Do shall-issues law reduce crime or not?

BUAN 6312.002: Applied Econometrics and Time Series Analysis

SRING 2023

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GROUP -VII

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May 12, 2023

Abstract

The impact of guns on crime in America has triggered a lot of public debate. Many strongly believe that state laws enabling citizens to carry concealed handguns had reduced crime. According to this view, gun control laws take away guns from law-abiding citizens, while would-be criminals ignore those leaving potential victims defenseless. Following this view, The National Rifle Association (NRA) and many politicians across the country advance the cause of greater freedom to carry guns.

As a result, many states in the United States have passed right-to-carry laws (also known as a shall-issue laws). A Shall-issue law is one that requires that governments issue concealed carry handgun permits to any applicant who meets the necessary criteria. These criteria are: the applicant must be an adult, have no significant criminal record, and no history of mental illness and successfully complete a course in firearms safety training (if required by law). If these criteria are met, the granting authority has no discretion in the awarding of the licenses, and there is no requirement of the applicant to demonstrate “good cause”.
We will analyze historical data on crime in the U.S to answer the question “Do shall-issueslaw reduce crime-or not?”

Guns is a balanced panel of data of 50 US states, plus the District of Columbia (for a total of 51 “states”), by year for 1977 - 1999. Each observation is a given state each year. There are a total of 51 states × 23 years = 1173 observations

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Introduction & Literature Review

How the Gun Became Integral to the Self-Identity of Millions of Americans, Over the past 150 years, American gun owners have gone from viewing their weapons largely as utilitarian farm tools to weapons that provide both a feeling of physical security and a sense of psychological solace. Guns' importance to their owners now goes much deeper than merely being implements of self-defense. The purpose of this study is to investigate the effect of shall-issue laws on crime rates in the United States. Specifically, we will use a difference-in-differences approach to estimate the causal effect of shall-issue laws on crime rates. This approach allows us to account for the potential confounding factors that may affect crime rates, such as differences in economic conditions, demographic factors, and law enforcement policies. To implement the DiD approach, we can start by defining a treatment group and a control group. The treatment group consists of states that have implemented shall-issues law, and the control group consists of states that have not. We can then estimate the following regression model:

$$CrimeRate = \alpha + \beta_1(Shall\text{–}IssueLaws) + \beta_2(Post\text{–}Implementation) + \beta_3(Shall\text{–}IssueLaws * Post\text{–}Implementation)$$

where β_3 is the DiD estimate of the causal effect of shall-issue laws on crime rates. We will also conduct sensitivity analyses to test the robustness of our results to different model specifications. Even we wanted to see how imposing law creating the impact of the crime rate so weelaborated the equation

$$CRIMEit = \alpha + \beta 1SHALLit + \beta 2POST\ it + \beta 3SHALLit \times POST\ it + \gamma Xit + \delta i + \mathrm{L}t + \varepsilon it$$

where CRIMEit is the crime rate for state i in year t, SHALLit is a dummy variable indicating whether state i has implemented shall-issues law in year t, POSTit is a dummy variable indicating whether the observation is after the implementation of shall-issues law, Xit is a vector of control variables that may affect crime rates, i is a fixed effect for state i, t is a fixed effect for year t, and it is the error term. The coefficient of interest is $beta3$, which measures the difference in crime rate changes between the treatment group and the control group after the implementation of shall-issues law. A significant negative coefficient of $\beta 3$ would suggest that the implementation of shall-issues law has a causal effect of reducing crime rates.

To improve the validity of the DiD analysis, we may also consider performing some robustness checks, such as testing for parallel trends assumption, exploring different specifications of the model, and checking for the presence of outliers or influential observations. Overall, the DiD approach provides a rigorous and flexible framework for studying the causal relationship between shall-issues law and crime rates from an econometrics perspective.

Dataset Description

In the file guns.dat we have data of Guns, which is a balanced panel of data on 50 US states, plus the District of Columbia (for a total of 51 "states"), by year for 1977 – 1999. Each observation is a given state each year. There are a total of 51 states × 23 years = 1173 observations. We will include all 50 states in our analysis, with a focus on the period after the implementation of shall-issue laws. We will use a pre-post design, comparing crime rates before and after the implementation of shall-issue laws in states that have implemented these laws with states that have not.

Variable	Definition
vio	violent crime rate (incidents per 100,000 members of the population)
rob	robbery rate (incidents per 100,000)
mur	murder rate (incidents per 100,000)
shall	= 1 if the state has a shall-carry law in effect in that year = 0 otherwise
incarc_rate	incarceration rate in the state in the previous year (sentenced prisoners per 100,000 residents; value for the previous year)
density	population per square mile of land area, divided by 1000
avginc	real per capita personal income in the state, in thousands of dollars
pop	state population, in millions of people
pm1029	percent of state population that is male, ages 10 to 29
pw1064	percent of state population that is white, ages 10 to 64
pb1064	percent of state population that is black, ages 10 to 64
stateid	ID number of states (Alabama = 1, Alaska = 2, etc.)
year	Year (1977-1999)

Figure 1: Dataset Description

Below are the statistics related to each variable in the dataset.

Variable	year	vio	mur	rob	incarc_rate	pb1064	pw1064
Min	77	47	0.2	6.4	19	0.2482	21.78
1st Qu	82	283.1	3.7	71.1	114	2.2022	59.94
Median	88	443	6.4	124.1	187	4.0262	65.06
Mean	88	503.1	7.665	161.8	226	5.3362	62.95
3rd Qu	94	650.9	9.8	192.7	291	6.8507	69.2
Max	99	2921.8	80.6	1635.1	1913	26.9796	76.53
Std Dev	6.636	334.28	7.523	170.51	178.89	4.89	9.762

Variable	pm1029	pop	avginc	density	stateid	shall
Min	12.21	0.4027	8.555	0.000707	1	0
1st Qu	14.65	1.1877	11.935	0.031311	16	0
Median	15.9	3.2713	13.402	0.081569	29	0
Mean	16.08	4.8163	13.725	0.352038	28.96	0.243
3rd Qu	17.53	5.6856	15.271	0.177718	42	0
Max	22.35	33.1451	23.647	11.10212	56	1
Std Dev	1.732	5.252	2.555	1.355	15.68	0.429

Figure 2: Data Statistics

Visualization Analysis

We started by visualizing the effect of each variable impacting the other variable. Firstly, we checked how variables in the dataset are changing with year and shall laws.

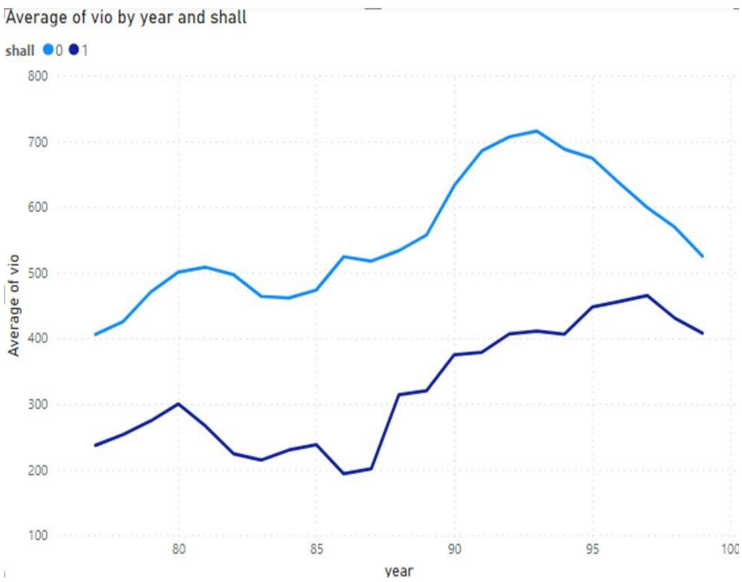


Figure 3: Change of Violent crime rate with year and shall law

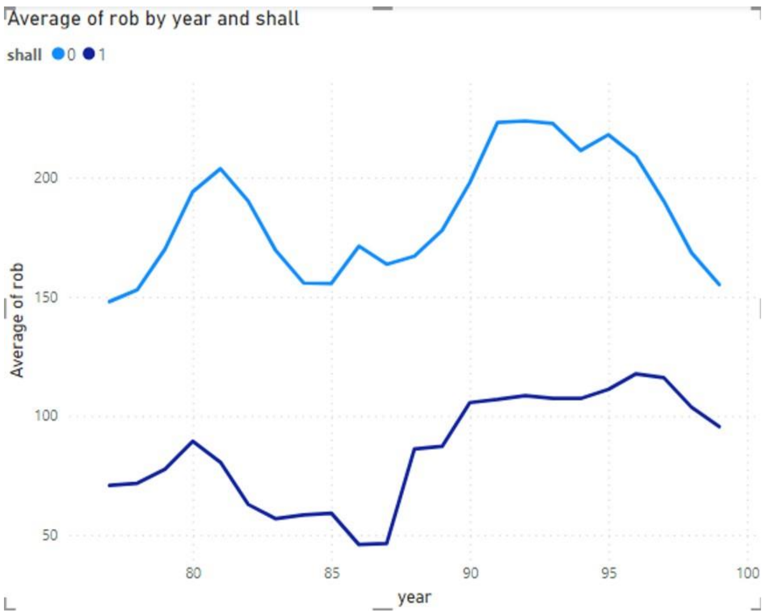


Figure 4: Change of Robbery rate with year and shall laws

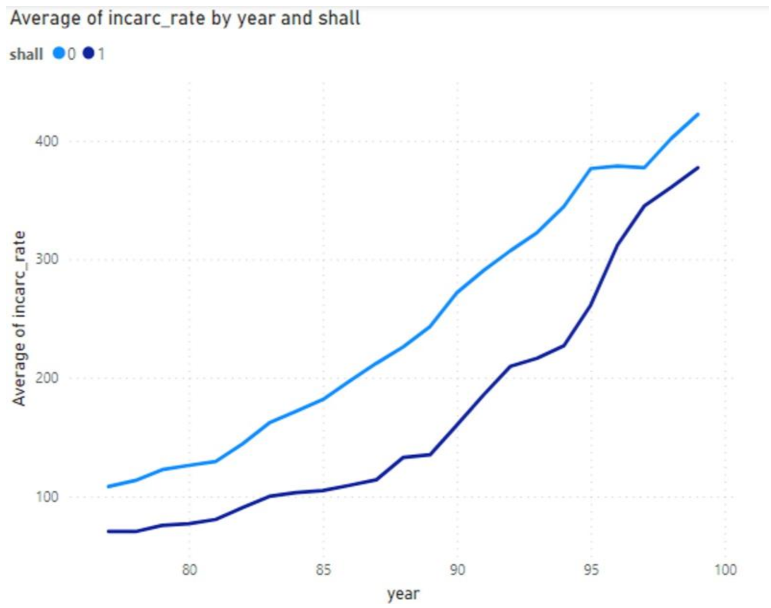


Figure 5: Change of incarceration rate with year and shall laws

We then checked the average violence rate for each state.

