**Group Project Report**

HOW GUN CONTROL LAWS HELP REDUCE CRIME RATE

Statistical Data Mining - ISM 6137

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# EXECUTIVE SUMMARY

This study investigates the relationship between gun laws and violent crime rates, focusing on data from 50 states in the United States from 2012 to 2020. Employing a panel data analysis using the two ways fixed effect (with time effect) PLM models with 450 data points, the research evaluates the effectiveness of various gun control measures in reducing violent crime and homicides. The findings highlight the significant impact of ammunition permit laws and universal background check laws on crime reduction. Specifically, ammunition permit laws are identified as the most effective, associated with a substantial 55.3% reduction in violent crime rates and a 29.8% decrease in homicides. Universal background check laws follow closely, contributing to a 22.5% decrease in violent crime rates and a notable 31.5% reduction in homicides. Based on these results, the study recommends prioritizing the implementation and enforcement of ammunition permit laws and universal background check laws by policymakers. These laws have demonstrated tangible effectiveness in curbing violent crime and homicides, underscoring their importance as key strategies in crime reduction efforts. Furthermore, the study emphasizes the necessity of ongoing research and evaluation to inform decision-making and the development of comprehensive crime prevention policies.

# PROBLEM DEFINITION & SIGNIFICANCE

The debate surrounding gun control measures is complex and often contentious. Understanding the real-world impact of gun control laws on reducing violent crime rates and homicides is critical for crafting effective policies. This project aims to address the following:

* **Core Question:** Do gun control laws significantly reduce violent crime rates and homicides, and, if so, which laws have the most pronounced effect?
* **Key Considerations:**
  + The impact of various gun control laws on different types of crime rates.
  + The influence of demographic factors (poverty, education, population density) on crime
  + The interaction between gun laws and demographics
  + Potential confounding variables

**Significance**

This research holds significant value for several reasons:

* **Policy Guidance:** Results can inform policymakers and law enforcement to design data-driven gun control policies for effective crime reduction.
* **Public Awareness:** Findings can enhance public understanding about the potential benefits and limitations of specific gun control measures.
* **Social Impact:** Reducing gun violence could lead to safer communities, lower healthcare costs from gun-related injuries, and improved overall well-being.
* **Academic Contribution:** This study adds to the growing body of research on gun control and violence prevention, potentially opening new avenues for investigation.

**Addressing the Problem Definition and Significance – A Brief Outline**

To tackle the core question of this study, here's a proposed approach:

1. **Data Collection:**
   * **Gun Laws:** Gather data on the presence/absence of various gun control laws (e.g., background checks, assault weapon bans, permit requirements) at the state level.
   * **Crime Rates:** Obtain crime statistics for violent crimes and homicides from reliable sources (e.g., FBI Uniform Crime Reports).
   * **Demographics:** Collect information on state-level demographics potentially related to crime (e.g., poverty rates, education levels, population density).
2. **Data Preparation and Exploratory Analysis**

* **Standardizing data and cleaning:** Normalize crime rates considering population, etc. Address inconsistencies, outliers, and missing values.
* **Visualization:** Create plots (histograms, scatterplots) to examine data distribution and preliminary trends in relationships between variables of interest.

1. **Statistical Modeling:**
   * **Panel Data Analysis:** Utilize appropriate panel data models (e.g., fixed effects, random effects, two-way fixed effects) to account for variability across states, time-variant factors, and unobserved heterogeneity.
   * **Testing and Validation:**
     + Test model assumptions (e.g., time-invariant effects, random vs. fixed effects).
     + Assess possible interaction effects between gun laws and demographic variables.
     + Compare model fit (AIC, BIC, R-squared) to select optimal models.
     + Conduct diagnostic tests to check for heteroskedasticity, serial correlation, and other issues.
2. **Interpreting Results**
   * **Effects of Individual Laws:** Identify gun laws with statistically significant effects on crime rates, quantifying the magnitude and direction of the effect.
   * **Policy Recommendations:** Provide evidence-based recommendations to policymakers on effective gun control measures.

# PRIOR LITERATURE

The literature on crime and crime prevention provides valuable insights into the potential impact of gun control laws on reducing crime rates. Mustard and Lott's study (1996) examines the relationship between right-to-carry concealed handguns laws and crime deterrence. While concealed handgun laws are associated with reductions in some types of crime, they also coincide with increases in others. Additionally, the impact of concealed handgun laws varies depending on factors such as population size and demographic characteristics. It lays a foundation for understanding the effects of firearm regulations on criminal behavior. Nagin's review (1998) synthesizes key findings in criminal deterrence research, outlining future opportunities to address the difficulties in assessing the effectiveness of policies for deterring crimes. This review offers perspectives that could inform the development of effective gun control policies which take in consideration of perceptions and response to policies, time factors of policies effectiveness and the relationship of sanction risk and crime behaviors, explaining why some policies stimulate the raise of certain crime types. The authors also suggest the law enforcement may exert deterrent effects on crime level, e.g. police and prison population. Abrahamse et al. (1991) contribute to this discourse by evaluating a program aimed at reducing repeat offenses, shedding light on strategies for addressing recidivism through interventions beyond legal measures alone. McDowall's exploration (2002) of criminological trends and research provides contextual understanding of the broad socioeconomics factors in preventing crimes. The study likely finds that community-based interventions, empowerment initiatives, policy changes, and addressing social factors are crucial in preventing violence and reducing injuries. It emphasizes the need for interdisciplinary approaches to tackle the complex issues surrounding violence effectively. Schreck, McGloin, and Kirk's study (2009) on the origins of violent neighborhoods highlights the complex nature of crime. The study suggests that violent and non-violent crimes tend to be correlated and the association of crime rate to the complex neighborhood structures and ties. The 2-step methods that the authors applied in the study also enlighten us in our research on multi-level, panel regression models. Kleck and Barnes (2014) investigate, in context of New York City, the relationship between police presence and crime deterrence. The findings suggest that neither police strength nor actual arrest rates had a significant positive impact on perceptions of arrest likelihood for different crime types. Additionally, the study highlights the complex interplay of individual-level and contextual factors in shaping perceptions of arrest risk, challenging traditional interpretations of the relationship between policing, arrest rates, and perceived deterrence of crime. Grucza et al. (2018) explore Declines in prevalence of adolescent substance use disorders and delinquent behaviors in the US. The results show that the reduction of substance use disorder SUD by 49% among 12 to 17-year-olds significantly reduced delinquent behaviors by 34%. Finally, Donohue, Aneja, and Weber's comprehensive assessment (2019) of right-to-carry laws and violent crime concluded that the adoption of RTC laws raises overall violent crimes in the 10 years after the laws are adopted. This finding could inform directly to our discussions on the role of gun control laws in shaping crime trends. Collectively, these studies contribute to our study on how gun control laws may help reduce crime rates by illuminating various factors and mechanisms at play in crime prevention efforts.

# DATA SOURCE AND PREPARATION

The data for this research paper was sourced from several reputable sources to ensure the reliability and accuracy of the information. The main data sources included *data.gov* for demographic data, state websites for gun law data, the FBI website for crime rate data, and *data.gov* for police officer data. These sources provided a comprehensive set of variables that allowed for a thorough analysis of the relationship between gun laws, crime rates, and other demographic factors.

The dataset contained a wide range of variables, including population demographics, various gun laws, crime rates, and police officer numbers. Each variable was measured differently based on its nature. For example, demographic variables such as population, poverty rate, and education rate were measured as counts or percentages, while gun laws were measured based on the presence or absence of specific laws in each state. Crime rates were typically measured as the number of incidents per 100,000 population.

For the analysis, we selected several two as dependent variables (DV) and independent variables (IV) based on their relevance to the research questions. The dependent variables included the violent crime rate and homicide rate, which were of primary interest in understanding the impact of gun laws on crime rates. The independent variables included population, police force rate, poverty rate, education rate, and various gun laws. These variables were chosen because they are commonly cited factors in studies of crime rates and were expected to have a significant impact on the dependent variables.

Data cleaning was an essential part of the analysis process to ensure the accuracy and consistency of the dataset. We began by renaming columns to ensure clarity and standardizing state names to ensure consistency across the dataset. We also addressed missing data by recovering missing police numbers for certain states and years by averaging adjacent years. Additionally, we omitted territories and territories from the analysis to focus on states.

The data preparation process involved careful sourcing of data from reliable sources, selection of relevant variables for analysis, and thorough cleaning to ensure the accuracy and consistency of the dataset. These steps were crucial in laying the foundation for a robust analysis of the relationship between gun laws, demographic factors, and crime rates.

# VARIABLE CHOICE

After merging demographic, police force, gun law and crime data sets then cleansing the consolidated single data set, our data set has 450 data points on 152 variables in 5 groups: key (state + year), crimes (violent, homicide, rape legacy, …), police force (male officer, female officer, …), demographic (population, poverty, ...), and gun laws (felony, buyer permitting, mental health prohibition of possession, … ). We, then, engineer the features and select predictors for our 2-step approach described in modeling section.

