Vulnerability, Infection, and Anti-discrimination Among Asian Americans and COVID-19: Explorations into Race and Health Intersections in California

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Introduction

The year 2020 was marred by the outbreak of COVID-19 as large numbers of people, rich or poor, powerful or powerless, succumbed to the disease. As of February 11th, 2021, there were 27,318,881 confirmed infection cases and 474,980 deaths in the United States (COVID Dashboard, 2020).

This pandemic marked a vivid but bitter example of how the increasingly interdependent world and human mobility inflamed the spread of emerging infectious diseases (Ali & Keil, 2006; Barnett & Walker, 2008). As the pandemic spread further through community transmission, COVID-19 infection and death rates were differentiated as the result of the pre-existing vulnerability caused by racial injustice, socioeconomic inequality, and policy responses (Berkowitz et al., 2020). A report shows Blacks and Latinx are 1.8 times, Native Americans are ~2.22 times, and Native Hawaiian and Pacific Islanders are 3.04 times more likely than Whites to get infected (The Atlantic, 2020). Moreover, recent research also found that while COVID-19 infection is associated with residential segregation between whites and racial minorities but is not sensitive to the level of density of Asians (Yang et al., 2020). Thus, understanding vulnerability among different groups and areas is an important

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foundation to better understand the spread of COVID-19 and its impact on people's health and lives.

Meanwhile, the initial outbreak and large-scale spread of COVID-19 detected in the Chinese city of Wuhan, made Asian/Asian Americans (particularly Chinese) highly suspect as carriers. The rhetoric of "Chinese virus," "Wuhan virus," and "Kung-Flu" repeatedly used by the former U.S. President and other politicians further fanned anti-Asian/Asian American flames. Discrimination or hate crimes against this group increased exponentially as a result, evident in increasing reports by mainstream media and community organizations alike. The STOP AAPI HATE website, launched on March 19, 2020 received 2583 incident reports by August 5. These were likely underreported, as not everyone who experienced discrimination would be willing to report or even knew of the website. Moreover, 93% of the 1497 incidents in the first 4 weeks were reported in English (Jeung & Nham, 2020). Many new immigrants with limited English proficiency may not have been aware of the website or would be unable to report in English, whereas those who could use other language options provided might be unwilling to do so, as immigrants are less likely to trust public institutions (Michelson, 2007).

The purpose of this paper, therefore, is to report and analyze the double victimization among Asians/Asian Americans: their vulnerability to COVID-19 and anti-Asian discrimination and to identify and visualize salient geographical patterns. Our analytical framework is based on the Social Vulnerability Index with theoretical grounding in the moral panic literature. We aim to explore a method to better analyze race-specific COVID-19 patterns. Although our empirical focus is on Asian/Asian Americans, our method (with necessary modifications) will be applicable to other vulnerable groups in order to contribute to the existing literature of social vulnerability. We present the results of our empirical work of correlation, variance analysis and GIS mapping, then summarize findings and data limitations, suggest future research directions while providing policy implications.

Analytical Framework, Theoretical Foundation, and Research Questions

Our guiding principles and theoretical underpinnings lie in the existing literature on social vulnerability and moral panic.

Analytical Framework: Social Vulnerability

Social vulnerability is an outcome of social inequalities—demographical differences and socioeconomic characteristics that affect people's susceptibility to hazard or disease and ability to cope, as well as place inequalities characterized by the economic and social vitality of the local environment.

Geographer Susan Cutter was the first to introduce such a framework (Cutter, 1996). In order to quantify and spatialize the patterns of vulnerabilities across groups and space, Cutter et al. (2003) developed the Social Vulnerability Index by grouping 42 variables of demographic, socioeconomic characteristics, and building environment into 11 factors using principal component analysis. These 11 factors were constructed into an additive model to compute a summary score to explain the social vulnerability to an environmental hazard.

Since 2000, the Center for Disease Control and Prevention (CDC) has developed its own Social Vulnerability Index (SVI) to quantify and identify which communities are more vulnerable to health hazards and emergencies. The CDC SVI includes population and household characteristics only to better reflect social vulnerability to health effects. Drawing on data from the U.S. census and American Community Survey (ACS), the CDC SVI assembles a set of 15 variables into four themes. They are (1) socioeconomic (below poverty, unemployment, income, no high school diploma); (2) household composition and disability (>=65 years old, <=17 years old, civilians with disability, and single-parent household); (3) minority and language (% minority population and those with limited English proficiency), and (4) housing and transportation (multi-unit structures, mobile homes, crowding, no vehicle, and group quarters, CDC, 2020, p. 3. Among the 15 variables, there is a single measure of minority population (% of total); the other 14 variables are all measurements of the total population. The SVI is based on the calculation of the overall percentile ranking by summing up the rankings of each theme with equal weight (CDC, 2018). The resulting index ranges from 0.0 to the 1.0 (most vulnerable). An SVI score of 0.8 for a particular area means it is more vulnerable than 80% of all criteria measured.

The Social Vulnerability framework has been widely applied in hazard management and pandemic preparedness (Schmidtlein et al., 2008; Kiltz et al., 2013). Scholors have used it to analyze the impacts of diseases and disasters, such as Ebola in Liberia (Stanturf et al., 2015), COVID-19 in Kenya and the U.S. (Macharia et al., 2020; Nayak et al., 2020), and heat effects and Lyme disease in the U.S. (Ratnapradipa et al., 2017; Lehnert et al., 2020). U.S. city, county and state governments have adopted CDC SVI as indicators for disaster and disease prevention and intervention. Despite existing and other newly-built relevant indices, the CDC SVI remains the most widely used measure for COVID-19 reporting and analyses so far.

Over time, scholars have adapted this framework to fit various research scenarios, including diversifying the selection of the specific variables, changing the scaling and combination of indicators, and adding weighed configurations to improve construct validity (Rufat et al., 2019; Khajehei et al., 2020). The selection or the combination of variables greatly impact which population is identified as vulnerable (Chakraborty et al., 2005; Jones & Andrey, 2007). In extant literature, such selections include percentage of different racial groups (Rufat et al., 2019) or the number of recent immigrants (Oulahen et al., 2015). The spatial scale of SVI analysis varies from census block group (Tate, 2012), census tract (Schmidtlein et al., 2008; Burton, 2010), to county levels (Yoon, 2012).

