Asian Hate Crimes After COVID

: State Vulnerability & Key Social Drivers

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ABSTRACT

This study examines the social and demographic factors contributing to the rise in anti-Asian hate crimes during the COVID-19 pandemic, focusing on which U.S. states were most vulnerable to these changes. Using Interrupted Time Series (ITS) analysis, correlational analysis, and fixed effects (FE) regression, the research explores the extent of COVID-19's impact on Asian-targeted hate crimes and evaluates how socioeconomic, demographic, and political factors influenced state-level vulnerability. The findings reveal that while COVID-19 significantly affected hate crime rates, only a subset of states experienced substantial increases. Key predictors of vulnerability included population density and the proportion of white poverty, both of which were positively linked to higher rates of anti-Asian hate crimes. These results highlight the importance of addressing structural and economic factors that drive hate crimes, particularly during periods of societal disruption. By identifying the factors that make certain states more susceptible to hate crime surges, this study provides a data-driven foundation for developing targeted policy interventions aimed at reducing bias-motivated violence during future crises.

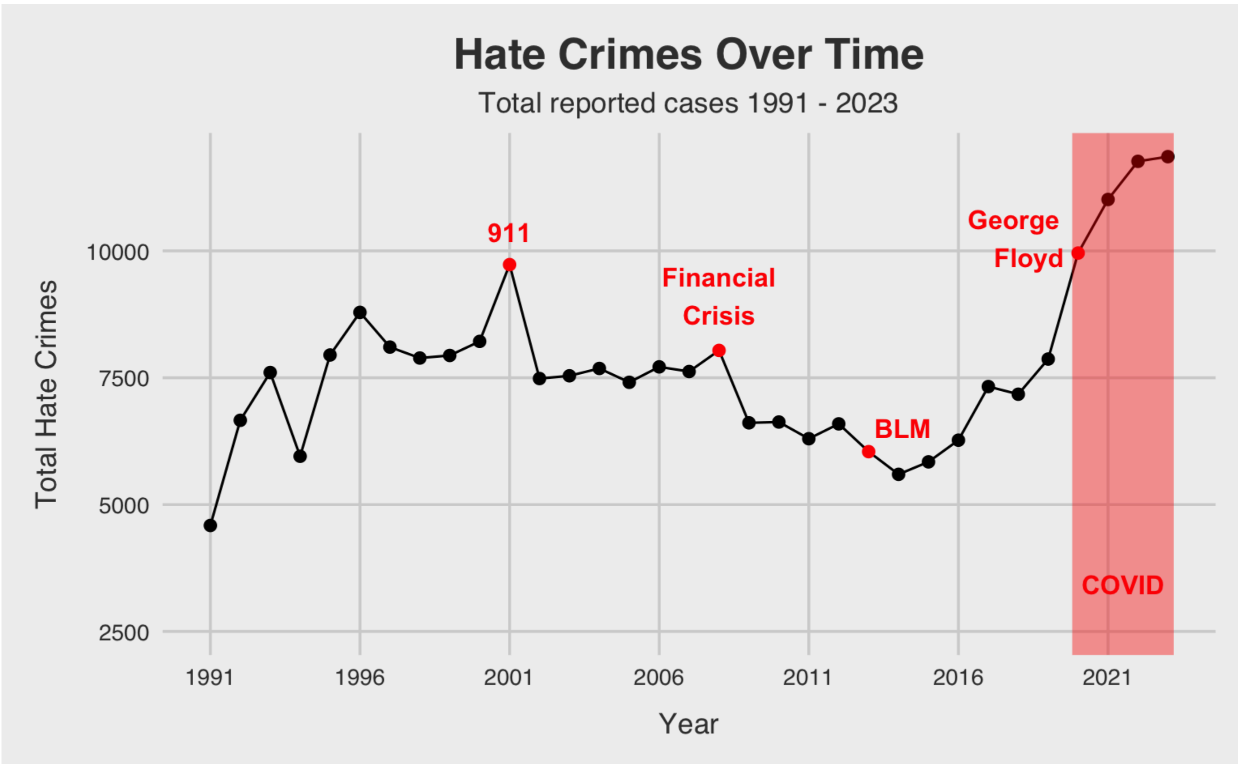
I. Introduction

1. Background

Hate crimes are criminal offenses motivated by bias against certain groups based on characteristics such as race, religion, or sexual orientation (Oxford English Dictionary, n.d.). In the United States, hate crime incidents have steadily risen over the years, with noticeable spikes following major societal disruptions. This trend is evident in Figure 1, which illustrates fluctuations in hate crime rates from 1991 to 2023, coinciding with significant events like the

9/11 attacks, the 2008 financial crisis, and, most recently, the COVID-19 pandemic. These instances suggest that societal instability can exacerbate existing prejudices, leading to a surge in hate-motivated violence.

