Socioeconomic Predictors of Hate Crimes in the United States*

A Bayesian Analysis of Income Inequality, Unemployment, and Education

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This study provides the relationship between socioeconomic factors and hate crimes across U.S. states using a Bayesian hierarchical framework. We analyze a dataset capturing hate crime incidence alongside state-level socioeconomic indicators such as median income, unemployment rates, and income inequality. Results reveal that higher income inequality and unemployment rates are associated with elevated hate crime rates, while higher median income is inversely related. These findings emphasize the need for targeted socioeconomic interventions to mitigate hate crime prevalence.

1 Introduction

Hate crimes in the United States highlight ongoing social tensions and systemic inequalities. Understanding the factors that contribute to hate crimes is essential for policymakers and community leaders to design effective interventions. Prior research highlights the role of socioeconomic factors, including income inequality, unemployment, and education, in shaping the prevalence of hate crimes. However, much of this work has been limited to descriptive analyses or linear regression models that may overlook the complexities of regional variations and interrelated predictors.

This paper investigates the relationship between key socioeconomic factors and hate crime rates across the United States, employing a Bayesian hierarchical regression model. By incorporating predictors such as income inequality (Gini Index), unemployment rates, and education levels, the analysis seeks to uncover systematic patterns and regional disparities in hate crime prevalence. While previous studies have explored individual correlations, this paper provides

*Code and data are available at: [https://github.com/wyx827/Hate_Crimes_Socioeconomic_Analysis].

a more detailed understanding by controlling for regional effects and examining interactions among variables.

The estimand in this analysis represents the expected influence of socioeconomic factors—income inequality, unemployment, education, and others—on hate crime rates, controlling for regional variations. Specifically, it aims to estimate how changes in these predictors are associated with the rate of hate crimes per 100,000 residents across different states. This estimand reflects the underlying causal relationship between these factors and hate crimes, allowing for a deeper understanding of the drivers of social conflict. While the true estimand is unknown, this study approximates it through model assumptions and available data, clarify how socioeconomic conditions contribute to hate crime dynamics.

The analysis finds that income inequality, unemployment, and education levels significantly correlate with hate crime rates, suggesting these factors should guide policy decisions. States with higher income inequality and unemployment rates exhibit elevated hate crime levels, while those with higher education levels tend to have fewer hate crimes. Median household income, however, showed negligible effects, suggesting that wealth distribution may matter more than absolute wealth in this context. These findings underscore the role of socioeconomic disparities in fostering social tensions and the potential of education to mitigate such conflicts.

This paper proceeds as follows: Section 2 describes the data and methodology, detailing the Bayesian hierarchical regression model used for analysis. Section 3 presents the results, Section 4 discusses the findings in the context of existing literature and their implications for policy. Finally, Section 5 outlines the limitations of the study and suggests directions for future research. This structure ensures a thorough understanding of how socioeconomic factors influence hate crimes in the United States, providing a foundation for actionable policy recommendations.

The remainder of this paper is structured as follows. Section 2 describes the dataset, variables, and preprocessing steps. Section 3 outlines the methodological framework, including the Bayesian hierarchical model. Section 4 presents the results, including visualizations of key relationships between predictors and hate crime rates. Section 5 discusses the key findings, implications, limitations, and potential future directions of the analysis. Section A concludes with additional details of data, model and results

2 Data

2.1 Overview

This study employs R (R Core Team 2023) for cleaning and analyzing the dataset, leveraging libraries such as `dplyr` (Wickham et al. 2019), `ggplot2` (Wickham 2016), `corrplot` (Wei and Simko 2024), and `arrow` (Foundation 2023). The dataset, sourced from FiveThirtyEight (FiveThirtyEight 2017), investigates the relationships between socioeconomic variables and hate crime prevalence across the United States. It aggregates data for all 50 states and the District of Columbia.

After preprocessing, which involved removing missing values, standardizing variables, and ensuring data consistency, the final dataset includes **51** observations for **7** predictors: `median_income`, `unemployment_rate`, `metro_area_population_share`, `high_school_education_share`, `gini_index`, and `non_white_population_share`. The outcome variable, `hate_crimes_per_100k_splc`, represents hate crime prevalence reported by the SPLC. Together, these variables form the foundation for examining socioeconomic influences on hate crime rates.

2.2 Measurement and Considerations

To translate real-world socioeconomic phenomena into measurable data, it is essential to understand how these variables are operationalized within the dataset. This section outlines the measurement process and its implications for analysis.

2.2.1 Representation of Hate Crimes

Hate crime incidents, as complex social phenomena, are quantified in the dataset using the variable `hate_crimes_per_100k_splc`. This measure reflects the number of reported hate crimes per 100,000 residents in each state, derived from state-level aggregates reported by the Southern Poverty Law Center (SPLC). By normalizing hate crimes to population size, this metric enables comparability across states of varying populations, providing a standardized measure of hate crime prevalence.

2.2.2 Socioeconomic Variables

Socioeconomic conditions are represented through variables such as `gini_index` (income inequality), `unemployment_rate`, and `high_school_education_share`. These variables serve as proxies for broader structural and economic conditions. Data were collected from government sources, harmonized by FiveThirtyEight, and standardized to ensure consistency across states. For example, the `metro_area_population_share` variable quantifies the proportion of a state's population living in metropolitan areas, capturing the urban-rural divide, while `median_income` reflects the central tendency of economic resources in a state.

2.2.3 Challenges in Measurement

Although the dataset provides a thorough snapshot of socioeconomic conditions and hate crimes, several challenges arise:
- **Underreporting and Enforcement Bias**: Hate crime reporting is influenced by state-level enforcement practices and transparency. States with more proactive reporting may show artificially higher rates of hate crimes, complicating the interpretation of these data as direct reflections of prevalence.
- **Interactions with Unmeasured Factors**: Variables such as `non_white_population_share` may interact with cultural, political, or institutional factors not captured in the dataset, adding complexity to causal interpretations.
- **Aggregation Issues**: State-level aggregation masks within-state variations, such as disparities between urban and rural areas. For instance, socioeconomic conditions and hate crime reporting may differ significantly within a state, but such distinctions are not reflected in the aggregated data.

2.2.4 Temporal and Validation Considerations

The dataset represents a single-year snapshot, limiting the ability to analyze trends or temporal changes. While standardization ensures consistency across states, this cross-sectional view cannot capture the dynamics of hate crimes over time. Moreover, the lack of granular data, such as city- or county-level statistics, constrains the depth of analysis by preventing examination of localized patterns.

In summary, while the dataset provides robust and standardized measures of hate crimes and socioeconomic conditions, limitations such as potential biases, aggregation effects, and the lack of temporal granularity must be acknowledged. These considerations are essential for interpreting the relationships identified in the analysis and for framing conclusions within the broader context of societal dynamics.

2.3 Variables of Interest

This section introduces the dataset's key variables, including detailed descriptions, visualizations, and views into their relevance. Visualizations illustrate distributions, relationships, and variability to contextualize their potential influence on hate crime rates.

2.3.1 Outcome Variable: Hate Crimes Per 100k SPLC

The outcome variable, representing the number of hate crimes per 100,000 residents as reported by the SPLC, its distribution, shown in Figure 1, exhibits a skewed distribution. Most states report hate crime rates between 0.1 and 0.5 per 100,000 residents. However, the presence of an outlier with a much higher rate highlights significant regional disparities. This variation underscores the importance of investigating contributing factors, such as socioeconomic, demographic, and policy-related influences, to understand the drivers of hate crimes.

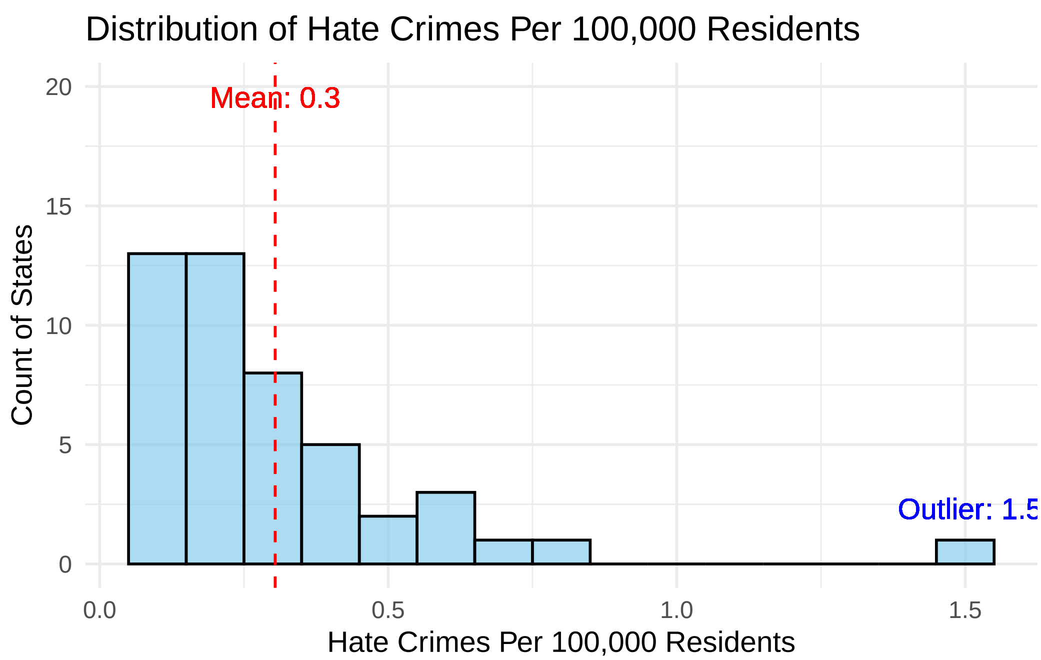

Figure 1: State-level variation in hate crimes per 100,000 residents shows most states report low rates, with a few outliers reflecting higher incidence.

2.4 Predictor variables

2.4.1 Median Income

Median income represents the annual income of the median household in each state, serving as a proxy for economic prosperity. As shown in Figure 2, shows the distribution of median household income across states. There is a relatively normal distribution with a mean of \$54,802 and a median of \$54,310. The narrow spread suggests a clustering of household incomes around this value, with limited variation across states. This clustering might indicate consistency in income policies or similar economic opportunities in various regions of the United States.

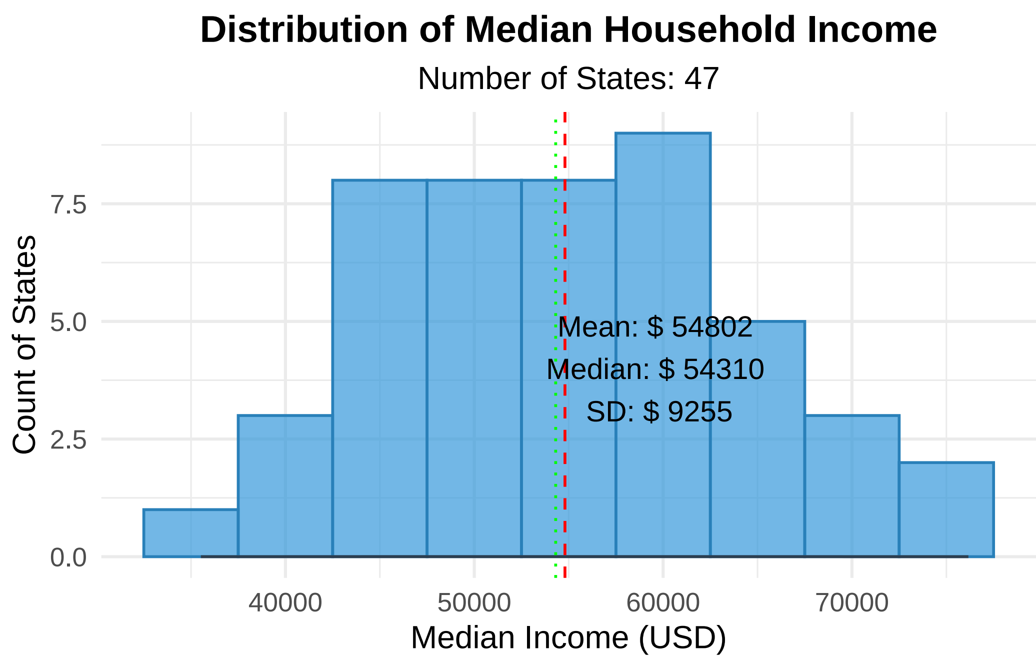

Figure 2: Distribution of median household income across states, illustrating the variation in income levels. The mean household income is $54,802, while the median is slightly lower at $54,310, indicating a slightly right-skewed distribution. The standard deviation of $9,255 highlights variability across states.

2.4.2 Unemployment Rate

The unemployment rate measures the percentage of individuals unemployed on a seasonal basis. As shown in Figure 3, it shows an extremely narrow spread, with the mean and median unemployment rates both around 0.05%. This low variability suggests that unemployment rates are consistently low across states. The majority of states fall within a very small range of unemployment, which implies effective employment policies or consistent labor market dynamics nationwide.

