More Than Just Words?: An Analysis of the Relationship between Local News Media and Hate Incidents in the United States

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Abstract

Recent conflicts among various social cleavages have been resulting in prevalent violence instead of peaceful coexistence, particularly in the United States. The most recently published FBI's Uniform Crime Reporting (UCR) report on hate crime revealed a recording-breaking number of more than 50 fatalities resulted from bias-motivated crimes in 2019. The year 2020 was followed by an alarming surge of hate crimes targeted toward Asian Americans amid the COVID-19 pandemic, with more than 3,000 cases being reported by the Stop AAPI Hate Crime initiative. Although there may be numerous factors including structural and socioeconomic variables that affect the incidence of hate crime, the effects of the language of local news media cannot be easily neglected with historical and empirical evidence suggesting words being more than "just words." Thus, the research employs a two-way fixed effects model to discern the possibly existing relation between local news media language targeted towards bias groups and hate crime incidents across all fifty states and the District of Columbia. The regression results show that the frequency of some keywords related to bias groups in the local news media is positively associated with variables related to hate incidents, exhibiting greater effects than general news coverage.

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1. Introduction

Recent conflicts among various social cleavages have been resulting in prevalent violence instead of peaceful coexistence, particularly in the United States. The most recently published FBI's Uniform Crime Reporting (UCR) report on hate crime revealed a recording-breaking number of more than 50 fatalities resulted from bias-motivated crimes in 2019.[1] There has also been a significant surge in hate crimes targeted towards Asian American communities following the COVID-19 pandemic, including the shootings in Atlanta suspected to be motivated out of hate resulting in the death of at least eight individuals, mostly from Asian descent.[2] The Stop AAPI (Asian American and Pacific Islander) Hate initiative received 3,795 reports of bias incidents against Asian Americans and Pacific Islanders from March 2020 to February 2021 across all fifty states,[3] while the Center for the Study of Hate & Extremism revealed an alarming rise of reported Anti-Asian hate crimes by nearly 150 percent.[4] Yet, hate incidents in reality may be even more widespread than what the reports suggest. The Pew Research Center survey reported around "three out of ten Asian adults" being subject to racial or ethnic slurs since the pandemic (Ruiz et al., 2020). The vulnerable population such as the elderly, adolescents, and women are frequently targeted by hate crimes, such as the deaths of Asian elderly including the 84-year-old Vicha Ratanapakdee brought to national attention by social activists like Amanda Nguyen.[5] While critics like Nguyen claim that such incidents are being neglected by mainstream

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[1] https://ucr.fbi.gov/hate-crime/2019/topic-pages/tables/table-2.xls
[2] https://www.usatoday.com/story/news/politics/2021/03/17/atlanta-shooting-sparks-calls-for-action-against-anti-asian-violence/4731957001/
[3] STOP AAPI Hate national report is accessible at https://secureservercdn.net/104.238.69.231/a1w.90d.myftpupload.com/wp-content/uploads/2021/03/210312-Stop-AAPI-Hate-National-Report-.pdf
[4] Cited from the CSUSB report accessible at https://www.csusb.edu/sites/default/files/FACT%20SHEET-%20Anti-Asian%20Hate%202020%20rev%203.21.21.pdf
[5] Nguyen's video can be found at https://www.instagram.com/reel/CK7vwR2HNM7/?utm_source=ig_embed

news media and not receiving the needed attention they deserve, xenophobic and racist rhetoric perpetuated in the news media has also been cited as one of the precursors of recent hate incidents following COVID-19 (Borja et al., 2020). Content analysis of the Stop AAPI initiative makes note of the anti-Chinese and racist rhetoric perpetrated by politicians and parroted by the media (2020).

The issue of the link between hate speech and hate crime is not at all new nor the sole byproduct of the recent pandemic. In its launch of the United Nations Strategy and Plan of Action on Hate Speech in 2019, the UN Secretary-General denounced hate speech as "a precursor to atrocity crimes" in regions including the United States.[6] Research of historical evidence, such as the horrendous Rwandan genocide suggests how hateful language of the extremist RTLM broadcast may not have been "just words" but incited real-life consequences such as aggression, violence, or even dire consequences as mass killings (Yanagizawa-Drott, 2014).

Thus, the research attempts to examine the link between the language in local news media and hate incidents. The study derives data related to the local news media coverage related to bias groups in Media Cloud, an open source platform with up-to-date news collections generated by its RSS feeds. The measured ratio is then examined with the variables related to hate incidents, derived from the data of the FBI Uniform Crime Reporting (UCR), Anti-Defamation League (ADL), and Stop AAPI Hate. The two-way fixed effects model is used to

[6] Full speech accessible at https://www.un.org/sg/en/content/sg/statement/2019-06-18/secretary-generals-remarks-the-launch-of-the-united-nations-strategy-and-plan-of-action-hate-speech-delivered

control for both time-variant and invariant characteristics across all fifty states and the District of Columbia.

While there has been various research linking social media language or news to particular regions and counties, most studies were not as comprehensive as this study, that uses state-level data of all fifty states of the United States. The regression results show some statistically significant findings with the frequency of keywords related to bias groups such as anti-immigrants, suggesting how the rise of hate speech in local news media can lead to an increase in levels of hate incidents in the corresponding regions toward the affected bias populations. The paper also brings the relevant context of the surge of hate crimes following COVID-19, comparing the effects of general news coverage related to the pandemic and the ones with anti-Chinese rhetoric. The results show much greater effects with anti-Chinese keywords, although the results were not statistically significant with time-fixed effects. Such findings would help readers discern and unravel the real-world implications of the language used by the media that make them more than mere rhetoric.

2. Literature Review

The FBI's Uniform Crime Reporting (UCR) defines "hate crime" as "criminal offense motivated, in whole or in part, by the offender's bias(es) against a race, religion, disability, sexual orientation, ethnicity, gender, or gender identity." [7] According to the United States Department of Justice, hate crime should satisfy both the definitions of "hate" and "crime," with a criminal offense motivated on the basis of the victim's perceived or actual bias.[8] Thus, an

[7] https://www.fbi.gov/services/cjis/ucr/hate-crime
[8] https://www.justice.gov/hatecrimes/learn-about-hate-crimes/chart

incident based on prejudice but does not include "violence, threats, or property damage" may count as "bias incident" or "hate incident" but not "hate crime." Due to the narrow definition of what counts as hate crime and the significant gap between the incidents being reported and the ones that occur in reality, hate crimes are most likely to go unreported while hate incidents without criminal offenses are not counted in law enforcements hate crime statistics.[9]

The complex nature of hate crimes makes the incidence of hate crime a demanding topic for research. Previous literature suggests hate crime may arise not just from a singular mechanism of prejudice on a bias group but from an intersection of multiple factors (Chakraborti and Garland, 2012; Gladfelter, Lantz et al., 2017). Socioeconomic factors such as economic levels, unemployment rates, social welfare spending, and law enforcement expenditures of communities (Gale, Health et al., 2002; Bennett, Danner et al., 2008; 2017) can affect the levels of certain bias crimes. Some studies also suggest demographic factors, such as the integration of ethnic minorities in explaining the rates of racially-biased hate crime (Green, Strolovitch et al., 1998). Research on violent crimes suggests that the correlation may not be due to mere ethnic diversity but rather the result of factors such as ethnic polarization (Soysa and Noel, 2018).

Socio-economic factors can have greater effects in the level of crime in combination with social psychological factors such as altruism and envy (Gale, Health et al., 2002). Implicit biases such as racial attitudes and prejudice can also affect real-life behavior, suggesting a possible connection between psychological factors in impacting real-life actions (Kurdi, Seitchik, et al., 2018; Orchard and Price, 2017; Leitner, Hehman et al., 2016). Others may also point to socio psychological explanations such as intergroup factors to explain the incidents of hate crime (Brown, Walters, et al., 2016). Further structural explanations of hate crime include the

[9] Thus, the article would use the word hate "incident" to include the broader scope of bias incidents both criminal and non-criminal, except for discussing the FBI UCR Hate Crime data.

perceived ‘difference’ of bias groups (Chakraborti and Garland, 2012) which is often perceived as a threat to people’s hierarchy or status quo (Perry 2001) and people’s place in society (Abrams, Swift et al., 2016). Racial groups in relative social hierarchy may point to differences between “us” and “them” by pinpointing those that do not “belong,” thereby trying to preserve their existing social status (Perry 2001). The act of making such distinctions can also be referred to as the act of “othering” that is commonly embedded in racist and xenophobic beliefs (Gover, Harper et al., 2020). However, the possibly existing effects alone would not be sufficient to explain the motivations behind hate incidents that often exhibit themselves in forms such as aggressive violence and killings with scarce evidence “explor[ing] the empirical link between prejudiced attitudes and discriminatory behaviours.” (Abrams, Swift et al., 2016, p. 133).