Figure 6: Average Violence rate in each state

Then, we checked the correlation between all variables.

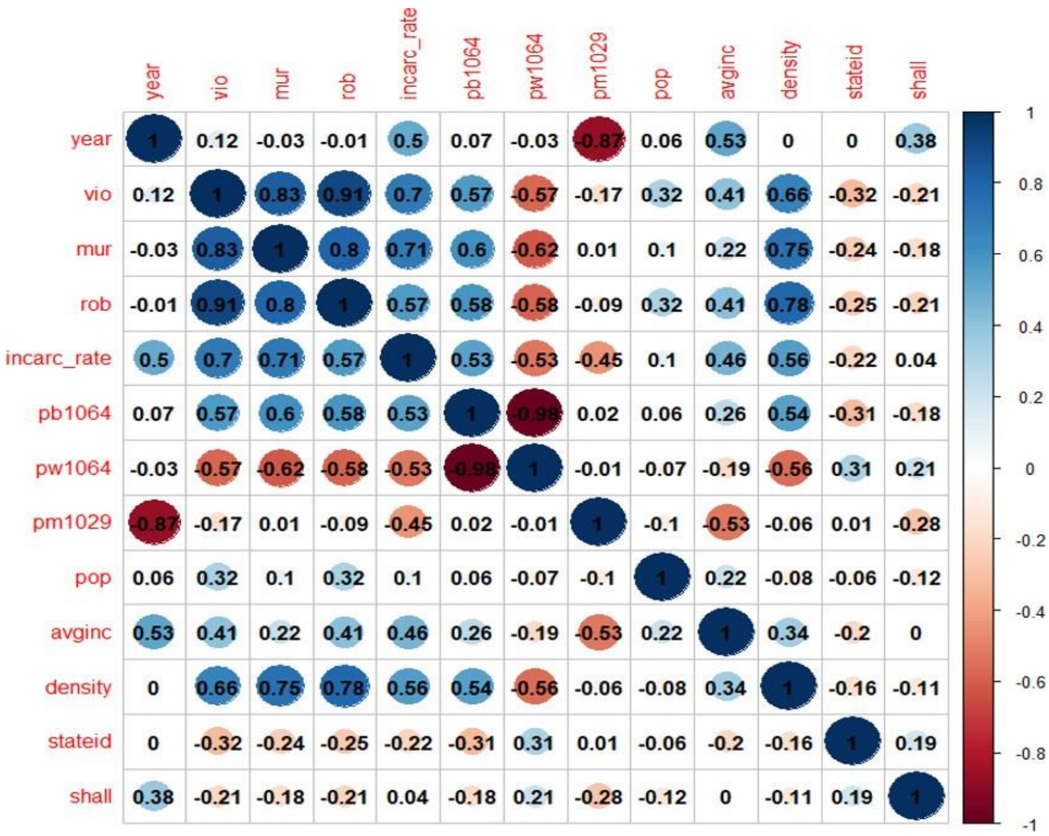


Figure 7: Correlation between the variables

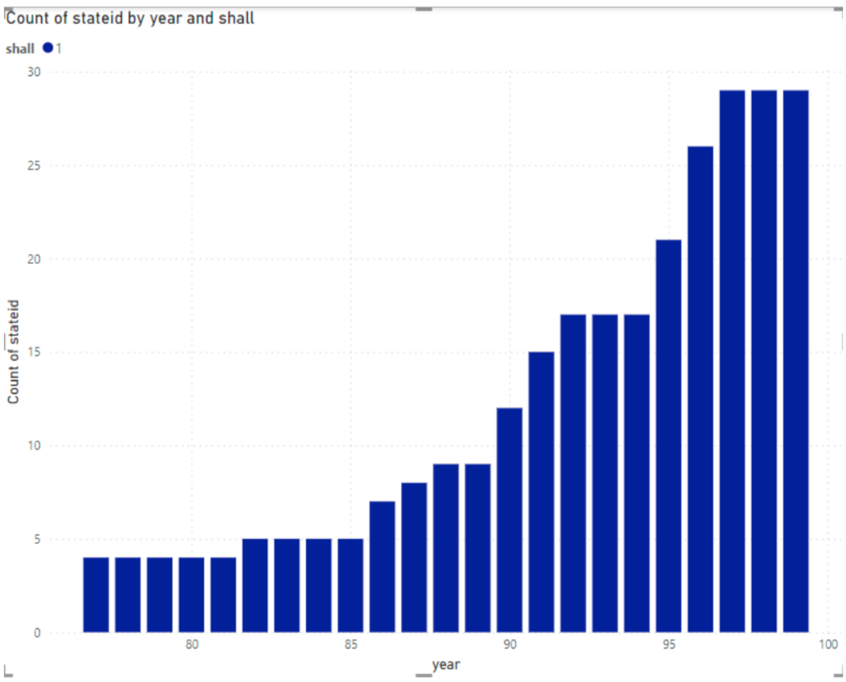
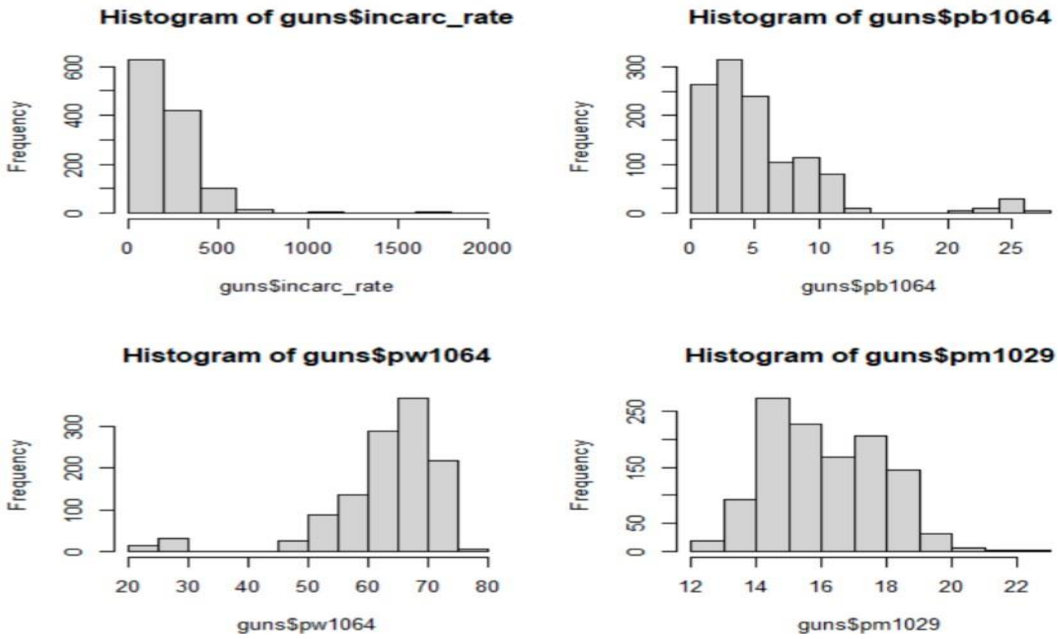
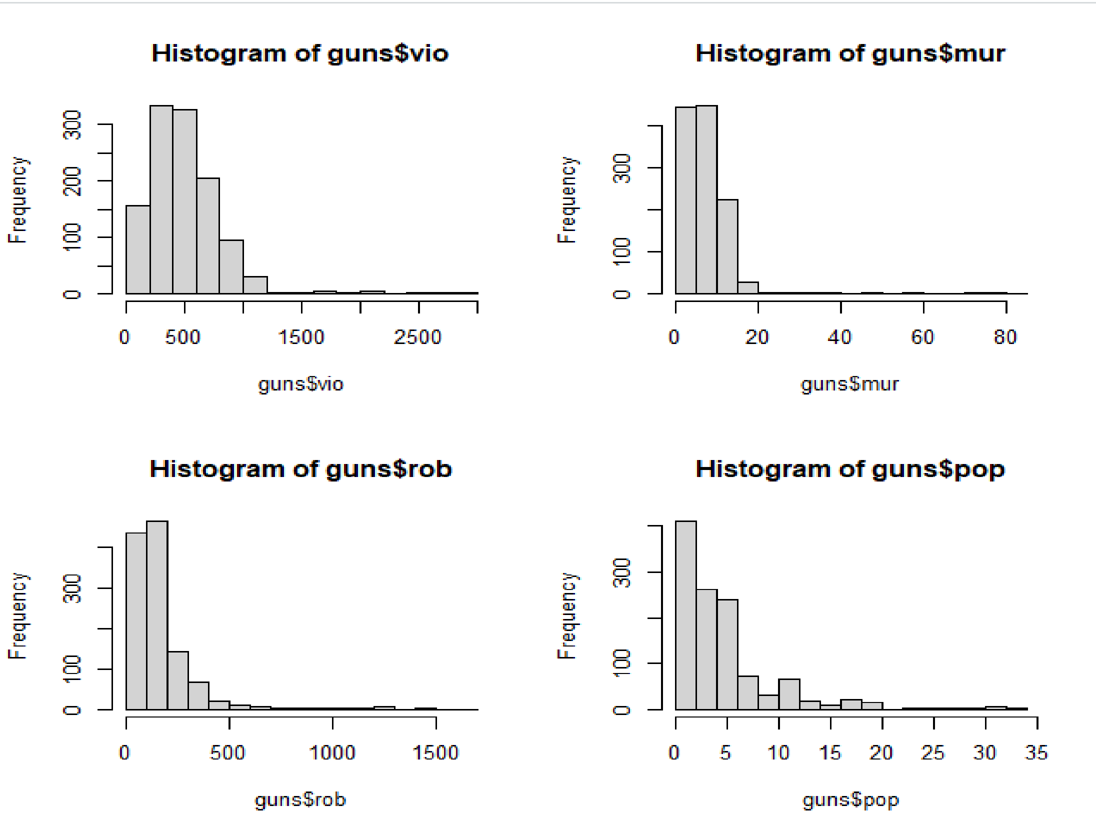


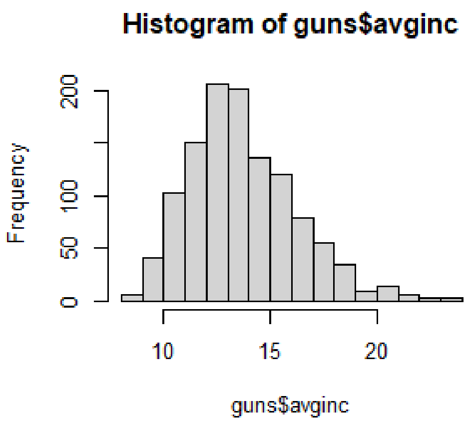
Figure 8: Implementation of shall laws

We, then, plotted the variation of each variable in the form of histogram to identify the skewness of data.