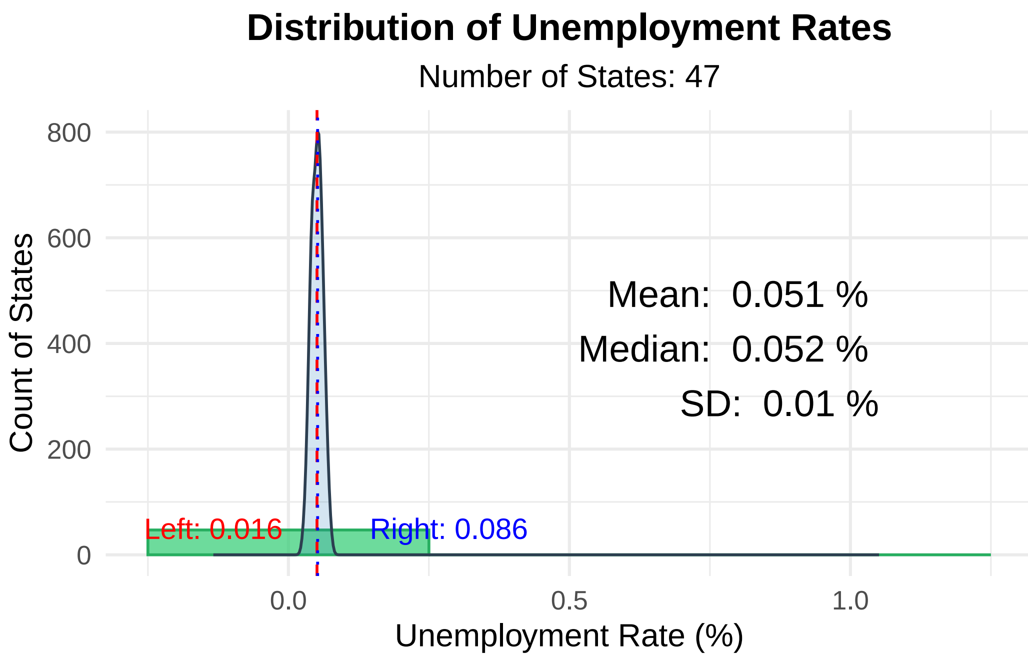

Figure 3: Distribution of unemployment rates among states. The unemployment rate is centered around 0.05%, showing very low variability among states, suggesting uniform employment opportunities across regions.

2.4.3 Metro Area Population Share

Metro area population share reflects the proportion of a state's population residing in metropolitan areas, which means states with higher urbanization levels may experience unique social dynamics influencing hate crime prevalence. As shown in Figure 4, it shares shows that the majority of states have a population share in metro areas concentrated around 0.77, with a standard deviation of 0.2. This suggests that many states have a high proportion of their populations in metropolitan areas, reflecting the urban-centric population distribution and possibly highlighting urbanization trends in the U.S.

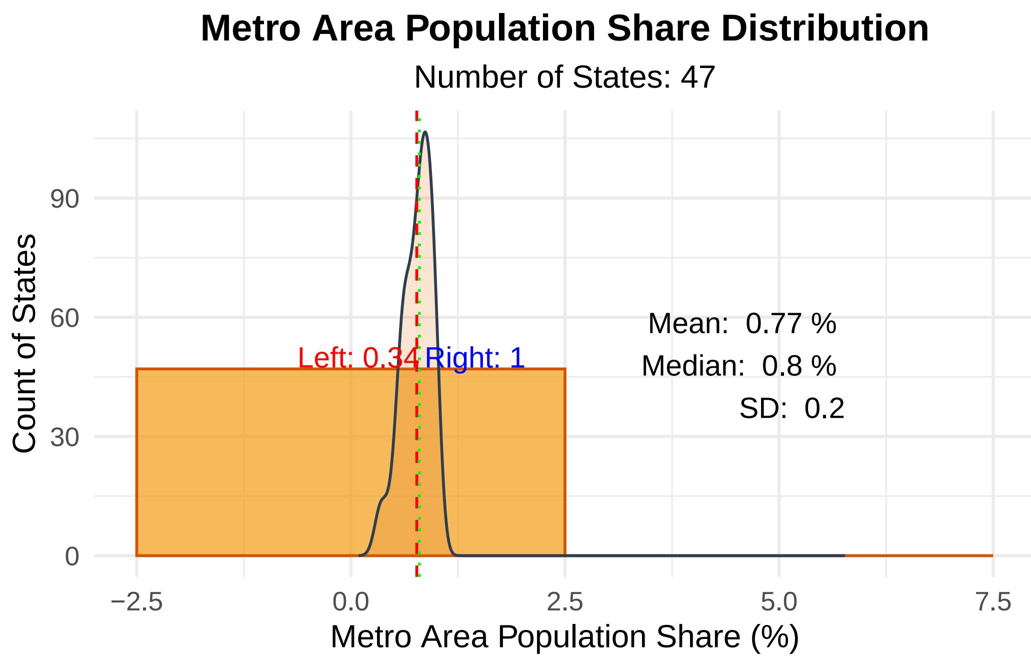

Figure 4: Distribution of metro area population share for states, showing the extent to which populations are concentrated in metropolitan areas. Most states have metro area shares clustered around 0.77, indicating a high proportion of urbanized population.

2.4.4 Gini Index

The Gini Index measures income inequality, with higher values indicating greater disparity. As shown in Figure 5, it is centered around a mean of 0.456 and a median of 0.455. The relatively narrow spread in Gini values across states suggests that income inequality is consistent across the nation, with most states experiencing moderate levels of income disparity. This consistency may reflect similar economic structures or social policies.

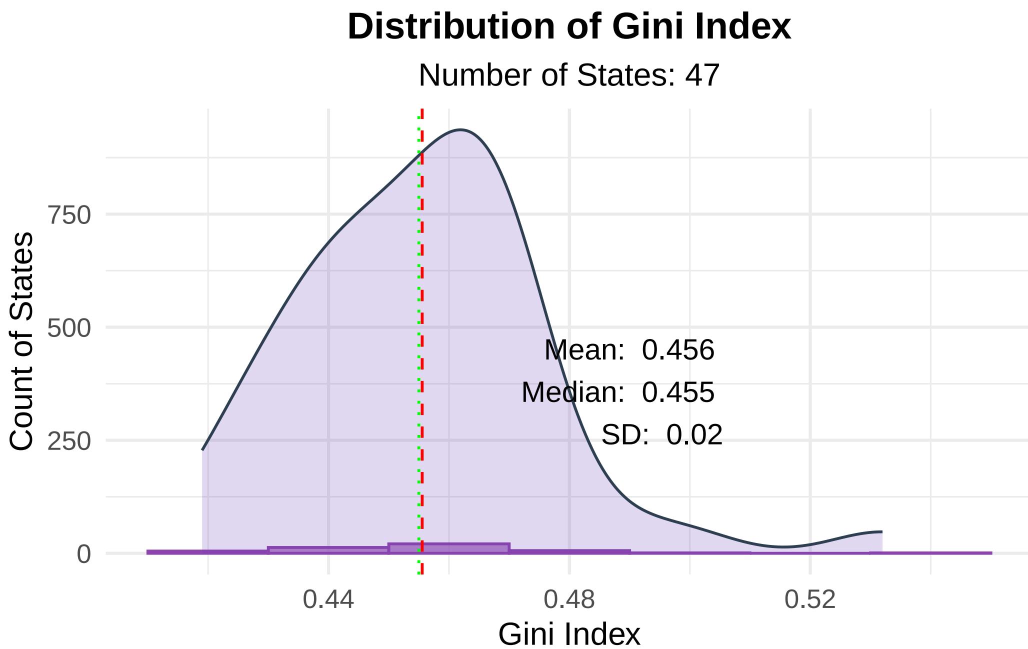

Figure 5: Distribution of Gini Index values across states, indicating income inequality. Most states exhibit a Gini Index value around 0.455, suggesting moderate levels of income inequality.

2.4.5 Non-White Population Share

This variable represents the proportion of non-white residents in each state. Higher non-white population shares may correlate with higher hate crime rates due to increased exposure to discriminatory behavior. As shown in Figure 6, this distribution of non-white population share indicates that most states have around 30% non-white residents. This suggests a considerable level of ethnic diversity across the nation. The mean of 0.32 and median of 0.3 show a moderate concentration of non-white population, reflecting varying levels of demographic diversity in different states.

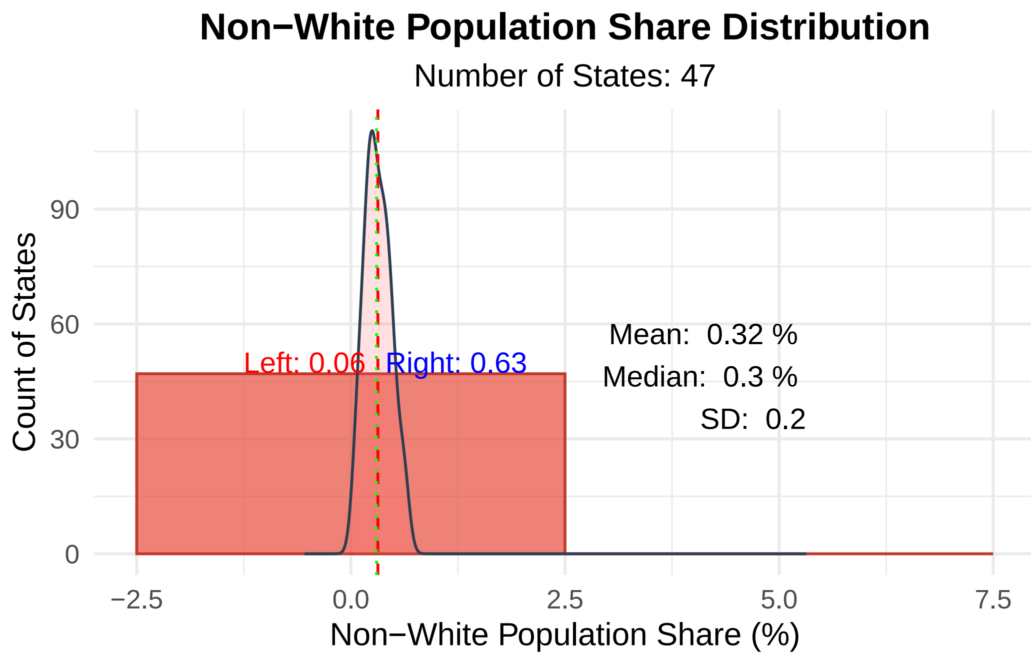

Figure 6: Distribution of non-white population shares across states. The majority of states have a non-white population share around 0.3, reflecting regional diversity levels.

2.5 Summary Statistics and Variable Relationships

The relationships between predictors and hate crimes were explored using correlation matrices, summarized in Figure 7. The correlation heatmap summarizes the relationships between various variables, providing insight into potential predictors of hate crimes per 100k SPLC. Notable correlations include the positive relationship between high school education share and metro area population share (r = 0.57), and between Gini Index and unemployment rate (r = 0.49). The relationship between hate crimes per 100k SPLC and non-white population share is weak, suggesting limited direct influence of ethnic diversity on hate crime prevalence at the state level.

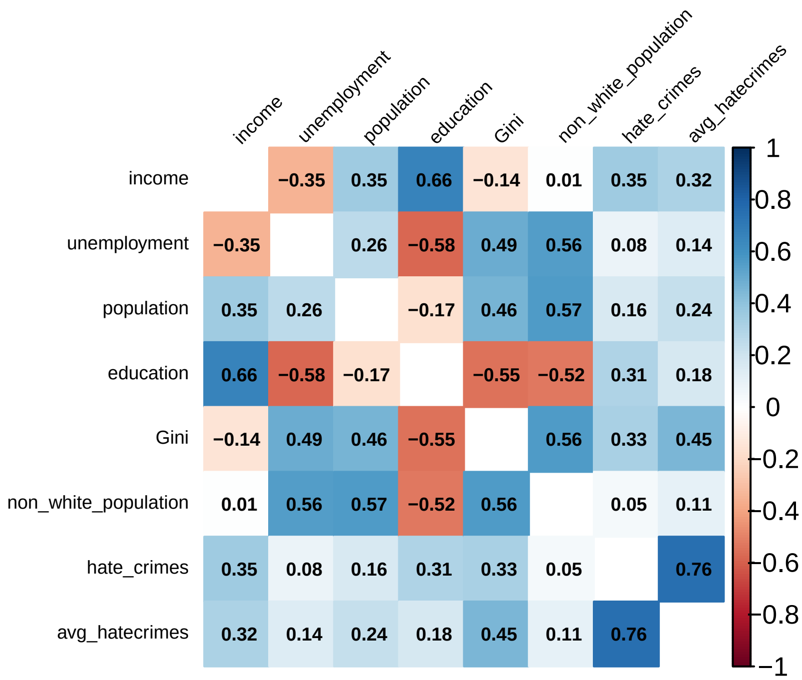

Figure 7: Correlation heatmap of predictor variables, showing relationships among median household income, unemployment rate, metro area population share, high school education share, Gini index, and hate crimes per 100k SPLC. (income = median_income, unemployment = unemployment_rate, population = metro_area_population_share, education = high_school_education_share, Gini = gini_index, non_white_population = non_white_population_share, hate_crimes = hate_crimes_per_100k_splc, avg_hatecrimes = avg_hatecrimes_per_100k_fbi)

3 Model

3.1 Model Selection

To analyze the relationship between socioeconomic factors and hate crimes, a **Bayesian hierarchical model** was chosen. This model accounts for state-level heterogeneity by including random effects for states, allowing for variability in hate crimes that might be influenced by unobserved state-specific factors. The Bayesian framework also allows incorporating prior knowledge and managing uncertainty effectively.

