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RESEARCH ARTICLE

Would violent tactics cost a democratic movement its international support? A critical examination of Hong Kong's anti-ELAB movement using sentiment analysis and topic modelling

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Abstract

This paper aims to address an important yet under-studied issue – how does violence from the side of the protestors affect overseas support for a democratic movement? The importance of this question is twofold. First, while violence and radicalization are not exactly unfamiliar territories for scholars of contentious politics, they do not receive as much attention when their effects spill beyond the domestic arenas. Second, this study seeks to examine international solidarity with democratic movements at the civil society level, which differs substantially from the conventional elite-centric approach when it comes to the intersection between democratization and international relations. Against this backdrop, this paper considers the relationship between violent tactics employed by the protestors during the anti-extradition movement and the sentiment expressed by people elsewhere towards the protests. To this end, a total of 9,659,770 tweets were extracted using Twitter Application Programming Interface during the period of 1 June 2019–31 January 2020. Leveraging computational methods such as topic modelling and sentiment analysis, findings in this paper demonstrate that a majority of foreign Twitter users were supportive of the protestors while held relatively negative sentiments against the government as well as the police. In addition, this study reveals that, broadly speaking, violence might cost a democratic movement by its international support, but could also garner more attention at times. Despite its restricted scope, this paper hopefully will shed some useful light on the dynamics underlying international solidarity for a democratic movement abroad as well as the complex mechanisms of interactions between people who protest at home and those who observe from overseas.

Key words: Contentious politics; democratization; sentiment analysis; topic modelling; Twitter

1. Introduction

While an extant amount of literature illuminates on why and how ordinary people organize themselves as rights-holders, what have received less attention are the reasons motivating bystanders to show solidarity with a political movement that does not necessarily have a direct impact on them. What is even more under-studied is the instance when such diplomatic support stems not from political elites, but instead from ordinary laymen. This puzzle is worthy of scholarly attention as this is exactly what we witnessed in today's world – pro-democracy protestors around the globe – Ukraine, Belarus, Hong Kong, Thailand and Myanmar – just to name a few, had invested tremendous effort in garnering support and attention from the rest of the world for their cause, mostly within the digital space.

Another equally important and related question is that – when violent tactics are employed by protestors, would that affect diplomatic support for the movement? Violence and radicalization are no strangers to scholars of contentious politics. Yet these topics have been rarely explored through the lens of external support for a democratic cause. When pressed with the exhaustion of peaceful means, protestors are forced into a difficult dilemma – if they continue with their peaceful approach, the movement may risk getting stuck in a deadlock with the authorities; and if they instead opt for violent means, would it cost the support of the bystanders which they would otherwise enjoy? In face of this seemingly self-evident trade-off, it would be helpful to first step back and ask – would violence cost external support? If so, to what extent?

Against this backdrop, this paper uses the anti-extradition movement in Hong Kong as a case study to consider the relationship between violent tactics employed by the protestors and the support expressed by people elsewhere towards the movement. Specifically, 'support' is measured in two ways – positive sentiment expressed and attention given on Twitter. Despite its restricted scope, this paper hopefully will shed some useful light on the dynamics underlying international solidarity for a democratic movement abroad as well as the complex mechanisms of interactions between people who protest at home and those who observe from overseas.

2. Literature review

Violence has been one of the central topics widely discussed in the realm of political science. Nieburg (1962) argues that the threat of violence, defined as 'direct or indirect action applied to restrain, injure or destroy persons or property', and the occasional outbreak of real violence, are essential elements in peaceful social change.[1] According to Nieburg (1962), such threat is common in political life (both international and domestic) and induces flexibility and stability in democratic institution.[2] Furthermore, Nieburg (1962) describes that '…underneath the norms of legal and institutional behaviour in national societies lies the great beast, the people's capability for outraged, uncontrolled, bitter and bloody violence'.[3] In a totalitarian or an authoritarian context, such capability of committing violence is regarded by Nieburg (1962) as 'a major restraint against completely arbitrary government'.[4]

During a civil unrest, it is almost natural for activists to escalate and turn to disruptive and violent tactics when their non-violent means exhaust. In the context of social movement, studies on violent tactics are often tied to those discussing radicalization. Haines, for instance, argues that almost all social movements are divided into the 'moderate' and 'radical' camps (Herbert, 1984).[5] Bifurcation has occurred, for example, in the US labour movement, the women's movement, the anti-nuclear movement and so forth. It is important to note here that although violence committed by protestors is generally considered to be radical, radicalization is not necessarily violent. A peaceful sit-in can be understood as 'more radical' or an 'escalated' action than say, signing a petition or making a donation to advocacy groups – all of these are non-violent yet could be regarded as 'radical' depending on the context. Also, radicalization may simply refer to a radical goal, which may and may not be achieved by violence. In the context of Hong Kong, for instance, the goal of gaining independence itself could well be argued as a 'radical' cause (when compared to the status quo of One Country Two Systems), yet it does not necessarily come with a concrete plan of committing actual violence.

Research on the effectiveness of violence in achieving goals of social movement has presented mixed results. For instance, Giugni (1998) argues that violence does not necessarily increase the odds of success.[6] On a similar note, research by Snyder (1978) shows that violent strikes initiated by the Italian workers had a higher tendency to fail compared to other peaceful actions.[7] In her research on protests in China, Cai (2019) makes similar observations – radical action fails to advance

[1]Nieburg (1962).
[2]*Ibid.*
[3]*Ibid.*
[4]*Ibid.*
[5]Herbert (1984).
[6]Giugni (1998).
[7]Snyder (1978).

its cause if violence on the part of the participants is perceived to be disproportionate.[8] Cai (2019) further suggests that tactical escalation might not always succeed in empowering a movement. In the case of the Umbrella Movement which took place in Hong Kong in 2014, for instance, certain violent tactics employed by the protestors were counter-productive as they damaged the image of the movement.[9] Apart from losing public support, violent tactics may not be desirable as they may serve as an excuse for the authorities to repress the movement, as Tarrow (1998) argues.[10] In sum, violence may cost public support by turning away peaceful protestors and garnering negative media coverage (Elsbach and Sutton, 1992).[11]

On the contrary, Gamson's (1990) research suggests that protestors who used violence in social movement in the USA had 'a higher-than-average success rate'.[12] Furthermore, O'Brien and Li (2006) found that violence may help keep the momentum of the movement by exerting a kind of 'excitement'.[13] Also, violent tactics may also contribute to more press attention. Violence on the side of the protestors could also produce 'positive radical flank effect' by casting actions of moderate activists in a more favourable light (Herbert, 1984).[14]

In light of this trade-off between the effectiveness of disruptive behaviours and the potential threat a disruptive tactic poses to the level of support, Wang and Piazza (2016) argue that whether protestors decide to deploy disruptive tactic is a 'function of the appeal of the protestors' claims and their choice of targets'.[15] This is where political allies become relevant in the equation. Jenkins and Perrow (1977) argue that 'movements of the powerless require strong and sustained outside support'.[16] Similarly, Tarrow (1988) suggests that 'challengers are encouraged to take collective action when they have allies who can act as friends in court, as guarantors against repression or as acceptable negotiators'.[17] Lipsky (1968) formulates that the problem of the powerless in protest activity is to activate 'third parties' to enter the implicit or explicit bargaining arena in ways favourable to the protestors.[18] In sum, garnering support from outside groups is crucial to generate success for a movement.

