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Reviving the "Yellow Peril" Digitally: Anti-Asian Hate on Twitter During the COVID-19 Pandemic

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Racist sentiments against Asian, specifically Chinese, communities have risen alongside the COVID-19 pandemic. Combining Twitter data, employment data, and COVID-19 case data, this study uses interrupted time series analysis and traditional time series analysis to investigate how the revival of anti-Asian sentiments on Twitter has been facilitated by the combination of elite discourse on social media, economic slowdown, and public health crises. Results suggest that tweets about the "Chinese virus" from former president Trump serve as elite cues that positively and significantly impact the spread of anti-Asian hate on Twitter. This correlation is unidirectional. In addition, newly confirmed COVID-19 cases and unemployment rates are also positively correlated with the increase in anti-Asian hate tweets. The results draw attention to how the historical racialization of Asian populations has been extended to the social media arena during the public health crisis.

Keywords: anti-Asian racism, social media, public opinion, COVID-19, elite cues, unemployment

In December 2019, a new coronavirus, COVID-19, was first reported in Wuhan, China (Johns Hopkins Coronavirus Resource Center, 2020). As the virus spread at an exponential rate, the World Health Organization (WHO) declared a global emergency in January 2020. Shortly, anti-Asian racism surged internationally (Gover, Harper, & Langton, 2020). Chinese and other Asian populations have been increasingly harassed, blamed, and stigmatized (Gover et al., 2020). In the United Kingdom, police forces

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have shown at least 267 anti-Asian hate crimes in the first three months of the pandemic, the number of which was higher than the total in 2018 and 2019 (Mercer, 2020). In Australia, racist graffiti, such as "death to dog eaters," and vandalism against people of Asian descent have been reported across the country (Human Rights Watch, 2020, para. 34). In the United States, within the first week of March 2020, the Center for Asian Americans and Pacific Islanders (AAPI) received 673 reports of COVID-19–related anti-Asian discrimination (Jeung, 2020). By the end of March 2022, the volume of reports rose to 11,467 (Stop AAPI Hate, 2022).

In addition to the rising anti-Asian attacks in physical spaces, social media have introduced new ways of spreading anti-Asian hate through racialized languages, hashtags, and slurs (Tahmasbi et al., 2021). Currently, nearly half of U.S. adults get news from social media sites. In particular, Twitter, widely used in the United States for political expression, is a primary news source for nearly 60% of its users (Walker & Matsa, 2021). Social media have been considered a vital component of the public sphere—a social and communicative space where different opinions are formed and expressed (Chambers, 2021; Habermas, 1989). It expands opinions that were previously restricted to private social spaces (McKinney, Houston, & Hawthorne, 2014) and allows citizens to participate directly in political discussions. During COVID-19, Twitter became a major channel to diffuse anti-Asian sentiments. Because traditional gatekeeping is lacking in social media, corporate logics often decide what content is allowed to spread, which also means that removing harmful content is often rare and not transparent. In addition, the technological affordances of social media—such as anonymity, algorithms that favor viral content, and features that encourage sharing, liking, commenting, and using hashtags—could contribute to the dissemination of hate messages (Ben-David & Fernández, 2016). Between November 2019 and March 2020, anti-Asian hate tweets increased by 68.4% on Twitter (Nguyen et al., 2020). Therefore, it is important to look into the rise of anti-Asian hate on Twitter during the pandemic.

Scholars have argued that the factors leading to anti-Asian hate are multifaceted. Frequent social media use and greater concerns about COVID-19 have been found to be associated with stronger anti-Asian attitudes (Croucher, Nguyen, & Rahmani, 2020; Reny & Barreto, 2020). Partisanship and ideological differences also play a role: Compared with the U.S. liberal media, conservative media adopted controversy and conspiracy frames more often in their coverage of China during COVID-19 (Zhang & Trifiro, 2022). Moreover, compared with Republicans and White legislators, Democrats and legislators of color are more likely to express counter-hate speech (Arora & Kim, 2020). While these studies remain highly illuminating, little quantitative research has been done to present a more holistic picture of how socioeconomic and discursive factors correlate with the rising anti-Asian sentiments on social media.

To fill this gap, this article centers on the following question: How did the pandemic status, economic slowdown, and racist discourses from political elites contribute to the anti-Asian rhetoric on social media platforms like Twitter? Specifically, the article uses interrupted time series and traditional time series to understand the effects of coronavirus cases, the national emergency order, economic slowdown, and political leaders, such as Donald Trump, on facilitating this revival of anti-Asian racism. It aims to show that anti-Asian racism on social media is not merely an individual behavior; it is largely shaped by socioeconomic and discursive forces.

Racialization of Asians and the Pandemic

The racialization of non-White immigrants as carriers of disease has deep roots in U.S. immigration history. Early immigrants have been strictly inspected for syphilis, polio, and other infectious diseases on arrival in the United States. In particular, Asian immigrants, mostly poor, have been stigmatized as "dirty" and "sick" (Markel & Stern, 2002). They were often called the "yellow peril": Unhealthy, diseased, and unworthy of American citizenship (Takaki, 1998).

Public health crises often exacerbate preexisting racial orders and generate new forms of hatred toward racial and ethnic minorities (McCoy, 2020). During the bubonic plague in San Francisco in the early 20th century, the then U.S. surgeon general labeled the plague as an "Oriental disease" (Elias, Ben, Mansouri, & Paradies, 2021, p. 784). As a result, Chinatown was the first to be quarantined, with a house-to-house inspection. This fueled the passage of the infamous Chinese Exclusion Act, the first law in the United States that barred immigration solely based on ethnicity. During the severe acute respiratory syndrome (SARS) breakout in the early 2000s, anti-Asian racism increased significantly in North America as the mainstream narratives repeatedly associated the disease with Asia and visual references, such as masked Asian faces (Leung, 2008). In 2009, the spread of H1N1 swine flu also saw many Mexicans and other Latino populations stigmatized as the carriers of the virus (McCauley, Minsky, & Viswanath, 2013). A few years later, the Ebola virus was perceived as the Black disease, and racial profiling against African immigrants significantly increased in countries such as the United States (Zurcher, 2014).

