State Vulnerability to COVID-19 Driven Asian Hate Crimes

: Pandemic Impact or Environmental Factors?

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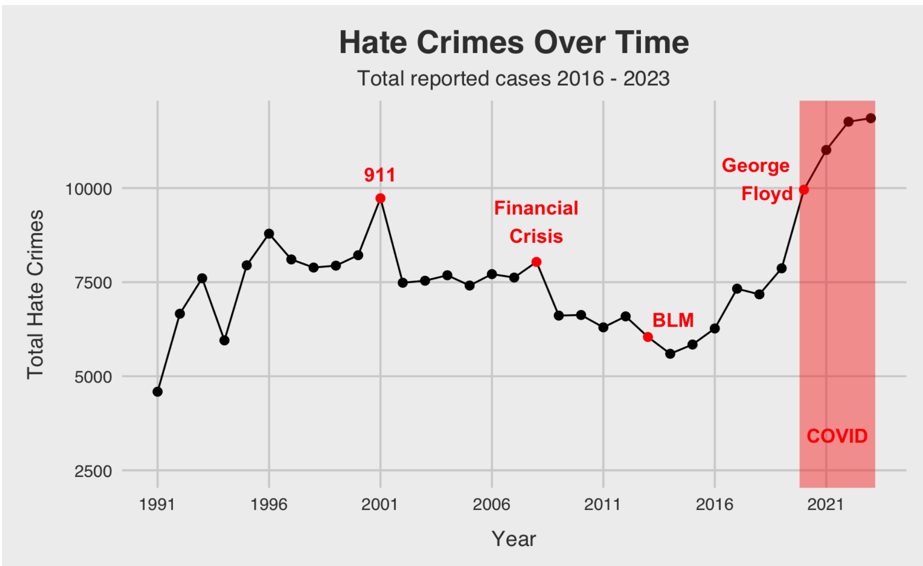
ABSTRACT

This study examines the social and demographic factors contributing to COVID-19-related increases in anti-Asian hate crimes across U.S. states, with a particular focus on identifying states most vulnerable to these shifts. Utilizing Interrupted Time Series (ITS) analysis, Fixed Effects (FE) regression, and clustering, this research investigates the extent of COVID-19's impact on Asian-targeted hate crimes and assesses whether socioeconomic, demographic, and political factors amplified this vulnerability. Results indicate that while COVID-19 significantly impacted hate crime rates, only a subset of states exhibited notable increases. Contrary to initial expectations, traditional social indicators—such as economic conditions, racial demographics, and political climate—did not consistently predict these heightened vulnerabilities. This study provides insights into the complexity of hate crime dynamics during a crisis, offering valuable data on state-specific vulnerabilities that may inform targeted interventions and policies to address bias-motivated violence during times of societal disruption.

I. Introduction

Hate crimes are criminal offenses driven by prejudice or bias against specific groups based on characteristics such as ethnicity, religion, or sexual orientation (Oxford English Dictionary, n.d.). In the United States, hate crime incidents have steadily increased over the years, with sharp surges often occurring during periods of social unrest or disruption. As illustrated in Figure 1, hate crime rates from 1991 to 2023 reveal noticeable spikes that coincide with pivotal societal events, such as the 9/11 attacks, the 2008 financial crisis, and, most recently, the COVID-19 pandemic. Each of these events aligns with marked increases in hate crime incidence, suggesting that societal upheavals may amplify certain biases, triggering temporary surges in hate-motivated violence (Perry, 2014).