One cannot ignore the effects of mass media in aggravating the structural and psychological factors behind hate crime. The media can affect the public opinion on various social issues through its agenda setting powers that can shape the audiences’ perception. (McCombs, Maxwell et al., 1972; Behr and Iyengar 1985; Iyengar 1996). The media’s representation of reality may not exactly mirror real-life as journalists assess the newsworthiness of incidents, often with systematic preference that leads to the gatekeeping effects of the media that can aggregate stereotypical stereotypes towards minority groups (Clayman, Steven et al., 1998; Lundman 2003). In addition, the news media can no longer be seen as just an objective messenger with an increasing trend of journalism towards greater extent of interpretation and opinion (Barnhurst 2014, pp. 111-141; Esser and Umbricht, 2014).

There exist selection biases as to which events receive more coverage in the news with certain terrorist attacks receiving greater media attention than others (Kearns, E.M., et al, 2018). The real-time study of media and incidences of local hate crime demonstrate proof of a causal relationship between media reporting of Jihadi attacks and anti-Muslim hate crime" (Ivandic, R, et al. 2019). There was a spike in local hate crimes that followed by numbers of news coverage, while 'placebo' attacks relatively less media attention were not followed by such spikes.

But important is not just the amount of media coverage, but how they are represented. The language of news media is an important means of conveying values, as language is not just linked to social norms but also hierarchy and power in society (Woolard and Schieffelin 1994; Perry 2001). Historical evidence has established links between the rhetoric of the media and real-life violence against affected populations with evidence from the effects of the RTLM radio broadcast in exhibiting greater level of aggregated attacks in the Rwandan Genocide (Yanagizawa-Drott, 2014) to the propaganda of pro-Nazi radio broadcasts inciting anti-Semitic acts. (Adena, Enikolopov et al., 2015).

More recent examples suggest how media's choices of words that may have an effect by portraying bias groups by associating them with stereotypes, particularly by associating crime and illegal activities associated with specific bias groups (Chiricos and Eschholz 2002; Stabile 2006; Dixon 2008; 2009; Frisby 2017; Farris and Mohamed 2018). One example is how the media can represent perpetrators in the public shootings differently depending on their race (Frisby 2017) The examination of the coverage related to public shootings from 2008 to 2016 showed how a larger proportion of Hispanic/black shooters as opposed to white were described as "thug," while a greater percentage of Muslim/black were described as "terrorist." On the other hand, white shooters are more likely to be associated with words "hero" or "mental illness," possibly in an attempt to justify their actions. Such media coverage also seemed to harbor prejudice as a larger percentage of survey respondents who read such coverage of mass shootings considered all people with mental illnesses as dangerous" opposed to those who don't. Exposure to such overrepresentation of Blacks in news viewing also had an effect in the perceptions of local viewers, with more likely to have harsher culpability towards Blacks and more likely to perceive Blacks as violent (Dixon 2008).

There have also been studies demonstrating the real-life effects of the political campaign's "dog-whistling," or the use of languages that do not seem discriminatory on the surface but discreetly disparage targeted social biases. (Mendelberg 2001; Valentino, Hutchings et al., 2002) News media's mentions of "law and order," "inner cities", or "welfare" has been often cited as examples of dog whistling, with attempts to steer the political discourse without explicitly mentioning race.[10] Slant language in the news media can also affect reader's policy issues, as cited from the study exploring the example of mass media's coverage of immigration (Djourelova, 2020). The study showed how the Associated Press(AP)'s ban on the term "illegal immigrant" and the decline of its usage in several other media sources led to significant impact on individual audiences' view on immigration and related policy issues.

In more recent years, U.S. President Donald Trump has made more explicit references to race than just implicit appeals like "dog-whistling," reinforcing negative stereotypes towards certain bias groups with rhetoric like "Kung flu," "thug," and "our heritage" in political campaigns.[11] The incidents of Trump's presidential campaigns making accusations like "wall" "criminal" correlated with greater police stops of bias groups (Grosjean, Masera et al., 2020). This suggests how discriminatory language can affect offline actions, perhaps by evoking certain internal attitudes such as fear or distrust towards bias groups.

[10] The examples can be found in these news articles: https://money.cnn.com/2016/10/19/news/dog-whistle-trump-clinton; https://www.vox.com/the-big-idea/2016/11/7/13549154/dog-whistles-campaign-racism
[11] https://www.washingtonpost.com/politics/with-kung-flu-thugs-and-our-heritage-trump-leans-on-racial-grievance-as-he-reaches-for-a-campaign-reset/2020/06/21/945d7a1e-b3df-11ea-a510-55bf26485c93_story.html

Following these examples of previous literature, this research provides a comprehensive quantitative study on whether the discriminatory language targeted towards certain biases in local media can be correlated with local incidences of hate crime. While there have been broader studies in criminology and sociology that try to explain the determinants of hate crime, the study focuses particularly on the effects of media's hate speech. The study makes a comprehensive scale of research with data of all fifty states and the District of Columbia on how the effects of the language used in local media can be correlated with local incidences of racial hate crime.

3. Theoretical Argument and Hypotheses

The main causal question of the paper is whether the frequency of discriminatory language targeted towards certain groups in the local news media would be associated with regional levels of hate incidents per capita.

The study hypothesizes that the news media with its agenda setting power and its biased rhetoric can reinforce and propagate the spread of xenophobic rationale to the mainstream. While previous literature suggests how overtly explicit racial arguments are easily rejected while subtle cues to racial arguments may possibly influence people's opinion forming (Mendelberg 2001; Valentino et al., 2002), more recent evidence suggests that the appeals no longer need to be implicit to be effective in priming people's opinions (Valentino et al., 2018). People can also employ rationales to justify their attitudes while denying their racist or xenophobic tendencies to reduce the social cost of stigmatization (Bonilla-Silva and Forman 2000; Burtzyn et al, 2020).

The changes in the norms of society no longer make discrimination as taboo as before, with open expressions of xenophobic and anti-immigrant views rising to mainstream following Trump's political campaigns (Bursztyn et al., 2017). The beginning of the COVID-19 pandemic also brought racist views to the public with “about four-in-ten U.S. adults" contending that “it has become more common for people to express racist views toward Asians" (Horowitz et al., 2020). The mass media can aggregate the effects of such ready-made explanations for prejudice in ways such as parroting and propagating the rhetoric. Such social environment can eventually lead to a social environment normalizing hate speech and condoning bias-motivated aggressions, which may in turn be correlated to a greater number of hate incidents.

Thus, the paper explores mainly two testable hypotheses:

Hypothesis 1. The rise of hate speech in the media would lead to a social environment normalizing hate speech and condoning bias-motivated aggressions, as evidenced by the rise of extremist and White Supremacist events.

Hypothesis 2. The rise of hate speech in the media would have a positive correlation with both hate crime and hate incidents, with larger effects on bias groups that are more closely related to the speech.

The research acknowledges that there may be alternative explanations to the outcome of interest, such as the coverage of hate crimes in the news media affecting the levels of hate crime in return (Miller and Albert, 2015). Others may also point to confounding factors such as socioeconomic variables that may affect both the increase or decrease of hate crime and hate speech in the news media. While acknowledging that the findings themselves cannot establish causality due to these limitations, the research seeks to unravel the possibly existing mechanism between the two variables.

4. Data and Research Design

Measurable variables for both hate incidents per capita and hate speech of the news media were introduced to identify the relation between the two. The unit of analysis is state and year-month for each of the 50 states and the District of Columbia from 2016 to 2020, with the corresponding measurement and data.

