Factors affecting homicide rates in the U.S

A comprehensive State level analysis to investigate the factors of homicide with recommendations for State officials to curtail homicide rate.

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Executive Summary

Homicide, the act of killing one human by another is the ultimate crime. Homicides have ripple effects that goes beyond the loss of human life. They affect not only the victim's family but have fiscal and psychosocial effects throughout the community. It is estimated that when accounting for direct and indirect costs, homicides cost communities on average $17.25 million per offense. With the number of homicides that occur in the United States each year dwarfing those of other developed countries, the aim of this project is to identify the driving factors and effective interventions to help ameliorate homicides in the United States.

To conduct this analysis, state-level data from 2010 to 2019 has been sourced and integrated from multiple government open data repositories. These include count data on homicides, police personnel, drug, and alcohol abusers. Because firearms are responsible for about 70% of the homicides in the US each year, we have also included the count of firearms and gun laws binary variables to analyze their intervention effects.

To get a good understanding of the data, time-continuous exploratory data analyses were conducted at the Country and State-levels. Using visualizations, we understood the relationship between the variables. After careful consideration, variables were then chosen for the model with the aim to explain their impact on the homicide rate in the US. Mixed-level models with homicide rates as the response were then implemented to understand the effects.

Some of the recommendations drawn for state and federal officials to curb homicide rates include:

- **Requiring firearm registrations for all owners,** thus decreasing homicides by 18.6 % for every 1% increase in firearms.
- **Increasing the number of law enforcement officers**, thus decreasing homicides around a 14.8% for every 1% increase in the number officers
- **Requiring firearm permit for all owners**, resulting in a 7.2% decrease homicide rates
- **Implementing firearm reporting laws**, thus decrease homicide rates by 4.5%

Our models have been consistent in indicating that gun policies do help in reducing homicides. Policies which demand gun owners to get a permit and register their guns once they own it would bring down the homicides rate. Also, increasing the number of police officer would have a lag effect showing to decrease homicides over time. Another key insight identified in these analyses were the apparent relationships of how increases in GDP per capita, and decreases in unemployment and income inequality seems to decrease homicides rates. Another recommendation from our analysis is to study how nascent laws like state-wide living-wage minimums be analyzed in the context of their effects in ameliorating homicides.

Problem Statement and Significance

The United States has the highest number of homicides per 100,000 people among developed countries. Apart from the loss of life, homicide can cause a disruption in the society and affect interpersonal relations. Homicides also impact the economy; a study has shown that homicides can cost the society $17.25 million per offense.
Many studies have linked the high number of homicides to the availability of guns in the United States. As per the second amendment in the United States, the people have the right to keep and bear arms. The reasoning behind this was to have a well-regulated militia, being necessary to the security of a free State. United States has the highest rate of deaths from gun violence in the world among developed countries with 3.96 deaths per 100,000 people in 2019. According to the Capitol's official record-keeping website Congress.gov, there have been around 110 laws related to guns introduced just in 2019.

This warrants for the need to determine the possible methods for curbing gun availability and identifying the other potential causes and interventions of homicides in the country.

Prior Literature

Studies attempting to find significant factors influencing homicides have been conducted for years. Typically, these studies focus on one possible cause of homicides in the United States. For example, there has been a study done to understand the effect of drugs and alcohol usage on homicides and whether immigration leads to increased homicide. In a study by W. Wieczorek, J. Welte and E. Abel, it was found that most homicide offenders engaged in excessive alcohol consumptions or a combination of excessive alcohol and drug consumption immediately prior to committing the crime. The drugs have psychopharmacological effects that leads to propensity of violence.

When considering psychological effects, it is important to understand what affects the mental state of the person to cause such crimes. Unemployment is one of the major factors that has a negative impact on the mental health. In a study done across countries, the negative effect of unemployment on mental health was stronger in countries with a weak level economic development, unequal income distributions or weak unemployment protection systems compared to other countries (K.I. Paul, K. Moser 2009).

Guns have been the primary choice of weapon for offenders, and there have been many studies linking ownership of guns with homicides. A study has shown that the increased availability of guns increases the probability of intention of homicidal intent. It also increases the probability of execution of homicidal intent (Wolfgang Stroebe 2015). Another study by Michael Siegel in 2013 showed that gun ownership was a significant predictor of firearm homicide rates. The model used in the study indicated that for each percentage point increase in gun ownership, the firearm homicide rate rose by 0.9%. Guns shows provide an easier means to purchase guns, but a study done by M. Duggan, R. Hjalmarsson, B. Jacob on two States found no evidence that gun shows increase or decrease homicides.

Gun laws which differ from state to state have been passed to keep the guns away from possible offenders. Having more restrictive gun laws have been associated with decreased rates of firearm homicides, even after adjusting for demographic and sociological factors. Laws that strengthen background checks and permit-to-purchase seemed to decrease firearm homicide rates. Specific laws directed at firearm trafficking, improving child safety, or the banning of military-style assault weapons were not associated with changes in firearm homicide rates (L.K. Lee, E.W Fleegler, C. Farrell 2017).

Data Sourcing

The data used for analysis was sourced from reliable state and organizational repositories such as the Murder Accountability Project (MAP), United States Department of Justice Bureau of Alcohol, Tobaccos, Firearms and Explosives (ATF), Substance Abuse and Mental Health Services Administration (SAMHSA), Federal Bureau of Investigation's Uniform Crime Reporting (FBI: UCR), United States Census Bureau, Bureau of Economic Analysis (BEA) , Kaiser Family Foundation (KFF), State Firearm Laws Organization and the National Center for Higher Education Management (NCHEM). Given that the enforcement of laws and criminal investigations would fall in the hands of the police force, the number of law enforcement officers by year is also sourced for analysis from the Uniform Crime Reporting division of the FBI.

The yearly state-level number of homicides, used as the dependent variable analyzed was sourced from the MAP which counts all homicide cases solved and unsolved. The count of firearms was combination of handguns, machine guns and short and long-barrel guns provided by the ATF. Classified gun laws were provided the State Gun Laws organization which categorizes and tracks all gun laws in effect by state overtime.

To account for the effect of drugs and alcohol on homicides as pointed by previous literature the number of drug users and the number of alcohol abusers was sourced from SAMHSA. To account for the high-risk situations that might arise in areas where drug dealing is common and the possible intervention of legalized marijuana laws, included were state-level data on recreational marijuana from ProCon website for the relevant years.

Lastly, socio-economic and demographic data for each state through the years was collected to analyze how these related factors, as indicated by prior literature, impact each states homicide rates. In particular state-level yearly GDP data was collected from KFF, high school graduation rates from the NCHEM, unemployment rate from the BEA and their respective Gini-Index coefficients from the U.S. Census. Number of individuals by age and ethnic group were also collected from the Census.