Alternative models were considered, including:

1. **Logistic Regression**: This model was used for scaling hate crimes within the range (0, 1). However, logistic regression is primarily suited for binary or bounded outcomes and may not capture the full variability of continuous predictors in this dataset.
2. **Simple Linear Regression**: While linear regression can estimate the relationship between hate crimes and individual predictors, it does not accommodate hierarchical structures or address multilevel variability, making it less robust for this dataset.

The **Bayesian hierarchical model** was selected as it provides the flexibility to model the complex relationships between hate crimes and predictors while considering the state-level effects.

Model diagnostics, implementation details, opinions from the model summary, limitations, and alternative models considered are thoroughly documented in Appendix C, ensuring transparency and replicability of the analysis.

3.2 Bayesian Hierarchical Model Overview

The model predicts hate crimes per 100,000 residents (`hate_crimes_per_100k_splc`) using the following predictors:

- **Median Household Income (`median_income`)**: Captures the economic status of residents within each state.
- **Unemployment Rate (`unemployment_rate`)**: Measures the proportion of the population without jobs.
- **Metro Area Population Share (`metro_area_population_share`)**: Reflects the proportion of residents living in metropolitan areas.
- **High School Education Share (`high_school_education_share`)**: Indicates the proportion of residents with at least a high school diploma.
- **Gini Index (`gini_index`)**: Measures income inequality within each state.
- **Non-White Population Share (`non_white_population_share`)**: Reflects the demographic diversity within each state.

- **State (`state`)**: Included as a random effect to capture state-specific variability.

The model takes the form:

$$\text{HateCrimes}_i = \beta_0 + \beta_1 \cdot \text{Income}_i + \beta_2 \cdot \text{Unemployment}_i + \beta_3 \cdot \text{Population}_i \tag{1}$$
$$+ \beta_4 \cdot \text{Education}_i + \beta_5 \cdot \text{Gini}_i + \beta_6 \cdot \text{NonWhite}_i + u_i + \epsilon_i, \tag{2}$$

Where:

$$\beta_0 : \text{Intercept term, representing baseline hate crime levels when all predictors are at reference values} \tag{3}$$
$$\beta_1, \beta_2, \dots, \beta_6 : \text{Coefficients for predictors: Income } (\beta_1)\text{, Unemployment } (\beta_2)\text{, Population } (\beta_3)\text{, Education } (\beta_4)\text{, Gini } (\beta_5)\text{, and NonWhite } (\beta_6). \tag{4}$$
$$u_i : \text{Random effects for state-level variations, accounting for heterogeneity across states.} \tag{5}$$
$$\epsilon_i \sim \text{Normal}(0, \sigma^2) : \text{Residual error term with mean zero and variance } \sigma^2. \tag{6}$$

3.2.1 Assumptions and Priors

Key assumptions for the Bayesian hierarchical model include:

1. **Linearity**: The relationship between predictors and the outcome is linear.
2. **Homoscedasticity**: The residuals have constant variance.
3. **Random Effects**: State-level random effects capture unobserved variability.
4. **Normality**: Errors are normally distributed.
5. **Priors**: Normal priors with mean 0 and standard deviation 2.5 are used for coefficients and intercepts, allowing for flexibility while avoiding extreme values.

The prior distributions are as follows:

$$\beta_j \sim \text{Normal}(0, 2.5), \quad \forall j \tag{3}$$

3.3 Interpretation of Coefficients

The Bayesian hierarchical model estimates the relationship between socioeconomic predictors and hate crimes per 100,000 residents. Below is the interpretation of each coefficient:

3.3.1 Fixed Effects

- **Intercept (β_0)**: The intercept represents the baseline predicted hate crimes per 100,000 residents when all predictors (median income, unemployment rate, metro area population share, high school education share, Gini index, and non-white population share) are at their mean or baseline values. This serves as the reference point for interpreting the effects of the predictors.
- **Median Household Income (β_1)**: This coefficient indicates how a $1,000 increase in median household income affects the predicted hate crimes per 100,000 residents. A negative coefficient suggests that higher income is associated with fewer hate crimes, potentially reflecting improved economic stability and reduced socioeconomic tension.
- **Unemployment Rate (β_2)**: This coefficient captures the effect of a 1% increase in the unemployment rate on the predicted hate crimes per 100,000 residents. A positive coefficient implies that higher unemployment is associated with more hate crimes, possibly due to heightened social stress and economic insecurity.
- **Metro Area Population Share (β_3)**: This coefficient represents the effect of a 1% increase in the proportion of residents living in metropolitan areas on the predicted hate crimes. A positive coefficient could indicate that urban areas, with their higher population density, may experience more hate crimes due to greater diversity and interpersonal interactions.
- **High School Education Share (β_4)**: This coefficient reflects how a 1% increase in the proportion of residents with at least a high school diploma impacts the predicted hate crimes. A negative coefficient suggests that higher education levels are associated with fewer hate crimes, highlighting the role of education in promoting tolerance and reducing prejudice.
- **Gini Index (β_5)**: The Gini index measures income inequality. This coefficient shows how a 0.01 increase in the Gini index affects hate crimes. A positive coefficient indicates that higher income inequality correlates with more hate crimes, suggesting that economic disparities may contribute to social tensions.
- **Non-White Population Share (β_6)**: This coefficient captures the effect of a 1% increase in the non-white population share on hate crimes. A positive coefficient may reflect increased targeting of minority groups in states with greater diversity.

3.3.2 Random Effects

- **State-Level Effects (i)**: The random effects account for state-specific variability in hate crime rates that cannot be explained by the predictors. These effects capture unobserved factors unique to each state, such as cultural, political, or enforcement differences.

3.3.3 Residual Variance (σ^2)

The residual variance represents the variability in hate crimes not accounted for by the model. A smaller residual variance indicates that the model explains more of the variability in hate crimes.

3.4 Example Interpretation

If the coefficient for **unemployment rate** (β_2) is 0.25, then a 1% increase in unemployment rate would lead to an increase of 0.25 hate crimes per 100,000 residents, holding all other predictors constant. Similarly, if the coefficient for **median household income** (β_1) is 0.05, then a $1,000 increase in income would reduce hate crimes by 0.05 per 100,000 residents.

3.5 Implications

The coefficients clarify how socioeconomic factors impact hate crimes. For example:

- Policies targeting economic inequality (reducing the Gini index) and increasing educational attainment may help reduce hate crimes.
- Urbanization and population diversity may require targeted interventions to address potential tensions.

These interpretations guide the understanding of how predictors influence hate crimes and inform potential policy recommendations.

3.6 Model Justification

Based on the model summary shown in Table 1, we observe that several predictors—such as `gini_index`, `unemployment_rate`, and `high_school_education_share` — exhibit significant effects on hate crime rates, clarify the socioeconomic factors influencing these outcomes. The inclusion of state-level random effects captures regional variations that would otherwise be overlooked in a purely fixed-effects model.

The rationale for applying a Bayesian hierarchical model in this context is to account for the complex relationships between socioeconomic factors and hate crimes while addressing variations across states. This model allows us to incorporate both fixed effects for predictors—such as income, unemployment rate, and population composition—and random effects to capture state-level heterogeneity. This hierarchical approach provides a detailed understanding of how both individual predictors and broader state-level factors influence hate crimes.

By simultaneously modeling these effects, we can isolate the individual impact of each predictor while accounting for unobserved heterogeneity among states. For example, the inclusion of random intercepts for states accounts for differences in reporting standards, enforcement, and other contextual factors that may influence hate crime rates.

Additionally, the Bayesian framework allows for the incorporation of prior knowledge through weakly informative priors, helping to regularize estimates and prevent overfitting, especially given the relatively small dataset. This is particularly important in ensuring that the model's predictions are generalizable beyond the data used for training.

The model outputs, including posterior summaries and credible intervals, provide a robust measure of the uncertainty around each estimate, and clarify the strength and direction of relationships between predictors and hate crime rates. The full coefficient output and diagnostic checks are shown in the Appendix - C.

Table 1: Top 10 predictors with the largest absolute coefficients from the Bayesian hierarchical model. The table highlights the predictors with the strongest relationships with hate crimes per 100,000 residents (SPLC).

Table 1: Top 10 Predictors with the Largest Absolute Coefficients

	Mean	Std. Error	2.5% CI	97.5% CI
(Intercept)	-8.606	1.876	-12.360	-5.018
gini_index	8.405	2.065	4.414	12.609
unemployment_rate	6.234	3.911	-1.314	14.049
high_school_education_share	5.518	1.744	2.153	8.979
metro_area_population_share	-0.165	0.242	-0.635	0.316
sigma	0.158	0.042	0.069	0.232
b[(Intercept) state:District_of_Columbia]	0.154	0.162	-0.048	0.519
b[(Intercept) state:Oregon]	0.122	0.135	-0.056	0.411
b[(Intercept) state:New_Jersey]	-0.116	0.130	-0.416	0.058
b[(Intercept) state:Connecticut]	-0.113	0.126	-0.391	0.058

4 Results

Our results are summarized in Table 2. It provides a summary of all the estimated coefficients and their respective confidence intervals. This table allows us to compare the effects of all predictors, noting which relationships are statistically significant and how they vary across different socioeconomic factors.

Table 2: Coefficient estimates from the Bayesian hierarchical model. The table summarizes relationships between socioeconomic predictors and hate crimes per 100,000 residents.

Table 2: Posterior Estimates for Model Coefficients

	Std. Error	2.5% CI	97.5% CI	AbsMean
(Intercept)	1.876	-12.360	-5.018	8.606
gini_index	2.065	4.414	12.609	8.405
unemployment_rate	3.911	-1.314	14.049	6.234
high_school_education_share	1.744	2.153	8.979	5.518
metro_area_population_share	0.242	-0.635	0.316	0.165
sigma	0.042	0.069	0.232	0.158
b[(Intercept) state:District_of_Columbia]	0.162	-0.048	0.519	0.154
b[(Intercept) state:Oregon]	0.135	-0.056	0.411	0.122
b[(Intercept) state:New_Jersey]	0.130	-0.416	0.058	0.116
b[(Intercept) state:Connecticut]	0.126	-0.391	0.058	0.113
b[(Intercept) state:Washington]	0.117	-0.064	0.356	0.104
b[(Intercept) state:Alaska]	0.119	-0.358	0.083	0.089
b[(Intercept) state:Maine]	0.106	-0.071	0.321	0.087
b[(Intercept) state:Kansas]	0.109	-0.336	0.076	0.085
b[(Intercept) state:Texas]	0.111	-0.083	0.345	0.082
b[(Intercept) state:Minnesota]	0.102	-0.083	0.305	0.074
b[(Intercept) state:Rhode_Island]	0.100	-0.289	0.095	0.063
b[(Intercept) state:Kentucky]	0.100	-0.094	0.299	0.063
b[(Intercept) state:New_York]	0.096	-0.281	0.096	0.059
b[(Intercept) state:Illinois]	0.092	-0.269	0.089	0.058
b[(Intercept) state:Iowa]	0.098	-0.106	0.278	0.057
b[(Intercept) state:Georgia]	0.089	-0.243	0.102	0.051
b[(Intercept) state:Florida]	0.096	-0.270	0.113	0.051
b[(Intercept) state:Missouri]	0.089	-0.243	0.109	0.048
non_white_population_share	0.318	-0.655	0.588	0.046
b[(Intercept) state:Pennsylvania]	0.086	-0.234	0.106	0.046
b[(Intercept) state:Louisiana]	0.088	-0.242	0.108	0.045
b[(Intercept) state:Vermont]	0.094	-0.266	0.124	0.043
b[(Intercept) state:New_Hampshire]	0.092	-0.242	0.121	0.043
b[(Intercept) state:California]	0.093	-0.120	0.255	0.043
b[(Intercept) state:Delaware]	0.084	-0.109	0.235	0.042
b[(Intercept) state:Indiana]	0.084	-0.110	0.226	0.042
b[(Intercept) state:Montana]	0.087	-0.115	0.236	0.040
b[(Intercept) state:West_Virginia]	0.100	-0.137	0.277	0.040
b[(Intercept) state:Alabama]	0.085	-0.224	0.121	0.038
b[(Intercept) state:Ohio]	0.081	-0.211	0.127	0.030