From a purely rational point of view, it may seem odd for people to spend time, money and energy in support of a movement that barely affects their lives (in some cases, such movement may even harm their privileged status in society). However, throughout the history of civil rights movement, the scenes of members of the privileged class joining the ranks of the oppressed to fight for equality were not uncommon. As a result, a wide array of literature had been dedicated to inspecting such out-group's support for the disadvantaged. For example, extensive surveys had been conducted to study out-group alliance (heterosexuals) with the in-group disadvantaged members (LGBT+ community) during the civil rights movement in 1960s (Fingerhut, 2011).[19] These studies reveal that the presence of empathetic feelings towards minorities group is a strong predictor for out-group alliance. In fact, such line of thinking aligns with what scholars found in prior research conducted in sociology and social psychology – moral conviction is an important variable to predict sympathy for the disadvantaged's fight for justice among the 'socially dominant group' (van Zomeren *et al*., 2012).[20]

While in-group's support for a cause that benefits mostly the out-group in a domestic context is relatively well-documented in the literature, research is scant when the question extents to an international level. In particular, it is observed that external dimensions of internal political change is

[8]Cai (2019).
[9]*Ibid.*
[10]Tarrow (1998).
[11]Elsbach and Sutton (1992).
[12]Gamson (1990).
[13]O'Brien and Li (2006).
[14]Herbert (1984).
[15]Dan and Alessandro (2016).
[16]Jenkins and Perrow (1977).
[17]Tarrow (1988).
[18]Lipsky (1968).
[19]Fingerhut (2011).
[20]See, for instance, Van Zomeren *et al.* (2012).

relatively underdeveloped both in the realms of comparative politics and international relations (Mcfaul, 2007).[21] The role of international actors was seen as the 'forgotten dimension in the study of democratic transition' (Mcfaul, 2007).[22] Worse still, research on how violence may cost international solidarity towards a democratic movement is even more scarce. On this, Cross and Snow (2012) observed that the radical is the subject of few studies.[23] A few studies have dedicated to such puzzle, yet all point to mixed conclusions. For instance, the study of Kudelia (2018) pointed to the success of protest violence during the Ukrainian Revolution in 2014, as evidenced by the fact that violent tactics employed by the protestors did not lead to the withdrawal of movement support from the international community.[24] For instance, although the USA condemned the 'aggressive actions of members of extreme-right group Pravyi Sektor', it maintained pressure on Yanukovyvh and blamed the Ukrainian government for escalation. On the contrary, another study conducted by Chenoweth and Cunningham (2013) finds that non-violent campaigns are 70% more likely to gain diplomatic backing through sanctions than violent ones.[25]

Theoretically, it would be important to understand what deters international solidarity with a social movement. Prior research suggests that radicalization of protests tend to correlate with a diminished support for their causes. That is, when peaceful sit-ins turn into violent riots, the public may not be as sympathetic with the protestors as it used to be. For instance, surveys conducted by Muñoz *et al.* (2019) find that street violence episode reduced support for the 15-M movement, an anti-austerity movement emerged in Barcelona during the financial crisis, 12 percentage points on average.[26]

Would this observation still hold in the case of support from abroad? On the surface, it is not difficult to imagine how both sides could possibly make a case. On the one hand, when violence erupts within reach, there is a higher chance that people who live nearby become the 'collateral damage', regardless of whether such damage is intentional. These people could be the owners of a vandalized shop, or someone who accidentally got hurt by a fire set by protestors on the street. In such regard, it seems natural for bystanders to prefer a more peaceful means of demonstration. This can hardly be the case, though, if these violent acts arise from afar. In addition, people may have a stronger sense of distaste for violence when they witness it first-hand. Such aversion, however, may dilute if they could only hear recounted stories by journalists on the newspaper or televisions. On the other hand, by the same token, this logic can go both ways: international bystanders may not fully understand the dynamics and logic of violent tactics employed by demonstrators on the ground. This may dissuade them from supporting a movement that is otherwise peaceful, noble and righteous. In the case of Hong Kong, someone who is not from the city might fail to get the point of protestors vandalizing Starbucks, an American multinational chain of coffeehouses.[27] In fact, a fraction of the Hong Kong's anti-government movement was so worried about losing the moral high grounds within the international community insofar that they committed themselves to the principle of 'peace, rationality and non-violence' and urged their peers to follow suit.[28]

Against this backdrop, this research is situated against the extant amount of scholarship which has viewed protest violence as a result of strategic, calculated choice of the protestors. Following this line of logic, protestors would opt for violent tactics if the benefits outweigh the costs. Specifically, this paper builds upon a rationalist approach to protest tactics and examines the actual risk of violent tactics alienating support from overseas and uses Hong Kong's anti-extradition movement in 2019 as a case study for further investigation.

[21] Mcfaul (2007).
[22] *Ibid.*
[23] Cross and Snow (2012).
[24] Kudelia (2018).
[25] Erica (2013).
[26] Muñoz and Anduiza (2019).
[27] Hong Kong Protesters are Targeting Starbucks (2019).
[28] Protesters in need of carrots after sticks (2019).

3. Anti-Extradition Law Amendment Bill (ELAB) movement in Hong Kong

Hong Kong had witnessed itself swept by waves of anti-government protests throughout the latter half of 2019. The movement was first triggered by the Hong Kong government's attempt to launch an unpopular extradition bill, which would have allowed for criminal suspects to be extradited to mainland China. Critics of the planned law had raised concerns over subjecting Hong Kong people to arbitrary detention and unfair trials in China. The bill prompted massive amount of protestors to take to the streets, with a 2 million turn-out (one in four Hong Kong residents) in one of the largest peaceful rallies held in mid-June 2019.[29] Although the bill was officially withdrawn in October 2019, the movement had then turned into a broader call for police accountability and universal suffrage. As the government had yet to respond to the other four demands laid by protestors, which included for the protests not to be characterized as a 'riot', amnesty for arrested protesters, an independent inquiry into alleged police brutality and the implementation of complete universal suffrage,[30] demonstrations continued in Hong Kong with an escalating level of violence from both sides.

Given the city's unique colonial history and the geo-political landscape amid the US–China trade war, protestors in Hong Kong had turned to the world for solidarity and support. Notably, the pro-democracy movement had been marked by its remarkable attempts to appeal to the city's international audience. For instance, when the anti-extradition movement first took off in June 2019 and in the wake of the G-20 meeting, activists in Hong Kong launched a worldwide promotion campaign by printing full-page advertisement on newspapers in countries including the USA, the UK, France, Germany and Japan.[31] Furthermore, in preparation for Washington's debate on the Hong Kong Human Rights and Democracy Act, activists from Hong Kong testified at the USA' Congressional-Executive Commission on China (CECC) in mid-September 2019.[32] The hearing was livestreamed on numerous media outlets in Hong Kong and watched by hundreds of thousands of people.[33] Numerous petitions had been put together to urge the White House and Hong Kong's American allies to back the city's suffragist cause.[34] The chanting of 'fight for freedom, stand with Hong Kong' had sent echoes through the streets in which demonstrations take place.[35]

Much of such effort to seek international solidarity had been invested through digital communication. As a result, social media platforms such as Twitter had become a battlefield for both sides of the fence. On the part of the authorities of both Hong Kong and China, Twitter could serve as a convenient and powerful boon for their propaganda campaigns. On 19 August 2019, Twitter revealed that 936 accounts originating from within China had created content aiming to undermine 'legitimacy and political positions of the protest movement on the ground' in Hong Kong.[36] Having confirmed that it was a coordinated state-backed operation, Twitter subsequently suspended approximately 200,000 accounts for their covert, manipulative behaviours on the platform.[37]

On the other hand, protestors in Hong Kong also utilized Twitter as a platform to coordinate efforts in shaping global discourse and appeal to overseas audience, using the hashtags such as #HongKong, #StandWithHK and #antielab. Activists, most of whom went anonymous online, had created a bot named @TwitterHelpBot as well as a channel (https://t.me/twittermansyunzou; with 35,560 subscribers as of 26 November 2019) on Telegram, a cloud-based instant messaging platform, to gather information and divide labour among activists. Followers of the bot and subscribers of the

[29]Over a million attend Hong Kong demo against controversial extradition law, organisers say (2019).