Data Preparation

Data preparation consisted of dropping special cases like District of Columbia. Factorizing categorical variables. Aggregating the number of pertinent firearms and non-murder violent crimes pertinent to homicides. Normalizing our count data to allow us to make equal comparisons across states. This was done by dividing each of the counts by their pertinent state population and multiplying the count by a conmesurate constant resulting in ratios that are easy to understand. For example, counts of firearms and law enforcement which rarely reach over 100,000 in total counts were counted in ratios per 1,000. Whereas larger population counts, like those of substance dependent users or ethnic population counts were counted in larger ratios of 100,000. For transformed variables whose distribution still remained Poisson-like, log-transformations were also.

Because our data consists of time-continuous observations with variables whose effects may be delayed in action, lagged effects for firearm policies and law enforcement were used. This takes into consideration that laws or increases in the number police officers might not have a substantial immediate effect but their effect may show in one or two years. This is specially applicable to understant the effect of new police officers who may benefit from the experience gained in in-field traning and required assimilation with the area in order to see the full effect of their addition.

Data Summary

The dataset has data for 51 states for 31 variables over 10 years from 2010 to 2019. This includes 25 gun related and 2 drugs related policies. The data has been summarized in the below table for some key variables the given time-period. The data is shown has been normalized byt transforming it to be per 100000 population.

	Average (U.S)	Maximum	Minimum
Homicides	4.65	11.5 (Louisiana)	1.51 (New Hampshire)
Violent Crime	372.42	753.14 (Alaska)	126.26 (Maine)
Total Weapons	1961	19156 (Wyoming)	343 (New York)
Law Enforcement Officers	199.79	336.57 (New Jersey)	109.57 (Mississippi)
Unemployment	5.78	8.08 (Nevada)	2.97 (North Dakota)
Gini index	0.458	0.506 (New York)	0.417 (Alaska)

Variables of choice

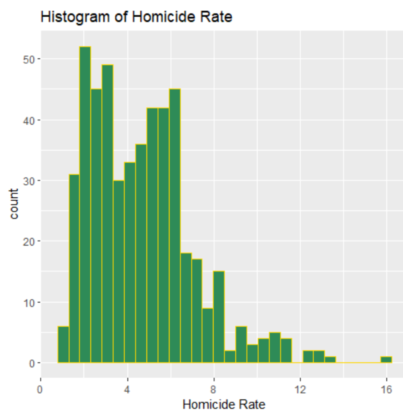
Using the literature review as guide in identifying important regressors for our the model. We have divided our variables into causes and interventions. The main focus of this study will be in the interventions because those are the most actionable solutions that state officials can apply. However, capturing the appropriate causes are also important as they help with the interpretation of what is driving homicides and help produce reliable coefficients for potential interventions.

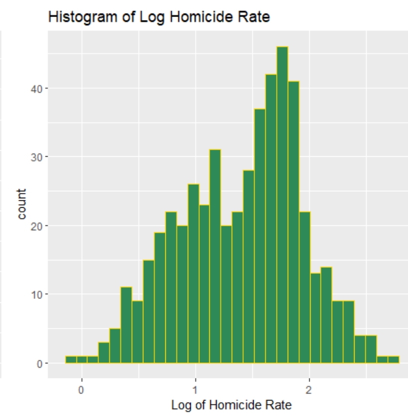
Causes	Effect	Rationale
NumDrugUsers	+	Psychoactive drugs show up in many homicidal events. Long-term treated patients also appear to be less likely to re-commit violent crimes.
NumAlcoholUsers	+	There is prevalence of alcohol usage in homicides. Increased rates of alcohols sales also correlate with increasing number of homicides
Violent Crime	+	Increased levels of crime in an area may make it more permissible for more violent crime like homicide (broken windows theory)
Serious Mental Illness	+	individuals with mental illness appear to have a higher propensity to be involved in potentially violent events that could lead to homicide.
Unemployment rate	+	As shown by previous research, unemployment rate is linked to economic distress which is also linked to high homicide rates
Gini Index	+	Increased income inequality results in more violent crime including homicide.
Firearms	+	Handguns, machine guns and others small projectile launchers registered in the state. More the number of weapons, the easier people have opportunity to convert intent into action.
Recreational Cannabis	+/-	This might decrease crime caused by illegal markets but at the same time, since cannabis induces paranoia, it might lead to a higher homicide rate.
Black	+	As per literature review, crime we expect that the proportion of Black population will be positively correlated with homicide rate.
Hispanic	+	As per our research, Hispanics are twice as likely to be incarcerated for violent crimes than White Non-Hispanics, therefore we expect some correlation between violent crime and Hispanic origin.
Adults 18-25	+	According to the Bureau of Justice Statistics, young adults are most vulnerable and perpetuators of violent crime including homicide.

Interventions	Effect	Rationale
LawEnforcementOfficers	-	Increased presence of law enforcement may act as deterrent from potential criminal activity (with a diminishing effect due to saturation)
Weapon Registration	-	Allows better tracking and accountability of weapon owners, which may decrease homicide.
Education	-	With education, we expect the population to have better opportunities for higher income and hence, a decrease in violent crime
Background Check	-	Will limit bad users (folks with substance abuse or past criminal history) from access
Gun Report	-	Allows better accountability of weapon owners, which may decrease homicide.
Permits	-	Restrict access, provides training and allow for better tracing of users.
Relinquish Guns	-	Ensures that people who get diagnosed with a mental problem or get convicted of a crime etc. Must surrender weapons meaning that there are less chances of weapons falling into the wrong hands, hence decreasing homicide.

Data Visualization

After transforming the number of homicides into a homicide rate per 100,000, the Poisson-like distribution of the dependent variable persisted. After a applying a log transformation the dependent variable now closely resembles a normal distribution. This permits the exploration of linear models with a greater chance of meeting the linear assumption required, instead of restricting our models to only generalized linear models with a Poisson distribution.