Naming the disease with geographic locations or ethnic groups is one reason that public health crises stir the stigmatization of ethnic communities. During the COVID-19 pandemic, calling the coronavirus "Chinese virus" or "Kung Flu" reinforced the historical trope of the "yellow peril." In addition, othering and scapegoating of Asian communities functioned as an additional mechanism that gave rise to racist sentiments since the dominant ideology of Whiteness projects non-White populations as the "Others."

The literature above implies that a pandemic like COVID-19 may revive the historical racialization of Asian populations. However, past research mainly used qualitative data, particularly historical documentation, to show that connection. There is little quantitative research on this relationship. To complement this gap, we used time series analysis to explore how the pandemic status affected anti-Asian discourse on social media. We selected two measures as proxies for the severity of the pandemic: The declaration of a national emergency and the newly confirmed COVID-19 daily cases. The declaration of national emergency was an indicator that the United States as a nation recognized the severity of the pandemic. It implied that the U.S. government was starting to give a coordinated response to the coronavirus. It can be used as a policy intervention that validated the threat of this virus to the health of the public. In addition, the daily new COVID-19 cases measured the magnitude and severity of the pandemic over time.

This revival of "yellow peril" during the COVID-19 pandemic happened with the support of social media—a crucial platform where public opinion is formed. Therefore, we put forth the following hypotheses:

H1a: *The rise of COVID-19 cases is related to the increased anti-Asian hate on social media.*

H1b: The declaration of COVID-19 as a national emergency is associated with an increase in anti-Asian hate on social media.

Economic Downturn and Anti-Asian Sentiments

The literature on ethnic violence suggests that racial experiences are always classed. Even when the economy is going well, minorities could face discrimination in the labor market, education, and access to health care (International Labor Organization, 2011). In worsened socioeconomic conditions, such as financial crises, scapegoating and other forms of exclusionary behaviors are often heightened (e.g., Bieber, 2020; Krell, Nicklas, & Ostermann, 1996; McLaren, 1999). Past research has shown that persecution of the Jews in medieval and early-modern Europe was most severe during negative economic shocks (Anderson, Johnson, & Koyama, 2017). Hindu-Muslim riots in India grew and declined with the economic bust and boom, respectively (Bohlken & Sergenti, 2010).

In the context of the United States, early Asian immigrants experienced racial animosity from White employers and fellow laborers in California between the 1840s and 1880s, especially during the recession in gold prices (Boswell, 1986). Asian immigrants, particularly Chinese immigrants or "coolies," were blamed for putting downward pressure on wages in manufacturing and menial service industries. During 1853–1854, when a recession in gold prices hit, competition for profitable mining claims intensified, and consequently, Chinese miners' mining claims were confiscated. Rather than forming a working-class coalition, White laborers aligned with White employers to ostracize Chinese laborers, which ultimately led to the passage of the Chinese Exclusion Act (Boswell, 1986). From "The Chinese Must Go!" in the 19th century to "Chinese virus" on today's social media, anti-Asian hate is not merely episodic but is sustained by racial capitalism that entrenches U.S. society (Man, 2020, para. 25). Asian Americans' "outsider" status makes anti-Asian sentiments remain "close to the surface" and "ready to be reinvigorated and acted upon with a contemporary twist" (Elias et al., 2021, p. 789).

In the first three months of the COVID-19 pandemic, the number of unemployed Americans increased by 14 million, exceeding the number during the Great Recession (Kochhar, 2020). The stock market crashed, and economic hardship threatened millions of families. The threat of the unknown virus and the economic downturn stirred up social groups to "other" this threat by blaming and scapegoating "out-groups" (Reny & Barreto, 2020). In our article, we use employment rates as an indicator of the economy, given their strong reflection of the economy's current state. Household spending primarily derives from job-related incomes, and the employment rate usually coincides closely with the ups and downs of the business cycle (Baum, 2019). Therefore, we hypothesize that

H2: The decrease in the employment rate is correlated with an increase in anti-Asian hate on social media.

Elite Cues and Anti-Asian Hate

An extensive body of literature has shown that elite cues shape citizens' attitudes (Broockman & Butler, 2017; Gabel & Scheve, 2007; Lenz, 2013; Zaller, 1992). Following elite cues theories, we define political elites as the group of actors whose occupations (e.g., presidents, policy experts, and journalists) afford them higher levels of influence over the public (Lasswell, 1952; Zaller, 1992). Elite cues then refer to the discourse, rhetoric, messages, and opinions of political elites.

Citizens are likely to rely on cues from experts and political elites to form their opinions on political issues (Downs, 1957). But what criteria do they rely on when choosing to take cues from elites? Opinion leadership literature suggests three criteria: The overall approval of the actor, the domain-specific knowledge that the actor possesses, and persuasive messages (Broockman & Bulter, 2017; Downs, 1957).

In the context of anti-Asian hate during the pandemic, Trump was one of the most influential elite figures who may have provoked anti-Asian hate on Twitter. First, from January to May 2020, when the pandemic started to unfold, Trump's approval rating reached a peak of 49% (Gallup, n.d.). Second, citizens may follow elected officials' opinions when they recognize legislators' possession of superior information, expertise, and judgment (Bianco, 1994). People may infer that their elected president is more familiar with the details of the pandemic status and trust his judgment. Therefore, Trump's voice carried great weight in shaping people's anti-Asian attitudes.

Finally, even if people did not approve of Trump and did not believe that Trump possessed enough pandemic-related expertise, they may still have been affected by Trump's discourse due to the message effect. When it comes to racism, studies have also shown that even implicit racist cues from political elites can prime racial attitudes (Valentino, Hutchings, & White, 2002), evoke anxiety (Brader, Valentino, & Suhay, 2008) and anger (Banks & Valentino, 2012), and steer voters to prioritize race-adjacent issues (Mendelberg, 2001). Based on a survey experiment, Anspach (2021) found that Trump's explicit racist messages heightened anti-Black attitudes, especially among those already harboring racial resentment. In another study, Newman et al. (2021) found evidence for the "Trump effect," in which exposure to racialized rhetoric could lead to potential racial prejudice. This effect was evident in Trump's speeches about Latino immigrants during the 2016 election, which influenced participants to express prejudice and accept prejudiced behaviors against Latinos. When it comes to Trump's anti-Asian discourse, since the outbreak of the COVID-19 pandemic, Trump repeatedly used racist terms such as "Chinese virus" to label this public health crisis despite WHO forbidding the association of diseases with specific places or ethnic groups. These discriminatory terms provided legitimacy for anti-Asian racism. The message effect is particularly strong considering Trump's use of Twitter. Trump held a central position in his extensive online network and possessed a highly unequal influence on others' attitudes and behaviors (Müller & Schwarz, 2023). His use of terms like "Chinese virus" was echoed by numerous political figures. For example, Senator Tom Cotton claimed, "Anyone who complains that it's racist or xenophobic to call this virus the Chinese coronavirus or the Wuhan virus is a politically correct fool" (Forgey, 2020, para. 20). Other Republican politicians like Senator Charles E. Grassley, Senator Bill Hagerty, and Senator Marshal Blackburn also posted similar anti-Asian tweets. These tweets had unique effects in an environment where false information was spread easily and when there was high tension in U.S.-China relations.