4.1 Measurement

The dependent variable is the incidence of reported hate incidents (or crimes) per 100,000 inhabitants for each state from the months of 2016 to 2020 within the recorded time frames of each hate incident dataset. The number of incidents with their corresponding month, year, and state was counted as one observation.

Although the reports of hate incidents include dates, the level of hate incidents on a daily basis would in most cases be zero for most observations. Thus, the data was aggregated at monthly level from 2016 onward until the most recent dates available for each hate incident datasets.

The per capita values derived by the U.S census bureau population estimates were used to account for the differing population of each state, which may influence the level of hate crime. The number of recorded hate incidents was divided by each corresponding year's population estimates, except for the year 2020, which used the estimates from the previous year. The variables then went through logarithmic transformation to account for the skewness of data.

The independent variable of hate speech is the percentage of the stories containing any of the list of keywords from 2016 to 2020. The use of ratio is to account for the differences in the number of news media for each state across the years. The daily ratios were aggregated to monthly-level on STATA, with each year-month of the state being counted as one observation (e.g: ratio of Alaska on Jan 2016, Alaska Feb 2016, etc.).

Unlike the hate incident datasets that provide specific city- or county-level data on where the crimes occurred, there are difficulties in selecting representative media corresponding to such specific location of the incidents. Large cities like New York and Los Angeles may be too broad and inclusive to determine "local" news sources on county-level, while small counties did not have much local news resource data. Another issue is that many of the regions had similar names or unclear county or town level boundaries. Location names like "Alameda, California" for instance, were classified differently in ways such as "Alameda county" and "Alameda city" in the FBI UCR dataset. Such distinctions would have been hard to make in searching for local news sources at county-level. To reduce such ambiguity, the data was aggregated at the state level for each year-month.

4.2 Data on hate incidents

1) FBI UCR Hate Crime Reports

The FBI collects data on hate crime under the Uniform Crime Reporting program following the Hate Crime Statistics Act, 28 U.S.C. § 534, legislated in 1990. The master dataset was derived from the Crime Data Explorer (CDE), which makes various data on crime publicly available. [12]

The website not only provides dates of the reported bias incidents but also other useful information such as information about the participating reporting agencies offenders' race, offense type such as its location defined by the Originating Identifier (ORI) code, victim type, and whether the incidents were incited by single or multiple biases such as race, religion, or sexual orientation.

The downloaded .csv file had a record of incident dates and locations of 209,442 locations from the year 1991 to 2019 including 50 states, District of Columbia, Guam, and Federal crimes. I only account for data of 28,729 hate crime incidents from 2016 to 2019 at the 50 states and the

[12] Accessible at https://crime-data-explorer.fr.cloud.gov/downloads-and-docs

District of Columbia.[13] The FBI categorizes hate crime offenses into categories with the most common offenses being simple or aggravated assault, destruction/damage/vandalism, intimidation, larceny, and burglary.

However, the FBI UCR dataset may not be representative of all the hate crime occurrences in reality due to the issue including underreporting, gaps, and errors (Maltz and Targonski, 2002). The narrow definition of what counts as hate crime in the FBI also does not include micro-aggregations and slurs that do not count as "crime" as mentioned previously in its definition. Furthermore, the most recently available data available in the FBI UCR hate crime dataset is up until 2019, not accounting for the recent contexts after 2020. To remedy some of the possible limitations of the dataset and account for representation of data related to more specific bias groups in more recent years, two additional datasets that record hate incidents related to specific groups were introduced from the ADL H.E.A.T Map and Stop AAPI Hate.

2) **ADL H.E.A.T Map**

The database of extremist and anti-Semitic incidents is derived from the Anti-Defamation League (ADL). The ADL keeps track of its records via its H.E.A.T (Hate, Extremism, Anti-Semitism, Terrorism) Map, the "first-of-its-kind interactive and customizable map detailing hate, extremist and antisemitic incidents by state and nationwide" devised by its Center on Extremism to record and visualize hate related occurrences.[14] The ADL kept track of 18,453 incidents from 2002 to 2020. The data is updated on a monthly basis with a combined record of anti-Semitic and

[13] Additional information is listed in Appendix A. Information on the methodology, including the list of bias-motivations and offense types published in 2019 can be found at https://ucr.fbi.gov/hate-crime/2019/resource-pages/methodology

[14] Retrieved from https://www.adl.org/education-and-resources/resource-knowledge-base/adl-heat-map

extremist incidents such as vandalism, harassment, assault, and White supremist propaganda incidents. Among all these incidents, I keep track of 17,894 incidents from 2016 to 2020. [15]

3) Stop AAPI Hate

The other hate incident dataset is from the Stop AAPI Hate (http://stopaapihate.org/), an initiative formed by the Asian Pacific Policy and Planning Council (AP3CON), Chinese for Affirmative Action (CAA) and the Asian American Studies Department at the San Francisco State University (AAS) to keep track of hate incidents against Asian Americans and Pacific Islanders followed by the COVID-19 pandemic. Its website allows its users to report hate crime incidents and releases monthly and quarterly reports derived from its users. The requested data from the AAPI included further details on each of the reported incidents such as the victim's ethnicity and offense type with the time the incidents were reported.[16]

Since the initiative began receiving reports in 2020, most of the reported hate incidents were from 2020 with only few reports reported in retrospect before 2020. Furthermore, the data was cleaned by the Stop AAPI Hate, some of the reported incidents had dates that were beyond the dates they were reported (e.g hate crime reported on 2020 report with an incident date of 2024). Such data were not included in the analysis. Therefore, the study used 245 hate incidents from the year 2020 only.

The datasets from the ADL and Stop AAPI Hate focus on each specific bias groups, unlike the FBI UCR hate crime reports that keeps track of hate crimes motivated by diverse biases such as gender identification, sex, and disability. The two datasets also record hate "incidents" that may not be considered criminal and may not be considered under the FBI's definition of hate crime.

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[15] More information can be found in Appendix B.

[16] Detailed reports of all the reported hate incidents with examples can be found at https://stopaapihate.org/reports/.

Such data may help shed light to some of the incidents that may not have been reported in the FBI hate crime data, reducing the potential issue of underreporting.

4.3 Data on hate speech

The data on the incidence of hate crime was merged with the data on the local digital news media sources extracted by Media Cloud (http://mediacloud.org). Media Cloud is an open platform that automatically collects its stories from user-generated collections of media sources via its RSS feeds. The platform includes geographical collections in over 100 countries in various languages as well as local-level news collections for numerous states and provinces as well as collections such as "U.S Top Digital Native Sources 2018," "U.S Top Newspapers 2018," with collections associated with political partisanships such as "center left," "right," and "center." [17]

For the purposes of the research, the "Explorer" component of Media Cloud was used to search for the number of keywords appearing in digital news media on a daily basis. The Explorer query searches for the listed keywords in each news story, returning the results that include any of the designated keywords in the story content.[18]

The keywords were searched in each of the state-level news collections in its "State & Local" sources of Media Cloud that contained local media contents from each of the fifty states and the District of Columbia. Three lists of keywords were designed to be indicative of discrimination towards each category of bias: 1) immigrants, 2) Jewish (religious-bias), 3) Black (racial bias). The selected list of keywords follow the suggestions of previous literature, each derived from the literature on immigrant news reporting by the Define American and the MIT

[17] More information can be found in its website https://mediacloud.org/.
[18] Further information about Media Cloud's query function can be found at https://mediacloud.org/support/query-guide.

Center for Civic Media[19], the AJC hate speech dictionary[20], and the NABJ Style Guide following its Statement on Capitalizing Black and Other Racial Identifiers.[21]

It would be critical to examine the context in which the keywords are used to examine if they are potentially relevant indicators of hate speech. To tackle the issue, Media Cloud offers additional features such as showing an ordered word cloud with "Top Words" or the most frequently used words. The search results shown in the ordered word cloud demonstrated further how words were used frequently in the representative samples taken from the media.