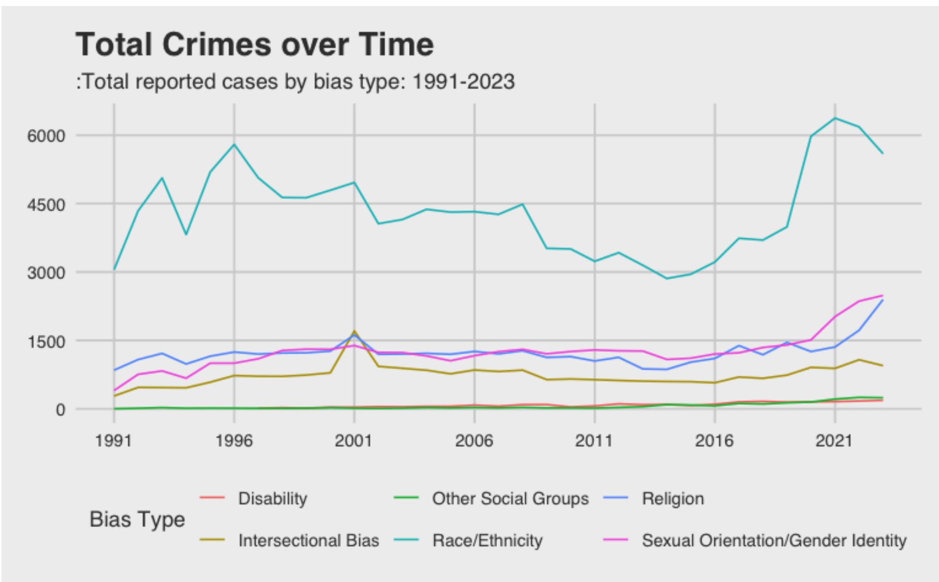


[Figure 1. Hate crimes over Time]

Among the various hate crime categories, race- and ethnicity-related offenses have been the most prevalent, with the COVID-19 pandemic bringing unprecedented attention to anti-Asian hate crimes. Reports and media coverage documented a significant rise in violence, harassment, and discrimination targeting Asian individuals and communities during the pandemic (Jeung et al., 2021). This study aims to determine whether COVID-19 substantially influenced this increase 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.

In response to the social dynamics surrounding hate crimes, this study addresses two central 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. Hae crime by bias type]

In developing these research questions, I hypothesize that the majority of states would display similar trends in rising anti-Asian hate crimes, as racial hate crimes are often influenced by nationwide factors and societal trends. Therefore, it is expected that most states will reflect similar vulnerability. Additionally, I posit that COVID-19 was not the only factor driving the increase in anti-Asian hate crimes; rather, associated social conditions, particularly those related to race and demographic makeup, may have intensified the impact of the pandemic on hate crimes. Given that this is a racial hate crime context, I hypothesize that race distribution will be among the most influential variables in predicting vulnerability.

While previous studies have explored individual factors such as socioeconomic conditions and political climates, these factors are often examined independently, with limited research integrating multiple variables to understand their combined impact on hate crime vulnerability. This study seeks to bridge this gap by examining how a range of social and demographic factors may collectively influence hate crime rates, focusing specifically on anti-Asian incidents during the COVID-19 pandemic. In addition, since reports indicate that anti-Asian hate crimes rose significantly during this period (Kim, 2022), this research aims to pinpoint which states experienced the sharpest increases and to determine whether these shifts were influenced primarily by COVID-19 or if pre-existing trends contributed to these increases.

II. Background

1.1. Literature Review

The impact of socioeconomic, demographic, and political factors on hate crimes is a critical area of research, particularly in understanding how bias-motivated violence is shaped and intensified by broader social contexts. Prior studies reveal that hate crimes often cluster around pivotal social and political events—such as elections or economic downturns—which amplify social tensions and creates negative feelings towards specific group (King, 2013). This phenomenon underscores the time-sensitive nature of hate crimes, supporting the current study's use of Interrupted Time Series (ITS) analysis to assess shifts in Asian-targeted hate crimes during COVID-19. While King's research focuses on short-term spikes in hate crimes, this study examines whether specific socioeconomic and demographic factors contribute to sustained increases over time, addressing a longer-term perspective.