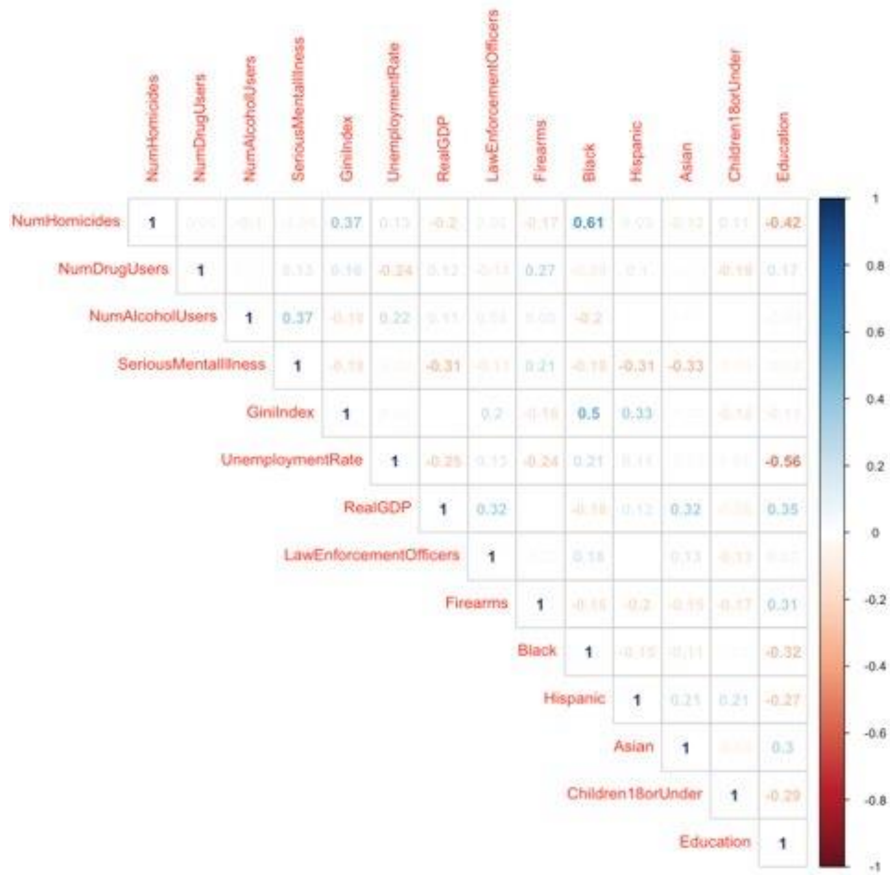
The analysis of correlations for the numeric variables explored revealed some key insights in the relationships between our Dependent Variable (DV) and Independent Variables (IV). These are noted along with the graph below:

DV-IV:

- Strong positive correlation exists between DV, income inequality index (.37) and rate of black population (.61).
- Strong negative correlation exists between DV and education (-.42)

IV-IV:

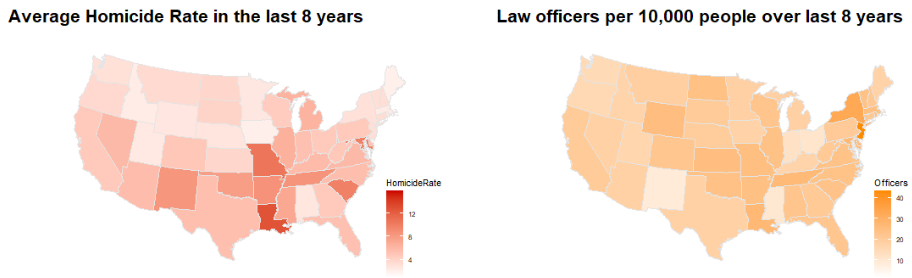
- Positive correlation between income inequality and minority populations, Black (.5) and Hispanic (.33).
- Unemployment rate is negatively correlated with Education (-.56).
- Black (-.32) and Hispanic (-.27) population have negative correlation with education whereas Asian population (.31) have a positive correlation with education.



The relationships between our independent variables must be noted all show values under 0.70, thus not indication high signs of multicollinearity. However, there are some signals here were higher presence of some socio-economic factors like education and inequality appear to be more prevalent in states with higher/lower proportions of certain ethnicities. This will be taken into consideration when interpreting our models.

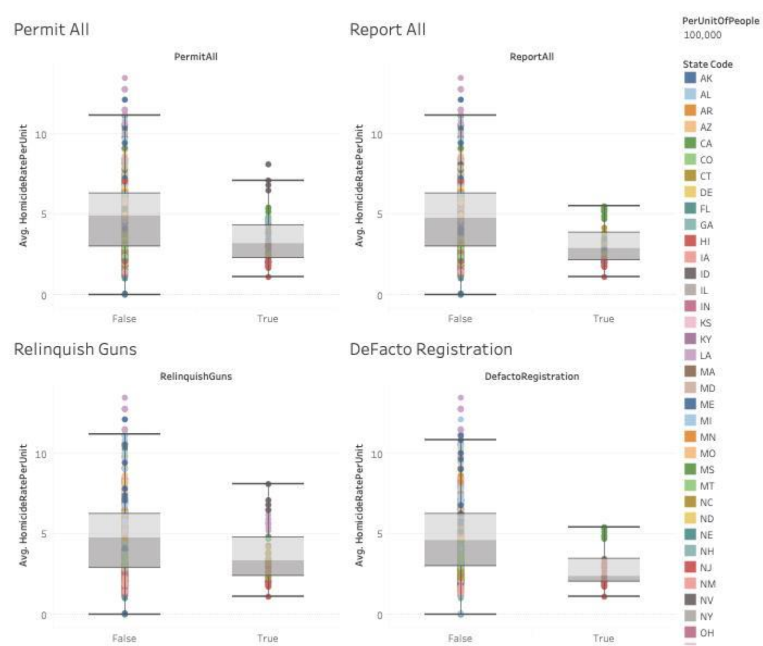
Efficacy of Law enforcement

Surprisingly, law enforcement rates did not have a strong negative correlation with homicide rate as anticipated. To visualize how the presence of police officers may relate in across states, a mapped plot of the homicide rate versus the rate of police officers was analyzed. From this plot, it is apparent that many of the states that have high concentrations of law enforcement officers, also show high homicide rates (i.e., Louisiana). Whereas other states that have a higher homicide rate do show lower number of law enforcement (i.e., New Mexico), as expected. These mixed results suggest that in some cases the number of homicides may be driving higher demands for police officers. To analyze the effectiveness of increases in police force size as desired for our analysis, the use of a lagged variable may be helpful.



Efficacy of Gun Laws

The U.S. has an abundant variety of gun laws. This is also demonstrated in the variety of gun law types we collected. To make better sense of the policies considered we used policies ideas suggested by the literature read which proposed increase tracking of firearms through federal gun registration laws. Leveraging this idea, analyzed were pertinent laws that would help limit access and improve tracking of arms at all levels of the purchase acquisition process. For example, we looked at laws that would first limit the access to qualified users, such as permits which often require training in gun handling practices for buyers. Second, we included Background checks to capture all states that may not require one as part of a permit process but still did some checks to limit user-eligibility to those without criminal or mental liabilities. Third we included laws that would capture transfers of weapons at first point-of-sale by looking at those that required dealers to report gun sales to the government. To capture those second-hand sales, we included gun registrations which require owners to report all owned guns to the state. Lastly, we included relinquish laws that grant the state permission to confiscate guns from those no longer eligible to own because of criminal or behavioral offenses.