By incorporating social characteristics such as race and ethnicity, the social vulnerability framework reveals that hazards or diseases may have a disproportional effect on certain populations. Studies find that minorities are more exposed to risks, due to cultural or linguistic barriers, lack of access to healthcare resources, and economic marginalization associated with their race and ethnicity (Hutchins et al., 2009; Kiltz et al., 2013). We use the social vulnerability framework, therefore, to guide our research because of its attentiveness to vulnerable populations and regional disparities.

Theoretical Framework: Moral Panics

Social vulnerability alone cannot explain why certain groups suffer more discrimination and hate crimes during disasters or pandemics. Moral panic theory enhances our understanding of the social construction of hate crimes and discriminations towards certain populations in general, and against Asians in the U.S. and elsewhere amid the COVID-19 crisis in particular. In *Folk Devils and Moral Panics*, Cohen (1972, p. 9) first systematically defined moral panic as “a condition, episode, person or group of persons emerges to become defined as a threat to societal values and interest.” Accordingly, the meaning of “folk devils” has evolved to be associated with the marginalized and demonized social groups such as people of color, immigrants, and people with HIV/AIDS, SARS and other communicable diseases (Muzzatti, 2005). Hence, the simultaneous intersection (Crenshaw, 1991) of one’s race, ethnicity, citizenship, and health conditions affect one’s social standing and relationships with others.

Moral panic theory has been used to investigate the intersections between race and health, particular on the stigmatization of certain social groups as carriers of disease across the globe. European Jews were blamed for the bubonic plague across Europe in the fourteenth and fifteenth centuries and were murdered or violently attacked as a result (Elwood, 1999). The 1918 influenza was commonly known as the “Spanish flu” even though the pandemic did not originate in Spain (Trilla et al., 2008). Similarly, other epidemics in the twentieth century also received colloquial names referencing a foreign group or area, including the Asian flu (1957–58), the Hong Kong flu (1968–69), and the Mexican swine flu (2009), reflecting xenophobic sentiment in public health history (Hoppe, 2018). The stigmatization associated with diseases went beyond naming. Discrimination is a significant consequence of moral panics, which often reinforce racial biases and stereotypes of minority populations. When the plague hit San Francisco at the turn of the twentieth century, Chinese were identified as health risks and Chinese residents were quarantined in San Francisco Chinatown and then nationally (McClain, 1988). The outbreak of severe acute respiratory syndrome (SARS) in Southern China in 2003 caused moral panics worldwide with Chinese and Asian communities being stigmatized for “inventing” the disease (Gilman, 2010). In many U.S. cities, Asian-owned businesses and Chinatowns suffered while people of Asian origin experienced various levels of discriminations from micro-aggression to physical attacks (Schram, 2003; Muzzatti, 2005).

Rooted in sociology, moral panic theory has been increasingly adopted by geographers to examine the inequality and geographical dimension of social relations (Knopp, 1997; Yoon, 2016). Most of these studies focused on everyday geographies of moral panics and rising fears about homosexuals, urban gangs and teen violence, illustrating how schools and family are the sites of moral panic and how local-level outbreaks of panics may stimulate wider fears within the society (Aitken, 2001; Luzia, 2008; Yoon, 2016). However, there is a lack of geographic research applying this framework to the study of discrimination amid pandemics. Our research uses the moral panic theory to investigate the hate crimes toward Asians during COVID-19 and adding to its usage in the geographical literature. Incorporating the geographic perspective of moral panics provides a spatially sensitive analysis of the landscape of hate crimes. It also enhances our understanding of how social constructions of discrimination are shaped by human intersections with the environment and the uses of everyday space.

Literature Gaps and Research Questions

Although SVI has become an umbrella analytical framework to gauge social vulnerabilities among various groups and areas, no customized SVI for a particular population group has been developed to the best of our knowledge. When examining the SVI among different population groups, existing work tends to replace a single variable (minority) with the percentage of a particular minority group (Burton, 2010; Yoon, 2012). However, when the study group is a specific minority, using CDC SVI for the general population without modification to focus on group-specific dynamics is not the best approach given it is lack of racial sensitivity measures. Moral panic theory connects pandemics to deep-rooted systematic racism, to reveal how racial discrimination and xenophobia propel backlash toward a particular social group and exaggerate fears of the disease itself. It cannot, however, fully explain the differentiation of discrimination and hate crime rates across regions.

We, therefore, aim to fill these gaps by addressing three research questions: (1) How can a customized SVI specifically applying to Asian communities be constructed and how does the resulting pattern differentiate from CDC SVI? (2) How can our measure of Asian-specific SVI explain the patterns of Asian COVID-19 infection incidence rate compared to the CDC's SVI? (3) Are there connections between the spatial distribution of Asian-specific SVI and anti-Asian discrimination and hate crimes?

Research Methods: Customized ASVI and Implementation

Data Sources

We collected the same 15 variables used in CDC's SVI calculation from the 2014 to 2018 ACS 5-year estimates at county- and census tract-level (U.S. Census Bureau, 2018). We then pooled the aforementioned set of four themes and 15 variables, but cross-tabulated them all with the "Asian alone" population and substituted "percentage minority population" with "percentage of foreign-born population." Asian-disaggregated summary datasets regarding (a) institutionalized population living in group quarters and (b) per household vehicle availability are not available in the ACS. Therefore, we substituted Asian data for institutionalized population from the 2010 census and per capita vehicle availability from the ACS.

The data for nation-wide county-level COVID-19 infections were pooled from the GitHub data repository for the 2019 Novel Coronavirus Visual Dashboard operated by the Johns Hopkins University Center for Systems Science and Engineering (Dong et al., 2020). Due to the lack of nation-wide racially disaggregated COVID-19 data released at the county level, we have limited our Asian COVID-19 analysis to the state of California. With the nation's highest Asian population, California had an early outbreak of COVID-19 and released race-specific data for 31 counties out of 58 countries. We used Google Search Results Scraper API provided by APIFY to collect Asian-specific COVID-19 infections data from each county's public health department, then manually verified the results for all 58 countries. All COVID-19 data were dated 4 November 2020 to rule out the further complicities as a result of variances introduced by holiday season travels and gatherings, the prevalence of new virus variants and vaccination distribution.

Methods

We first tested the validity of the CDC SVI as an analytical tool for COVID-19 analysis. We conducted a set of four thematic partial regressions and a full regression using 15 normalized variables from the CDC's SVI dataset to predict the COVID-19 incidence rate (infection per 100,000 population) at the county level.