In addition to the unidirectional effect of elite cues on public opinion, past studies have also pointed out the endogeneity problem of elite communication on public opinion. In other words, the relationship between elite discourses and mass opinions may be reciprocal (Gabel & Scheve, 2007). Therefore, our study also examines temporal dynamics between Trump's discourse and the public's anti-Asian sentiments. Our third hypothesis is that when Trump tweeted on "Chinese virus," the mass public expressed more negative attitudes toward the Asian community. In other words,

H3: Trump's tweets on "Chinese virus" increased anti-Asian hate posts on Twitter.

Methods

Data and Sample[2]

Our investigation capitalizes on four data sources:

1. Daily reported new COVID-19 cases data set from the Centers for Disease Control and Prevention (CDC). According to the COVID Data Tracker (Centers for Disease Control and Prevention, n.d.), total national cases are based on aggregate counts of new COVID-19 cases reported by state and territorial jurisdictions to the CDC since January 23, 2020, with the exception of persons repatriated to the United States from Wuhan and Japan.
2. The U.S. national employment data from the Opportunity Insights Economic Tracker (Opportunity Insights, n.d.). This data set combined several data sources to obtain information on employment and earnings and provide a representative picture of private nonfarm employment in the United States. In the analyses, we used the employment level for all workers as the main employment indicator.
3. Donald Trump's tweets. Using the Trump Twitter Archive (Brown, 2021), we collected 612 tweets of Trump from January 1, 2020, to August 8, 2020, using keywords including corona, China, Chinese, Wuhan, virus, and COVID. The research team randomly selected 90 tweets (14.7%) from the 612 tweets for double coding between three coders. We first double-coded 60 tweets, and 11 codes emerged in this round.[3] Then another 30 tweets were assigned for the second round of double coding based on the 11 codes. After each round of independent coding, the team met to check the coding agreement, resolve discrepancies, and reach a consensus on how to handle similar issues that might arise later. The kappa statistic was calculated to measure inter-coder reliability, which is the consistency of coding among different coders (Cooper, Hedges, & Valentine, 2009). The kappa statistic of the 11 codes ranged from 0.64 to 1, suggesting that the researchers achieved substantial agreement on all 11 codes (McHugh, 2012). Then the research team proceeded to independently code the remaining tweets by Trump. Among the 11 codes, "Chinese virus" was the main focus in our analyses, which was used by the Trump administration to refer to the coronavirus disease. This code includes any reference in Trump's tweets that (1) blamed China or Chinese people for the virus, (2) mentioned that the virus originated in China, or (3) included anti-Asian related hashtags.

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[2] More details can be found in the Supplementary Materials: https://docs.google.com/document/u/1/d/e/2PACX-1vSN3PjUG0Jsp9RVOiqaQm4meGdGjCO_TAOBTPxp-f9o-UF0sVMrMTCIQWiRCssZVw/pub.

[3] Eleven codes emerged from this round of coding: China, coronavirus, attacking China, U.S.-China relations, Chinese virus, economy, coronavirus response, attacking media, nationalist aggression, national pride, partisanship, and racism.

4. The Twitter COVID-HATE data set collected by He et al. (2021). This data set is the largest data set of anti-Asian hate tweets in the context of the COVID-19 pandemic. He et al. (2021) used a keyword-based approach to collect COVID-19 tweets through Twitter's APIs. They identified anti-Asian hate tweets published between January 15, 2020, and August 8, 2020, using a text classifier that achieved high classification accuracy (more details on the data set are included in the Supplementary Materials). Because the format of the tweet geolocation information in their data set lacks granularity, we used the Python package "Geocoder" to translate this geolocation information into country information. For the purpose of testing our hypotheses, our final data set only included U.S. tweets. In addition, we removed Trump's tweets from the COVID-HATE data set to account for the confounding effect.

The overlapped date range for all data sets was from January 23 to August 8, 2020. After the four different data sets were aggregated and merged to the national level according to date, the final data set contained a sample of 199 time points.

Analytical Strategies and Measures

A combination of interrupted time series analysis and traditional time series was applied to test the hypotheses. They were suitable for examining the change of anti-Asian Twitter discourses over time. The interrupted times series analysis was useful for examining all the hypotheses and the effects of interventions: The effects of the declaration of COVID-19 as a national emergency, the number of COVID-19 cases, and the employment rate on anti-Asian hate. Meanwhile, we applied the traditional time series analysis to further examine whether the relationship between Trump's tweets on "Chinese virus" and anti-Asian sentiments among the public was reciprocal or unidirectional. Below are descriptions of the two types of analytical methods.

Interrupted Times Series

We adopted an interrupted time series design without comparison groups to analyze how socioeconomic factors and political elites' discourses affected the variation of anti-Asian sentiments on Twitter. A time series is a series of data points indexed in temporal order, creating a sequential pattern of a variable over time. Interrupted time series is a quasi-experimental design in which the effects of an intervention at a specific time point are evaluated by comparing outcome measures obtained at time intervals before and after the intervention (Shadish, Cook, & Campbell, 2002; Wagner, Soumerai, Zhang, & Ross-Degnan, 2002). One of the greatest strengths of interrupted time series studies is the intuitive graphical presentation of results (Wagner et al., 2002). Visually, we could compare the time series patterns before and after the intervention and assess if, after the intervention, the time series pattern had changed noticeably in relation to the pre-intervention pattern (Wagner et al., 2002).

In this study, we treated March 13, 2020, the day when COVID-19 was declared a U.S. national emergency, as the intervention and ran a linear regression model using the described interrupted time series design (*American Journal of Managed Care*, 2021). The following variables were included in the model.