1. Select dependent variables: we are interested in analyzing felony crimes. Therefore, within 11 available crime types in the data set, we choose ‘Violent crime’ and ‘Homicide’ as 2 dependent variables. These 2 crime types may behave differently, we will model and analyze them separately. To amplify the effect of gun laws which are the focus of our study, we normalize the dominators like population. Instead of, raw case numbers per case types, we will assess the rate of crime by 1000 inhabitants i.e. number of cases \* 1000 / population.
2. Select independent variables (predictors): while focus on analyzing effect of gun laws, we also include IVs from other 2 groups to reduce potential bias of models. Our predictor table and related engineering process are depicted below:

|  |  |
| --- | --- |
| **Predictor / Group** | **Engineering process** |
| **Demographics** | |
| Population (millions of people) | Normalize by divide by 1 million. |
| Poverty Rate (per 1000 people) | Poverty number \* 1000 / population |
| Education Rate (per 1000 people) | Education number \* 1000 / population |
| **Police force** | |
| Ratio of police (per 1000 people) | Total number of police \* 1000 / population |
| **Gun Laws** | |
| *Strength of law categories, to be used in step 1 of modeling* | |
| Dealer Regulation | Count key laws related to dealer regulation have been issued |
| Buyer Regulation | Count key laws related to buyer regulation have been issued |
| Prohibitions for high-risk gun possession | Count key laws related to Prohibitions for high-risk gun possession have been issued |
| Background checks | Count key laws related to Background checks have been issued |
| Ammunition regulations | Count key laws related to Ammunition regulations have been issued |
| Possession regulations | Count key laws related to Possession regulations have been issued |
| Concealed carry permitting | Count key laws related to Concealed carry permitting have been issued |
| Assault weapons and large-capacity magazines | Count key laws related to Assault weapons and large-capacity magazines have been issued |
| Child access prevention | Count key laws related to Child access prevention have been issued |
| Gun trafficking | Count key laws related to Gun trafficking have been issued |
| Preemption | Count key laws related to Preemption have been issued |
| Immunity | Count key laws related to Immunity have been issued |
| Domestic violence | Count key laws related to Domestic violence have been issued |
| *Presence of individual law (yes / no), to specify effect of each individual law* | |
| Dealerh | State dealer license required for sale of handguns |
| Permitlaw | Permit process involves law enforcement |
| Fingerprint | Buyers must be fingerprinted at point of purchase |
| Registration | Gun owners must register their handguns with the state |
| Age restrictions | Count if there is a law restrict age on buyer regulation |
| Violentpartial | Firearm possession is prohibited for all people with a felony conviction or Violent Misdemeanor |
| Danger | Firearm possession is prohibited if person is deemed by court to be a danger to oneself or others |
| Drug misdemeanor | Firearm possession is prohibited for people with a drug misdemeanor conviction |
| Alctreatment | Firearm possession is prohibited for some people with alcohol-related problems |
| Universal | Universal background checks required at point of purchase for all firearms |
| Universalpermit | Background checks conducted through permit requirement for all firearm sales (or universal background checks) |
| Mentalhealth | Required background checks include an explicit requirement for search of state mental health records |
| Ammlicense | Vendor license required to sell ammunition |
| Ammpermit | Permit required to purchase ammunition |
| Ammrestrict | All of the state’s high-risk gun possession prohibitions also apply to ammunition possession |
| Ammage | Purchase of any type of ammunition restricted to age 18 or 21 |
| Possess age restrict | No possession of handguns / long gun until certain age |
| Open carry | No open carry of handguns / long gun is allowed in public places |
| Conceal permit | Permit required to carry concealed weapons |
| Conceal background | Concealed carry permit process requires a background check |
| Assault weapon ban | Ban on sale of assault weapons beyond just assault pistols |
| Assault weapon magazine | Ban on sale large capacity magazines beyond just ammunition for pistols |
| Childaccess lock | Safety lock required for handguns |
| Childaccess storage | All firearms in a household must be stored securely (locked away) at all times. Criminal liability for negligent storage of guns, regardless of whether child gains access |
| Trafficking | No person may purchase a handgun with the intent to re-sell to a person who is prohibited from buying or possessing a firearm |
| Straw purchase | No person may purchase a firearm on behalf of another person |
| Microstamp | All handguns sold must have either ballistic fingerprinting or microstamping so that they can be identified if used in a crime |
| Personalized | State has a law that requires review of personalized gun technology |
| Preemption | State law does not preempt local regulation of firearms in any way |
| Immunity | No law provides blanket immunity to gun manufacturers or prohibits state or local lawsuits against gun manufacturers |
| Domestic misdemeanor | All people convicted of a misdemeanor crime of domestic violence are prohibited from possessing firearms |
| Dvro | State law automatically prohibits domestic violence-related restraining order (DVRO) subjects from possessing firearms |

# DESCRIPTIVE ANALYSIS AND DATA VISUALIZATIONS

Firstly, we visualize the crime rates after engineering them (calculated per 1000 of inhabitants).

Figure 1 shows us the distributions of all analyzed crimes (homicide and violent) seem follow Poisson distribution and the corresponding log transformations look normality. The homicide rate spreads from 0.009 to 0.162 with mean of 0.048 case per 1000 inhabitants. New Hampshire is one of States have the lowest homicide rate while the Louisiana has always led homicide rate over 9 years (figure 2). The violent rate is 100 times homicide rate on the same period, spreads from 1.068 to 9.093 cases per 1000 inhabitants. The ‘safe’ States keep their crime rate stably low, while the rates in most violent States fluctuated on the trend of increment.

|  |  |
| --- | --- |
|  |  |

A graph of a crime rate

Description automatically generatedA graph of a crime rate

Description automatically generated

Figure 1. Histograms of Violent Crime & Homicide rate

|  |  |
| --- | --- |
|  | A graph of different colored lines  Description automatically generated |

# Figure 2. Plot of homicide rate and violent crime rate of the top & bottom 3 states

The below figure 3 shows that the medians of homicide rate are lower in states which require background check on mental health records while the medians of violent rate in states restrict permission for purchase of ammunition are higher than the states don’t.

|  |  |
| --- | --- |
|  |  |

Figure 3. Effects of certain laws on homicide and violent rate

The correlation chart shows there are noticeable high correlations between the low education rate to the poverty rate and the population. The chart also depicts the positive correlation between demographic features to both analyzed dependent variables.

A graph of a crime

Description automatically generated with medium confidence

Figure 4. Correlation chart of demographics IVs to DVs

# MODELS

The dataset includes 450 data points of 50 states in 9 years from 2012 to 2020. Each data point includes demographic variables, police enforcement, and 134 applied gun laws.

This dataset is a panel data, a special type of multi-level data. It is the cross-sectional time series data which the behavior of entities are observed across time. In our dataset, ‘state’ is the higher level and ‘year’ is the lower level. In such dataset, there are dependencies data points within a group – ‘state’; and there may be effects of time over the period – ‘year’. Our models should address these 2 critical attributes of the dataset. And plm is a most suitable model.

Plm is an R package, is designed to make the estimation of panel linear models, on panel data. Plm provides functions to estimate various varieties of panel models and to draw robust inference.

To analyze the impact of 134 gun-laws on violent crime rate and homicide rate, we design our modeling in 2 steps:

1. Step 1: modeling on the strictness of each law categories (14 categories) to infer how law categories effect the 2 analyzed crime rates.
2. Step 2: modeling on selected potential high-impact gun-laws to draw inference on crime rates and to have recommendations.

In step 1, we engineer our predictors based on a hypothesis that, the more laws issued in a category, the stronger that law category is. For example, California has issued 15 laws related to Dealer Regulation in 2020 while Florida has issued on 5 laws in the same category in the same year. We hypothesize that California’s Deal Regulation is stricter, stronger than Florida’s.

We applied various versions of plm models on log transformation of analyzed crime rates (violent crime and homicide) as dependent variables and 4 demographic features & 13 law-categories as independent variables. The model varieties include “pooling”, “random effect”,   
“fixed effect” and “fixed effect with time (two ways)” . Then, we compared and tested models to select the most fitted ones. The below figure is example of “fixed effect with time” models.

plm\_fix\_time\_vc1 <- plm(log(violent\_crime) ~ population + police + poverty + education + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg + concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence, data = d, model="within", effect = "twoways")

# plm\_fix\_time\_hc1 <- plm(log(homicide) ~ population + police + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg + concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence, data = d , model="within", effect = "twoways")

Figure 5 – plm models of “fixed effect with time” for log(violent) & log(homicide)

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Dependent variable:

------------------------------------------------------------------------------------------

log(violent\_crime)

(1) (2) (3) (4)

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population 0.002 (0.004) 0.011 (0.008) -0.074\*\*\* (0.027) -0.072\*\*\* (0.026)

police 0.143\*\*\* (0.026) -0.003 (0.015) -0.015 (0.014) -0.020 (0.014)

poverty 0.003\*\*\* (0.001) -0.002\*\*\* (0.001) -0.002\*\*\* (0.001) -0.001 (0.001)

education 0.002 (0.002) 0.001 (0.001) -0.001 (0.002) 0.003\* (0.002)

dealerreg -0.056\*\* (0.028) -0.029 (0.029) -0.024 (0.032) -0.027 (0.031)

buyerreg 0.004 (0.010) 0.013 (0.009) 0.025\*\* (0.010) 0.027\*\*\* (0.010)

prohibition 0.008 (0.010) -0.001 (0.014) -0.006 (0.016) -0.008 (0.015)

backgroundcheck 0.009 (0.007) 0.002 (0.004) -0.001 (0.004) -0.002 (0.004)

ammunition 0.072\*\*\* (0.025) -0.036 (0.022) -0.053\*\* (0.023) -0.058\*\*\* (0.022)

possessreg 0.029\*\* (0.012) -0.007 (0.009) -0.015 (0.009) -0.018\* (0.009)

concealcarry 0.030\*\*\* (0.010) -0.009 (0.006) -0.006 (0.006) -0.001 (0.006)

assaultweapon -0.026 (0.016) -0.004 (0.017) 0.0003 (0.018) -0.0004 (0.017)

chileaccess -0.009 (0.013) -0.021\*\* (0.010) -0.021\*\* (0.010) -0.023\*\* (0.010)

guntrafficking 0.003 (0.021) 0.021 (0.024) 0.021 (0.026) 0.017 (0.025)

preemption -0.087\*\* (0.034) 0.027 (0.042) 0.046 (0.052) 0.044 (0.050)

immunity -0.183\*\*\* (0.049) -0.164 (0.130)

domesticviolence -0.003 (0.006) -0.003 (0.003) -0.005 (0.003) -0.007\*\* (0.003)

Constant 0.138 (0.124) 1.486\*\*\* (0.125)

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Observations 450 450 450 450