As Table 1 suggests, in both partial and full regressions, most of the CDC's SVI variables demonstrated statistically significant effect on the county-level COVID-19 incidence rate, except for income, access to personal vehicle, and English proficiency. Our partial regression analysis of variance (ANOVA) showed that minority/language and socioeconomic vulnerability are important predictors of COVID-19 infection, explaining 18–19% of the variances in the models, while household composition and housing and transportation vulnerability both explained 13–14% of the variance. Our full regression ANOVA indicates that the CDC's SVI variables explained 34% of the variance in COVID-19 incidence rate. As the "% of variance

Table 1 Regression on CDC SVI and COVID-19 incidence rate

	m1		m2		m3		m4		m5	
	Effect	% VE	Effect	% VE	Effect	% VE	Effect	% VE	Effect	% VE
Socioecon		18.48								18.48
Poverty	929.13*	1.59							489.78*	1.59
Unemployed	867.77*	8.56							−418.07*	8.56
Income	108.4**	0.66							−57.821	0.66
No high school	560.1*	7.67							539.15*	7.67
Household composition				14.02						8.66
Under17			85.46*	5.78					293.58*	2.48
65+			−227.37*	3.12					140.01*	2.69
Disability			57.44	0.97					315.36*	2.68
Single parent			378.71*	4.16					129.67*	0.81
Minority						19.24				2.44
Minority share					656.84*	19.23			342.9*	1.90
Limit English					18.2	0.01			−201.06*	0.54
Housing and transport								12.55		4.43
Multi-unit							193.06*	0.10	257.33*	0.17
Mobile home							341.93*	5.90	108.73*	0.17
Crowding							283.04*	2.76	−124.41*	0.91
No vehicle							−66.59	0.01	−205.14*	0.87
Group quarter							300.2*	3.78	307.38*	2.30
Total										**34.01**

Data Source: US Bureau of the Census, 2014–18 American Community Survey
Note: *p <0.01, **<0.05
Abbreviation: *VE* variance explained

explained" column in model 5 shows, among the four themes, socioeconomic vulnerability remained as a strong predictor, whereas the other themes have decreasing power in explaining COVID-19 infection. Considering that the CDC's SVI framework has demonstrated satisfactory capability in explaining COVID-19, we chose to follow the CDC's calculations with our customization to Asian populations.

We aim to develop an ASVI that is directly comparable to the CDC SVI and whose method has adaptability potential to other vulnerable groups in order to portray group-specific vulnerability more accurately. We calculated the percentage difference between the Asian and general population for the 15 sociodemographic variables, and then used them as a set of weighting factors to apply to the CDC SVI raw scores. We then calculated the average Asian weights by each theme and the overall average and applied them to the CDC SVI and its four themed indices to construct the ASVI, along with four themed indices for more detailed comparisons. For instance, a place with a 0.8 CDC SVI but its Asian population could have a 20% overall lower score than the general population. We thus apply the weight [.8* (1–0.2)] to calculate an ASVI of 0.64, indicating the Asian population is less vulnerable than the general population in this place. Any ASVI above 1.0 indicates that the Asian population in the given area is more vulnerable compared to the general population anywhere in the nation. The resulting group-specific SVI allows comparisons with the CDC SVI, and among group-specific SVI including place-to-place variations.

We used these data to compose ASVI, then mapped them nationally to reveal the most vulnerable areas for Asian populations. Mapping the differences between Asian specific and CDC's SVIs allowed us to determine where in the country Asian populations have the sharpest difference from the CDC SVI of general population in order to reveal where Asian population are the most or least vulnerable. We used three categories of ASVI in the mapping: being higher, lower, or similar to (within) 50% range of CDC SVI.

Using race-specific COVID-19 data among the 31 California counties, we examined the Asian-specific COVID-19 statistics in relation to the ASVI comparison with the CDC SVI at a county level. We conducted correlations and variance analysis between ASVI (both overall score and the four themes) and Asian COVID-19 incidence rate (calculated as number of Asian COVID-19 infections per 100,000 Asian population), and compared those results to the analysis using the CDC's SVI and overall COVID-19 incidence rate (Table 2).

Finally, we analyzed the 815 reported anti-Asian discrimination and hate cases located in California from the national database of STOP AAPI HATE that included spatial references, and their correlation with Theme 3 of ASVI versus CDC SVI. We produced two maps of the geographical locations of anti-Asian incidents by city and overlaid them onto Asian-specific SVI at the census-tract level to visualize the fine-tuned spatial patterns of vulnerability and hate crimes in Southern Los Angeles County and surrounding area, and the San Francisco Bay Area.

