

BUAN 6312.001 Applied Econometrics  
and Time Series Analysis

The Effects of Concealed Gun Laws in  
America

Gabriel Shoaib (gxs142030)

Rahul Reddy Muppidi (rmr170430)

Shaheer Ali (sxa121530)

Lohith Pingili (lxp171130)

## Introduction:

The report analyzes the data to answer the following question, “Do shall-issues law reduce crime- or not?” The analysis provided sheds light on the statistics behind crime activity in the United States over the span of 29 years. By understanding the trends of violence, robberies, incarceration rate, and murder as well as data on the demographic the states and the wider country, one can understand the impact that concealed handgun laws have on the nation.

## Background Information on Shall-Law:

Most of states currently have the Shall-law already in place, with the rest of the states having the May-law in place, with a few states not having any concealed gun laws present. Shall-law allows constituents to possess a concealed handgun license and allowing them to carry a handgun in permitted areas. Basic of requirements to obtain a license consist of passing a background check, attending a gun safety class, paying a fee, and a few other criteria set by designated States.

## Data

Total Records: 1173

Total Number of Empty Variables: 0

Time Span: 1977-1999

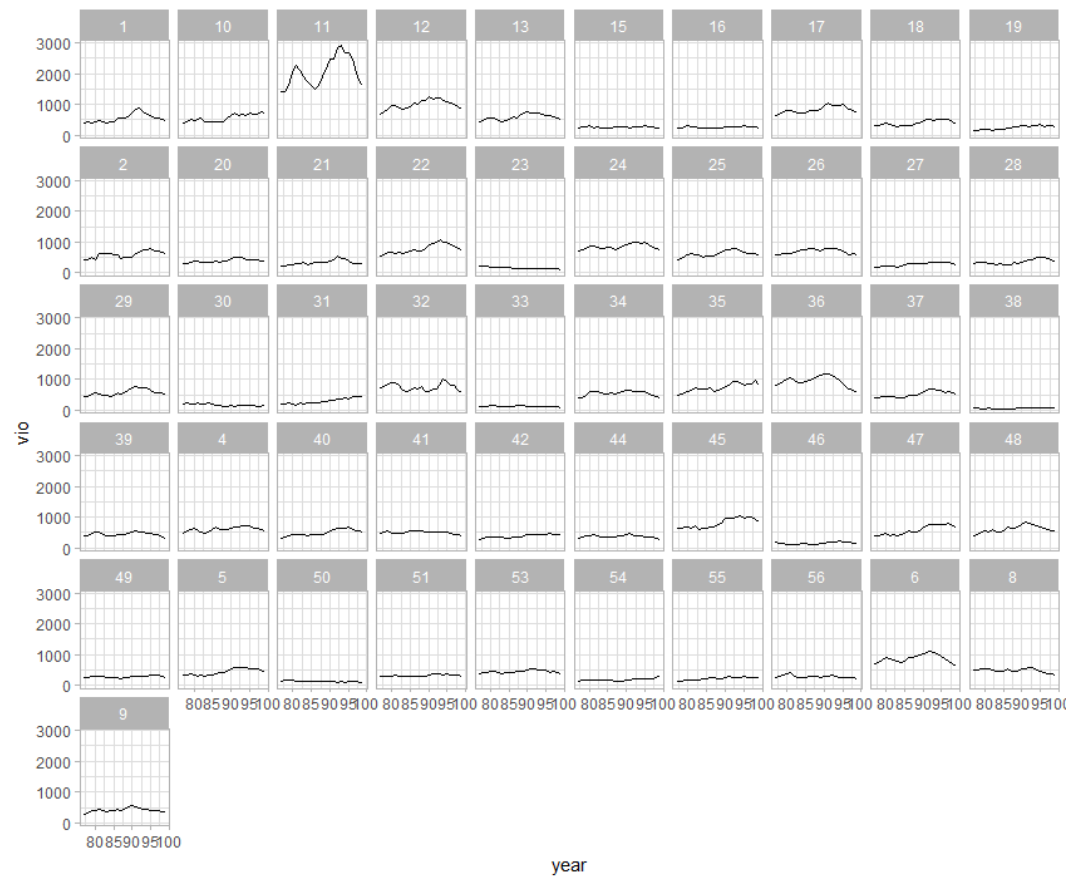
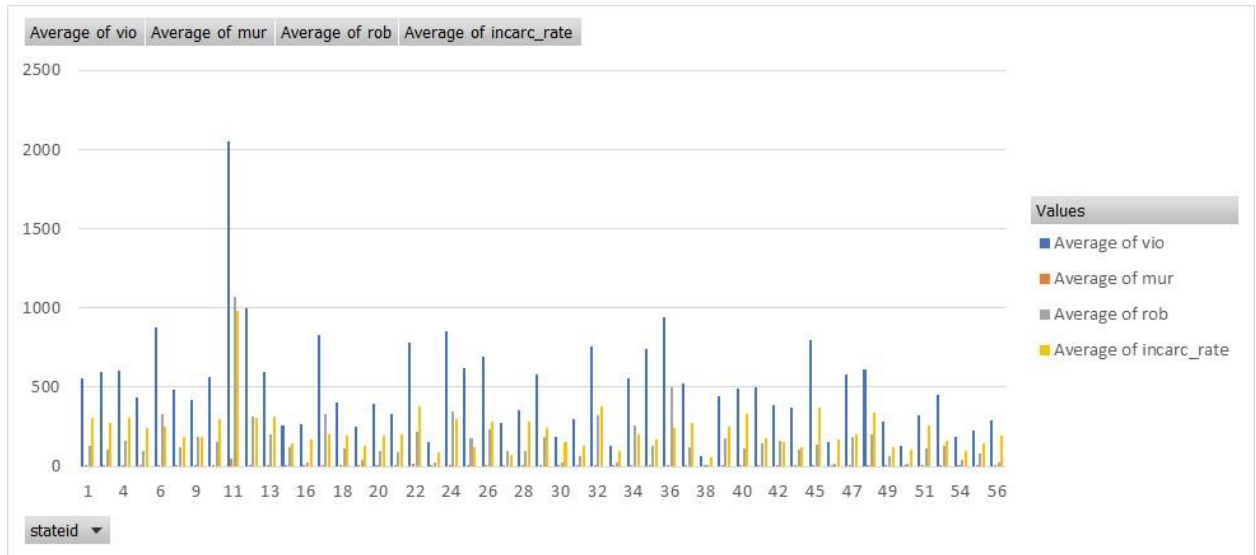
Number of State Id: 52

