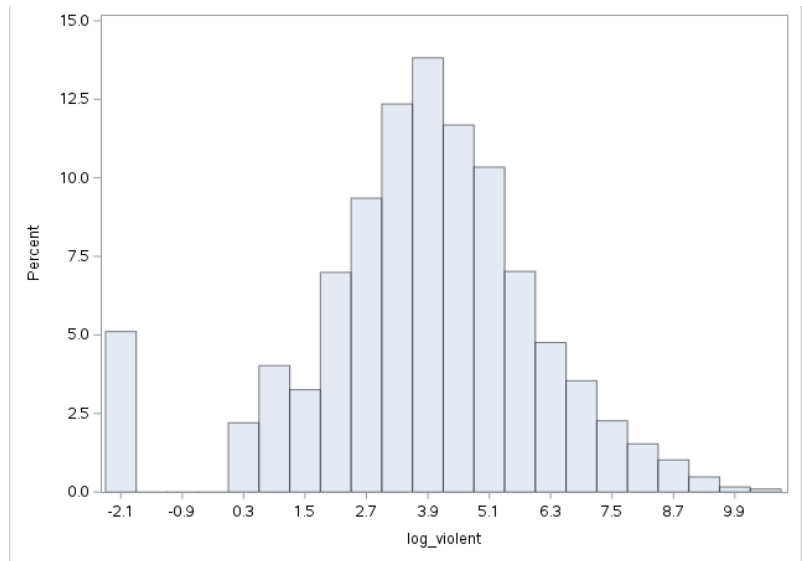


Introduction

People and news outlets are often concerned about the violent crime rate rising and want to know what might be done to lower violent crime. Violent crime has both obvious and obscured adverse effects on the well-being of a person and community. Violent crime has been linked to “asthma, hypertension, cancer, stroke and mental disorders” (Office of the Assistant Secretary for Health, n.d.). What causes violent crime is different in different parts of the world (Wolf et al., 2014). This report will explore county level factors which are related to violent crime rates in the United States.

Figure 1: Distribution of the log of the number of violent crimes



Methods

All calculations were done using SAS On Demand for Academics. Graphics were created using SAS and Tableau. The log of the number of violent crimes recorded in 2016 in each United States county FIPS code was modeled using multiple linear regression. In total 3133 counties were included in analysis. Crime data was obtained from ICPSR. Social vulnerability variable data was obtained from the Agency for Toxic Substance and Disease Registry. Data on weather anomalies by county in 2016 was retrieved from the National Centers for Environmental Information. Counties were categorized into four regions based on the regions used by the U.S. Census Bureau. The Midwest was used as the reference region.

Violent crime was log transformed based on Box-Cox analysis ($\lambda = 0$). Predictors were chosen for their hypothesized and established relationships to violent crime, discussed in detail below. Initially, many predictors were examined. Predictors with high skew were compared to a log transformed version of the predictor to see if correlation and residuals of single linear regression were improved. If significantly improved, the log version was used. Predictors in groups with high collinearity were compared to one another to determine which predictor of the group would provide the most accurate model of violent crime without creating inflated standard errors or flipped sign beta coefficients. One step that was taken to reduce collinearity between population size and other predictors was to convert social vulnerability variables such as count of persons uninsured and count of all persons who were not identified as white non-Hispanic into rates by dividing by the total population of the county and multiplying by 100. Another step taken to reduce collinearity was the creation of a city score variable. An observation was given a score of 0 to 3 based on being in the 95th percentile or greater for each of the following: the rate of crowded housing units per 100 people, the rate of multiunit housing per 100 people, and the rate of households with no vehicle per 100 people. Counties with large metropolitan areas tended to score higher compared to rural counties.

Once a set of reasonable predictors without major standard error inflation due to collinearity was identified final model selection began using Cp scores. The following variables entered the model selection process (all shown in Table 1): region, city score, uninsured rate per 100, minority rate per

100, two degrees hotter, non-elderly adult population, log per capita income, log area, and two interaction terms (uninsured rate per 100 * minority rate per 100 & two degrees hotter * uninsured rate per 100). The best model according to Cp selection criteria included all the above variables except for city score, two degrees hotter, and one of the region dummy variables. All region dummy variables and two degrees hotter were forced into the model to maintain the integrity of the region variable and adhere to the principle of hierarchy. Centering of variables did not improve residuals and was not done for the final model.