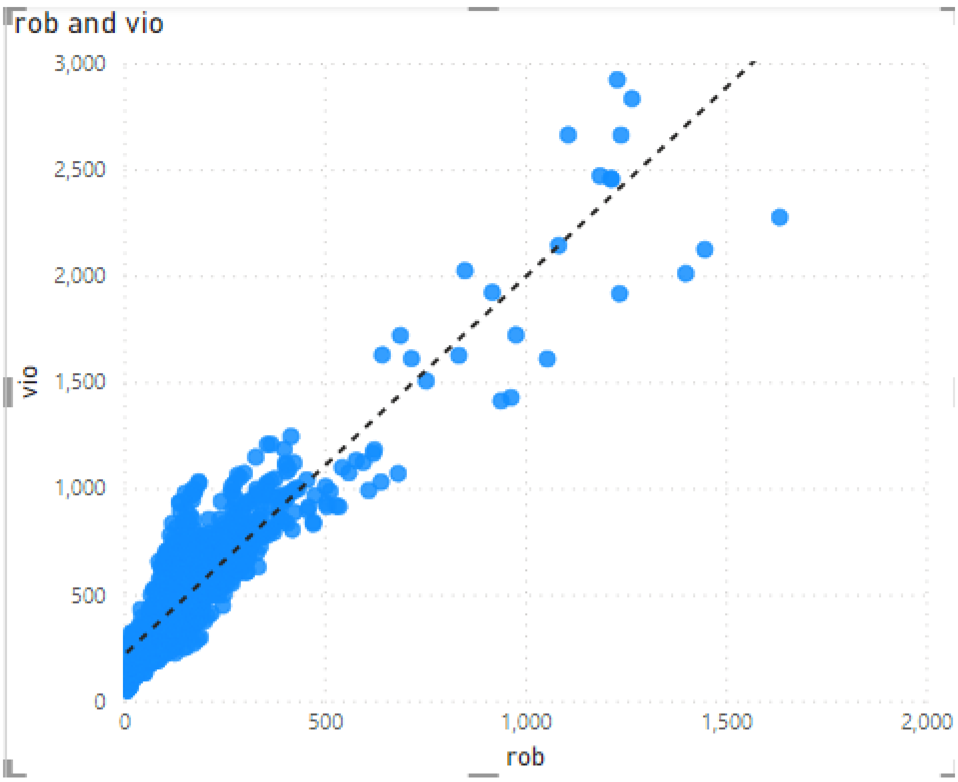
Histograms of all variables:

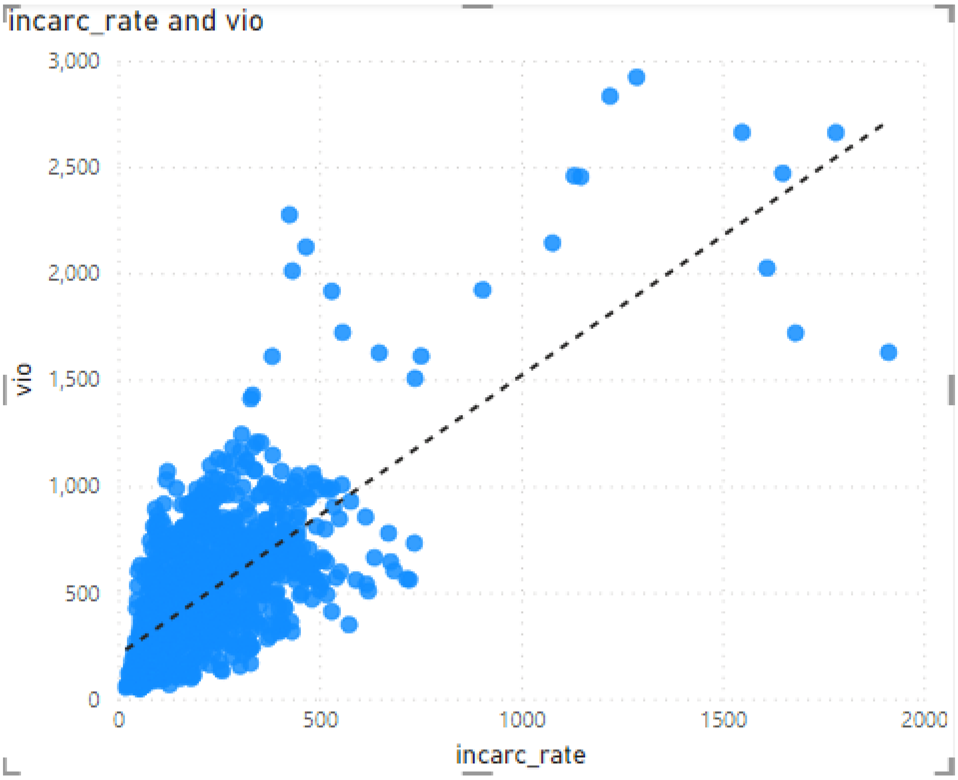


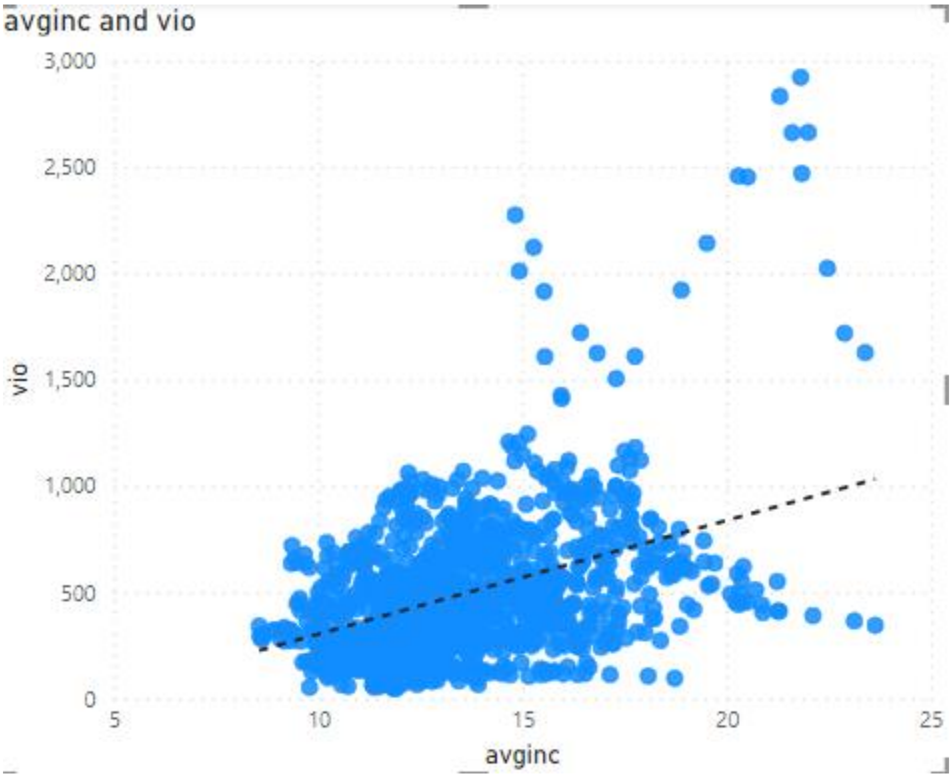


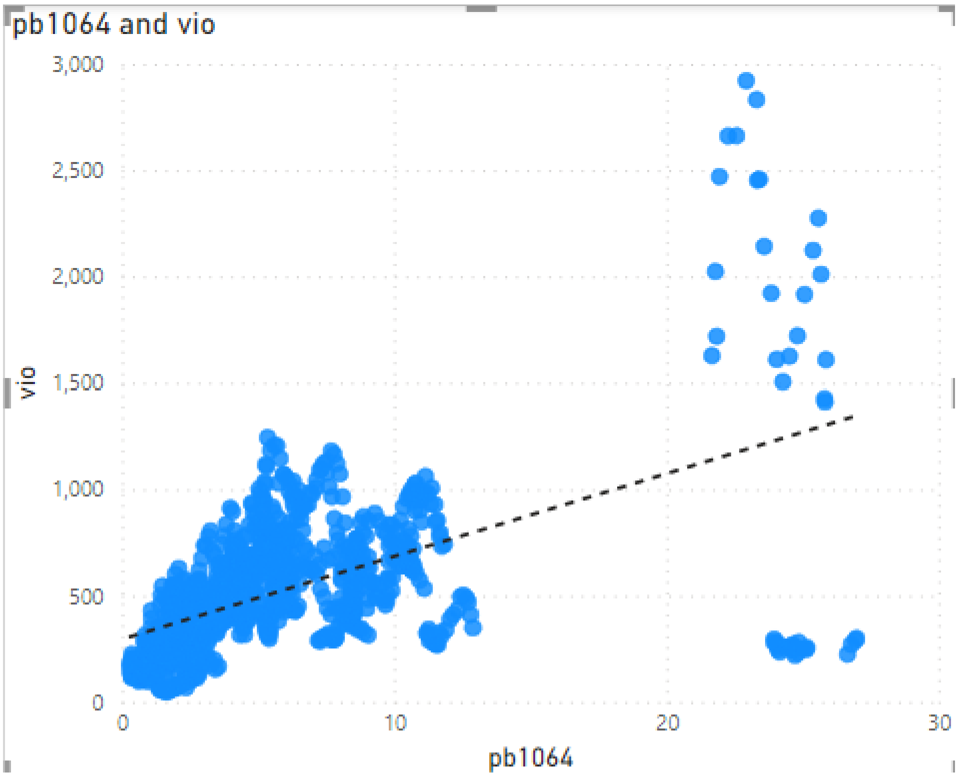


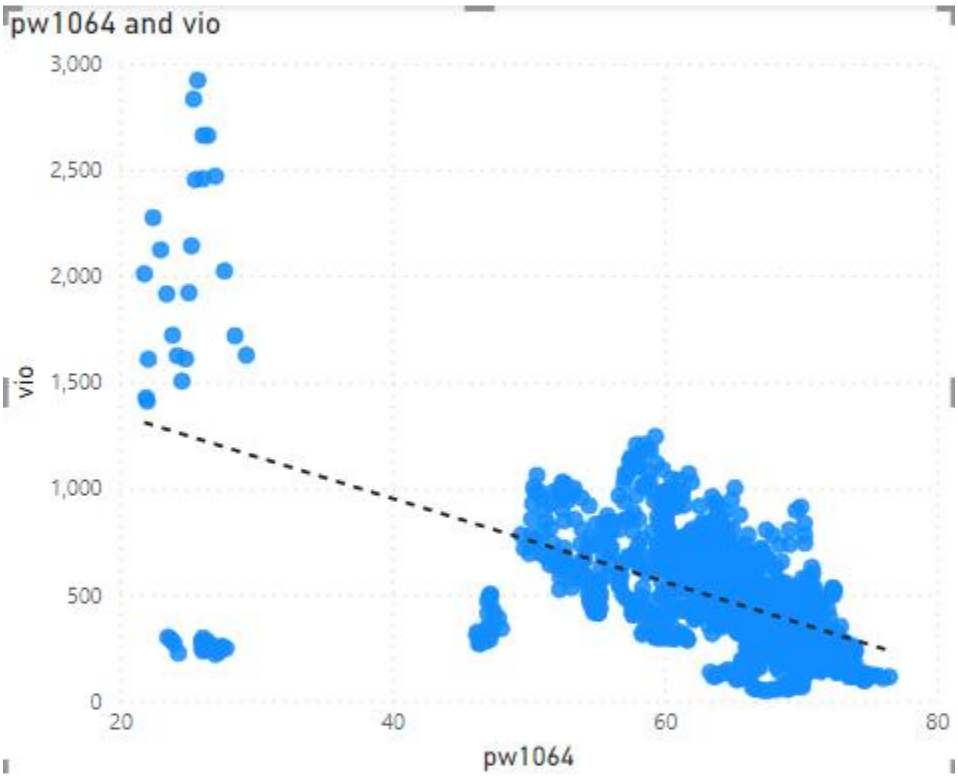
Relation between Violent crime rate and other variables:




incarc_rate and vio
3,000
2,500
2,000
1,500
1,000
500
0
vio
0
500
1000
1500
2000
incarc_rate


avginc and vio
3,000
2,500
2,000
1,500
1,000
500
0
vio
5
10
15
20
25
avginc


pb1064 and vio
3,000
2,500
2,000
1,500
1,000
500
0
vio
0
10
20
30
pb1064


pw1064 and vio
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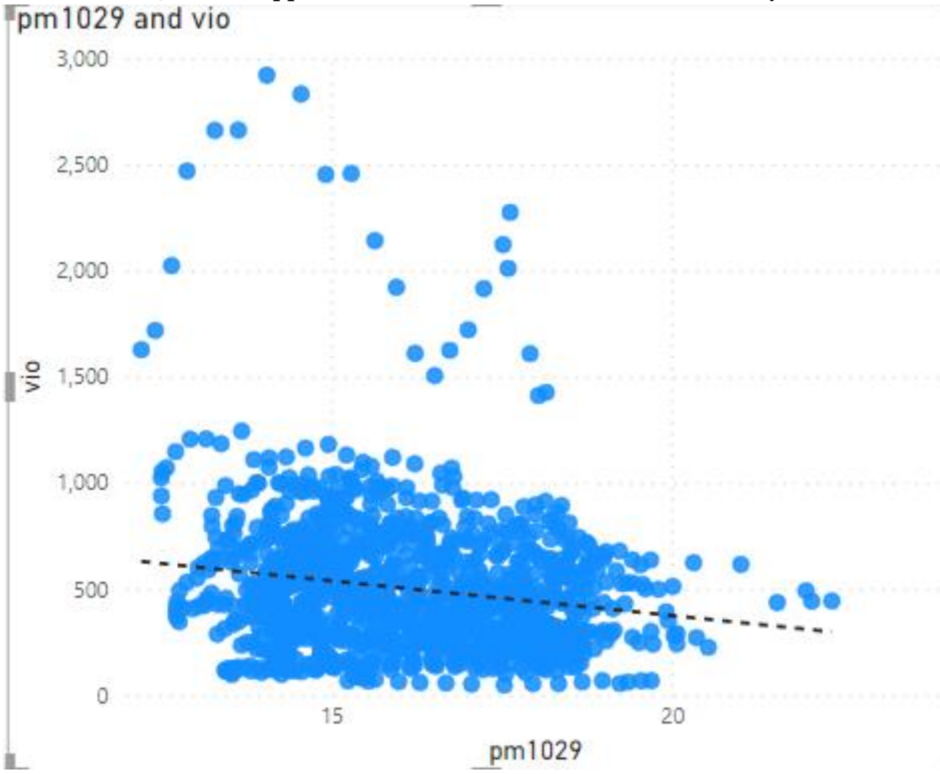
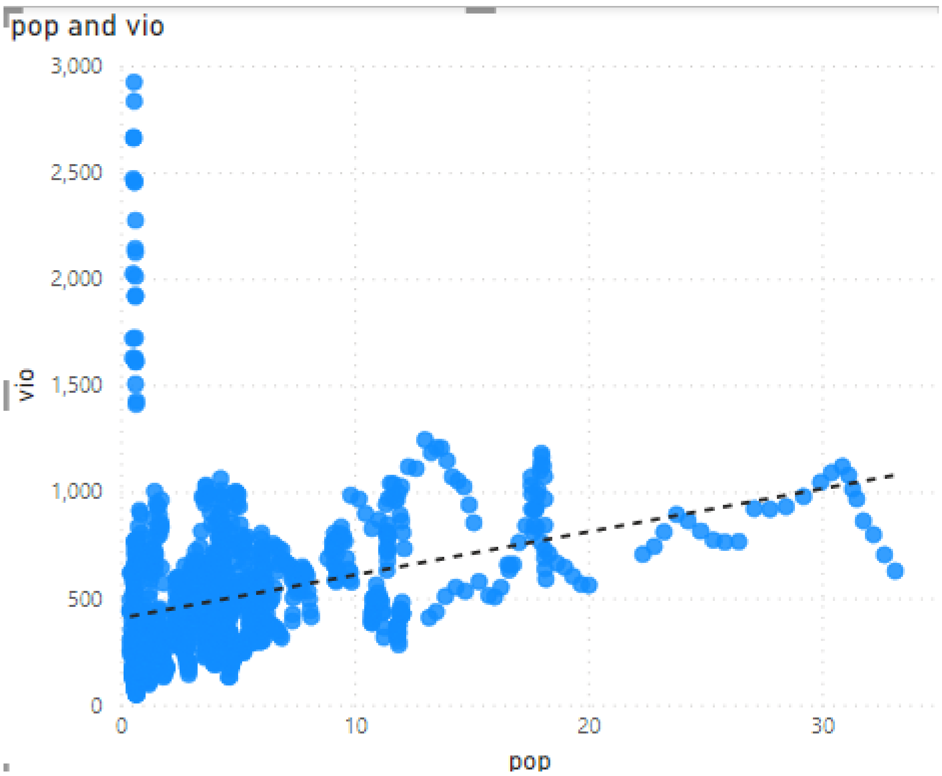
2,500
2,000
1,500
1,000
500
0
vio
20
40
60
80
pw1064


pm1029 and vio
3,000
2,500
2,000
1,500
1,000
500
0
vio
15
20
pm1029


pop and vio
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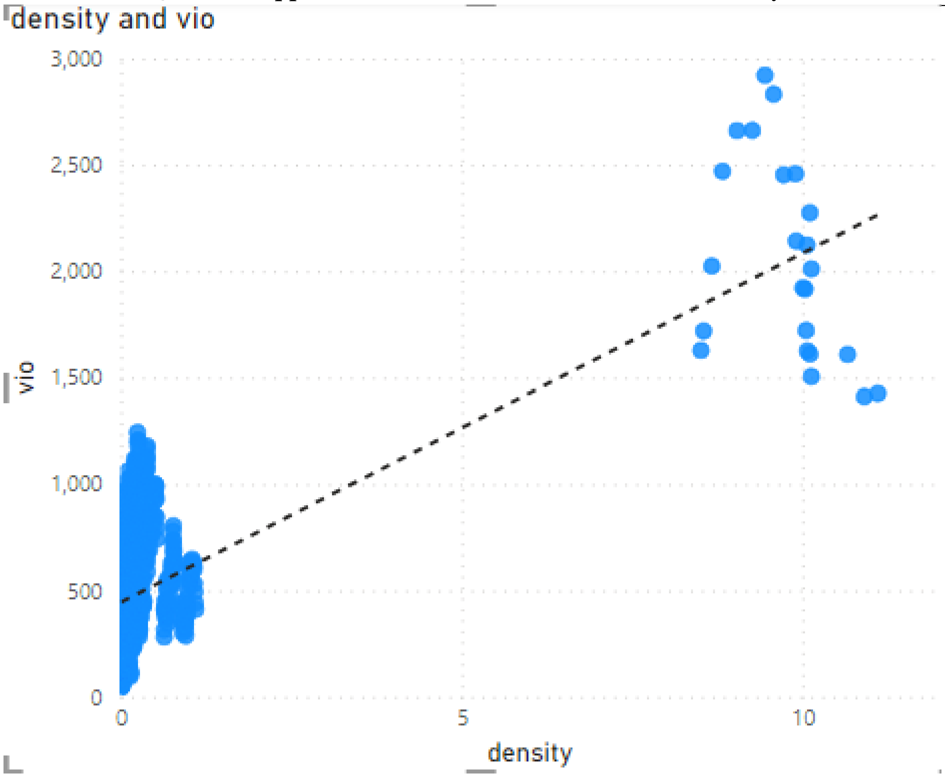
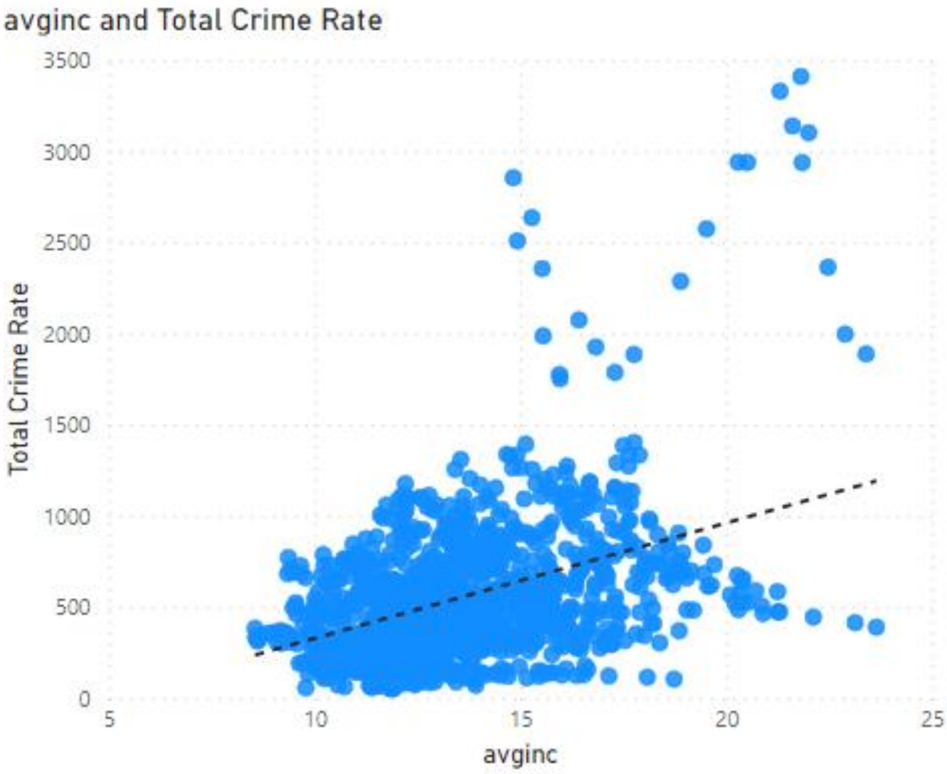
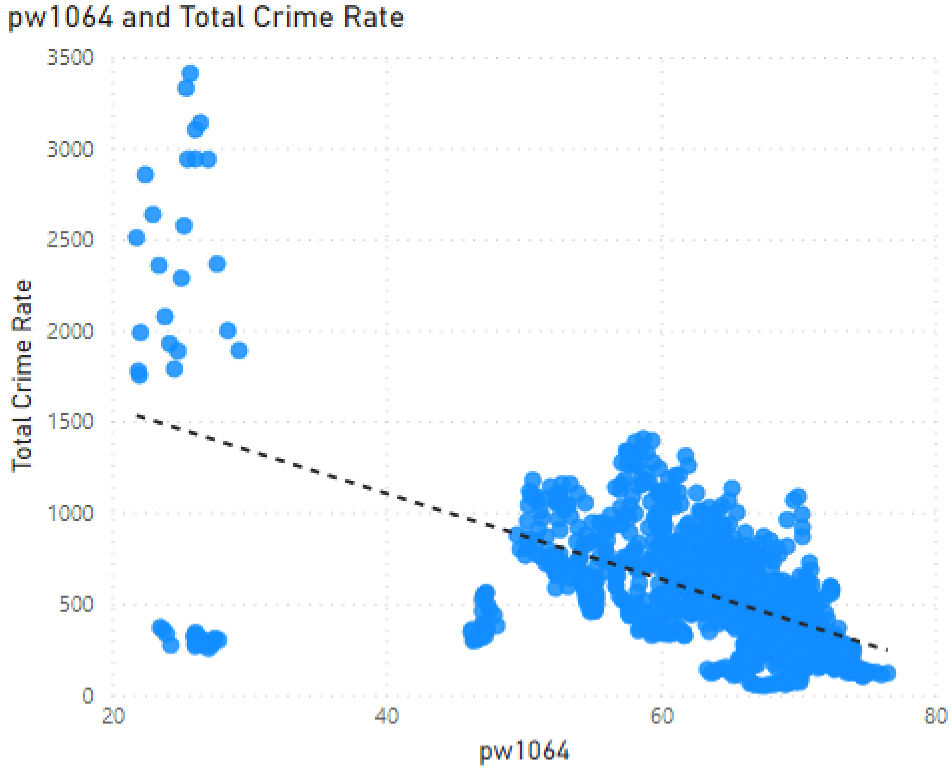
2,500
2,000
1,500
1,000
500
0
vio
0
10
20
30
pop