Variable	Mean	Standard Deviation
vio	503.1	334.2772
mur	7.665	7.52271
rob	161.8	170.51
incarc_rate	226.6	178.8881
Pb1064	5.3362	4.885688
Pw1064	62.950	9.761527
Pm1029	16.080	9.761527
Avginc	13.725	2.554543
density	0.352	1.355472

## DATA EXPLORATION

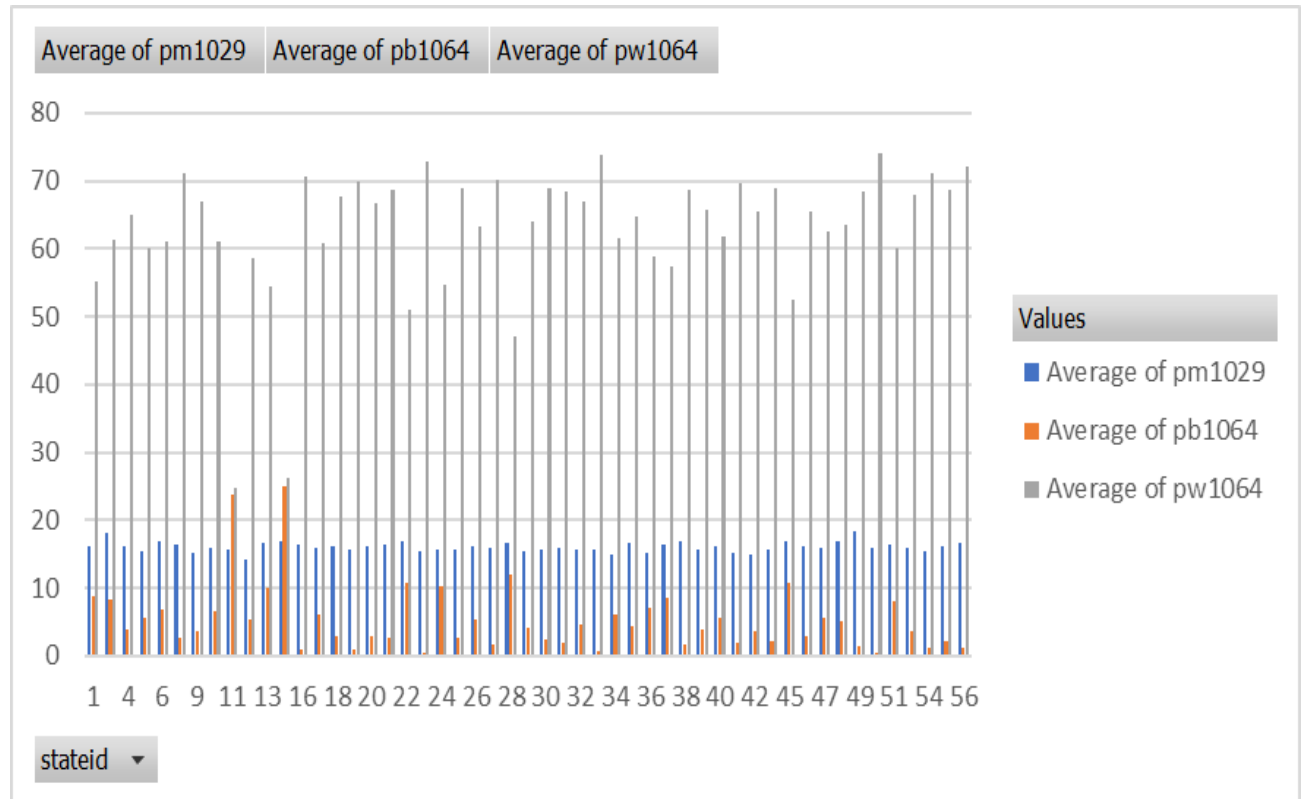
### States behavior:

We performed the Data exploration to better understand the relationship between the various variables. We first tried to observe the violent crime, robbery, murder and incarceration rate behavior across different states.



As we could see from the above two plots, State 11 has a peculiar behavior. All the rates have been very high. Let's check if we could find any reasons or explanations for these high crime rates.

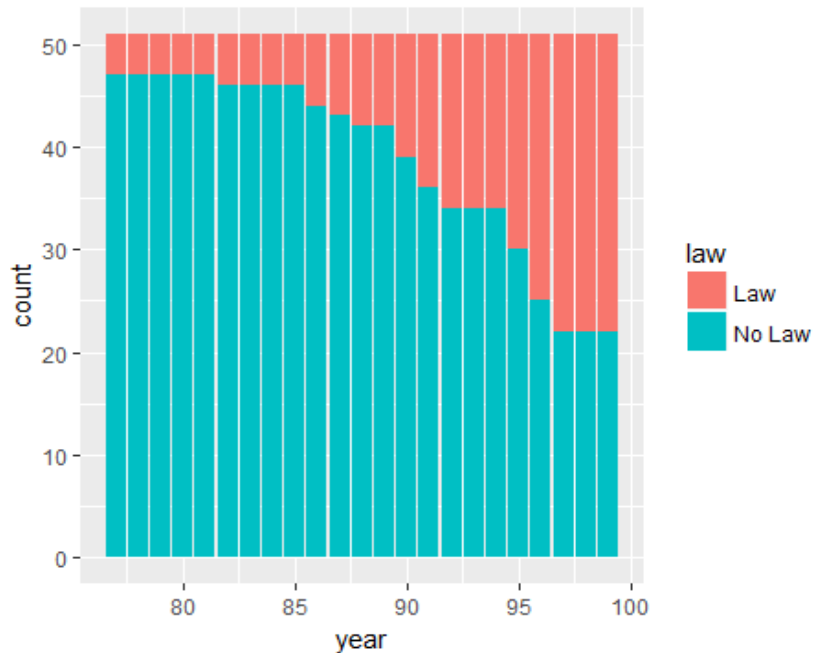
The below plot state id vs percent of state population those are male, black and Whites



