we use in our paper, and columns (4) and (5) are the relevant political tendencies of the media obtained from external sources: https://zh.m.wikipedia.org/zh-hk/%E9%A6%99%E6%B8%AF%E5%82%B3%E5%AA%92%E7%88%AD%E8%AD%B0.

Table 13: Objectivity and impartiality of our tendency scores

C Differences Between Simplified and Traditional Chinese

In the late 19th century, the Simplified Chinese writing system was developed in mainland China to improve the literacy rate by making it easier for people to read and write. Before that, if people wanted to be cultured Chinese citizens, they had to learn at least 4,000 characters, which were relatively sophisticated. Since its creation, Simplified Chinese has become the official standard and the preferred style of writing for mainland Chinese people. However, in places like Hong Kong, Taiwan, and Macao, Traditional Chinese is still the dominant writing system.

During the simplification of Chinese, approximately 1,027 characters were deleted. Reformers believed that these characters meant the same thing. At the same time, reformers adopted many strategies to simplify the form of the characters. For example, replacing cursive characters with simpler characters and symbols, or removing some characters completely and creating new characters from scratch. Reformers somehow created a simpler version of the traditional characters while retaining their original forms. Figure 6 provides an example to illustrate how different are Simplified characters from Traditional characters. For example, the Simplified Chinese character of expressing intimacy is "亲" while the Traditional character for intimacy is "親".

Note: Source from https://zhuanlan.zhihu.com/p/96208556.

Figure 6: An illustration of the differences between Simplified Chinese and Traditional Chinese

D Density of the Comments Received by Opposing Camps

In Figure 7, we plot the distribution of $Opposite_{i,t-1}$ for each media outlet according to its political tendency. The figure shows that the distribution of $Opposite_{i,t-1}$ for the media in each political group shows an asymmetric bimodal shape, this is also the case for the centrist media. We suspect this is due to the fact that iconic media exist at both ends of the political spectrum. These flag media are usually read by many people and receive a lot of comments, play a leading role in the variation of $Opposite_{i,t-1}$.

