# #WashTheHate: Understanding the Prevalence of Anti-Asian Prejudice on Twitter During the COVID-19 Pandemic


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***Abstract*—Prejudice and hate directed toward Asian individuals has increased in prevalence and salience during the COVID-19 pandemic, with notable rises in physical violence. Concurrently, as many governments enacted stay-at-home mandates, the spread of anti-Asian content increased in online spaces, including social media. In the present study, we investigated temporal and geographical patterns in social media content relevant to anti-Asian prejudice during the COVID-19 pandemic. Using the Twitter Data Collection API, we queried over 13 million tweets posted between January 30, 2020, and April 30, 2021, for both negative (e.g., #kungflu) and positive (e.g., #stopAAPIhate) hashtags and keywords related to anti-Asian prejudice. In a series of descriptive analyses, we found differences in the frequency of negative and positive keywords based on geographic location. Using burst detection, we also identified distinct increases in negative and positive content in relation to key political tweets and events. These largely exploratory analyses shed light on the role of social media in the expression and proliferation of prejudice as well as positive responses online.**



***Index Terms*—COVID-19, racism, social media, AAPI, Twitter**


## I. Introduction

On January 4, 2020, the World Health Organization (WHO) reported that it was monitoring an outbreak of a new virus in the Wuhan, Hubei Province of China [1]. At this time, knowledge of and concern about the virus from the public was limited. Less than one month later, however, on January 30, the WHO declared the spread of the virus, termed COVID-19, a public health emergency, bringing global attention to this widespread health concern [1], [2]. The name 'coronavirus' was developed according to WHO's "Best Practices for the Naming of New Human Infectious Diseases," which recommends avoiding any cultural, social, regional, or ethnic associations when naming a disease [3]. Despite these recommendations, given the origins of the virus, COVID-19 was frequently referred to in the media as the "Chinese virus," the "Wuhan virus," and the "Asian virus" [4]–[7]. While some have argued that this terminology is not inherently racist given the virus' origin, anti-Asian prejudice did notably increase in prevalence and salience during this time [8], [9]. For example, police reports in the U.S. involving anti-Asian hate and physical violence against Asian Americans and Pacific Islanders (AAPI) increased 145% in 2020 compared to previous years [10] and Stop AAPI Hate–a non-profit organization dedicated to reducing anti-Asian prejudice–reported 2,583 incidents of anti-Asian prejudice between March 18, 2020 and August 5, 2020 [11].

Increases in anti-Asian prejudice have also been observed in online spaces, including social media. The Anti-Defamation League, for instance, reported an 85% increase in anti-Asian discrimination online [12]. To illustrate, during the first months of the pandemic, 72,000 posts on Instagram contained the hashtag #WuhanVirus, while another 10,000 contained the hashtag #KungFlu [13]. Notably, social media posts (i.e., tweets) generated by President Trump and other political leaders used the phrase "Chinese Virus" [8]. The role of these tweets in promoting the continued use of the term is perhaps reflected by the finding that 18% of tweets using anti-Asian hashtags referred to Trump in some capacity [8], [14]. In fact, recent research by Kim and Kesari [15] identified marked increases in anti-Asian terminology after President Trump first started using similar language. Interestingly, counter-hate (i.e., positive language intended to combat hateful messages) that drew connections between anti-Asian terminology and xenophobia and prejudice also increased during this time [15].

The goal of the present study was to investigate temporal and geographical patterns in social media content relevant to anti-Asian prejudice and positive (i.e., counter-hate) messages