R2 0.335 0.083 0.128 0.105

Adjusted R2 0.309 0.047 -0.020 -0.069

F Statistic 12.791\*\*\* (df = 17; 432) 39.123\*\*\* 3.514\*\*\* (df = 16; 384) 2.744\*\*\* (df = 16; 376)

===========================================================================================================

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

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Dependent variable:

-----------------------------------------------------------------------------------------

log(homicide)

(1) (2) (3) (4)

----------------------------------------------------------------------------------------------------------

population -0.001 (0.005) 0.034\*\*\* (0.010) 0.128\*\*\* (0.049) -0.046 (0.045)

police 0.091\*\*\* (0.032) 0.015 (0.029) 0.021 (0.031) -0.043\* (0.026)

poverty 0.002 (0.001) -0.003\*\*\* (0.001)

education 0.010\*\*\* (0.002) -0.002 (0.003)

dealerreg -0.071\*\* (0.034) -0.014 (0.052) 0.045 (0.069) 0.038 (0.057)

buyerreg 0.036\*\*\* (0.013) -0.010 (0.018) -0.019 (0.022) -0.005 (0.018)

prohibition 0.016 (0.012) 0.029 (0.023) 0.063\* (0.034) 0.030 (0.028)

backgroundcheck 0.001 (0.009) 0.006 (0.009) 0.012 (0.009) -0.001 (0.008)

ammunition 0.031 (0.032) -0.001 (0.042) -0.016 (0.049) -0.035 (0.040)

possessreg 0.030\*\* (0.015) -0.0001 (0.017) -0.013 (0.019) -0.031\* (0.016)

concealcarry 0.046\*\*\* (0.013) -0.011 (0.013) -0.038\*\*\* (0.013) 0.003 (0.011)

assaultweapon 0.015 (0.020) -0.014 (0.031) -0.016 (0.038) -0.006 (0.032)

chileaccess -0.042\*\*\* (0.016) -0.011 (0.019) -0.001 (0.022) -0.012 (0.018)

guntrafficking 0.014 (0.027) -0.044 (0.042) -0.001 (0.056) -0.008 (0.046)

preemption -0.200\*\*\* (0.042) -0.035 (0.068) 0.029 (0.111) 0.052 (0.092)

immunity -0.308\*\*\* (0.061) -0.376\*\* (0.157)

domesticviolence -0.006 (0.007) -0.004 (0.007) 0.007 (0.007) -0.017\*\*\* (0.006)

Constant -4.509\*\*\* (0.154) -2.650\*\*\* (0.198)

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Observations 450 450 450 450

R2 0.459 0.117 0.072 0.063

Adjusted R2 0.438 0.082 -0.079 -0.114

F Statistic 21.573\*\*\* (df = 17; 432) 57.065\*\*\* 2.150\*\*\* (df = 14; 386) 1.800\*\* (df = 14; 378)

==========================================================================================================

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01F Statistic 12.791\*\*\* (df = 17; 432) 57.065\*\*\* 2.150\*\*\* (df = 14; 386) 1.800\*\* (df = 14; 378)

==========================================================================================================

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Figure 6 – stargazers of step 1 models on log(violent) & log(homicide)

The models (except pooling) are quite stable on estimating log(violent crime rate), the ammunition seems the most effective to reduce violent crime rate by around 5% for each law issued. While, the results are various between models on estimating log(homicide rate).

The models are compared with various testing models, as below table:

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Pooling vs. Effect** | **Random vs. Fixed** | **Without or with time** |
| Violent crime rate | Lagrange Multiplier Test results p-value < 2.2e-16  🡪 significant effects | F test results p-value = 0.02838  🡪 Fixed effect is better | F test for twoways effects results p-value = 1.489e-05  🡪 time effect is better |
| Homicide | Lagrange Multiplier Test results p-value < 2.2e-16  🡪 significant effects | F test results p-value = 0.4162  🡪 No different  But F test for twoways effects results p-value < 2.2e-16 🡪 fixed effect with time is better | F test for twoways effects results p-value < 2.2e-16  🡪 time effect is better |

🡺 “Fixed time effect” models are suitable for both log(violent) and log(homicide).

Per the “Fixed time effect” models (model 4 in stargazer), the ammunition law contributes to reduce violent crime rate by 5% and homicide by 3.5% for each law issued.

Next step, we analyze the impact of each individual gun law on violent crime rate and homicide rate. Like step 1, we applied, compared and tested various models – “pool”, “random”, “fixed effect”, and “fixed effect with time effect”. The result is summarized below, and the details (stargazers) are included in the appendix.

DV: log(violent\_crime) : top 5 contributors

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Random effect** | **fixed effect** | **fixed effect with time effect** |
| background.universal1 | -0.208\*\*\* | -0.215\*\*\* | -0.225\*\*\* |
| background.mentalhealth1 | -0.069 | -0.128 | -0.176\* |
| ammunition.ammpermit1 | -0.455\*\* | -0.508\*\*\* | -0.553\*\*\* |
| conceal.background1 | -0.105\*\*\* | -0.114\*\*\* | -0.115\*\*\* |
| childaccess.storage1 | -0.146\*\* | -0.138\* | -0.185\*\*\* |

DV: log(homicide) : top 5 contributors

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Random effect** | **fixed effect** | **fixed effect with time effect** |
| background.universal1 | -0.195\* | -0.296\*\*\* | -0.315\*\*\* |
| background.mentalhealth1 | -0.048 | -0.238 | -0.301 |
| ammunition.ammpermit1 | 0.011 | -0.127 | -0.298 |
| ammunition.ammlicense1 | -0.108 | -0.125 | -0.084 |
| childaccess.storage1 | -0.132 | -0.061 | -0.228\* |

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Pooling vs. Effect** | **Random vs. Fixed** | **Without or with time** |
| Violent crime rate | Lagrange Multiplier Test results p-value < 2.2e-16  🡪 significant effects | F test results p-value = 0.2492  🡪 Fixed effect is better.  But F test for twoways effects results p-value < 0.0005016 🡪 fixed effect with time is better | F test for twoways effects results p-value = 3.3e-06  🡪 time effect is better |
| Homicide | Lagrange Multiplier Test results p-value < 2.2e-16  🡪 significant effects | F test results p-value = 9.9e-09  🡪 Fixed effect is better | F test for twoways effects results p-value < 2.2e-16  🡪 time effect is better |

🡺 “Fixed time effect” models are suitable for both log(violent) and log(homicide).

Per the “Fixed time effect” models, the ammunition permit law contributes to reduce violent crime rate by 55.3% (most effective) and homicide by 29.8% (3rd effective), and the universal background check law contributes to reduce violent crime rate by 22.5% (2nd most effective) and homicide by 31.5% (most effective).

# QUALITY CHECKS

There are certain assumptions and concerns which need to be tested and addressed to ensure trustworthy of the selected models, include: serial correlation if the data set observed on long time series, stationarity, cross sectional dependency, and heteroskedasticity.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **plm\_fix\_time\_vc1** | **plm\_fix\_time\_vc2** | **plm\_fix\_time\_hc1** | **plm\_fix\_time\_hc2** |
| Serial correlation | Breusch-Godfrey/Wooldridge test results p-value < 2.2e-16  🡪 there is serial correlation but within 9 periods, we can accept it | Breusch-Godfrey/Wooldridge test results p-value < 2.2e-16  🡪 there is serial correlation but within 9 periods, we can accept it | Breusch-Godfrey/Wooldridge test results p-value =2.295e-06  🡪 there is serial correlation but within 9 periods, we can accept it | Breusch-Godfrey/Wooldridge test results p-value = 3.559e-07  🡪 there is serial correlation but within 9 periods, we can accept it |
| Stationarity | Augmented Dickey-Fuller Test results p-value = 0.01 🡪 stationary (passed) | | Augmented Dickey-Fuller Test results p-value = 0.01 🡪 stationary (passed) | |
| Cross sectional dependency | Pesaran CD test results p-value = 0.1274  🡪 Passed | Pesaran CD test results p-value = 0.07934  🡪 Passed | Pesaran CD test results p-value = 0.201  🡪 Passed | Pesaran CD test results p-value = 0.1233  🡪 Passed |
| Heteroskedasticity | Breusch-Pagan test results p-value < 2.2e-16  🡪 Failed | Breusch-Pagan test results p-value < 2.2e-16  🡪 Failed | Breusch-Pagan test results p-value = 7.85e-07  🡪 Failed | Breusch-Pagan test results p-value = 2.09e-12  🡪 Failed |

🡪 There is the heteroskedasticity issue for all 4 models. We applied HCSE to deal with heteroskedasticity for all 4. The results of models after applied below HCSEs are included in the Appendix.

coeftest(plm\_fix\_time\_vc1, vcovHC)

coeftest(plm\_fix\_time\_vc2, vcovHC)

coeftest(plm\_fix\_time\_hc1, vcovHC)

coeftest(plm\_fix\_time\_hc2, vcovHC)

# RECOMMENDATIONS

Based on the results from the "Fixed time effect" models, it is evident that ammunition permit laws and universal background check laws play a crucial role in reducing violent crime rates and homicides. Specifically, the ammunition permit law is the most effective, contributing to a 55.3% reduction in violent crime rates and a 29.8% reduction in homicides. On the other hand, universal background check laws are the second most effective, leading to a 22.5% decrease in violent crime rates and a 31.5% decrease in homicides.  
  
Therefore, it is recommended that policymakers prioritize the implementation and enforcement of ammunition permit laws and universal background check laws to effectively reduce violent crime rates and homicides. These laws have demonstrated significant impact and should be considered as key strategies in crime reduction efforts. Additionally, continued research and evaluation of the effectiveness of these laws, along with other potential interventions, are essential for informed decision-making and the development of comprehensive crime prevention policies.