Economic instability and inequality have also been identified as drivers of hate crimes, with socioeconomic distress creating an environment where minority groups are more frequently scapegoated. Raj (2022) analyzed how variables such as unemployment, poverty, and income inequality correlate with rising bias-motivated incidents, finding that these conditions can heighten social frustration and amplify hostility toward minority communities. Building on Raj's findings, this study incorporates variables like GDP, unemployment, and poverty rates to assess whether states that exhibited increased vulnerability to hate crimes during the pandemic had underlying economic stressors. Although Raj's work offers valuable insights into the relationship between economic distress and social hostility, it does not examine how these factors function within the extended context of a global crisis. This study addresses this gap by analyzing the potential long-term economic effects of COVID-19 on hate crime rates

Demographic composition is another crucial factor in hate crime vulnerability, as shifts in racial and social diversity can often lead to social tensions. Diaz-Faes and Pereda (2020) describe how hate crimes are embedded within broader social hierarchies and dynamics. Their review suggests that hate crimes are not isolated occurrences but part of a larger pattern where demographic changes, such as an increase in minority populations, can incite backlash. This research incorporates these insights by analyzing demographic factors like racial composition and age distribution across states, exploring whether states with larger Asian populations or younger demographics experienced greater hate crime increases after COVID-19. Unlike prior research, this study situates these demographic factors within the unique context of a global health crisis, providing a nuanced perspective on how structural characteristics might intersect with large-scale disruptions to influence hate crimes.

Wang (2002) argued that everyday discrimination is often reinforced by political and social environments that may subtly endorse or legitimize bias. This research considers political leaning as a variable to assess whether certain political climates were more conducive to bias-motivated crimes during the pandemic. While Wang's research broadly addresses how social contexts influence bias, the present study narrows this focus to hate crimes specifically, investigating how state-level political affiliations might correlate with pandemic-related hate crime trends.

1.1.1. 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 moves from 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. Identifying specific state-level vulnerabilities in this context is both timely and essential for understanding the broader social implications of crises like COVID-19.

1.2. Ethical Considerations

In conducting this research, ethical considerations are central due to the sensitive nature of hate crime data and the potential implications of the findings. Since hate crime incidents often affect vulnerable communities, this study handles the data with care to ensure that no findings reinforce negative stereotypes or unfairly attribute blame to any group or region. Though the analysis uses state-level, aggregate data with no personally identifying information, the implications of discussing racial or demographic factors demand a balanced approach, especially when examining social and political characteristics that may contribute to bias-motivated violence.

Furthermore, while demographic and socioeconomic variables are essential for understanding broader trends, they are not used to imply that any particular attribute causally determines hate crime prevalence. Instead, these factors are analyzed within the structural and social contexts of the COVID-19 pandemic, aimed at highlighting potential vulnerabilities rather than making stereotypes about particular groups. By adhering to these ethical practices, this study seeks to provide insights that can inform supportive, data-driven policies while respecting the communities that are most affected by hate crimes.

III. Data and Method

1. Data collection and variables description

This study utilizes the hate crime statistics dataset provided by the FBI's 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 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:

Type	Name	Description
Demographic	Race Distribution	Proportion of the population identifying as Asian, Black, Hispanic, and White
	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	GDP	State GDP per capita, serving as a measure of economic output and prosperity
	Unemployment Rate	Average state unemployment rate

	Population Density	Residents per square mile in each state
	Poverty Rate	Percentage of the population living below the poverty line
	College Degree Rate	Proportion of the population with at least a bachelor's degree
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: "Did COVID-19 lead to an immediate, sustained, combined, or no effect on Asian hate crime cases, and were certain states more vulnerable?" 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. 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 next section.

2.1.3. 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 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

2.1.4. Steps for ITS

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.

2.2. Fixed Effect Model

2.2.1. 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 covariates such as age distribution, racial composition, gender ratio, GDP, and other socioeconomic 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.

2.2.2. Limitations

Due to the nature of demographic data, which tends to exhibit limited variability over short periods, multicollinearity among these variables was a concern. Initial diagnostic checks using Variance Inflation Factor (VIF) analysis identified high collinearity among variables representing age, race, and gender proportions. Consequently, adjustments were made by removing variables with high VIF scores. The final model included selected age and race groups, socio-economic indicators, and one gender variable (Female) to minimize multicollinearity while maintaining interpretability.