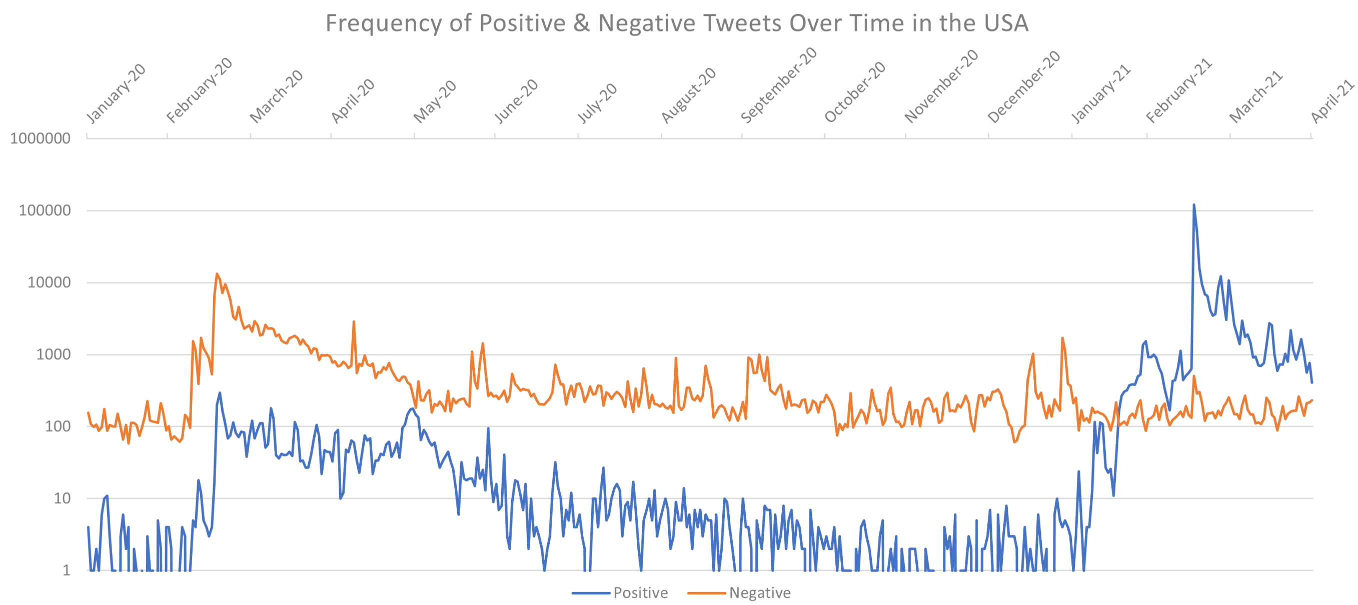



Fig. 1. Logarithmic scale of the number of negative and positive tweets between January 2020 and April 2021.

during the COVID-19 pandemic. Crucially, whereas other research has explored anti-Asian prejudice in online spaces during COVID-19 [8], [14]–[20], the present study makes a vital contribution by (1) covering a significantly longer time frame than those previously studied (i.e., 15 months); (2) considering both negative (i.e., anti-Asian) and positive hashtags during this period; (3) employing temporal analyses involving burst detection; and (4) integrating findings from data obtained using keyword searches as well as the 1% general sample stream on Twitter.

## II. Data

All data were collected according to Twitter data collection guidelines and using the proper API access provided to researchers [21], [22]. In the following sections, we refer to anti-Asian content as ”negative” and counter-hate content as ”positive.”

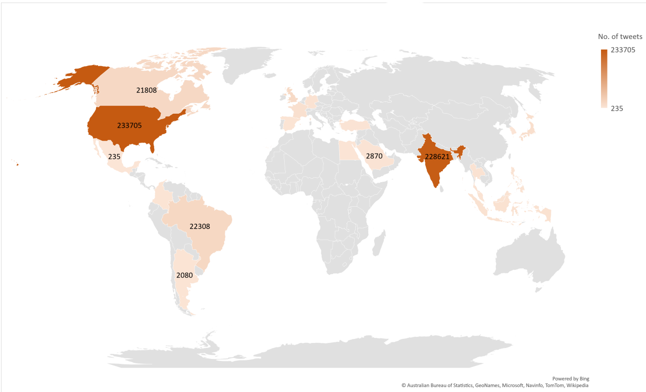
**Archive Dataset.** Using the Twitter Data Collection API[1], we queried tweets containing negative and positive hashtags and keywords related to anti-Asian prejudice from January 30, 2020 to April 30, 2021. This time frame was selected to correspond with the date on which the World Health Organization indicated the spread of COVID-19 was a global health issue and the start of AAPI Heritage Month the following year (when positive AAPI messages might increase independent of COVID-19). We used 12 specific negative hashtags/keywords as indicators of anti-Asian prejudice (#batsoup, #chinavirus, #gobacktochina, #chinesevirus, #chineseplague, #gook, #chinaliedpeopledied, #kungflu, #wuflu, #chingchong, #makechinapay, #ccpvirus) and 5 specific positive hashtags/keywords (#hateisavirus, #Iamnotavirus, #racismisavirus, #washthehate, #stopasianhate), which were chosen based on the relevant literature [19], news publications [23]–[25], and social media posts discussing anti-Asian attitudes during the beginning of the pandemic. The total sample consisted of 13,008,053 tweets from 3,298,940 distinct users.

**1% Dataset.** The 1% sample stream dataset was generated from Twitter's sample stream endpoint[2], which provides access to a roughly 1% random sample of publicly available tweets in real-time. This dataset was compiled from the tweets gathered over the course of 24 hours (August 1-2, 2021) to estimate the amount of activity that 1% of the Twitter platform could generate in one day. 4,093,933 tweets were collected in this sample from 2,956,806 distinct users.