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# APPENDIX 1 – STARGAZER

=======================================================================================================================

Dependent variable:

------------------------------------------------------------------------------------------

log(violent\_crime)

(1) (2) (3) (4)

-----------------------------------------------------------------------------------------------------------------------

police 0.147\*\*\* (0.026) -0.001 (0.014) -0.004 (0.014) -0.006 (0.014)

poverty 0.0003 (0.001) -0.001\*\* (0.001) -0.001\*\* (0.001) 0.0001 (0.001)

education 0.008\*\*\* (0.002) 0.001 (0.001) -0.0002 (0.001) 0.003 (0.002)

dealerreg.dealerh1 -0.070 (0.063) 0.027 (0.047) 0.039 (0.048) 0.029 (0.047)

buyerreg.permitlaw1 -0.210\*\* (0.086) 0.052 (0.101) 0.125 (0.114) 0.161 (0.110)

buyerreg.fingerprint1 0.138 (0.086) 0.142 (0.273) -0.006 (0.100) -0.008 (0.097)

buyerreg.age1 0.116\*\*\* (0.041) 0.088 (0.056) 0.073 (0.060) 0.069 (0.059)

prohibition.violentpartial1 0.027 (0.047) 0.145 (0.160)

prohibition.danger1 -0.129\*\*\* (0.046) -0.035 (0.049) -0.012 (0.053) -0.013 (0.051)

prohibition.drugmisdemeanor1 0.294\*\*\* (0.071) -0.076 (0.075) -0.123 (0.081) -0.125 (0.078)

prohibition.alctreatment1 0.112 (0.070) 0.135\*\* (0.066) 0.167\*\* (0.070) 0.163\*\* (0.067)

background.universal1 -0.119 (0.091) -0.208\*\*\* (0.050) -0.215\*\*\* (0.051) -0.225\*\*\* (0.050)

background.universalpermit1 0.243\*\* (0.101) 0.167\*\*\* (0.062) 0.178\*\*\* (0.065) 0.192\*\*\* (0.063)

background.mentalhealth1 -0.215\*\* (0.099) -0.069 (0.087) -0.128 (0.098) -0.176\* (0.095)

ammunition.ammlicense1 0.365\*\*\* (0.118) 0.019 (0.061) 0.016 (0.062) 0.040 (0.059)

ammunition.ammpermit1 0.297\*\* (0.118) -0.455\*\*\* (0.111) -0.508\*\*\* (0.116) -0.553\*\*\* (0.112)

possessreg.agerestrict1 -0.023 (0.053) -0.036 (0.160)

possessreg.carry1 0.082 (0.050) 0.063 (0.078) 0.047 (0.091) 0.020 (0.089)

conceal.permit1 -0.045 (0.089) 0.041 (0.030) 0.049 (0.030) 0.068\*\* (0.029)

conceal.background1 0.192\*\* (0.087) -0.105\*\*\* (0.037) -0.114\*\*\* (0.037) -0.115\*\*\* (0.036)

assaultweapon.ban1 0.027 (0.168) -0.141 (0.285)

assaultweapon.magazine1 -0.188 (0.117) 0.218\*\*\* (0.070) 0.236\*\*\* (0.074) 0.233\*\*\* (0.071)

childaccess.lock1 -0.051 (0.099) 0.158 (0.263)

childaccess.storage1 -0.367\*\*\* (0.096) -0.146\*\* (0.071) -0.138\* (0.073) -0.185\*\*\* (0.070)

trafficking1 -0.056 (0.054) 0.012 (0.045) 0.019 (0.046) -0.008 (0.045)

strawpurchase1 0.016 (0.105) 0.205 (0.295)

microstamp1 0.504\*\*\* (0.140) 0.053 (0.060) 0.049 (0.061) 0.095 (0.059)

personalized1 0.256\* (0.145) -0.260 (0.370)

preemption1 -0.168 (0.102) -0.073 (0.251)

immunity1 -0.174\*\*\* (0.052) -0.352\*\* (0.172)

domestic.misdemeanor1 0.151\*\*\* (0.044) 0.034 (0.030) 0.031 (0.030) 0.028 (0.029)

dvro1 -0.148\*\*\* (0.047) 0.041 (0.029) 0.038 (0.030) 0.030 (0.029)

Constant 0.129 (0.136) 1.317\*\*\* (0.166)

-----------------------------------------------------------------------------------------------------------------------

Observations 450 450 450 450

R2 0.440 0.215 0.244 0.233

Adjusted R2 0.397 0.154 0.098 0.064

F Statistic 10.219\*\*\* (df = 32; 417) 113.883\*\*\* 5.065\*\*\* (df = 24; 376) 4.660\*\*\* (df = 24; 368)

=======================================================================================================================

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

=====================================================================================================================

Dependent variable:

----------------------------------------------------------------------------------------

log(homicide)

(1) (2) (3) (4)

---------------------------------------------------------------------------------------------------------------------

police 0.072\*\* (0.030) 0.016 (0.030) -0.007 (0.029) -0.026 (0.026)

poverty -0.0004 (0.001) -0.004\*\*\* (0.001) -0.002\*\* (0.001) 0.001 (0.001)

education 0.017\*\*\* (0.002) 0.002 (0.003) -0.011\*\*\* (0.003) -0.003 (0.004)

dealerreg.dealerh1 -0.046 (0.074) -0.018 (0.097) 0.066 (0.102) 0.022 (0.091)

buyerreg.permitlaw1 -0.243\*\* (0.100) -0.183 (0.170) 0.125 (0.244) 0.197 (0.216)

buyerreg.fingerprint1 0.014 (0.100) -0.044 (0.271) 0.024 (0.213) 0.057 (0.190)

buyerreg.age1 0.185\*\*\* (0.048) 0.117 (0.099) 0.004 (0.129) -0.061 (0.115)

prohibition.violentpartial1 0.021 (0.054) 0.102 (0.156)

prohibition.danger1 -0.024 (0.053) 0.035 (0.090) 0.042 (0.112) 0.052 (0.099)

prohibition.drugmisdemeanor1 0.332\*\*\* (0.083) 0.031 (0.135) 0.012 (0.174) 0.026 (0.153)

prohibition.alctreatment1 0.051 (0.081) -0.081 (0.128) 0.284\* (0.149) 0.269\*\* (0.132)

background.universal1 0.026 (0.106) -0.195\* (0.108) -0.296\*\*\* (0.109) -0.315\*\*\* (0.097)

background.universalpermit1 0.247\*\* (0.117) 0.286\*\* (0.130) 0.368\*\*\* (0.138) 0.359\*\*\* (0.123)

background.mentalhealth1 -0.436\*\*\* (0.115) -0.048 (0.152) -0.238 (0.209) -0.301 (0.187)

ammunition.ammlicense1 0.243\* (0.137) -0.108 (0.135) -0.125 (0.132) -0.084 (0.116)

ammunition.ammpermit1 0.542\*\*\* (0.138) 0.011 (0.215) -0.127 (0.247) -0.298 (0.218)

possessreg.agerestrict1 -0.190\*\*\* (0.062) -0.166 (0.163)

possessreg.carry1 0.047 (0.058) 0.088 (0.123) 0.069 (0.195) 0.003 (0.173)

conceal.permit1 -0.473\*\*\* (0.104) -0.091 (0.068) -0.004 (0.063) 0.076 (0.057)

conceal.background1 0.565\*\*\* (0.101) 0.043 (0.084) -0.023 (0.080) -0.065 (0.071)

assaultweapon.ban1 -0.056 (0.196) 0.144 (0.320)

assaultweapon.magazine1 -0.386\*\*\* (0.137) -0.146 (0.138) -0.067 (0.157) -0.004 (0.139)

childaccess.lock1 0.125 (0.115) 0.212 (0.268)

childaccess.storage1 -0.541\*\*\* (0.111) -0.132 (0.146) -0.061 (0.155) -0.228\* (0.137)

trafficking1 -0.007 (0.062) 0.001 (0.092) 0.081 (0.099) 0.020 (0.088)

strawpurchase1 0.005 (0.122) 0.118 (0.302)

microstamp1 0.342\*\* (0.163) -0.156 (0.133) -0.208 (0.130) -0.072 (0.116)

personalized1 1.086\*\*\* (0.169) 0.477 (0.402)

preemption1 -0.122 (0.119) -0.131 (0.271)

immunity1 -0.249\*\*\* (0.060) -0.517\*\*\* (0.168)

domestic.misdemeanor1 0.003 (0.052) -0.071 (0.064) -0.068 (0.064) -0.063 (0.057)

dvro1 -0.080 (0.055) 0.066 (0.063) 0.024 (0.063) -0.012 (0.056)

Constant -4.505\*\*\* (0.158) -2.717\*\*\* (0.225)

---------------------------------------------------------------------------------------------------------------------

Observations 450 450 450 450

R2 0.602 0.133 0.217 0.087

Adjusted R2 0.572 0.066 0.065 -0.114

F Statistic 19.738\*\*\* (df = 32; 417) 63.976\*\*\* 4.349\*\*\* (df = 24; 376) 1.461\* (df = 24; 368)

=====================================================================================================================

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**APPENDIX 2 – HCSES**

> coeftest(plm\_fix\_time\_vc1, vcovHC)

t test of coefficients:

Estimate Std. Error t value Pr(>|t|)

population -0.07201310 0.04898853 -1.4700 0.142398

police -0.01968012 0.02158341 -0.9118 0.362449

poverty -0.00089599 0.00143514 -0.6243 0.532796

education 0.00312350 0.00264960 1.1789 0.239200

dealerreg -0.02665913 0.04981066 -0.5352 0.592821

buyerreg 0.02706974 0.02656346 1.0191 0.308830

prohibition -0.00767094 0.02297377 -0.3339 0.738641

backgroundcheck -0.00160987 0.00840177 -0.1916 0.848151

ammunition -0.05759125 0.01986244 -2.8995 0.003957 \*\*

possessreg -0.01753666 0.01644856 -1.0662 0.287039

concealcarry -0.00101563 0.00689531 -0.1473 0.882980

assaultweapon -0.00042616 0.01827298 -0.0233 0.981406

chileaccess -0.02334426 0.01312643 -1.7784 0.076143 .