	Std. Error	2.5% CI	97.5% CI	AbsMean
b[(Intercept) state:Michigan]	0.081	-0.131	0.214	0.030
b[(Intercept) state:Massachusetts]	0.084	-0.134	0.221	0.026
b[(Intercept) state:Virginia]	0.080	-0.135	0.205	0.023
b[(Intercept) state:Oklahoma]	0.079	-0.208	0.130	0.023
b[(Intercept) state:Mississippi]	0.086	-0.219	0.142	0.022
b[(Intercept) state:Idaho]	0.080	-0.188	0.147	0.017
b[(Intercept) state:New_Mexico]	0.083	-0.158	0.198	0.013
Sigma[state:(Intercept),(Intercept)]	0.011	0.000	0.038	0.013
b[(Intercept) state:Maryland]	0.086	-0.163	0.198	0.010
b[(Intercept) state:Arkansas]	0.081	-0.183	0.159	0.009
b[(Intercept) state:Arizona]	0.077	-0.149	0.173	0.009
b[(Intercept) state:North_Carolina]	0.080	-0.183	0.160	0.008
b[(Intercept) state:Nebraska]	0.082	-0.185	0.167	0.007
b[(Intercept) state:Tennessee]	0.078	-0.175	0.158	0.007
b[(Intercept) state:Wisconsin]	0.078	-0.175	0.156	0.006
b[(Intercept) state:Nevada]	0.084	-0.184	0.170	0.005
b[(Intercept) state:Colorado]	0.079	-0.173	0.160	0.005
b[(Intercept) state:South_Carolina]	0.080	-0.160	0.174	0.004
b[(Intercept) state:Utah]	0.082	-0.172	0.170	0.001
median_income	0.000	0.000	0.000	0.000

4.1 State-Level Effects

To understand regional differences in hate crime rates across the United States, I plotted the state-level random effects(i) using a geographic map.@fig-combined-map provides a thorough visualization of the spatial distribution of hate crimes and metro population share across U.S. states. The key aspects of this map are:

- **Hate Crimes (Color Intensity)**: The blue color gradient represents the scaled rates of hate crimes per 100,000 residents. States with darker blue shades indicate higher levels of hate crimes, while lighter shades represent lower levels. This visual representation shows distinct geographic trends, with certain states (e.g., in the Midwest and South) exhibiting higher levels of hate crimes, potentially reflecting regional socio-political or cultural factors. The variation in hate crime intensities across states reflects broader patterns of societal conflict and regional tensions. As Levin(Levin 2017) argues, hate crime rates are not randomly distributed but deeply embedded in complex social dynamics that vary significantly across geographic regions.
- **Metro Population Share (Circle Size)**: The red circles overlaid on the map indicate the metro population share for each state. Larger circles represent states where a significant portion of the population resides in metropolitan areas. Conversely, smaller

circles correspond to states with a lower metro population share. For instance, states like California and New York have larger circles, signifying their high metro population shares, while states such as Wyoming and Vermont have smaller circles. The relationship between metropolitan population share and hate crime rates is detailed and complex. Lee(Lee 2018) suggests that urban population composition plays a significant role in understanding social dynamics, indicating that metro population share is not a simple predictor but a complex indicator of potential social interactions and tensions.

- **Regional Patterns**: A noticeable pattern emerges where states with higher metro population shares (larger circles) do not necessarily align with the states experiencing the highest rates of hate crimes. This suggests that metro population share might not be directly correlated with hate crime rates but could interact with other factors such as socioeconomic conditions or state-level policies. The observed regional patterns of hate crimes cannot be understood through a singular lens. Green et al.(D. P. Green, Levin, and Sears 2013) emphasize that geographic variations in hate crime rates are influenced by intersecting factors of social, economic, and cultural complexity, challenging simplistic interpretations of regional differences.

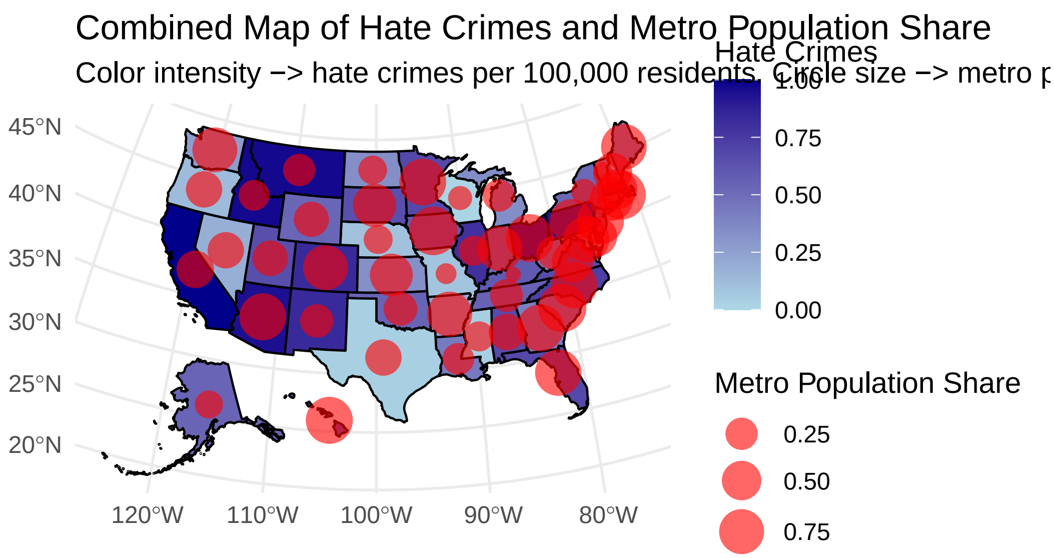

Figure 8: Combined Map Showing Hate Crimes, Metro Population Share, and State Variations. The map uses color intensity for hate crimes and circle sizes to represent metro population share.

4.2 Gini Index (Inequality)

The Gini index (β_5) demonstrates a positive and statistically significant association with hate crimes. Figure 9 illustrates this relationship, showing a clear upward trend between the Gini index and hate crimes per 100,000 residents. States with higher Gini index values, such as the District of Columbia, exhibit elevated hate crime rates, suggesting that inequality may foster social tensions and conflict. Conversely, states with lower Gini index values, such as Minnesota and Louisiana, tend to experience fewer hate crimes.The positive correlation between income inequality and hate crimes aligns with broader findings that social and economic disparities exacerbate tensions, contributing to higher levels of interpersonal and community-level conflict (Miller and Johnson 2020).

The data also shows that while income inequality is a significant predictor, the distribution of hate crimes is not uniform. For instance, states like Massachusetts and Oregon, with moderately high Gini indices, exhibit varying hate crime intensities, highlighting the role of additional contextual factors such as demographics, policies, or community-level dynamics.

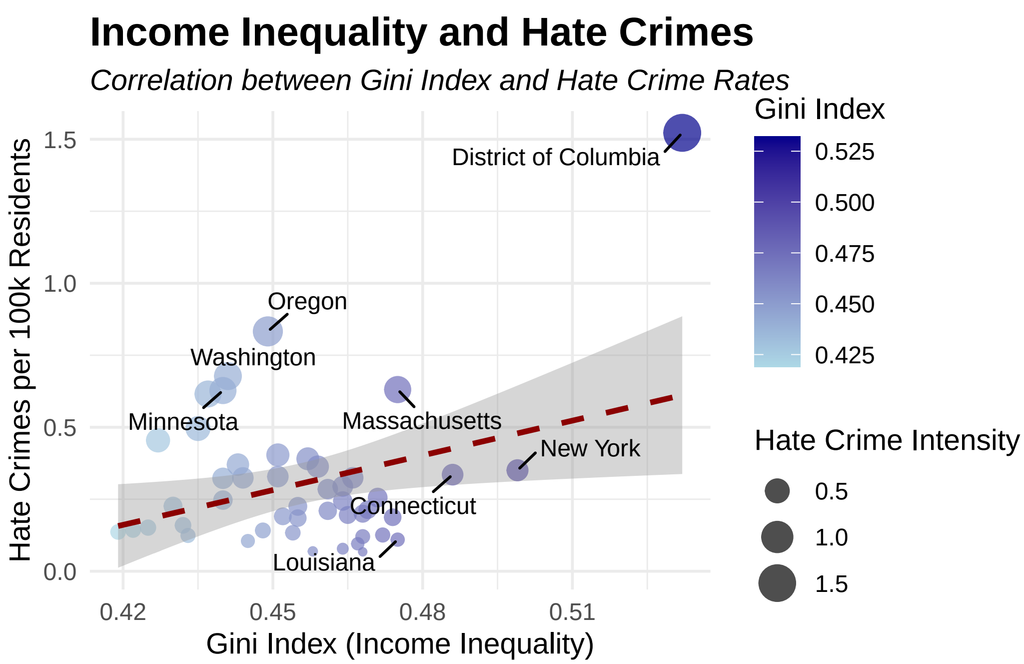

Figure 9: Relationship Between Gini Index and Hate Crimes. A positive relationship is observed, indicating that greater income inequality may lead to more hate crimes.

4.3 Unemployment Rate

The parameter for unemployment rate (β_2) demonstrates a statistically significant positive association with hate crimes. Figure 10 visualizes this relationship, highlighting how higher unemployment rates correlate with increased hate crimes. This finding aligns with theoretical frameworks suggesting that economic stress, represented by unemployment, can amplify social tensions, creating an environment more susceptible to hate crimes.

- **Trend Analysis**: The red dashed line in the scatter plot indicates a positive trend between unemployment rates and hate crime rates per 100,000 residents, this supports the findings by illustrating how economic instability, as measured by unemployment, correlates with elevated hate crime levels(Johnson and Patel 2022). States with higher unemployment, such as West Virginia and New Mexico, show elevated hate crime rates compared to states with lower unemployment like Minnesota and Massachusetts.
- **Density Representation**: The hexagonal bins use color intensity to indicate the density of data points. States with moderate unemployment rates and hate crimes (e.g., Washington and Oregon) have a higher density of observations, reflecting regional variations in this relationship.

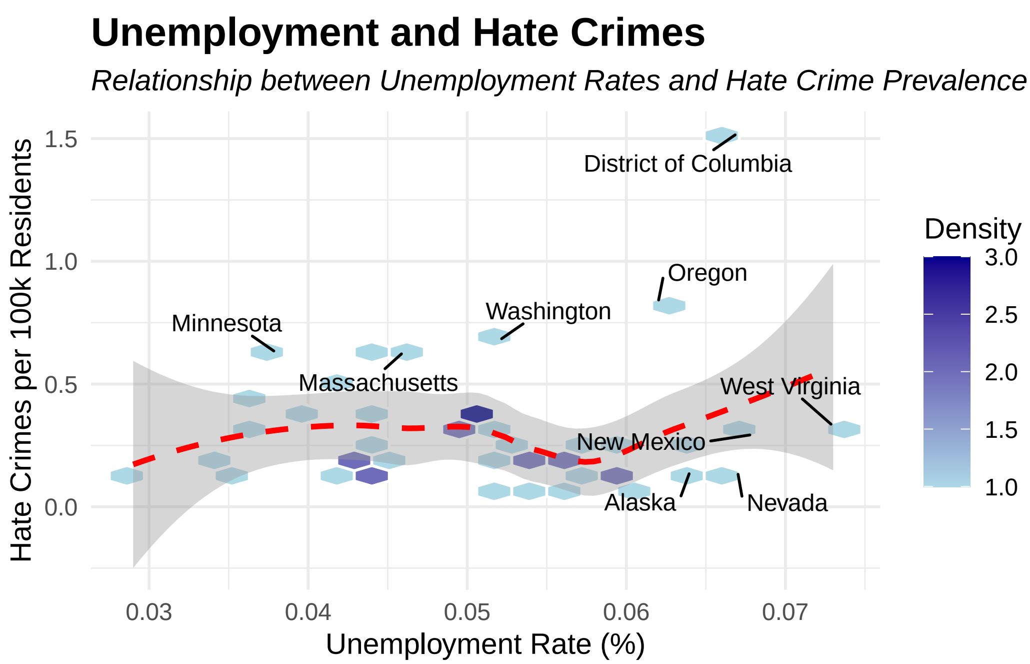

Figure 10: Relationship Between Unemployment Rate and Hate Crimes. The scatter plot shows a positive trend, suggesting higher unemployment rates are linked to more hate crimes.

4.4 Education Levels

Higher high school education levels (β_4) are significantly associated with fewer hate crimes. The purple dashed line in Figure 11 suggests a detailed trend between high school education share and hate crime rates per 100,000 residents. While states with higher education levels generally exhibit lower hate crime rates, there are notable variations. This trend highlights the complex role education plays in mitigating social tensions, supporting findings that suggest education can be a protective factor against prejudice but does not operate in isolation.