2.2.3. Mathematical equation for the model

The fixed effects model is specified as follows where η_i represents state-specific effects, λ_i represents year-specific effects, and ϵ_{it} is the error term. This model estimates the within-state impact of each covariate over time while controlling for time-invariant factors.

$$Total\ hate\ crimes_{it} = \beta_0 + \beta_1 young_{it} + \beta_2 middle\_Aged_{it} + \beta_3 Asian_{it} + \ldots + \eta_i + \lambda_i + \epsilon_{it}$$

2.2.4. Steps for FE model

The data was filtered to include Asian hate crime cases in identified vulnerable states. A master dataset containing all independent variables (e.g., age distribution, unemployment rate) was then created, with each row representing a state's variable values and year. 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.

2.3. K-means Clustering

2.3.1. Description and Suitability of K-means Clustering

To address the limitations of the FE model's susceptibility to multicollinearity, K-means clustering was used. This approach allows exploration of correlations among social and demographic factors with states that exhibited significant increases in COVID-related Asian hate crimes. Clustering groups states based on similarities in social, economic, and demographic characteristics, identifying common traits within each cluster. This method is useful for examining patterns across multiple variables without assuming linear relationships.

2.3.2. Steps for clustering method

The dataset for the FE model was adapted for clustering by excluding non-essential columns such as state and year. To determine the optimal number of clusters, the Within-Cluster Sum of Squares (WSS) method was used, visualized through an elbow plot generated with the fviz_nbclust function. The plot suggested four clusters (k = 4) as the most representative structure for the data. The K-means algorithm was then applied to the standardized data, iteratively adjusting cluster centroids until an optimal arrangement was achieved. A table was created to show each state's cluster assignment, revealing states with similar social and demographic profiles.

IV. Results

1. Interrupted Time Series (ITS) Analysis

This analysis used three main parameters: Time (indicating the underlying pre-pandemic trend), Intervention (capturing the immediate change associated with the pandemic's onset in March 2020), and Time Since Intervention (reflecting any ongoing trend change after the 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 1 summarizes the ITS results for 14 states identified as "vulnerable" among the 52 total. Focusing on these states reveals significant Intervention and/or Time Since Intervention effects.

	Dependent variable:														
	Total Hate Crimes														
	Arizona	California	Federal	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)	(15)
Time	-0.006	0.044	-0.000	0.008^{*}	0.004^{*}	-0.004	-0.000	-0.011	0.004^{*}	-0.002	0.001	0.074^{***}	-0.011	0.0004	0.037^{*}
	(0.005)	(0.066)	(0.010)	(0.005)	(0.002)	(0.006)	(0.002)	(0.007)	(0.002)	(0.002)	(0.006)	(0.020)	(0.049)	(0.010)	(0.021)
Intervention	0.495^{**}	11.335^{***}	1.896^{***}	0.172	0.007	-0.003	0.142^{**}	1.298^{***}	-0.003	0.256^{***}	0.628^{**}	2.401^{***}	8.117^{***}	1.418^{***}	1.803^{**}
	(0.221)	(2.772)	(0.435)	(0.190)	(0.090)	(0.233)	(0.070)	(0.274)	(0.090)	(0.078)	(0.253)	(0.837)	(2.040)	(0.403)	(0.872)
Time Since Intervention	0.003	-0.140	-0.046^{***}	-0.016^{**}	-0.007^{**}	0.020^{**}	-0.003	-0.009	-0.008^{**}	-0.005	-0.011	-0.116^{***}	-0.065	-0.005	-0.061^{*}
	(0.008)	(0.100)	(0.016)	(0.007)	(0.003)	(0.008)	(0.003)	(0.010)	(0.003)	(0.003)	(0.009)	(0.030)	(0.074)	(0.015)	(0.032)
Constant	0.288^{*}	1.803	0.000	-0.053	-0.056	0.230	0.000	0.576^{***}	-0.032	0.075	0.064	-0.262	1.013	0.129	0.549
	(0.155)	(1.945)	(0.305)	(0.134)	(0.063)	(0.164)	(0.049)	(0.192)	(0.063)	(0.055)	(0.178)	(0.587)	(1.432)	(0.283)	(0.612)
Note:															$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