guntrafficking 0.01732478 0.01422089 1.2183 0.223888

preemption 0.04352150 0.03396161 1.2815 0.200811

domesticviolence -0.00726672 0.00598484 -1.2142 0.225438

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> coeftest(plm\_fix\_time\_vc2, vcovHC)

t test of coefficients:

Estimate Std. Error t value Pr(>|t|)

police -5.9366e-03 1.6787e-02 -0.3536 0.7238141

poverty 9.0978e-05 1.3324e-03 0.0683 0.9455981

education 2.8642e-03 2.2916e-03 1.2499 0.2121382

dealerreg.dealerh1 2.8534e-02 2.6756e-02 1.0664 0.2869202

buyerreg.permitlaw1 1.6059e-01 4.2118e-02 3.8127 0.0001611 \*\*\*

buyerreg.fingerprint1 -7.7021e-03 2.7177e-02 -0.2834 0.7770212

buyerreg.age1 6.9185e-02 7.2155e-02 0.9588 0.3382736

prohibition.danger1 -1.2805e-02 5.2171e-02 -0.2454 0.8062507

prohibition.drugmisdemeanor1 -1.2543e-01 6.4084e-02 -1.9572 0.0510741 .

prohibition.alctreatment1 1.6339e-01 1.7589e-02 9.2897 < 2.2e-16 \*\*\*

background.universal1 -2.2531e-01 4.2405e-02 -5.3133 1.869e-07 \*\*\*

background.universalpermit1 1.9159e-01 7.5965e-02 2.5220 0.0120886 \*

background.mentalhealth1 -1.7627e-01 7.6794e-02 -2.2954 0.0222730 \*

ammunition.ammlicense1 4.0089e-02 2.2833e-02 1.7558 0.0799608 .

ammunition.ammpermit1 -5.5261e-01 1.0129e-01 -5.4558 8.971e-08 \*\*\*

possessreg.carry1 2.0017e-02 3.1309e-02 0.6394 0.5229920

conceal.permit1 6.8221e-02 6.9012e-02 0.9885 0.3235381

conceal.background1 -1.1478e-01 7.0724e-02 -1.6229 0.1054621

assaultweapon.magazine1 2.3299e-01 1.0124e-01 2.3013 0.0219325 \*

childaccess.storage1 -1.8500e-01 4.2760e-02 -4.3265 1.954e-05 \*\*\*

trafficking1 -7.9717e-03 3.1052e-02 -0.2567 0.7975399

microstamp1 9.4668e-02 3.9782e-02 2.3797 0.0178362 \*

domestic.misdemeanor1 2.7667e-02 3.6245e-02 0.7633 0.4457507

dvro1 2.9678e-02 3.1689e-02 0.9366 0.3496019

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> coeftest(plm\_fix\_time\_hc1, vcovHC)

t test of coefficients:

Estimate Std. Error t value Pr(>|t|)

population -0.04560337 0.03376677 -1.3505 0.177651

police -0.04340425 0.02426446 -1.7888 0.074448 .

dealerreg 0.03750023 0.02156915 1.7386 0.082918 .

buyerreg -0.00522821 0.01077603 -0.4852 0.627837

prohibition 0.03005505 0.01708714 1.7589 0.079399 .

backgroundcheck -0.00093641 0.00635075 -0.1474 0.882856

ammunition -0.03457765 0.02243661 -1.5411 0.124123

possessreg -0.03060799 0.01009583 -3.0317 0.002599 \*\*

concealcarry 0.00337843 0.01346276 0.2509 0.801992

assaultweapon -0.00599150 0.03343369 -0.1792 0.857872

chileaccess -0.01226551 0.01998091 -0.6139 0.539676

guntrafficking -0.00753758 0.05760187 -0.1309 0.895958

preemption 0.05179834 0.02382108 2.1745 0.030289 \*

domesticviolence -0.01734806 0.00769136 -2.2555 0.024672 \*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> coeftest(plm\_fix\_time\_hc2, vcovHC)

t test of coefficients:

Estimate Std. Error t value Pr(>|t|)

police -0.02566727 0.02131942 -1.2039 0.2293871

poverty 0.00065308 0.00165306 0.3951 0.6930148

education -0.00262315 0.00346535 -0.7570 0.4495551

dealerreg.dealerh1 0.02218643 0.02538400 0.8740 0.3826709

buyerreg.permitlaw1 0.19678053 0.05559363 3.5396 0.0004521 \*\*\*

buyerreg.fingerprint1 0.05734748 0.06276459 0.9137 0.3614771

buyerreg.age1 -0.06136285 0.05092902 -1.2049 0.2290278

prohibition.danger1 0.05237312 0.06507081 0.8049 0.4214181

prohibition.drugmisdemeanor1 0.02551956 0.06515181 0.3917 0.6955111

prohibition.alctreatment1 0.26947665 0.04622573 5.8296 1.216e-08 \*\*\*

background.universal1 -0.31485614 0.03916618 -8.0390 1.249e-14 \*\*\*

background.universalpermit1 0.35900514 0.06909376 5.1959 3.383e-07 \*\*\*

background.mentalhealth1 -0.30090104 0.08065868 -3.7305 0.0002212 \*\*\*

ammunition.ammlicense1 -0.08400542 0.03447882 -2.4364 0.0153063 \*

ammunition.ammpermit1 -0.29809429 0.06373299 -4.6772 4.090e-06 \*\*\*

possessreg.carry1 0.00257847 0.05597830 0.0461 0.9632858

conceal.permit1 0.07645603 0.04580802 1.6691 0.0959572 .

conceal.background1 -0.06518365 0.06435437 -1.0129 0.3117801

assaultweapon.magazine1 -0.00384763 0.05831817 -0.0660 0.9474323

childaccess.storage1 -0.22792247 0.11036146 -2.0652 0.0396005 \*

trafficking1 0.01989132 0.02953310 0.6735 0.5010351

microstamp1 -0.07206062 0.07962800 -0.9050 0.3660755

domestic.misdemeanor1 -0.06306411 0.06649422 -0.9484 0.3435407

dvro1 -0.01235531 0.05908858 -0.2091 0.8344873

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

# APPENDIX 3 – R CODE

rm(list=ls())

#install.packages("dplyr")

library(rio)

library(lubridate)

library("dplyr")

#Load data

setwd("/Users/tavishtran/Library/CloudStorage/OneDrive-Personal/1 - Master Degree/S2-ISM6137/Project/Data")

police <- import("Police Count Data.csv")

crime <- import("estimated\_crimes\_1979\_2022.xlsx")

gunlaw <- import("Gunlaw.xlsx")

state <- import("State.xlsx")

demographics <- import("demographics.xlsx")

head(police)

head(crime)

head(gunlaw)

head(state)

head(demographics)

#process data

colnames(police)[which(names(police)=="data\_yeArkansas")] <- "year"

colnames(police)[which(names(police)=="state\_abbr")] <- "state"

colnames(state)[which(names(state)=="State\_Abbr")] <- "state\_abbr"

colnames(state)[which(names(state)=="State")] <- "state"

colnames(police)[which(names(police)=="male\_officer\_Connecticut")] <- "male\_officer"

colnames(police)[which(names(police)=="male\_civilian\_Connecticut")] <- "male\_civilian"

colnames(police)[which(names(police)=="male\_total\_Connecticut")] <- "male\_total"

colnames(police)[which(names(police)=="female\_officer\_Connecticut")] <- "female\_officer"

colnames(police)[which(names(police)=="female\_civilian\_Connecticut")] <- "female\_civilian"

colnames(police)[which(names(police)=="female\_total\_Connecticut")] <- "female\_total"

colnames(police)[which(names(police)=="officer\_Connecticut")] <- "officer"

colnames(police)[which(names(police)=="civilian\_Connecticut")] <- "civilian"

colnames(police)[which(names(police)=="total\_pe\_Connecticut")] <- "total\_pe"

colnames(crime)[which(names(crime)=="state\_name")] <- "state"

crime$state\_abbr <- tolower(crime$state\_abbr)

crime$state <- tolower(crime$state)

gunlaw$state <- tolower(gunlaw$state)

police$state <- tolower(police$state)

state$state <- tolower(state$state)

state$state\_abbr <- tolower(state$state\_abbr)

demographics$state <- tolower(demographics$state)

table(police[police$year >= 2012 & police$year <= 2022,]$year, police[police$year >= 2012 & police$year <= 2022,]$state) #

# -> west virginia missed out police number in 2014

table(crime[crime$year >= 2012 & crime$year <= 2022,]$year, crime[crime$year >= 2012 & crime$year <= 2022,]$state\_abbr)

# -> only Peurto Rico missed out crime date from 2017 - 2022, pr will be omitted from analysis anyway

table(gunlaw[gunlaw$year >= 2012 & gunlaw$year <= 2022,]$year, gunlaw[gunlaw$year >= 2012 & gunlaw$year <= 2022,]$state)

# -> only gunlaw data from 2012 to 2020, no DC law.

table(demographics[demographics$year >= 2012 & demographics$year <= 2022,]$year, demographics[demographics$year >= 2012 & demographics$year <= 2022,]$state)

# -> no missing data

unique(state$state)

#clean data

#Recover wv police number in 2014

wv\_total\_pe\_2014 = (police[police$state == "west virginia" & police$year == 2013,"total\_pe"] + police[police$state == "west virginia" & police$year == 2015,"total\_pe"]) / 2

police[nrow(police)+1,c("state","year","total\_pe")] = c("west virginia",2014, wv\_total\_pe\_2014)

police <- police[,c("state","year","total\_pe")]

police$year <- as.integer(police$year)

police$total\_pe <- as.integer(police$total\_pe)

str(police)

#remove territories, remain only 50 states + 1 Federal District

state = state[which(state$state != "virgin islands, u.s." & state$state != "guam" & state$state != "american samoa" & state$state != "district of columbia"

& state$state != "puerto rico" & state$state != "northern mariana islands" & state$state != "united states minor outlying islands"),]

#create year dataframe

year\_df = data.frame(year = c(2012:2022))