Table 1: Baseline Characteristics of Variables				
Variable	Mean $\pm$ Stdev	Median (Range)	Pearson Correlation with Log(Violent Crime)	P value
Violent Crime	382.563 $\pm$ 1666.660	49.100 (44556)	NA	NA
Log(Violent Crime)*	3.756 $\pm$ 2.294	3.894 (13.007)	NA	NA
City Score³	0.151 $\pm$ 0.406	0.000 (3.000)	0.1819	<0.0001
Uninsured Rate per 100*	11.908 $\pm$ 5.093	11.228 (49.807)	-0.0499	0.0052
Non-Elderly Adult Population	63393.691 $\pm$ 208366.698	15629.00 (6533117)	0.44451	<0.0001
Log(non elderly adults)*	9.759 $\pm$ 1.509	9.657 (11.761)	0.8713	<0.0001
Per Capita Income	25019.250 $\pm$ 5983.141	24250.00 (56834)	0.15434	<0.0001
Log(per capita income)*	10.101 $\pm$ 0.226	10.096 (1.927)	0.1511	<0.001
Area	1110.313 $\pm$ 3597.773	614.033 (145491)	-0.03030	0.0899
Log(area)*	6.486 $\pm$ 0.902	6.420 (11.170)	-0.0221	0.2157
Minority Rate per 100*	22.854 $\pm$ 19.950	15.389 (99.217)	0.2798	<0.0001
Region* n (%)	Mean of log(violent crime) $\pm$ Stdev	Median of log(violent crime) (Range)	ANOVA F stat 83.18	<0.0001¹
Northeast 217 (6.93%)	5.298 $\pm$ 1.742	5.011 (12.093)	Note: all regions are statistically different from one another by Tukey Studentized Range Test, except for South and West.	
Midwest 1054 (33.64%)	3.015 $\pm$ 2.340	3.222 (12.53)		
South 1422 (45.39%)	4.048 $\pm$ 2.060	4.176 (12.618)		
West 440 (14.04%)	3.825 $\pm$ 2.532	2.532 (13.007)		
Two Degrees Hotter*⁴ n (%)	Mean of log(violent crime) $\pm$ Stdev	Median of log(violent crime) (Range)	Two Sample T Stat	P-value
No 1770 (56.50%)	3.245 $\pm$ 2.300	3.437 (12.653)	14.84	<0.0001 ²
Yes 1363 (43.50%)	4.419 $\pm$ 2.111	4.432 (13.007)		

* Variable was included in the final model.

¹Levene's Test for Homogeneity of Variance indicated heterogeneity, therefore Welch's ANOVA test was also conducted, finding a p-value of <0.0001.

²Equality of Variance testing indicated unequal variances, therefore Satterthwaite methods were used.

³Score of city qualities based on rates of crowded housing, multiunit homes, and households without a vehicle.

⁴Whether the average temperature of the county in July 2016 was 2+ degrees warmer than historical averages.

Table 1, above, reports the mean, median, standard deviation, and range of each variable. Pearson correlation coefficients for the relationship between numeric continuous variables and the log of the number of violent crimes recorded and associated p-values are also reported. For the categorical variable region, 1-way ANOVA F-statistic and associated p-value are reported. For the dichotomous variable "two degrees hotter," which indicates if a county experienced a July that was two or more degrees hotter than historical averages, two-sample T-statistic and associated p-value are reported.

Table 2 reports the results of single linear regression of the log of the number of violent crimes recorded in each county by each of the potential predictor variables. Additionally, table 2 shows the results of multiple regression for each the interaction terms in the presence of the terms interacting.

Table 3A shows a comparison of the final model with and without the city score variable. This table highlights the conclusion that city score was no longer valuable after adjusting for all other variables. Table 3B reports the results of the final multiple linear regression model.

Table 4 reports comparisons of the final model with and without selected counties. This table highlights the robustness of the model findings and is discussed in further detail below.

Analysis & Review of Predictors

The predictors which made it into the final model selection process are described below, with a brief explanation of why the predictor was included, any considerations concerning its inclusion and any special characteristics of the predictor.

The first predictor listed in the model is region, which was included as a categorical variable with the Midwest for reference. Different regions of the United States will experience important differences in unobserved factors. They may have different cultures, politics, population demographics, levels of education etc., which the region variable attempts to account for. The Northeast contained 6.93% of counties, the Midwest 33.64%, the South 45.38%, and the West 14.04%. As shown in Table 1, all regions had statistically different levels of violent crime, except

Predictor	$\hat{\beta}$	95% CI for β	P Value
Northeast ¹	2.28276	1.95990, 2.60562	<0.0001
South ¹	1.03262	0.85658, 1.20865	<0.0001
West ¹	0.80960	0.56377, 1.05542	<0.0001
Uninsured Rate per 100	-0.02250	-0.03826, -0.00673	0.0052
Minority Rate per 100	0.03217	0.02830, 0.03604	<0.0001
Two Degrees Hotter	1.17366	1.01683, 1.33049	<0.0001
Log(non-elderly adults)	1.32498	1.29883, 1.35112	<0.0001
Log(per capita income)	1.53182	1.18067, 1.88297	<0.0001
Log(area)	-0.05630	-0.14545, 0.03285	0.2157
City Score	1.02727	0.83267, 1.22188	<0.0001
Interaction of Uninsured Rate and Minority Rate ²	-0.00336	-0.00391, -0.00281	<0.0001
Interaction of Two Degrees Hotter and Uninsured Rate ³	-0.07838	-0.10952, -0.04724	<0.0001

¹Region variables were analyzed in a single regression model with the Midwest as the reference.
²In the presence of uninsured rate and minority rate.
³In the presence of two degrees hotter and uninsured rate.

for the South and the West, which were not statistically different from one another in terms of the mean of the log of the number of violent crimes per county. Table 2 shows that all regions were statistically related to the outcome when included in a model together.