Using these features, I experimented in the keywords in "United States – National" collection of media sources fetched from January 1st, 2016 to December 31st, 2020. This ensured that the query included relevant materials, although it may not have completely ruled out the possibility of including several news sources with irrelevant content.[22]

The first query with the list of anti-immigrant keywords are as follows: [illegals, chain migration, anchor baby, anchor babies, immigrant parasite, immigrant invasion, migrant invasion, immigrant invading, migrant invading]. The first five lines of the ordered word cloud that show the most frequently used keywords related to the search are listed below.

Figure 1. Five rows of "Top Words" from the query of anti-immigrant keywords

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[19] Ndulue, Bermejo, et al, 2019 "The Language of Immigration Reporting: Normalizing vs. Watchdogging in a Nativist Age," https://www.defineamerican.com/journalismreport
[20] AJC Translate Hate Glossary retrieved from https://www.ajc.org/translatehate
[21] NABJ Style Guide can be found at https://www.nabj.org/page/styleguide
[22] Examples of representative news articles from the query results can be found in Appendix C.

The second list containing anti-Semitic keywords are “blood libel,” cabal, deicide, “dual loyalty”, “The Goyim Know,” "Holocaust denial,” "Jewish lightning,” "Zionist Occupied Government" and QAnon.

The third list of anti-Black keywords are "colored people", darkie, "inner city", mulatto, negro, nigger, and Sambo.

In addition to these keywords, Asian American communities such as the Stop AAPI Hate initiative have been arguing against xenophobic and scapegoating anti-Chinese rhetoric such as “Kung Flu” or “China virus” following the COVID-19 pandemic. Thus, the list of relevant keywords that may affect Asian American and Pacific Islander communities (“China virus,” “Chinese virus,” “Kung flu,” “Wuhan virus”) were generated to examine its possible effects on the Stop AAPI dataset for the year 2020 only. The list of words related only to COVID-19 (“coronavirus,” “covid,” “covid19,” “corona”) was also created to compare the effects of hate speech compared to news coverage on the pandemic in general.

Lastly, one would have to test the placebo effects of keywords not directly related to hate speech to account for the possible confounding factors that can be confused as the effects of hate speech. Thus, the list of ten random words were created using an online “random word generator” to test for placebo effects. The words were [search, art, discovery, spooky, confused, tendency, temporary, obsolete, detailed, decorate, father, and stay]. The query yields a greater variety of topics one may find in daily news, although there are overlapping political topics with other lists of keywords including “immigration.” [23]

The data including the ratio of all these lists of words were imported from the state-level news sources collections including all fifty states and the District of Columbia, with the dates

[23] The “Top Words” results for all the list of keywords can be found in the Appendix D.

from January 1st, 2016 to December 31st, 2020. The task of searching for the keywords and downloading data from each of the state-level collections were done manually for the first round of lists. The rest of the process was mostly automated with a Python script that repeats the process of fetching data for the given query of keywords across different news media collections. The process was monitored with the Python 'watchdog' library that tracked changes in the file directory and visually inspected again to ensure that they were downloaded without error.[24]

The .csv file of the query results include data with dates from January 1st, 2016 to December 31st, 2020, corresponding to the extent of the hate crimes and incidents datasets. The data includes the count of news stories that contain the keywords, the total number of news stories on each given date, and the ratio that shows the proportion of stories containing the keywords to the number of total stories.

4.4 Merged data

The reported hate crime incidents were merged with the data extracted from the existing state-level geographical collections of Media Cloud at state-level. Below is the table of the main hate crime/incidents per capita variables used in the study.

Table 1. Descriptive Statistics of Main Variables

Variables	Mean	Std. Dev	Min	Max	N
FBI UCR hate crime data 2016-2019					
Hate crimes per capita	.2157327	.3549146	0	4.675883	2448
Racial/ ethnic/ ancestry-bias crimes per capita	.1245062	.1983974	0	2.446374	2448
Anti-Arab crimes per capita	.0025064	.013132	0	.2916238	2448
Anti-Black crimes per capita	.0560253	.0822282	0	1.439044	2448
Anti-Hispanic crimes per capita	.0136377	.0417704	0	.7127106	2448
Anti-Asian crimes per capita	.0035149	.0129355	0	.1458119	2448
Religious bias crimes per capita	.0374409	.0645483	0	.5832477	2448
Anti-Jewish crimes per capita	.0193611	.0474146	0	.5629242	2448
Anti-Muslim crimes per capita	.0070805	.0235726	0	.4276264	2448

[24] The Python script can be found in Appendix E.

ADL HEAT Map data 2016-2020					
Incidents per capita	.1053368	.2115417	0	4.006481	3060
anti-Semitic incidents per capita	.0415756	.0813667	0	.9977949	3060
extremist incidents per capita	.0007313	.00516	0	.1351899	3060
White supremacist event per capita	.0022916	.0151504	0	.4276264	3060
White supremacist propaganda per capita	.0650914	.1921833	0	4.004113	3060
Stop AAPI Hate incidents data 2020					
Incidents per capita	.0387371	.1257184	0	1.842015	612
Media Cloud Ratio 2016-2020					
ratio of stories with Anti-immigrant keywords	.0811275	.023804	0	.2666667	3060
ratio of stories with Anti-Semitic keywords	.0002411	.0004187	0	.0114943	3060
ratio of stories with Anti-Black keywords	.0015073	.0012754	0	.025641	3060
ratio of stories with random keywords (placebo)	.1560715	.0463911	0	.3888889	3060
Media Cloud Ratio 2020					
ratio of stories with anti-Chinese keywords	.0011018	.0008455	0	.0052614	612
ratio of stories with COVID-19 related keywords	.3595531	.1776258	.0072236	.754717	612

4.5 Research Design

The ratio measures of hate speech from Media Cloud were merged with the different datasets related to hate incidents and extremist events. The data for both dependent and independent variables were merged one-by-one, with each observation showing variables of one year-month for each state-level. The one-on-one merging of the datasets are as follows:

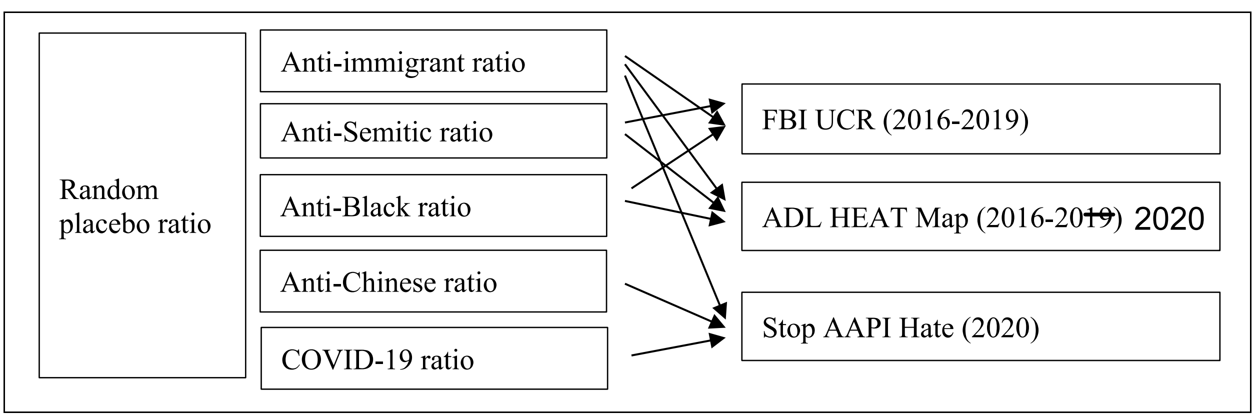

Figure 2. One-on-one merging of ratios and hate incidents data

The research uses a regression model with state and year-fixed effects model to account for time-invariant state characteristics and nation-wide trends in hate speech and hate crime across time. The regression equation is as follows:

$$HateCrime_{s,t} = \gamma_s + \gamma_t + \beta\, HateSpeech_{s,t} + X_{s,t}\Phi + \epsilon_{s,t}$$

$HateCrime_{s,t}$ refers to the number of reported hate crime incidents per 100,000 population in state s during time t. I include the state fixed-effect γ_s to account for any state-level time-invariant biases across the localities. γ_t is the time fixed effect that accounts for yearly confounders. $HateSpeech_{s,t}$ is the proportion of keywords appearing on local news media in state s during time t. $X_{s,t}\Phi$ is a vector of control variables that includes all other time-varying control factors that may influence the state's hate crime rate over time such as income, unemployment, poverty, law enforcement level, and change in racial demographics.