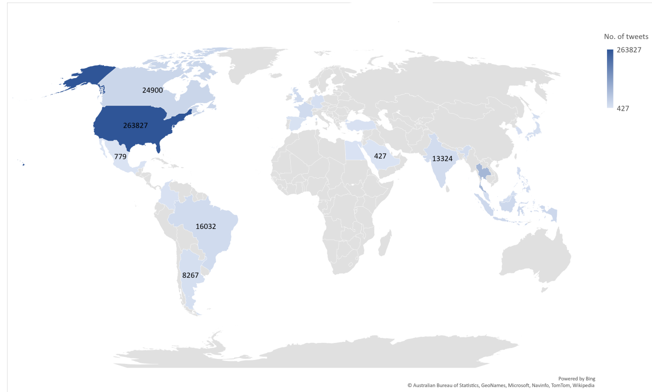
**Geographic Location Labeling.** During the collection of both datasets, a filter was applied to collect a list of users that had publicly available geolocation data through their location setting. To perform descriptive analyses based on geographic location, we devised a geolocation labeling strategy similar to Jiang and colleagues [26]. This strategy was necessary because less than 0.5% of the tweets in our dataset had available geo_place information. For our analysis, we considered the state granularity for the tweets originating in the U.S. and the country granularity for the tweets originating in other countries, based on self-reported user profile locations. Using a fuzzy text matching algorithm [27], pre-processed user-reported locations were matched against a set of predetermined locations inside and outside of the U.S. The similarity between

[1]https://developer.twitter.com/en/docs/twitter-api

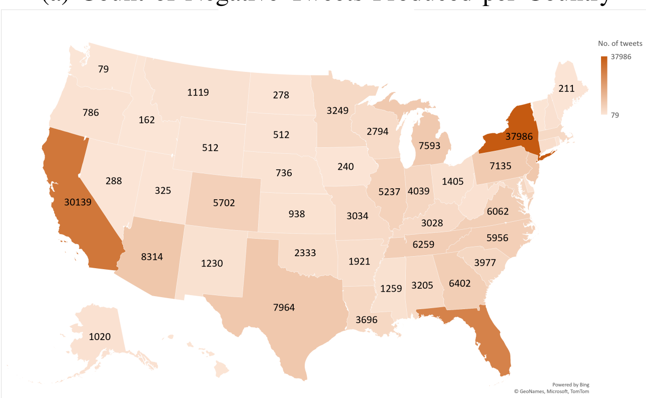
[2]https://developer.twitter.com/en/docs/twitter-api/tweets/volume-streams



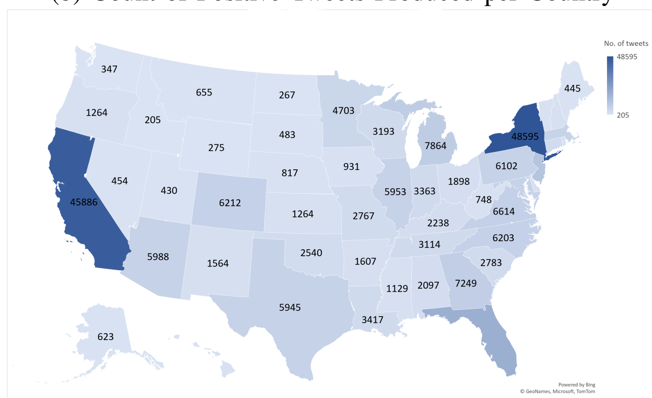

(a) Count of Negative Tweets Produced per Country




(b) Count of Positive Tweets Produced per Country




(c) Count of Negative Tweets Produced in the U.S.




(d) Count of Positive Tweets Produced in the U.S.

Fig. 2. Cumulative frequency of negative and positive tweets by geographic location.

user-reported locations and predetermined locations was computed using the edit distance metric. The score threshold to consider a matching pair of locations, which was set to 80%, was defined based on a validation analysis conducted by an external human annotator who manually verified a random sample of labeled locations considering country names and U.S. state names. Considering the precision validation measure (TP/(TP + FP)), the geolocation labeling strategy achieved a predictive positive value of 99.8% for the U.S. locations and varied from 89.8% to 100% for the other countries that, together with the U.S., account for 90% of the collected data. The set of predetermined locations inside the U.S. consisted of state names and state abbreviations. The set of predetermined locations outside the U.S. was built using the top 20 countries with the most Twitter users as of July 2020[3] and their five most populous cities[4]. To avoid ambiguity, only the country abbreviations that didn't overlap with a U.S. state abbreviation were included. Additionally, we used an ambiguous locations list–built throughout the testing process–to adjust the geolocation labeling by removing ambiguous matches. (An example of an ambiguous match is the token 'valencia,' which can refer to a city in Spain and a town in California.)