#construct permutation of state and year to be analyze

state\_year = merge(state,year\_df,all.x = TRUE, all.y =TRUE)

rm(year\_df, state,wv\_total\_pe\_2014)

police <- merge(state\_year, police, by = c("state","year"), all.x = TRUE)

gunlaw <- merge(state\_year, gunlaw, by = c("state","year"), all.x = TRUE)

demographics <- merge(state\_year,demographics, by = c("state","year"), all.x = TRUE)

crime <- merge(state\_year,crime, by = c("state","year"), all.x = TRUE)

crime$state\_abbr.x <- NULL

crime$state\_abbr.y <- NULL

police$state\_abbr <- NULL

demographics$state\_abbr <- NULL

gunlaw$state\_abbr <- NULL

gunlaw$lawtotal <- NULL

crime <- merge(crime, demographics, by = c("state","year"))

crime <- merge(crime, police, by = c("state","year"))

crime <- merge(crime, gunlaw, by = c("state","year"))

colSums(is.na(police)) #50 Missing 2022 data (50 states)

colSums(is.na(demographics)) #No NA

colSums(is.na(gunlaw)) #100 NA, Missing 2021 & 2022 data (50 states)

colSums(is.na(crime))

crime = na.omit(crime) #omit NA (drop 2021 and 2022 in analysis)

gunlaw = na.omit(gunlaw)

#Feature engineering

str(crime)

str(gunlaw)

# Select felony crimes only

crime.eng <- crime[,c("violent\_crime","homicide")]

crime.eng$crimetotal <- crime$violent\_crime + crime$homicide + crime$rape\_legacy + crime$rape\_revised + crime$aggravated\_assault

# Assess seriousness of 14 legals scheme by numbers of law issued

#deal regulation

crime.eng$dealerreg <- crime$dealer + crime$dealerh + crime$recordsdealer

#buyer regulation

crime.eng$buyerreg <- crime$waiting + crime$waitingh + crime$permit + crime$permith +

crime$permitlaw + crime$fingerprint + crime$training + crime$registration + crime$registrationh +

crime$defactoreg + crime$defactoregh + crime$age21handgunsale + crime$age18longgunsale +

crime$age21longgunsaled + crime$age21longgunsale + crime$loststolen + crime$onepermonth

#Prohibitions for high-risk gun possession

crime.eng$prohibition <- crime$felony + crime$violent + crime$violenth + crime$violentpartial + crime$invcommitment +

crime$invoutpatient + crime$danger + crime$drugmisdemeanor + crime$alctreatment + crime$alcoholism +

crime$relinquishment

#background check

crime.eng$backgroundcheck <- crime$universal + crime$universalh + crime$gunshow + crime$gunshowh + crime$universalpermit + crime$universalpermith +

crime$backgroundpurge + crime$threedaylimit + crime$mentalhealth + crime$statechecks + crime$statechecksh

#Ammunition regulations

crime.eng$ammunition <- crime$ammlicense + crime$ammrecords + crime$ammpermit + crime$ammrestrict + crime$amm18 + crime$amm21h + crime$ammbackground

#possession regulation

crime.eng$possessreg <- crime$age18longgunpossess + crime$age21handgunpossess + crime$age21longgunpossess + crime$gvro +

crime$gvrolawenforcement + crime$college + crime$collegeconcealed + crime$elementary + crime$opencarryh + crime$opencarryl +

crime$opencarrypermith + crime$opencarrypermitl

#Concealed carry permitting

crime.eng$concealcarry <- crime$permitconcealed + crime$mayissue + crime$showing + crime$ccrevoke +

crime$ccbackground + crime$ccbackgroundnics + crime$ccrenewbackground

#Assault weapons and large-capacity magazines

crime.eng$assaultweapon <- crime$assault + crime$onefeature + crime$assaultlist + crime$assaultregister + crime$assaulttransfer +

crime$magazine + crime$tenroundlimit + crime$magazinepreowned

#Child access prevention

crime.eng$chileaccess <- crime$lockd + crime$lockp + crime$locked + crime$lockstandards + crime$capliability + crime$capaccess +

crime$capuses + crime$capunloaded + crime$cap14 + crime$cap16 + crime$cap18

#Gun trafficking

crime.eng$guntrafficking <- crime$traffickingbackground + crime$traffickingprohibited + crime$traffickingprohibitedh +

crime$strawpurchase + crime$strawpurchaseh + crime$microstamp + crime$personalized

#Preemption

crime.eng$preemption <- crime$preemption + crime$preemptionnarrow + crime$preemptionbroad

#Immunity

crime.eng$immunity <- crime$immunity

#Domestic violence

crime.eng$domesticviolence <- crime$mcdv + crime$mcdvdating + crime$mcdvsurrender + crime$mcdvsurrendernoconditions + crime$mcdvsurrenderdating +

crime$mcdvremovalallowed + crime$mcdvremovalrequired + crime$incidentremoval + crime$incidentall +

crime$dvro + crime$dvrodating + crime$exparte + crime$expartedating + crime$dvrosurrender + crime$dvrosurrendernoconditions + crime$dvrosurrenderdating +

crime$expartesurrender + crime$expartesurrendernoconditions + crime$expartesurrenderdating +

crime$dvroremoval + crime$stalking

#crime.eng$violent\_crime <- NULL

#crime.eng$homicide <- NULL

crime.eng$year <- crime$year

crime.eng$state <- crime$state

crime.eng$population <- crime$Population / 1000000 # x millions of population

crime.eng$police <- crime$total\_pe \* 1000 / crime$Population #Police force rate per 1000 population

crime.eng$poverty <- crime$BelowPovertyLevel \* 1000 / crime$Population #Poverty rate per 1000 ppl

crime.eng$education <- crime$Lessthanhighschoolgraduate \* 1000 / crime$Population #Education rate per 1000 ppl

crime.eng$crimetotal <- crime.eng$crimetotal \* 1000 / crime$Population #Total felony crime rate per 1000 ppl

crime.eng$violent\_crime <- crime$violent\_crime \* 1000 / crime$Population #Violent crime rate per 1000 ppl

crime.eng$homicide <- crime$homicide \* 1000 / crime$Population #Homicide rate per 1000 ppl

str(crime.eng)

#selected laws to be analyzed

crime.law <- crime[,c("violent\_crime","homicide")]

crime.law$year <- crime$year

crime.law$state <- crime$state

crime.law$population <- crime$Population / 1000000 # x millions of population

crime.law$police <- crime$total\_pe \* 1000 / crime$Population #Police force rate per 1000 population

crime.law$poverty <- crime$BelowPovertyLevel \* 1000 / crime$Population #Poverty rate per 1000 ppl

crime.law$education <- crime$Lessthanhighschoolgraduate \* 1000 / crime$Population #Education rate per 1000 ppl

crime.law$violent\_crime <- crime$violent\_crime \* 1000 / crime$Population #Violent crime rate per 1000 ppl

crime.law$homicide <- crime$homicide \* 1000 / crime$Population #Homicide rate per 1000 ppl

crime.law$dealerreg.dealerh <- crime$dealerh

crime.law$buyerreg.permitlaw <- crime$permitlaw

crime.law$buyerreg.fingerprint <- crime$fingerprint

crime.law$buyerreg.registrationh <- crime$registrationh

crime.law$buyerreg.age <- ifelse(crime$age21handgunsale + crime$age21handgunsale + crime$age18longgunsale + crime$age21longgunsaled > 0,1,0)

crime.law$prohibition.violentpartial <- ifelse(crime$felony + crime$violentpartial >0, 1, 0)

crime.law$prohibition.danger <- crime$danger

crime.law$prohibition.drugmisdemeanor <- crime$drugmisdemeanor

crime.law$prohibition.alctreatment <- crime$alctreatment

crime.law$background.universal <- ifelse(crime$universal + crime$universalh > 0, 1, 0)

crime.law$background.universalpermit <- ifelse(crime$universalpermit + crime$universalpermith >0, 1, 0)

crime.law$background.mentalhealth <- crime$mentalhealth

crime.law$ammunition.ammlicense <- crime$ammlicense

crime.law$ammunition.ammpermit <- crime$ammpermit

crime.law$ammunition.ammrestrict <- crime$ammrestrict

crime.law$ammunition.ammage <- ifelse(crime$amm18 + crime$amm21h > 0, 1, 0)

crime.law$possessreg.agerestrict <- ifelse(crime$age21handgunpossess + crime$age18longgunpossess + crime$age21longgunpossess > 0, 1, 0)

crime.law$possessreg.carry <- ifelse(crime$opencarryh + crime$opencarryl + crime$opencarrypermith + crime$opencarrypermitl> 0, 1, 0)

crime.law$conceal.permit <- crime$permitconcealed

crime.law$conceal.background <- crime$ccbackground

crime.law$assaultweapon.ban <- ifelse(crime$assault + crime$onefeature + crime$assaultlist> 0, 1, 0)

crime.law$assaultweapon.magazine <- ifelse(crime$magazine + crime$tenroundlimit + crime$magazinepreowned> 0, 1, 0)

crime.law$childaccess.lock <- ifelse(crime$lockd + crime$lockp + crime$lockstandards> 0, 1, 0)

crime.law$childaccess.storage <- ifelse(crime$locked + crime$capliability + crime$capaccess> 0, 1, 0)

crime.law$childaccess.storage <- ifelse(crime$locked + crime$capliability + crime$capaccess> 0, 1, 0)

crime.law$trafficking <- ifelse(crime$traffickingbackground + crime$traffickingprohibited + crime$traffickingprohibitedh> 0, 1, 0)

crime.law$strawpurchase <- ifelse(crime$strawpurchase + crime$strawpurchaseh > 0, 1, 0)

crime.law$microstamp <- crime$microstamp

crime.law$personalized <- crime$personalized

crime.law$preemption <- ifelse(crime$preemption + crime$preemptionnarrow + crime$preemptionbroad> 0, 1, 0)

crime.law$immunity <- crime$immunity

crime.law$domestic.misdemeanor <- ifelse(crime$mcdv + crime$mcdvsurrendernoconditions + crime$mcdvremovalallowed + crime$stalking > 0, 1, 0)

crime.law$dvro <- crime$dvro

names <- c(9:40)

crime.law[,names] <- lapply(crime.law[,names] , factor)

str(crime.law)