Fluctuation in the number of news reports can also be due to many other sources outside the effects of news reporting. Some states have meager news reports with less than ten counts a day, while others may have more than hundreds. There is also a relative dearth of the early years of news reports collected digitally than in the more recent years. Thus, the study excludes the early years prior to 2016 with less data and uses the "ratio" of the frequency of keywords in the news media instead of just the numeric count of the keywords appearing on news media to help remedy the issue. Placebo list of words not related to hate speech was also introduced to further push a causal claim on the results.

Another possible issue is that the prevalence of keywords related to hate may increase as the result of news coverage on hate incidents rather than causing them. To remedy this issue of potential reverse causality, lags for the treatment were introduced. The introduction of lags would help compare the contemporaneous and the long-lasting effects of speech.

5. Main Results

5.1 Effects of anti-immigrant speech

First, I examine the regression results of the measurement of anti-immigrant speech on the extremist and White supremacist incidents recorded in the ADL H.E.A.T Map.

Table 2. Effects of anti-immigrant hate speech on extremist and White supremacist incidents 2016-2020

	(1)		**(2)**	
	log (extremist incidents per capita)		**log (White supremacist event per capita)**	
Anti-immigrant news ratio	0.009 (0.005)		0.023* (0.009)	
Anti- immigrant news ratio (lagged)		0.019* (0.009)		0.014 (0.008)
Placebo news ratio coefficient	0.006* (0.003)		0.004 (0.004)	
Placebo news ratio coefficient (lagged)		0.010* (0.005)		0.006 (0.005)
Constant	0.002 (0.002)	0.001 (0.002)	-0.004*** (0.001)	-0.003*** (0.001)
N	3060	3009	3060	3009
R-squared	0.023	0.026	0.175	0.177
State FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

t statistics in parentheses: * p<0.1, ** p<0.05, *** p<0.01

As shown in the two columns of Table 2, the results showed positive correlation for both extremist incidents and White supremacist events, supporting Hypothesis 1. The regression with White supremacist event in column 2 showed a positive correlation with statistical significance at 10% level that outweighs the coefficient of the placebo. The regression with extremist incidents in column 1 also showed a positive correlation with statistical significance at 10% level, although one should take the results with caution as the placebo also demonstrated statistically significant positive correlation with slightly lower coefficient.

Next, I report the results for the measures of anti-immigrant hate speech on hate crime variables to test Hypothesis 2 of the relation between hate speech and hate incidents. The regression results in Table 2 show the effects of immigrant hate speech with the corresponding hate crime reports of 2016 to 2019 from the FBI UCR.

In both columns 1 and 2, the regression of anti-immigrant speech with hate crime per capita show high statistical significance at 5% level with greater coefficients than the placebo effect generated with random keywords. This suggests a strong positive correlation between immigrant hate speech and hate crime levels.

Table 3. Effects of anti-immigrant speech on bias-motivated hate crimes 2016-2019

	(1) log (All hate crime per capita)		**(2) log (All racial/ethnic/ancestry bias-crimes per capita)**		**(3) log (All religious bias-crimes per capita)**	
Anti-immigrant news ratio	0.314** (0.107)		0.290*** (0.084)		0.052 (0.048)	
Anti-immigrant news ratio (lagged)		0.225* (0.110)		0.156 (0.085)		0.051 (0.048)
Placebo news ratio coefficient	0.109 (0.067)		0.085 (0.052)		0.031 (0.029)	

Placebo news ratio coefficient (lagged)		0.100 (0.070)		0.079 (0.056)		0.061* (0.030)
Constant	0.044* (0.021)	0.052* (0.021)	0.029 (0.016)	0.039* (0.016)	0.001 (0.006)	0.002 (0.006)
N	2448	2397	2448	2397	2448	2397
R-squared	0.772	0.774	0.649	0.653	0.398	0.401
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

t statistics in parentheses: * $p<0.1$, ** $p<0.05$, *** $p<0.01$

The regression was also examined with the two most typical biases of hate crime: race/ethnicity/ancestry and religion. The results listed in Table 2 show how the effects show strong statistical significance at 1% level with the log of racial, ethnic, and ancestry bias crimes per capita in column 2. The effects have a stronger positive and statistically significant relation that affects racial/ethnic/and ancestry bias crimes than religious bias crimes demonstrated in column 3. Religious bias crimes per capita also show positive relation, although not statistically significant.

It is worth noting that the positive correlation between all reported hate crimes per capita and anti-immigrant news ratio shown in column 1 lasts with a month lag at 10% statistical significance. Further examination of the effects of racial/ethnic/ancestry bias crimes and religious bias crimes also demonstrate positive correlation, although they fall short of statistical significance. The positive signs of the coefficients persisting with lags prove that the correlation may not just be due to the contemporaneous effects of the hate crimes on news reports.

While there is no equivalent measure of hate crimes motivated by immigrant biases in the data to further test the hypothesis, one can examine potentially related sub-categories to estimate the possible effects:

Table 4. Effects of anti-immigrant speech on specific categories of bias-motivated hate crimes 2016-2019

	(1) log (Anti-Black crimes per capita)		(2) log (Anti-Hispanic crimes per capita)		(3) log (Anti-Asian crimes per capita)		(4) log (Anti-Arab crimes per capita) (racial bias)		(5) log (Anti-Muslim crimes per capita) (religious bias)	
Anti-immigrant news ratio	0.117* (0.052)		0.064** (0.024)		0.020 (0.010)		0.019 (0.012)		0.023 (0.019)	
Anti-immigrant news ratio (lagged)		0.051 (0.051)		0.056* (0.024)		0.026* (0.013)		0.005 (0.007)		-0.009 (0.020)
Placebo news ratio coefficient	0.019 (0.032)		0.020 (0.017)		0.017 (0.011)		0.003 (0.004)		-0.003 (0.013)	
Placebo news ratio coefficient (lagged)		0.038 (0.035)		0.013 (0.023)		0.018* (0.008)		0.005 (0.004)		0.012 (0.012)
Constant	0.015 (0.011)	0.021 (0.012)	-0.007* (0.002)	-0.007* (0.002)	0.001 (0.003)	-0.000 (0.003)	-0.002* (0.001)	-0.001 (0.001)	0.000 (0.002)	0.003 (0.002)
N	2448	2397	2448	2397	2448	2397	2448	2397	2448	2397
R-squared	0.433	0.439	0.487	0.498	0.125	0.125	0.210	0.214	0.128	0.131
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

t statistics in parentheses: * p<0.1, ** p<0.05, *** p<0.01

The results in Table 4 show positive correlations for all sub categories with coefficients larger than the placebo effects, except for anti-Muslim crimes with one month lag in column 5. The relation is most notable with statistical significance in the instance of anti-Black crime and anti-Hispanic, each with 10% and 5% of statistical significance as shown in columns 1 and 2. The anti-Asian crime in column 3 also exhibit statistical significance at 10% level with one month lag, although one should note that the placebo effects show a slightly lower positive correlation with statistical significance as well.

The robust significance found in these specific racial biases suggest a strong meaningful correlation between anti-immigrant hate speech and hate crimes against people of color, most notably those motivated by anti-Hispanic bias. The results suggest interesting implications, considering how the time period from 2016 to 2019 coincide with the propagation of Trump's political rhetoric. Trump has often been criticized for his xenophobic rhetoric against immigrants, especially towards Hispanics. Trump's most noted controversial political campaign was to build a wall against Mexico, denouncing the Mexicans as "criminals" or "rapists." Such disparaging effects of hate speech in the news media may have aggregated hate incidents against Hispanics during the affected time period.

Finally, I examined the Stop AAPI Hate data to see if the effects of anti-immigrant speech are replicated in Anti-Asian and Pacific Islanders incidents. Tthe effects showed statistically significant positive correlation with one month lag when only the state-fixed effects were applied, similar to the results of Table 4. However, the results showed negative correlation when the month-fixed effects were also applied.