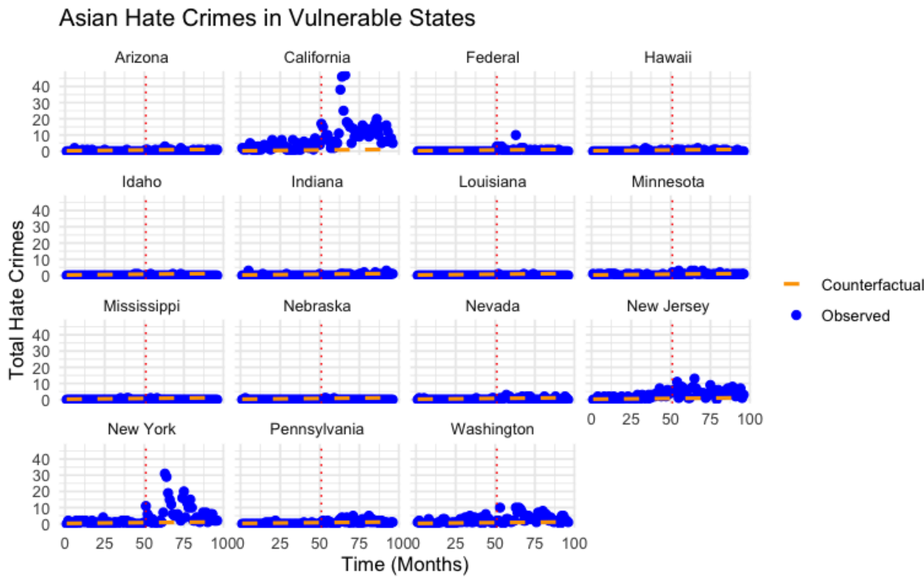
[Table 1. ITS Results table]

California reported a notable Intervention effect with a coefficient of 11.335 ($p < 0.001$), 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 8.117 ($p < 0.001$), indicating an immediate rise in hate crimes with the onset of the pandemic. New Jersey had an Intervention coefficient of 2.401 ($p < 0.01$) and a negative Time Since Intervention coefficient (-0.116, $p < 0.01$), 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, $p < 0.05$), as well as a negative Time Since Intervention coefficient (-0.007, $p < 0.01$), indicating a decrease in hate crimes over time after the initial pandemic rise. Indiana's positive Time Since Intervention coefficient (0.020, $p < 0.05$) suggests a continued upward trend post-intervention, while Nevada showed significant positive Intervention coefficients (0.628, $p < 0.05$), indicating an immediate pandemic-related increase. Washington exhibited both a significant Intervention effect (1.803, $p < 0.05$) and a negative Time Since Intervention coefficient (-0.061, $p < 0.1$), signaling an initial spike followed by a decline. Minnesota had a significant Intervention effect (1.298, $p < 0.001$) without a sustained change, indicating only an immediate rise in hate crimes.

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

[Table 2. Effect type sorted table(summary of table 1)]

Figure 2 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, and New Jersey.



[Figure 2. Counterfactual plots for 14 vulnerable states]

2. Fixed Effect Model

The fixed effects model results, displayed in Table 3, show that only GDP per capita was statistically significant ($p < 0.001$), with an estimated coefficient of 1929.5, suggesting a positive association between GDP and total hate crimes. However, no other demographic or socioeconomic factors—such as age groups, racial proportions, gender, unemployment, or poverty—were statistically significant. Additionally, many covariates had large standard errors, indicating considerable uncertainty in these estimates.