As we could see from the above plots percent of state population those are blacks are high in state 11 and whites is less in state 11. This could be one possible reason for a very high crime rate in state 11.

## Distribution of shall law (Trend before Introduction and after Introduction)

Now let's check the distribution of shall law for all the states across all the years



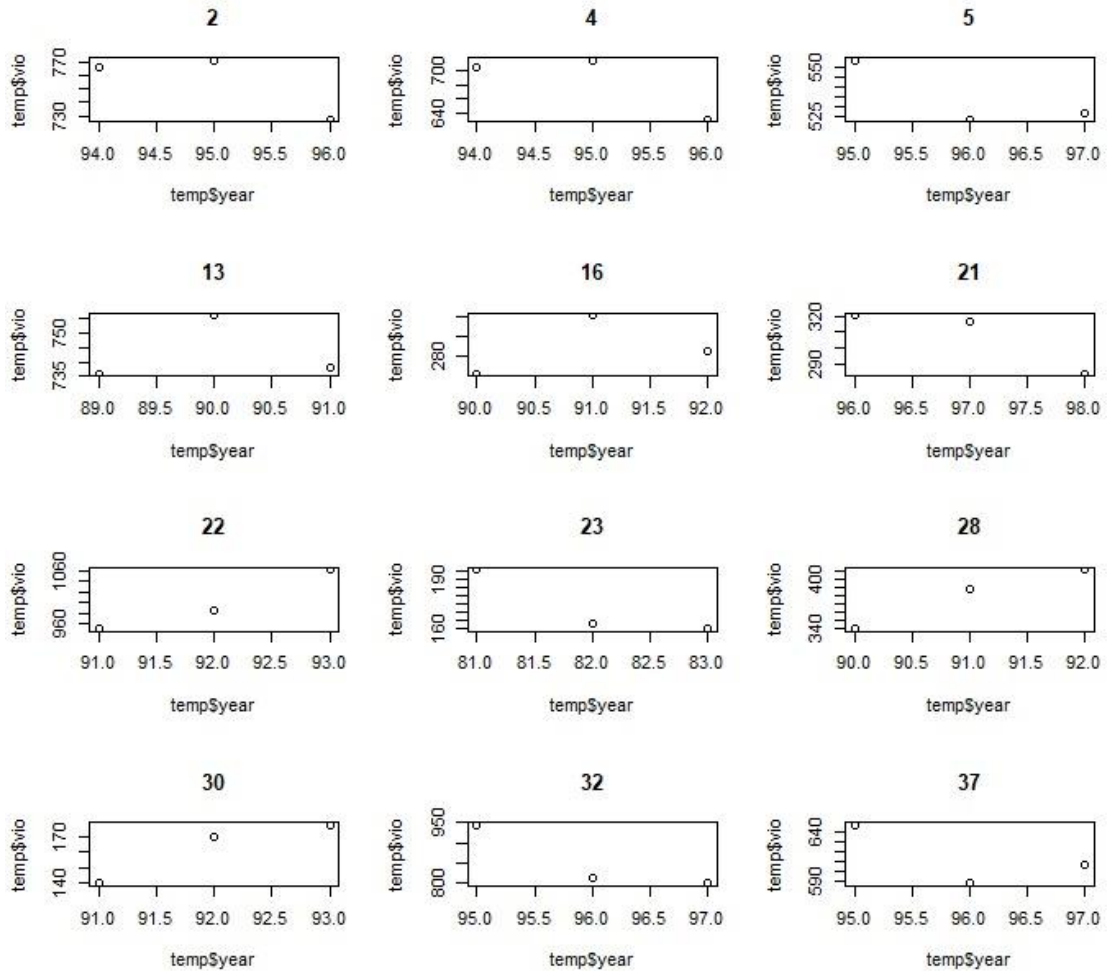
From the above graph we could say there are few states which always had state law right from the year 1977 and few never had shall law. So below are the states which never had shall law and list of states which always had shall law.