Table 5. Effects of anti-immigrant speech on specific categories of bias-motivated hate incidents of 2020

	Dependent variable: log (Anti-Asian and Pacific Islanders Hate Incidents per capita) (year 2020)			
Anti-immigrant news ratio	-0.463 (0.236)		-0.479 (0.283)	
Anti-immigrant news ratio (lagged)		1.134*** (0.327)		-0.648 (0.350)
Placebo news ratio coefficients	0.839*** (0.098)		-0.080 (0.156)	
Placebo news ratio coefficients (lagged)		0.179* (0.080)		0.077 (0.158)

Constant	0.031* (0.015)	-0.040* (0.019)	0.008 (0.018)	-0.004 (0.015)
N	612	561	612	561
R-squared	0.239	0.278	0.501	0.517
State FE	YES	YES	YES	YES
Month FE	NO	NO	YES	YES

t statistics in parentheses: * p<0.1, ** p<0.05, *** p<0.01

5.2 Effects of anti-Semitic speech

Next, we focus on the impact of anti-Semitic speech, as reported in Table 6 and Table 7. The regression results of the ADL dataset reveal inconsistent results with a mixture of signs in the coefficients throughout.

Table 6. Effects of anti-Semitic speech on anti-Semitic and Extremist incidents 2016-2020

	(1) log (all incidents per capita)		(2) log (Anti-Semitic incidents per capita)		(3) log (extremist incidents per capita)		(4) log (White Supremacist events per capita)	
Anti-Semitic news ratio	-3.107 (3.151)		-2.606 (1.633)		-0.278 (0.176)		0.032 (0.235)	
Anti-Semitic news ratio (lagged)		4.796 (3.893)		-1.215 (1.606)		0.103 (0.401)		0.954 (0.663)
Placebo ratio coefficient	0.075 (0.067)		-0.029 (0.026)		0.006* (0.003)		0.004 (0.004)	
Placebo ratio coefficient (lagged)		0.005 (0.074)		-0.031 (0.025)		0.010* (0.005)		0.006 (0.005)
Constant	-0.037*** (0.010)	-0.039*** (0.010)	-0.003 (0.004)	-0.003 (0.004)	0.002 (0.002)	0.002 (0.002)	-0.002*** (0.000)	-0.045*** (0.000)
N	3060	3009	3060	3009	3060	3009	3060	3009
R-squared	0.456	0.459	0.459	0.463	0.022	0.021	0.174	0.178
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

t statistics in parentheses: * p<0.1, ** p<0.05, *** p<0.01

Table 7. Effects of anti-Semitic speech on bias-motivated hate crimes 2016-2019

	(1) log (All hate crime per capita)		(2) log (All racial bias-crimes per capita)		(3) log (All religious bias-crimes per capita)		(4) log (Anti-Semtic crimes per capita)	
Anti-Semitic news ratio	-0.602 (4.707)		-0.662 (3.280)		0.076 (1.919)		-0.891 (1.089)	
Anti-Semitic news ratio (lagged)		6.878 (5.338)		2.538 (3.980)		1.921 (2.816)		-1.172 (0.874)
Placebo ratio coefficient	0.109 (0.067)		0.085 (0.052)		0.031 (0.029)		-0.008 (0.016)	
Placebo ratio coefficient (lagged)		0.100 (0.070)		0.079 (0.056)		0.061* (0.030)		0.006 (0.018)
Constant	0.068*** (0.018)	0.066*** (0.018)	0.052*** (0.015)	0.050*** (0.015)	0.005 (0.005)	0.005 (0.004)	0.004 (0.004)	0.004 (0.004)
N	2448	2397	2448	2397	2448	2397	2448	2397
R-squared	0.771	0.774	0.647	0.653	0.397	0.401	0.477	0.482
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

t statistics in parentheses: * p<0.1, ** p<0.05, *** p<0.01

The inconsistency of the regression results do not in themselves help demonstrate the effects of the rise in anti-Semitic speech. The regression results with the hate crime dataset showed similar findings with inconsistent signs of coefficients, which did not suggest substantial evidence to back the hypothesis.

5.3 Effects of anti-Black speech

In Table 8, the regression results with extremist and White Supremacist incidents demonstrated a positive relationship that disappeared with one month lag in White Supremacist events. Yet, the results did not yield any findings over the statistically significant threshold.

Table 8. Effects of anti-Black speech on extremist and White Supremacist incidents 2016-2020

	(1) **log (extremist incidents per capita)**		**(2)** **log (White Supremacist events per capita)**	
Anti-Black news ratio	0.105 (0.128)		0.031 (0.128)	
Anti-Black news ratio (lagged)		0.064 (0.091)		-0.038 (0.104)
Placebo ratio	0.006* (0.003)		0.004 (0.004)	
Placebo ratio (lagged)		0.010* (0.005)		0.006 (0.005)
Constant	0.002 (0.002)	0.002 (0.002)	-0.002*** (0.000)	-0.002*** (0.000)
N	3060	3009	3060	3009
R-squared	0.022	0.021	0.174	0.177
State FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

t statistics in parentheses: * p<0.1, ** p<0.05, *** p<0.01

In Table 9, the regression results with anti-Black speech show a constant positive effect after the one-month lag. Moreover, the incidence on religious bias crimes per capita is statistically significant at the 10% level with one month lag, suggesting that the rise of anti-Black speech could be indicative of rise of religious-bias crime per capita after one month of news coverage. Yet, the results need be taken with caution as the coefficient of the placebo effect also showed statistically significant positive relationship with less size.

Table 9. Effects of anti-Black speech on bias-motivated hate crimes 2016-2019

	(1) log (All hate crime per capita)		(2) log (All racial bias-crimes per capita)		(3) log (All religious bias-crimes per capita)		(4) log (Anti-Black crimes per capita)	
anti-Black news ratio	-0.104 (1.742)		-0.697 (1.227)		0.632 (0.691)		-1.016 (0.704)	
anti-Black news ratio (lagged)		2.311 (2.119)		1.079 (1.410)		2.140* (1.039)		0.888 (1.134)
Placebo ratio	0.109 (0.067)		0.085 (0.052)		0.031 (0.029)		0.019 (0.032)	
Placebo ratio (lagged)		0.100 (0.070)		0.079 (0.056)		0.061* (0.030)		0.038 (0.035)
Constant	0.068*** (0.018)	0.068*** (0.018)	0.052*** (0.014)	0.051*** (0.015)	0.005 (0.005)	0.005 (0.005)	0.024* (0.011)	0.024* (0.011)
N	2448	2397	2448	2397	2448	2397	2448	2397
R-squared	0.771	0.774	0.647	0.653	0.397	0.403	0.433	0.439
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

t statistics in parentheses: * p<0.1, ** p<0.05, *** p<0.01

5.4 Effects of anti-Chinese rhetoric in the coverage of COVID-19

The Stop AAPI Hate dataset was used in addition to the previous findings to examine the effects of the hate rhetoric surrounding the recent pandemic. The results in Table 10 show a stronger, positive correlation to state-level incidence of hate crime than just coverage of COVID-19 or the results for placebo effects. However, the results should be taken with caution since some of the coefficients did not have statistical significance with month-fixed effects.