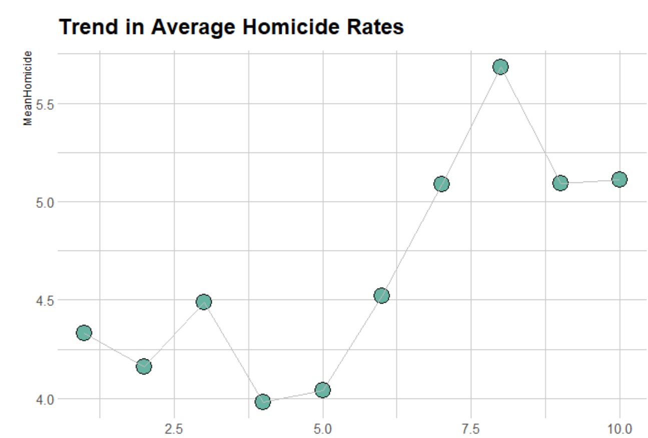
To explore the efficacy of these laws in reducing Homicide rate, we used a boxplot comparison between states that had and did not have these laws. For the selected laws analyzed the average homicide rate for states with these laws is lower than those without. Comparing the effectiveness across laws it appears that reporting and registration perform better than the other.

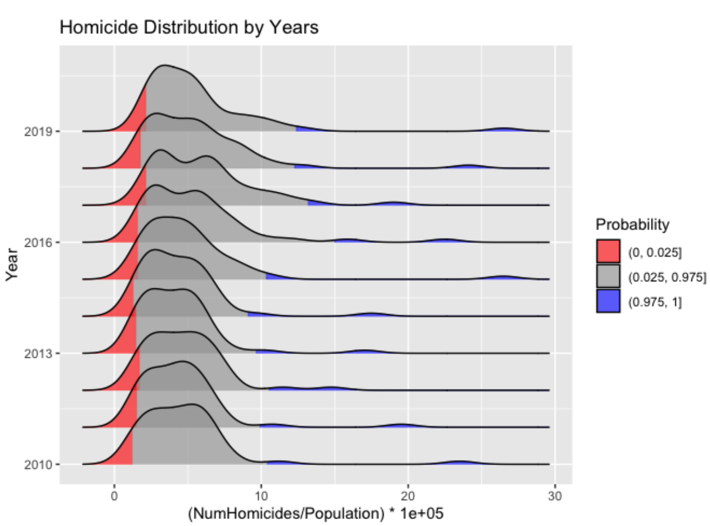
The time continuous effect that gun laws has was also analyzed to try to understand the effects for the same states as these laws were applied. Using background checks as an example, we can observe 2 insights. First, homicide rates in states where these gun laws are in effect (green lines) appear to be lower than the those without. Moreover, Nevada and Pennsylvania show a steep decline in homicide rates after the law was put into place. This could indicate an actual effect of the law but requires further evidence.

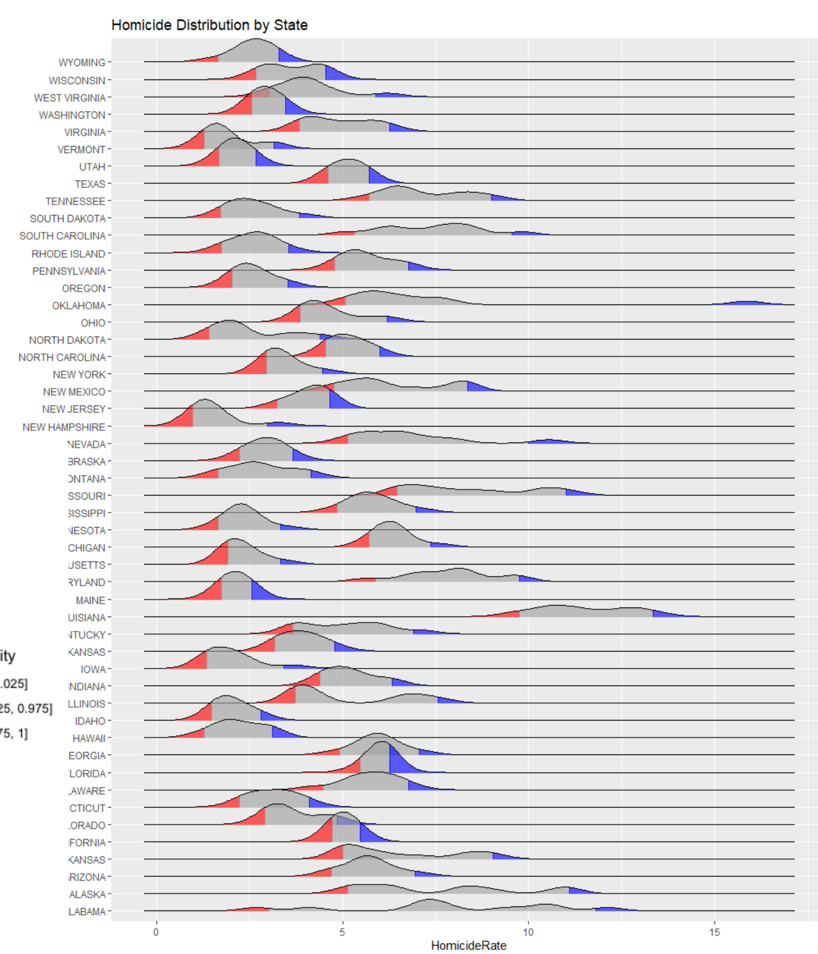
Independence

To analyze same-state observations taken through time we must consider ways to control for the autocorrelation that will exist when looking at observations that are based on the same entity. Visualizing the distribution in homicide rates across the different states, for example, allow us to see that certain inherit conditions may exist with each entity which would make certain states like Louisiana have significantly higher rates than the average.

Similarly, we must account for year-specific conditions that may have led to greater homicides as apparent in the trend of homicides through years below. To capture the dependence in our observations and the variation between each, we leverage mixed-effects models using both states and years as random effects.