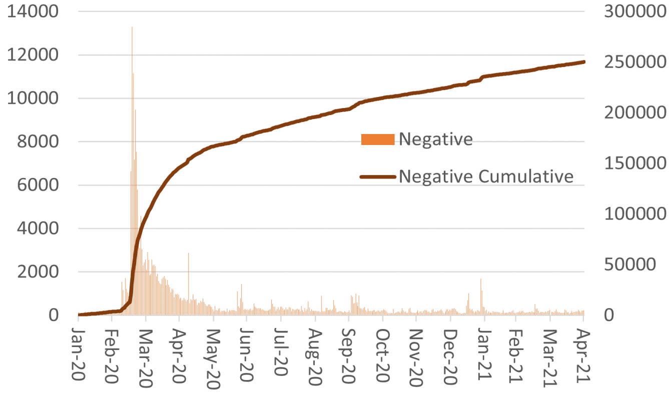
[3]https://www.statista.com/statistics/242606/number-of-active-twitter-users-in-selected-countries/

[4]https://worldpopulationreview.com/world-cities

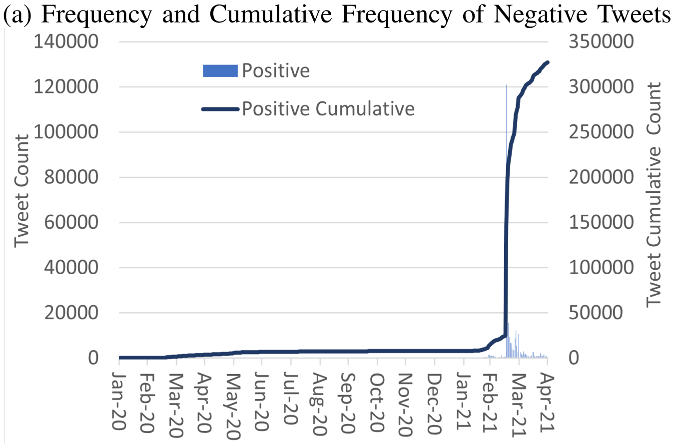
## III. Results

A series of exploratory descriptive analyses were performed to shed light on the frequency of negative (anti-Asian) and positive (counter-hate) hashtag and keyword use throughout the pandemic and how their use might vary over time and by geographic location.

**Descriptive Analyses.** As shown in Fig. 1, the use of negative hashtags and keywords to reference the COVID-19 pandemic before March 2020 was low. However, within that month, there was a marked increase in the use of negative keywords, with the frequency of negative keywords reaching its peak. Although considerably less frequent throughout most portions of the timeline, the use of positive keywords, in contrast, culminated in major spikes in late February 2021. As shown in Fig. 2, globally, 4,521,457 distinct tweets contained at least one of the 12 negative keywords, with most of this content generated in the U.S. and India (USA = 233,705 tweets; IND = 228,621 tweets). 6,660,469 distinct tweets contained at least one of the 5 positive keywords, with most of the positive content also generated in the U.S., followed by Thailand (USA = 263,827 tweets; TH = 82,696 tweets). In the U.S., New York, California, and Florida were the largest producers of negative content (NY = 37,986 tweets; CA = 30,139 tweets; FL = 27,076). Notably,

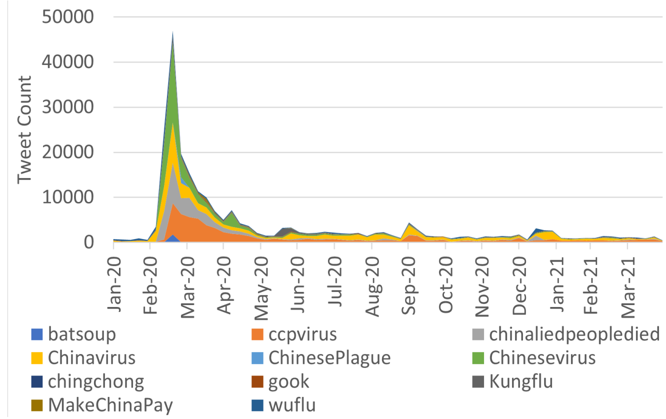



(a) Frequency and Cumulative Frequency of Negative Tweets

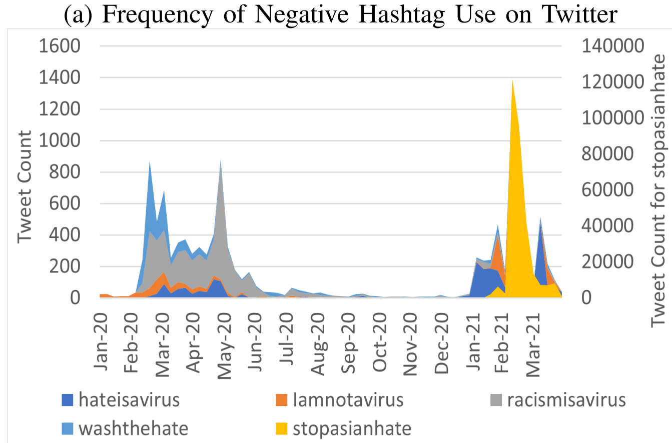



(b) Frequency and Cumulative Frequency of Positive Tweets

Fig. 3. Frequency and cumulative frequency of negative and positive tweets over time in the U.S.