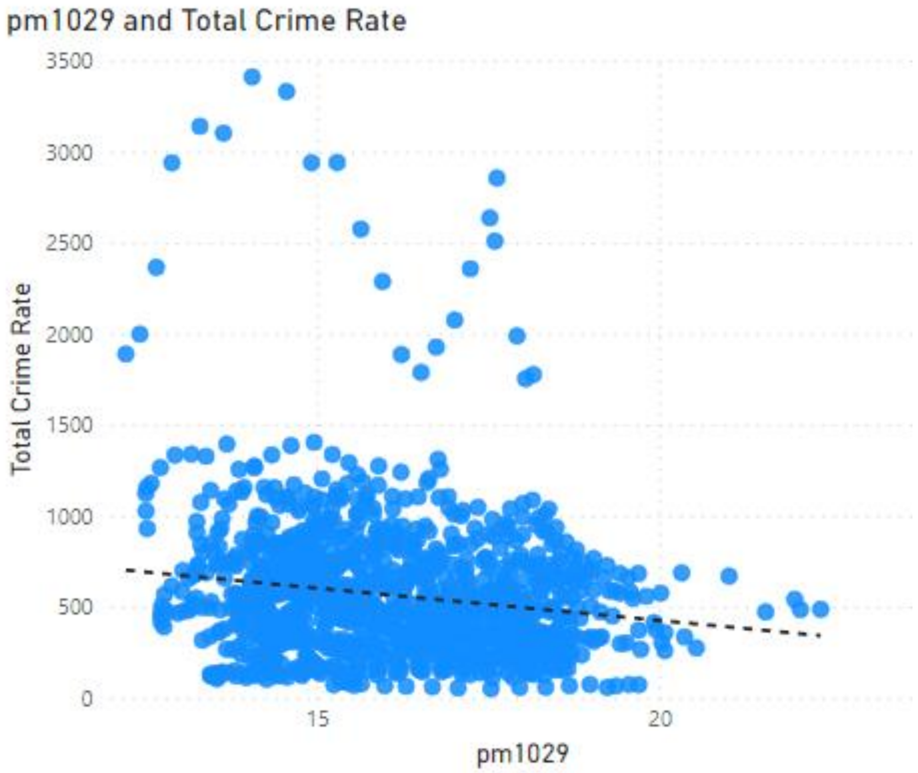


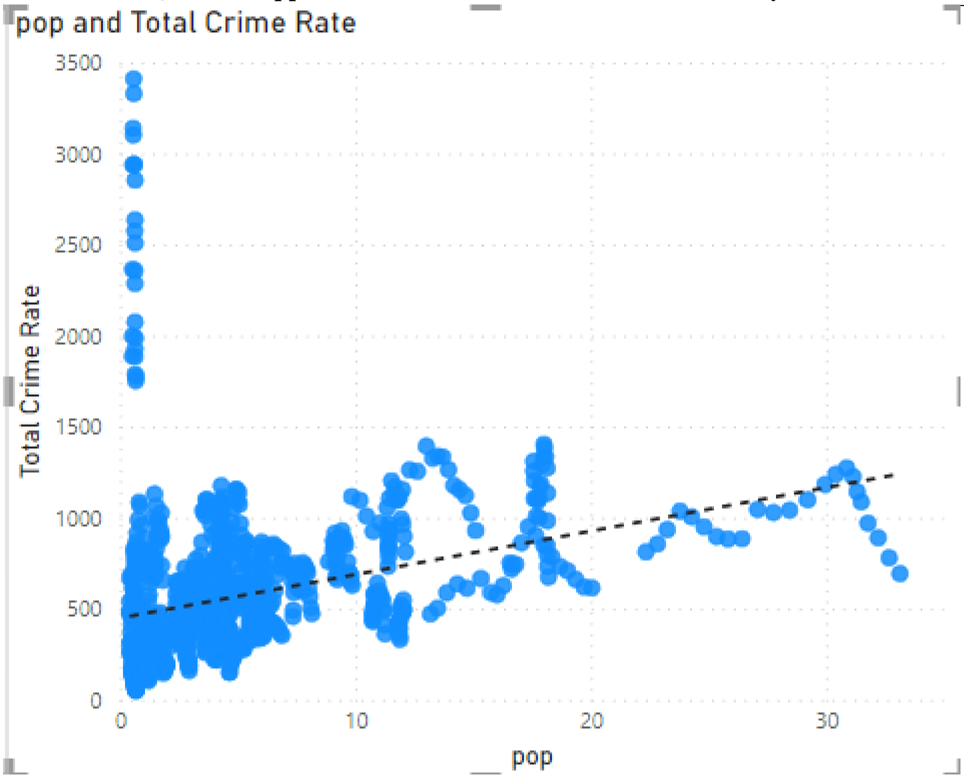
As murder rate, robbery rate and violent crime rate are strongly correlated, we can add these 3 variables and take an average and consider it as Total Crime rate. We can check the effect of this newly created variable (Total Crime rate) on other variables and decide whether we can use it as a dependent variable in our regression analysis Then, we checked the variation of other variables with respect to total crime rates.

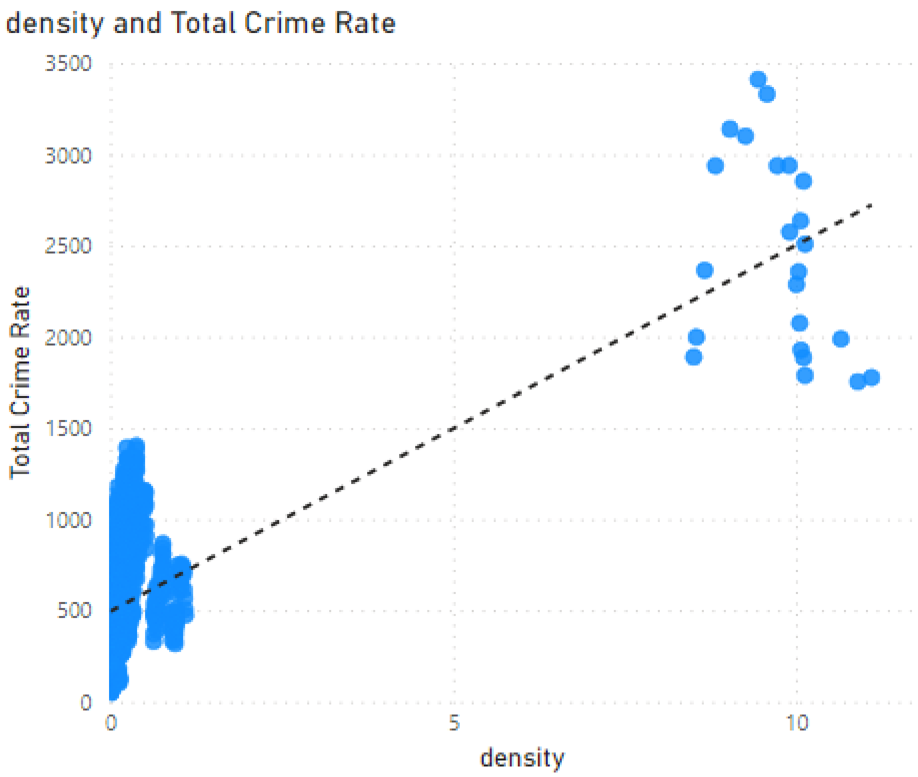
Relation between Total crime rate and other variables:




pw1064 and Total Crime Rate
3500
3000
2500
2000
1500
1000
500
0
Total Crime Rate
20
40
60
80
pw1064


pm1029 and Total Crime Rate
3500
3000
2500
2000
1500
1000
500
0
Total Crime Rate
15
20
pm1029


pop and Total Crime Rate
Total Crime Rate
3500
3000
2500
2000
1500
1000
500
0
0
10
20
30
pop


density and Total Crime Rate
Total Crime Rate
3500
3000
2500
2000
1500
1000
500
0
0
5
10
density

As the effect of other variables on Total Crime rate is the same as Violent crime rate, we can consider Total Crime rate as our dependent variable which is the sum of violent crime rate, robbery rate and murder rate. As the distributions for Total Crime rate, incarc_rate and density are positively skewed, we can use log transformation of these variables in the model.