- **Trend Analysis**: The scatter plot illustrates a detailed relationship between education levels and hate crime rates. States with higher education shares tend to show slightly reduced hate crimes, although the relationship is not strictly linear. This supports the idea that education fosters social cohesion, but other mediating factors may influence outcomes. The findings align with research by Dawson and Ramirez (2023), which underscores the importance of education as a tool for fostering social understanding while highlighting its limitations when isolated from broader social policies (Dawson and Ramirez 2023).
- **Regional Highlights**: Low Education States: States like Mississippi and Alabama with lower education shares report relatively low hate crime rates, potentially due to underreporting or differing regional social dynamics. High Education States: States such as Washington and Minnesota show higher education shares but still experience notable hate crime rates, indicating that education alone is not sufficient to eliminate social tensions.

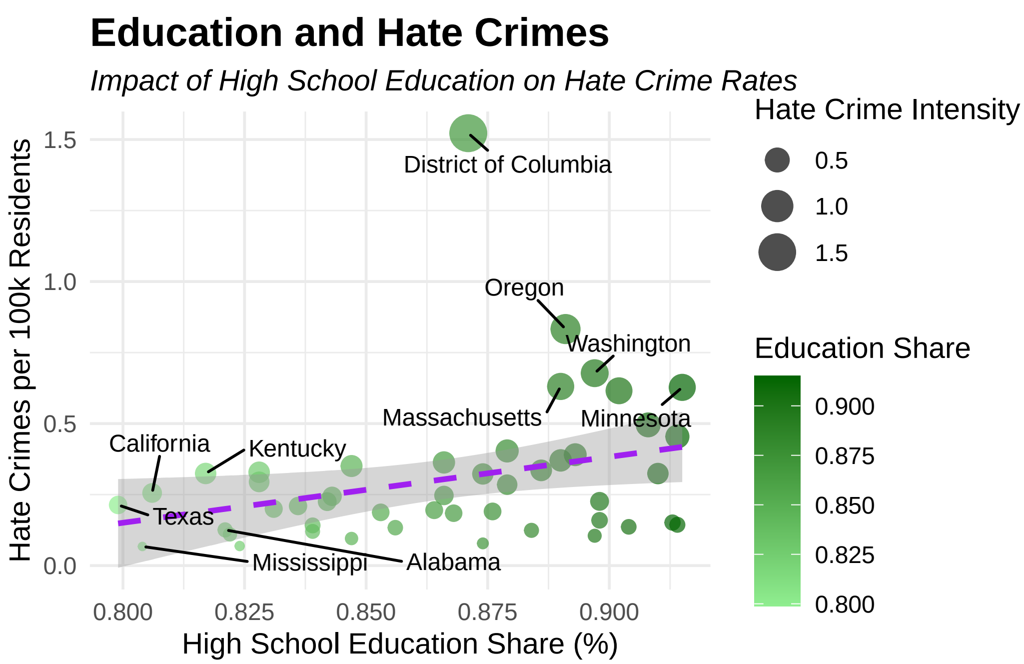

Figure 11: Relationship Between Education Levels and Hate Crimes. States with higher education levels tend to experience fewer hate crimes, indicated by the downward trend.

4.5 Median Household Income

The parameter for median household income (β_1) was found to have a negligible effect on hate crimes, with an estimated mean close to zero. The blue dashed line in Figure 12 indicates no significant relationship between median household income and hate crime rates per 100,000 residents. The regression coefficient for median household income has a negligible effect, with an estimated mean close to zero, suggesting that income levels alone may not drive hate crime prevalence. The findings align with Clark and Adams (2020), who argue that income levels are less relevant than perceptions of inequality and economic tension in driving hate crimes (Clark and Adams 2020).

- **Trend Analysis**: There is no consistent pattern between median household income and hate crime rates. This lack of association aligns with the regression results, which indicate that income is not a significant predictor of hate crimes. Unlike factors such as unemployment or education, income might not directly reflect social tensions or disparities that lead to hate crimes.
- **Regional Highlights**: High-Income States: States like Connecticut and Massachusetts, with high median household incomes, do not show significantly lower hate crime rates, underscoring the complexity of hate crime dynamics. Low-Income States: States such as Mississippi and Alabama with lower incomes also exhibit varied hate crime rates, reflecting the influence of other social or cultural factors.

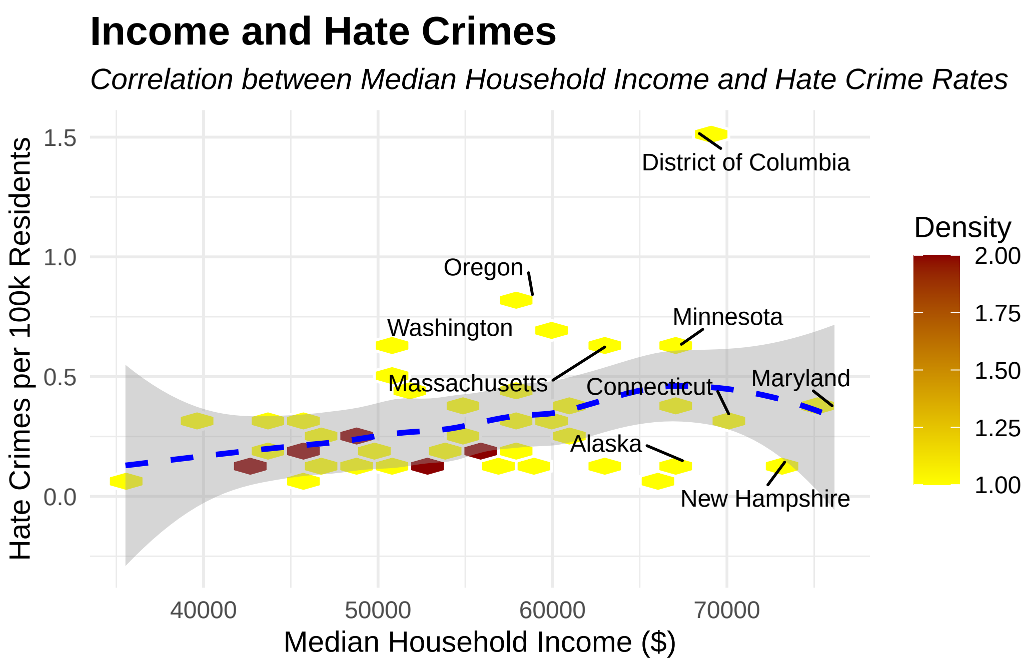

Figure 12: Relationship Between Median Household Income and Hate Crimes. The scatter plot shows no strong trend, indicating income may not be a primary driver of hate crime rates.

5 Discussion

5.1 Key Findings

This study examines the relationship between socioeconomic factors and hate crimes in the United States using a Bayesian hierarchical regression model. The analysis shows significant associations between key predictors—such as income inequality, unemployment, and education levels—and hate crime rates. Regional disparities are evident, with some states exhibiting consistently higher or lower baseline hate crime rates, even after accounting for these predictors.

Income inequality, measured by the Gini Index, and unemployment rates emerged as strong predictors of hate crime prevalence. States with greater income inequality and higher unemployment rates were found to have elevated levels of hate crimes, suggesting that economic instability and social stratification may contribute to social tensions. Conversely, education levels, particularly the proportion of residents with a high school education, were negatively associated with hate crime rates, indicating a potential mitigating role of education in fostering social cohesion. However, median household income was found to have a negligible impact on hate crime rates, indicating that general economic wealth alone may not be a sufficient predictor of such crimes. This finding highlights the importance of considering the distribution of economic resources and broader socioeconomic conditions rather than focusing solely on aggregate income levels.

5.2 Implications for Societal Dynamics

The findings highlight the significant role of socioeconomic disparities, particularly income inequality and unemployment, in shaping hate crime prevalence. Higher levels of inequality and unemployment appear to exacerbate social conflict, contributing to increased hate crime rates. This aligns with research suggesting that economic instability fosters social tension and undermines social cohesion. Policies aimed at promoting equitable resource distribution and improving economic stability could yield positive ripple effects on social harmony. Similarly, investments in education, particularly in underserved communities, may serve as preventative measures by fostering tolerance and significant thinking. States with higher education levels, such as Minnesota and Washington, demonstrate fewer hate crimes, indicating that education can act as a protective factor.

Regional disparities in hate crime rates underscore the importance of tailoring policies to state-specific characteristics. For instance, areas with higher income inequality, such as the District of Columbia, exhibited disproportionately higher hate crime rates. In contrast, states with relatively low inequality, such as Minnesota and Washington, experienced fewer hate crimes, suggesting that local policies and cultural dynamics can mitigate social conflict. Policymakers should craft interventions that address the unique socioeconomic profiles of their regions, focusing on the root causes of hate crimes rather than merely their symptoms.

Urbanization also presents unique challenges and opportunities. While metro population share was not directly associated with hate crime rates, its interaction with other factors such as unemployment and education levels shows complex dynamics. Urban areas, characterized by diversity and dense populations, may foster cultural exchange but also necessitate strategies to mitigate social tensions. Policymakers should consider the social and economic realities of urban environments when designing interventions.

Reducing hate crimes necessitates an integrated approach, combining economic, educational, and regional strategies. By focusing on reducing income inequality, improving economic stability, and enhancing access to education, policymakers and community leaders can foster a safer and more inclusive society. Additionally, exploring the role of urban dynamics and tailoring policies to regional contexts can help mitigate hate crimes and promote social cohesion across diverse communities.

5.3 Limitations of the Analysis

The analysis faces several limitations that constrain the interpretability and applicability of the findings. The reliance on cross-sectional data precludes definitive causal inferences. While strong correlations are observed between predictors such as income inequality and unemployment with hate crime rates, it remains uncertain whether these factors directly contribute to higher hate crimes or if unmeasured variables, such as political polarization, cultural differences, or social media influence, play a more substantial role.

Aggregating data at the state level presents another limitation, as it obscures intra-state variations. This approach fails to capture significant differences between urban, suburban, and rural areas, where economic conditions, law enforcement practices, and social dynamics can vary significantly. For example, metropolitan centers may experience hate crimes driven by different factors than those in less densely populated regions, but this distinction is lost in state-level summaries. The aggregation thus simplifies the diverse social and economic landscapes within states, reducing the model's ability to reflect localized dynamics.

The assumption of linear relationships between predictors and hate crimes is another constraint. Real-world phenomena often involve non-linear interactions and feedback loops that cannot be captured by the current model. For instance, the relationship between unemployment and hate crimes may intensify at certain thresholds or diminish under specific social support structures, distinctions that are overlooked in a linear framework.

The exclusion of demographic and political variables limits the thoroughness of the analysis. Factors such as race, ethnicity, age, and political affiliation likely play significant roles in hate crime dynamics, yet their absence from the model restricts deeper views For instance, demographic diversity within urban centers or the political leanings of specific regions could influence hate crime rates in ways that remain unexplored. Similarly, the metro population share, treated as a singular variable, oversimplifies the complexity of urban environments, failing to account for variations in cultural diversity, economic inequality, or law enforcement resources within cities.

5.4 Weaknesses and next steps

The analysis faces limitations in accounting for dynamic and temporal factors that influence hate crimes. Hate crime rates can experience sudden spikes in response to unforeseen social or political events, such as controversial legislation, high-profile court cases, or significant social movements. The model's reliance on static, cross-sectional data prevents it from capturing how these events shape hate crime trends over time. This temporal limitation highlights the need for more dynamic modeling frameworks that incorporate time-sensitive data.

To address these weaknesses, future research should prioritize incorporating temporal datasets to analyze changes in hate crimes over time, especially in response to major societal events. Including additional demographic and political predictors—such as race, ethnicity, age, and political affiliation—could provide a deeper understanding of hate crime dynamics. Furthermore, using more granular geographic data at the city or county level would better capture localized variations and reduce the oversimplification inherent in state-level analyses.

Additionally, exploring non-linear modeling approaches could uncover complex interactions and thresholds in the relationships between predictors and hate crimes. For instance, the influence of unemployment or income inequality may intensify or diminish depending on other social conditions, which are overlooked in the current linear framework. Investigating these interaction effects, along with community-level intervention strategies, could pave the way for a more detailed understanding of the underlying factors contributing to hate crimes and inform more targeted and effective policies.

A Appendix: Surveys, Sampling, and Observational Data

A.1 Objective and Overview

The aim of this appendix is to assess the data collection methods, sampling approach, and observational considerations related to the socioeconomic analysis of hate crimes. By examining the methodology in depth, we aim to validate the representativeness and robustness of the dataset and address inherent challenges in observational data, particularly concerning biases in underreporting and geographic variations.