Design-Related Variables

There were two design-related variables: Date and policy. The date variable indicated the sequence of the dates between January 15, 2020, and August 8, 2020, which centered on March 13, 2020. The policy variable was a binary variable with 0 indicating the dates before March 13, 2020, and 1 representing the dates on and after March 13, 2020.

Outcome Variables

The outcome variable was the number of tweets that contained anti-Asian hate sentiments. Figure 1 presents the trend of anti-Asian hate on Twitter between January 15 and August 8, 2020.

Variables of Interest

There were three time-varying variables in the model: Newly confirmed COVID-19 cases, employment rates for all workers, and Trump's tweets on "Chinese virus." All variables were at the daily level. Figures 2, 3, and 4 display the trend of Trump's tweets on "Chinese virus," national employment rates, and newly confirmed COVID-19 cases, respectively.

The regression model is specified as the following:

$$Hate_{ti} = \beta_0 + \beta_1 Policy_{ti} + \beta_2 Date_{ti} + \beta_3 (Policy \times Date)_{ti} + \beta_4 COVID\_Cases_{ti} + \beta_5 Employment_{ti} \\ + \beta_7 Trump\_ChineseVirus_{ti} + \varepsilon_{ti}$$

where $Hate_{ti}$ denotes the number of anti-Asian hate tweets at t time points. $Policy_{ti}$ is a dichotomous variable indicating pre- and post-intervention period (0 = pre-intervention, 1 = post-intervention). The intervention was the declaration of COVID-19 as a U.S. national emergency on March 13, 2020. $Date_{ti}$, centered on March 13, 2020, is a continuous variable indicating the day of observations. $COVID\_Cases_{ti}$, $Employment_{ti}$, and $Trump\_ChineseVirus_{ti}$ represent daily confirmed COVID-19 cases, national employment rates, and the number of Trump's tweets on "Chinese virus," respectively. $\varepsilon_{ti} \sim N(0,\, \delta_{\varepsilon}^2)$ is the independent and identically distributed error term.

Traditional Time Series Analysis

In addition, traditional time series analysis allows us to examine how the dynamics among variables play out or change over time. This analytical strategy was especially beneficial when investigating whether racially charged elite cues stimulated more hate tweets from the public or the reverse.

In our traditional time series analysis, the unit of analysis was one day. Using the collected data, we constructed four time series: A daily count of the anti-Asian hate tweets and three factors that may have influenced the public's discourse on anti-Asian hate, including (1) daily reported new COVID-19 cases, (2) the U.S. national employment rates, and (3) Trump's tweets on "Chinese virus."

Time series analysis strictly requires stationarity (Box, Jenkins, Reinsel, & Ljung, 2015; Brocklebank & Dickey, 2003), which indicates that the covariance is normalized over time within the same time lag. We first used three-unit root tests (e.g., the Augmented Dickey-Fuller test, the Kwiatkowski-Phillips-Schmidt-Shin test, and the variance ratio test) to determine whether each time series was stationary. All the time series except Trump's tweets on "Chinese virus" were nonstationary. Therefore, we used the *difference* process to transform the nonstationary series into stationary series (Box et al., 2015; Brocklebank & Dickey, 2003). Then we constructed vector autoregressive (VAR) models and used Granger causality analysis to further examine the proposed hypotheses.

Vector autoregressive models have fewer restrictions and allow us to examine the dynamics across various endogenous and exogenous variables (Freeman, Williams, & Lin, 1989; Wells et al., 2019). Since the endogenous variables in the VAR model are the ones that can be explained by other variables in the model, we included the hate tweets and Trump's tweets on "Chinese virus" as endogenous variables. The two exogenous variables were the COVID cases and the employment rate. We applied the Bayesian information criteria to determine that the optimal lag length for our VAR model was two (Ahelegbey, Billio, & Casarin, 2016). After constructing the VAR model, we conducted additional bivariate analyses between Trump's tweets on "Chinese virus" and hate tweets on Twitter using Granger causality tests. Although it does not test a true cause-and-effect relationship, the Granger causality test is a common analysis to further interpret the VAR model as it tells us if a particular variable comes before another in the time series. More importantly, the Granger causality was used to provide results of temporal dynamics between Trump's "Chinese virus" tweets and anti-Asian sentiments on Twitter.

Results

Descriptive Analyses

Figures 1–4 present the trends of the outcome variable, anti-Asian hate tweets, and the three variables of interest: Trump's tweets on "Chinese virus," national employment rates, and the number of daily confirmed COVID-19 cases. Figure 1 shows that anti-Asian hate in the United States (*Min* = 6.0, *Max* = 4,313.0, *Mean* = 782.9, *SD* = 626.7) increased remarkably on Twitter between mid-March and late August. It also had great variations across that time even after we excluded the three peaks in mid-March, mid-April, and late July (*Min* = 6.0, *Max* = 1,825.0, *Mean* = 676.1, *SD* = 382.8).[4]

As shown in Figure 2, Trump frequently tweeted discourses on "Chinese virus" (*Min* = 0, *Max* = 7, *Mean* = 0.35, *SD* = 0.84) from mid-March to early June as well as from July to early August. Figure 3 indicates that the national employment rate for all workers (*Min* = −0.23, *Max* = 0.01, *Mean* = −0.09, *SD* = 0.08) decreased substantially since mid-March and then gradually increased since May 2020. The national employment rate reached its trough in mid-April. In Figure 4, the number of COVID-19 cases (*Min* = 0, *Max*

[4] Please find the explanations for the spikes in the Supplementary Materials: https://docs.google.com/document/d/e/2PACX-1vSN3PjUG0Jsp9RVOiqaQm4meGdGjCO_TAOBTPxp-f9o-UF0sVMrMTCIQWiRCssZVw/pub

= 77,268, *Mean* = 25,500, *SD* = 21,685.82) started to increase dramatically soon after mid-March and continued to increase over the target time span.