One of the most highly related social vulnerability variables was the uninsured rate. Conceptually higher levels of uninsured residents should lead to lower levels of medical care, which in turn should lead to higher levels of substance abuse, which has been shown to be positively related to violent crimes such as murder (Goldstein, 1985).

Expansion of medical insurance through Medicaid has been tied to lower rates of aggravated assault, primarily through the expansion of access to substance abuse treatment (Wen, Hockenberry & Cummings, 2017; Vogler, 2017). The percent of the population that is uninsured is correlated with the percent unemployed, the percent below the poverty line and the percent without a high school diploma ($r = 0.27, 0.51, 0.52$ respectively.) Unsurprisingly, when variables for all these factors were included in one model, there was a high degree of collinearity and large variance inflation factors (VIF) were observed. As Table 1, shows the mean uninsured rate was 11.908

people per 100 residents. Though single regression of log violent crimes by uninsured rates, shown in Table 2, shows that violent crimes fall with higher uninsured rates, this is likely the result of confounding by population size of the county, which is negatively correlated with uninsured rate. When adjusted for log of the number of non-elderly adult residents, uninsured rate becomes positively correlated with violent crime, as is expected based on the literature. The uninsured rate has a right skew. Log transformation of the uninsured rate did not improve the model goodness of fit or residual diagnostics.

It has long been observed that cities have higher crime rates than other places (Glaeser & Bruce, 1999; Wolf et al., 2014). Though the theories as to why this is vary greatly, the fact remains that any model of violent crime must differentiate between regions with a large metropolitan area and areas without one. The method for creating the city score is described in the methods section. Over 80% of counties received a city score of zero while only 6 counties received a city score of 3. Of these, 5 were clustered around New York City and 1 was San Francisco County, California. Los Angeles County, California and Cook County, Illinois received city scores of 2, likely because their cities are more spread out geographically. Table 1 shows that the city score is significantly and positively correlated with the log number of violent crimes in a county, as expected. City score is the one variable that was not kept in the final model after selection using Cp scores. After adjustment for all other variables included in the selection process, city score ceased to be statistically significant or meaningfully interpretable. When adjusted for all other variables, city score had a negative relationship with violent crime and p-value of 0.6764.

Race and ethnicity are important factors in the United States. The category that one falls into correlates with many other factors, such as housing and neighborhoods, educational opportunities, discrimination, and experience with violence. In 2016, the rate of violent victimization was highest for non-Hispanic black persons in the United States (Oudekerk, 2020). Additionally, in the United States, slightly more than half of people arrested for nonfatal violent crimes are not classified as non-Hispanic White (Beck, 2018). Together, these facts indicate that the racial/ethnic makeup of a community may be an important proxy variable in predicting how much violent crime will occur. As Table 1 shows, the mean percent minority in a county was 22.854. Table 2 shows that the minority rate is significantly and positively correlated with log number of violent crimes. The minority rate has a right skew. Log transformation of the minority rate did not improve the model goodness of fit or residual diagnostics.

As climate change impacts the environment, abnormally high temperatures are an increasingly important factor to consider when looking at outcomes such as violent crime (Harp, & Karnauskas, 2020). On abnormally hot day, increases in violent crime can lead to as much as 15% increase in arrests (Behrer & Bolotnyy, 2021). The impacts of heat on violent crime rates appear to be especially apparent in less well-off areas, potentially due to with how both heat and material circumstances affects our psychology (Behrer & Bolotnyy, 2021). Slightly less than half of counties (43.5%) had a mean temperature that was two degrees or more above average in July of 2016.

The total population of a county was reduced by the population of adults over aged 65 and older and by the population of minors under age 17. Non-elderly adults were used as the population predictor variable as 88.9% of violent offenders arrested in 2016 fell into this category (Federal Bureau of Investigation, 2016). The number of non-elderly adults was log transformed to improve correlation with log violent crimes and to stabilize residuals. This log transformed variable yielded a higher Pearson correlation to log violent crimes than the log of the total population of a county. Overall, the non-elderly adult population was the strongest predictor of the number of violent crimes (after log transformations). Though area is not directly thought to be linked to violent

crimes, it is a necessary adjusting variable to account for the density of the population. Area was log transformed to stabilize residuals.

Lower per capita income has been shown to be associated with higher homicide rates (Gobaard et al., 2022). It is a good proxy for many other circumstances that may affect violent crime rates as well. Per capita income was log transformed to improve correlation with log violent crime and to stabilize residuals. This transformation is common practice due to the skewed nature of income distributions. Additionally, per capita income displayed a nonlinear correlation with violent crime, which was improved with natural log transformation.