A.2 Core Objectives

1. **Evaluate Representativeness**: Ensure the dataset accurately reflects the socioeconomic and hate crime patterns across U.S. states.
2. **Mitigate Bias**: Address potential biases in hate crime reporting, such as enforcement disparities or demographic underrepresentation.
3. **Assess Limitations in Observational Data**: Examine the constraints of relying on state-level aggregated data and propose improvements.

A.3 Sampling Strategy

A.3.1 Population and Sampling Frame

The dataset used in this study aggregates state-level statistics on hate crimes, socioeconomic variables (e.g., income, unemployment), and demographic factors. The sampling frame includes:

- Hate crime data sourced from the Southern Poverty Law Center (SPLC), representing reported incidents per 100,000 residents.
- Socioeconomic data derived from government records and standardized by FiveThirtyEight, covering variables like Gini Index and metro area population share.

These data sources provide a thorough view of state-level trends, but they remain subject to sampling and reporting challenges

A.3.2 Challenges in Representativeness

1. **Underreporting Bias**: States with more stringent enforcement may report higher hate crime rates, while states with less transparency or fewer resources may underreport incidents. For example, variations in hate crime reporting standards between states have been documented in previous research (Investigation 2022).
2. **Aggregation Bias**: State-level aggregation may obscure local variations, such as urban vs. rural dynamics. This could lead to oversimplified conclusions, as urban centers often have different socioeconomic profiles and hate crime dynamics compared to rural areas (Lichter and Brown 2020).

A.3.3 Proposed Stratification Variables

To improve future data representativeness:

- Income Groups: Low (<$30,000), Middle ($30,000-$75,000), High (>$75,000).
- Educational Attainment: No, High school diploma, Bachelor's degree, Graduate degree.
- Geographic Division: Urban, Suburban, Rural.

This approach aligns with best practices in survey sampling and could enhance the granularity and interpretability of the dataset (Atkinson and Brandolini 2001).

A.4 Recruitment and Reporting Challenges

A.4.1 Recruitment and Data Sources

Data from the SPLC and FiveThirtyEight rely on third-party reporting and standardized government data. However:

- **Hate Crime Reporting**: Hate crime data from the SPLC and FBI often rely on third-party reporting. Victims' reluctance to report incidents due to fear of retaliation or mistrust in law enforcement can result in underreporting, a common challenge in hate crime research.
- **Socioeconomic Data**: Metrics like the Gini Index provide meaningful observations into inequality but fail to capture short-term economic shocks or rapid social changes that may influence hate crime rates.

A.4.2 Survey Design for Future Studies

Future surveys could incorporate the following elements to address current data limitations:

1. **Incident-Level Surveys**: Collect firsthand accounts from victims of hate crimes.
2. **Socioeconomic Surveys**: Gather real-time data on income, unemployment, and community-level education access.

An ideal survey instrument would include stratified random sampling, targeted outreach in underrepresented communities, and questions designed to capture both quantitative and qualitative dimensions of hate crimes and socioeconomic conditions (Groves et al. 2013).

A.4.2.1 Proposed Structure for the Survey Instrument

Title: Survey on Socioeconomic Factors and Hate Crime Prevalence

Section 1: Introduction and Consent

- Purpose: Explain the study's goal (e.g., understanding the relationship between socioeconomic conditions and hate crimes).
- Confidentiality: State that responses are anonymous and data will be aggregated.
- Consent: Include an opt-in clause to confirm voluntary participation.

Section 2: Demographic Information

- Age Group: Under 18, 18–24, 25–34, 35–44, 45–54, 55–64, 65+.
- Gender: Male, Female, Non-binary, Prefer not to say.
- Race/Ethnicity: White, Black, Hispanic, Asian, Other.
- Political Affiliation: Democrat, Republican, Independent, Other.

Section 3: Socioeconomic Factors

- Income Level: Below $30,000, $30,000–$75,000, Above $75,000.
- Employment Status: Employed, Unemployed, Retired, Student.
- Education Level: High School or less, Some College, Bachelor's Degree, Graduate Degree.
- Urban/Rural Classification: Urban, Suburban, Rural.

Section 4: Hate Crime Awareness

- Experience: "Have you or someone you know experienced a hate crime?" (Yes/No)

- Perception: Rate your perception of hate crime prevalence in your area (1 = Very Low, 5 = Very High).
- Reporting: "Do you believe hate crimes are underreported in your state?" (Yes/No/Not Sure).

Section 5: Perception of Socioeconomic Conditions

- Economic Stress: "Do you believe unemployment contributes to social tension in your community?" (Likert scale: Strongly Agree to Strongly Disagree).
- Income Inequality: "How significant is income inequality in your community?" (1 = Insignificant, 5 = Very Significant).

Section 6: Law Enforcement and Policy

- Trust in Law Enforcement: "How effective do you think law enforcement is in addressing hate crimes?" (1 = Ineffective, 5 = Very Effective).
- Policy Recommendations: Open-ended: "What policies would you recommend to reduce hate crimes?"

Section 7: Conclusion

- Thank You Note: Express gratitude for participation.
- Contact Information: Provide details for respondents to reach out with questions or concerns.

A.5 Data Validation and Quality Assurance

A.5.1 Validation Protocols

To ensure data reliability:

1. **Cross-Verification**: Compare hate crime data with records from multiple sources, such as FBI statistics and independent research studies (Investigation 2022).
2. **Standardization**: Normalize socioeconomic indicators to allow for comparability across states while accounting for regional disparities (Atkinson and Brandolini 2001).
3. **Outlier Analysis**: Identify and investigate states with anomalously high or low hate crime rates, as these may indicate either unique social conditions or data inconsistencies.

A.5.2 Ethical Considerations

1. **Informed Consent**: Ensure participants in supplementary surveys understand the study's objectives and have the option to withdraw.
2. **Anonymity**: De-identify survey responses to protect participants, particularly in sensitive areas such as hate crime reporting.

A.6 Observational Data Considerations

A.6.1 Temporal Constraints

The static, cross-sectional nature of the current dataset limits the ability to analyze trends over time. This prevents understanding how hate crime rates respond to legislative changes, economic crises, or significant social events. Incorporating longitudinal data would allow for the analysis of these dynamic relationships (Donald P. Green and McFall 2017).

A.6.2 Interaction Effects

The linear assumptions in the current model may overlook interaction effects between variables. For example: **Income Inequality and Metro Population Share**: Higher income inequality in densely populated states may exacerbate social tensions differently than in rural states, as suggested by research on urban-rural disparities (Lichter and Brown 2020).

A.7 Geographic Heterogeneity

State-level data do not account for intra-state heterogeneity. For example:

- **Urban vs. Rural Variations**: Urban centers may have higher hate crime rates due to greater population density and heterogeneity, whereas rural areas may experience different patterns of social conflict.
- **Policy Implications**: Disaggregating data by metropolitan statistical areas (MSAs) could provide actionable observations for policymakers.

A.7.1 Implications for Policy and Research

1. **Granular Data Collection**: Collecting city- and county-level hate crime data can provide actionable observations into localized patterns.
2. **Dynamic Modeling**: Incorporate time-series data to analyze how hate crime rates respond to socioeconomic changes or political events.
3. **Expanded Demographic Metrics**: Include race, age, and political affiliation to understand the broader context of hate crime dynamics.

A.8 Conclusion

The methodology employed in this study highlights significant gaps in the measurement and analysis of hate crimes and their socioeconomic determinants. Future research should prioritize granularity, temporal analysis, and expanded demographic considerations to improve the reliability and applicability of findings. Addressing these methodological gaps can enhance policy interventions to mitigate hate crimes.

B Additional data details

B.1 Outcome Variable: Hate Crimes Per 100k SPLC

The histogram Figure 1 visualizes the distribution of hate crimes per 100,000 residents across U.S. states, as reported by the SPLC.

- **Concentration of Values**:

1. The majority of states report hate crime rates below 0.5 per 100,000 residents.
2. A substantial portion of states cluster between 0.0 and 0.3 hate crimes per 100,000 residents, indicating that low rates are common nationwide.

- **Skewed Distribution**: The distribution is right-skewed, with a long tail extending toward higher hate crime rates. This suggests that while most states experience relatively low hate crime rates, a few states report significantly higher rates.

- **Outliers**: There is at least one state with a hate crime rate exceeding 1.0 per 100,000 residents, marking it as an outlier with unusually high prevalence. (State:District of Columbia, with hate crime rate **1.522302**)

- **Implications for Analysis**:

1. The variability in hate crime rates emphasizes the importance of analyzing socioeconomic factors to understand why certain states report higher rates.

2. The skewness and presence of outliers highlight the need for robust statistical techniques to ensure results are not overly influenced by extreme values.

This visualization provides a foundational understanding of the outcome variable, setting the stage for exploring relationships with predictor variables like income inequality, unemployment, and urbanization.

B.2 Detailed predictor variables interpretations:

- As shown in Figure 2, most states report median incomes between \$50,000 and \$55,000. States with lower median incomes tend to report higher rates of hate crimes, suggesting an inverse relationship. This relatively symmetric distribution suggests a moderate level of economic consistency nationwide, indicating that while individual states experience variations, there's a notable economic equilibrium. The narrow spread implies that most states maintain similar economic conditions, with fewer extremes of wealth. This uniformity could reflect national economic policies, labor market structures, and broader economic opportunities that create a somewhat standardized income environment across different regions of the United States.
- As shown in Figure 3, unemployment rates range from 1.6% to 8.6%. States with higher unemployment rates may experience greater economic distress, potentially influencing hate crime rates. The right skew indicates that while the majority of states maintain low unemployment levels, a few states encounter more significant employment difficulties. This pattern shows the uneven economic recovery and structural differences across state economies. The distribution hints at underlying economic disparities, where some regions may struggle with job creation, industrial transitions, or structural economic challenges, while others maintain robust employment markets.
- Metro area population share reflects the proportion of a state's population residing in metropolitan areas, with most states showing 60-70% of their population concentrated in metropolitan areas. States with higher urbanization levels may experience unique social dynamics influencing hate crime prevalence. As shown in Figure 4, urbanized states report a higher concentration of hate crimes. This left-skewed distribution underscores a strong trend towards urban living, reflecting broader societal shifts in population concentration. The pattern suggests significant economic, social, and demographic transformations, where urban centers increasingly become engines of economic activity, innovation, and cultural exchange. The variation in metro population shares indicates diverse state-level characteristics, with some regions more urbanized than others, reflecting different historical, economic, and geographic development patterns.
- The Gini Index measures income inequality, with higher values indicating greater disparity. As shown in Figure 5, states clustering around 0.4-0.5, which is indicating substantial and consistent income disparities across the nation, higher Gini Index values also tend to report higher rates of hate crimes, underscoring the influence of economic inequality.

This relatively symmetric distribution suggests that income inequality is a systemic issue rather than a localized phenomenon. The narrow spread implies that states experience similar patterns of wealth concentration, pointing to broader economic structures that perpetuate inequality. The Gini Index highlights the challenges of economic mobility, suggesting that regardless of geographic location, most states grapple with significant economic stratification that potentially impacts social mobility, economic opportunities, and overall societal cohesion.

- This variable represents the proportion of non-white residents in each state. Higher non-white population shares may correlate with higher hate crime rates due to increased exposure to discriminatory behavior. As shown in Figure 6, this distribution varies significantly across states, with an average around 30-35% and a right-skewed distribution. This pattern indicates increasing racial and ethnic diversity across states, with some regions experiencing much higher proportions of non-white populations. The right skew suggests a dynamic demographic landscape, where some states are experiencing more rapid diversification than others. This distribution reflects broader societal changes, including immigration patterns, historical migration trends, and shifting cultural compositions. The variation in non-white population shares underscores the complex and evolving nature of racial and ethnic demographics in the United States, highlighting the need for detailed understanding of social dynamics and representational challenges.

C Additional Model details

C.1 Full Model Summary

Table 3: Coefficient estimates from the Bayesian hierarchical model. The table shows the relationship between predictors and hate crimes per 100,000 residents (SPLC).