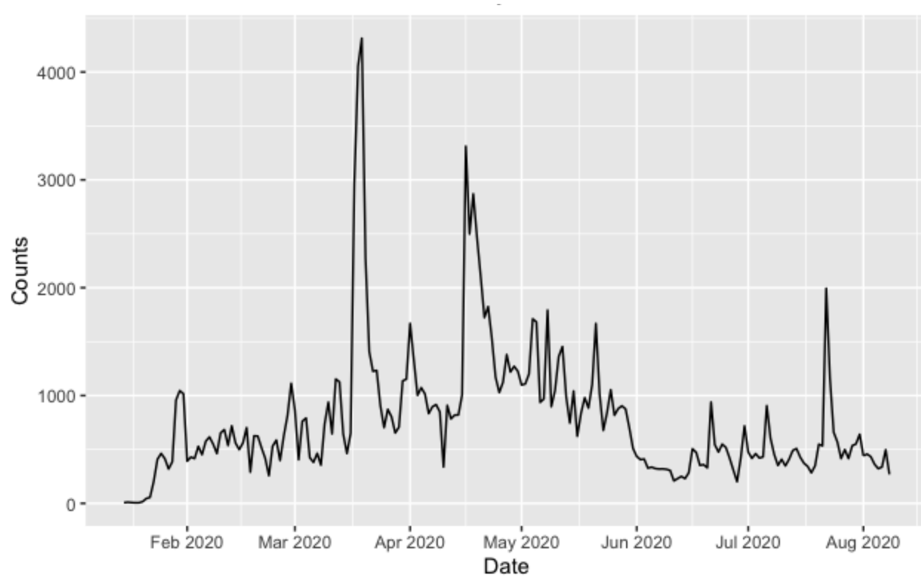

Figure 1. The number of anti-Asian hate tweets by date.

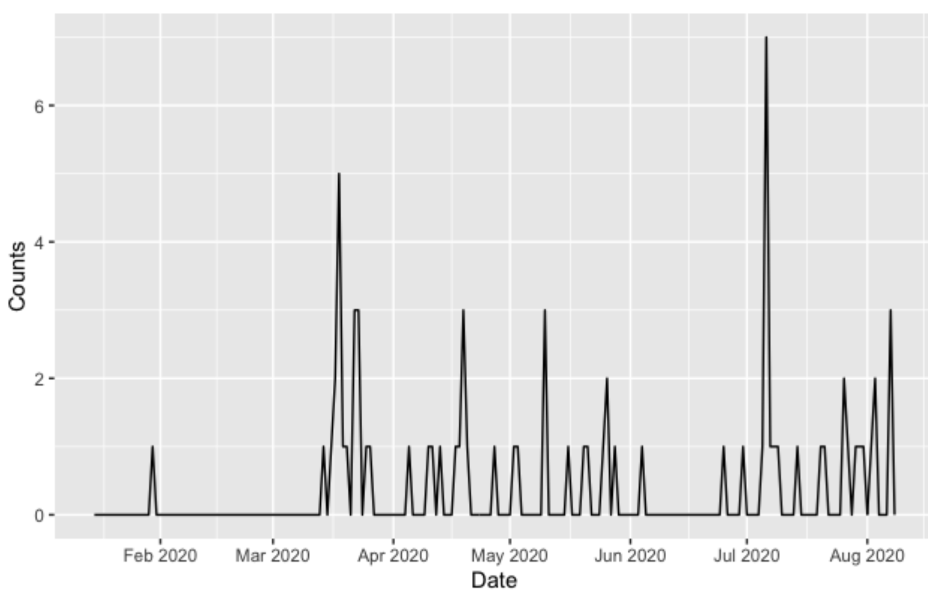

Figure 2. The number of Trump's tweets on "Chinese virus" by date.

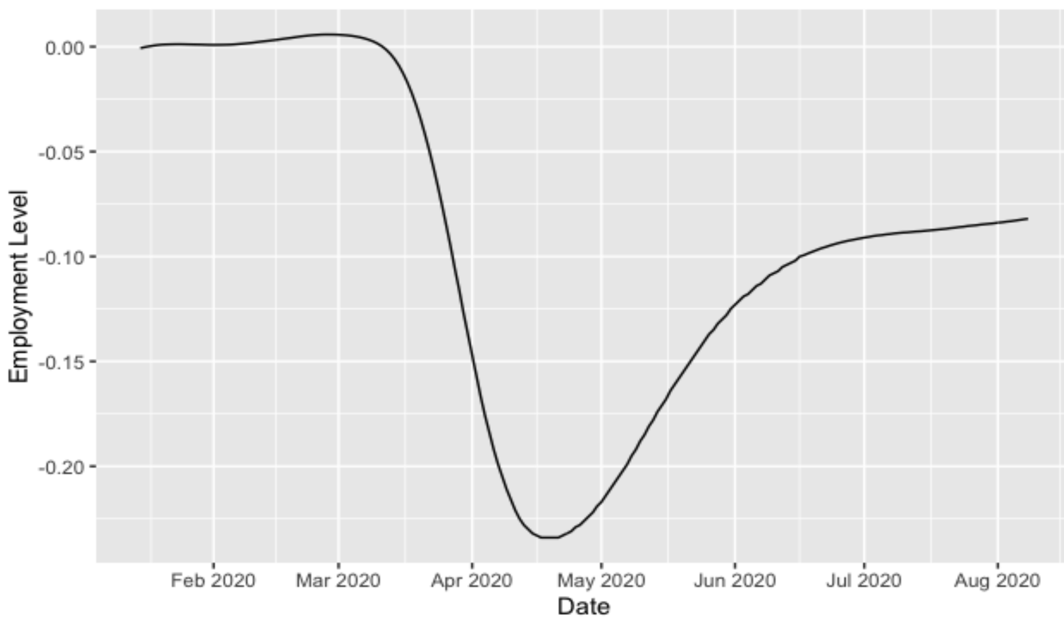

Figure 3. The trend of national employment rate by date.