Models:

Base Mixed Effects model controlling for the collinearity from same-state samples across years by using these two variables as random effects. This model includes interactions between: 1) the number of firearms and firearm registrations laws to examine curtailing effect this policy may have in homicides, 2) Gini index coefficients and unemployment rate to measure the augmented effect on homicides that the presence of both may cause, and 3) expected positive impact that relinquishment laws may have in decreasing homicides as violent crimes increase

```
re5 <- lmer(log(NumHomicides) ~ NumDrugUsers +  NumAlcoholUsers + SeriousMentalIllness
          + Children18orUnder + log(Black) + log(Hispanic) + log(Asian)  + Education
          + log(RealGDP) + log(LawEnforcementOfficers)
          + CannabisRecreational + PermitAllFirearms + UniversalBackgroundCheck
          + ReportAllFirearms + GiniIndex*UnemploymentRate
          + log(Firearms)*GunRegistration +  RelinquishGun*ViolentCrime
           + (1| State) +  (1 | Year)  , data=data, REML = F)
```

Mixed effect model with lags controlling for delayed effects from certain gun and cannabis laws that may not see an immediate impact on homicides. Lags are also applied to violent crimes to consider the time it may take to track down firearm owners who must relinquish their weapons, and a lag on the number of law enforcement to account for the delayed impact that new recruits may have in decreasing homicides.

```
re6 <- lmer(log(NumHomicides) ~ NumDrugUsers + NumAlcoholUsers + SeriousMentalIllness
          + Children18orUnder + log(Black) + log(Hispanic) + log(Asian) + Education
          + log(RealGDP) + log(LawEnforcementOfficers) + CannabisRecreational
          + PermitAllFirearms + UniversalBackgroundCheck + ReportAllFirearms
          + GiniIndex*UnemploymentRate + log(Firearms)*GunRegistration
          + RelinquishGun*ViolentCrime + log(OneLagLawEnforcement) + OneLagCannabisRec
          + OneLagGunPermit + OneLagBackground + OneLagGunReport
          + log(Firearms)*OneLagGunRegister + log(OneLagFirearms)*(GunRegistration
          + OneLagGunRegister) + RelinquishGun*OneLagViolentCrime
           + (1| State) +  (1 | Year), data=data, REML = F)
```

Mixed effect model with two lags in law enforcement that may account for the added value that more experienced police officers may have in decreasing homicides.

```
re7 <- lmer(log(NumHomicides) ~ NumDrugUsers + NumAlcoholUsers + SeriousMentalIllness
          + Children18orUnder + log(Black) + log(Hispanic) + log(Asian) + Education
          + log(RealGDP) + log(LawEnforcementOfficers) + CannabisRecreational
          + PermitAllFirearms + UniversalBackgroundCheck + ReportAllFirearms
          + GiniIndex*UnemploymentRate + log(Firearms)*GunRegistration
          + RelinquishGun*ViolentCrime + log(OneLagLawEnforcement) + OneLagCannabisRec
          + OneLagGunPermit + OneLagBackground + OneLagGunReport
          + log(Firearms)*OneLagGunRegister + log(OneLagFirearms)*(GunRegistration
          + OneLagGunRegister) + RelinquishGun*OneLagViolentCrime
          + log(TwoLagLawEnforcement)
          + (1| State) +  (1 | Year), data=data, REML = F)
```

	Dependent variable:		
	log(NumHomicides)		
	TwoLag (1)	OneLag (2)	Interactions (3)
NumDrugUsers	0.00004 (0.0001)	0.00004 (0.0001)	0.00004 (0.00005)
NumAlcoholUsers	0.00001 (0.00002)	0.00000 (0.00002)	-0.00000 (0.00001)
SeriousMentalIllness	0.00003 (0.00004)	0.00003 (0.00004)	0.00003 (0.00003)
Children18orUnder	0.00000 (0.00001)	0.00000 (0.00001)	0.00001 (0.00001)
log(Black)	0.214*** (0.039)	0.210*** (0.038)	0.203*** (0.037)
log(Hispanic)	-0.033 (0.054)	-0.034 (0.054)	-0.025 (0.051)
log(Asian)	0.076 (0.069)	0.074 (0.069)	0.094 (0.065)
Education	-0.010 (0.009)	-0.011 (0.009)	-0.010 (0.008)
log(RealGDP)	-0.361* (0.217)	-0.371* (0.214)	-0.396** (0.197)
log(LawEnforcementOfficers)	-0.025 (0.047)	-0.023 (0.047)	-0.002 (0.044)
CannabisRecreationalYes	0.043 (0.082)	0.045 (0.081)	0.022 (0.059)
PermitAllFirearmsYes	-0.010 (0.185)	-0.009 (0.185)	-0.173** (0.086)
UniversalBackgroundCheckYes	0.030 (0.068)	0.029 (0.067)	-0.009 (0.052)
ReportAllFirearmsYes	-0.045 (0.118)	-0.035 (0.117)	-0.051 (0.107)
GiniIndex	0.006 (0.036)	0.009 (0.036)	0.012 (0.032)
UnemploymentRate	-0.131 (0.215)	-0.092 (0.212)	-0.150 (0.169)
log(Firearms)	-0.135 (0.130)	-0.143 (0.130)	-0.001 (0.034)
GunRegistrationYes	-0.037 (0.204)	-0.031 (0.203)	-0.106 (0.137)
RelinquishGunYes	-0.519 (0.413)	-0.573 (0.406)	-0.455 (0.343)
ViolentCrime	0.001** (0.001)	0.001** (0.0005)	0.002*** (0.0002)
GiniIndex:UnemploymentRate	0.003 (0.005)	0.002 (0.005)	0.003 (0.004)
log(Firearms):GunRegistrationYes	2.158* (1.145)	2.076* (1.136)	0.020 (0.255)
RelinquishGunYes:ViolentCrime	0.002 (0.002)	0.002 (0.002)	0.001 (0.001)
log(OneLagLawEnforcement)	-0.071 (0.044)	-0.064 (0.044)	
OneLagCannabisRecYes	-0.049 (0.083)	-0.048 (0.081)	
OneLagGunPermitYes	-0.062 (0.182)	-0.071 (0.181)	
OneLagBackgroundYes	-0.016 (0.078)	-0.020 (0.077)	
OneLagGunRegisterYes	-0.155 (0.224)	-0.159 (0.222)	
log(OneLagFirearms)	0.131 (0.131)	0.141 (0.130)	
OneLagViolentCrime	0.001 (0.001)	0.001 (0.001)	
GunRegistrationYes:log(OneLagFirearms)	-2.347* (1.219)	-2.275* (1.210)	
RelinquishGunYes:OneLagViolentCrime	-0.001 (0.002)	-0.001 (0.002)	
log(TwoLagLawEnforcement)	-0.052 (0.053)		
Constant	2.935 (3.213)	2.947 (3.195)	2.944 (2.844)
Observations	296	298	349
Log Likelihood	65.243	66.402	79.510
Akaike Inf. Crit.	-56.486	-60.804	-105.019
Bayesian Inf. Crit.	80.057	72.292	-0.932
Note:			*p<0.1; **p<0.05; ***p<0.01