Table 3: Posterior Estimates for Model Coefficients

	Mean	Std. Error	2.5% CI	97.5% CI
(Intercept)	-8.606	1.876	-12.360	-5.018
median_income	0.000	0.000	0.000	0.000
unemployment_rate	6.234	3.911	-1.314	14.049
metro_area_population_share	-0.165	0.242	-0.635	0.316
high_school_education_share	5.518	1.744	2.153	8.979
gini_index	8.405	2.065	4.414	12.609
non_white_population_share	-0.046	0.318	-0.655	0.588
b[(Intercept) state:Alabama]	-0.038	0.085	-0.224	0.121
b[(Intercept) state:Alaska]	-0.089	0.119	-0.358	0.083
b[(Intercept) state:Arizona]	0.009	0.077	-0.149	0.173

	Mean	Std. Error	2.5% CI	97.5% CI
b[(Intercept) state:Arkansas]	-0.009	0.081	-0.183	0.159
b[(Intercept) state:California]	0.043	0.093	-0.120	0.255
b[(Intercept) state:Colorado]	-0.005	0.079	-0.173	0.160
b[(Intercept) state:Connecticut]	-0.113	0.126	-0.391	0.058
b[(Intercept) state:Delaware]	0.042	0.084	-0.109	0.235
b[(Intercept) state:District_of_Columbia]	0.154	0.162	-0.048	0.519
b[(Intercept) state:Florida]	-0.051	0.096	-0.270	0.113
b[(Intercept) state:Georgia]	-0.051	0.089	-0.243	0.102
b[(Intercept) state:Idaho]	-0.017	0.080	-0.188	0.147
b[(Intercept) state:Illinois]	-0.058	0.092	-0.269	0.089
b[(Intercept) state:Indiana]	0.042	0.084	-0.110	0.226
b[(Intercept) state:Iowa]	0.057	0.098	-0.106	0.278
b[(Intercept) state:Kansas]	-0.085	0.109	-0.336	0.076
b[(Intercept) state:Kentucky]	0.063	0.100	-0.094	0.299
b[(Intercept) state:Louisiana]	-0.045	0.088	-0.242	0.108
b[(Intercept) state:Maine]	0.087	0.106	-0.071	0.321
b[(Intercept) state:Maryland]	0.010	0.086	-0.163	0.198
b[(Intercept) state:Massachusetts]	0.026	0.084	-0.134	0.221
b[(Intercept) state:Michigan]	0.030	0.081	-0.131	0.214
b[(Intercept) state:Minnesota]	0.074	0.102	-0.083	0.305
b[(Intercept) state:Mississippi]	-0.022	0.086	-0.219	0.142
b[(Intercept) state:Missouri]	-0.048	0.089	-0.243	0.109
b[(Intercept) state:Montana]	0.040	0.087	-0.115	0.236
b[(Intercept) state:Nebraska]	-0.007	0.082	-0.185	0.167
b[(Intercept) state:Nevada]	-0.005	0.084	-0.184	0.170
b[(Intercept) state:New_Hampshire]	-0.043	0.092	-0.242	0.121
b[(Intercept) state:New_Jersey]	-0.116	0.130	-0.416	0.058
b[(Intercept) state:New_Mexico]	0.013	0.083	-0.158	0.198
b[(Intercept) state:New_York]	-0.059	0.096	-0.281	0.096
b[(Intercept) state:North_Carolina]	-0.008	0.080	-0.183	0.160
b[(Intercept) state:Ohio]	-0.030	0.081	-0.211	0.127
b[(Intercept) state:Oklahoma]	-0.023	0.079	-0.208	0.130
b[(Intercept) state:Oregon]	0.122	0.135	-0.056	0.411
b[(Intercept) state:Pennsylvania]	-0.046	0.086	-0.234	0.106
b[(Intercept) state:Rhode_Island]	-0.063	0.100	-0.289	0.095
b[(Intercept) state:South_Carolina]	0.004	0.080	-0.160	0.174
b[(Intercept) state:Tennessee]	-0.007	0.078	-0.175	0.158
b[(Intercept) state:Texas]	0.082	0.111	-0.083	0.345
b[(Intercept) state:Utah]	-0.001	0.082	-0.172	0.170
b[(Intercept) state:Vermont]	-0.043	0.094	-0.266	0.124
b[(Intercept) state:Virginia]	0.023	0.080	-0.135	0.205

	Mean	Std. Error	2.5% CI	97.5% CI
b[(Intercept) state:Washington]	0.104	0.117	-0.064	0.356
b[(Intercept) state:West_Virginia]	0.040	0.100	-0.137	0.277
b[(Intercept) state:Wisconsin]	-0.006	0.078	-0.175	0.156
sigma	0.158	0.042	0.069	0.232
Sigma[state:(Intercept),(Intercept)]	0.013	0.011	0.000	0.038

C.2 Diagnostics and Validation

C.2.1 Trace Plot for MCMC Chains

The trace plots (Figure Figure 13) shows the Markov Chain Monte Carlo (MCMC) trace for each parameter in the Bayesian hierarchical model. The chains represent iterations for four independent MCMC chains for parameters including median_income, unemployment_rate, metro_area_population_share, high_school_education_share, gini_index, and non_white_population_share. The consistent overlap and lack of visible drift across chains suggest good mixing and convergence of the chains, indicating that the MCMC sampling is stable and has likely reached equilibrium.

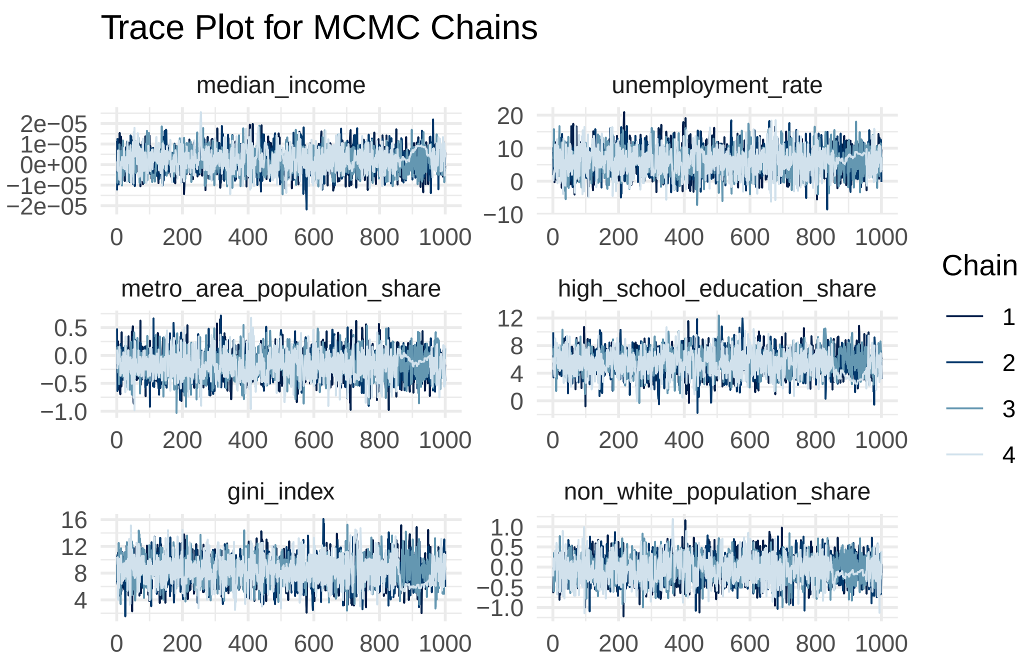

Figure 13: Trace plot of MCMC chains for the Bayesian model coefficients.

C.2.2 Posterior Predictive Checks

Posterior predictive checks (Figure Figure 14) compares the observed density (thick black line, `y`) of the outcome variable (hate_crimes_per_100k_splc) with the densities generated from posterior predictive simulations (thin blue lines, `y_rep`). The posterior predictive checks help evaluate whether the Bayesian model accurately captures the observed data distribution.

- **Alignment between y and y_rep:** The observed density (black line) closely matches the simulated densities (blue lines), especially around the peak region and overall shape of the distribution. This suggests that the model successfully reproduces the key features of the observed data.
- **Discrepancies**:Minor deviations between the observed and simulated densities are visible in the tails. For example: At lower values of hate crimes, the model slightly underestimates the density. At higher values, the variability in the simulated densities increases. These discrepancies might indicate areas where the model could be refined by considering additional predictors or adjusting prior distributions.
- **Model Validity**: Overall, the close alignment between the observed and predicted densities suggests that the model provides a reasonable fit for the data. The high fidelity of the posterior predictive checks supports the validity of the Bayesian hierarchical model for understanding the relationship between socioeconomic factors and hate crimes.

This PPC interpretation highlights the model's strength in capturing the central tendencies of the observed data while identifying potential areas for improvement in modeling extreme values.

C.3 Implementation

The model is implemented in R (R Core Team 2023) using the `rstanarm` package (Goodrich et al. 2022) to perform Bayesian regression analysis. Weakly informative priors are applied to all regression coefficients to regularize estimates and reduce the risk of overfitting. Specifically, the priors for the coefficients of the predictor variables are assumed as follows:

$$\beta_j \sim \text{Normal}(0, 10), \quad \text{for } j = 1, 2, \dots, 6, \tag{4}$$

where (β_j) represents the coefficients of the predictor variables. These priors assume that most coefficients are close to zero but allow for sufficient flexibility to detect meaningful effects when supported by the data.

The intercept term follows a similar prior:

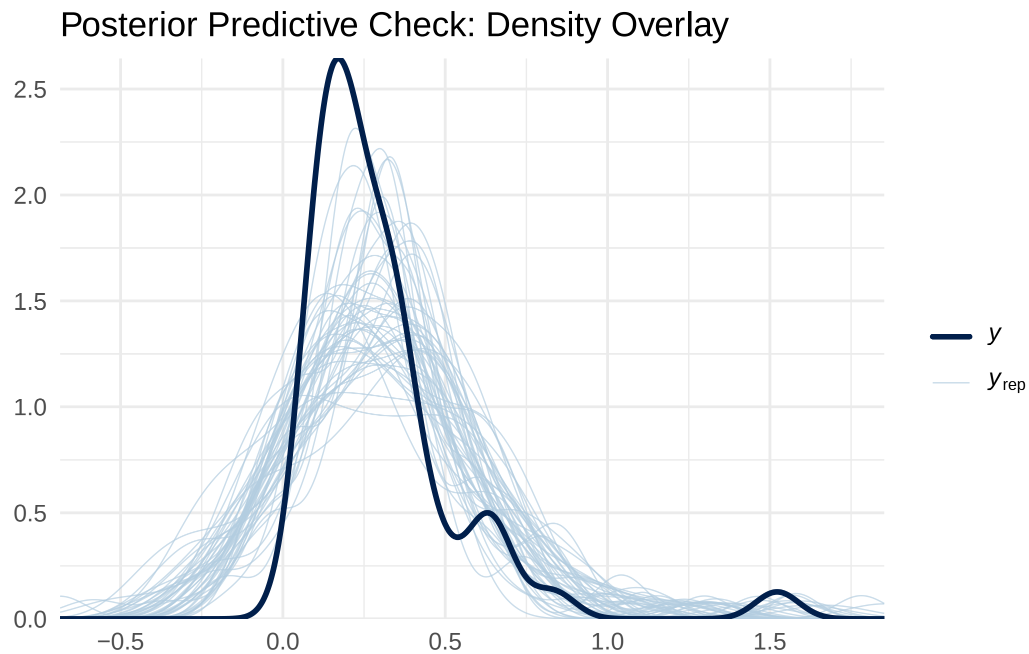

Figure 14: Posterior predictive checks for the Bayesian hierarchical model.

$$\beta_0 \sim \text{Normal}(0, 10). \tag{5}$$

The variance parameter for the residuals, σ^2, is assigned a default prior provided by `rstanarm`, which assumes a weakly informative exponential distribution. This choice ensures that the variance is constrained within a reasonable range while still allowing for variability in the data.

The model is fitted using Markov Chain Monte Carlo (MCMC) sampling, with default settings in `rstanarm`. These include four chains, each with 2,000 iterations (1,000 for warm-up and 1,000 for posterior sampling). The MCMC diagnostics, including trace plots and $\hat{R}$ convergence statistics, confirm that the chains have converged and that the posterior samples are reliable.

All computations are performed using parallel processing to optimize runtime, leveraging the multi-core capabilities of the `rstanarm` package. The results, including posterior summaries and credible intervals, are used to quantify uncertainty in the parameter estimates and to make probabilistic inferences about the relationships between predictors and the outcome variable.

C.4 Observations from Model Summary

- **Direction and Magnitude**: The signs and magnitudes of the coefficients clarify the strength and direction of each predictor's relationship with hate crimes. For example, the

Gini index and unemployment rate have strong positive relationships with hate crimes, suggesting that economic instability and inequality are key drivers.

- **Policy Implications**: Reducing income inequality (lower Gini index) and increasing educational attainment (higher high school education share) could potentially mitigate hate crimes.
- **Statistical Significance**: The t-statistics for the coefficients indicate the strength of evidence against the null hypothesis (no effect). Predictors with high absolute t-statistics are more likely to have a meaningful impact on hate crimes.

C.5 Limitations

While the model provides robust views, it has certain limitations. For instance:

- **State-Level Bias**: While random effects capture unobserved heterogeneity, they do not directly explain why certain states have higher or lower hate crime rates. Qualitative research could complement these findings by exploring state-specific factors.
- **Reporting Bias in Hate Crime Data**: Hate crime data may suffer from underreporting or reporting inconsistencies. The data may underreport hate crimes in certain states, introducing bias that the model cannot fully address. Further validation with alternative datasets, such as FBI reports, could improve reliability.
- **Cross-Sectional Analysis**: The dataset represents a single year, limiting views into temporal trends.