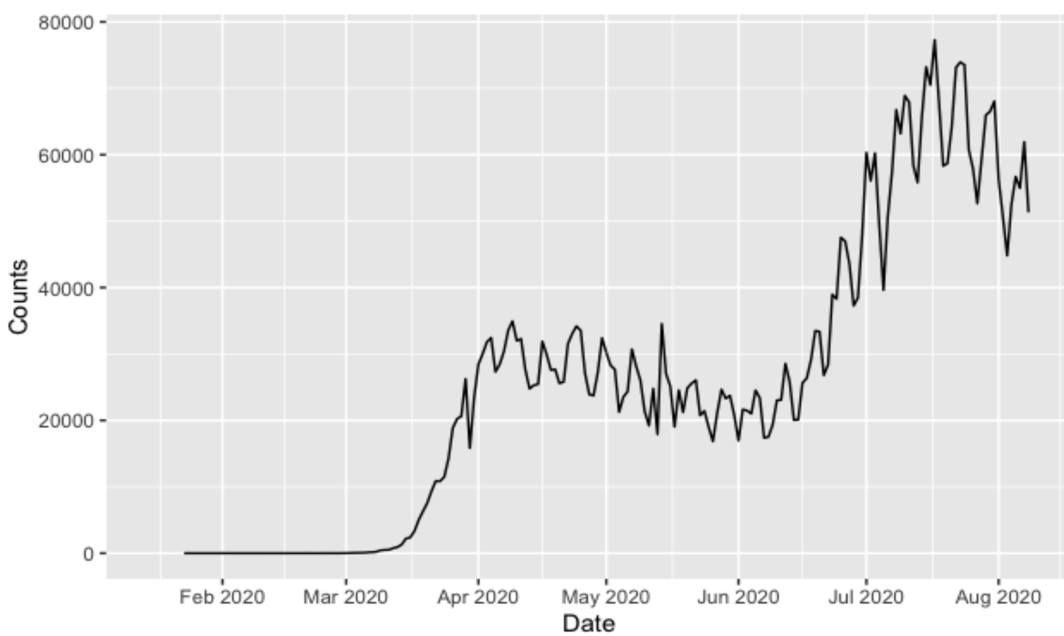

Figure 4. The number of newly confirmed COVID-19 cases by date (reported by Centers for Disease Control and Prevention [CDC], 2021).

Figure 5 displays the trends of anti-Asian hate tweets with an indicator of the intervention, which is the declaration of COVID-19 as a U.S. national emergency on March 13, 2020, during the designated time span. Before the intervention, there was a gradual increase in anti-Asian hate tweets, but the average volume was below 1,000 per day. Then the anti-Asian hate tweets increased dramatically and peaked shortly after the intervention. Besides, anti-Asian hate remained at a high level until late May 2020 although the overall trend decreased after the intervention. Since June 2020, the number of anti-Asian hate tweets became stable and stayed at a lower level compared with the pre-intervention and early post-intervention periods.

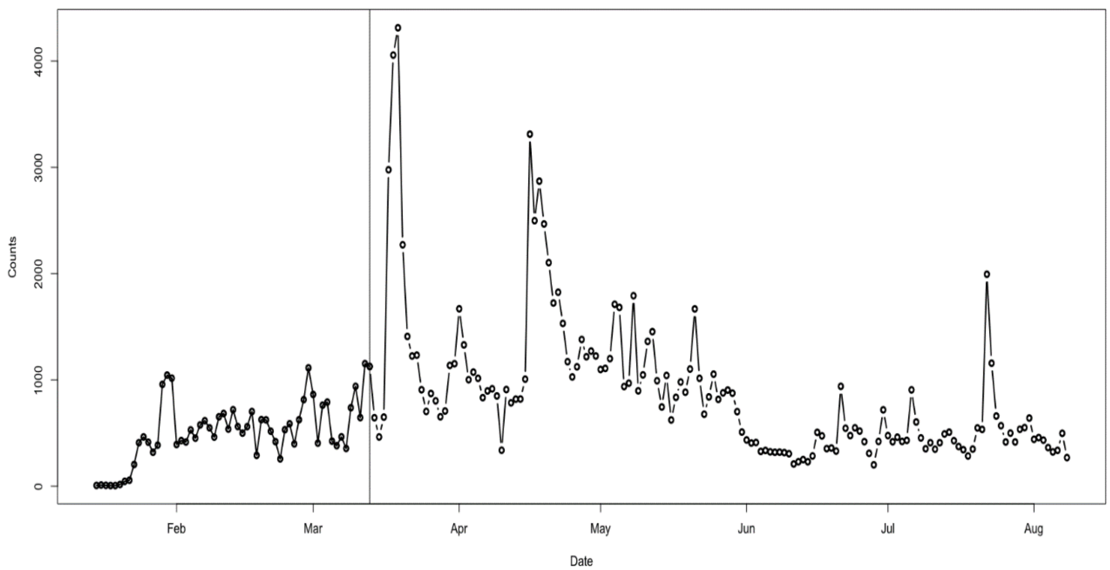

Figure 5. The number of anti-Asian hate tweets by date with indicator of intervention.

Economic and Health Factors

Table 1 presents the regression results using an interpreted time series approach. When all the other variables are constant, the number of newly confirmed COVID-19 cases has a positive effect on the spread of anti-Asian tweets at a 90% confidence level ($\beta = 0.224$, $p = .075$). This supports H1a, stating that the rise of COVID-19 cases is related to the increased anti-Asian hate on social media. The interaction term of date and policy is negatively associated with the spread of anti-Asian hate tweets, which is statistically significant ($\beta = -0.666$, $p = .002$). It means that anti-Asian hate on Twitter was gradually diminishing in the post-intervention time. This seems to contradict what is hypothesized in H1b, possibly due to the sharp increase of anti-Asian hate tweets right after the policy intervention—the declaration of COVID-19 as a U.S. national emergency on March 13, 2020. Also, anti-Asian hate reached its peak shortly after the policy intervention date and then gradually decreased. Therefore, it is not surprising that the overall trend of anti-Asian hate tweets after policy intervention is decreasing.

Table 1. Ordinary Least Squares Regression Analysis of the Spread of Anti-Asian Tweets With Interrupted Time Series Design.

Explanatory Variables	Coeff.	*SE*	*t*-value	*p* Value
Intercept	0.554***	0.165	3.348	0.001
Policy intervention	−0.207	0.257	−0.804	0.422
Date	−0.544**	0.168	−3.235	0.001
Policy intervention × Date	−0.666**	0.209	−3.189	0.002
New COVID-19 cases	0.224†	0.125	1.791	0.075
Employment	−0.176†	0.094	−1.882	0.061
Trump on "Chinese virus"	0.280***	0.056	4.966	0.000

Note. *N* = 199. All results are standardized. *SE* = robust standard errors.
****p* < .001, ***p* < .01, **p* <.05, † < .1.