Table 2 ASVI and COVID-19 infection rate: Selected counties in California

County	# Asian population	# Asian infection	Asian Incidence rate	Total Incidence rate	SVI	SVI Social economic	SVI household composition	SVI minority and language	SVI housing and transportation	ASVI	ASVI social economic	ASVI household composition	ASVI minority and language	ASVI housing and transport.	Difference SVI v ASVI
Alameda	479,923	2545	530.3	1445.7	0.47	0.25	0.02	0.98	0.92	0.85	0.19	0.02	4.49	1.03	−0.38
Contra Costa	184,230	1094	593.8	1676.5	0.41	0.25	0.14	0.96	0.48	0.65	0.17	0.12	3.38	0.65	−0.24
Fresno	99,118	1620	1634.4	3176.7	0.96	0.92	0.69	0.99	0.84	1.14	0.67	0.65	2.27	0.67	−0.18
Glenn	819	21	2534.8	2472.4	0.89	0.86	0.82	0.95	0.49	1.42	0.58	1.49	1.52	1.12	−0.53
Kern	40,788	820	2010.4	3839.5	0.97	0.94	0.56	0.98	0.92	1.02	0.51	0.47	2.01	0.73	−0.06
Kings	5639	79	1401.0	5658.4	0.97	0.93	0.61	0.98	0.94	1.00	0.42	0.55	1.70	0.99	−0.03
Lake	617	14	2269.0	1135.3	0.92	0.80	0.89	0.83	0.84	2.80	0.83	0.80	4.29	4.26	−1.88
Los Angeles	1,446,614	9321	644.3	3105.3	0.77	0.62	0.10	0.99	0.90	0.96	0.38	0.09	2.70	0.73	−0.19
Marin	14,528	109	750.3	2769.0	0.27	0.03	0.08	0.84	0.70	0.51	0.03	0.06	3.23	1.31	−0.24
Mendocino	1576	6	380.7	1359.1	0.88	0.70	0.82	0.88	0.85	1.34	0.52	0.83	1.93	1.82	−0.46
Merced	19,605	589	3005.0	3521.7	0.97	0.96	0.72	0.99	0.83	1.02	0.73	0.67	1.77	0.60	−0.05
Monterey	23,502	144	612.7	2722.4	0.80	0.58	0.35	0.99	0.84	0.80	0.36	0.36	1.29	0.92	−0.01
Napa	10,894	253	2322.4	1510.8	0.51	0.26	0.10	0.95	0.82	0.65	0.17	0.11	2.11	0.97	−0.14
Orange	629,543	2863	454.8	1908.4	0.42	0.32	0.05	0.97	0.57	0.66	0.25	0.04	3.57	0.57	−0.25
Plumas	140	4	2580.0	457.3	0.27	0.26	0.37	0.55	0.24	2.28	0.58	0.22	14.80	1.06	−2.01
Riverside	148,272	943	943.0	2809.4	0.79	0.69	0.38	0.97	0.66	0.97	0.43	0.32	2.39	0.62	−0.17
Sacramento	234,093	2209	943.6	1721.3	0.73	0.53	0.36	0.95	0.76	1.22	0.47	0.33	3.76	0.67	−0.48
San Benito	1724	41	2400.5	2353.2	0.52	0.50	0.39	0.98	0.20	0.51	0.28	0.30	1.49	0.20	0.02
San Bernardino	147,531	1531	1037.7	3027.3	0.90	0.83	0.47	0.98	0.81	1.11	0.43	0.40	2.62	0.72	−0.20
San Diego	385,885	624	624.0	1728.5	0.56	0.39	0.06	0.96	0.84	0.79	0.28	0.05	3.00	0.80	−0.23
San Francisco	294,399	1557	528.8	1424.1	0.39	0.22	0.00	0.97	0.95	0.80	0.24	0.00	4.81	1.01	−0.41

(continued)

Table 2 (continued)

County	# Asian population	# Asian infection	Asian Incidence rate	Total Incidence rate	SVI	SVI Social economic	SVI household composition	SVI minority and language	SVI housing and transportation	ASVI	ASVI social economic	ASVI household composition	ASVI minority and language	ASVI housing and transport.	Difference SVI v ASVI
San Joaquin	111,312	1454	1306.0	2908.5	0.89	0.76	0.60	0.98	0.81	1.30	0.57	0.56	3.26	0.67	−0.41
San Luis Obispo	8199	69	841.6	1533.7	0.37	0.23	0.05	0.84	0.78	0.75	0.22	0.04	3.41	1.67	−0.37
San Mateo	214,272	1112	519.0	1497.4	0.27	0.12	0.02	0.97	0.60	0.49	0.08	0.02	4.23	0.85	−0.22
Santa Barbara	19,899	183	919.6	2237.9	0.71	0.52	0.11	0.97	0.92	0.88	0.44	0.09	1.87	1.27	−0.17
Santa Clara	682,809	2669	390.9	1318.6	0.36	0.19	0.03	0.98	0.73	0.69	0.14	0.02	4.98	0.83	−0.34
Santa Cruz	9917	42	423.5	1084.9	0.54	0.43	0.03	0.93	0.90	0.75	0.39	0.03	1.82	1.52	−0.20
Solano	67,274	893	893.0	1753.4	0.59	0.37	0.27	0.96	0.69	0.97	0.24	0.26	3.89	0.64	−0.38
Sonoma	19,822	178	898.0	2013.4	0.40	0.26	0.09	0.90	0.65	0.62	0.21	0.07	2.86	0.86	−0.21
Stanislaus	29,089	72	248.6	3282.6	0.87	0.81	0.64	0.97	0.60	1.00	0.60	0.59	2.08	0.49	−0.13
Tulare	16,323	339	2076.8	3849.7	0.94	0.97	0.63	0.99	0.64	0.95	0.54	0.69	1.45	0.59	−0.01
Ventura	61,247	322	525.5	1745.5	0.48	0.34	0.12	0.96	0.55	0.52	0.19	0.10	1.86	0.56	−0.04

Data Source: US Bureau of the Census, 2014–18 American Community Survey; Department of Public Health, various counties

Empirical Results: ASVI, COVID-19 Impacts, and Anti-Asian Racism

Asian SVI v. CDC's SVI

Upon customizing the CDC SVI to ASVI, we were able to reveal the differential patterns of vulnerability between Asians and the general population in the United States. Due to the small size of Asian population in many regions of the country, we only were able to produce a robust index for 2873 counties (leaving the remaining 268 without a score, shown as blank in Fig. 1). The overall ASVI pattern shows that high score areas include agricultural or ranch regions such as the Appalachian area, the Central Valley, Imperial Valley, and Northern part of California, and Southern Oregon, as well as the Rust Belt region, Midwest, and deep South. These regions are often characterized by low socioeconomic status (SES) and precarious housing conditions among Asian population.

Comparing Asian-specific to CDC SVI reveals distinct differential patterns (Fig. 2). Most of the counties for which we produced ASVI have ASVI higher than their CDC SVI level (about 77% counties are higher than 50%). These counties spread across the country with the exceptions of parts of California, Florida, Mountain region, Lower Midwest, and the South. Notably, this pattern is driven largely by the difference in Theme 3 variables (minority/foreign-born and language) in the calculation of ASVI as compared to CDC's SVI, indicating language barriers among Asian population, given that 66% of them nationwide are immigrants (U.S. Census Bureau, 2018).

Another 13% of the counties have ASVI similar to their CDC SVI (within 50% difference). These counties are concentrated mostly in the Pacific Northwest, Southern California, Florida, but also scattered across the Sunbelt region and clustered around New York-New Jersey area. These areas tend to be traditional or emerging gateway regions for Asian immigrants and have higher shares of Asian population than other regions. Their Asian populations also have relatively high social-economic status, high English proficiency and better housing conditions, similar to or exceeding those of the general local population while surpassing those among most Asian populations across the nation.

The ASVI in the remaining 10% counties are **lower** than the CDC SVI by at least 50% (see Fig. 2). These counties are scattered in the middle part of the nation. Moreover, all of these counties are non-gateway regions for Asian immigrants and have small Asian populations. In these regions, the difference between the two indices is driven mainly by higher socioeconomic vulnerability and household composition/disability vulnerability rankings among their general populations and relatively low rankings among their Asian populations. Racially-disaggregated vulnerability analysis among the general population and finer-scale geographic analyses among Asians are needed to fully explore these patterns.