-**Potential Omitted Variables**: The model does not include cultural or political variables that may influence hate crimes. Future models could incorporate additional predictors, such as political polarization or media coverage, to enhance explanatory power.

C.6 Alternative Models

- **Logistic Regression**: Scaled hate crime data was modeled with a logistic regression. While effective for bounded data, it was less appropriate for continuous hate crime rates.
- **Simple Linear Regression**: Clarified individual predictors but lacked the flexibility of random effects modeling.

D Additional Results

D.1 State-Level Effects

Based on the map (Figure 8), it also underscores the importance of considering regional characteristics when addressing hate crimes. For example, policies in high-crime states might need to be tailored to account for both urban and rural dynamics. It also highlights the need to explore how metro population share influences social cohesion, law enforcement efficiency, and resource allocation, which may indirectly affect hate crime rates. Addressing hate crimes requires detailed, context-sensitive policy approaches. As Jenness and Grattet(Jenness and Grattet 2001) demonstrate, effective hate crime interventions must move beyond generic strategies to develop targeted responses that account for local social, demographic, and institutional characteristics.

D.2 Unemployment Rate

Based on Figure 10, there are some notable outliers like District of Columbia suggest unique socio-economic or demographic factors that exacerbate hate crime occurrences, independent of unemployment rate alone. This relationship underscores the role of economic stability in fostering or mitigating social cohesion. Regions experiencing high unemployment might benefit from targeted socio-economic policies to address root causes of hate crimes, such as community support programs or economic revitalization strategies.

D.3 Education Levels

Based on Figure 11, The District of Columbia stands out as an outlier, with both high education levels and elevated hate crime rates. This unique context underscores how demographic and socio-political factors interplay with education to shape hate crime patterns. The findings suggest that while education can play a significant role in reducing hate crimes, its effectiveness is contingent upon broader socio-economic and policy contexts. Strategies to mitigate hate crimes should integrate education with interventions addressing economic stability, cultural dynamics, and institutional structures.

D.4 Median Household Income

Based on Figure 12, The District of Columbia appears as an outlier with both high income levels and elevated hate crime rates, highlighting that income alone cannot explain hate crime variations and pointing to the influence of demographic or political contexts. The analysis suggests that while income inequality (measured by the Gini index) has a positive correlation with hate crimes, absolute income levels do not exhibit a clear relationship. This finding emphasizes the importance of addressing relative disparities and underlying social structures rather than focusing solely on economic prosperity to mitigate hate crimes.

E Datasheet

This whole datasheet is extracted of the questions from **"Datasheets for Datasets"**(Gebru et al. 2021).

Motivation

1. *For what purpose was the dataset created? Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.*
   - The dataset was created by FiveThirtyEight to explore the relationship between socioeconomic factors and the prevalence of hate crimes across U.S. states. It includes variables that clarify economic, demographic, and social conditions that may influence hate crime occurrences.
2. *Who created the dataset (for example, which team, research group) and on behalf of which entity (for example, company, institution, organization)?*
   - The dataset was collected and published by FiveThirtyEight, a data journalism platform known for high-quality data analysis.
3. *Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.*
   - The dataset was funded as part of FiveThirtyEight's investigative journalism projects.
4. *Any other comments?*
   - This dataset provides a thorough overview of hate crimes, contextualized within socioeconomic indicators, making it useful for research, analysis, and policymaking.

Composition

1. *What do the instances that comprise the dataset represent (for example, documents, photos, people, countries)? Are there multiple types of instances (for example, movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.*
   - Each instance in the dataset represents a U.S. state, with corresponding socioeconomic and hate crime data aggregated for a specific year.
2. *How many instances are there in total (of each type, if appropriate)?*

- The dataset contains 51 rows, representing all 50 states and the District of Columbia.

3. *Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (for example, geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (for example, to cover a more diverse range of instances, because instances were withheld or unavailable).*

   - The dataset is not a sample; it represents all states in the U.S.

4. *What data does each instance consist of? "Raw" data (for example, unprocessed text or images) or features? In either case, please provide a description.*

   - Each instance includes the following variables: State: Name of the state. Median Household Income: Median income in each state. Share Unemployed (Seasonal): Percentage of the population unemployed on a seasonal basis. Gini Index: Measure of income inequality. Share of Population in Metro Areas: Percentage of people living in metropolitan areas. Non-White Population Share: Percentage of non-white residents. Hate Crimes per 100,000 SPLC: Hate crimes as reported by the SPLC. Average Hate Crimes per 100,000 FBI: FBI-reported hate crime averages.

5. *Is there a label or target associated with each instance? If so, please provide a description.*

   - The primary target variable is "Hate Crimes per 100,000 SPLC."

6. *Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (for example, because it was unavailable). This does not include intentionally removed information, but might include, for example, redacted text.*

   - Some states may have missing data for certain socioeconomic metrics due to incomplete reporting or data availability issues.

7. *Are relationships between individual instances made explicit (for example, users' movie ratings, social network links)? If so, please describe how these relationships are made explicit.*

   - Relationships between states may exist due to geographic proximity or similar economic and demographic trends.

8. *Are there recommended data splits (for example, training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.*

   - The dataset can be split into training and test datasets for predictive modeling, with a typical split of 70% for training and 30% for testing.

9. *Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.*
    - There may be redundancies in similar metrics (e.g., SPLC and FBI hate crime counts), which should be addressed during analysis.
10. *Is the dataset self-contained, or does it link to or otherwise rely on external resources (for example, websites, tweets, other datasets)? If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (that is, including the external resources as they existed at the time the dataset was created); c) are there any restrictions (for example, licenses, fees) associated with any of the external resources that might apply to a dataset consumer? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.*
    - The dataset is self-contained but references external sources such as the SPLC and FBI for hate crime statistics.
11. *Does the dataset contain data that might be considered confidential (for example, data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)? If so, please provide a description.*
    - The dataset contains only aggregated data, so no personally identifiable information (PII) is included.
12. *Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why.*
    - The dataset does not include offensive content. However, the sensitive nature of hate crime data requires careful handling.
13. *Does the dataset identify any sub-populations (for example, by age, gender)? If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.*
    - Sub-populations are defined by variables such as race, income, and urbanization levels.
14. *Is it possible to identify individuals (that is, one or more natural persons), either directly or indirectly (that is, in combination with other data) from the dataset? If so, please describe how.*
    - No individuals are identifiable in this dataset.
15. *Does the dataset contain data that might be considered sensitive in any way (for example, data that shows race or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.*

- Sensitive data includes race demographics and income levels, requiring ethical considerations during analysis.

16. *Any other comments?*

    - No

Collection process

1. *How was the data associated with each instance acquired? Was the data directly observable (for example, raw text, movie ratings), reported by subjects (for example, survey responses), or indirectly inferred/derived from other data (for example, part-of-speech tags, model-based guesses for age or language)? If the data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.*

    - The data was sourced from public records, including the SPLC, FBI, and the U.S. Census Bureau.

2. *What mechanisms or procedures were used to collect the data (for example, hardware apparatuses or sensors, manual human curation, software programs, software APIs)? How were these mechanisms or procedures validated?*

    - Data was compiled by FiveThirtyEight using manual aggregation and automated collection techniques.

3. *If the dataset is a sample from a larger set, what was the sampling strategy (for example, deterministic, probabilistic with specific sampling probabilities)?*

    - The dataset includes all available states, with no additional sampling.

4. *Who was involved in the data collection process (for example, students, crowdworkers, contractors) and how were they compensated (for example, how much were crowdworkers paid)?*

    - FiveThirtyEight staff collected and processed the data as part of their journalism work.

5. *Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (for example, recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.*

    - The data was collected and compiled for a specific year (e.g., 2016).

6. *Were any ethical review processes conducted (for example, by an institutional review board)? If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation.*

- The dataset does not include private data but still requires ethical handling due to its sensitive nature.

7. *Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (for example, websites)?*
   - Data was obtained directly from the SPLC, FBI, and Census Bureau.
8. *Were the individuals in question notified about the data collection? If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself.*
   - N/A
9. *Did the individuals in question consent to the collection and use of their data? If so, please describe (or show with screenshots or other information) how consent was requested and provided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented.*
   - N/A
10. *If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate).*
    - N/A
11. *Has an analysis of the potential impact of the dataset and its use on data subjects (for example, a data protection impact analysis) been conducted? If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation.*
    - N/A
12. *Any other comments?*
    - No

Preprocessing/cleaning/labeling

1. *Was any preprocessing/cleaning/labeling of the data done (for example, discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? If so, please provide a description. If not, you may skip the remaining questions in this section.*
   - Missing values were imputed or dropped; Variables were renamed for clarity; Data was normalized where needed.

2. *Was the "raw" data saved in addition to the preprocessed/cleaned/labeled data (for example, to support unanticipated future uses)? If so, please provide a link or other access point to the "raw" data.*
    - Raw data is available in CSV format on the FiveThirtyEight GitHub repository
3. *Is the software that was used to preprocess/clean/label the data available? If so, please provide a link or other access point.*
    - Data preprocessing was conducted using R (R Core Team 2023) with packages such as tidyr (Wickham et al. 2019)
4. *Any other comments?*
    - No

Uses

1. *Has the dataset been used for any tasks already? If so, please provide a description.*
    - The dataset has been used by FiveThirtyEight for their reporting on hate crimes, exploring the relationship between socioeconomic factors and the prevalence of hate crimes across U.S. states.
2. *Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point.*
    - The dataset is available in CSV format on the FiveThirtyEight GitHub repository
3. *What (other) tasks could the dataset be used for?*
    - The dataset can be used for: Predictive modeling of hate crime occurrences. Policy evaluation for reducing hate crimes. Identifying regional disparities in hate crime prevalence. Exploring the influence of socioeconomic factors like inequality and unemployment on crime.
4. *Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a dataset consumer might need to know to avoid uses that could result in unfair treatment of individuals or groups (for example, stereotyping, quality of service issues) or other risks or harms (for example, legal risks, financial harms)? If so, please provide a description. Is there anything a dataset consumer could do to mitigate these risks or harms?*
    - Potential issues include: Aggregated data might mask localized trends or distinctions. Bias in reporting (e.g., differences between SPLC and FBI data) might skew results. Care must be taken to avoid stereotyping regions or groups based on hate crime rates. To mitigate risks, dataset consumers should validate findings with supplementary sources and consider regional or temporal biases in the data.

5. *Are there tasks for which the dataset should not be used? If so, please provide a description.*

    - The dataset should not be used to draw conclusions about individual-level behaviors or characteristics, as it is aggregated at the state level. It should also not be used to make causal inferences without careful statistical validation.

6. *Any other comments?*

    - This dataset is a meaningful resource for understanding broad trends but requires careful handling to avoid misinterpretation.

Distribution

1. *Will the dataset be distributed to third parties outside of the entity (for example, company, institution, organization) on behalf of which the dataset was created? If so, please provide a description.*

    - Yes, the dataset is publicly available via FiveThirtyEight's GitHub repository.

2. *How will the dataset be distributed (for example, tarball on website, API, GitHub)? Does the dataset have a digital object identifier (DOI)?*

    - The dataset is available in CSV format on the FiveThirtyEight GitHub repository. It does not have a DOI.

3. *When will the dataset be distributed?*

    - The dataset has already been distributed and is publicly available.

4. *Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? If so, please describe this license and/ or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.*

    - The dataset is distributed under FiveThirtyEight's open-data terms of use, available on their GitHub page.

5. *Have any third parties imposed IP-based or other restrictions on the data associated with the instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.*

    - No known IP-based or other restrictions have been imposed.

6. *Do any export controls or other regulatory restrictions apply to the dataset or to individual instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.*

    - No known export controls or regulatory restrictions apply to the dataset.

7. *Any other comments?*

    - The dataset is freely accessible and highly meaningful for academic and policy-oriented research.

Maintenance

1. *Who will be supporting/hosting/maintaining the dataset?*

    - FiveThirtyEight maintains the dataset on their GitHub repository.

2. *How can the owner/curator/manager of the dataset be contacted (for example, email address)?*

    - Contact information is not provided directly

3. *Is there an erratum? If so, please provide a link or other access point.*

    - No formal erratum is listed, but updates or corrections are typically documented on the GitHub repository.

4. *Will the dataset be updated (for example, to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to dataset consumers (for example, mailing list, GitHub)?*

    - Updates are made periodically by FiveThirtyEight and communicated through GitHub.

5. *If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (for example, were the individuals in question told that their data would be retained for a fixed period of time and then deleted)? If so, please describe these limits and explain how they will be enforced.*

    - Not applicable, as this dataset contains only aggregated state-level data.

6. *Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to dataset consumers.*

    - Older versions are available on GitHub and will remain accessible.

7. *If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to dataset consumers? If so, please provide a description.*

    - There is no formal mechanism for external contributions. Users can fork the repository to extend or augment the dataset.

8. *Any other comments?*

   - The dataset is robust for its intended purpose but may require updates to remain relevant as new hate crime data becomes available.

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