Results

In total seven predictors and two interaction terms were included in the final multiple linear regression model, described in Table 3B and Equation 1. The final predictions by county compared to real violent crime by county is shown in Figure 7. The final model for the log number of violent crimes in a county in 2016 explained 78.36% of the variability and had a root mean square error of 1.069, which was 3.5 times larger than the dependent mean. The overall final model was highly

Table 3A: Model Comparisons	R ²	Root MSE	# of Predictors	F-Stat	Residuals
Model without City Score	0.7836	1.06912	11	1027.38	Assumptions not perfectly met.
Model with City Score	0.7836	1.06926	12	941.53	Not improved

Table 3B: Multiple Regression Results						
Variable	$\hat{\beta}$	Standard Error	t-Value	p-value	95% Confidence Limits	
Intercept	-3.60711	1.04329	-3.46	0.0006	-5.65271	-1.56152
Northeast	-0.09502	0.08970	-1.06	0.2895	-0.27090	0.08086
South	0.06127	0.05830	1.05	0.2934	-0.05305	0.17559
West	0.10241	0.07376	1.39	0.1651	-0.04222	0.24704
Uninsured Rate per 100	0.03417	0.00761	4.49	<.0001	0.01924	0.04910
Minority Rate per 100	0.02581	0.00272	9.49	<.0001	0.02048	0.03114
Two Degrees Hotter	-0.14132	0.11544	-1.22	0.2210	-0.36766	0.08503
Log(non-elderly adults)	1.31775	0.01488	88.55	<.0001	1.28857	1.34693
Log(per capita income)	-0.64542	0.10137	-6.37	<.0001	-0.84418	-0.44666
Log(area)	0.05210	0.02617	1.99	0.0465	0.00079853	0.10341
Interaction of Uninsured Rate and Minority Rate	-0.00136	0.00016	-8.48	<.0001	-0.00167	-0.00104
Interaction of Two Degrees Hotter and Uninsured Rate	0.02689	0.00837	3.21	0.0013	0.01048	0.04329

significant with a F-statistic of 1027.38 and associated p-value of <0.0001. The final model did not have concerning levels of colinearity. All elevated VIFs (greater than 3) could be explained by interaction terms. Assumptions for modeling were only partially met. The residuals were roughly normally distributed, however, there was a left skew, explained in the limitations. Additionally, there was a left megaphone pattern to the residuals when plotted against the predicted log number of violent crimes, also discussed in the limitations.

Equation 1: $\ln(\text{violent}) = -3.60711 - 0.09502(\text{Northeast} = 1) + 0.06127(\text{South} = 1) + 0.10241(\text{West} = 1) + 0.03417(\text{Uninsured Rate per 100}) + 0.02581(\text{Minority Rate per 100}) - 0.14132(\text{Two Degrees Hotter} = 1) + 1.31775 \ln(\text{non-elderly adults}) - 0.64542 \ln(\text{per capita income}) + 0.05210 \ln(\text{area}) - 0.00136(\text{Uninsured Rate per 100}) * (\text{Minority Rate per 100}) + 0.02689(\text{Uninsured Rate per 100}) * (\text{Two Degrees Hotter} = 1)$

For every one percentage point increase in the percent of the population that was uninsured the number of violent crimes predicted in the county rose by approximately 3.417% in counties with an all-non-Hispanic White population without a summer heat wave, after adjusting for all other variables. For every one percentage point increase in the percent of the population that was uninsured the number of violent crimes predicted in the county rose by approximately 6.106% in counties with an all-non-Hispanic White population with a summer heat wave, after adjusting for all other variables. For every one percentage point increase in the percent of the population that was a racial/ethnic minority, the number of violent crimes predicted rose by approximately 2.581% in counties with a fully insured population, after adjusting for all other variables. Counties in the Northeast had approximately 9.502% fewer predicted violent crimes than similar counties in the Midwest. Counties in the South had approximately 6.127% more predicted violent crimes than similar counties in the Midwest. Counties in the West had approximately 10.241% more predicted violent crimes than similar counties in the Midwest.

It would be predicted that for every one percent increase in the non-elderly adult population, the number of violent crimes predicted would rise by approximately 131.775%, after adjusting for all other variables. However, this approximation is not reliable due to the large percent change. Similarly, the predicted 64.542% decrease in predicted violent crime for every one percent increase in per capita income does not hold up reliably due to the large percent change. The beta coefficient for whether there was an abnormally hot July was not statistically significant, nor did the sign match what was expected based on literature and single linear regression. Therefore, any interpretation of it should be made with caution. Similarly, there is no current theoretical underpinning presented to interpret the beta coefficient for area as it was included to account for the large variability in size and population density that exists between counties. Interpretations of the beta coefficient for area should be made with caution.

Discussion

An explanation for how percent of the population that is uninsured might interact with the percent of the population that is a racial/ethnic minority to affect the number of violent crimes in a county is not readily present in the literature. However, there are several potential explanations. The most likely of which is that these two population parameters are acting as proxies for other factors that affect violent crime. This seems likely given the geographic distribution of counties with both high values for uninsured rate and minority population rate. These counties are concentrated in Alaska and the southern border of Texas. Additionally, there are several counties in the west that correspond to the locations of Native American reservations, shown in Figure 6 (Bureau of Indian Affairs, 2016) Compared to counties with lower minority rates and uninsured rates, counties with high values for the interaction term had a higher proportion of the population that was under the age of 18. This interaction term follows a phenomenon seen in the data. When the model (without minority rate or associated interaction) is run on counties with a minority rate of above the mean, increasing uninsured rates correlate with increasing violent crimes. However, when the model is run on counties with a minority rate below the mean, increasing uninsured rates correlate with

decreasing violent crimes. One could explore dichotomizing these variables and interaction to simplify.