ASVI and COVID-19 Incidence Rate

In order to understand how our ASVI explains the patterns of COVID-19 as compared to the CDC's SVI, we conducted two series of correlations and variance analysis using county-level race-specific COVID-19 data in California: (a) between COVID-19 incidence rate and the CDC's SVI components and (b) between Asian COVID-19 incidence rate and our ASVI components.

Table 2 shows COVID-19 incidence rates for the 31 counties in CA, and the comparison between ASVI and CDC SVI and their thematic scores. The six counties (Merced, Plumas, Glenn, San Benito, Napa, and Lake) with the highest Asian incidence rates are all in North or Central CA agricultural areas. Five out of the six also have higher Asian incidence rates than that of the general population. All but one has a higher ASVI than SVI, with the differences ranging from .05 to 2.01. Plumas, Lake, and Glenn are the only three among the 31 counties that have a higher than .5 difference, suggesting Asians there are more vulnerable than their general population (see Fig. 2). On the other hand, most of the 31 counties have a much lower Asian incidence rate than the overall incidence rate in the same county (<=500). The largest Asian population concentrated areas in the state have the highest differentials between Asian and total infection incidence rates: the differences in San Francisco Bay Area counties (Alameda, Contra Costa, San Francisco, San Mateo, and Santa Clara) vary from −895 to −1083; whereas such incidence rate differentials in Southern California counties (Los Angeles, Orange, Riverside, San Bernardino, San Diego) are even higher (−1105 to −2461). In all 10 of these counties, the ASVI rates are lower than the SVI rates. This illustrates that concentration of Asian population, which is the key component of CDC's SVI construction (using all minority population), does not necessarily lead to higher Asian COVID-19 incidence rates. In contrast, our ASVI allows for more nuanced analysis of the social

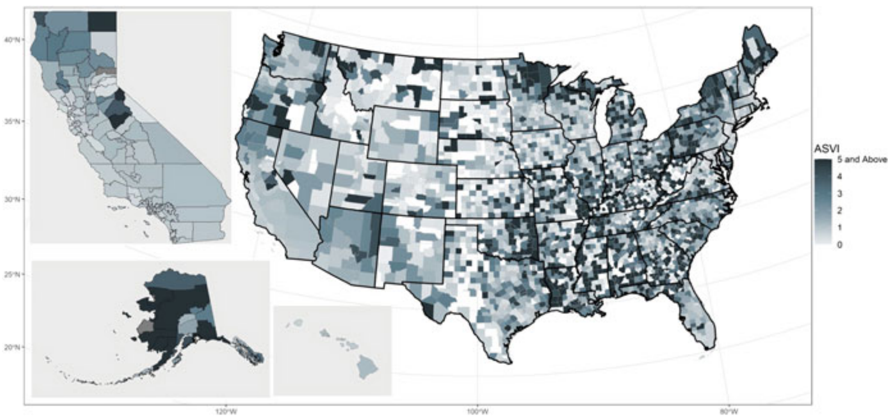

Fig. 1 Asian-specific Social Vulnerability Index (ASVI) scores by county

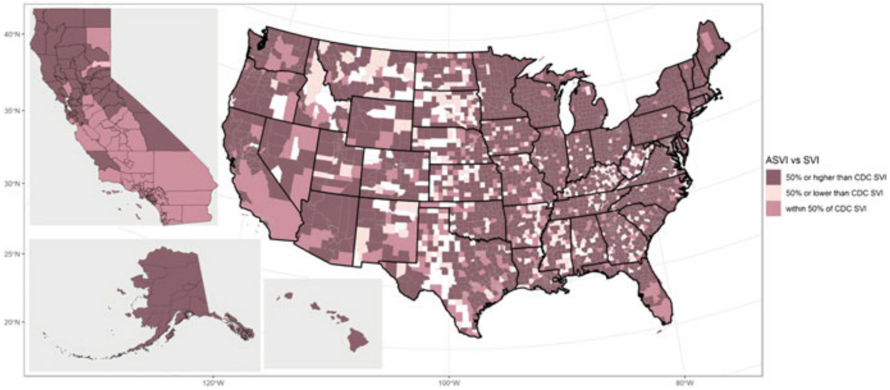

Fig. 2 ASVI and CDC SVI differentials

vulnerability within minority populations and thus serves as a better tool in identifying and predicting Asian communities at higher risk of contracting COVID-19.

Research has shown that cultural variation can affect public health interventions (Vaughan & Tinker, 2009). Given that California was exposed to COVID-19 earlier than most of the country, and Asians are more likely to practice collective social norms and prioritize obligations over personal desires, their behaviors may have helped contain community virus transmission in the face of COVID-19 (Van Bavel et al., 2020). A similar pattern is observed in Toronto, another North American city with high Asian concentrations in several Chinatowns and ethnoburbs, where East Asians count for 13% of total population, but only 6% of the COVID-19 cases (City of Toronto, 2021).

In the correlation and variance analysis (Table 3), we found CDC's SVI components had demonstrated strong capability in predicting county-level overall COVID-19 incidence rates in California, explaining 94% of the variance in the model. The socioeconomic vulnerability theme acted as the strongest predictor of COVID-19 incidence rates, holding a relatively strong positive correlation of 0.69 and explaining a total of 62.5% of the variance. Household composition vulnerability theme also acted as a relatively strong predictor of COVID-19 incidence rate, with a moderate positive correlation of 0.45 and explaining 15.6% of the variance. However, despite having statistically significant correlations as previous national-level studies suggested, the minority and language vulnerability theme only explained a very small fraction of the variance in COVID-19 incidence rates (Mahajan & Larkins-Pettigrew, 2020). The sheer share of minority population among the Californian counties have explained virtually zero variance in COVID-19 incidence rates, suggesting that race alone cannot be considered as the decisive determinant of COVID-19 vulnerability. As racial disparity in health is often associated with socioeconomic disadvantages, cultural or linguistic barriers, and limited community resources, this result further strengthens the importance of using racially-

Table 3 Correlation analysis and variance analysis using SVI, ASVI components in relation to overall and Asian COVID-19 incidence rate