[30]Hong Kong protests: What are the 'five demands'? What do protesters want? (2019).

[31]'Stand with Hong Kong': G20 appeal over extradition law crisis appears in over 10 int'l newspapers (2019).

[32]Hong Kong activists Denise Ho and Joshua Wong testify at US congressional hearing on protests (2019).

[33]For instance, the livestream video broadcasted on the Facebook page of Apply Daily, one of the biggest media outlets in Hong Kong, had over 896,000 views. For the full video, see https://www.facebook.com/hk.nextmedia/videos/382504319332172?sfns=mo.

[34]See, for instance, 'Extradition Law Amendment in Hong Kong – Threat to Personal Safety and Freedom' (2019).

[35]Hong Kong Protesters Squeeze Access to the Airport (2019).

[36]Information operations directed at Hong Kong (2019).

[37]Information operations directed at Hong Kong (2019).

channels were given various tweet and re-tweet tasks on a daily basis. Usually, these tweets contained latest updates of the on-going protests in Hong Kong, often with infographics and footages with English subtitles. Specific instructions were provided with regards to mannerism and language of tweets as well as whom to engage with on Twitter. For instance, concerning the District Council Election held on 24 November 2019, subscribers of the said channel were advised to mention (a function on Twitter) Marco Rubio, Rick Scott, Marsha Blackburn, Cory Gardner, Michael Waltz and Kevin McCarthy, American politicians who were believed to be pro-Hong Kong, in order to draw their attention.

4. Hypothesis, conceptualization and operationalization

This study is inspired by one general puzzle – will violent tactics drive away international support for a social movement? To address this question, two hypotheses are developed:

H1 Reported violence committed by the protestors led to decreased *support* from observers abroad.

H2 Reported violence committed by the protestors led to decreased *attention* from observers abroad.

Here, it is important to make some conceptual clarifications. By its nature, tactical escalation should involve an increased level of disruptiveness (O'Brien and Li, 2006).[38] Cross and Snow (2012) define a radical as a 'social movement activist who embraces direct action and high-risk options, often including violence against others, to achieve a state goal'.[39] Furthermore, they (Cross and Snow, 2012) note that the level of 'risk' is highly dependent on the contexts, but in general it shall include a certain degree of illegality. Following Tarrow's classification, this study distinguishes between 'contained', 'disruptive' and 'violent' collective action. For the purpose of evaluating the potential harm brought by violent tactics on foreign support for a movement, this paper focuses exclusively on violence in protests. According to Tarrow, violent collective action is distinct from the other categories because violent tactics entail a different set of acts that lead to intentional damage to persons or property, beyond merely interrupting the routine operations of a target or everyday social life. Adopting this approach, violent tactics here refer to the more extreme instances of disruptive tactics, involving physical damage to persons/property. Specifically for this paper, violence is defined as a direct action to injure or destroy a person or a property. As such, in the case of Hong Kong's anti-extradition movement, keywords used to collect relevant tweets and news reports were 'violence, violent, Molotov cocktails, vandalize'.

Note the word 'reported' in H1 and H2. It points to the fact that this research is not primarily concerned with the actual violence committed by the protestors. Rather, it merely refers to violent episodes that were broadcasted. This is because for those who were observing the protests from overseas, they would not have had the first hand information on the ground. It is reasonable to assume that they received information either through social media (with Twitter being the primary channel) or through news channels. In other words, what actually happened in the protest sites might not matter as much as what was being reported. Thus, in this paper, 'reported violence' refers to a tweet or a news report that mentioned the violent tactics employed by protestors in Hong Kong.

Last but not least, 'decreased support' in H1 is measured in two ways – the change of absolute count of negative tweets and the change of absolute count of all tweets (regardless of their sentiment class). The rationale of having the latter measurement is to capture the possibility whereas people simply were turned away by the violent aspects of the protests and chose not to engage in the discussion on Twitter anymore. Thus, while it is important to measure the change in sentiment, it is equally important to consider the change in the volume of attention among foreign observers.

[38] O'Brien and Li (2006).

[39] Cross and Snow (2012).

5. Methodology

5.1. Independent variable – violent tactics employed by protestors

The independent variable in both H1 and H2 is violent tactics imposed upon by protestors during the anti-extradition movement in Hong Kong. Recall that in this study, violence is defined as a direct action to injure or destroy a person or a property. Recall also that in both H1 and H2, it is *reported* violence that matters, not violence *per se*. Against this backdrop, I measured reported violence in two ways – those which were reported in the media and those that were mentioned on Twitter. For the news, I built an automated web crawler to collect news that appeared on Google News with 'Hong Kong' and either the following keywords: vandalize, vandalism, vandalized, vandalised, arrow, petrol bomb, Molotov cocktail or Molotov. These keywords were chosen on the basis that three primary violent tactics were observed to be adopted by protestors in Hong Kong, namely, vandalism, arrows and petrol bombs. All of these news crawled here were published from 1 June 2019 to 31 January 2020.

As for tweets, I collected them through the Twitter Application Programming Interface (API) v2. These tweets contain keywords including Hong Kong, #HongKong,HK or #HK, together with either vandalize, vandalise, vandalized, vandalised, vandalism, arrow, petrol bomb, Molotov cocktail or Molotov. The API returns a JavaScript object notation (JSON) containing all meta-data associated with the tweet, including the post itself, screen name of the user, URL attached to the post (if any), hashtags attached, number of favourites and retweets, among other variables. Twitter is well known among academics, researchers and/programmers for the relatively open access to its data, with its API enabling registered developers to retrieve at most 1% sample of all the data that fits the parameters set by users. These parameters include keywords (words, phrases and hashtags), geographical location and user id (Morstatter *et al.*, 2013).[40]

It is worth noting that given the API is the only sanctioned access point to Twitter data at scale, and that Twitter is a private commercial company which does not offer full access to its data, researchers often have to navigate the 'black box' and have little chance of obtaining a truly representative sample for analysis. This is a fundamental problem of all research drawings on third-party APIs – it is an unavoidable aspect of doing 'big data' research (Bruns and Highfield, 2013).[41] Some of these difficulties can be partially resolved by working around the system. For instance, Morstatter *et al.* (2013) and his collaborators find that streaming API data is often misleading when the amount of data collected is small.[42] It, however, works reasonably well for a larger set of data,[43] which is the case in this project.

The unit of measurement for the independent variable in this research is the number of tweets and news that mentioned the violence exercised by protestors. A total of 161 news and 178,289 tweets were collected.

5.2. Outcome variable 1 – negative sentiment in tweets

This paper uses posts on Twitter as a proxy to examine how overseas audience observed and responded to the anti-extradition protests in Hong Kong. To address H1, it is essential to examine the sentiments displayed in tweets in relation to Hong Kong's anti-extradition movement. To this end, the methodology proceeded in three steps. First, I crawled the posts that were attached with hashtags relating to the protests from publicly available Twitter streams during 1 June 2019–31 January 2020. These hashtags include #antielab, #standwithhongkong, #standwithhk, #hkprotests, #hongkongprotests, #freehongkong, #soshk and #fightforfreedom. To ensure that data extracted in the later stage of the research would not be biased against a particular entity, hashtags with a negative connotation or with an explicit reference to a specific group, such as #policeterrorism and #hongkongpolice, are removed from the list. Hashtags such as #standwithHK and #standwithHongKong were used interchangeably by users in Twitter, but both were kept in order to ensure that the search parameter

[40]Morstatter *et al.* (2013).