It is thought that heat increases violent crime through psychological changes that affect aggressive behavior (Behrer & Bolotnyy, 2021). It is perhaps unsurprising then that heat and high rates of uninsured residents work together to increase violent crime in a county. Insurance rates not only affect what medical care one may or may not get for pre-existing psychological issues but may also proxy other material circumstances (i.e. full time employment, housing with air conditioning, early childhood development) that may determine how vulnerable one is to the negative effects of heat. Once the interaction between if the July 2016 was two or more degrees hotter than normal and the percent of the population that is uninsured was added to the model, the beta coefficient for two degrees hotter flipped signs. However, this is not concerning. This beta coefficient ceases to be statistically significant on its own, with more information being derived from the interaction term,

which shows that as the percent uninsured rises in counties with an unusually hot summer so does the number of violent crimes, adjusted for other factors.

Selected Counties

Table 4 shows comparisons in beta coefficients for the final model when run on the full data set and subsets of the data. The first comparison shows the effect of removing the counties with the largest populations, which the model tended to overestimate, as shown in figure 5, when predicting the

Table 4: Comparing models with and without highly influential observation	<i>Final Model</i> – full data β	Data without 10 highest population counties $\hat{\beta}$	Data without 10 most influential counties $\hat{\beta}$	Data without counties with 0 violent crimes $\hat{\beta}$
Intercept	-3.60711	-3.70119	-3.74337	7.03814
Northeast	-0.09502	-0.10667	-0.09973	-0.09801
South	0.06127	0.05359	0.01514	-0.00900
West	0.10241	0.10889	0.09035	-0.07501
Uninsured Rate per 100	0.03417	0.03431	0.03838	0.00814
Minority Rate per 100	0.02581	0.02597	0.02372	0.01419
Two Degrees Hotter	-0.14132	-0.14225	-0.11706	-0.00485
Log(non-elderly adults)	1.31775	1.32382	1.31638	1.15040
Log(per capita income)	-0.64542	-0.64331	-0.63305	-0.40089
Log(area)	0.05210	0.05409	0.05218	0.08448
Interaction of Uninsured Rate and Minority Rate	-0.00136	-0.00136	-0.00119	-0.00110
Interaction of Two Degrees Hotter and Uninsured Rate	0.02689	0.02729	0.02508	0.01049

number of violent crimes. The second comparison shows the effect of removing the counties with the most influence (as measured by Cook's Distance). The third comparison shows the effect of removing all counties with zero reported violent crimes, to examine the effect of potential excess zeros due to lack of reporting. These comparisons show that the conclusion of the model is robust to changes in the dataset and that the direction of correlation and approximate magnitude of effect of each of the variables, except for region, holds.

Limitations

There is a left megaphone pattern, significant heteroscedasticity, and a slight inverse U shape, shown in the graph of the residuals by the log of the number of violent crimes, shown in Figure 2

below. This pattern is in part because a log transformed outcome variable was used for an outcome which can take a value of zero that has been given a nominal value to avoid errors due to taking the natural log of zero. Any predicted value of less than zero essentially translates to a prediction of zero violent crimes, however, because of the log transformation, the actual predicted value can range from 0 to negative infinity. Any county with a predicted value of one violent crime that had no violent crimes will automatically have a large negative residual. Counties can have a large negative residual, even when the actual predicted value is relatively close to the actual number of violent crimes. Alcorn County, Mississippi, highlighted in the Figure 2, had no violent crimes, however, the model predicts that it would have 86 violent crimes, resulting in it being an extreme outlier. Meanwhile Los Angeles, California had 44,556 violent crimes and the model predicts it would have 182,345 violent crimes. Yet Los Angeles is not considered an outlier.

Additionally, Figure 2 shows a striped pattern between -3 and 2 on the x-axis. The number of violent crimes is a countable integer value. These lines correspond to counties with 0, 1, 2, 3... violent crimes. As the number of violent crimes increases the outcome begins to behave more and more like a true continuous variable.

Due to the heteroscedasticity, the confidence intervals of this model are likely a misrepresentation of the precision of the model. Standard error calculations rely on a constant variance, which does not hold in this case. Finally, this model is not meant to be interpreted as a model of causative factors. All data represented in the model is ecologic with no temporal connection between predictors and violent crime. Crime data may not be complete and may involve imputation for counties not reporting to the FBI.