(a) Frequency of Negative Hashtag Use on Twitter



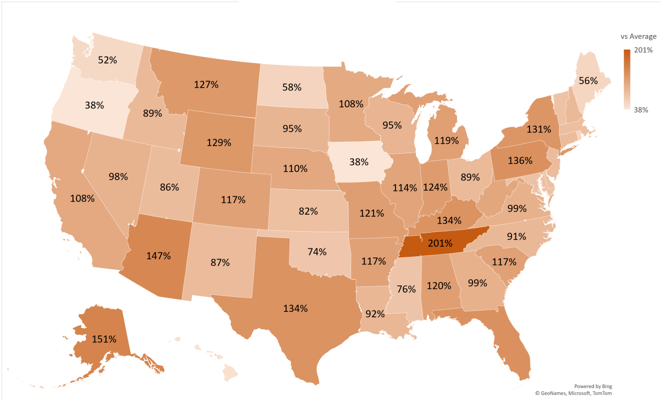

(b) Frequency of Positive Hashtag Use on Twitter

Fig. 4. Frequency of negative and positive hashtags used in the U.S.

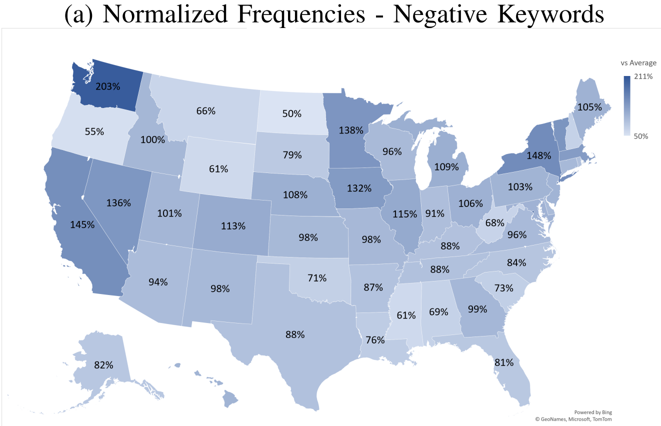
however, California and New York also produced the most content containing positive keywords (CA = 45,886; NY = 48,595). Fig. 3 depicts usage trends of negative and positive keywords specifically in the U.S over time. These trends are similar to those found globally, with sharp spikes of negative activity following President Trump's first use of the term "Chinese Virus" in March 2020. Additionally, this figure also illustrates that although there were more tweets containing positive keywords utilized in the U.S., these tweets were mainly generated between February 2021 and April 2021. That is, they coincided with a prominent event that occurred in the U.S.–the Atlanta-area spa shootings that resulted in the deaths of multiple individuals of Asian descent [28]. There was minimal use of these keywords during the early months of the pandemic. Out of the negative tweets produced in the U.S., the most frequently used negative hashtag was "ccpvirus," followed by "chinavirus" and "chinesevirus" (see Fig. 4). The most frequently used positive hashtags in the U.S. were "stopasianhate" and "hateisavirus."

**Analysis Using the 1% Dataset.** The goal of this task was to normalize the frequencies of tweets based on the amount of overall Twitter activity in each state of the U.S. To this end, an initial ratio was computed by dividing the counts of positive and negative tweets with valid geolocation in the archive dataset by the count of tweets in the 1% dataset for each state. Then, the average initial ratio was computed across all states (i.e., 4.277 for positive keywords and 3.786 for negative keywords). A new ratio was calculated for each state dividing the initial ratio by the average ratio. The final ratios for negative and positive keywords are reported in Fig. 5. As depicted, Tennessee had the highest ratio of negative keywords (i.e., 201% higher than the average), followed by Alaska, which was 151% higher than the average. Washington DC, on the other hand, had the highest ratio of positive keywords (i.e., 211% higher than the average), followed by Washington state (i.e., 203% higher than the average) and New York (i.e., 148% higher than the average).