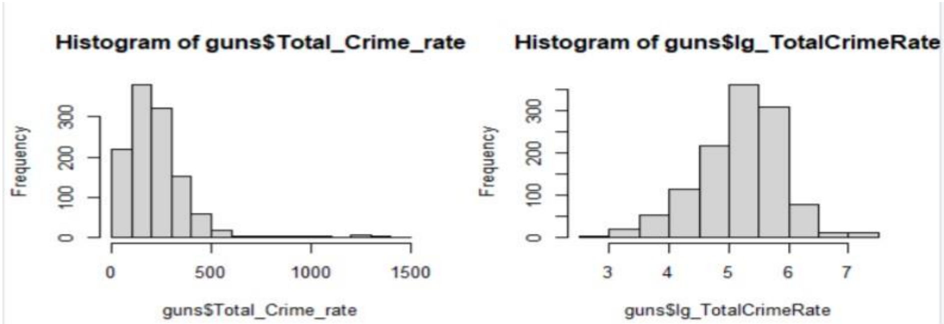


Figure 9: Histogram of total crime rate and log(total crime rate)

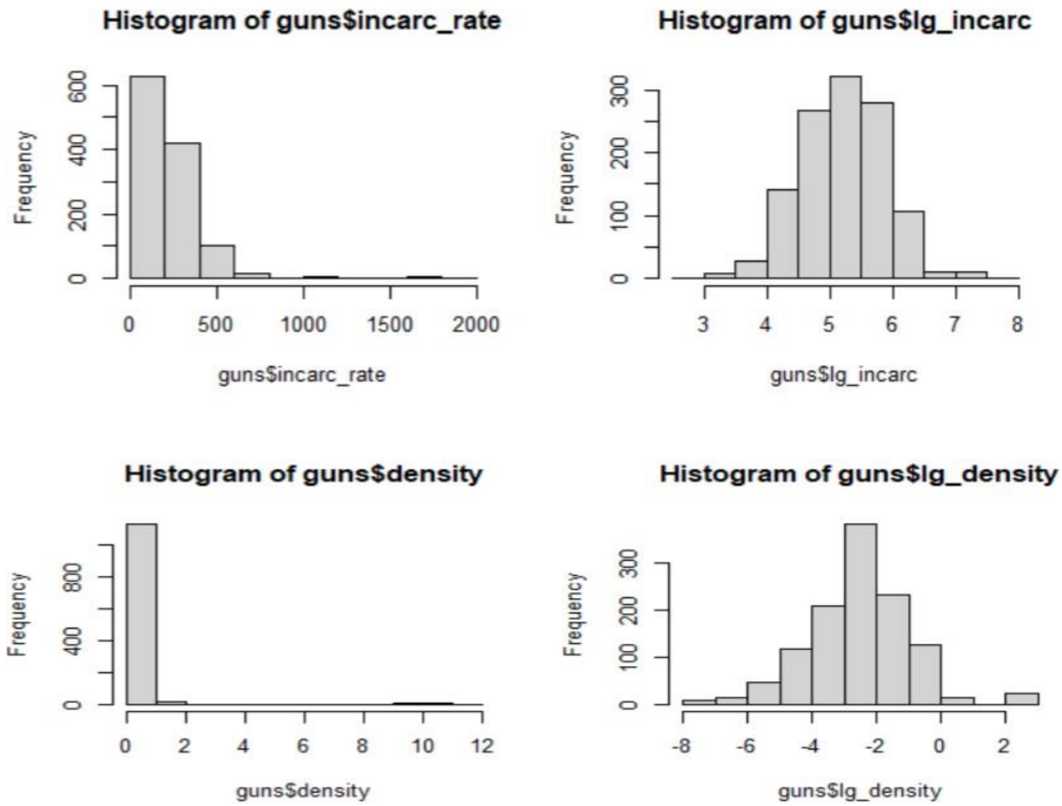


Figure 10: Comparison of histogram for log transformed variable

As the distribution of Total Crime Rate is positively skewed and approximates to normal distribution, we can use log transformation of this variable as a dependent variable.

However, while performing regression, we can check once by considering violent crime rate, robbery rate and murder rate individually as a dependent variable and then we can compare the results with considering Total Crime Rate as a dependent variable.

Below are the statistics for newly created variable Total Crime Rate:

Descriptive statistics of Total Crime rate variable:

Variable	Total Crime rate	lg_TotalCrimeRate
Min	18.13	2.898
1st Qu	121.23	4.798
Median	196.77	5.282
Mean	224.19	5.189
3rd Qu	284.03	5.649
Max	1409.97	7.251
Std Dev	166.83	0.69

Figure: Descriptive Statistics of total crime rate

Regression Analysis

Linear Regression

We have started our analysis by observing the effect of shall variable on log - transformed Total Crime Rate variable and below is the output observed.

```
> #Effect of shall on crime rate
> model1 <- lm(lg_TotalCrimeRate~shall, data=guns)
> summary(model1)

Call:
lm(formula = lg_TotalCrimeRate ~ shall, data = guns)

Residuals:
     Min       1Q   Median       3Q      Max
-2.41481 -0.44068  0.05869  0.44844  1.93876

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.31256    0.02201  241.40   <2e-16 ***
shall       -0.50754    0.04465  -11.37   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6558 on 1171 degrees of freedom
Multiple R-squared:  0.09939,	Adjusted R-squared:  0.09862
F-statistic: 129.2 on 1 and 1171 DF,  p-value: < 2.2e-16
```

Figure: Estimating the effect of shall on Total crime rate variable

As per the above output, presence of the shall law leads to a substantial decrease in total crime rates by 50.75%.

However, it's important to note that since the "shall" variable is the only explanatory variable used in this model, we cannot rule out the possibility that other factors could be influencing the relationship between the "shall" law and

```
> #Effect of shall in presence of other variables
> model1_2 <- lm(lg_TotalCrimeRate~lg_incarc+pb1064+pw1064+pm1029+pop+avginc+lg_density+shall
> summary(model1_2)

Call:
lm(formula = lg_TotalCrimeRate ~ lg_incarc + pb1064 + pw1064 +
    pm1029 + pop + avginc + lg_density + shall, data = guns)

Residuals:
     Min       1Q   Median       3Q      Max
-1.29521 -0.25076  0.00369  0.26785  1.06896

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.938830   0.510027  -1.841   0.0659 .
lg_incarc    0.671481   0.026250  25.581  < 2e-16 ***
pb1064       0.013400   0.014968   0.895   0.3708
pw1064       0.006168   0.007313   0.843   0.3992
pm1029       0.125582   0.010629  11.816  < 2e-16 ***
pop          0.028627   0.002394  11.958  < 2e-16 ***
avginc       0.028627   0.006631   4.317 1.72e-05 ***
lg_density   0.118181   0.009324  12.675  < 2e-16 ***
shall       -0.306614   0.029458 -10.409  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3865 on 1164 degrees of freedom
Multiple R-squared:  0.6891,	Adjusted R-squared:  0.6869
F-statistic: 322.4 on 8 and 1164 DF,  p-value: < 2.2e-16
```

the total crime rate.

Figure: Effect of shall on Total Crime rate in presence of other factors

By incorporating additional variables into the model, it becomes apparent that the presence of when "shall" law leads to a substantial reduction in total crime rate specifically, by 34.42%, and this result is statistically significant.

It is possible that the introduction of these new variables has led to a decrease in the coefficient associated with "shall" as it is no longer the sole explanatory variable for Total crime rate and other variables are now providing a better explanation.

Based on the given output, it appears that the variables "pb1064" and "pw1064" are not statistically significant. This means that their coefficients are not significantly different from zero, indicating that they have no meaningful impact on the outcome variable. The race of a person does not affect the overall crime rate in each state.

F- Test

We perform F-test to check the joint significance of these variables.

```
> linearHypothesis(model1_2, c("pb1064=0","pw1064=0"))
Linear hypothesis test

Hypothesis:
pb1064 = 0
pw1064 = 0

Model 1: restricted model
Model 2: lg_TotalCrimeRate ~ lg_incarc + pb1064 + pw1064 + pm1029 + pop +
    avginc + lg_density + shall

  Res.Df    RSS Df Sum of Sq    F Pr(>F)
1   1166 173.99
2   1164 173.87  2   0.12247 0.41 0.6638
```

Figure: F-test

As p-value >0.05, we fail to reject the Null Hypothesis and conclude that pb1064 and pw1064 are not significant and can be removed from the model.

We drop pb1064 and pw1064 and then re-run regression on the above model.

```
> #Dropping pb1064 & pw1064 as they are not significant
> model1_3 <- lm(lg_TotalCrimeRate~lg_incarc+pm1029+pop+avginc+lg_density+shall, data = guns)
> summary(model1_3)

Call:
lm(formula = lg_TotalCrimeRate ~ lg_incarc + pm1029 + pop + avginc +
    lg_density + shall, data = guns)

Residuals:
     Min       1Q   Median       3Q      Max
-1.30925 -0.24869  0.00515  0.26603  1.07693

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.624040   0.242251  -2.576   0.0101 *
lg_incarc    0.677867   0.021014  32.257  < 2e-16 ***
pm1029       0.129840   0.008974  14.468  < 2e-16 ***
pop          0.028307   0.002320  12.202  < 2e-16 ***
avginc       0.031795   0.005613   5.664 1.86e-08 ***
lg_density   0.118193   0.008250  14.327  < 2e-16 ***
shall       -0.301074   0.028546 -10.547  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3863 on 1166 degrees of freedom
Multiple R-squared:  0.6888,	Adjusted R-squared:  0.6872
F-statistic: 430.2 on 6 and 1166 DF,  p-value: < 2.2e-16
```

Figure: Regression results after dropping of variables

After dropping the variables which were not significant in the previous regression, the coefficients of the variables become more precise.

Check for non-linearity

As all the variables are linearly related with Total crime rate variable, including quadratic term in the model would not be required.

Check for collinearity

To check for collinearity in the model, we shall use the VIF factor as below.

```
> #To check collinearity in the model
> vif(model1_3)
 lg_incarc     pm1029        pop     avginc lg_density      shall
  1.520915   1.897846   1.166078   1.614925   1.319733   1.178174
>
```

Figure: Collinearity check

From the above result, VIF values are less than 5 and hence, no collinearity is present inthe model.

Check for Heteroskedasticity

To check for heteroskedasticity we use the White Test as below.

```
> library(lmtest)
> bptest(model1_3)

	studentized Breusch-Pagan test

data:  model1_3
BP = 66.354, df = 6, p-value = 2.282e-12
```

Figure: Heteroskedasticity check

We reject the Null hypothesis and conclude that heteroskedasticity is present in the model. Since the dataset provided covers various states in the USA over a considerable period of time, there is a possibility of heteroskedasticity as the error terms may vary across different time periods. To analyze this data, we can treat it as panel data and apply fixed-effect, and random-effect models through regression.