Figure 2: Residuals by Log Violent

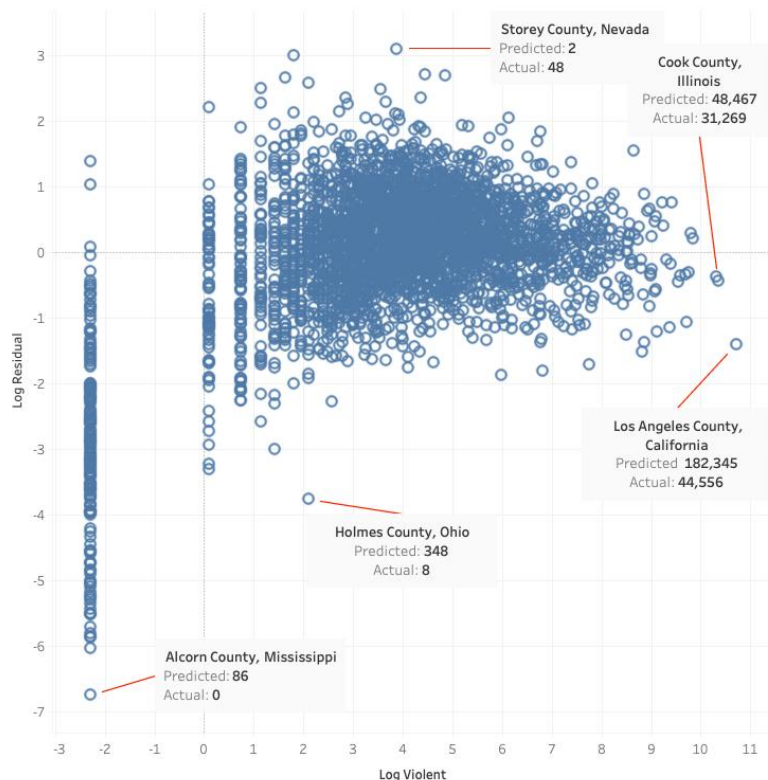


Figure 3: Leverage and Residuals

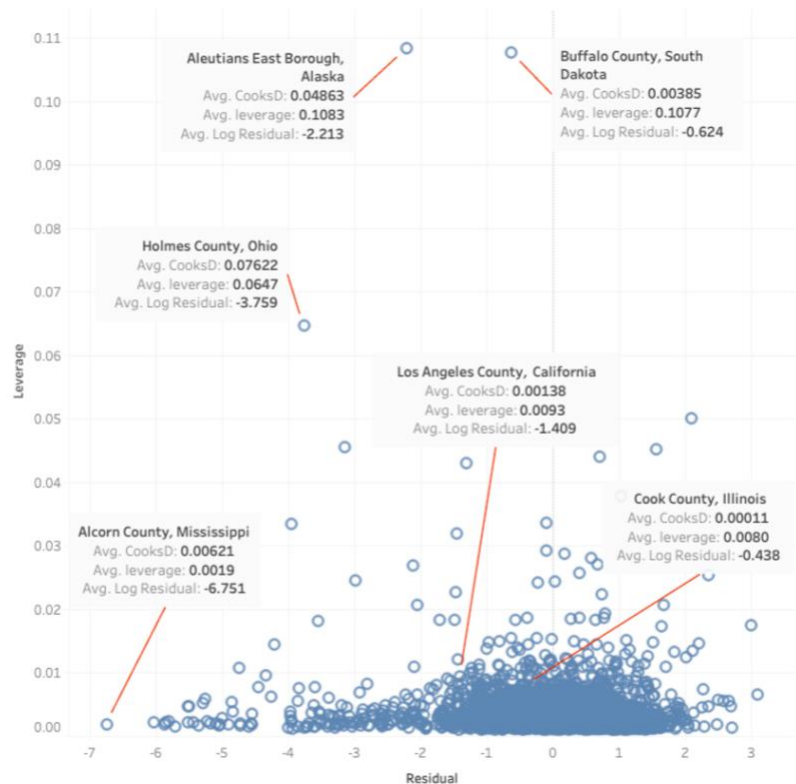


Figure 4: Predictions of Violent Crime by Actual Violent Crime on the log scale

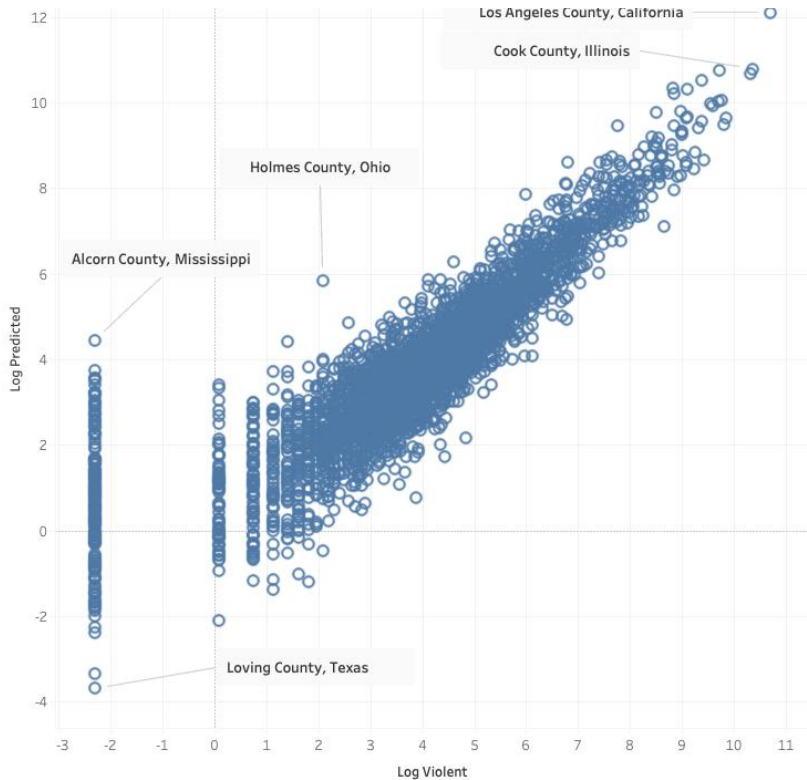
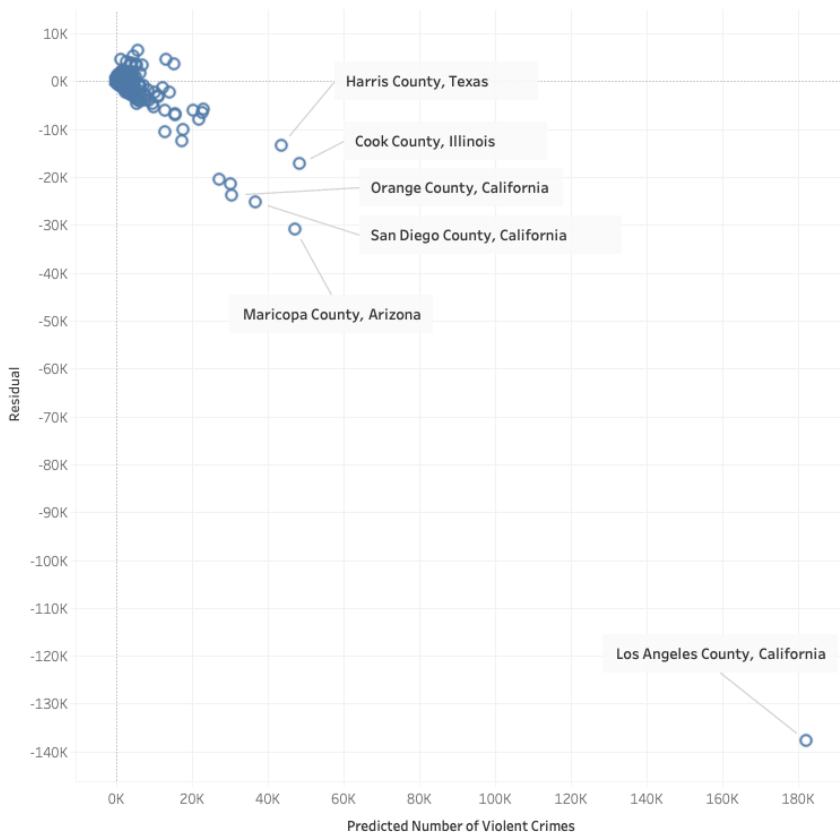


Figure 5: Predictions of Violent Crime by Actual Violent Crime



Conclusions

Violent crime is a complex parameter that is difficult to predict. This exploratory analysis found that the size of the non-elderly adult population was the most significant predictor of the number of violent crimes. This analysis also reinforced the notion that vulnerable communities are at higher risk for violent crime. Communities with lower income, higher uninsured rates and higher percent minority population had more violent crime after adjusting for region, heat anomaly, population, and area. This analysis identified two significant interaction terms. First, it was found that there is an attenuation of the increase in violent crime for communities with high uninsured rates and high minority rates. The communities identified by this interaction term are highly vulnerable communities with many children. The second significant interaction term was between having an abnormally hot July and uninsured rate. This positive interaction term indicates that communities that are more vulnerable to the heat experience higher increases in violent crime due to heat waves compared to those that are less vulnerable to the heat. The findings of this report support investing in vulnerable communities as a crime prevention strategy.