FIGURE 1. Hate Crimes over Time

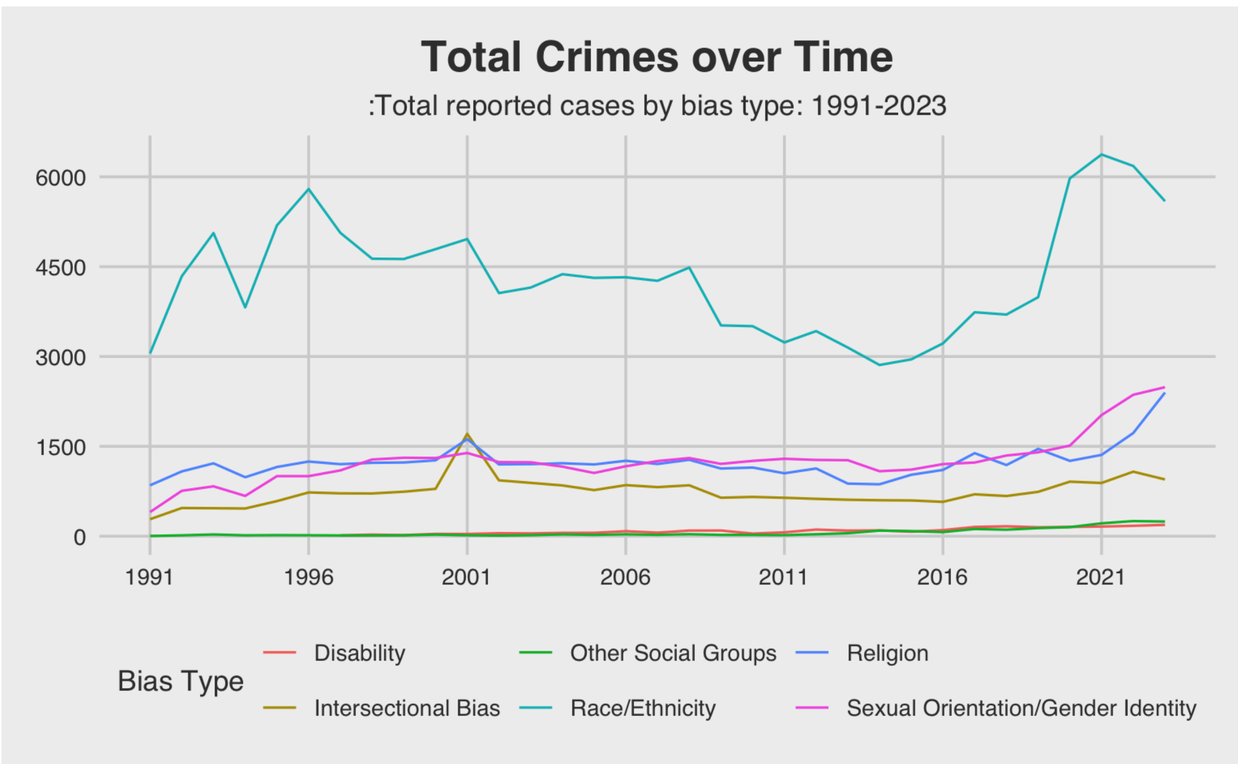


Among various categories of hate crimes, race and ethnicity-related offenses are consistently the most prevalent. The COVID-19 pandemic intensified this trend, sparking a dramatic rise in anti-Asian hate crimes. Reports and media coverage have documented a surge in violence, harassment, and discrimination against Asian communities during this period (California Department of Justice, 2022). This study aims to determine whether COVID-19 substantially influenced this increase across U.S. states equally and to investigate the social and demographic factors that might exacerbate vulnerability to hate crimes across U.S. states. By identifying patterns and potential predictors, this research seeks to understand if particular social factors are associated with heightened anti-Asian hate crime rates and whether these factors, alongside COVID-19, uniquely contributed to the surge.

To restate this research, this study poses two primary research questions:

1. How did COVID-19 influence Asian-targeted hate crimes, and which states were particularly vulnerable to this effect?
2. Was COVID-19 the sole factor influencing the rise in anti-Asian hate crimes, or were additional social factors at play?

FIGURE 2. Hate crime by bias type



I hypothesize that hate crime trends would be similar across states, given that racial hate crimes are often influenced by nationwide societal conditions. It is also anticipated that COVID-19 alone does not fully explain the rise in anti-Asian hate crimes; rather, social factors related to race and demographic characteristics may have intensified this impact. In particular, a higher proportion of noncitizens is expected to be a significant predictor of increased vulnerability to hate crimes. By answering these questions, this study aims to provide a more comprehensive understanding of the complex interplay between public health crises, social conditions, and hate crime vulnerability.

2. Literature Review

The impact of socioeconomic, demographic, and political factors on hate crimes is a critical area of research, especially in understanding how social contexts shape and intensify bias-motivated violence. Previous studies reveal that hate crimes often cluster around major social and political events, such as elections or economic downturns, which can amplify social tensions and increase negative sentiment toward specific groups (Wang, 2021; King, 2013). Gover et al. (2020) argue that hate crimes against Asian Americans during the COVID-19 pandemic were driven by both individual and institutional-level racism, exacerbating existing social inequalities. Similarly, Han et al. (2022) found that the racialization of COVID-19 as the "Chinese virus" contributed to a surge in anti-Asian hate crimes, illustrating how public rhetoric can reinforce social "othering" and deepen inequality. This context highlights the time-sensitive nature of hate crimes and supports the use of Interrupted Time Series (ITS) analysis to assess shifts in Asian-targeted hate crimes during COVID-19. Unlike King's (2013) focus on short-term spikes, this study examines whether specific socioeconomic and demographic factors contribute to sustained increases over time.

Economic instability and inequality are significant drivers of hate crimes, as socioeconomic distress often creates an environment where minority groups are scapegoated. Raj (2022) analyzed variables such as unemployment, poverty, and income inequality, finding that these conditions heighten social frustration and hostility toward marginalized communities. This study builds on Raj's findings by incorporating economic indicators like unemployment, and poverty rates to determine if states that exhibited increased vulnerability to hate crimes during COVID-19 had preexisting economic stressors. While Raj's work highlights the general relationship between economic distress and bias-motivated incidents, this study extends the analysis to explore how these factors function in the context of a global health crisis. This research aims to provide a more comprehensive understanding of how economic conditions shape hate crime trends.

Demographic changes have long been linked to hate crime trends, as shifts in racial and social diversity often generate social tensions. Diaz-Faes and Pereda (2020) argue that hate crimes are embedded within broader social hierarchies and dynamics, where demographic changes—such as an increase in minority populations—can trigger a backlash. This study will incorporate these insights by examining demographic factors like racial composition and age distribution across states. The analysis focuses on whether states with larger Asian populations or younger demographics experienced greater increases in hate crimes following COVID-19. Unlike prior studies, this research situates demographic factors within the broader context of a global health crisis, providing a more nuanced perspective on how structural characteristics interact with large-scale disruptions to influence hate crime rates.

Wang (2021) demonstrated the predictive capacity of socioeconomic and demographic factors on hate crime rates, finding that income inequality, the proportion of noncitizens, and median household income were significant predictors of hate crime vulnerability. This study employs Wang's analytical framework to explore how demographic and economic factors influence state-level differences in anti-Asian hate crime trends. By leveraging Wang's method, the current research seeks to identify which social and economic variables had the strongest impact on hate crime rates during the COVID-19 pandemic. Wang's findings offer a methodological foundation for this study's approach to understanding cross-state variations in hate crime vulnerability.

3. Gaps in Prior Literature

Despite the insights provided by existing studies, most research on the socioeconomic, demographic, and political drivers of hate crimes remains qualitative. This lack of quantitative analysis limits the capacity to empirically measure the extent and impact of these factors in real-world data. Studies like those by Diaz-Faes and Pereda (2020) and Raj (2022) establish foundational frameworks but fall short of providing empirical validation. This study addresses this gap by using quantitative methods to examine the statistical associations between socioeconomic, demographic, and political factors and anti-Asian hate crimes during the COVID-19 pandemic. Through this approach, the study enables empirical testing of relationships previously explored only theoretically, offering statistical clarity on hate crime vulnerability in a period of global upheaval. This quantitative approach expands upon observation to actionable insights, allowing policymakers to consider data-driven findings in designing targeted interventions. By addressing the academic understanding of hate crimes, this study also equips community leaders with practical strategies to counteract bias-motivated violence during social instability.

Moreover, although prior research has successfully linked socioeconomic and demographic factors to hate crime trends, a significant gap remains in understanding state-level differences in hate crime vulnerability during major disruptions like the COVID-19 pandemic. Existing studies, such as those by Han et al. (2022), have focused on national-level trends or specific urban contexts, but little attention has been paid to cross-state variations. Additionally, few studies have examined how multiple demographic and economic factors interact to shape hate crime vulnerability. This study addresses these gaps by identifying which states experienced the most significant increases in hate crimes and pinpointing the demographic and socioeconomic factors that influenced these patterns. By focusing on cross-state differences, this research provides a deeper understanding of how large-scale crises impact hate crime trends across diverse social contexts.

4. Ethical Considerations

Ethical considerations are essential to this study due to the sensitive nature of hate crime data and the potential social implications of its findings. Hate crimes often affect vulnerable communities, and there is a responsibility to handle the data with care to prevent the reinforcement of negative stereotypes or the attribution of blame to specific groups or regions. To achieve this, the analysis focuses on understanding broader structural and social contexts rather than making causal claims about the role of any single demographic or socioeconomic variable in hate crime prevalence. This approach aims to highlight vulnerabilities rather than stigmatize communities, ensuring that the research informs supportive, data-driven policies.

A critical ethical priority is the protection of anonymity and data confidentiality. This study uses publicly available crime databases and datasets from government agencies and nonprofit organizations, all of which are aggregated at the state or city level. No personally identifiable information, such as names, addresses, or other unique identifiers, is collected, stored, or analyzed. By relying on de-identified, aggregate data, the study ensures that no specific individuals can be linked to any hate crime incident. This method aligns with best practices for data privacy and complies with ethical guidelines for research involving sensitive topics.