The best model is the mixed effects model with two lags because it best represents our understanding of how socio-economic factors and delayed effects that policy interventions may have on homicide rates. Marginal effects:

- Every one percent increase in the Black populations increases homicides by 21.4 percent. It is worth noting, this may be attributed to the high correlation that exists between inequality and the percentage of black people in a state, which may be absorbing this effect.
- Every additional 1,000 persons with drug abuse problems increases homicides by 4 percent
- Every additional 1,000 persons with mental illnesses increase homicides by 3 percent
- Every additional 1,000 persons with alcohol abuse increase homicides by 1 percent
- Every one percent increase in per capita GDP decreases homicides by 36.1 percent
- Every one percent increase in firearms increases homicides by 0.4 percent when there is no firearm registration laws, but it decreases homicides by 18.6% when there is a firearm registration law
- Every one percent increase in the number of law enforcement officers will decrease homicides by 14.8 percent
- State firearm permit laws decrease homicide rates by 7.2 percent
- State firearm reporting laws decrease homicide rates by 4.5 percent
- Every one-point coefficient increase in the Gini index increases homicides by 0.6 percent with an additive impact of 0.3 percent for every percent increase in unemployment.

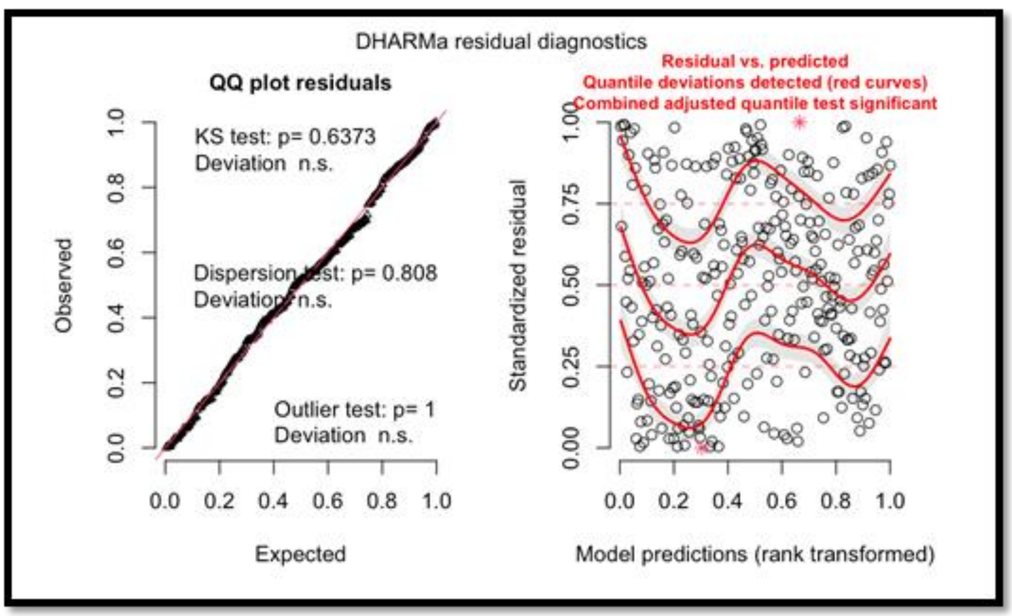
Random Effects

Examining the random effects for the two-lag model shows that while accounting for our fixed effect the states with the lowest propensity of homicides include Massachusetts, with 40% decrease, and New York, with 39% decrease in homicide rates. While the ones with the highest propensity are Pennsylvania, with a 35% increase, and Wyoming with 45% increase in homicides.

Random Effects			
Highest propensity		Lowest propensity	
WYOMING	0.45	MASSACHUSETTS	-0.40
PENNSYLVANIA	0.35	NEW YORK	-0.39
MISSOURI	0.31	IOWA	-0.36
KENTUCKY	0.27	NEW HAMPSHIRE	-0.32
OKLAHOMA	0.26	MINNESOTA	-0.27

Quality Checks

By using states and years in our random effects, we control for the dependency that exists between states from year to year. The correlation plot and VIF test gives no indication for multicollinearity between the non-transformed variables used in our model. And using the simulated analysis of the DHARMa package for hierarchal model diagnostics, our model passes the normality and homoscedasticity tests. However, it is apparent from the Residual vs. Predicted graph that there appears to be an underlying structure not captured by our model. Despite this sign of a potential bias, we believe this model provides a helpful representation for the impacts of our regressors on the homicide rate.



Recommendations

Focusing on ways to decrease homicides we would remiss not to mention that there are significant signs that a state's increase in overall wealth (as measured by GDP per capita), decrease in income inequality and decrease unemployment rate all help decrease homicides. We thus, first recommend that future analysis on homicides should investigate some of the nascent laws (i.e. minimum living-wage policies) for which little state-level data is available at the moment.

Some actionable policies that could be used by the States to decrease homicides which could be enacted include:

- Increasing the size of law enforcement details
- Requiring gun registrations for all guns that an owner possess, so that all weapons could be accounted and tracked.
- Enacting firearm permit laws which would require owners to gain experience in gun-handling.
- Enacting firearm reporting laws which would require wholesale sellers to report each gun sale and new owner to local officials.

References

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Lee LK, Fleegler EW, Farrell C, et al. Firearm laws and firearm homicides: a systematic review. JAMA Intern Med. 2017;177(1):106-119.

Phillips, Julie and Kenneth Land. 2012. "The link between unemployment and crime rate fluctuations: An analysis at the county, state, and national levels." Social Science Research. Vol. 41, no. 3. p. 681-694.