**Burst Analysis.** We used Kleinberg's burst analysis algorithm [29] to identify bursts of heightened negative and positive keyword use across time. This approach identifies bursts of activity in a series of events by modeling the transitions between two states–baseline and bursty. Bursty states are associated with periods of time when an event (e.g., negative or positive tweets) is unusually frequent. The approach uses two main parameters, *s* and *gamma*, which affect different




(a) Normalized Frequencies - Negative Keywords




(b) Normalized Frequencies - Positive Keywords

Fig. 5. Normalized comparison of the frequencies of negative and positive keywords. The raw frequencies of the sample stream were first divided by the total number of tweets in the archive search produced in each state. Then, these ratios were averaged across all states.

aspects of the way the algorithm detects bursts.

- *s*: This parameter controls the threshold of event frequencies, or intensiveness, for each state. Higher values of this parameter will require stronger increases of activity to detect a burst.
- *gamma*: Gamma controls the difficulty of changing states. Higher values of this parameter will require more effort to switch states.

Multiple *s* and *gamma* parameters for determining the sensitivity of the bursts were assessed in an iterative fashion. For example, as the *s* parameter cannot be less than or equal to 1, steadily decreasing values of *gamma* were tested ranging from the default of 1 to 0. During many of these combinations of *s* and *gamma* values, either the analysis resulted in a binary burst (i.e., all of the data represents a burst of activity or none of the activity is considered a burst) or the bursts were inconsequential. From this testing, values of 1.1 for the *s* parameter and 0.0 for *gamma* were selected, as these values provided optimal visual output.

We performed separate burst analyses (with the same parameters) for the datasets with negative and positive keywords. Specifically, we used the burst detection algorithm to identify bursts in discrete bundles of events, where each bundle was defined as the set of negative or positive tweets received in a single day. For this analysis, we considered the tweets in the U.S. based on the geolocation labeling strategy previously described. To facilitate the processing of large frequency values using the Python Burst Detection library[5], we applied a logarithmic transformation before feeding the data to the algorithm. The output of this burst analysis step was a set of date ranges for the identified bursts.

**Negative Keyword Use.** The dates identified in the burst analysis were labeled with events on a timeline corresponding to the use of anti-Asian terminology (e.g., "Chinese virus," "China virus") on President Trump's Twitter account, key political events, and COVID-19 milestones. In total, 8 bursts of activity were identified (labeled A through H in Fig. 6). Events were taken from dates up to 2 days before and after the beginning and end of the date ranges identified by the burst analysis. Events for Bursts A through F correspond primarily with tweets posted by (and originating from) Trump's Twitter account [30]. Events for Bursts G and H were taken from news media coverage of significant events [31], [32] that occurred at the time, as well as from the CDC's COVID-19 pandemic timeline [33].

**Positive Keyword Use.** Evaluating the positive keyword use, 3 bursts of activity were identified, ranging from March 17, 2020 to June 16, 2020; June 19, 2020 to June 30, 2020; and February 2, 2021 to April 4, 2021 (Fig. 7). These bursts in positive keyword use immediately followed increases in physical violence and hate in-person toward Asian Americans. For example, from March to June 2020, the Federal Bureau of Investigation reported increases in crimes directed toward Asian Americans (https://crime-data-explorer.fr.cloud.gov/pages/explorer/crime/hate-crime). Further, the burst of positive activity following February 2, 2021 culminates in a marked increase in physical violence against Asian individuals. For example, within this time frame, the highly-publicized Atlanta-area spa shootings occurred, in which Asian women were targeted, leading to the deaths of 8 individuals [28]. There were also several reports of individuals of Asian descent being verbally and physically assaulted in public, resulting in serious injury or death [34], [35]. The burst in positive keyword use, in the form of prosocial, counter-hate messages, could be interpreted as a protective response to raise awareness as protests, rallies, and non-profit organizations were developed to fight this hostility [36]–[38].

## IV. Discussion and Concluding Remarks

The present study investigated temporal and geographic trends in anti-Asian prejudice and counter-hate messages on Twitter in the 15 months after the World Health Organization declared COVID-19 a public health emergency. Consistent with other recent research, our findings indicate that the

[5] https://pypi.org/project/burst_detection

## Timeline of Negative Hashtags and Phrases Used on Twitter

**March 16th, 2020** The United States will be powerfully supporting those industries, like Airlines and others, that are particularly affected by the Chinese Virus. We will be stronger than ever before! *-Trump Twitter Quote*
**March 18th, 2020** For the people that are now out of work because of the important and necessary containment policies, for instance the shutting down of hotels, bars and restaurants, money will soon be coming to you. The onslaught of the Chinese Virus is not your fault! Will be stronger than ever! *-Trump Twitter Quote*
I always treated the Chinese Virus very seriously, and have done a very good job from the beginning, including my very early decision to close the "borders" from China - against the wishes of almost all. [….]*-Trump Twitter Quote*