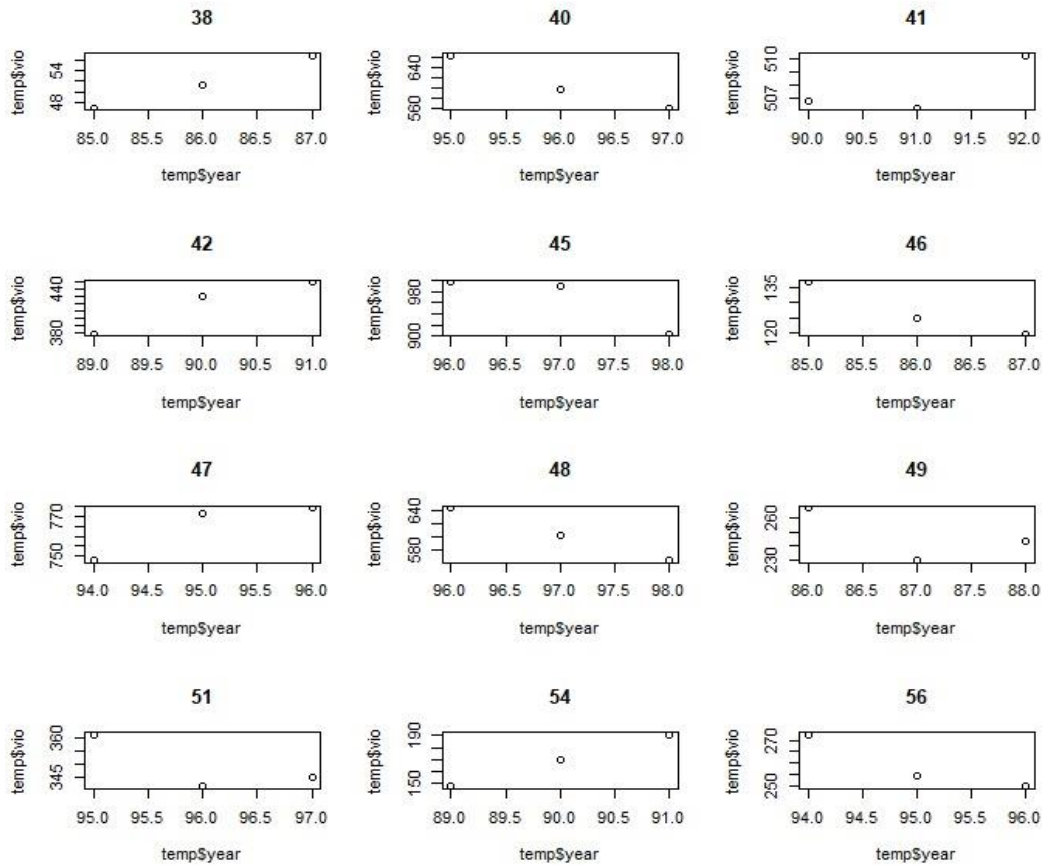
States Which never had shall law	States which always had shall law
1	18
6	33
8	50
9	53
10	
11	
15	
17	
19	
20	
24	
25	
26	
27	
29	
31	
34	
35	
36	
39	
44	
55	

Excluding both, states which always and never had shall law we tried analyzing the remaining states crime rate behavior for three different consecutives years:

- Year before the introduction of shall law
- Year of the introduction of shall law
- Year after the introduction of shall law

Below are the plots which observe violence crime rate across three different years (year before introduction, year of introduction and year after introduction shall law) for each state