#Data visualization

hist(crime.eng$homicide, main = "Histogram of homicide rate (per 1000 people)", xlab = "Homicide rate") #polinomial

hist(crime.eng$violent\_crime, main = "Histogram of violent crime rate (per 1000 people)", xlab = "Violent Crime rate") #polinomial

hist(log(crime.eng$homicide), main = "Histogram of log of homicide rate", xlab = "Log of Homicide rate") #look normalized

hist(log(crime.eng$violent\_crime),main = "Histogram of log of violent crime rate (per 1000 people)", xlab = "Log of Violent Crime rate") #look normalized

boxplot(crime.eng$violent\_crime ~ crime.eng$year)

boxplot(crime.eng$homicide ~ crime.eng$year)

boxplot(crime.law$violent\_crime ~ crime.law$ammunition.ammpermit + crime.law$year)

boxplot(crime.law$violent\_crime ~ crime.law$background.universalpermit + crime.law$year)

boxplot(crime.law$homicide ~ crime.law$background.mentalhealth + crime.law$year)

summary(crime.law$homicide)

summary(crime.law$violent\_crime)

#least violent

subset(temp1) %>%

arrange((violent\_crime)) %>%

group\_by(year) %>%

slice(1)

#most violent

subset(temp1) %>%

arrange(desc(violent\_crime)) %>%

group\_by(year) %>%

slice(1)

#least homicide

subset(temp1) %>%

arrange((homicide)) %>%

group\_by(year) %>%

slice(1)

#most homicide

subset(temp1) %>%

arrange(desc(homicide)) %>%

group\_by(year) %>%

slice(1)

crime.law[which(crime.law$ammunition.ammpermit == 1 & crime.law$year == 2013),"state"]

crime.law[which(crime.law$ammunition.ammrestrict == 1 & crime.law$year == 2020),"state"]

crime.law[which(crime.law$background.mentalhealth == 1 & crime.law$year == 2020),"state"]

library(ggplot2)

d <- crime.law

d$mental.year <- interaction(crime.law$background.mentalhealth,crime.law$year)

d$ammpermit.year <- interaction(crime.law$ammunition.ammpermit,crime.law$year)

d$ammrest.year <- interaction(crime.law$ammunition.ammrestrict,crime.law$year)

ggplot(d,aes(x = mental.year,y=homicide,fill=background.mentalhealth))+

geom\_boxplot(outlier.color="black") +

theme(axis.text.x = element\_text(angle = 90, hjust = 1), axis.title.x=element\_blank())

ggplot(d,aes(x = ammpermit.year,y=violent\_crime,fill=ammunition.ammpermit))+

geom\_boxplot(outlier.color="black") +

theme(axis.text.x = element\_text(angle = 90, hjust = 1), axis.title.x=element\_blank())

ggplot(d,aes(x = ammrest.year,y=violent\_crime,fill=ammunition.ammrestrict))+

geom\_boxplot(outlier.color="black") +

theme(axis.text.x = element\_text(angle = 90, hjust = 1), axis.title.x=element\_blank())

#ALL States

#crime.law %>%

ggplot(data= crime.law,aes(year, violent\_crime)) +

geom\_point(aes(colour = factor(state)), size = 1)+

geom\_line(aes(group = factor(state), colour = factor(state)))+

theme(axis.text.x = element\_text(angle = 90, hjust = 1), axis.title.x=element\_blank())

ggplot(data= crime.law,aes(year, homicide)) +

geom\_point(aes(colour = factor(state)), size = 1)+

geom\_line(aes(group = factor(state), colour = factor(state)))+

theme(axis.text.x = element\_text(angle = 90, hjust = 1), axis.title.x=element\_blank())

#For the largest 4 states

d = crime.law [which(crime.law$state %in% c("florida","california","new york","texas")), ]

ggplot(data= crime.law,aes(year, violent\_crime)) +

geom\_point(aes(colour = factor(state)), size = 1)+

geom\_line(aes(group = factor(state), colour = factor(state)))+

theme(axis.text.x = element\_text(angle = 90, hjust = 1), axis.title.x=element\_blank())

ggplot(data= d,aes(year, homicide)) +

geom\_point(aes(colour = factor(state)), size = 1)+

geom\_line(aes(group = factor(state), colour = factor(state)))+

theme(axis.text.x = element\_text(angle = 90, hjust = 1), axis.title.x=element\_blank())

temp1 <- crime.eng[,c("year","state","violent\_crime","homicide","population")]

temp1$totallaw <- crime.eng$dealerreg + crime.eng$buyerreg + crime.eng$prohibition + crime.eng$backgroundcheck + crime.eng$ammunition + crime.eng$possessreg + crime.eng$concealcarry + crime.eng$assaultweapon + crime.eng$chileaccess + crime.eng$guntrafficking + crime.eng$preemption + crime.eng$immunity + crime.eng$domesticviolence

#least popuplation

subset(temp1,year == 2020) %>%

arrange((population)) %>%

group\_by(year) %>%

slice(1:3)

#most popuplation

subset(temp1,year == 2020) %>%

arrange(desc(population)) %>%

group\_by(year) %>%

slice(1:3)

#most gun law

subset(temp1,year == 2020) %>%

arrange(desc(totallaw)) %>%

group\_by(year) %>%

slice(1:3)

#most gun law

subset(temp1,year == 2020) %>%

arrange(desc(totallaw)) %>%

group\_by(year) %>%

slice(1:3)

#least gun law

subset(temp1,year == 2020) %>%

arrange((totallaw)) %>%

group\_by(year) %>%

slice(1:3)

#least homicide

subset(temp1, year == 2020) %>%

arrange((homicide)) %>%

group\_by(year) %>%

slice(1:3)

#most homicide

subset(temp1, year == 2019) %>%

arrange(desc(homicide)) %>%

group\_by(year) %>%

slice(1:5)

#For the above states

#state\_name = c("florida","california","texas","wyoming","vermont","alaska","massachusetts","connecticut",

# "idaho","mississippi","missouri","maine","new hampshire","vermont","alaska","new mexico","tennessee")

state\_name\_bylaw= c("california","massachusetts","connecticut",

"idaho","mississippi","missouri")

state\_name\_bypopulation = c("florida","california","texas","wyoming","vermont","alaska")

state\_name\_safety = c("maine","new hampshire","vermont","alaska","new mexico","tennessee")

state\_name\_homicide = c("maine","new hampshire","vermont","missouri","louisiana","south carolina")

d = crime.law [which(crime.law$state %in% state\_name\_homicide), ]

ggplot(data= d,aes(year, homicide)) +

geom\_point(aes(colour = factor(state)), size = 1)+

geom\_line(aes(group = factor(state), colour = factor(state)))+

theme(axis.text.x = element\_text(angle = 90, hjust = 1), axis.title.x=element\_blank())

table(crime.eng$year, crime.eng$state)

# 50 states in 9 years from 2012 to 2020

#correlation

library(PerformanceAnalytics)

df <- crime.eng

df$state <- NULL

df$year <- NULL

df <- df[,c(1:2,17:20)]

str(df)

chart.Correlation(df)

df <- crime.eng

df$state <- NULL

df$year <- NULL

df <- df[,c(1:2,4:16)]

str(df)

chart.Correlation(df)

#Modelling for violent crime

library(lme4)

library(plm)

glm\_vc1 <- glm(violent\_crime ~ population + police + poverty + education + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence + as.factor(year),

data = crime.eng,family=quasipoisson (link=log))

glmer\_vc1 <- glmer(violent\_crime ~ population + police + poverty + education + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence + (1|state / year) , data = crime.eng, family=poisson (link=log))

d <- pdata.frame(crime.eng, index=c("state","year"))

plm\_pool\_vc1 <- plm(log(violent\_crime) ~ population + police + poverty + education + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence,

data = d,model="pool")

plm\_ran\_vc1 <- plm(log(violent\_crime) ~ population + police + poverty + education + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence,

data = d,model="random")

plm\_fix\_vc1 <- plm(log(violent\_crime) ~ population + police + poverty + education + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence,

data = d,model="within")

plm\_fix\_time\_vc1 <- plm(log(violent\_crime) ~ population + police + poverty + education + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence,

data = d,model="within", effect = "twoways")

#Modelling for homicide

glm\_hc1 <- glm(homicide ~ population + police + poverty + education + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence + as.factor(year),

data = crime.eng,family=quasipoisson (link=log))

glmer\_hc1 <- glmer(homicide ~ population + police + poverty + education + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence + (1|state / year) , data = crime.eng, family=poisson (link=log))

d <- pdata.frame(crime.eng, index=c("state","year"))

plm\_pool\_hc1 <- plm(log(homicide) ~ population + police + poverty + education + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence,

data = d,model="pool")

plm\_ran\_hc1 <- plm(log(homicide) ~ population + police + poverty + education + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence,

data = d,model="random")

plm\_fix\_hc1 <- plm(log(homicide) ~ population + police + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence,

data = d,model="within")

plm\_fix\_time\_hc1 <- plm(log(homicide) ~ population + police + dealerreg + buyerreg + prohibition + backgroundcheck + ammunition + possessreg +

concealcarry + assaultweapon + chileaccess + guntrafficking + preemption + immunity + domesticviolence,

data = d,model="within", effect = "twoways")

#Outcome

lme4::ranef(glmer\_vc1)

ranef(plm\_ran\_vc1)

fixef(plm\_fix\_vc1)

fixef(plm\_fix\_time\_vc1)

lme4::ranef(glmer\_hc1)

ranef(plm\_ran\_hc1)

fixef(plm\_fix\_hc1)

fixef(plm\_fix\_time\_hc1)