**March 22nd, 2020** My friend (always there when I've needed him!), Senator @RandPaul, was just tested "positive" from the Chinese Virus. That is not good! He is strong and will get better. Just spoke to him and he was in good spirits. *-Trump Twitter Quote*

**May 25th, 2020** Great reviews on our handling of Covid 19, sometimes referred to as the China Virus. Ventilators, Testing, Medical Supply Distribution, we made a lot of Governors look very good - And got no credit for so doing. Most importantly, we helped a lot of great people! *-Trump Twitter Quote*

**June 25th, 2020** The number of China Virus cases goes up, because of GREAT TESTING, while the number of deaths (mortality rate), goes way down. The Fake News doesn't like telling you that! *-Trump Twitter Quote*

**July 7th, 2020** "COVID-19 (China Virus) Death Rate PLUNGES From Peak In U.S." A Tenfold Decrease In Mortality. [….]*-Trump Twitter Quote*
**July 8th, 2020** Economy and Jobs are growing MUCH faster than anyone (except me!) expected. Job growth is biggest in history. China Virus Mortality Rate is among the LOWEST of any country. [….]*-Trump Twitter Quote*

**July 20th, 2020** We are United in our effort to defeat the Invisible China Virus, and many people say that it is Patriotic to wear a face mask [….]*-Trump Twitter Quote*
**July 21st, 2020** You will never hear this on the Fake News concerning the China Virus, but by comparison to most other countries, [….]*-Trump Twitter Quote*

**July 26th, 2020** Because of my strong focus on the China Virus, including scheduled meetings on Vaccines, our economy and much else, I won't be able to be in New York to throw out the opening pitch for the @Yankees on August 15th. We will make it later in the season! *-Trump Twitter Quote*

**September 18th, 2020** Biden FAILED BADLY with the Swine Flu. It was the Gang That Couldn't Shoot Straight". He didn't have a clue. We have done an incredible job with the much tougher China Virus! *-Trump Twitter Quote*

**October 5th, 2020** ....invincible hero, who not only survived every dirty trick the Democrats threw at him, but the Chinese virus as well. He will show America we no longer have to be afraid." @MirandaDevine @NYPost Thank you Miranda. Was over until the Plague came in from China. Will win anyway! *-Trump Twitter Quote*
**October 7th, 2020** My highly regarded Executive Order protected 525,000 American jobs during the height of the Chinese Plague. Democrats want to have Open Borders! RT @stclairashley: The only thing Trump has called a lid on is China virus *-Trump Twitter Quote*
Just spoke with Prime Minister @BorisJohnson of the United Kingdom. Very thankful for his friendship and support as I recovered from the China Virus. [….]*-Trump Twitter Quote*

**October 11th, 2020** […] during the Obama/Sleepy Joe Biden Administration, even as we round the turn on the China Plague. Thank you. Next year will be the BEST EVER!!! *-Trump Twitter Quote*
**October 12th, 2020** Big spike in the China Plague in Europe and other places that the Fake News used to hold up as examples of places [….]*-Trump Twitter Quote*
**October 13th, 2020** Totally Negative China Virus Reports. Hit it early and hard. Fake News is devastated. They are very bad (and sick!) people! *-Trump Twitter Quote*

**January 16th, 2021** "Officials warned that the UK variant of coronavirus could become the main strain in the US come March. The CDC worries the variant will have rapid growth, causing President-elect Joe Biden to ramp up vaccine distribution." *-BBC News Article*

**January 18th, 2021** "U.S COVID-19 death toll surpasses 400,000." *-CDC Timeline*
**January 20th, 2021** "President Joe Biden was officially inaugurated." *-CBS News Article*

**January 26th, 2021** "Worldwide COVID-19 cases surpass 100 million." *-CDC Timeline*

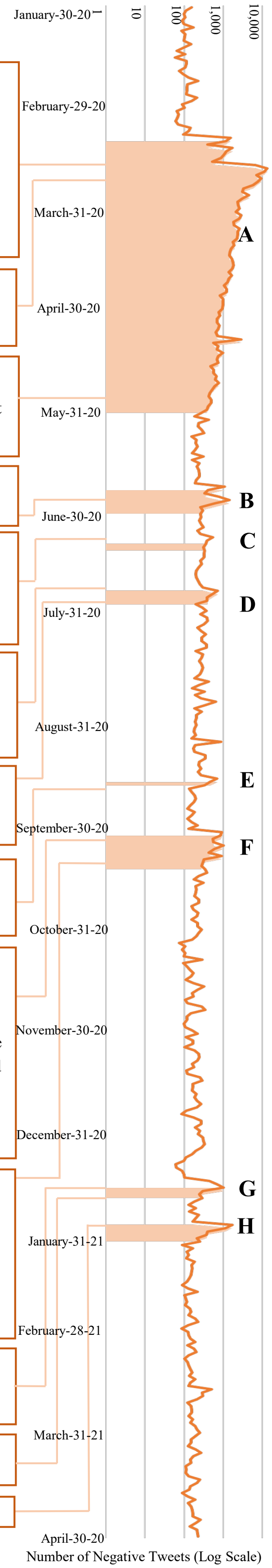



Fig. 6. Timeline of negative hashtags and phrases with a subset of representative tweets occurring within bursts of heightened anti-Asian activity.