Young	−200.713	GDP	1929.519
	(207.325)		(277.305)
Middle-Aged	−189.583	Density	−2379.227
	(160.811)		(4128.216)
Asian	5.189	Average Unemployment	−8.275
	(13.364)		(38.864)
White	501.147	Health Status	−0.803
	(656.936)		(29.686)
Hispanic	651.445	Poverty Rate	−41.656
	(459.057)		(68.586)
Female	−76.542	Fixed Effects for state and year included.	
	(64.980)		

Fixed Effects Model Results for Total Hate Crimes

[Table 3. Fixed Effect Model results]

3. K-means Clustering

The clustering analysis grouped states into four distinct clusters based on social, economic, and demographic characteristics, as shown in Table 4. Each cluster represents states with similar profiles. For instance, Cluster 1 includes Idaho, Indiana, Minnesota, and Nebraska, while Cluster 2 comprises Arizona, California, Nevada, and Washington. Clusters 3 and 4 have smaller state groups, each showing unique social and economic profiles.

state	cluster
Idaho	1
Indiana	1
Minnesota	1
Nebraska	1
Arizona	2
California	2
Nevada	2
Washington	2
Louisiana	3
Mississippi	3
Hawaii	4
New Jersey	4
New York	4
Pennsylvania	4

[Table 4. Cluster for each state]

V. 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, with pre-existing trends or sustained effects rather than immediate spikes. In Idaho, for example, a rising trend was evident even before COVID-19, implying that factors influencing hate crimes were active 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 significance findings.

2. Correlation Between Factors and Racial Bias Hate crimes

Within the vulnerable states, what social factors influence the hate crime rate the most was tried to be answered through the Fixed effect model. While the fixed effects model was initially chosen to control for unobserved heterogeneity, the results indicate that it may not be the most suitable method for this analysis. The lack of significant findings, coupled with the high standard errors, suggests that the model is struggling to distinguish the independent contributions of each socio-economic and demographic factor on hate crime rates. The high standard errors are problematic because they indicate a lack of precision in the model's parameter estimates, which limits the ability to draw reliable inferences about the effect of each variable. Large standard errors often suggest that the model is unable to fully capture the unique impact of each predictor due to potential overlap or collinearity among variables. In this case, high multicollinearity likely contributed to these inflated standard errors, as overlapping demographic proportions (e.g., age, race, and gender) made it challenging to isolate the individual effects of each covariate. Despite efforts to address this issue through variable selection and transformations, the multicollinearity persisted, compromising the model's interpretability and reliability.

Another key limitation of the FE model in this context is the limited year-over-year variability in demographic and social factors, which change only gradually within each state. Due to this stability, the model struggled to capture meaningful shifts in hate crime trends based on these predictors, further restricting its ability to attribute variance in hate crimes to specific factors with confidence. This lack of variability, combined with high multicollinearity, suggests that the FE model may not adequately capture the dynamics driving hate crime rates in response to short-term events like the COVID-19 pandemic.

In summary, the FE model's limitations suggest that factors beyond static socioeconomic and demographic characteristics may play a larger role in influencing hate crime rates, particularly in the context of sudden societal shifts such as those experienced during the pandemic.

3. Do States Share Common Social Factors?

Given the Fixed Effects model's limitations, clustering analysis offers a potentially viable alternative by grouping states based on shared characteristics, allowing exploration of whether states with similar ITS results fall into the same clusters. Unlike regression models, clustering avoids interpretability challenges related to multicollinearity and provides a nuanced view of states' shared characteristics.

The clustering results in Table 4, however, did not align with states showing significant increases in COVID-related Asian hate crimes. This suggests that hate crime patterns may not directly correlate with social and demographic factors or that no clear grouping pattern exists that aligns with these trends. While the FE model results indicated high standard errors and lacked significant predictors, the clustering analysis further suggests that states do not share common social factors that might explain their ITS outcomes. In other words, Table 4 (cluster assignments) and Table 2 (effect type summary) show no significant overlap, implying that no single set of social factors predicts increased Asian hate crimes following COVID-19.