[41]Bruns *et al.* (2013).

[42]Morstatter *et al.* (2013).

[43]*Ibid.*

was sufficiently wide to cover relevant discussion with regards to the protests in Hong Kong. A total 9,659,770 tweets were collected.

Second, prior to data analysis, several steps were taken for data cleaning. Using the Natural Language Toolkit package in Python, all stop words including conjunctions, connectives, propositions and pronouns were removed from the original texts. In other words, only terms that are contextually relevant are preserved to be used for data analysis at the later stage. Links attached to the tweets are also removed. To streamline the dataset and to ensure a more accurate result of word frequency, different expressions of the same words are collapsed as one word manually. This is a common data cleaning process in textual analysis called stemming. For instance, the word counts for 'democracy', 'democratic' and 'democracies' were combined as one; so as 'election' and 'elections'. This step prevents double-counting of words that share very similar meaning. In addition, as programming in Python is case-sensitive, all capitals in the dataset are replaced by lower cases. All 'cleaned' texts (all emojis, punctuations and stop-words removed) are first being 'tokenized', meaning that a full sentence is broken down into words that carry substantial meaning. For instance, a tweet like 'Hong Kong is officially a police state' would be converted into 'Hong', 'Kong', 'officially', 'police' and 'state'.

Given that this research is concerned primarily with how foreigners perceived the anti-extradition movement, only tweets posted from outside of Hong Kong were included for analysis. According to the geo-locations tagged in each tweet, the top location of these tweets were sent from the USA, followed by Japan, the UK, Taiwan and Canada. Given that the countries that were most outspoken (both favourably and otherwise) about the protests in Hong Kong had been English-speaking, most notably the Five Eye Alliance (Australia, Canada, New Zealand, the UK and the USA),[44] this paper focuses primarily on tweets that were written in English.

Last but not least, sentiment analysis was performed on the cleaned and filtered tweets. In essence, sentiment analysis is a classification problem by nature, which involves the determination of emotional orientation of a given text. Textual data, in this case tweets, can be classified into positive, neutral or negative through a computed polarity score. Such method has been utilized in a wide array of contexts, such as reviewing hotels, detecting depression symptoms as well as predicting electoral results. Sentimental analysis is usually carried out at either the document-level or the sentence level. In the case of analysing tweets, however, the document in most cases is also the sentence. This is due to the fact that given the 280-character limit on Twitter, posts are usually short and comprised of only one to two sentences. A Python library TextBlob was used to conduct sentiment analysis.[45]

5.3. Outcome variable 2 – total counts of tweets

The total counts of tweets are served here as a proxy to measure the attention generated from the anti-extradition movement on Twitter. This is an important addition to outcome variable 1 (negative sentiment), because it could well be possible that while reported violence might not lead to more negative sentiment towards the protestors, the foreign bystanders simply did not care about the movement as much due to the outbreak of violence. The implicit assumption here is that, while people are more generous in lending their support towards peaceful demonstrations, they would grow more hesitant when presented with news concerning with the more violent aspects of a social movement. In order to capture such nuance, total counts of tweets are taken into consideration when modelling the effects brought by violent tactics adopted by protestors. Its methodology is relatively straightforward – posts that are relevant to the anti-extradition movement were collected using Twitter's API,

[44]Five Eyes Countries Issue Joint Statement on Hong Kong (2019).

[45]TextBlob is an open sourced library built for Natural Language Processing (NLP) and allows researchers to evaluate the sentiment of tweets. Once fed with the input (i.e., cleaned tweets), TextBlob runs its algorithm and computes polarity and subjectivity for each text. Polarity describes how much a text is negative or positive, whereas subjectivity measures how much a text is objective or subjective. This is achieved by using TextBlob's built-in lexicon. Ultimately, TextBlob gives a compound score, ranging from −1 to +1 (−1 being most negative; +1 being most positive) for each text and classifies it to either positive, negative or neutral.

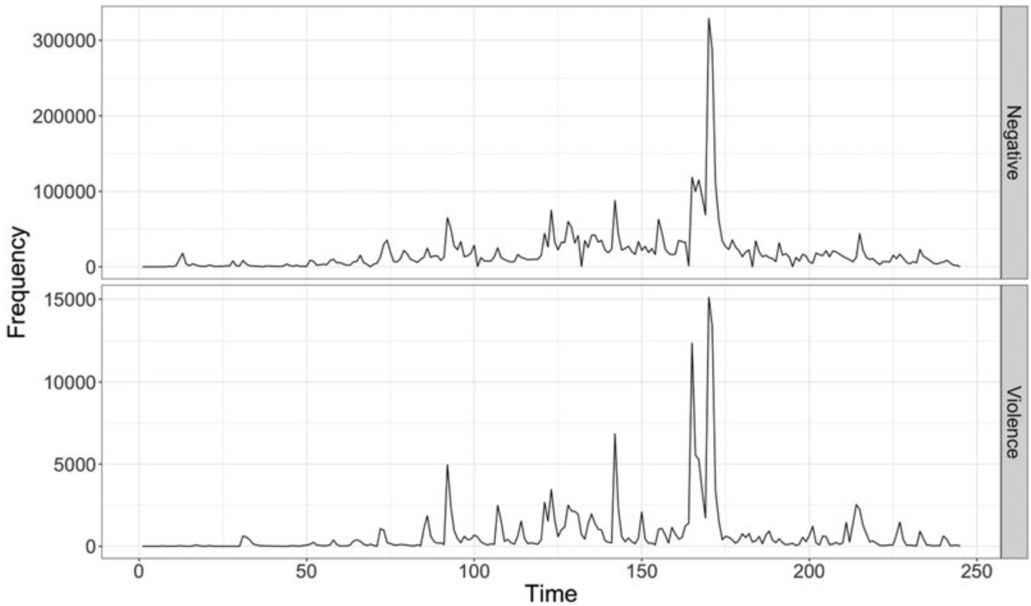

Figure 1. Time series of reported violence and negative sentiment.

as discussed in Section 5.1. These tweets were then counted on a daily basis. H2 holds if reported violence is negatively related to the total counts of tweets.

Given that both independent and dependent variables in this research involve tweets which discussed the anti-extradition movement in Hong Kong, it is likely that there might be duplicates across these two datasets. In order to avoid any confounding effect and double-counting within the models, all duplicated tweets were removed using their unique id assigned by Twitter to each post.

6. Results and discussion

Before delving into results of various models, it is perhaps useful to first look at the descriptive statistics of the variables. Recall that the predictor variable in both H1 and H2 is reported violence from the side of the protestors, which is measured by the tweets and news mentioned various violent tactics employed during the anti-ELAB movement. Using the method explained in Section 5.1, a total of 161 news articles as well as 178,289 tweets were collected. As an exploratory exercise, I carried out sentiment analysis using these tweets, and found that, 67.7% of these tweets are of negative sentiment, while only 9.5% are positive. Its mean compound sentiment score is −0.36, and the median is −0.59. This is unsurprising in the sense that when extreme behaviours of protestors are put under the spotlight, the sentiment score swings to the negative end of the spectrum. This is in contrast to the overall sentiment towards protestors as a whole, which is overwhelmingly positive (mean of compound sentiment score = 0.14; median = 0.18). However, such findings should not be overexaggerated, for the amount of these tweets was barely noticeable compared to the overall size of the entire discussion over the anti-ELAB movement within the Twitterspace.