The employment rate has a negative and statistically significant impact on the spread of anti-Asian hate Tweets at a 90% confidence level ($\beta = -0.176$, $p = .061$). This implies that the decrease in employment rate is correlated with an increase in anti-Asian hate on social media, which is consistent with what is hypothesized in H2.

The Influence of Elite Cues

In accordance with H3, Table 1 shows that Trump's tweets on "Chinese virus" have a positive and statistically significant impact on the spread of anti-Asian hate on Twitter ($\beta = 0.280$, $p = .000$). It implies that the more Donald Trump mentioned "Chinese virus" and related terms in his Twitter, the more anti-Asian tweets appeared on Twitter.

To further examine H3, in particular, to gather more robust evidence on the temporal dynamics and the influence between hate tweets among the public and Trump's tweets on "Chinese virus," we implemented analytical strategies from the traditional timer series: The VAR model and Granger causality analysis. Table 2 displays the estimates and significant levels of the VAR models. First, focusing on the first half of the table where hate tweets were the dependent variable, the results show that the change in the number of hate tweets on Twitter is positively related to the changes in the number of hate tweets two days before that and the number of Donald Trump's tweets the day before. In other words, after Trump tweeted "Chinese virus," anti-Asian tweets surged a day later. In the second half of the table, where Trump's tweets on "Chinese virus" were the dependent variable, results suggest that the change in the number of Trump's tweets on "Chinese virus" was mainly influenced by the change in his own tweets two days and one day before. However, the number of hate tweets among the public did not induce Trump to tweet about "Chinese virus." When the number of hate tweets on Twitter increased, Trump tweeted "Chinese virus" less. Since past research suggested that VAR estimates are difficult to interpret (Benati & Surico, 2009), we further interpret the VAR models by examining the Granger causality results.

Table 2. Vector Autoregression of Anti-Asian Hate Tweets and Trump Tweets on "Chinese Virus."

Dependent Variable	Explanatory Variables	Hate Tweets
Hate Tweets $_t$	Hate tweets $_{t-1}$	−0.013
	Trump tweets on "Chinese virus" $_{t-1}$	82.140**
	Hate tweets $_{t-2}$	−0.143*
	Trump tweets on "Chinese virus" $_{t-2}$	3.231
	Constant	−4.467
Trump Tweets on "Chinese virus"$_t$	Hate tweets $_{t-1}$	0.000†
	Trump tweets on "Chinese virus" $_{t-1}$	−0.520***
	Hate tweets $_{t-2}$	−0.000*
	Trump tweets on "Chinese virus" $_{t-2}$	−0.318***
	Constant	0.005

Notes. ****p* < .001, ***p* < .01, **p* <.05, † < .1.

Table 3 displays the results of the two-day Granger causality tests. The results further confirmed the unidirectional relationship between Trump's "Chinese virus" tweets and hate tweets on Twitter. In comparison, the reversed influence of Trump's "Chinese virus" tweets on hate tweets did not achieve the conventional level of statistical significance. More specifically, the significant effect of Trump's "Chinese virus" tweets on hate tweets rejected the null hypothesis that Trump's tweets on "Chinese virus" do not explain the variation in the public's hate tweets. It confirmed the alternative hypothesis that Trump's tweets on "Chinese virus" Granger-caused[5] the change in the number of the public's hate tweets. Therefore, the significant results confirmed the unidirectional relationship between Trump tweets and hate tweets. This supports H3 and is consistent with the interrupted time series analysis result. The relationship between COVID-19 cases, employment rates, and hate tweets was not examined in the Granger causality test because the test requires all variables to be endogenous.

We used the Durbin-Watson test to conduct a post-hoc analysis on the co-integration between Trump's tweets on "Chinese virus" and hate tweets on Twitter. The results showed that autocorrelation in the residuals of the two time series was nonsignificant, assuring that all the autoregressive components had been accounted for (Savin & White, 1977).

Table 3. Granger Causality Tests Between Trump on "Chinese Virus" and Hate Tweets.

Tests	*F* Statistic
Trump on "Chinese virus" ⟶ Hate tweets	7.136***
Hate tweets ⟶ Trump on "Chinese virus"	0.502

Notes. ****p* < .001, ***p* < .01, **p* <.05, † < .1

[5] Granger causality test is a common analysis to further interpret the VAR model as it tells us if a particular variable comes before another in the time series. In our study, "Granger-cause" means that Trump's tweets on "Chinese virus" were helpful in forecasting the public's hate tweets. In other words, the past values of Trump's tweets significantly predicted the future values of the public's hate tweets.

Discussion

The Pandemic and Anti-Asian Hate Tweets

Our interrupted time series analysis indicates that newly confirmed COVID-19 cases were positively correlated with anti-Asian hate tweets. This positive correlation could be partially explained by popular assumptions that COVID-19 originated from and was even “produced” in China. Conspiracy theories about Chinese people consuming bats and Wuhan lab’s manufacturing of coronaviruses spread on social media and stirred strong anti-China sentiments (Landay & Hosenball, 2021). The scapegoating practices against Asian and Asian Americans rose rapidly as COVID-19 surged and hospitalization rates jumped. Many people started to see Asian communities not only as disease carriers but also as culprits of the deaths of thousands of Americans in general (Gardner, Briggs, & Ryan, 2021). This finding reveals a historical continuation of the racialization of Asian populations, in which anti-Asian racism remains latent when the society is prospering and stable but surges when health crises occur.

Although the national emergency policy proved to be insignificant in the spread of anti-Asian hate tweets, the remarkable increase of anti-Asian hate sentiments on social media in the early stage of post-intervention is not neglectable. When Trump declared COVID-19 as a national emergency, which he then proudly promoted on his Twitter account, it triggered a big wave of anti-Asian sentiments online. The public responses on social media in the immediate days of this executive order were likely a result of venting the long-held anti-Asian sentiments in the United States.