Figure 6: Interaction between uninsured rate and minority rate

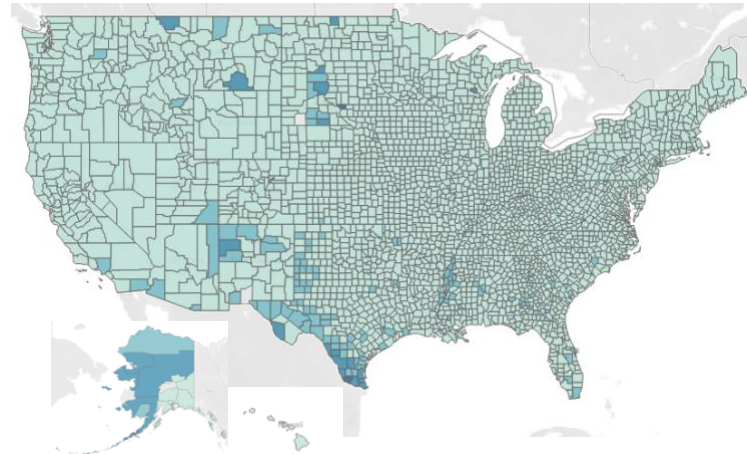
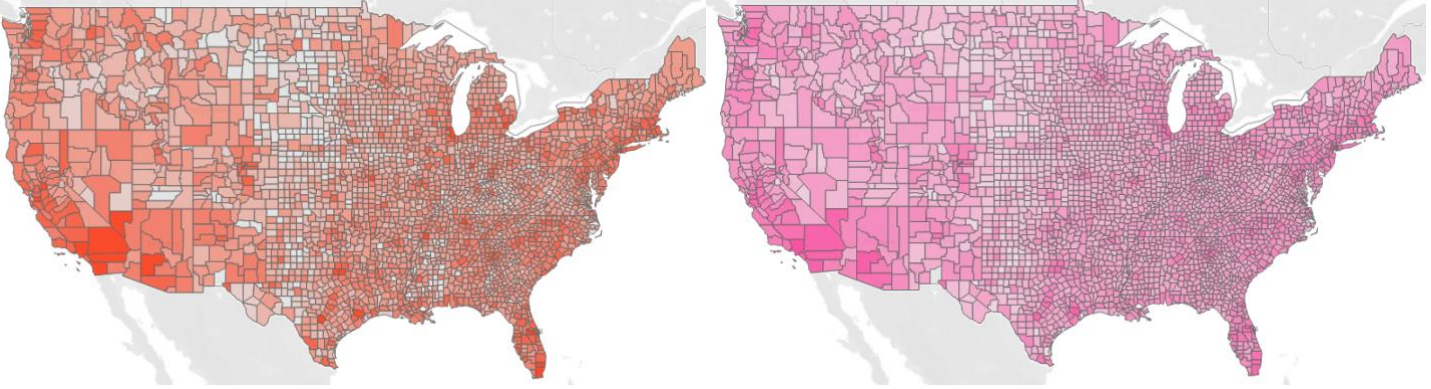


Figure 7: Map of Violent Crime in 2016 (left, red) vs Predicted Violent Crime (right, pink)



References:

- Beck, A. (2018). *Race and Ethnicity of Violent Crime Offenders and Arrestees* (Statistical Brief NCJ 255969). Bureau of Justice Statistics U.S. Department of Justice. <https://bjs.ojp.gov/content/pub/pdf/revcoa18.pdf>
- Behrer, A. P., & Bolotnyy, V. (2022). *Heat, Crime, and Punishment*. The World Bank. <https://doi.org/10.1596/1813-9450-9909>
- Bureau of Indian Affairs. (2016). *Indian Lands of Federally Recognized Tribes of the United States* [Map]. DEPARTMENT OF THE INTERIOR OFFICE OF TRUST SERVICES. <https://www.bia.gov/sites/default/files/dup/assets/bia/ots/webteam/pdf/idc1-028635.pdf>
- Federal Bureau of Investigation. Table 20. (2016). Retrieved April 21, 2023, from <https://ucr.fbi.gov/crime-in-the-u.s/2016/crime-in-the-u.s.-2016/tables/table-20>
- Glaeser, E. L., & Sacerdote, B. (1999). Why is There More Crime in Cities? *Journal of Political Economy*, 107(S6), S225–S258. <https://doi.org/10.1086/250109>
- Goldstein, P. J. (1985). The Drugs/Violence Nexus: A Tripartite Conceptual Framework. *Journal of Drug Issues*, 15(4), 493–506.
- Harp, R. D., & Karnauskas, K. B. (2020). Global warming to increase violent crime in the United States. *Environmental Research Letters*, 15(3), 034039. <https://doi.org/10.1088/1748-9326/ab6b37>
- NOAA National Centers for Environmental information. (2023, April). *Climate at a Glance: County Mapping*. <https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/county/mapping>
- Office of the Assistant Secretary for Health. (n.d.). *Crime and Violence—Healthy People 2030* | health.gov. Retrieved April 15, 2023, from <https://health.gov/healthypeople/priority-areas/social-determinants-health/literature-summaries/crime-and-violence>
- Oudekerk, B. (2020). *Violent Victimization by Race or Ethnicity, 2005-2019* (Selected Findings NCJ 255578). Bureau of Justice Statistics U.S. Department of Justice. <https://bjs.ojp.gov/content/pub/pdf/vvre0519.pdf>
- Vogler, J. (2017). Access to Health Care and Criminal Behavior: Short-Run Evidence from the ACA Medicaid Expansions. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3042267>
- Want to reduce violence? Invest in place. (n.d.). Retrieved April 15, 2023, from <https://www.brookings.edu/research/want-to-reduce-violence-invest-in-place/>
- Wen, H., Hockenberry, J. M., & Cummings, J. R. (2017). The effect of Medicaid expansion on crime reduction: Evidence from HIFA-waiver expansions. *Journal of Public Economics*, 154, 67–94. <https://doi.org/10.1016/j.jpubeco.2017.09.001>
- Wolf, A., Gray, R., & Fazel, S. (2014). Violence as a public health problem: An ecological study of 169 countries. *Social Science & Medicine*, 104, 220–227. <https://doi.org/10.1016/j.socscimed.2013.12.006>