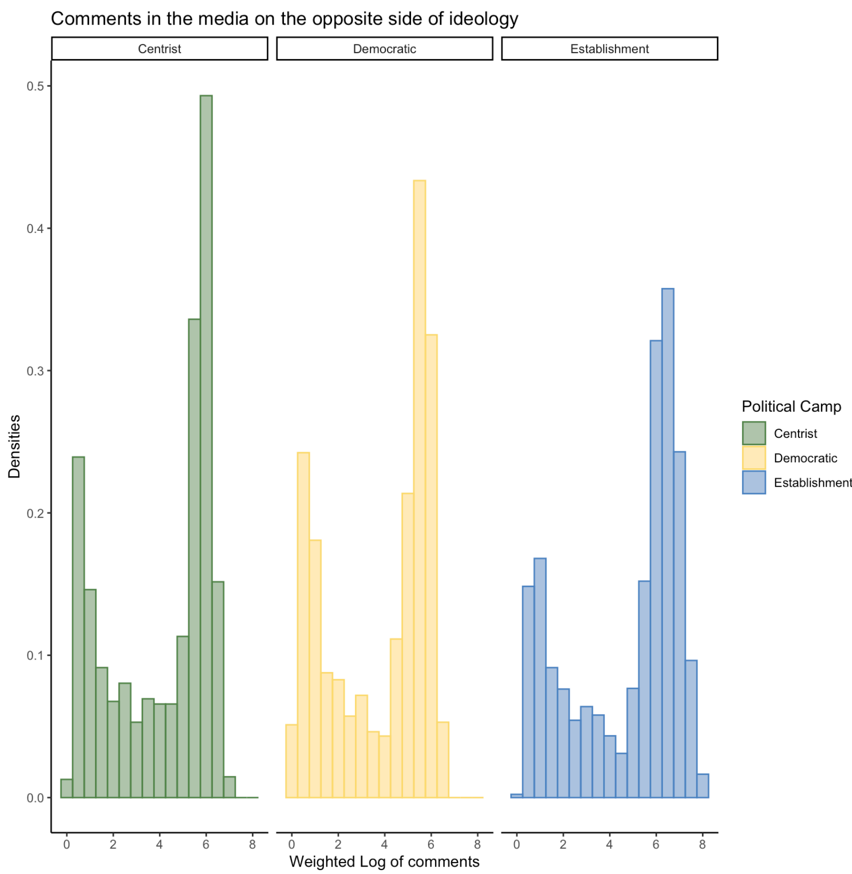

Figure 7: Density of $Opposite_{i,t-1}$

E Identifying the Distraction Effect

In Table 14, we provide statistical evidence illustrating the effect of distraction on the number of comments. To this end, we construct two additional variables: $Opposite^{r}_{i,t-1}$, the weighted average log of retweets in the opposing media at $t-1$ and $Opposite^{l}_{i,t-1}$, the weighted average log of likes received by the opposing media at $t-1$. These two variables respectively represent the potential influence and quality of news stories in other media.

The results show that if other media outlets publish high-quality or influential news the day before, it will have a significant negative effect on today's the comments in today's media. By further controlling the cross-terms, we find that this negative distraction effect may be attenuated when the quality of news in other media is high (more likes), or the news is highly influential (more retweets), and get receives many comments at the same time. In other words, it means that hot news may have been published the day before and that the discussion of this hot topic may spill across the media and cause positive externalities.

Dependent variable: $\log Comments_{i,t}$			
	(1)	(2)	(3)
News and comments			
$News_{i,t}$	-0.0002	-0.0001	-0.001^{***}
	(0.0002)	(0.0002)	(0.0002)
$\log Comments_{i,t-1}$	-0.010^{***}	-0.010^{***}	-0.010^{***}
	(0.002)	(0.002)	(0.002)
$Opposite^{c}_{i,t-1}$	-0.033^{***}	-0.033^{***}	-0.033^{***}
	(0.009)	(0.009)	(0.009)
Other media's retweets and likes			
$Opposite^{r}_{i,t-1}$		-0.097^{***}	
		(0.018)	
$Opposite^{l}_{i,t-1}$			-0.011^{***}
			(0.001)
$Opposite^{r}_{i,t-1} \times Opposite^{c}_{i,t-1}$		0.012^{***}	
		(0.001)	
$Opposite^{l}_{i,t-1} \times Opposite^{c}_{i,t-1}$			0.001^{***}
			(0.0001)
Media characteristics	YES	YES	YES
Time FE	YES	YES	YES
Media FE	YES	YES	YES
Observations	8,760	8,760	8,760
R^2	0.997	0.997	0.997
Adjusted R^2	0.997	0.997	0.997

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parentheses. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where the $x = 0$, and $\log(x)$ does not exist.

Table 14: Effect of distraction from other media's retweets and likes

F Impact of the Number of Simplified Chinese Users on Comments

We take into account the fact that some active users may make multiple comments on a particular news story, which may lead us to overestimate the impact of Simplified Chinese characters on the number of comments. In Table 15, we replace $SimCom_{i,t-1}$ with the number of Simplified Chinese users denoted by $SimUsers_{i,t-1}$. To construct this variable, we calculate the total number of identifiable Simplified Chinese users per media per day based on their user ID, so that repeated comments from a given user are not counted.

Dependent variable: $\log Comments_{i,t}$				
	(1)	(2)	(4)	(6)
	Full	Full	Pro-democratic	Establishment
News and comments				
$News_{i,t}$	-0.0002	-0.001^{***}	-0.001^{***}	-0.003^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\log Comments_{i,t-1}$	-0.010^{***}	-0.015^{***}	-0.003	0.019^{***}
	(0.002)	(0.002)	(0.003)	(0.003)
$Opposite_{i,t-1}$	-0.033^{***}	-0.020^{**}	-0.083^{***}	0.048^{***}
	(0.009)	(0.009)	(0.025)	(0.025)
$\log SimUsers_{i,t-1}$		0.101^{***}	0.099^{***}	0.078^{***}
		(0.004)	(0.006)	(0.006)
$Tendency_i \times \log SimUsers_{i,t-1}$			-0.002	0.016^{***}
			(0.002)	(0.002)
News and comments	YES	YES	YES	YES
Media characteristics	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Media FE	YES	YES	YES	YES
Observations	8,760	8,760	3,285	4,380
R^2	0.997	0.997	0.998	0.998
Adjusted R^2	0.997	0.997	0.998	0.998

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where $x=0$, and $\log(x)$ does not exist. In column (3), we select the pro-democracy media subsample and their political tendency scores are all negative. In column (4), we select the pro-establishment media subsample and their political tendency scores are all positive. The period is set according to the table provided in Appendix A.