Data Sources

Murder Accountability project - http://www.murderdata.org

Substance Abuse and Mental Health Services(SAMHSA) - https://www.samhsa.gov/

Bureau of Alcohol, Tobacco, Firearms and Explosives (ATF) -https://www.atf.gov/

Federal Bureau of Investigation (FBI) - https://www.fbi.gov/

Census Bureau - https://www.census.gov/

The State Science & Technology Institute (SSTi) - https://ssti.org/

Bureau of Economic Analysis (BEA) - https://www.bea.gov/

State Firearm Laws - https://www.statefirearmlaws.org/

Appendix

```
library(here)
library(readxl)

# Read Data
df <- read_excel(here("data", "HomicideData_Original_revised.xlsx"), sheet="HomicideData")

# Check Nulls
colSums(is.na(df))

#----------------------------------- Preparing Data --------------------------------library(dplyr)
# Removing DC - not a state
df <- df %>% filter(StateCode !="DC")
# Grouping Firearms
df <- df %>% mutate(Firearms = AnyOtherWeapon1 + Machinegun3 + ShortBarreledRifle5 + ShortBarreledShotgun6)
# Grouping Violent Crime Except Murder
df <- df %>% mutate(VCNotMurder = RapeVC + AggravatedAssaultVC + RobberyVC)
# Selecting data of interest for modeling
data <- df %>% select(Year, State, NumHomicides, Firearms, NumDrugUsers, NumAlcoholUsers, SeriousMentalIllness,Po
pulation, RealGDP, GiniIndex, UnenemploymentRate, LawEnforcementOfficers, CannabisMedical, CannabisRecreational,
SubAbuseInpatientCareBeds, VCNotMurder,PropertyCrime, White, Black, Hispanic, Asian, `Children 0-18`, `Adults 19-25`,
`Adults 26-34`, Education,
              PermitAllFirearms, reportall, defactoreg, relinquishment, UniversalBackgroundChecksAllFirearms, Universal
Permit
)
# Rename Variables in Data
data <- data %>% rename(ViolentCrime = VCNotMurder, BedsForAbuse = SubAbuseInpatientCareBeds,
               UnemploymentRate = UnenemploymentRate,
               ReportAllFirearms = reportall, GunRegistration = defactoreg,
               Children18orUnder = `Children 0-18`,
               RelinquishGun = relinquishment,
               Adult19to25 = `Adults 19-25`,
               Adult26to34 = `Adults 26-34`,
               UniversalBackgroundCheck = UniversalBackgroundChecksAllFirearms)
# Checking data
colSums(is.na(data))

#----------------------------------- Feature Engineering --------------------------
# Factorize
cols <- c("PermitAllFirearms", "ReportAllFirearms", "GunRegistration", "CannabisMedical", "CannabisRecreational","Reli
nquishGun", "UniversalBackgroundCheck")
for (col in cols){
  data[[col]] <- factor(data[[col]], levels = c(0,1), labels = c("No", "Yes"))
}

# Year to Factor
data$Year <- relevel(factor(data$Year), "2010")

# convert to Pop estimate - all except laws, gini, and unemployment rate
unit_of_people <- 100000
# cols
cols <- c("NumDrugUsers",  "NumAlcoholUsers", "SeriousMentalIllness", "ViolentCrime",
```

```
        "PropertyCrime", "BedsForAbuse", "NumHomicides",  "White", "Black", "Hispanic", "Asian",
        "Children18orUnder","Adult19to25", "Adult26to34")
data[cols] <- (data[cols] / data[["Population"]]) * unit_of_people

# Different Scale Law Enforcement
data["LawEnforcementOfficers"] <- (data["LawEnforcementOfficers"]/data["Population"]) * 1000

# Different Scale Firearms
data["Firearms"] <- (data["Firearms"]/data["Population"]) * 1000

# Real GDP per Capita
data$RealGDP <- data$RealGDP/data$Population

# convert Gini to percentage
data['GiniIndex'] = data['GiniIndex'] * 100

# Creating Lags
data <- data %>%
  arrange(Year) %>%
  group_by(State) %>%
  mutate(OneLagLawEnforcement = lag(LawEnforcementOfficers),
       OneLagGunPermit = lag(PermitAllFirearms),
       OneLagGunRegister = lag(GunRegistration),
       OneLagGunReport = lag(ReportAllFirearms),
       OneLagGunRelinquish = lag(RelinquishGun),
       OneLagBackground = lag(UniversalBackgroundCheck),
       OneLagCannabisRec = lag(CannabisRecreational),
       OneLagCannabisMed = lag(CannabisMedical),
       OneLagViolentCrime = lag(ViolentCrime),
       OneLagFirearms = lag(Firearms),
       TwoLagLawEnforcement = lag(LawEnforcementOfficers, 2),
       TwoLagGunPermit = lag(PermitAllFirearms, 2),
       TwoLagGunRegister = lag(GunRegistration, 2),
       TwoLagGunReport = lag(ReportAllFirearms, 2),
       TwoLagGunRelinquish = lag(RelinquishGun, 2),
       TwoLagBackground = lag(UniversalBackgroundCheck, 2),
       TwoLagCannabisRec = lag(CannabisRecreational, 2),
       TwoLagCannabisMed = lag(CannabisMedical, 2),
       TwoLagViolentCrime = lag(ViolentCrime, 2),
       TwoLagFirearms = lag(Firearms,2))

# ---------------------------------- Exploratory Data Analysis -------------------
library(ggplot2)
library(maps)
library(ggthemes)
library(ggridges)
# Distribution of Dependent Variable
x1<-ggplot(df, aes(x=NumHomicides)) + geom_histogram(color="gold",fill="seagreen")+ggtitle("Histogram of Homicide
Rate")+xlab("Homicide Rate")

x2<-ggplot(df, aes(x=log(NumHomicides))) + geom_histogram(color="gold",fill="seagreen")+ggtitle("Histogram of Log
Homicide Rate")+xlab("Log of Homicide Rate")
```

```
cowplot::plot_grid(x1, x2)

# Distribution by State
ggplot(data, aes(x = NumHomicides, y = State, group= State, fill = factor(stat(quantile)))) +
  stat_density_ridges(
    geom = "density_ridges_gradient",
    calc_ecdf = TRUE,
    quantiles = c(0.025, 0.975)
  ) +
  scale_fill_manual(
    name = "Probability", values = c("#FF0000A0", "#A0A0A0A0", "#0000FFA0"),
    labels = c("(0, 0.025]", "(0.025, 0.975]", "(0.975, 1]")
  ) +
  labs(title = 'Homicide Distribution by State')

# Correlation Plots
temp <- data %>% select(NumHomicides, ViolentCrime, NumDrugUsers, NumAlcoholUsers, SeriousMentalIllness, GiniInd
ex,
                        UnemploymentRate,RealGDP,LawEnforcementOfficers,Firearms,Black,Hispanic,Asian,Children18orUnder,E
ducation)