	Overall			Asian		
	Correlation	p-value	% VE	Correlation	p-value	% VE
Poverty	0.590	0.000	35.6%	0.376	0.033	22.1%
Unemployed	0.526	0.002	0.4%	−0.163	0.380	3.7%
Logged income	−0.585	0.000	1.6%	−0.533	0.002	1.9%
No high school diploma	0.786	0.000	24.8%	0.541	0.002	0.6%
Socioeconomic vulnerability	0.691	0.000	62.5%	0.542	0.001	28.2%
Above 65	−0.658	0.000	2.9%	−0.068	0.715	23.8%
Under 17	0.757	0.000	2.3%	0.644	0.000	0.8%
With disability	−0.112	0.540	1.3%	0.342	0.060	4.7%
Single parent household	0.807	0.000	9.1%	0.374	0.038	0.9%
Household composition vulnerability	0.446	0.010	15.6%	0.539	0.001	30.2%
Minority	0.561	0.000	0.0%	–	–	–
Foreign-born	–	–	–	−0.284	0.121	0.1%
Limited English	0.538	0.001	5.7%	−0.036	0.849	9.2%
Minority and language vulnerability	0.124	0.499	5.7%	0.124	0.499	9.3%
Live in multi-unit structure	−0.229	0.206	4.8%	−0.328	0.072	0.2%
Live in mobile home	−0.151	0.409	1.6%	0.276	0.133	0.2%
Live in crowding household	0.517	0.002	1.2%	0.271	0.141	2.7%
No vehicle available	−0.077	0.673	0.0%	−0.218	0.238	1.7%
Live in group quarter	0.376	0.034	2.6%	0.024	0.898	5.7%
Housing and transport. Vulnerability	0.237	0.191	10.2%	0.112	0.541	10.5%
Total	**0.664**	**0.000**	**94.0%**	**0.466**	**0.007**	**69.9%**

Data Source: U.S. Bureau of the Census 2014–18. American Community Survey Department of Health, various California counties
Abbreviation: *VE* variability explained

disaggregated social vulnerability measures when analyzing racial disparity during the pandemic (Hutchins et al., 2009; Kiltz et al., 2013).

As Table 3 shows, in the correlation and variance analysis between ASVI components and Asian COVID-19 incidence rates, we found that the socioeconomic vulnerability theme remains a strong predictor, holding a moderate positive correlation of 0.54 and explaining 28% of the variance in Asian COVID-19 incidence rates. However, the household composition vulnerability theme became a more important predictor for COVID-19 incidence rates among Asian populations. The ASVI household composition vulnerability theme had a moderate positive correlation of 0.54 and explained 30.2% of the variance in Asian COVID-19 incidence rate, almost twice that of the CDC SVI's household composition vulnerability theme. These differences again highlight the importance of collecting and using racially-disaggregated social vulnerability measures, as minority groups could be impacted differently by different social vulnerability components.

Anti-Asian Discrimination Amid COVID-19

While our ASVI explains the susceptibility to COVID-19 experienced by Asians, the anti-Asian incident data help us to better understand their vulnerability to discrimination in the face of COVID-19. In discussing the vulnerability associated with "viral panic," that is, anxiety towards infectious diseases, Herring (2009) argues there are two aspects of vulnerability: vulnerability to pandemics and vulnerability to stigma, which is what Asians are currently facing. In general, crimes motivated by bias against race/ethnicity/ancestry were the top category (57.6%) among all reported hate crime incidents in 2018 (FBI, 2019). This is a portent of a surge in hate crimes against Asian Americans amid COVID-19 (Margolin, 2020). What Asians/Asian Americans are currently experiencing is similar to the prejudice, discrimination and racism against Muslim Americans following the 9/11 attack (Peek, 2011).

Triangulating information from public polls with the data from the STOP AAPI HATE website (https://stopaapihate.org, 2020) and drawing on the literature of moral panic, we reveal that a moral panic against Asians/Asian Americans is taking place during the COVID-19 crisis. Recent national polls among the public reflect a *consensus* associating COVID-19 with Asians, especially Chinese. According to the Harris Poll COVID-19 survey conducted among 1993 U.S. adults between April 3rd and 5th 2020 about 52% of the respondents strongly or somewhat agreed with Thump's characterizing the coronavirus as "The Chinese Virus." While 58% of the respondents believed the Chinese government was culpable for the spread of coronavirus in the U.S., only 42% blamed it on the slow response by the U.-S. government (The Harris Poll, 2020). Labelling the COVID-19 as "Chinese virus" and "Wuhan virus" and connecting the pandemic to specific people and place, further demonstrates the presence of *hostility* from the moral panic perspective as described by Goode and Ben-Yehuda (1994).

Such anti-Chinese sentiment directly motivates anti-Asian racist actions. A report based on the data from STOP AAPI HATE website summarizes the main categories of the reported discrimination incidents as verbal harassment, shunning, being barred from business and transportation, and physical assault. Race and ethnicity are cited as the top two reasons for those discriminatory actions. The situation is similar to what happened during the SARS epidemic (Schram, 2003; Muzzatti, 2005), but with a much wider scope: anti-Asian discrimination has spread nationwide to 45 states and Washington DC (Jeung & Nham, 2020). The geographical distribution of reported incidents, however, is uneven. 822 cases were reported in California from March 19–June 17, counting for 39% of the national total. Among those, 815 cases had locational references for where they happened. We used these California cases for analysis and mapping in this section.

The descriptive details provided in the 815 reported incidents are disturbing. The anti-Asian incidents happened everywhere, from businesses, neighborhoods, public streets or parks, schools, to transportation. Perpetrators were from different racial groups and all walks of life: clients, coworkers, housemates, landlords or neighbors, whereas victims varied from children to elderly with a much higher proportion of women who are customers, medical professionals, neighbors, and school teachers. Among the 457 victims who reported such incidents with specific ethnicity identified, East Asians count for almost 82% (including 241 Chinese, 79 Korean, 32 Japanese, and 22 Taiwanese), followed by Southeast Asians (34 Filipino/a, 25 Vietnamese, 9 Hmong, 5 Laotian, 4 Thai, 3 Cambodians, 2 Mien, and 1 Indonesian) and South Asians (1).