Table 15: Impact of the number of Simplified Chinese users on the number of comments

G Word frequencies in comments

We analyze the top 2,389 Chinese words in the comments of 44 Hong Kong media. For each media outlet, we calculate the number of comments in which each word appears. Table 16 shows the 20 most frequently used words in both the Simplified and Traditional Chinese comments. Table 17 shows the 20 most frequently used words in the Simplified Chinese comments only.

Word (Simplified and Traditional Chinese)	English translation	Number of comments
香港	Hong Kong	3964719
警察	Police	1833570
黑警	Black Cops	1726330
支持	Support	1612831
港人	People of Hong Kong	1459500
香港人	People of Hong Kong	1351098
加油	Cheering	1158435
暴徒	Rioter	925817
政府	Government	869283
市民	Citizen	865593
中國	China	734305
曱甴	Roaches	727006
记者/記者	Journalist	708053
大陆/大陸	Mainland	696563
垃圾	Rubbish	631595
仆街	Planking	625636
已經	Already	608400
小心	Be careful	556834
點解	Why	532728
應該	Be supposed to	480071
港警	Hong Kong Police	456732
社会/社會	Society	424704

Note: We treat Simplified and Traditional Chinese words with the same meaning but different writing as one word, for example, "国家" (Simplified Chinese) and "國家" (Traditional Chinese). Although most characters are the same in Simplified and Traditional Chinese, some words are clearly not used in mainland China. We do not filter out the sample for words like "已经" (already) and "应该/應該" (be supposed to) that may appear frequently in English but are not clearly oriented, because they have meaning in Chinese.

Table 16: Frequency of words in comments

H Ratio of Simplified and Traditional Chinese Comments

In Table 18, we report the number of users and the number of comments from different subsamples filtered by the ratio of Simplified and Traditional Chinese comments.

Word (Simplified Chinese)	English translation	Number of comments
香港	Hong Kong	298272
暴徒	Rioter	165951
支持	Support	133219
警察	Police	131974
废青	Decadent youth	109783
中国	China	96513
加油	Cheering	77724
没有	Be without	73078
曱甴	Roaches	70532
香港人	People of Hong Kong	66823
美国	United States	61933
不要	Do not	50078
垃圾	Rubbish	42411
记者	Journalist	42048
知道	Rubbish	40660
香港警察	Hong Kong police	39489
大陆	Mainland	38351
现在	At present	37463
应该	Be supposed to	36222
黑警	Black Cops	35774
国家	Nation	34111
多谢	Many thanks	33478

Note: We do not filter out the sample for words like "没有" (be without), "不要" (do not), and "应该" (be supposed to) that may appear frequently in English but are not clearly oriented, because they have meaning in Chinese.

Table 17: Frequency of words in Simplified Chinese comments

I Dynamics of News Releases

In this section, we provide some supplementary statistical evidence of the dynamics of media content (i.e., news reports). To study the dynamics of a media's news provision, we use the following regression model:

$$News_{i,t} = \delta_n News_{i,t-1} + \delta_c \log Comments_{i,t-1} + \delta_o^n Opposite_{i,t-1}^n + \delta_o^c Opposite_{i,t-1}^c + \beta_m' Media_{i,t} + \mu_i + \nu_t + \xi_{i,t},$$

where compared with the regression model for news comments, both the number of news releases and the number of comments at $t-1$ are controlled simultaneously. Due to pos-