The dependent variable in H1 is negative sentiment towards the anti-extradition movement. Out of the total 9,659,770 tweets collected, the sentiment classifier identified 5,049,069 of them as positive. Figures 1 and 2 show the numeric count of frequency of these words. In addition, Table 1 presents a sample of tweets being classified as positive, negative and neutral, respectively.

Recall that H1 concerns with the level of support towards Hong Kong's anti-extradition movement while H2 deals with the level of attention. Accordingly, I built two simple regression models to test the

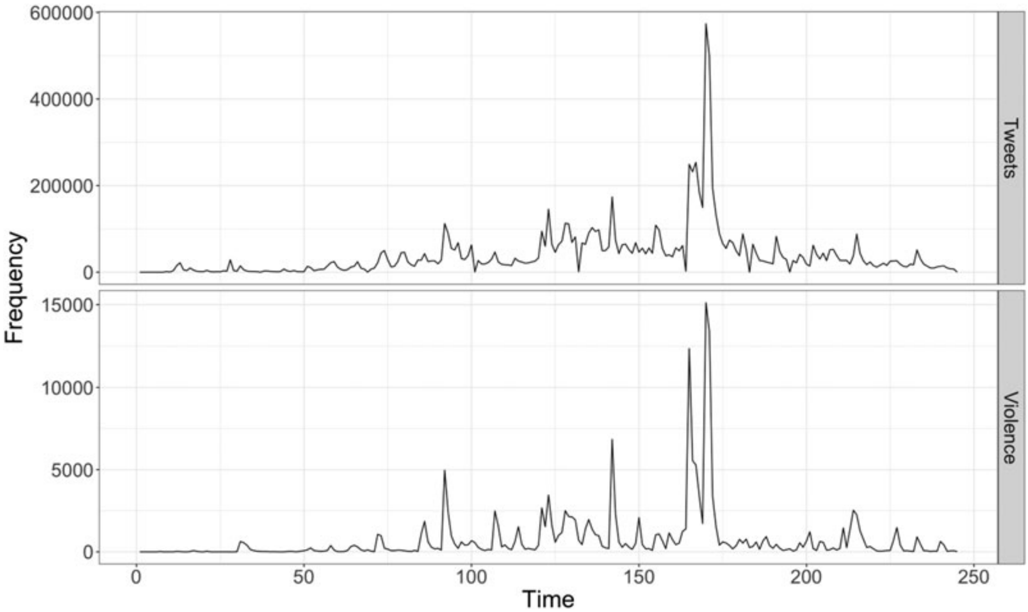

Figure 2. Time series of reported violence and total tweets.

Table 1. Samples of positive, neutral and negative tweets

Positive tweets
A clear pathway remains for passers-by despite growing crowds at the Hong Kong airport
Thank you and please pass the legislation ASAP!
We (Ukraine) must stand with Hongkongers and defend democracy.
It's graduation season in Hong Kong, and students are demonstrating their attitude in their own creative ways.
Just landed in HK airport and ready to meet the #antiELAB protesters at HK airport. Announcement is broadcasted in arrival hall.
Neutral tweets
Two Hongkongers have taken a protest banner to the top of Mount Everest, according to the Democracy for Hong Kong group.
Kwai Fong Lennon Wall
The Beijing-aligned government of Hong Kong has just refused to allow pro-democracy activist Joshua Wong to stand as a candidate.
At the Legislative Council meeting in #HongKong today, pro-democracy councillors stood in silent tribute for 3 minutes to Chow Tsz Lok who died from fall injuries.
From makeshift protective gear to strategizing through encrypted apps, these are the tactics of Hong Kong's anti-government protesters.
Negative Tweets
@hkpoliceforce enters Yat Sang Hs, a subsidized-sale public housing in #HK, to make arrests. Ppl in Tuen Mun come to st tn to complain abt a suspected 'tear gas trial at a nearby military/police base' yst. Residents cursed the force when they retreated.
White House deliberates block on all US investments in China. Not a moment too early.
Today I'm introducing new legislation to impose Global Magnitsky sanctions on Beijing officials & their collaborators who seek to repress Hong Kong. The situation there is urgent. Proud to be joined by @SenRickScott & @JohnCornyn.
Statement: Hong Kong Watch condemns the disqualification of @joshuawongcf from standing for election. A clear example of political screening, and a breach of the right to stand in free and fair elections.
This is disgusting. Where is the accountability?

two hypotheses, respectively. A regression model allows for a linear relationship between the forecast variable y and a single predictor variable x. In this study, a linear regression model is fitted to the time-series data.

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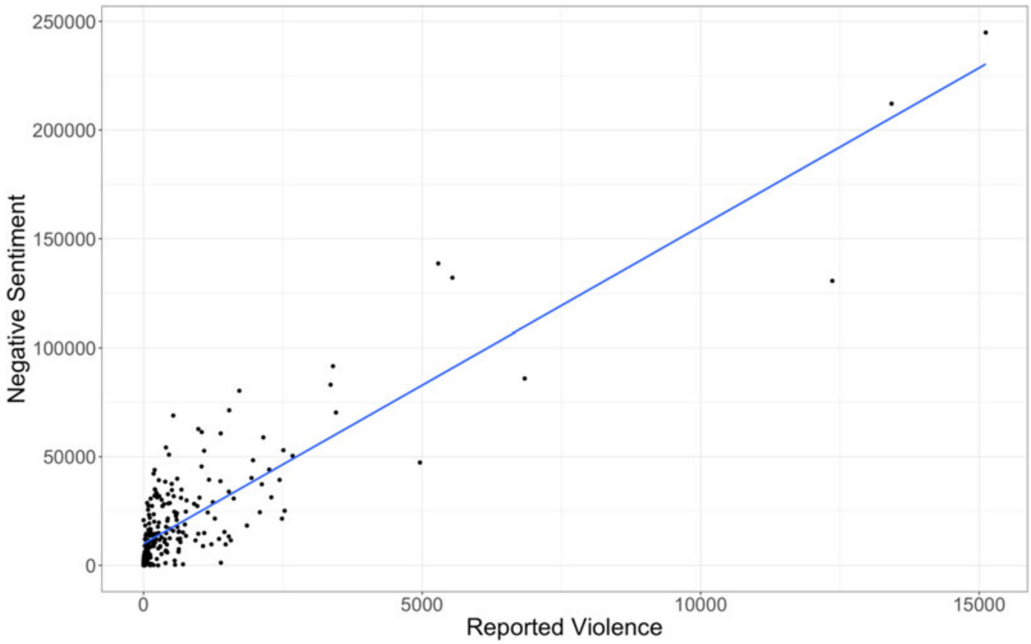

Figure 3. Scatter plot of reported violence and negative sentiment.

Figure 1 shows time series of frequencies of reported violent tactics employed by protestors (x) and negative sentiment shown in tweets in relation to the anti-extradition movement in Hong Kong (y). From there, we can observe that the spikes of the two time series generally follow a similar pattern, with both attaining the highest when the movement entered its 180 days. This would make sense as it was around the same time when the violence from both sides attain its peak – the police sieged several university campuses with tear gas and rubber bullets in November 2019 and in return, protestors made petrol bombs and attacked with arrows. On the other hand, Figure 2 presents the time series of frequencies of reported violent tactics and total tweets, with the latter spiked also around November 2019.

In addition, Figure 3 shows scatter plot of reported violence against negative sentiment along with the estimated regression line. The fitted line has a positive slope, reflecting the positive relationship between reported violence and negative sentiment.