Table 10. Effects of different COVID-19 coverage on hate incidents per capita

	Dependent variable: log (Anti-Asian and Pacific Islanders Hate Incidents per capita) (year 2020)							
Anti-Chinese news ratio	34.922*** (8.188)				13.694 (9.038)			
Anti-Chinese news ratio (lagged)		27.942*** (5.444)				3.489 (8.253)		
COVID-19 news ratio			0.152*** (0.020)				0.179** (0.055)	
COVID-19 news ratio (lagged)				-0.060* (0.026)				0.177** (0.068)
Placebo news ratio coefficients	0.839*** (0.098)		-0.080 (0.156)		0.839*** (0.098)		-0.080 (0.156)	
Placebo news ratio coefficients (lagged)		0.179* (0.080)		0.077 (0.158)		0.179* (0.080)		0.077 (0.158)
Constant	-0.012 (0.011)	-0.007 (0.013)	-0.026* (0.012)	0.026* (0.013)	-0.039* (0.017)	-0.023* (0.010)	-0.002 (0.011)	-0.065*** (0.019)
N	612	561	612	561	612	561	612	561
R-squared	0.326	0.311	0.323	0.270	0.505	0.515	0.504	0.518
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	NO	NO	NO	NO	YES	YES	YES	YES

6. Discussion

6.1 Discussion of main results

The paper examined the effects of the media's hate speech on the incidents of hate crimes and incidents. The theory was that the hate speech would affect the social environment by making it more justifiable to openly express discriminatory beliefs, with a higher likelihood of exhibiting them in ways such as violence that are often noted in hate crimes and incidents. The theory was tested with two hypotheses. First, the effects of hate speech on affecting the social environment would be evidenced by the rise in the levels of extremist and White Supremacist incidents. Second, the effects would then be shown in the rise of hate incidents and hate crimes that follow.

The research found some support for both hypotheses, with several statistically significant positive associations observed in the dependent variables tested with the regression on anti-immigrant speech two-way fixed effects. The findings show statistically significant positive correlation for people of color, with its effects consistent with or without lags in the measure of anti-Hispanic hate crimes reported in the FBI UCR dataset. It is worth noting how the years from 2016 to 2019 observed in the data has been the time when the Trump administration propagated anti-immigrant rhetoric, mostly by associating Hispanics to negative imagery such as "rapist" or "criminal."

Another important finding of the study was that it observed greater positive regression results between anti-Chinese rhetoric and hate incidents reported to the Stop AAPI Hate initiative than just the effects of the coverage of COVID-19. The results had strong statistical significance with state-fixed effects, but not when adjusted with month-fixed effects. Additional data for the year following 2020 would help examine whether there may exist positive correlation with statistical significance with year-fixed effects.

On the other hand, the regression results showed inconsistent findings for the effects of anti-Semitic speech and results without statistical significance for anti-Black speech. The exception was that anti-Black speech showed positive with statistical significance for hate crimes motivated by religious biases, either with or without one month lag. The results show interesting findings that can bring further implications, although it differs from the results predicted by the original hypothesis that hate speech would greatly affect the groups that are more closely affected by the hate speech than those that are not.

In conclusion, while the regression results for anti-Semitic and anti-Black speech remained inconclusive mostly without statistical significance, the study found an interesting pattern with anti-immigrant speech that may demonstrate its potential effects on the rise of hate crime and incidents. The xenophobic hate speech in the news media in its coverage related to COVID-19 also had greater effects on the incidents of affected biases rather than just coverage in general.

6.2 Discussion for future research

Despite some noteworthy findings, there are several improvements that can be made for future analysis. To begin with, results can vary depending on how the research is designed to measure hate speech. While the Media Cloud is a helpful platform for searching designated topics, the query results also contained self-narratives of hate incidents and articles that criticize rather than endorse rhetoric indicative of hate speech. Further refined search showing only the news articles using or parroting hate speech in the news media would show clearer results that identify the effects of hate speech only.

In addition, as previously mentioned, hate crimes as well as bias incidents are greatly underreported, with potential flaws in the existing datasets. Such issues in data make the data on hate crime and hate incident fall short of reality. While tackling the issue of underreporting remains a challenging issue, the FBI hopes to alleviate some the noted problems in its data along with its recent development of the Crime Data Explorer (CDE). Updates include the adaptation of new features, input from federal agencies other than the UCR, and quarterly updates to remedy the issues noted in its previous annual publications. [25] Initiatives like the Anti-Defamation League and the Stop AAPI also continue to documentation bias incidents with

[25] Accessible at https://www.theiacp.org/sites/default/files/December%202019%20Tech%20Talk.pdf

extensive research on the root causes of hate incidents. The continuation of data collection and research would help advance the study on what constitutes as hate speech and how it can cause real harm in society.

6.3 Discussion of policy implications

The results showing the potential effects of the news media's reporting also have several implications for policy making. The potential damaging effects of journalism in contributing to an environment that condones prejudiced beliefs as evidenced in this study illustrate the need for the discourse of the role of journalism and the news media crucial, especially in its coverage of minorities. While it would be advisable for journalists to consult their own personal biases before drafting their news headlines, ethical codes or guidelines can also be implemented for journalists to follow. As cited in the previous literature review section, mass media channels such as the Associated Press made conscious changes in their AP Stylebook to change the way they describe undocumented immigrants.[26] Meanwhile, organizations like the National Association of Black Journalists (NABJ) offers a Style Guide for journalists following its Statement on Capitalizing Black and Other Racial Identifiers.[27]

However, the potential clash of freedom of speech and the ethics of journalism remain a potential issue. Efforts to counter hate speech in the news media can curtail and limit the use of language, which can even lead to censorship. The United Nations, in its announcement of the launching of its Strategy and Plan of Action on Hate Speech, warned how the cause of hate speech can "be abused as an excuse to persecute anyone daring to criticize the authorities," which can lead to the risks of "imposing uniformity of views, curtailing dissent and shrinking

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[26] https://blog.ap.org/announcements/illegal-immigrant-no-more

[27] The NABJ Style Guide can be found at https://www.nabj.org/page/styleguide

civic space” (2019). Further discussion on the discourse seems necessary to set the appropriate boundaries between the freedom of expression and tackling hate speech, along with the calls for additional research and data as mentioned in the previous section.

Action can be taken not only towards the language of news media but also toward advancing a fairer amount of representation in the media. The mainstream media has been criticized for its lack of coverage on issues that deserve much national attention, such as the neglecting coverage on incidents affecting vulnerable populations such as Asian elders being targeted and murdered by anti-Asian crimes as previously mentioned. Given its immense influence, the media can encourage the discourse on the protection of minorities, as well as facilitating the much needed conversation lacking in terms of diversity such as race, gender, and ethnicity.

Lastly, individuals should be informed and be conscious of their media consumption as to not fall prey to the effects of discriminatory rhetoric. One should actively speak against any animosity and violence they may encounter whether in the political discourse or in daily life to hinder such behavior from being socially acceptable.

7. Conclusion

The research findings suggest that words may not just be ‘just words,’ particularly when they are used in the local news media. Considering how the hate speech keywords exhibited greater coefficient results, even when they dealt with the same issue of COVID-19, the words of journalism cannot be said to be irrelevant to the changes in the social and political climate.

The results would have vast implications, particularly given the recent context of rising hate crime amid the diversification of society. Further research and data collection would help identify the effects illustrated in the paper.

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Appendix

Appendix A. Additional information on FBI UCR hate crime data

Table A1. FBI UCR hate crimes per year

Hate crimes per year (state-level)	**Count**	**%**
2016	6,273	21.84
2017	7,322	25.49
2018	7,165	24.94
2019	7,969	27.74
Total	**28,729**	**100.00**

Table A2. FBI UCR hate crimes categorized by bias motivation

Bias motivation (include multi-bias)	**Count**	**%**
Race/Ethnicity/Ancestry	16,533	57.55
Religion	6,212	21.62
Sexual orientation	4,870	16.95
Gender identification	667	2.32
Disability	596	2.07
Total	**28,729**	**100.00**

Appendix B. Additional information on ADL H.E.A.T Map data

Table B1. ADL H.E.A.T Map reported incidents per year

Reported incidents per year (state-level)	**Count**	**%**
2016	1,324	7.40
2017	2,491	13.92
2018	3,053	17.06
2019	4,730	26.43
2020	6,296	35.18
Total	**17,894**	**100.00**