Sub-samples	Traditional comments	Simplified comments	Users	Δ% Traditional comments	Δ% Simplified comments	Δ% Number of users
$SRatio \geq 1\%$	10,779,797	2,090,570	249,710	44.901%	2.164%	99.166%
$SRatio \geq 5\%$	2,269,922	1,908,730	192,683	78.943%	8.698%	22.837%
$SRatio \geq 10\%$	1,114,627	1,828,538	171,062	50.896%	4.201%	11.221%
$SRatio \geq 20\%$	628,941	1,759,991	154,153	43.574%	3.749%	9.885%
$SRatio \geq 100\%$	184,590	1,557,524	123,029	70.651%	11.504%	20.190%
$SRatio \geq 500\%$	45,585	1,255,914	111,081	75.305%	19.365%	9.712%
$SRatio \geq 1000\%$	23,235	1,097,458	107,571	49.029%	12.617%	3.160%
Total number of users	269,930					
Total number of comments	29,935,825					
Total number of Simplified Chinese Comments	2,136,813					
Total number of Traditional Chinese Comments	19,564,449					

Note: Column 5, 6, and 7 are the rates of change based on the results of Column 1, 2, and 3. For example: $78.943\% = \frac{2,269,922-1,114,627}{1,114,627}$.

Table 18: Ratio of Simplified and Traditional Chinese comments

sible competition between media outlets for a news release, we control for the number of comments in other media and the number of news releases in other media, $Opposite^{n}_{i,t-1}$ and $Opposite^{c}_{i,t-1}$ respectively. For $Media$, we do not control for the total number of commenters because the increase in the number of commenters is directly caused by the increase in the number of news releases.[32] μ_i and ν_t two components of media and time fixed effects and $\xi_{i,t}$ is the unobserved error term.

Table 19 reports the estimation results. The number of comments has a significant negative effect on the number of news releases on a given day, which shows that too many comments suppress news output. Jeon and Nasr (2016) and Chiou and Tucker (2017) theoretically and empirically study the impact of external search engines (i.e., news aggregators) on news production. However, if the platform is also a natural news aggregator, the effect of media competition on the platform will be ignored. Our results show that news output from opposing media has a significant positive effect on news output from the focal media. This finding indicates that the media compete with each other and that the increase in the number of news releases from rival media will urge other media to produce more news to avoid the loss of readers. We find that news output from pro-establishment media is significantly higher than that from pro-democracy media. As pro-establishment media are ideologically more oriented toward Beijing, they pay more attention to ideological propaganda than other types of media.

In addition, we control for the frequency of democratic appeals ($LHK_{i,t-1}$) and abusive words ($PL_{i,t-1}$) in the comments in column (6).[33] The regression results show that ideological expressions do not significantly affect the number of news stories published by the media. However, the number of news stories is significantly affected by negative emotions in comments. These findings suggest that the media may not care about the rational arguments that take place on their pages. They even encourage such arguments because they generate traffic dividends. However, negative emotions in comments affect consumers' loyalty to the media, which encourages them to reduce the amount of news stories published to appease consumers.

[32]We control for the total number of commenters in the previous regression model to control for repeated comments.

[33]We do not control for police-related comments because these words are directed to police-related events.

Dependent variable: $News_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)
News and comments						
$News_{i,t-1}$	0.332***	0.332***	0.310***	0.314***	0.293***	0.293***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
$\log Comments_{i,t-1}$	0.366***	0.329***	0.461***	−0.766***	−0.486***	−0.464***
	(0.022)	(0.036)	(0.053)	(0.052)	(0.061)	(0.061)
$Opposite^{n}_{i,t-1}$		−0.003	0.057***	−0.029***	0.078***	0.058***
		(0.007)	(0.019)	(0.006)	(0.018)	(0.018)
$Opposite^{c}_{i,t-1}$		0.160*	−0.428	0.367***	−0.079	0.108
		(0.097)	(0.426)	(0.095)	(0.407)	(0.409)
Comments words						
$LHK_{i,t-1}$ (Liberate Hong Kong)						−0.002
						(0.003)
$PL_{i,t-1}$ (Planking)						−0.002***
						(0.001)
Media characteristics						
$Tendency_i$				0.218***	0.705**	0.707**
				(0.058)	(0.313)	(0.313)
$\log Followers_i$				0.452***	0.812*	0.798*
				(0.079)	(0.467)	(0.466)
$\log Retweets_{i,t}$				1.242***	1.374***	1.376***
				(0.110)	(0.120)	(0.120)
$\log Likes_{i,t}$				0.236***	0.190*	0.168*
				(0.091)	(0.099)	(0.099)
Time FE			YES		YES	YES
Media FE			YES		YES	YES
Observations	8,760	8,760	8,760	8,760	8,760	8,760
R^2	0.890	0.890	0.907	0.900	0.916	0.916
Adjusted R^2	0.890	0.890	0.903	0.899	0.912	0.912