temp <- subset(temp, select = -State)
PerformanceAnalytics::chart.Correlation(temp, pch= "+", upper.panel =F)
correlations=cor(temp,use = "pairwise.complete.obs")
corrplot::corrplot(correlations,method = "number",type="upper")

# Homicides Over The Years Per State
US <- map_data("state")
US$region<-toupper(US$region)
US$State<-US$region
head(US)
# Joining long-lat to data
temp<-left_join(US,data[ which(as.numeric(data$Year)>1), ],by="State")
# Yearly datat
Y19<-data %>%
  filter(Year=="2019")
Y18<-data  %>%
  filter(Year=="2018")
Y17<-data  %>%
  filter(Year=="2017")
Y16<-data  %>%
  filter(Year=="2016")
Y15<-data  %>%
  filter(Year=="2015")
Y14<-data %>%
  filter(Year=="2014")
Y13<-data  %>%
  filter(Year=="2013")
Y12<-data  %>%
  filter(Year=="2012")
Y11<-data  %>%
  filter(Year=="2011")
```

```
Y10<-data  %>%
  filter(Year=="2010")
# Plot Map
p0 <- ggplot(data = temp,
            mapping = aes(x = long, y = lat, group = group, fill = NumHomicides))
p1 <- p0 + geom_polygon(color = "gray90", size = 0.1) +
  coord_map(projection = "albers", lat0 = 39, lat1 = 45)
p2 <- p1 + scale_fill_gradient(low = "white", high = "Red3") +
  labs(title = "Homicide Rate through the years")
p3<-p2 + theme_map()+facet_wrap(temp$Year)
p4<-
p3+theme(legend.position=c(.65, .22), legend.direction = "horizontal",legend.title = element_text(size = 18),legend.text
= element_text(size = 16),legend.key.size = unit(1, "cm"),
            legend.key.width = unit(1,"cm"),legend.margin =margin(r=30,l=30,t=10,b=1)  )
p4

# Effects of laws
library(lattice)
bwplot(NumHomicides ~ PermitAllFirearms, data, xlab = "Permit Firearms", ylab= "Homicide
Rate", names=c("No", "Yes"))
bwplot(NumHomicides ~ ReportAllFirearms, data, xlab = "Report Firearms Sales", ylab= "Homicide
Rate", names=c("No", "Yes"))
bwplot(NumHomicides ~ GunRegistration, data, xlab = "Firearm Registration", ylab= "Homicide
Rate", names=c("No", "Yes"))
bwplot(NumHomicides ~ RelinquishGun, data, xlab = " Relinquish Firearm", ylab= "Homicide
Rate", names=c("No", "Yes"))
bwplot(NumHomicides ~ UniversalBackgroundCheck, data, xlab = " Universal Background", ylab= "Homicide
Rate", names=c("No", "Yes"))

# ---------------------------------------- Modeling -----------------------------
library(lme4)
library(DHARMa)
# Multilevel Model - Interactions Only
re5 <- lmer(log(NumHomicides) ~ NumDrugUsers +  NumAlcoholUsers + SeriousMentalIllness + Children18orUnder
          + log(Black) + log(Hispanic) + log(Asian)  + Education + log(RealGDP) + log(LawEnforcementOfficers)
          + CannabisRecreational + PermitAllFirearms + UniversalBackgroundCheck + ReportAllFirearms
          + GiniIndex*UnemploymentRate + log(Firearms)*GunRegistration +  RelinquishGun*ViolentCrime
          + (1| State) +  (1 | Year)  , data=data, REML = F)
# Assumption Checking
simulationOutput <- simulateResiduals(fittedModel = re5, plot = F)
plot(simulationOutput)

# Multilevel Model -  One Lag
re6 <- lmer(log(NumHomicides) ~ NumDrugUsers + NumAlcoholUsers + SeriousMentalIllness + Children18orUnder + log(
Black) + log(Hispanic) + log(Asian) + Education + log(RealGDP) + log(LawEnforcementOfficers)
+ CannabisRecreational + PermitAllFirearms + UniversalBackgroundCheck + ReportAllFirearms + GiniIndex*Unemployme
ntRate + log(Firearms)*GunRegistration + RelinquishGun*ViolentCrime + log(OneLagLawEnforcement)
+ OneLagCannabisRec + OneLagGunPermit + OneLagBackground + OneLagGunReport + log(Firearms)*OneLagGunRegist
er + log(OneLagFirearms)*(GunRegistration + OneLagGunRegister) + RelinquishGun*OneLagViolentCrime + (1| State)
+  (1 | Year), data=data, REML = F)
# Assumption Checking
simulationOutput <- simulateResiduals(fittedModel = re6, plot = F)
```

```
plot(simulationOutput)

# Multilevel Model -  Two Lag
re7 <- lmer(log(NumHomicides) ~ NumDrugUsers + NumAlcoholUsers + SeriousMentalIllness + Children18orUnder
         + log(Black) + log(Hispanic) + log(Asian) + Education + log(RealGDP) + log(LawEnforcementOfficers)
         + CannabisRecreational + PermitAllFirearms + UniversalBackgroundCheck + ReportAllFirearms
         + GiniIndex*UnemploymentRate + log(Firearms)*GunRegistration + RelinquishGun*ViolentCrime
         + log(OneLagLawEnforcement)
+ OneLagCannabisRec + OneLagGunPermit + OneLagBackground + OneLagGunReport
         + log(Firearms)*OneLagGunRegister + log(OneLagFirearms)*(GunRegistration + OneLagGunRegister)
+ RelinquishGun*OneLagViolentCrime
         + log(TwoLagLawEnforcement)
         + (1| State) +  (1 | Year), data=data, REML = F)
# Assumption Checking
simulationOutput <- simulateResiduals(fittedModel = re7, plot = F)
plot(simulationOutput)

# Simple Model to test Multicollinearity VIF
simple <- lmer(log(NumHomicides) ~ NumDrugUsers +  NumAlcoholUsers + SeriousMentalIllness + Children18orUnder
         + log(Black) + log(Hispanic) + log(Asian) + Education + RealGDP + log(LawEnforcementOfficers)
         + CannabisRecreational + PermitAllFirearms + UniversalBackgroundCheck + ReportAllFirearms
         + GiniIndex + UnemploymentRate + log(Firearms) + GunRegistration +  RelinquishGun + ViolentCrime
         + (1| State) +  (1 | Year)  , data=data, REML = F)
car::vif(simple)
temp <- as.data.frame(vif(simple)) %>% arrange(`vif(simple)`)
# openxlsx::write.xlsx(temp, "VIF.xlsx", row.names = T, sheetName = "VIF")

# ---------------------------------------- Compare Models ------------------------
stargazer::stargazer(re7, re6, re5, simple, type="text", single.row = T, column.labels = c("TwoLag","OneLag", "Interaction
s", "Base"))

# Two Lag Model Used - Check Random Effects
ranef(re7)$State %>% arrange(`(Intercept)`)
ranef(re7)$Year

# Look at effect for Unemployment*Gini Interaction - Using model re5, with similar coefficients for display
library(effects)
effects <- allEffects(re6)
plot(effects, selection=15)
```