II. Data and Method

1. Data collection and variables description

This study utilizes the hate crime statistics dataset provided by the Federal Bureau of Investigation's (FBI) Crime Data Explorer, which includes detailed information on reported hate crime incidents. Each record specifies the type of bias, the offender's race, and the state where the crime occurred. To assess COVID-19's impact on hate crimes, hate crime incidents were aggregated monthly for each state. However, one limitation of this dataset is its reliance on reported incidents, which may lead to underreporting as some victims may avoid contacting law enforcement due to distrust or fear (FBI, 2024). Furthermore, restricted demographic information on offenders limits the ability to assess unique offender characteristics that could influence hate crimes. Despite these constraints, the dataset provides valuable insights into state-level patterns, facilitating an examination of how different environmental factors may drive biases.

In addition to the FBI data, this study includes various socioeconomic and demographic variables from FRED, KFF, Federal Election Commission, NCSL, and World Population Review to explore factors potentially influencing Asian-targeted hate crimes during COVID-19. These variables capture a range of social, economic, and demographic dimensions that may contribute to state-level variations in hate crime vulnerability. Each variable and its relevance to the analysis are described below. These variables were chosen for their potential theoretical link to hate crime vulnerability, as suggested by prior research (Wang, 2021). The inclusion of diverse variables ensures a comprehensive assessment of the structural, demographic, and economic factors that may influence hate crimes.

TABLE 1. Variables' Description

Type	Name	Description
Demographic	Percentage of Non-Citizens	Proportion of state residents who are not U.S. citizens
	Age Distribution	Proportion of the population within age brackets 18-24, 25-64, and 65+
	Gender Distribution	Proportion of the population identifying as female and male
Socioeconomic	Percentage of White Poverty	Proportion of White individuals living below the poverty line
	Unemployment Rate	Average state unemployment rate
	Population Density	Residents per square mile in each state
	Gini Index	Income inequality within the state, 0 represents perfect equality and 1 represents perfect inequality
	College Degree Rate	The proportion of the population with at least a bachelor's degree
	Median household Income	Median household income for the state
Health and Social Well-being Variables	Health Status	Self-reported overall health rating for each state's population
	Political Affiliation	Dominant political affiliation in the state, coded as 1 for Democratic and 0 for Republican

2. Method

2.1. Interrupted Time Series (ITS) Analysis

2.1.1. Description and Suitability of ITS

The Interrupted Time Series (ITS) analysis is a statistical technique that assesses the effect of an intervention or event on an outcome over time by comparing pre- and post-intervention trends. In this study, ITS divides time into pre-COVID-19 and post-COVID-19 periods to examine changes in hate crime trends potentially linked to the pandemic. This method is well-suited to analyze large-scale events, such as the COVID-19 pandemic, as it allows us to identify shifts in hate crime rates that may have been directly influenced by such an unprecedented event.

The primary question addressed by the ITS analysis is: "How did COVID-19 influence Asian-targeted hate crimes, and which states were particularly vulnerable to this effect?" ITS is appropriate here because COVID-19 is a distinct, global event, enabling a clear intervention period beginning in March 2020. Additionally, the dataset spans multiple years, facilitating a longitudinal view of trends both before and after the pandemic. This approach is advantageous as it identifies potential changes in hate crime rates specifically associated with COVID-19 without requiring a control group.

2.1.2. Mathematical equation for the model

The ITS model employed here is defined as follows, with each coefficient described below:

$$Total\ hate\ crime_t = \beta_0 + \beta_1 \times time + \beta_2 \times intervention + \beta_3 \times time\ since\ intervnetion + \epsilon_t$$

- $Total\ hate\ crime_t$: The total count of hate crimes at the time t
- β_0 : Baseline level of hate crimes before the intervention
- $\beta_1 \times time$: General trend in hate crimes over time before the intervention
- $\beta_2 \times intervention$: Immediate impact of the intervention (COVID-19 onset), set to 0 before and 1 after the intervention

- $\beta_3 \times time\ since\ intervention$: Trend change post-intervention, indicating whether hate crimes increased or decreased over time after COVID-19's onset
- ϵ_t : Error term capturing unobserved factors affecting hate crimes at time t

2.1.3. Methodology

The ITS model used data from 2016 to 2023 to ensure consistency around the intervention (March 2020). This timeframe allows a clear comparison of hate crime trends before and after the pandemic, providing insights into whether observed changes relate to the pandemic or reflect broader trends. For analysis, a continuous "Time" variable was created to measure time progression from January 2020 to December 2023. Additionally, indicator variables were added to mark the intervention period (pre=0, post=1) and to account for any gradual changes following COVID-19's onset.

Each state was analyzed individually to identify regional differences in COVID-19's impact on Asian hate crimes. Three components were included in each state's model: the baseline trend, the intervention level change, and the post-intervention trend. This approach not only identifies immediate shifts due to the intervention but also highlights lasting impacts on hate crime trends, providing a deeper understanding of COVID-19's effect on Asian hate crimes.

2.1.4. Limitations

While ITS effectively captures trends before and after the intervention, it cannot account for all confounding factors. COVID-19 may not be the only driver behind the rise in Asian hate crimes, as the model does not isolate additional influencing variables. This limitation will be addressed using the Fixed Effects (FE) model discussed in the other section.

2.2. Correlational Analysis

2.2.1. Description and Suitability of Correlational Analysis

The correlational analysis was conducted to identify initial patterns and relationships between socioeconomic and demographic variables and Asian-targeted hate crimes. This analysis helps to establish preliminary insights into which variables are most strongly associated with changes in hate crimes before and after the COVID-19 pandemic, proven by a prior study (Wang, 2021). By comparing correlations from pre-COVID (2016–2019) and post-COVID (2020–2023) periods, this method highlights shifts in the influence of specific variables over time, providing a basis for selecting predictors for further modeling.

2.2.2. Methodology

The original dataset was filtered into two subsets: one for pre-COVID (2016–2019) and one for post-COVID (2020–2023). Each subset retains all years within its respective time period. The analysis focused on 11 key predictors, including socioeconomic, demographic, and structural variables; redundant variables (e.g. Female, Middle-aged) were excluded to avoid redundancy in the analysis. Hate crime data were aggregated into annual totals for each state and converted into hate crime cases per 100,000 population. This adjustment accounts for population differences across states, allowing for cross-state comparability.

Correlation coefficients were calculated separately for pre- and post-COVID periods using Pearson's correlation method, which quantifies the linear relationship between each predictor and hate crime rates. This computes pairwise correlations between the dependent variable (cases of hate crimes per 100,000) and the selected predictors for each period. The resulting correlation matrices for the pre-COVID and post-COVID periods were visualized using heatmaps. Each heatmap displays the correlation coefficients between predictors and hate crime cases. To facilitate interpretation, the coefficients were color-coded: strong positive correlations were shaded red, strong negative correlations were shaded blue, and near-zero correlations were white. The correlation coefficients were also displayed as numeric values on each tile for clarity.

2.2.3. Limitations

It is important to note that correlation does not imply causation. While the analysis identifies patterns in the relationships between predictors and hate crimes, these relationships may be driven by unobserved confounding factors. Moreover, since the analysis includes multiple observations per state (rather than state-level averages), the relationships reflect a mix of both within-state and between-state differences. This method does not control for unobserved, time-invariant characteristics specific to each state, which may introduce bias in the correlation estimates. This correlational analysis serves as a foundation for the fixed effects model, where the insights gained from shifts in the strength of predictors (e.g., changes in the correlation of density or share of non-citizens) inform the selection of variables to include in the model.