Panel Data Analysis

Pooled OLS model with robust SE

```
> #Pooled model with robust SE
> pooled_model <- plm(lg_TotalCrimeRate~lg_incarc+pm1029+pop+avginc+lg_density+shall, data = guns,index=c('stateid','year'), model='poolin
g')
> summary(pooled_model)
Pooling Model

Call:
plm(formula = lg_TotalCrimeRate ~ lg_incarc + pm1029 + pop +
    avginc + lg_density + shall, data = guns, model = "pooling",
    index = c("stateid", "year"))

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.3092501 -0.2486910  0.0051504  0.2660335  1.0769338

Coefficients:
              Estimate Std. Error  t-value  Pr(>|t|)
(Intercept) -0.6240397  0.2422511  -2.5760   0.01012 *
lg_incarc    0.6778674  0.0210143  32.2574 < 2.2e-16 ***
pm1029       0.1298400  0.0089743  14.4680 < 2.2e-16 ***
pop          0.0283073  0.0023200  12.2015 < 2.2e-16 ***
avginc       0.0317949  0.0056133   5.6642 1.859e-08 ***
lg_density   0.1181928  0.0082496  14.3271 < 2.2e-16 ***
shall       -0.3010737  0.0285458 -10.5470 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    559.19
Residual Sum of Squares: 173.99
R-Squared:      0.68885
Adj. R-Squared: 0.68725
F-statistic: 430.229 on 6 and 1166 DF, p-value: < 2.22e-16
> coeftest(pooled_model, vcov. = vcovHC, type = "HC1")

t test of coefficients:

              Estimate Std. Error t value  Pr(>|t|)
(Intercept) -0.6240397  0.7428343 -0.8401 0.4010362
lg_incarc    0.6778674  0.0701193  9.6673 < 2.2e-16 ***
pm1029       0.1298400  0.0233923  5.5505 3.524e-08 ***
pop          0.0283073  0.0086836  3.2599 0.0011468 **
avginc       0.0317949  0.0164309  1.9351 0.0532229 .
lg_density   0.1181928  0.0290031  4.0752 4.909e-05 ***
shall       -0.3010737  0.0826884 -3.6411 0.0002834 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure: Pooled OLS model output

Based on the output of Pooled model with robust Standard error, it appears that the regression coefficients remain consistent with the earlier performed regression. However, the significance of variables seems to have shifted. Estimators obtained from Pooled OLS model are not Best Linear Unbiased Estimator (BLUE).

Fixed Effect model

We will use Fixed effect model for further estimation:

```
> fe_model <- plm(lg_TotalCrimeRate~lg_incarc+pm1029+pop+avginc+lg_density+shall, data = guns,index=c('stateid','year'), model='within')
> summary(fe_model)
Oneway (individual) effect Within Model

Call:
plm(formula = lg_TotalCrimeRate ~ lg_incarc + pm1029 + pop +
    avginc + lg_density + shall, data = guns, model = "within",
    index = c("stateid", "year"))

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.59475260 -0.10326928  0.00043068  0.11124118  0.53907467

Coefficients:
             Estimate Std. Error t-value Pr(>|t|)
lg_incarc  -0.0311101  0.0280642 -1.1085  0.26787
pm1029     -0.0452009  0.0083006 -5.4455 6.35e-08 ***
pop         0.0119805  0.0092971  1.2886  0.19779
avginc     -0.0038930  0.0058832 -0.6617  0.50829
lg_density -0.1626872  0.0874181 -1.8610  0.06300 .
shall       0.0313431  0.0182039  1.7218  0.08539 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    33.904
Residual Sum of Squares: 30.604
R-Squared:      0.097313
Adj. R-Squared: 0.052017
F-statistic: 20.0515 on 6 and 1116 DF, p-value: < 2.22e-16
> |
```

Figure: Fixed effect model output

Adding state fixed effects has an impact on the results. The coefficient on "shall" decreases significantly from 0.301 to 0.031. This suggests that the earlier specification without fixed effects had important omitted variable bias. The estimate of the effect of "shall issue" laws on the violent crime rate is no longer statistically significant, implying that these laws may not have a significant impact on total crime rates.

The regression model with fixed effects is considered more credible since it controls for unobserved characteristics that vary between states but remain constant over time.

Entity fixed Time Effect model

We further estimate the effect of shall and other variables on crime rate using entity fixed time effect model as below:

```
odel='within')
> summary(efte_model)
Oneway (individual) effect Within Model

Call:
plm(formula = lg_TotalCrimeRate ~ lg_incarc + pm1029 + pop +
    avginc + lg_density + shall + as.factor(year), data = guns,
    model = "within", index = c("stateid", "year"))

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.4572971 -0.0789396  0.0042558  0.0792123  0.6008706

Coefficients:
                     Estimate  Std. Error t-value  Pr(>|t|)
lg_incarc          -0.12997515  0.02766243 -4.6986 2.952e-06 ***
pm1029              0.07949519  0.01089896  7.2938 5.771e-13 ***
pop                 0.00259168  0.00778484  0.3329   0.73926
avginc              0.00074615  0.00598151  0.1247   0.90075
lg_density         -0.18872120  0.07485951 -2.5210   0.01184 *
shall              -0.01804836  0.01704766 -1.0587   0.28997
as.factor(year)78   0.06395525  0.02762578  2.3151   0.02079 *
as.factor(year)79   0.18153712  0.02794438  6.4964 1.247e-10 ***
as.factor(year)80   0.25225462  0.02816926  8.9550 < 2.2e-16 ***
as.factor(year)81   0.26784560  0.02873860  9.3201 < 2.2e-16 ***
as.factor(year)82   0.25283539  0.03022652  8.3647 < 2.2e-16 ***
as.factor(year)83   0.22145090  0.03237021  6.8412 1.305e-11 ***
as.factor(year)84   0.24813462  0.03489105  7.1117 2.067e-12 ***
as.factor(year)85   0.30459697  0.03747566  8.1279 1.174e-15 ***
as.factor(year)86   0.39370049  0.04070754  9.6714 < 2.2e-16 ***
as.factor(year)87   0.39623891  0.04385857  9.0345 < 2.2e-16 ***
as.factor(year)88   0.46464307  0.04719346  9.8455 < 2.2e-16 ***
as.factor(year)89   0.53175616  0.05037341 10.5563 < 2.2e-16 ***
as.factor(year)90   0.66187803  0.05370199 12.3250 < 2.2e-16 ***
as.factor(year)91   0.73614099  0.05629915 13.0755 < 2.2e-16 ***
as.factor(year)92   0.77270340  0.05928231 13.0343 < 2.2e-16 ***
as.factor(year)93   0.80411802  0.06134378 13.1084 < 2.2e-16 ***
as.factor(year)94   0.80206539  0.06375653 12.5801 < 2.2e-16 ***
as.factor(year)95   0.80892794  0.06636102 12.1898 < 2.2e-16 ***
as.factor(year)96   0.76411353  0.06891026 11.0885 < 2.2e-16 ***
as.factor(year)97   0.74533367  0.07122342 10.4647 < 2.2e-16 ***
as.factor(year)98   0.69403994  0.07377068  9.4081 < 2.2e-16 ***
as.factor(year)99   0.64269465  0.07564594  8.4961 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    33.904
Residual Sum of Squares: 20.905
R-Squared:      0.3834
Adj. R-Squared: 0.33943
F-statistic: 24.2942 on 28 and 1094 DF, p-value: < 2.22e-16
```

Figure: Entity fixed effect model output

The coefficient on "shall" decreases even further to 0.018, and it is no longer significant. This suggests that there is no significant relationship between "shall issue" laws and the total crime rate.

Random effects model

Below is the output obtained on estimating the effect on Total crime rate variable using random effect model

```
> re_model <- plm(lg_TotalCrimeRate~lg_incarc+pm1029+pop+avginc+lg_density+shall, data = guns,index=c('stateid','year'), model='random')
> summary(re_model)
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = lg_TotalCrimeRate ~ lg_incarc + pm1029 + pop +
    avginc + lg_density + shall, data = guns, model = "random",
    index = c("stateid", "year"))

Balanced Panel: n = 51, T = 23, N = 1173

Effects:
                  var std.dev share
idiosyncratic 0.02742 0.16560 0.236
individual    0.08893 0.29821 0.764
theta: 0.885

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.5447816 -0.1149503  0.0059446  0.1215070  0.4805109

Coefficients:
              Estimate Std. Error z-value  Pr(>|z|)
(Intercept)  5.4346801  0.2781741 19.5370 < 2.2e-16 ***
lg_incarc    0.0555934  0.0280474  1.9821  0.047465 *
pm1029      -0.0128566  0.0080224 -1.6026  0.109026
pop          0.0186791  0.0064785  2.8833  0.003936 **
avginc      -0.0033255  0.0060306 -0.5514  0.581337
lg_density   0.1454713  0.0287068  5.0675 4.031e-07 ***
shall       -0.0072569  0.0186588 -0.3889  0.697331
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    40.853
Residual Sum of Squares: 35.991
R-Squared:      0.11902
Adj. R-Squared: 0.11449
Chisq: 157.524 on 6 DF, p-value: < 2.22e-16
```

Figure: Random effect model output

Hausman test

We cannot use random effects as data is not random and there might be endogeneity issue, we can test using Hausman test.

```
> phtest(fe_model,re_model)

        Hausman Test

data:  lg_TotalCrimeRate ~ lg_incarc + pm1029 + pop + avginc + lg_density +  ...
chisq = 2122.7, df = 6, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent

>
```

Figure: Hausman Test output

As p-value is less that 0.05, we reject the Null hypothesis and conclude that endogeneity problem exists and hence, fixed effects model would be appropriate.

Panel Data Analysis using log(vio) as dependent variable

We have repeated the above estimations by using log(vio) as dependent variable to check significance of shall on only violent crime rate (excluding murder and robbery rate)

Pooled OLS model with log(vio) as dependent variable:

```
> #using log(vio) as y
> model2 <- lm(lg_vio~lg_incarc+pm1029+pb1064+pw1064+pop+avginc+lg_density+shall, data = guns)
> summary(model2)

Call:
lm(formula = lg_vio ~ lg_incarc + pm1029 + pb1064 + pw1064 +
    pop + avginc + lg_density + shall, data = guns)

Residuals:
     Min       1Q   Median       3Q      Max
-1.24130 -0.23687  0.01159  0.25764  1.10485

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.181654   0.490211   0.371 0.711031
lg_incarc    0.693567   0.025230  27.490  < 2e-16 ***
pm1029       0.116764   0.010216  11.430  < 2e-16 ***
pb1064       0.003313   0.014386   0.230 0.817931
pw1064       0.003358   0.007029   0.478 0.632982
pop          0.024075   0.002301  10.463  < 2e-16 ***
avginc       0.023299   0.006374   3.655 0.000268 ***
lg_density   0.092888   0.008961  10.365  < 2e-16 ***
shall       -0.282684   0.028313  -9.984  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3715 on 1164 degrees of freedom
Multiple R-squared:  0.6713,    Adjusted R-squared:  0.669
F-statistic: 297.1 on 8 and 1164 DF,  p-value: < 2.2e-16

> coeftest(model2, vcov. = vcovHC, type = "HC1")

t test of coefficients:

              Estimate Std. Error t value  Pr(>|t|)
(Intercept)  0.1816538  0.5714627  0.3179 0.7506366
lg_incarc    0.6935672  0.0246505 28.1360 < 2.2e-16 ***
pm1029       0.1167641  0.0098848 11.8124 < 2.2e-16 ***
pb1064       0.0033125  0.0160370  0.2066 0.8363936
pw1064       0.0033576  0.0080255  0.4184 0.6757537
pop          0.0240749  0.0024971  9.6411 < 2.2e-16 ***
avginc       0.0232989  0.0061111  3.8125 0.0001448 ***
lg_density   0.0928883  0.0093021  9.9857 < 2.2e-16 ***
shall       -0.2826839  0.0299170 -9.4489 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure: Pooled OLS model output

As per above output, when considering log(vio) i.e. log transformation of violent crime rate as dependent variable, presence of the "shall law" leads to a substantial reduction in violent crime rates, specifically by 28.27%, and this result is statistically significant.