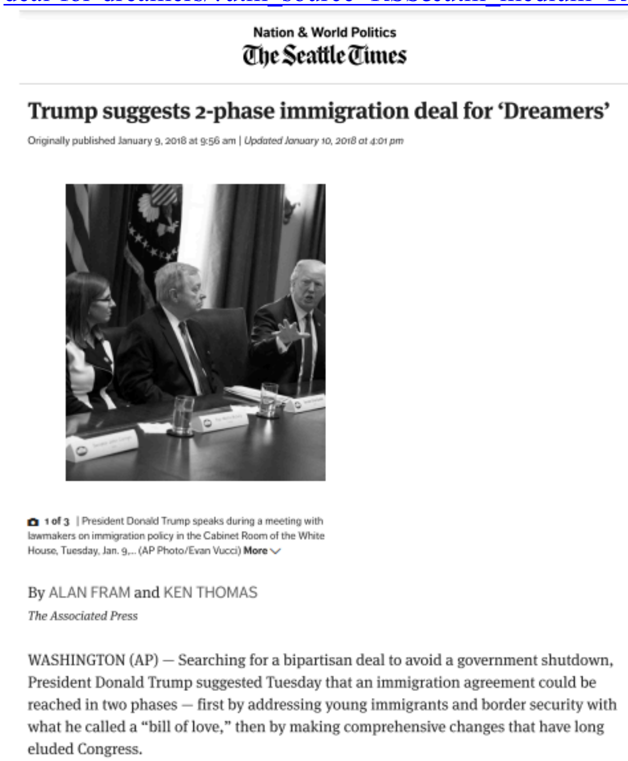
Table B2. ADL H.E.A.T Map categorized by incident types

Incident type (including overlaps)	**Count**	**%**
Anti-Semitic incidents (Assault, Harrassment, Vandalism)	8,596	48.04
Extremist incidents (murders, Extremist/Police Shootouts)	143	0.80
Terrorist Plots & Attacks	101	0.56
White Supremacist Events	304	1.70
White Supremacist Propaganda	9,486	53.01
Total	**17,894**	**100.00**

Appendix C. Sample news articles from the Media Cloud queries

Figure C2. Example of US national-level query with anti-immigrant keywords

(full article: https://www.seattletimes.com/nation-world/nation-politics/trump-suggests-2-phase-immigration-deal-for-dreamers/?utm_source=RSS&utm_medium=Referral&utm_campaign=RSS_all)



Nation & World Politics

The Seattle Times

Trump suggests 2-phase immigration deal for 'Dreamers'

Originally published January 9, 2018 at 9:56 am | *Updated January 10, 2018 at 4:01 pm*

1 of 3 | President Donald Trump speaks during a meeting with lawmakers on immigration policy in the Cabinet Room of the White House, Tuesday, Jan. 9,... (AP Photo/Evan Vucci) **More**

By ALAN FRAM and KEN THOMAS

The Associated Press

WASHINGTON (AP) — Searching for a bipartisan deal to avoid a government shutdown, President Donald Trump suggested Tuesday that an immigration agreement could be reached in two phases — first by addressing young immigrants and border security with what he called a "bill of love," then by making comprehensive changes that have long eluded Congress.

Figure C2. Example of US national-level query with anti-Semitic keywords

(full article: https://www.washingtonpost.com/business/energy/qanon-the-conspiracy-theorycreeping-into-us-politics/2020/09/22/9f7486a6-fcf8-11ea-b0e4-350e4e60cc91_story.html?utm_source=rss&utm_medium=referral&utm_campaign=wp_business)

Figure C3. Example of US national-level query with anti-Black keywords

(full article: https://www.vox.com/policy-and-politics/2017/6/6/15739538/bill-maher-n-word-real-time-racism)

Figure C4. Example of US national-level query of anti-Chinese keywords related to COVID-19

(full article: https://americanfreepress.net/trump-fauci-the-virus/?utm_source=rss&utm_medium=rss&utm_campaign=trump-fauci-the-virus)

Home › National News › Trump, Fauci & the Virus

Trump, Fauci & the Virus

September 25, 2020 Staff National News 2

By Donald Jeffries

Figure C5. Example of US national-level query of general COVID-19 related keywords

(full article: https://www.thedailybeast.com/johnson-and-johnson-halts-covid-19-vaccine-study-after-participant-comes-down-with-unexplained-illness)

Johnson & Johnson Halts COVID-19 Vaccine Study After Participant Comes Down With 'Unexplained Illness'

HITTING THE BRAKES

Danika Fears Breaking News Editor
Published Oct. 12, 2020 9:39PM ET

Chandan Khanna/Getty

Johnson & Johnson hit pause on its clinical trial for a coronavirus vaccine after a study participant came down with an "unexplained illness," the company told STAT. "We must respect this participant's

Figure C6. Example of US national-level query of random keywords

(full article: https://www.refinery29.com/en-us/2019/08/241598/teddy-quinlivan-transgender-model-chanel-beauty?utm_source=feed&utm_medium=rss)

Model Teddy Quinlivan Just Became The First Openly Trans Face Of Chanel Beauty

JACQUELINE KILIKITA
AUGUST 28, 2019, 1:00 AM

Yesterday, Teddy Quinlivan, a model and activist who has walked for Gucci, Chloé, and Louis Vuitton and worked with beauty brands such as Milk Makeup and Redken, took to Instagram to announce the exciting news that she is the first openly transgender person to work for Chanel.

Quinlivan shared a video from the beauty campaign, in which she's shown applying the brand's Rouge Coco lipstick in Légende, alongside an emotional caption. "I find I don't

Appendix D. Full list of "Top Words" from the Media Cloud queries

Figure D1. "Top Words" from the query of anti-immigrant keywords

Figure D2. "Top Words" from the query of anti-Semitic keywords

Figure D3. "Top Words" from the query of anti-Black keywords

Figure D4. “Top Words” from the query of anti-Chinese keywords related to COVID-19

Figure D5. “Top Words” from the query of general COVID-19 related keywords

Figure D6. “Top Words” from the query with random keywords

Appendix E. Python automation script code

Note: The code was run on a .py file with Python IDLE Shell 3.9.2 on a 1440 x 900 MacBook Air screen.

```
import os
import time
import datetime
import pyautogui

pyautogui.PAUSE = 3
pyautogui.FAILSAFE = True

list = ["Alaska", "Alabama", "Arkansas", "Arizona", "California United", "Colorado", "Connecticut", "Delaware", "Florida", "Georgia United", "Hawaii", "Iowa", "Idaho", "Illinois", "Indiana", "Kansas", "Kentucky", "Louisiana", "Massachusetts United", "Maryland", "Maine", "Michigan", "Minnesota", "Missouri", "Mississippi", "Montana United", "North Carolina", "North Dakota", "Nebraska", "New Hampshire", "New Jersey", "New Mexico", "Nevada", "New York", "Ohio", "Oklahoma", "Oregon", "Pennsylvania", "Rhode Island", "South Carolina", "South Dakota", "Tennessee", "Texas", "Utah", "Virginia", "Vermont", "Washington", "Wisconsin", "West Virginia", "Wyoming"]

for i in list:

    pyautogui.doubleClick(606, 505)
    pyautogui.doubleClick(189, 318)
    pyautogui.doubleClick(649,230)

    pyautogui.typewrite(i)
    pyautogui.press("enter")
    pyautogui.PAUSE
    pyautogui.moveTo(1105,488,0.5)
    pyautogui.click(1105,488)

    pyautogui.moveTo(105,509)
    pyautogui.click(105,509)
    pyautogui.moveTo(899,432)
    pyautogui.click(1254,614)
    pyautogui.scroll(-11)
```

```
pyautogui.moveTo(1198,653)
pyautogui.click(1198,653)
pyautogui.PAUSE
pyautogui.moveTo(1196,675)
pyautogui.click(1196,675)

print(i, datetime.datetime.now())


pyautogui.click(1396,675)
pyautogui.scroll(200)
pyautogui.click(895,450)


import time
import datetime
from watchdog.observers import Observer
from watchdog.events import FileSystemEventHandler
from time import sleep


class EventHandler(FileSystemEventHandler):
  def on_created(self, event):
    print(i, datetime.datetime.now(), end='')
    sleep(1)


if __name__ == "__main__":
  path = "/Users/ann/Downloads"
  event_handler = EventHandler()
  observer = Observer()
  observer.schedule(event_handler, path, recursive=True)
  observer.start()
try:
    while True:
      time.sleep(2)
      break
except:
    self.observer.stop()
```

```
        print("Error")
        self.observer.join()


    pyautogui.click(1396,675)
    pyautogui.scroll(200)
    pyautogui.click(897,400)
```