2.3. Fixed Effect Model

2.3.1. Description and Suitability of Fixed Effect(FE) model

While the ITS model captures Asian hate crime trends pre- and post-COVID-19 and identifies states with significant increases, the FE model further explores additional socioeconomic and demographic factors that might influence these trends. By controlling for unobserved, time-invariant characteristics within states and common temporal effects, the FE model isolates the impact of socioeconomic variables indicators on hate crimes. This approach is particularly relevant for longitudinal data from 2016 to 2023, as it minimizes potential biases associated with omitted variables that remain constant within states over time.

2.3.2. Methodology

Data from 2016 to 2023 were used to estimate the fixed effects model. The rationale for including data before COVID-19 is to capture pre-existing trends that may affect hate crimes and avoid falsely attributing all observed changes to the pandemic. The inclusion of pre-COVID data increases the precision of the model and ensures a more robust analysis of temporal changes. This approach also aligns with prior research, such as Wang (2021), which emphasizes the importance of incorporating pre-event data when analyzing changes resulting from societal disruptions.

The selection of predictors for the fixed effects model was guided by the findings from the correlational analysis. The correlation analysis compared the relationships between predictors and hate crimes during the pre-COVID (2016–2019) and post-COVID (2020–2023) periods. Variables that showed consistently strong correlations or notable shifts in influence from pre- to post-COVID were selected for the fixed effects model. These predictors were standardized to place them on a comparable scale, facilitating the interpretation of regression coefficients. Categorical variables such as political affiliation were transformed into binary indicators to ensure compatibility with the fixed effects modeling approach.

2.3.3. Limitations

While the fixed effects model controls for unobserved, time-invariant characteristics specific to each state, it still has some limitations. One key limitation is that certain demographic predictors (e.g., gender distribution and age distribution) exhibit minimal variability over time. This stability makes it difficult for the model to detect the effects of these predictors, even if they are important contributors to hate crimes.

III. Results

1. Interrupted Time Series (ITS) Analysis

This analysis used three main parameters: Time, Intervention, and Time Since Intervention. Across states, significance levels varied, with certain states displaying notable changes in these parameters, indicating different impacts of COVID-19 on Asian hate crime trends. Table 2 summarizes the ITS results for 14 states identified as “vulnerable” among the 52 total(including Puerto Rico and DC). Focusing on these states reveals significant Intervention and/or Time Since Intervention effects.

TABLE 2. Interrupted Time Series Analysis Results

	Dependent variable:													
	Total Hate Crimes													
	Arizona	California	Hawaii	Idaho	Indiana	Louisiana	Minnesota	Mississippi	Nebraska	Nevada	New Jersey	New York	Pennsylvania	Washington
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Time	-0.01	0.04	0.01*	0.004*	-0.004	-0.00	-0.01	0.004*	-0.002	0.001	0.07***	-0.01	0.0004	0.04*
	(0.01)	(0.07)	(0.005)	(0.002)	(0.01)	(0.002)	(0.01)	(0.002)	(0.002)	(0.01)	(0.02)	(0.05)	(0.01)	(0.02)
Intervention	0.50**	11.33***	0.17	0.01	-0.003	0.14**	1.30***	-0.003	0.26***	0.63**	2.40***	8.12***	1.42***	1.80**
	(0.22)	(2.77)	(0.19)	(0.09)	(0.23)	(0.07)	(0.27)	(0.09)	(0.08)	(0.25)	(0.84)	(2.04)	(0.40)	(0.87)
Time Since Intervention	0.003	-0.14	-0.02**	-0.01**	0.02**	-0.003	-0.01	-0.01**	-0.005	-0.01	-0.12***	-0.07	-0.01	-0.06*
	(0.01)	(0.10)	(0.01)	(0.003)	(0.01)	(0.003)	(0.01)	(0.003)	(0.003)	(0.01)	(0.03)	(0.07)	(0.01)	(0.03)
Constant	0.29*	1.80	-0.05	-0.06	0.23	0.00	0.58***	-0.03	0.08	0.06	-0.26	1.01	0.13	0.55
	(0.16)	(1.95)	(0.13)	(0.06)	(0.16)	(0.05)	(0.19)	(0.06)	(0.05)	(0.18)	(0.59)	(1.43)	(0.28)	(0.61)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

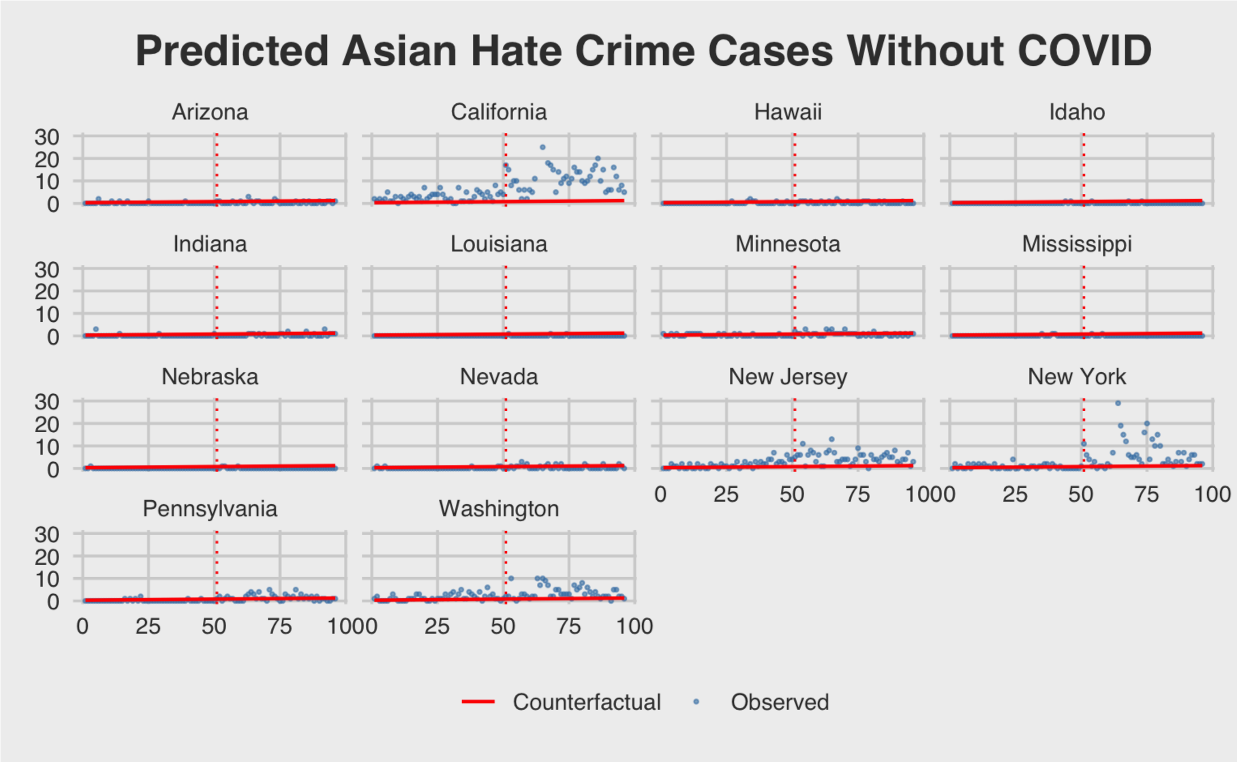
California reported a notable Intervention effect with a coefficient of 11.33 ($p < 0.01$), marking a substantial increase in Asian hate crimes post-pandemic onset—one of the highest among the states analyzed. New York similarly showed a strong Intervention effect of 8.12 ($p < 0.01$), indicating an immediate rise in hate crimes with the onset of the pandemic. New Jersey had an Intervention coefficient of 2.40 ($p < 0.01$) and a negative Time Since Intervention coefficient (-0.12, $p < 0.01$), showing an initial increase in hate crimes post-COVID-19, followed by a gradual decline. Idaho displayed a pre-pandemic increasing trend with a significant Time coefficient (0.004, $p < 0.1$), as well as a negative Time Since Intervention coefficient (-0.01, $p < 0.05$), indicating a decrease in hate crimes over time after the initial pandemic rise. Indiana’s positive Time Since Intervention coefficient (0.02, $p < 0.05$) suggests a continued upward trend post-intervention, while Nevada showed significant positive Intervention coefficients (0.63, $p < 0.05$), indicating an immediate pandemic-related increase. Washington exhibited both a significant Intervention effect (1.80, $p < 0.05$) and a negative Time Since Intervention coefficient (-0.06, $p < 0.1$), signaling an initial spike followed by a decline. Minnesota had a significant Intervention effect (1.30, $p < 0.01$) without a sustained change, indicating only an immediate rise in hate crimes.