Jeung et al. (2020) categorized the anti-Chinese rhetoric used by perpetrators into five major themes, that is, virulent animosity (60.4%), scapegoating of China (23.2%), anti-immigrant nativism (19.4%), racist characterizations of Chinese (18.4%), and racial slurs (14.2%). Asians were called racial slurs such as "Chink," "gook," "hoarer," or "whores," and blamed for bringing the virus to the U.S. as "bat-/rat-eaters." The upsurge in incidents exhibited the increasing hostility towards Asians during the pandemic. One victim from the Central Valley of California reported "I was shopping & child grabbed my arm. Child said I should go back to my country & I was reason his father died. ... [there were] ignorant people who make fun of how I talk and look and tell me to go home. But this is scariest & saddest experience I've had in US since about 1977." The reported incidents not only showcased how Asian Americans are scapegoated as the source of the pandemic, but also revealed how verbal attacks are rampant, assaulting the more vulnerable groups such as women and children.

In addition to verbal attacks, Asians were spat upon with stuff thrown at them or physically assaulted/injured, and their cars and properties damaged. One victim in San Diego stated "I was physically assaulted by a man in his late 50s. The sucker punch resulted in the loss of my left eye. I needed 3 surgeries and more is needed in the future." The most severe incidents of physical attack happened in 9% of the cases in San Francisco. Alarmingly, in city of San Jose, the core of Silicon Valley where Asian populations have relatively high SES, physical assaults also counted for 14.3% of all reported cases, a clear indication that such violence is more racially motivated. Both perpetrators and victims are aware of the political environment and attribute to statements about "Chinese virus," or directly quote perpetrators' own statements supporting the former President, such as "[Trump's] description of Covid-19 as the Chinese virus is the most accurate thing he has ever said."

Goode and Ben-Yehuda (1994) propose five key indicators of moral panic: concern (anxiety over the reported incidents), hostility (towards individuals), consensus (united negative reactions in the public), disproportionality (panics disproportionate to the objective threats posed), and volatility (swift rate of emergence). Therefore, these five key features are in full display in these reported incidents: the *concerns* for COVID-19 turned to *hostility* toward Asian persons and bodies, which reached *consensus* among people. These incidents showed a clear pattern that the hatred and associated moral panic increased drastically, reflecting the *volatility* of the moral panic. The volume and velocity of the surge of anti-Asian racism within the U.S. suggests panic are *disproportionally* targeting Asians amid the COVID-19. The moral panics then reinforced the stigmatization of the marginalized groups, putting Asians in an even more disadvantaged position during the pandemic (Gilman, 2010; Muzzatti, 2005). There is ample evidence that Asians are afraid of going to public places to avoid physical attack and mental trauma.

Although we did not construct the ASVI to predict the rate of anti-Asian discrimination incidents, our correlation analysis indicates that the number of anti-Asian incidents has a stronger significant positive correlation with Theme 3 (percent foreign-born and limited English proficiency (LEP) among Asian population) of ASVI than that of CDC SVI (percent minority and LEP). It indicates such incidents are more likely to occur in those areas with higher percentage of immigrants and Asian population with limited English-speaking capability (Fig. 3). Figures 4 and 5 further illustrate the anti-Asian incidents at city level and overlaid with the Theme 3 of ASVI at census tract-level. The high occurrences happened in various parts of the San Francisco Bay Area, particularly San Francisco, East Bay cities and the heart of Silicon Valley (Cupertino and San Jose). The following incident happened in America's most liberal city, Berkeley: "I was harassed by deaf white guy... He asked me to pack up all clothes in suitcase and 'go back to China'! Go! Go! F†k too many Asians in America." In Southern California, anti-Asian cases occurred along the Santa Monica, Hollywood, Downtown LA and Pasadena corridor, but also in Huntington Beach area where the census tract scored high vulnerability in ASVI Theme 3. There were six incidents reported in that small beach city alone in the first 3 months, including a victim "was called 'chinaman' and other derogatory names. Implied I was carrying the COVID-19 virus." These incidents illustrate how moral panic manifests itself in the form of racial hatred, taking place in residential neighborhoods and public places alike, and in both liberal and conservative areas.

We caution, however, not to take these existing data for granted as the true numbers or geographical representations of anti-Asian discrimination cases. There are other likely explanations for such disparities reported. Active and educational actions taken by progressive government agencies, mainstream and ethnic media, and community organizations could encourage the willingness to report hate incidents. Therefore, this could be more of a reflection of Asian American self-efficacy than their higher susceptibility for hate crimes. Therefore, concerted efforts are needed to combat anti-Asian racism and protect persons of Asian descent.

Summary and Conclusion

The impacts of the COVID-19 pandemic in the U.S. are characterized with racial disparity, leaving communities of color at higher risk of infection and death. It is timely and critical to search for a tool that could be used to conduct group-specific analysis on racially disaggregated data when they become available. While the CDC's SVI framework remains a useful tool for identifying vulnerable

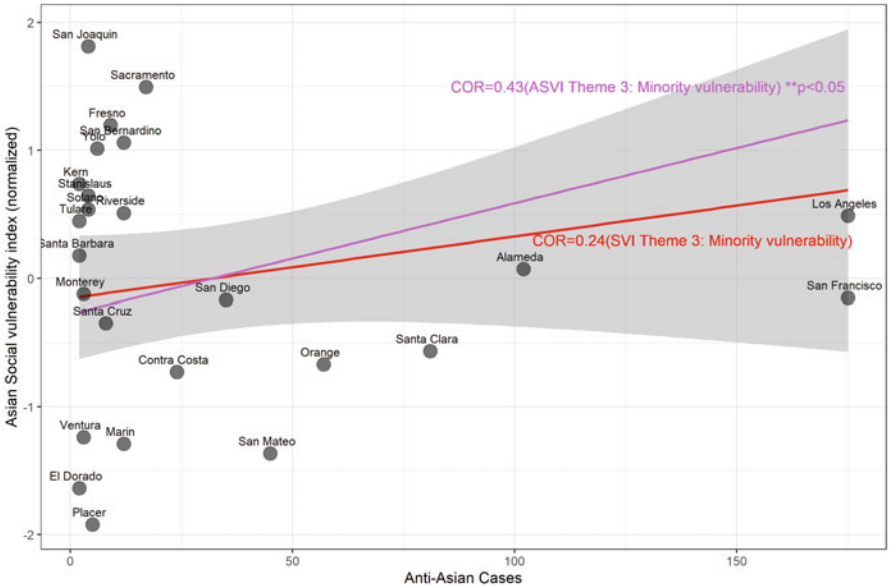

Fig. 3 Theme 3 (ASVI v SVI) and anti-Asian discrimination cases by census tract, CA

communities, we also found that the distribution of racial minorities alone cannot effectively explain the disparity in COVID-19 infections.