Table 2 provides further information about the fitted model. The first column of coefficients gives an estimate of each β coefficient. The slope coefficient for H1 shows that a 1% point increase in reported violence results on average in 17.4% units increase in negative sentiment. Similar results can be observed for H2, in which 1% point increase in reported violence leads to an average increase of 17.4% percentage points in total tweets about the anti-extradition movement in Hong Kong. The second column gives its standard error. Finally, the last column reports the R^2, which is a way to summarize how well a linear regression model fits the data. From that, we can safely conclude that both models perform reasonably well as they explain more than 80% (~83% for H1 and ~81% for H2) of the variation in the data. In addition, we can observe that estimates for both models have a P-value of <0.05, meaning that they are statistically significant.

From these models, two conclusions can be drawn. First, it appears that H1 holds, meaning that reported violence is correlated with negative sentiments displayed by foreign bystanders during the anti-extradition movement. Second, model 2 suggests that H2 is rejected in the sense that reported violence committed by protestors is, in fact, positively correlated with attention given to the movement (measured in the volume of related tweets). This hints on the possibility that in the event in which

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Table 2. Results from statistical models

Simple regression model			
Model 1: Association between violence and negative sentiments in tweets			
Coefficients			
	Estimate	Std. error	R^2
(Intercept)	6171.6204***	947.0854	0.8301
Violence	17.4252	0.5056	
Model 2: Association between Violence and Total Volume of Tweets.			
(Intercept)	16116.8838	1829.1876	0.8142
Violence	32.0059***	0.9784	
ADL model			
Model 1: Association between violence and negative sentiments in tweets			
Coefficients			
	Estimate	Std. error	*F*-statistics
(Intercept)	14895.10***	2194.61	
Negative sentiment, 5 lags	−0.40***	0.14	
Violence, 5 lags	16.28***	2.60	0.25
Model 2: Association between violence and total volume of tweets			
(Intercept)	30466.00***	4953.51	
Total counts of tweets, 10 lags	0.4562***	0.1480	
Violence, 10 lags	−10.53***	5.23	0.04
Granger causality tests			
Model 1: Association between violence and negative sentiments in tweets			
	Lags chosen	*F*-test	
	5	15.40***	
Model 2: Association between violence and total volume of tweets			
	10	6.7273***	

people aboard observe the violent tactics employed by pro-democracy protestors, they may have a negative sentiment towards the movement as a whole. However, this does not hinder them from continuing to give their attention at all. Quite the contrary, results from this research seem to imply that the more violence is observed, the more attention a social movement will receive, at least within a digital space.

However, it is important to note that, due to the serial nature of time-series data, it is possible to have autocorrelations in the model, that is, the outcome variable is explained by the past values of itself. In a simple regression model, it is difficult to isolate this factor and examine to what extent it affects the estimates. In addition, with the presence of autocorrelations, the R^2 tends to be overestimated. To resolve this, I also built an autoregressive distributed lag (ADL) model which allows for us to take into consideration the past values of the outcome variables and their effects in relation to the predictors.[46]

Table 2 reports the results from the ADL model with the appropriate number of lags chosen by the four aforementioned criteria. It shows that for H1, even accounting for the past values of the outcome variable, reported violence on the side of the protestors is still positively correlated with negative sentiment from foreign observers. Interestingly, for H2, the results seem to have reversed from what is observed in a simple regression model. From Table 2, we can still observe that in the presence of the past values of the outcome variable, reported violence is actually negatively correlated with the volume of the relevant tweets. In other words, results of the ADL model suggest that the more violence that is reported in the newspaper or on Twitter, the more likely that the total counts of tweets in relation to the anti-extradition movement will drop. Note that the ADL models for both hypotheses are statistically significant.

To further make sure that these conclusions are robust, Granger causality tests were carried out for both models. Granger causality test is useful to test whether one variable is useful in forecasting

[46]Before an ADL model is to be constructed, an important first step is to select the number of lags to be included in the system. Recall that the unit of measure throughout this study is day, meaning that all variables are measured on a daily basis. In such case, one lag in the ADL model refers to 1 day, two lags refers to 2 days, etc. To find the optimal number of lags, upon which a model would be built with the least noise and most accuracy, I employed four information criteria, namely, Akaike information criterion (AIC), Bayesian information criterion (BIC), Schwarz criterion (SC) and final prediction error (FPE).

another. The null hypothesis is that time series x does not Granger-cause time series y. The term 'Granger-causes' means that knowing the value of time series x at a certain lag is useful for predicting the value of time series y at a later time period. This test produces an F-test statistics with a corresponding P-value. If the P-value is less than a certain significance level (i.e., $\alpha = 0.05$), then we can reject the null hypothesis and conclude that we have sufficient evidence to say that time series × Granger-causes time series y.

From Table 2, we can observe that both models have a P-value below 0.05, which gives us sufficient ground to reject the null hypothesis. In other words, in both cases, the predictor (reported violence) is helpful in predicting the outcome variables (negative sentiments and total volume of related tweets).

It is important to note, however, that while supervised machine learning (technique adopted thus far in this paper) has generally performed well on datasets such as movie or product reviews, issues may arise in a more complicated setting. For instance, for a comment 'this movie is good', it is almost certain that it is directed towards the movie itself. However, it is not as straightforward to interpret results of a sentiment classifier for a social movement which involves a variety of stakeholders. In the anti-ELAB movement, for example, a tweet stating 'it is appalling for the police to arrest peaceful protestors' may confuse the classifier – it may have correctly identified 'appalling' as a signal for a negative sentiment, but such sentiment is, in fact, directed against the police, instead of the anti-ELAB movement itself. Considering such caveat, several steps had been taken to ensure the robustness of the models presented above.

First, it is important to identify the primary parties involved in the anti-ELAB movement. To do so, the topic modelling technique was employed. Put simply, topic modelling is a type of unsupervised machine learning, meaning that it can be carried out without the active input of predefined labels or categories (the so-called training set). Its goal is to represent each document as a mixture of topics. For this study, the topic modelling technique was employed to identify topic domains which would be useful for further investigation. Considering the anti-extradition movement had lasted for more than 6 months, with numerous petitions, rallies and sit-ins taking place, often at the same time, involving a wide range of stakeholders, it is expected that tweets pertaining to the movement would be sparse and messy. In such cases, topic modelling is particularly useful when we want to explore the texts with no clear preconceptions of topics that are discussed in a certain communication environment (Petchler and González-Bailón, 2015).[47]

Drawing upon these results, it could be deduced that English tweets posted from abroad revolved primarily around three topics, namely, police brutality, China's influence as well as various protest events initiated by the protestors. I then used several corresponding keywords to extract these subsets of tweets from the entire dataset (see Table 3). These subsets of tweets then served as the input for simple regression, auto-regression and Granger causality tests as explained above.

Tweets that pertained to China were largely negative. Out of the total 838,210 tweets that mentioned the Beijing authority, 35.3% ($n = 295{,}852$) were classified as positive and 43.4% ($n = 363{,}461$) as negative. A similar observation could be made to the police – more than 51% of the tweets were negative, while only 26.4% were positive. In contrast, sentiment towards protestors were generally positive, with more than 47% of the tweets being identified as positive and only 20.7% of them being negative. On a scale from −1 to 1 (negative score means negative sentiment and vice versa), protestors are also the only group that received a positive compound sentiment score (mean = 0.14; median = 0.18). Also, the compound sentiment score for police (mean = −0.23; median = −0.34) is far lower than that for China (mean = −0.05; median = 0). This is surprising given that in a broader sense the anti-extradition movement was ultimately a democratic movement, with one of the five core demands being universal suffrage in Hong Kong. The focus, however, had seemed to shift away from fighting against the Chinese Communist Party (CCP) and the Hong Kong government as the movement started to revolve around issues such as police brutality, assuming posts on Twitter are good proxies to measure the pulse of the protest.