TABLE 3. Effect Type Sorted Table

Immediate Change	Sustained Change	Both
Arizona California Louisiana Minnesota Nebraska Nevada New York Pennsylvania Washington	Hawaii Indiana Idaho Mississippi New Jersey	New Jersey Washington

Figure 3 displays counterfactual plots for the 14 vulnerable states, comparing observed hate crime trends with hypothetical counterfactual values assuming no pandemic intervention. The plots show sharp deviations from counterfactual predictions post-March 2020 in states like California, New York, New Jersey, Pennsylvania, and Washington.

FIGURE 3. Counterfactual Plots For 14 Vulnerable States

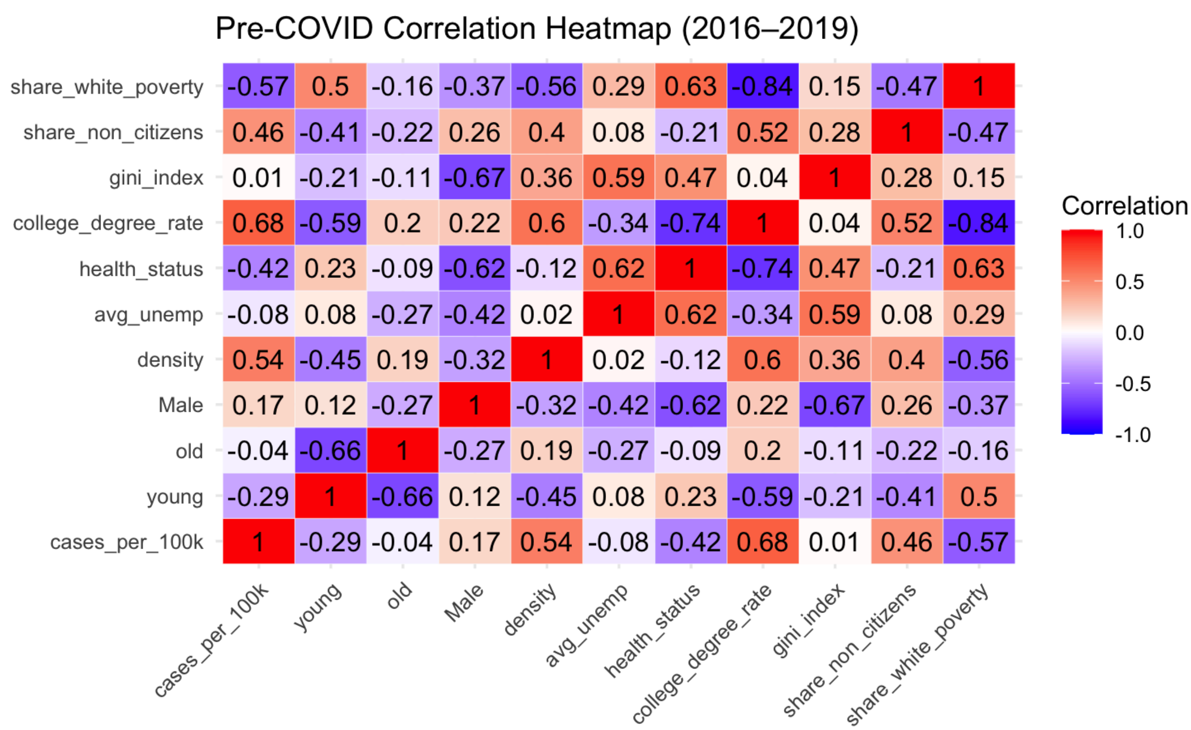


2. Correlational Analysis

To investigate the factors influencing Asian hate crimes, correlation analyses were conducted separately for the pre-COVID (2016–2019) and post-COVID (2020–2023) periods. By analyzing the relationships between cases of Asian hate crimes per 100,000 population and various demographic, socioeconomic, and structural predictors, the study identified significant changes in these relationships over time.

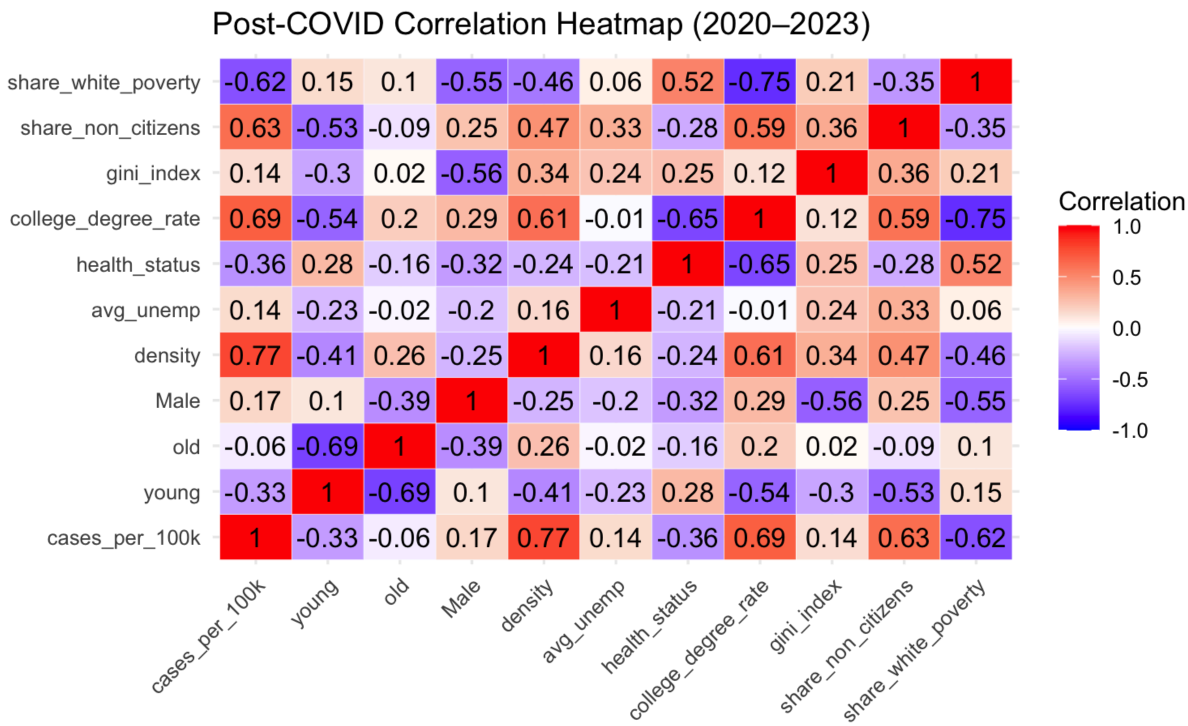
Before COVID (figure 4), certain predictors showed notable correlations with Asian hate crimes. For instance, the college degree rate (r=0.68) exhibited a strong positive correlation, suggesting that states with higher educational attainment tended to have more reported Asian hate crimes. Similarly, density (r=0.54) displayed a strong positive relationship, indicating that urbanized areas were associated with higher hate crime rates. Conversely, the share of white poverty (r=−0.57) and health status (r=−0.42) demonstrated strong negative correlations, implying that economically distressed white populations and better health conditions in states were linked to fewer hate crimes.