#Test Collinearity

library(car)

vif(glmer\_vc1)

vif(plm\_pool\_vc1)

vif(plm\_ran\_vc1)

vif(glmer\_hc1)

vif(plm\_pool\_hc1)

vif(plm\_ran\_vc1)

#Test Pool, Fixed and Random

plmtest(plm\_pool\_vc1) #pool test

plmtest(plm\_pool\_hc1) #pool test

#fixed vs random

pFtest(plm\_fix\_vc1,plm\_ran\_vc1) #0.02

pFtest(plm\_fix\_hc1,plm\_ran\_hc1) #0.4

pFtest(plm\_fix\_time\_hc1,plm\_ran\_hc1) #0.4

#time effect

pFtest(plm\_fix\_time\_vc1,plm\_fix\_vc1) #1.4e-05

pFtest(plm\_fix\_time\_hc1,plm\_fix\_hc1) #2.2e-16

#Interpretation

library(stargazer)

stargazer(plm\_pool\_vc1,plm\_ran\_vc1,plm\_fix\_vc1,plm\_fix\_time\_vc1, title="Compare", type="text", single.row=TRUE)

stargazer(plm\_pool\_hc1,plm\_ran\_hc1,plm\_fix\_hc1,plm\_fix\_time\_hc1, title="Compare", type="text", single.row=TRUE)

# Modelling with all relevant laws

str(crime.law)

d <- crime.law

d <- pdata.frame(d, index=c("state","year"))

plm\_pool\_vc2 <- plm(log(violent\_crime) ~ police + poverty + education + dealerreg.dealerh + buyerreg.permitlaw + buyerreg.fingerprint + buyerreg.age

+ prohibition.violentpartial + prohibition.danger + prohibition.drugmisdemeanor + prohibition.alctreatment

+ background.universal + background.universalpermit + background.mentalhealth

+ ammunition.ammlicense + ammunition.ammpermit + possessreg.agerestrict + possessreg.carry # possess may not impact

+ conceal.permit + conceal.background + assaultweapon.ban + assaultweapon.magazine

+ childaccess.lock + childaccess.storage

+ trafficking + strawpurchase + microstamp + personalized

+ preemption + immunity + domestic.misdemeanor + dvro

, data = d, model="pool")

plm\_ran\_vc2 <- plm(log(violent\_crime) ~ police + poverty + education + dealerreg.dealerh + buyerreg.permitlaw + buyerreg.fingerprint + buyerreg.age

+ prohibition.violentpartial + prohibition.danger + prohibition.drugmisdemeanor + prohibition.alctreatment

+ background.universal + background.universalpermit + background.mentalhealth

+ ammunition.ammlicense + ammunition.ammpermit + possessreg.agerestrict + possessreg.carry # possess may not impact

+ conceal.permit + conceal.background + assaultweapon.ban + assaultweapon.magazine

+ childaccess.lock + childaccess.storage

+ trafficking + strawpurchase + microstamp + personalized

+ preemption + immunity + domestic.misdemeanor + dvro

, data = d, model="random")

plm\_fix\_vc2 <- plm(log(violent\_crime) ~ police + poverty + education + dealerreg.dealerh + buyerreg.permitlaw + buyerreg.fingerprint + buyerreg.age

+ prohibition.violentpartial + prohibition.danger + prohibition.drugmisdemeanor + prohibition.alctreatment

+ background.universal + background.universalpermit + background.mentalhealth

+ ammunition.ammlicense + ammunition.ammpermit + possessreg.agerestrict + possessreg.carry # possess may not impact

+ conceal.permit + conceal.background + assaultweapon.ban + assaultweapon.magazine

+ childaccess.lock + childaccess.storage

+ trafficking + strawpurchase + microstamp + personalized

+ preemption + immunity + domestic.misdemeanor + dvro

, data = d, model="within")

plm\_fix\_time\_vc2 <- plm(log(violent\_crime) ~ police + poverty + education + dealerreg.dealerh + buyerreg.permitlaw + buyerreg.fingerprint + buyerreg.age

+ prohibition.violentpartial + prohibition.danger + prohibition.drugmisdemeanor + prohibition.alctreatment

+ background.universal + background.universalpermit + background.mentalhealth

+ ammunition.ammlicense + ammunition.ammpermit + possessreg.agerestrict + possessreg.carry # possess may not impact

+ conceal.permit + conceal.background + assaultweapon.ban + assaultweapon.magazine

+ childaccess.lock + childaccess.storage

+ trafficking + strawpurchase + microstamp + personalized

+ preemption + immunity + domestic.misdemeanor + dvro

, data = d, model="within", effect = "twoways")

plm\_pool\_hc2 <- plm(log(homicide) ~ police + poverty + education + dealerreg.dealerh + buyerreg.permitlaw + buyerreg.fingerprint + buyerreg.age

+ prohibition.violentpartial + prohibition.danger + prohibition.drugmisdemeanor + prohibition.alctreatment

+ background.universal + background.universalpermit + background.mentalhealth

+ ammunition.ammlicense + ammunition.ammpermit + possessreg.agerestrict + possessreg.carry # possess may not impact

+ conceal.permit + conceal.background + assaultweapon.ban + assaultweapon.magazine

+ childaccess.lock + childaccess.storage

+ trafficking + strawpurchase + microstamp + personalized

+ preemption + immunity + domestic.misdemeanor + dvro

, data = d, model="pool")

plm\_ran\_hc2 <- plm(log(homicide) ~ police + poverty + education + dealerreg.dealerh + buyerreg.permitlaw + buyerreg.fingerprint + buyerreg.age

+ prohibition.violentpartial + prohibition.danger + prohibition.drugmisdemeanor + prohibition.alctreatment

+ background.universal + background.universalpermit + background.mentalhealth

+ ammunition.ammlicense + ammunition.ammpermit + possessreg.agerestrict + possessreg.carry # possess may not impact

+ conceal.permit + conceal.background + assaultweapon.ban + assaultweapon.magazine

+ childaccess.lock + childaccess.storage

+ trafficking + strawpurchase + microstamp + personalized

+ preemption + immunity + domestic.misdemeanor + dvro

, data = d, model="random")

plm\_fix\_hc2 <- plm(log(homicide) ~ police + poverty + education + dealerreg.dealerh + buyerreg.permitlaw + buyerreg.fingerprint + buyerreg.age

+ prohibition.violentpartial + prohibition.danger + prohibition.drugmisdemeanor + prohibition.alctreatment

+ background.universal + background.universalpermit + background.mentalhealth

+ ammunition.ammlicense + ammunition.ammpermit + possessreg.agerestrict + possessreg.carry # possess may not impact

+ conceal.permit + conceal.background + assaultweapon.ban + assaultweapon.magazine

+ childaccess.lock + childaccess.storage

+ trafficking + strawpurchase + microstamp + personalized

+ preemption + immunity + domestic.misdemeanor + dvro

, data = d, model="within")

plm\_fix\_time\_hc2 <- plm(log(homicide) ~ police + poverty + education + dealerreg.dealerh + buyerreg.permitlaw + buyerreg.fingerprint + buyerreg.age

+ prohibition.violentpartial + prohibition.danger + prohibition.drugmisdemeanor + prohibition.alctreatment

+ background.universal + background.universalpermit + background.mentalhealth

+ ammunition.ammlicense + ammunition.ammpermit + possessreg.agerestrict + possessreg.carry # possess may not impact

+ conceal.permit + conceal.background + assaultweapon.ban + assaultweapon.magazine

+ childaccess.lock + childaccess.storage

+ trafficking + strawpurchase + microstamp + personalized

+ preemption + immunity + domestic.misdemeanor + dvro

, data = d, model="within", effect = "twoways")

stargazer(plm\_pool\_vc2,plm\_ran\_vc2,plm\_fix\_vc2,plm\_fix\_time\_vc2, title="Compare", type="text", single.row=TRUE)

stargazer(plm\_pool\_hc2,plm\_ran\_hc2,plm\_fix\_hc2,plm\_fix\_time\_hc2, title="Compare", type="text", single.row=TRUE)

#Test

library(car)

#Test Pool, Fixed and Random

plmtest(plm\_pool\_vc2) #pool test

plmtest(plm\_pool\_hc2) #pool test

#fixed vs random

pFtest(plm\_fix\_vc2,plm\_ran\_vc2) #0.2492

pFtest(plm\_fix\_hc2,plm\_ran\_hc2) #9.938e-09

pFtest(plm\_fix\_time\_vc2,plm\_ran\_vc2) #3.371e-06

#time effect

pFtest(plm\_fix\_time\_vc2,plm\_fix\_vc2) #3.371e-06

pFtest(plm\_fix\_time\_hc2,plm\_fix\_hc2) #2.2e-16

#serial correlation

pbgtest(plm\_fix\_time\_vc1)

pbgtest(plm\_fix\_time\_vc2)

pbgtest(plm\_fix\_time\_hc1)

pbgtest(plm\_fix\_time\_hc2)

#Stationary test

library(tseries)

adf.test(crime.law$violent\_crime, k=2)

adf.test(crime.law$homicide, k=2)

#Cross sectional dependency

pcdtest(plm\_fix\_time\_vc1, test = c("cd"))

pcdtest(plm\_fix\_time\_vc2, test = c("cd"))

pcdtest(plm\_fix\_time\_hc1, test = c("cd"))

pcdtest(plm\_fix\_time\_hc2, test = c("cd"))

#Heteroskedasticity

library(lmtest)

bptest(plm\_fix\_time\_vc1,studentize=F)

bptest(plm\_fix\_time\_vc2,studentize=F)

bptest(plm\_fix\_time\_hc1,studentize=F)

bptest(plm\_fix\_time\_hc2,studentize=F)

#HCSE to deal with Heteroskedasticity

coeftest(plm\_fix\_time\_vc1, vcovHC)

coeftest(plm\_fix\_time\_vc2, vcovHC)

coeftest(plm\_fix\_time\_hc1, vcovHC)

coeftest(plm\_fix\_time\_hc2, vcovHC)