The Influence of Economic Downturn

Our study shows that the drop in employment rates, as a result of the lockdown policies across the country, also contributed to anti-Asian sentiment on social media. This result suggests that anti-Asian prejudice is not merely a racial behavior but also a classed one. Racial and ethnic minorities are often assigned as responsible for fiscal distress and become targets of blame and violence. In the case of COVID-19, Chinese and Chinese Americans were blamed for not only health crises but also job losses. Combined with the loss of incomes in many American families, the rising unemployment rate during the early stage of the COVID-19 pandemic pushed many people to blame Asian and Asian American populations. It echoed the historical marginalization of Asian immigrants in the 19th century when White laborers blamed the Chinese for the slim job opportunities and low wages in manufacturing. Compared with White, Black, and Hispanic populations, Asian Americans have suffered the most from long-term unemployment because of COVID-19. In the first quarter of 2021, almost half of the unemployed Asian Americans were without work for more than six months (U.S. Bureau of Labor Statistics, n.d.). This number was higher than those of long-term jobless workers in the Black population (43%), Hispanic population (39%), and White population (39%; Ramirez, 2021). It is crucial to note the often-neglected dual impact of racism and job losses on Asian communities due to the pandemic.

Our finding, however, contradicts Lu and Sheng’s (2020) research, which indicated no significant impact of the economic downturn on the rising racial antagonism. Lu and Sheng (2020) adopted a different method to measure economic impact: The proportion of the area’s annual average employment in two categories, "leisure and hospitality" and "education and health services." While those two service industries seem to be good indicators of the region's economy, they neglect other occupations that have been severely impacted during COVID-19, such as retail businesses, real estate, and international/domestic transportation. Our article, which uses the unemployment rate from more industries as the indicator of the economy, offers a more robust measure of the national economy. It covers a representative picture of private nonfarm employment in the United States and provides good coverage of workers at the bottom of the wage distribution, a group of particular interest given their volatile employment rates over the business cycle (Chetty, Friedman, Hendren, Stepner, & Team, 2020).

The War on Twitter: "Chinese Virus" and Anti-Asian Hate Tweets

Our results demonstrate that Donald Trump's political discourse on "Chinese virus" was a key factor contributing to the rise of anti-Asian hate tweets during the pandemic. The effect was strong and significant even after controlling for the influence of the pandemic and economic downturn. Meanwhile, the public's anti-Asian sentiments did not have the same impact on political leaders' racial attitudes. The results extend the literature of elite cues and public opinion by confirming that Trump's anti-Asian cues led to anti-Asian hate on social media.

Since political communication often takes place in a bounded space with a high level of competition, elite cues may open up discursive opportunities for social exclusions (Ferree, 2003; Koopmans & Statham, 2006). Discursive opportunities are often considered as the aspects of the public discourse or political culture that allow a message to gain visibility, legitimacy, and resonance in the public sphere (Koopmans & Statham, 2006). Trump's "Chinese virus" tweets created legitimacy for criticizing China and Asian Americans for the pandemic, allowing the issue to be further discussed in the social media arena. Our results also extend the existing literature on the "Trump effect," revealing that Trump's racially inflammatory language had concrete and significant impacts on emboldening the public to express anti-Asian attitudes. This effect was particularly salient when other political elites accepted or endorsed Trump's racist messages.

This research reminds us of the role of social media in shaping racial and political attitudes in the contemporary era (Gantt Shafer, 2017; Jakubowicz, 2017). The pandemic outbreak was accompanied by an "infodemic" (World Health Organization, 2020)—a flow of misinformation about the virus fueled on social media. Trump made 30,573 false or misleading claims during his presidency, according to independent fact-checkers (Kessler, Rizzo, & Meg, 2021). A large number of those were made on Twitter, where he had nearly 89 million followers. Due to the false information about the virus and the Asian communities, the spread of anti-Asian racism and hatred online was more severe compared with that during previous pandemics, such as SARS in 2003. Croucher et al.'s (2020) survey-based study argues that the belief in the fairness and accuracy of social media was associated with anti-Chinese attitudes during the pandemic. This evidence shows that the discursive power of Trump was tightly connected with the power of social media to exacerbate racial hostility during a public health crisis.

Conclusion

Our research demonstrates that anti-Asian racism has deep roots in history, the socioeconomic system, and political discourse. Using the interrupted time series analysis and traditional time series analysis, we present robust results that Trump's tweets on "Chinese virus" played a significant role in spreading anti-Asian sentiments on social media. Meanwhile, the rise of COVID-19 cases and the decrease in employment rate were positively correlated with the increase in anti-Asian hate tweets. This article contributes to the literature by examining how anti-Asian sentiments on social media were systematically enhanced by a series of socioeconomic and political factors rather than being a result of individual behaviors. It expands the existing literature by employing a quantitative inquiry to confirm that the elite-driven rhetoric exacerbated the racialization of Asians during the pandemic, leading to the normalization of anti-Asian hate at the mass public level.

There are two limitations to this study. First, this study only provides a snapshot of the spread of anti-Asian hate on social media because it solely focused on Twitter. Future studies may include other platforms, such as Facebook, Reddit, and TikTok, to present a more representative pattern of anti-Asian hate speech. Also, this research primarily examined the influence of the discourse from a single political elite. It is worthwhile to examine the impact of the discourse from a broader network of political elites in the future. More studies are also needed to examine the relationship between online anti-Asian racist discourses and the engagement in racist behaviors offline. In addition, it will be productive to extend this research to examine the global story of how a series of socioeconomic factors and other political elites' discourses enhance anti-Asian sentiments.

We need collaborative efforts from the federal, legislative, industrial, nonprofit sectors and the general public to counter the revival of anti-Asian hate on social media. On May 20, 2021, President Biden signed the COVID-19 Hate Crimes Bill into law. While this is a critical step in recognizing the ongoing racism that affects the lives of Asian populations, it is only the beginning. In future public health crises, public health agencies should be aware of a potential rise in racist sentiment and prepare guidelines for politicians, media, and the public to describe outbreaks in scientific terms instead of discriminatory rhetoric. Trump was banned from Twitter in January 2020, two days after his supporters attacked the Capitol, but his account was reactivated in November 2022 by Twitter's new owner Elon Musk. This raised a key question on how to effectively prevent the spread of hate speech on social media. Online platforms such as Twitter need to work with communication practitioners to strengthen their regulations to reduce the spread of misinformation and hate speech. On the ground level, there also needs to be more education on the issue of anti-Asian racism. Schools, media, and other public education venues have a responsibility to inform the general public about the history of anti-Asian racism, the trauma that Asian groups have suffered, and collective actions that could help fight against hate. Supporting campaigns like Stop AAPI Hate and other grassroots organizations that commit to racial justice is also important in this effort. Only by addressing the structural racism on these various platforms can we create a safe, healthy environment for Asian communities in the United States and around the world.

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