FIGURE 4. Pre-CPVID Correlation Heatmap



Post-COVID, several predictors showed marked shifts. Density (r=0.77) became even more strongly correlated with hate crimes, reflecting the intensification of urban vulnerabilities during the pandemic. The share of non-citizens (r=0.63) also strengthened its positive correlation, likely reflecting the rise of anti-immigrant sentiment during COVID-19. Interestingly, the relationship between average unemployment and Asian hate crimes reversed. While unemployment had a weak negative correlation pre-COVID (r=−0.08), this changed to a weak positive correlation post-COVID (r=0.14), suggesting that the economic instability caused by the pandemic may have contributed to increased hate crimes.

FIGURE 5. Pre-CPVID Correlation Heatmap



Other predictors exhibited stability across both periods. For example, the male proportion and the percentage of the older population consistently showed weak correlations with hate crimes. Additionally, predictors such as the Gini index (income inequality) and the share of younger populations exhibited only minor shifts, with neither showing strong correlations in either period.

3. Fixed Effect Model

A fixed effects model was employed to explore within-state variations in Asian hate crimes from 2016 to 2023. This model controlled for state-specific characteristics that remain constant over time, isolating the effects of temporal changes in predictors. Predictors included in the model were density, college degree rate, share of non-citizens, share of white poverty, and health status, as these variables exhibited stronger correlations with hate crimes and demonstrated notable shifts post-COVID.

The results identified density ($p<0.01$) and the share of white poverty ($p<0.05$) as significant predictors. Both predictors had positive associations with Asian hate crimes. Higher population density was strongly linked to increased hate crimes, consistent with findings from the correlation analysis. Similarly, the positive relationship between white poverty and hate crimes indicates that states experiencing higher economic distress among white populations tended to report more Asian hate crimes.

TABLE 4. Fixed Effect Model Results

Predictor	Coefficient
Density	22.94***
College Degree Rate	0.54
Share Non-Citizens	0.11
Share White Poverty	0.93**
Health Status	-0.35

Predictors such as the college degree rate, share of non-citizens, and health status, while strongly correlated in earlier analyses, were not statistically significant in the fixed effects model. This lack of significance reflects the model's focus on within-state temporal variation, which limits its ability to detect predictors that change minimally over time.

IV. Discussion and Interpretation

1. Identifying Vulnerable States: Significant Shifts in Asian Hate Crimes Post-COVID-19

The ITS analysis provides a nuanced picture of how Asian hate crimes responded to the pandemic across various U.S. states. Contrary to expectations that most states would display an immediate rise in hate crimes post-March 2020, only 14 states showed statistically significant increases. This finding highlights COVID-19's varied impact on racial hate crimes, suggesting that additional factors may have influenced hate crimes differently across states.

Potential explanations for these disparities include local demographic factors, such as the size and visibility of Asian communities in each state. States with larger Asian populations might have experienced more pronounced increases due to heightened public visibility and scapegoating. Conversely, states with smaller Asian populations may not have experienced such dynamics as strongly. Socioeconomic and cultural factors could also have played a role. For instance, states with higher unemployment, economic distress, or social unrest during the pandemic might have been more prone to increases in hate crimes as displaced frustration manifested as hostility. Additionally, regional attitudes toward race and diversity, which vary widely across the U.S., may have influenced the level of tolerance or hostility faced by Asian communities during this period.

Analyzing states with significant Intervention effects offers additional insight. For example, California and New York, both with large Asian communities, saw substantial immediate increases, supporting the idea that larger, visible populations may increase vulnerability to racial targeting in crises. Similarly, New Jersey and Washington exhibited notable increases, potentially due to substantial Asian populations coupled with social or economic stressors. Meanwhile, states like Idaho and Indiana showed distinct patterns, characterized by pre-existing trends or sustained effects rather than immediate spikes, which contradicts a prior study by Han et al. (2022). In Idaho, for example, a rising trend was evident even before COVID-19, implying that factors influencing hate crimes were active even before the pandemic and continued throughout it. Nevada's pattern of an immediate increase followed by a gradual decline suggests that while the pandemic's initial impact was severe, other factors may have subsequently moderated hate crime rates.

While ITS offers valuable insights, it also has limitations. The model assumes that the intervention (COVID-19's onset) would yield an immediate impact, but behavioral responses to a global crisis may develop gradually. Thus, ITS may not capture delayed responses in states where anti-Asian sentiment took time to build or where protective factors buffered initial effects. Additionally, ITS doesn't account for external variables, such as socioeconomic factors, local political climates, or media coverage, which likely influenced hate crime trends in varied ways across states. Without these variables, the model cannot directly assess their impact or interactions with the intervention effect. Since ITS treats each state independently, it overlooks possible interstate interactions or regional spillover effects, which could obscure patterns across neighboring states with shared cultural or media influences. Lastly, differences in state-level hate crime reporting may lead to inconsistencies or underreporting, potentially affecting significant findings.

2. Correlations Between Crime Cases and Predictors

The correlation analysis revealed critical insights into the changing dynamics of predictors before and after COVID. For example, the intensified relationship between density and hate crimes (r=0.77 post-COVID) highlights the heightened vulnerabilities of urban areas during societal crises. This finding aligns with Wang's (2021) conclusion that urbanization is a key structural factor in hate crime activity, particularly during periods of instability.

The shift in the relationship between average unemployment and hate crimes is particularly notable and interesting. Pre-COVID, unemployment rates showed a weak negative correlation ($r=-0.08$), suggesting that higher unemployment slightly reduced hate crime activity, possibly due to decreased social interactions during periods of economic inactivity. However, post-COVID, unemployment was weakly positively correlated ($r=0.14$), reflecting the economic instability caused by widespread job losses during the pandemic. This shift indicates that the economic hardships and frustrations experienced during COVID may have fueled xenophobia and resentment, contributing to the rise in hate crimes.

Certain predictors, such as the Gini index and male proportion, exhibited limited changes in their relationships with hate crimes. For example, the Gini index showed a small increase in its correlation ($r=0.01$ pre-COVID to $r=0.14$ post-COVID), but its overall influence remained modest. Similarly, the male proportion maintained a weak and stable correlation across both periods, suggesting that gender demographics did not significantly influence Asian hate crime trends.

3. Key socio-economic, demographic, and structural factors

The fixed effects model offered valuable insights by isolating within-state temporal changes to identify predictors of Asian hate crimes. Among the predictors analyzed, density and share of white poverty emerged as significant variables. Understanding why these factors are significant and how they contribute to changes in hate crimes is key to interpreting these findings.