VI. Conclusion

1. Final Discussion

This study aimed to investigate the social and demographic factors contributing to COVID-related increases in Asian hate crimes across U.S. states. Three methodological approaches—Interrupted Time Series (ITS), Fixed Effects (FE) regression, and clustering—were employed to capture different aspects of the relationship between social factors and vulnerability to hate crimes during the pandemic. However, contrary to initial expectations, the factors analyzed did not consistently predict which states experienced an increase in hate crimes, suggesting complexities in the dynamics behind these incidents and highlighting limitations in the capacity of current quantitative models to fully capture the nuanced drivers of hate crimes.

The ITS analysis identified 14 states with significant increases in Asian hate crimes following the pandemic's onset. Subsequent analyses using FE regression and clustering provided limited insights into why these specific states were more affected. The FE regression, while controlling for state and year, yielded high standard errors and few statistically significant coefficients, indicating substantial unexplained variance and multicollinearity. Similarly, the clustering method did not reveal distinct, meaningful groupings, suggesting that the states with increased hate crimes did not share clear social or demographic commonalities based on the selected variables. Collectively, these findings imply that the rise in Asian hate crimes following COVID-19 may not be adequately explained by standard demographic or socioeconomic indicators alone. Tentatively, this may suggest that COVID-19 itself was a primary driver behind this increase, potentially influencing hate crime more broadly.

2. Implications

These findings hold important implications. First, they suggest that conventional social and demographic factors may not be the main drivers of hate crimes, especially during rapid societal changes like a pandemic. This underscores the potential importance of qualitative and context-specific factors, such as media influence, political rhetoric, or cultural attitudes, which were not captured in this dataset. The limited predictive power of the analyzed factors highlights the need for a more nuanced, interdisciplinary approach to studying hate crimes. Policymakers and community organizations may need to adopt context-sensitive interventions, moving beyond demographic trends to assess hate crime vulnerability. Additionally, this study underscores the importance of real-time monitoring and response, as hate crime dynamics can shift rapidly in response to major events.

3. Limitations

This study faced several limitations that may have influenced the results. First, while valuable, social and demographic factors alone may not capture all the drivers of hate crimes, particularly those arising from sudden societal shifts. Variables like media sentiment, public policy responses, or cultural changes could not be included but may have played a significant role during the pandemic. Second, multicollinearity was a recurring issue, particularly in the FE regression, due to inherent correlations among demographic proportions (e.g., race, age, gender). Efforts to reduce multicollinearity through variable selection and transformations helped, but residual effects likely remained, impacting the model's precision and interpretability. Lastly, the lack of significant results from clustering and other methods suggests that the selected variables may not have been sensitive enough to capture the complex social dynamics behind COVID-related hate crimes. The limitations of these quantitative models underscore the need for complementary qualitative research to better understand underlying factors.

4. Future Research Directions

Future research should build on these findings by exploring alternative variables and methodologies that may better capture the unique drivers of hate crimes. Integrating qualitative insights, such as community interviews or analyses of political and media narratives, could provide valuable context that quantitative models alone cannot capture. Additionally, advanced statistical techniques or machine learning models, such as Principal

Component Analysis (PCA) to address multicollinearity or Random Forests to detect potential nonlinear relationships, could be considered. Expanding the study to examine the influence of policy interventions or cultural factors on hate crimes could also yield more meaningful insights. Repeating this analysis with updated and more granular data may further improve accuracy and relevance.

In conclusion, while this study did not identify clear demographic or social predictors for COVID-related increases in Asian hate crimes, it provides a critical foundation for understanding the limitations of current quantitative approaches in hate crime research. Addressing these gaps through interdisciplinary methods and broader data sources will be essential for developing effective, targeted responses to hate crimes in a rapidly changing social landscape.

VII. References

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VIII. Appendices

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