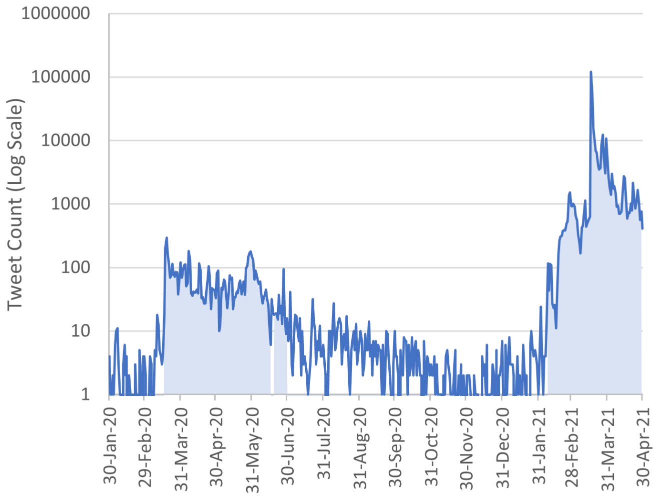



Fig. 7. Bursts of heightened positive activity.

increased prevalence of anti-Asian prejudice during early stages of the pandemic was a global phenomenon [39]. Our findings also, however, revealed geographic differences in the frequency of negative (anti-Asian) and positive (counter-hate) content generated by Twitter users within the U.S. For instance, New York, California, and Florida were the largest producers of negative keywords, overall, in our archived dataset (based on our query of over 13 million tweets). However, a complementary analysis performed on a random sample of approximately 1% of publicly available tweets from a single date yielded additional insights. When considering the 1% of tweets on a given day, the states with the highest ratio of negative keywords to all Twitter content generated by users in the state were Tennessee and Alaska. In contrast, whereas California and New York were the largest producers of positive keywords in our archived dataset, Washington DC had the highest ratio of positive keywords in the 1% dataset, followed by Washington state and New York. The greater positive Twitter content generated by users in New York, in particular, is interesting in light of the relatively higher rate of crime targeting AAPI individuals in this state. That is, data from Stop AAPI Hate [40] indicates that out of 9,081 reported incidents of anti-Asian hate (i.e., physical violence, online harassment, civil rights violations) in the U.S. from March 2020 to June 2021, roughly 15% occurred in New York. The dynamic ways in which prejudice manifests itself in face-to-face interactions and online spaces–and the role of social media in conveying messages of support and solidarity in response to acts of racial animosity–warrant further empirical attention.

Using burst analysis, we identified several significant surges (i.e., bursts) in the frequency of both anti-Asian and counter-hate keywords on Twitter. Examination of these bursts in relation to relevant content generated by President Trump on Twitter, political events, and key milestones in the COVID-19 timeline helps contextualize these temporal findings and underscores the extent to which social media can both reflect and influence anti-Asian sentiment. Crucially, our results are largely consistent with previous research indicating that President Trump's use of politically incorrect terminology when discussing political events has led to increases in White nationalist ideals and racism [41], broadly, and the finding that bursts of negative activity occurred after President Trump started using anti-Asian rhetoric in his tweets, speeches, and interviews during the pandemic [8]. Furthermore, the complexity of the prejudice fueled by and evident throughout the pandemic is perhaps illustrated by the political connotation of some of the anti-Asian keywords. For example, "ccpvirus"–in reference to the Chinese Communist Party–likely stemmed from news reports that this political party withheld information about COVID-19 during the early months of the pandemic [42].

Finally, our findings also suggest that positive online activity may act as a protective response, bringing heightened awareness to anti-Asian prejudice through "hashtag activism." It remains unclear, however, whether surges in the use of positive keywords (e.g., #hateisavirus, #stopasianhate) led to a measurable reduction in verbal and physical attacks against AAPI individuals; notably, similar campaigns aimed at reducing violence have lost momentum over time [43]. Nonetheless, our hope is that our efforts to expand on recent research in this area will contribute to a deeper understanding of how prejudice and hatred, as well as empathy and counter-hate, proliferates online during global crises.

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