3.1. Population Density

Density ($p<0.01$) showed a strong and statistically significant positive relationship with Asian hate crimes. This finding underscores the role of urbanization in hate crime dynamics. High-density areas inherently increase opportunities for social interactions, which may exacerbate tensions between groups, particularly during societal disruptions like COVID-19. Previous studies, including Wang (2021), highlight that urban environments amplify the visibility of minority groups, which can trigger biases and prejudices among majority populations, particularly in periods of heightened stress.

Furthermore, the pandemic disproportionately impacted urban areas, with stricter lockdown measures, higher unemployment rates, and increased stress levels, potentially contributing to the rise in hate crimes. This result aligns with research by Legewie and Schaeffer (2016), who found that urban settings with concentrated populations tend to experience greater intergroup conflict. From a policy perspective, this result emphasizes the need for targeted interventions in urban areas, such as community-building programs or anti-hate initiatives, to address hate crimes effectively in high-density regions.

The significance of density as a predictor also points to the role of visibility and proximity. In densely populated areas, minority groups may become more visible, which, combined with stereotypes and scapegoating during crises, can lead to heightened hostility. This suggests that urbanization amplifies the structural vulnerabilities of marginalized groups, particularly during periods of social and economic uncertainty.

3.2. Share of White Poverty

The share of white poverty ($p<0.05$) was another significant predictor in the fixed effects model. This positive relationship indicates that increases in white poverty within states over time are associated with higher rates of Asian hate crimes. This result diverges from the negative correlation found in the broader correlation analysis, where higher overall levels of white poverty were associated with fewer hate crimes. The fixed effects model, however, captures temporal changes within states, suggesting that rising economic distress among white populations can intensify scapegoating and resentment directed at minority groups.

This finding aligns with the frustration-aggression hypothesis (Dollard et al., 1958), which posits that economic hardships, such as rising poverty, can lead to frustration among individuals. This frustration is often displaced onto scapegoated groups, in this case, Asian populations, particularly during the COVID-19 pandemic when Asians were falsely associated with the virus.

Furthermore, these findings partially align with Wang's (2021) study, which identified urbanization and economic inequality as key predictors of hate crimes. Her study concluded that economic instability heightened the likelihood of hate crimes as economically distressed groups redirected their frustrations onto visible minorities. However, the current study extends this understanding by focusing on temporal changes within states rather than cross-sectional patterns alone. This approach reveals that shifts in structural (urban density) and economic (white poverty) factors influence hate crimes in real-time, offering a deeper perspective on how societal crises like COVID-19 exacerbate existing vulnerabilities. This insight is essential for informing policy, as it highlights the need for flexible, time-sensitive interventions that address both structural and economic drivers of hate crimes.

4. Implications

The findings of this study highlight the complex nature of hate crime dynamics, particularly in the context of anti-Asian hate crimes during the COVID-19 pandemic. Two key factors—urban density and the share of white poverty—emerged as significant predictors, highlighting the interplay between structural and economic influences. Urban density serves as a structural factor, illustrating how the physical and social environments of densely populated areas can shape hate crime trends. On the other hand, the share of white poverty reflects an economic dimension, emphasizing how financial hardship can fuel intergroup conflict and scapegoating.

From a practical perspective, these findings point to two possible intervention strategies. First, addressing the vulnerabilities of urban areas through community-building initiatives, increased access to public resources, and enhanced law enforcement in high-density neighborhoods could help reduce hate crime incidents. By fostering social cohesion in these areas, communities may become more resilient to the social pressures that contribute to hate crime. Second, addressing the root causes of economic distress, particularly among economically disadvantaged white populations, could reduce the frustrations that often manifest as scapegoating and hate crime. Economic support initiatives, such as job training programs or financial assistance, could play a role in mitigating these effects. These implications can address economic distress through targeted support for disadvantaged communities could mitigate hate crimes.

V. Conclusion

1. Final Discussion

This study investigated the social and demographic factors contributing to COVID-related increases in Asian hate crimes across vulnerable states. While the analysis identified significant predictors, the overall findings suggest that these predictors alone may not fully explain the complexity behind the rise in Asian hate crimes during the pandemic. This highlights the limitations of quantitative models in capturing nuanced social dynamics.

The ITS analysis identified 14 states that experienced significant increases in Asian hate crimes after the pandemic's onset. The correlational analysis revealed key shifts in the relationship between demographic and socioeconomic factors before and after COVID-19. Among these, population density and the percentage of white poverty showed notable increases in their association with Asian hate crimes post-COVID. The fixed effects regression further confirmed these two predictors as significant factors influencing the rise in Asian hate crimes. Specifically, states with higher population density and greater shares of white poverty were more likely to report increases in Asian hate crimes, even after controlling for state and year-fixed effects.

This finding aligns with prior research that highlights the role of social stratification and population concentration in increasing Asian hate crimes (Wang, 2021). Higher population density can increase interactions between people, which may heighten tensions during times of crisis. Similarly, poverty among white communities may lead to scapegoating, where economically struggling groups blame minority communities due to perceived competition or cultural beliefs. These findings highlight the need to view hate crimes as complex issues shaped by both structural conditions and specific social situations.

The findings of this study offer valuable insights into the causes of hate crimes and provide guidance for shaping policy interventions. Policymakers and community organizations can use these findings to design more effective strategies. Addressing white poverty and reducing tensions linked to high population density—through targeted community programs or public education campaigns—may help decrease the risk of hate crimes. Additionally, the study emphasizes the importance of real-time monitoring and adaptive interventions that can respond quickly to sudden societal changes, like those triggered by COVID-19. It also highlights the value of combining quantitative analysis with qualitative insights to better understand the underlying factors driving hate crimes.

2. Limitations

This study faced several limitations that must be considered when interpreting the findings. First, the reliance on reported hate crime data from the FBI introduces the possibility of underreporting, as victims may hesitate to report incidents due to distrust in law enforcement or fear of retaliation. Additionally, the correlational analysis and fixed effects model focused on a limited set of variables, which may not fully capture the complex social dynamics underlying hate crimes. Factors such as media narratives, political rhetoric, and localized policy changes could not be included but may have significantly influenced hate crime patterns during the pandemic.

Moreover, the small sample size of state-level data from 2016 to 2023 may limit the generalizability of the findings. While the inclusion of both pre-and post-COVID data was justified to capture long-term trends, future studies with larger and more granular datasets could yield more robust insights.

3. Future Research Directions

Future research should explore additional variables and methods to build on these findings. Integrating qualitative data, such as interviews with affected communities or analyses of political and media narratives, could provide valuable context to supplement quantitative models. Advanced methodologies, such as Random Forests or Causal Inference Trees, could help detect nonlinear relationships and better capture the interplay of multiple factors driving hate crimes.

Additionally, expanding the scope of the analysis to include local-level data, such as city- or neighborhood-level hate crime reports, may provide a more nuanced understanding of regional variations. Examining the role of policy interventions, such as anti-hate crime legislation or public awareness campaigns, could also shed light on effective strategies for mitigating hate crimes during societal crises. It is hoped that these findings and implications will serve as a foundation for society to mitigate and prevent indiscriminate discrimination and violence against marginalized groups during future societal disruptions.