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where $x = 0$, and $\log(x)$ does not exist.

Table 19: A regression model for news releases

I.1 News Quality and Political Tendency

To strengthen the above results, we further test the above effects in Table 20. We examine how the political tendency of a news media outlet is correlated with news quality and the number of identifiable Simplified Chinese users. We control for the number of news releases, the total number of followers, the total number of comments, and media and time fixed effects in the regression models. Columns (1) and (2) show that pro-establishment media receive fewer likes and retweets. We consider that the number of likes indicates news quality and the number of retweets indicates news influence. In this case, the results indicate that the quality and potential influence of news stories from pro-establishment media are lower than those of pro-democracy media. Column (3) shows that the proportion of users with mainland background in the pro-establishment media group is significantly higher than in the pro-democracy media group, which is related to the fact that the political ideology of the pro-establishment camp is much closer to that of Beijing. These results further indicate the trade-off between quantity and quality. Pro-establishment media focus more on propaganda, and netizens from mainland China are more supportive of their articles. However, their overall quality and social acceptance are often lower than those of pro-democracy media.

Dependent variable:					
	$\log Retweets_{i,t}$	$\log Likes_{i,t}$	$\log SimUsers_{i,t}$	$\log NewSimUsers_{i,t}$	$\log InactiveSimUsers_{i,t}$
	(1)	(2)	(3)	(4)	(5)
$Tendency_i$	−0.577***	−0.230***	0.169***	0.209***	0.200***
	(0.056)	(0.045)	(0.025)	(0.025)	(0.026)
$News_{i,t}$	0.026***	0.025***	0.014***	0.014***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\log Followers_i$	−0.513***	−0.171**	0.229***	0.241***	0.231***
	(0.086)	(0.069)	(0.038)	(0.039)	(0.039)
$\log Comments_{i,t}$	0.913***	0.764***	0.479***	0.422***	0.393***
	(0.008)	(0.007)	(0.004)	(0.004)	(0.004)
Time FE	YES	YES	YES	YES	YES
Media FE	YES	YES	YES	YES	YES
Observations	8,760	8,760	8,760	8,760	8,760
R^2	0.915	0.922	0.935	0.904	0.904
Adjusted R^2	0.911	0.918	0.932	0.900	0.900

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are reported in brackets. We use $\log(x+1)$ for the logarithm transformation of variable x to avoid the situation where $x = 0$, and $\log(x)$ does not exist. $SimUsers_{i,t}$ is the total number of identifiable Simplified Chinese users per media per day based on user ID. $NewSimUsers_{i,t}$ is the daily number of new identifiable Simplified Chinese users appearing under each media. $DeadSimUsers_{i,t}$ is the number of identifiable Simplified Chinese users that disappear under each media every day (they are no longer active in subsequent data).

Table 20: Further tests of the identified effects

In columns (4) and (5), we specifically look at the effect of political tendency on users joining and leaving a group. We find that in the pro-establishment media group, Simplified Chinese users are more active in joining and leaving: more Simplified Chinese users join the discussion or leave Facebook permanently every day. One of the reasons may be that during the protests in Hong Kong in 2019, Facebook was worried that accounts created in mainland China were part of a coordinated attempt to undermine the "legitimacy and political positions of the protest movement." Based on this consideration, Facebook may have closed the accounts of some mainland Chinese users, rendering their accounts invalid and requiring them to register new accounts to support the speech.[34]

[34]Source: https://www.bbc.com/news/technology-49402222.