Our analyses show that the Asian-specific SVI we constructed illustrates well the COVID-19 dynamics among Asian populations, pointing to the need to customize the CDC SVI when examining situations faced by different racial or other vulnerable groups. Our findings reveal that the creation of ASVI is innovative and meaningful. Our analysis suggests that unequal socioeconomic status associated with race leads to the racial disparity in COVID-19 vulnerability. It also provides a basis for future analysis of racial-disparity in hazard and disaster vulnerability as it enables researchers to study the racial and intra-group variation of social vulnerability and allows both race-specific comparison and place-to-place race-specific comparison.

The connection between ASVI and Asian COVID-19 statistics shows that higher ASVI areas have suffered higher Asian incidence rates compared to that of the total population. Moreover, similar patterns (on theme 3) are evident for the anti-Asian racist incidents reported by the national database, even though more educational efforts and anti-racism statements and actions by Asian American community organizations, government and media may have played a role in the higher reporting of incidents in Asian immigrant gateways.

This study contributes to the literature on disaster and pandemic preparation, and ethnic and health geography. One strength of this research is that we pioneered a generalizable method to compose a group-specific SVI that can apply to other vulnerable groups, segmented by race/ethnicity or other indicators, to reveal the nuanced and complex social consequences of hazard and emergencies. It also helps

Fig. 4 ASVI (Theme 3) and anti-Asian discrimination incidents, Los Angeles area, CA

better understand the alarming and disturbing divide in American society. Labeling the coronavirus as "Chinese virus" further stimulates xenophobia and anti-Asian sentiment. Such rhetoric directly contributed to the moral panic among general population that contributed to racial discrimination against Asian Americans in the nation. This evidence-based research reflects that anti-Asian hate cases and racial disparities in health outcomes during COVID-19 result from systemic racism and structural inequality engrained within U.S. society.

Our work provides policy implications about where to allocate more resources to assist Asian populations in combatting COVID-19, and for future disaster and epidemic preparation. Specifically, we urge the following policy and community actions. First, we encourage state and county government agencies to collect and release more race-specific COVID-19 data for disaggregated analysis and evidence-based policy making. Second, mounting top-down condemnation of anti-Asian racial discrimination by international, national and local authorities, such as the UN report (UN, 2020) and President Biden's Memorandum (The White House, 2021). Third, law enforcement agencies in those places with multiple anti-Asian racist acts reported should begin to prosecute perpetrators to demonstrate that these crimes will be punished by law. Fourth, we promote wider educational efforts to the general public on anti-racism history through K-12, higher education and outreach, and media outreach beyond Asian immigrant gateway areas. Finally, it is critical to

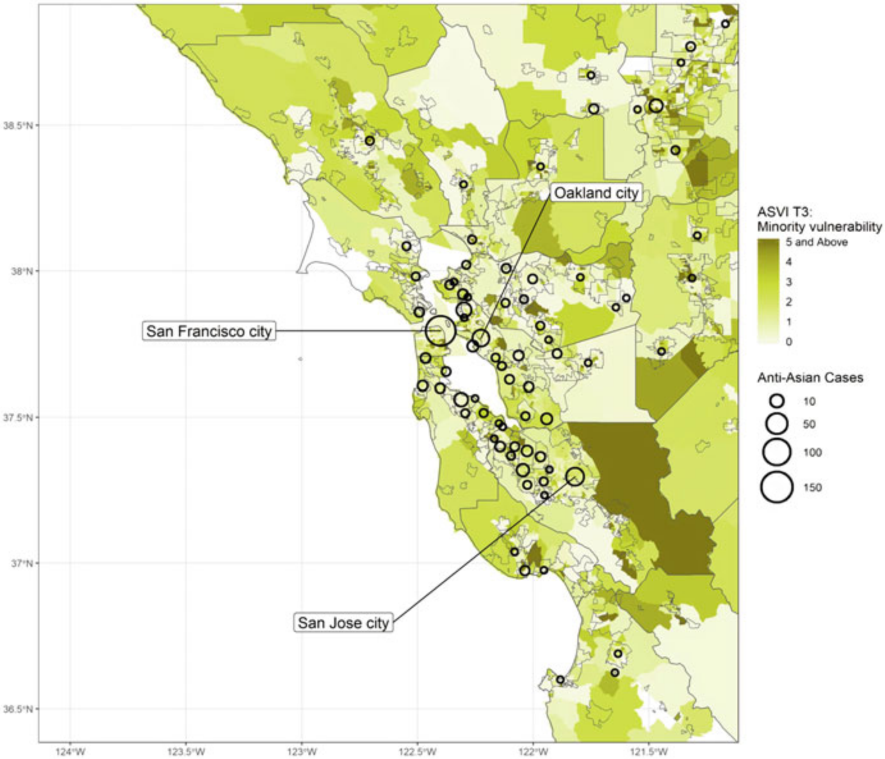

Fig. 5 ASVI (Theme 3) and anti-Asian discrimination incidents, San Francisco area, CA

mount a grassroots national anti-racism campaign that rallies all those who share the mission to combat deep-rooted systemic racism and structural inequality that results in anti-Asian crimes and the disproportionally high infection and death rates among other major minority groups amid COVID-19.

This study has several limitations primarily due to data unavailability, under-reporting, and bias. There is a lack of nationwide racially desegregated infection and death data by county or other finer scale of geographies as the overwhelming majority of the 3141 counties nationwide have not released such statistics. Moreover, hate crime data are self-reported with under-reporting and self-selection among those who chose to report.

Despite these limitations, this study is innovative and paves the way for future research. For instance, analysis at more refined geographical scale will be needed to further explore the difference between the CDC's SVI and a racially-disaggregated SVI. More specific COVID-19- or pandemic vulnerability (DeCapprio et al., 2020) data (such as existing life expediency, preexisting medical conditions by group, and distribution of essential workers), or resiliency (Census Bureau's "Community Resiliency Estimates"), all which can be further explored and developed and mapped. More nuanced analysis can be conducted to investigate to what extent different sub-Asian groups and occupations may experience social vulnerabilities differently. Qualitative work can add more nuance to the explanations of the observed patterns. Last, but not least, there are both in or across-group data collections and analyses regarding racial disparities and health effects at national or state-levels. These include the Asian & Pacific Islander American Health Forum and the statewide multi-group California Health Interview Survey along with numerous other race-specific COVID-19 studies. More concerted efforts for collaboration and cross-referencing would strengthen the research and serve the purpose of anti-racism and health equality among various groups.

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