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VII. Appendix A. Related Documents

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VIII. Appendix B. Technical Appendices

1. Data Processing

To conduct this analysis, 49 datasets containing socioeconomic, demographic, and hate crime data were combined into a single dataset. Each dataset contained annual information for different variables, spanning multiple years. The data was processed and merged using a join function to align observations by matching on shared keys (e.g., state, year). This process ensured that each row of the final dataset corresponded to a unique state-year observation, enabling comprehensive analysis of hate crime trends and their relationship with social and demographic factors. Data cleaning steps included handling missing values, standardizing variable names, and ensuring consistent data types for analysis.

2. Statistical Test Codes

2.1. ITS

The following R code was applied to model hate crime rates over time:

```
lm(total_hate_crimes ~ time + intervention + time_since)
```

The model was applied separately for each state using the *group_split()* function, ensuring that a unique ITS model was created for each state. This approach allowed for state-specific analysis of how hate crimes changed after the onset of COVID-19.

2.2. Correlation analysis

The *cor()* function was used to calculate the correlation between predictors and hate crime rates.

2.3. FE regression

The *feols()* function (from the fixest package) was employed, suited for high-dimensional fixed effects such as state and year, enabling the analysis of predictor-outcome relationships within each state over time.

IX. Appendix C. ITS Results

TABLE C. ITS Full Results

	Alabama	Alaska	Arizona	Arkansas	California	Colorado	Connecticut	Delaware	District of Columbia	Federal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Time	0.000	-0.001	-0.006	0.002	0.044	0.006	-0.006	-0.001	0.002	-0.000
	(0.002)	(0.001)	(0.005)	(0.002)	(0.066)	(0.008)	(0.006)	(0.002)	(0.005)	(0.010)
Intervention	0.026	0.054	0.495**	0.025	11.335***	0.594*	0.051	0.031	-0.151	1.896***
	(0.071)	(0.059)	(0.221)	(0.072)	(2.772)	(0.318)	(0.231)	(0.073)	(0.216)	(0.435)
Time Since Intervention	0.002	0.001	0.003	-0.004	-0.140	-0.012	0.008	0.001	0.011	-0.046***
	(0.003)	(0.002)	(0.008)	(0.003)	(0.100)	(0.012)	(0.008)	(0.003)	(0.008)	(0.016)
Constant	-0.000	0.058	0.288*	-0.033	1.803	0.076	0.474***	0.033	0.078	0.000
	(0.050)	(0.042)	(0.155)	(0.050)	(1.945)	(0.223)	(0.162)	(0.051)	(0.152)	(0.305)

Note:

Florida	Georgia	Guam	Hawaii	Idaho	Illinois	Indiana	Iowa	Kansas	Kentucky	Louisiana
(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
0.007	0.005	-0.000	0.008*	0.004*	-0.003	-0.004	-0.002	0.0002	-0.003	-0.000
(0.004)	(0.005)	(0.001)	(0.005)	(0.002)	(0.007)	(0.006)	(0.003)	(0.003)	(0.005)	(0.002)
-0.009	0.137	0.093	0.172	0.007	0.424	-0.003	0.060	0.111	0.333*	0.142**
(0.179)	(0.222)	(0.058)	(0.190)	(0.090)	(0.283)	(0.233)	(0.138)	(0.135)	(0.195)	(0.070)
-0.008	-0.008	-0.002	-0.016**	-0.007**	0.009	0.020**	0.001	-0.002	-0.008	-0.003
(0.006)	(0.008)	(0.002)	(0.007)	(0.003)	(0.010)	(0.008)	(0.005)	(0.005)	(0.007)	(0.003)
-0.054	-0.020	0.000	-0.053	-0.056	0.201	0.230	0.129	0.054	0.266*	0.000
(0.126)	(0.156)	(0.041)	(0.134)	(0.063)	(0.198)	(0.164)	(0.097)	(0.095)	(0.137)	(0.049)

					Dependent variable:					
					Total Hate Crimes					
Maine	Maryland	Massachusetts	Michigan	Minnesota	Mississippi	Missouri	Montana	Nebraska	Nevada	New Hampshire
(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
-0.001	0.00005	0.011	-0.003	-0.011	0.004*	0.001	0.002	-0.002	0.001	-0.0003
(0.003)	(0.003)	(0.017)	(0.007)	(0.007)	(0.002)	(0.004)	(0.001)	(0.002)	(0.006)	(0.002)
0.037	0.142	1.153	0.363	1.298***	-0.003	0.144	-0.021	0.256***	0.628**	0.106
(0.141)	(0.135)	(0.709)	(0.291)	(0.274)	(0.090)	(0.148)	(0.059)	(0.078)	(0.253)	(0.100)
0.006	-0.003	-0.014	-0.003	-0.009	-0.008**	-0.002	-0.003	-0.005	-0.011	-0.002
(0.005)	(0.005)	(0.026)	(0.011)	(0.010)	(0.003)	(0.005)	(0.002)	(0.003)	(0.009)	(0.004)
0.057	0.059	0.690	0.405*	0.576***	-0.032	0.048	-0.035	0.075	0.064	0.047
(0.099)	(0.094)	(0.497)	(0.204)	(0.192)	(0.063)	(0.104)	(0.041)	(0.055)	(0.178)	(0.070)

New Jersey	New Mexico	New York	North Carolina	North Dakota	Ohio	Oklahoma	Oregon	Pennsylvania	Rhode Island	South Carolina	Tennessee
(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)	(41)	(42)	(43)	(44)
0.074***	0.001	-0.011	0.001	0.001	0.010*	-0.000	0.010	0.0004	0.001	-0.001	0.004
(0.020)	(0.001)	(0.049)	(0.006)	(0.001)	(0.006)	(0.002)	(0.008)	(0.010)	(0.002)	(0.002)	(0.004)
2.401***	0.028	8.117***	-0.112	-0.047	-0.019	0.119	0.105	1.418***	0.034	0.045	0.002
(0.837)	(0.059)	(2.040)	(0.234)	(0.042)	(0.250)	(0.090)	(0.334)	(0.403)	(0.083)	(0.099)	(0.171)
-0.116***	-0.002	-0.065	0.012	-0.001	-0.009	-0.0004	-0.001	-0.005	-0.001	0.004	-0.001
(0.030)	(0.002)	(0.074)	(0.008)	(0.002)	(0.009)	(0.003)	(0.012)	(0.015)	(0.003)	(0.004)	(0.006)
-0.262	0.004	1.013	0.140	-0.008	0.018	0.000	0.009	0.129	0.007	0.046	0.029
(0.587)	(0.042)	(1.432)	(0.164)	(0.029)	(0.176)	(0.063)	(0.234)	(0.283)	(0.058)	(0.069)	(0.120)

Texas	Utah	Vermont	Virginia	Washington	West Virginia	Wisconsin	Wyoming
(45)	(46)	(47)	(48)	(49)	(50)	(51)	(52)
0.009	-0.001	0.002	0.004	0.037*	0.004	0.001	0.000
(0.008)	(0.004)	(0.002)	(0.006)	(0.021)	(0.003)	(0.004)	(0.001)
0.535	0.159	-0.090	-0.106	1.803**	-0.149	-0.019	0.003
(0.351)	(0.174)	(0.103)	(0.268)	(0.872)	(0.114)	(0.163)	(0.042)
-0.016	0.004	0.004	0.008	-0.061*	-0.001	0.011*	0.001
(0.013)	(0.006)	(0.004)	(0.010)	(0.032)	(0.004)	(0.006)	(0.002)
0.160	0.056	-0.038	0.146	0.549	-0.016	0.025	-0.000
(0.246)	(0.122)	(0.072)	(0.188)	(0.612)	(0.080)	(0.114)	(0.030)

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$