Fixed effect model with log(vio) as dependent variable

```
> fe_model <- plm(lg_vio~lg_incarc+pm1029+pb1064+pw1064+pop+avginc+lg_density+shall, data = guns, index=c('stateid','year'), model='within')
> summary(fe_model)
Oneway (individual) effect Within Model

Call:
plm(formula = lg_vio ~ lg_incarc + pm1029 + pb1064 + pw1064 +
    pop + avginc + lg_density + shall, data = guns, model = "within",
    index = c("stateid", "year"))

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.5621921 -0.0989159  0.0089916  0.1020525  0.5887111

Coefficients:
             Estimate Std. Error t-value  Pr(>|t|)
lg_incarc  -0.0672299  0.0282092 -2.3833  0.017327 *
pm1029     -0.0690675  0.0083143 -8.3071 2.821e-16 ***
pb1064      0.0952893  0.0150322  6.3390 3.352e-10 ***
pw1064      0.0428067  0.0052073  8.2205 5.591e-16 ***
pop         0.0243860  0.0092824  2.6271  0.008729 **
avginc     -0.0041476  0.0057273 -0.7242  0.469107
lg_density -0.2518321  0.0859535 -2.9299  0.003460 **
shall      -0.0379065  0.0189886 -1.9963  0.046147 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 28.562
R-Squared:      0.22362
Adj. R-Squared: 0.1832
F-statistic: 40.1082 on 8 and 1114 DF, p-value: < 2.22e-16
```

Figure: Fixed effect model output

According to the fixed effect model output, the impact of the "shall law" on violent crime rates decreases by 3.7%. The "shall" variable is still statistically significant at a 5% significance level, but not at a 1% significance level. It is important to note that the significance of the "shall" variable is reduced in this model as compared to the pooled OLSmodel with robust standard error.

Entity fixed time effect model with log(vio) as dependent variable:

```
n')
> summary(fte_model)
Oneway (individual) effect Within Model

Call:
plm(formula = lg_vio ~ lg_incarc + pm1029 + pop + avginc + lg_density +
    shall + as.factor(year), data = guns, model = "within", index = c("stateid",
    "year"))

Balanced Panel: n = 51, T = 23, N = 1173

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.4450261 -0.0775677  0.0050345  0.0778975  0.6822647

Coefficients:
                     Estimate Std. Error t-value  Pr(>|t|)
lg_incarc          -0.1023783  0.0278205 -3.6800 0.0002446 ***
pm1029              0.0756543  0.0109613  6.9020 8.671e-12 ***
pop                 0.0053033  0.0078293  0.6774 0.4983169
avginc              0.0023046  0.0060157  0.3831 0.7017274
lg_density         -0.2600797  0.0752874 -3.4545 0.0005725 ***
shall              -0.0269500  0.0171451 -1.5719 0.1162673
as.factor(year)78   0.0664786  0.0277837  2.3927 0.0168918 *
as.factor(year)79   0.1843693  0.0281041  6.5602 8.272e-11 ***
as.factor(year)80   0.2453828  0.0283303  8.6615 < 2.2e-16 ***
as.factor(year)81   0.2529155  0.0289029  8.7505 < 2.2e-16 ***
as.factor(year)82   0.2452658  0.0303993  8.0681 1.865e-15 ***
as.factor(year)83   0.2227221  0.0325552  6.8414 1.303e-11 ***
as.factor(year)84   0.2635974  0.0350905  7.5119 1.207e-13 ***
as.factor(year)85   0.3209545  0.0376899  8.5157 < 2.2e-16 ***
as.factor(year)86   0.4077476  0.0409402  9.9596 < 2.2e-16 ***
as.factor(year)87   0.4153289  0.0441093  9.4159 < 2.2e-16 ***
as.factor(year)88   0.4855666  0.0474632 10.2304 < 2.2e-16 ***
as.factor(year)89   0.5493649  0.0506613 10.8439 < 2.2e-16 ***
as.factor(year)90   0.6820438  0.0540089 12.6284 < 2.2e-16 ***
as.factor(year)91   0.7453916  0.0566209 13.1646 < 2.2e-16 ***
as.factor(year)92   0.7869260  0.0596212 13.1988 < 2.2e-16 ***
as.factor(year)93   0.8180721  0.0616944 13.2601 < 2.2e-16 ***
as.factor(year)94   0.8132012  0.0641209 12.6823 < 2.2e-16 ***
as.factor(year)95   0.8179912  0.0667403 12.2563 < 2.2e-16 ***
as.factor(year)96   0.7725692  0.0693041 11.1475 < 2.2e-16 ***
as.factor(year)97   0.7607234  0.0716305 10.6201 < 2.2e-16 ***
as.factor(year)98   0.7143514  0.0741923  9.6284 < 2.2e-16 ***
as.factor(year)99   0.6637102  0.0760783  8.7240 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 21.145
R-Squared:      0.42524
Adj. R-Squared: 0.38426
F-statistic: 28.9074 on 28 and 1094 DF, p-value: < 2.22e-16
```

Figure: Entity Fixed Time effect model output

The effect of shall becomes insignificant at 5% significance level in the entity fixed timeeffect model as seen in the above output.

Random effect model with log(vio) as dependent variable:

```
> #Random effect model
> re_model <- plm(lg_vio~lg_incarc+pm1029+pop+avginc+lg_density+shall, data = guns, index=c('stateid','year'), model='random')
> summary(re_model)
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = lg_vio ~ lg_incarc + pm1029 + pop + avginc + lg_density +
    shall, data = guns, model = "random", index = c("stateid",
    "year"))

Balanced Panel: n = 51, T = 23, N = 1173

Effects:
                  var std.dev share
idiosyncratic 0.02723 0.16503 0.241
individual    0.08579 0.29291 0.759
theta: 0.8833

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.5436345 -0.1095026  0.0073866  0.1156155  0.4940351

Coefficients:
              Estimate Std. Error z-value  Pr(>|z|)
(Intercept)  6.0936208  0.2751513 22.1464 < 2.2e-16 ***
lg_incarc    0.0836024  0.0277598  3.0116 0.0025984 **
pm1029      -0.0193293  0.0079433 -2.4334 0.0149569 *
pop          0.0173471  0.0063753  2.7210 0.0065086 **
avginc      -0.0003941  0.0059725 -0.0660 0.9473896
lg_density   0.1038636  0.0280964  3.6967 0.0002184 ***
shall       -0.0167761  0.0184899 -0.9073 0.3642413
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    42.94
Residual Sum of Squares: 35.367
R-Squared:      0.17636
Adj. R-Squared: 0.17212
Chisq: 249.672 on 6 DF, p-value: < 2.22e-16
> |
```

Figure: Random effect model output

In random effects model, the effect of shall is still insignificant as seen in the above output.

Hausman Test for log(vio) as dependent variable:

```
> phtest(fe_model,re_model)

        Hausman Test

data:  lg_vio ~ lg_incarc + pm1029 + pb1064 + pw1064 + pop + avginc +  .
chisq = 687.05, df = 6, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent
```

Figure: Hausman Test output

Above Hausman test suggests that a fixed effect model is appropriate for this dataset even while considering log(vio) as dependent variable.

Limitations of the dataset

- Limited time frame: The dataset covers the years 1977 to 1999. This time frame may not capture more recent changes in gun violence laws or other factors that could influence crime rates. It is important to consider whether the findings from this period can be applied to the present day accurately.

- Potential omitted variables: The dataset includes variables such as population, income, and demographics, but it may not account for all relevant factors that could impact crime rates. There might be other unobserved variables, such as cultural factors, law enforcement strategies, or economic conditions, which could confound the relationship between shall-issue laws and crime rates.

- Causality and endogeneity: Establishing a causal relationship between shall-issue laws and crime rates can be challenging. Factors such as reverse causality (where crime rates influence the enactment of laws) or omitted variable bias could affect the analysis. Careful consideration and robust statistical methods are required to address these issues.

- Potential measurement errors: The accuracy and reliability of the variables in the dataset can be subject to measurement errors or inconsistencies. For example, crime reporting practices may vary across states, leading to differences in the quality of crime rate data. It is essential to account for any potential measurement errors when interpreting the results.

- Small sample size: The dataset consists of 50 states plus the District of Columbia, resulting in a relatively small sample size. This could limit the statistical power and precision of the analysis, particularly when examining subgroups or conducting moredetailed investigations.

- Potential selection bias: The dataset may be subject to selection bias if states that implemented shall-issue laws differ systematically from those that did not. This could introduce bias in the estimated effects of the laws on crime rates.

- Ecological fallacy: The dataset provides state-level aggregated data, which means that any conclusions drawn are at the aggregate level and may not necessarily apply to individuals within those states. It is important to avoid making individual-level inferences based solely on state-level data.
- Changes in law enforcement practices: The dataset does not explicitly capture changes in law enforcement practices or policies, which can vary across states and influence crime rates independently of gun laws. These factors should be considered when interpreting the relationship between shall-issue laws and crime rates.
- One key limitation to our dataset is the overall size used in the different rates used in the model. (i.e vio, rob, mur) Having only 100,000 people as your sample size does not accurately estimate their crime rates. We have cities that reach as high as 7-8 million in population. Therefore, having small estimates of 100,000 does segment the data to specific regions, it doesn't not give an accurate interpretation of these important variables in our model.
- Another limitation on the data would be other variables that are not included in the model that directly affect incarceration rate. These variables could be ones that affect the judicial process. The criminal justice system in America is a very complicated and complex process that is manipulated by many different factors. There are mistrials that occur that would improperly affect our incarceration rate even if a crime truly has been committed.

Conclusion

The regression model may not account for all the relevant variables that could potentially affect the relationship between concealed weapons laws and crime rates, such as other policy measures related to shall issue laws.

Additionally, it's possible that the relationship between crime rates and concealed weapons laws is bidirectional, with high crime rates leading to changes in policy. After controlling for both state and time fixed effects, the results suggest that there is no significant effect of concealed weapons laws on violent crime rates, robbery rates, or murder rates. These findings are the most reliable among the results obtained from the analysis.

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