[47] Petchler and González-Bailón (2015).

Table 3. Compound score for sentiments towards different stakeholders

	Police	China	Protestors
Keywords	Police, HKPF	China, Beijing, CCP	Protestor, demonstrator
Mean	−0.23	−0.05	0.14
Median	−0.34	0.00	0.18
Positive	134,418 (26.4%)	295,852 (35.3%)	120,118 (47.6%)
Negative	261,894 (51.5%)	363,461 (43.4%)	80,092 (31.7%)
Neutral	112,249 (22.1%)	178,897 (21.3%)	52,265 (20.7%)

Table 4. Results from statistical models for different stakeholders

Simple regression model			
Model 1a: Association between violence and negative sentiments in tweets (towards China)			
Coefficients	Estimate	Std. error	R^2
(Intercept)	573.4***	97.7	0.7
Violence	1.2***	0.1	
Model 1b: Association between violence and negative sentiments in tweets (towards police)			
Coefficients			
(Intercept)	−7.3	124.1	0.7
Violence	1.5***	0.01	
Model 1c: Association between violence and negative sentiments in tweets (towards protestors)			
Coefficients			
(Intercept)	−24.1	111.3	0.4
Violence	0.70***	0.01	
ADL Model			
Model 2a: Association between violence and negative sentiments in tweets (towards China)			
Coefficients	Estimate	Std. error	*F*-statistics
(Intercept)	968.5***	199.5	19.5
Negative sentiment, 6 lags	0.3***	0.1	
Violence, 6 lags	0.1	0.3	
Model 2b: Association between violence and negative sentiments in tweets (towards police)			
Coefficients			
(Intercept)	484.4***	143.6	70.9
Negative sentiment, 5 lags	−0.7***	0.2	
Violence, 5 lags	1.9***	0.4	
Model 2c: Association between violence and negative sentiments in tweets (towards protestors)			
Coefficients			
(Intercept)	385.2***	119.4	
Negative sentiment, 7 lags	−0.1	0.1	
Violence, 7 lags	0.2	0.1	3.1
Granger causality tests			
	Lags chosen	*F*-test	
Model 2a	6	3.8***	
Model 2b	5	31.9***	
Model 2c	7	50.5***	

****P*-value <0.001; ***P*-value <0.01; **P*-value <0.05.

Table 4 presents the results of the simple regression model. Interestingly, violence reported on the side of protestors is positively correlated with all of the three variables, namely, negative sentiment towards China, the police as well as protestors. Note that the coefficient for negative sentiment towards protestors is slightly lower than the other two, hinting on the possibility that while violent tactics on the side protestors might bring a detrimental image to all relevant parties, it would hurt the protestors the least when compared to the authorities. This observation holds true also in the auto-regression models. It can be observed from Table 4 that only models with negative sentiment towards China and the police produce statistically significant results, despite the fact that their coefficients are quite small – 0.1 and 1.9 for China and government, respectively. The model with negative sentiment towards protestors, on the other hand, is not statistically significant.

7. Limitations

One of the primary limitations of this study lies in the presence of bots and trolls on Twitter. In fact, this holds true to every study that utilizes data extracted from social media platforms, as effective strategies for bot detection are yet to be readily available. However, while it is impossible to be completely immune to this problem, I am not convinced that the data quality in this paper is severely compromised by bots and trolling activities. This is primarily due to the fact that during the anti-extradition movement, Twitter had actively identified state-sponsored bots and subsequently suspended these accounts.[48] Content published through these automated accounts were also removed from the platform. In other words, when the data were collected retrospectively through the Twitter API, these bots-generated tweets had already been filtered out.[49] While this approach essentially relies on Twitter's algorithms and may be still far from ideal, the fact that a majority of bot-like behaviours were excluded from the data set ensures the rigour of this study.

In addition, the way how sentiments of the tweets were classified into different classes is not without its flaws. In particular, this study filtered only a fraction of what was collected for the sentiment analysis by selecting a couple of key stakeholders to identify tweets which were targeted at either side of the protests. The rationale behind this approach is that the anti-extradition movement took place for more than half a year, with numerous events and developments taking place almost on a daily basis. Due to the extremely complex nature of the movement, it is difficult if not impossible to carry out sentiment analysis when the primary subject is not clear – some tweets discussed extensively on the US sanctions against the Chinese and Hong Kong governments, others were about police brutality against protestors. Against this backdrop, the best possible way to work around this is to first pinpoint key players during the protests and used them as proxies to measure sentiments towards the movement in general, although it would also mean discarding many tweets which were relevant to the protests but did not specifically address a particular player. The decision was made here to forego the breadth of the dataset for the sake of the rigour of the sentiment analysis. Prior study has also followed a similar approach (Bakliwal *et al*., 2013).[50]

8. Conclusion

First and foremost, given that the anti-extradition movement in Hong Kong, at least on paper, had largely embraced the so-called universal values such as freedom, human rights, democracy, the rule of law and so forth, and given that most users who discussed the protests on Twitter were tweeting from democracies, one's first intuition would be that people within the Twitterspace generally lent their support to the pro-democracy protestors. Empirically, findings from this paper confirm such impression. In general, the sentiments towards both the police and the Chinese government leaned mostly negative, while that towards the protestors were largely positive.

Perhaps more surprising is that the sentiment score is lower for the police than that for China. This result can safely be interpreted that tweets were more lenient towards Beijing than the police force in Hong Kong. In a way, this observation, although came somewhat as a surprise, is not completely out of place. As known to many, the anti-extradition protests had in many instances turned from peaceful demonstrations to violent clashes between the police and protestors. More often than not, graphics of these vicious confrontations were shared widely and virally on social media, which of course included Twitter. This may be a reason why the police could easily appear to be the villain, while CCP members remained 'behind the scene'. The exact reason behind such a puzzle is beyond the scope of this paper, but it definitely leaves an eminent room for future research to examine how these political actors, even from the same camp, may be portrayed differently under different political circumstances.

[48]Information operations directed at Hong Kong (2019).

[49]Twitter has instead published them in a separate domain. See Disclosing networks of state-linked information operations we've removed (2020).

[50]See, for instance, Bakliwal *et al.* (2013). Sentiment Analysis of Political Tweets: Towards an Accurate Classifier.

This paper introduces a dynamic approach to examine international support for a democratic movement that takes place from afar. In particular, this research is deeply interested in how violence on the side of the protestors may/may not cost a movement's foreign support. Situated at prior scholarships in contentious politics, this paper hypothesizes that H1: reported violence committed by the protestors led to decreased *support* from observers abroad; H2: reported violence committed by the protestors led to decreased *attention* from observers abroad.

The results from this study, in general, support H1, meaning that violence reported on the side of the protestors was positively correlated with negative sentiment towards the anti-ELAB movement. On the other hand, H2 is largely rejected, with violent tactics being positively correlated with the total amount of tweets mentioning the movement. Evidence in this paper demonstrates that when the more violent and radical tactics were employed by protestors, public opinion from abroad could turn sour. However, such negative sentiment towards the police or the Chinese government was not negligible either.

As a whole, the model proposed in this paper hopefully will help advance our understanding of social movements with more attention paid to support lent by external parties. In particular, I hope this paper serves as a stepping stone for future research that aims to conceptualize and quantitatively measure external support for contentious movement. This is exceptionally important in places where democratic movements could hardly succeed without considerable attention or even concrete action (such as sanctions in the case of Hong Kong) from the international solidarity.

Methodologically, computational methods such as natural language processing and topic modelling, open many new opportunities for political scientists interested to explore the complex dynamics of social and political movements. On the whole, this paper is an attempt to contribute to the growing body of scholarship in the field of computational social sciences, with a special focus on applying various textual analysis techniques to understanding the motivations behind solidarity (or lack of) with popular protests sprung abroad.

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References

Bakliwal A, Foster J, van der Puil J, OBrien RD, Tounsi L and Hughes M (2013) Sentiment Analysis of Political Tweets: Towards an Accurate Classifier.

Bruns A and Highfield T (2013) Political networks on Twitter. *Information, Communication & Society* **16**(5), 667–691. doi: 10.1080/1369118X.2013.782328.

Bruns A, Highfield T and Burgess J (2013) The Arab spring and social Media audiences: English and Arabic Twitter users and their networks. *American Behavioral Scientist* **57**, 871–898.

Cai Y (2019) 8. Protesters and tactical escalation. In Ngok M and Edmund WC (eds), *The Umbrella Movement*. Amsterdam: Amsterdam University Press, pp. 209–232.

Chenoweth E and Cunningham KG (2013) Understanding nonviolent resistance: an introduction. *Journal of Peace Research* **50**(3), 271–276. doi: https://doi.org/10.1177/0022343313480381.

Cross R and Snow DA (2012) Radicalism within the context of social movements: processes and types. *Journal of Strategic Security* **4**(4), 115–130.

Disclosing networks of state-linked information operations we've removed (2020) 12 June 2020, Available at https://blog.twitter.com/en_us/topics/company/2020/information-operations-june-2020.

Elsbach K and Sutton R (1992) Acquiring organizational legitimacy through illegitimate actions: a marriage of institutional and impression management theories. *Academy of Management Journal* **35**, 699–738.

Erica C (2013) Terrorism and democracy. *Annual Review of Political Science* **16**, 355–378.

Extradition Law Amendment in Hong Kong – Threat to Personal Safety and Freedom (2019) 15 May 2019, Available at https://petitions.whitehouse.gov/petition/extradition-law-amendment-hong-kong-threat-personal-safety-and-freedom.

Fingerhut D (2011) Straight allies: what predicts heterosexuals' alliance with the LGBT community?. *Journal of Applied Social Psychology* **41**, 2230–2248.

Five Eyes Countries Issue Joint Statement on Hong Kong (2019) The Diplomat, 19 November 2019, Available at https://thediplomat.com/2020/11/five-eyes-countries-issue-joint-statement-on-hong-kong/.

Gamson WA (1990) *The Strategy of Social Protest*. Belmont, CA: Wadsworth Pub.

Giugni M (1998) Was it worth the effort? The outcomes and consequences of social movements. *Annual Review of Sociology* **24**, 371–393.

Herbert HH (1984) Black radicalization and the funding of civil rights: 1957–1970. *Social Problems* **32**, 31–43.

Hong Kong activists Denise Ho and Joshua Wong testify at US congressional hearing on protests (2019) Hong Kong Free Press, 17 September 2019, Available at https://www.hongkongfp.com/2019/09/17/live-hong-kong-activists-denise-ho-joshua-wong-testify-us-congressional-hearing-protests/.

Hong Kong Protesters Are Targeting Starbucks (2019) Apple Could Be Next, New York Times, 15 October 2019, Available at https://www.nytimes.com/2019/10/15/business/hong-kong-starbucks-vandalism.html.

Hong Kong Protesters Squeeze Access to the Airport (2019) New York Times, 1 September 2019, Available at https://www.nytimes.com/2019/09/01/world/asia/hong-kong-protests-arrests-airport.html.

Hong Kong protests: What are the 'five demands'? What do protesters want? (2019) South China Morning Post, 20 August 2019, Available at https://www.scmp.com/yp/discover/news/hong-kong/article/3065950/hong-kong-protests-what-are-five-demands-what-do.

Information operations directed at Hong Kong (2019) Twitter Safety, 19 August 2019, Available at https://blog.twitter.com/en_us/topics/company/2019/information_operations_directed_at_Hong_Kong.html.

Jenkins J and Perrow C (1977) Insurgency of the powerless: farm worker movements (1946–1972). *American Sociological Review* **42**, 249.

Kudelia S (2018) When numbers are not enough: the strategic use of violence in Ukraine's 2014 revolution. *Comparative Politics* **50**, 501–521.

Lipsky M (1968) Protest as a political resource. *American Political Science Review* **62**, 1144–1158.

Mcfaul M (2007) Ukraine imports democracy: external influences on the orange revolution. *International Security* **32**, 45–83.

Morstatter F, Pfeffer J, Liu H and Carley KM (2013) Is the sample good enough? Comparing data from twitter's streaming API with Twitter's firehose. In Proceedings of the 7th International Conference on Weblogs and Social Media, ICWSM 2013 (pp. 400–408). AAAI press.

Muñoz J and Anduiza E (2019) 'If a fight starts, watch the crowd': the effect of violence on popular support for social movements. *Journal of Peace Research* **56**, 485–498.

Muñoz P, Kimmitt J, Kibler E and Farny S (2019) Living on the slopes: entrepreneurial preparedness in a context under continuous threat. *Entrepreneurship & Regional Development* **31**(5–6), 413–434. doi: 10.1080/08985626.2018.1541591.

Nieburg HL (1962) The threat of violence and social change. *American Political Science Review* **56**, 865–873.

O'Brien K and Li L (2006) *Rightful Resistance in Rural China (Cambridge Studies in Contentious Politics)*. Cambridge: Cambridge University Press.

Over a million attend Hong Kong demo against controversial extradition law, organisers say (2019) Hong Kong Free Press, 9 June 2019, Available at https://hongkongfp.com/2019/06/09/just-no-china-extradition-tens-thousands-hong-kong-protest-controversial-new-law/.

Petchler R and González-Bailón S (2015) 24. Automated content analysis of online political communication. In Coleman S and Freelon D (eds), *Handbook of Digital Politics*. London: Edward Elgar, pp. 433–450.

Protesters in need of carrots after sticks (2019) South China Morning Post, 19 August 2019, Available at https://www.scmp.com/comment/opinion/article/3023417/protesters-need-carrots-after-sticks.

Snyder D (1978) Collective violence: a research agenda and some strategic considerations. *Journal of Conflict Resolution* **22**, 499–534. doi: https://doi.org/10.1177/002200277802200309.

'Stand with Hong Kong': G20 appeal over extradition law crisis appears in over 10 int'l newspapers (2019) South China Morning Post, 28 June 2019, Available at https://hongkongfp.com/2019/06/28/stand-hong-kong-g20-appeal-extradition-law-crisis-appears-10-intl-newspapers/.

Tarrow S (1988) National politics and collective action: recent theory and research in Western Europe and the United States. *Annual Review of Sociology* **14**, 421–440.

Tarrow S (1998). *Power in Movement: Social Movements and Contentious Politics (2nd ed., Cambridge Studies in Comparative Politics)*. Cambridge: Cambridge University Press.

Van Zomeren M, Leach CW and Spears R (2012) Protestors as 'passionate economists': a dynamic dual pathway model of approach coping with collective disadvantage. *Personality and Social Psychology Review* **16**, 180–199.

Wang D and Piazza A (2016) The use of disruptive tactics in protest as a trade-off: the role of social movement claims. *Social Forces* **94**, 1675–1710. doi: https://doi.org/10.1093/sf/sov124.

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