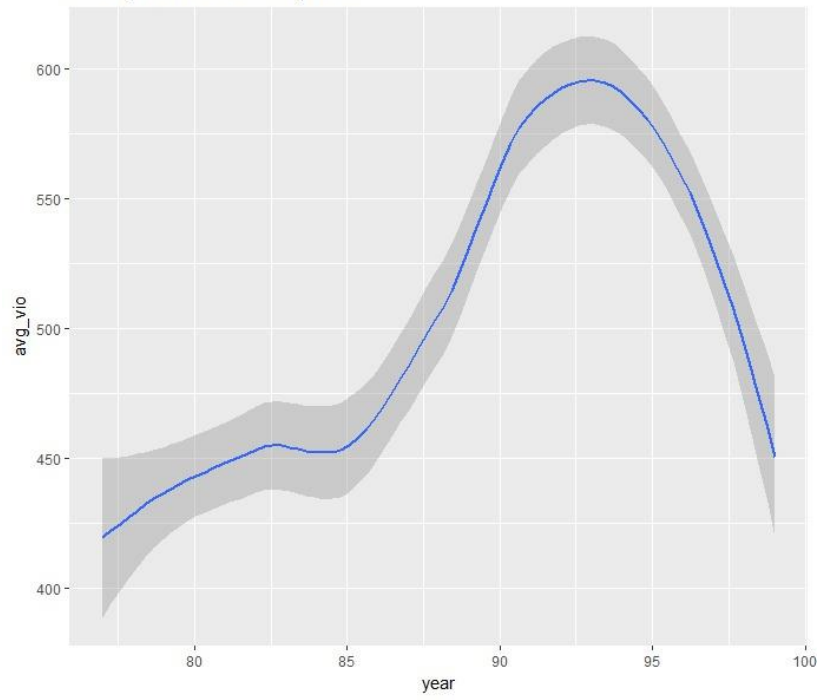


So for few states we can see the crime rates either increases or decreases the immediate years after the introduction of shall law. So there isn't any regularize trend here.

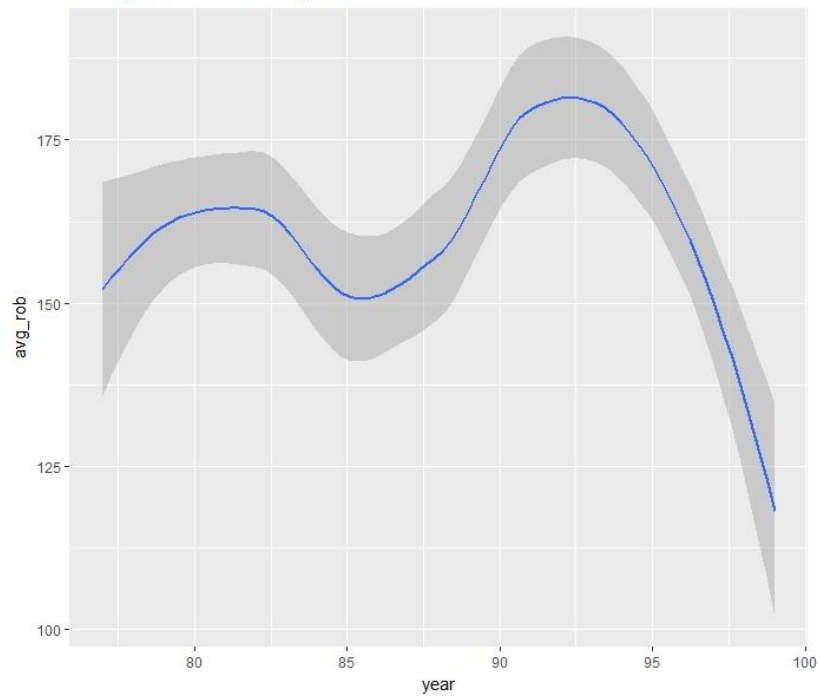
### Trend of the dependent variables across years:

Let's check out how our dependent variables violent crime, robbery and murder rate trends across all the years for all the states.

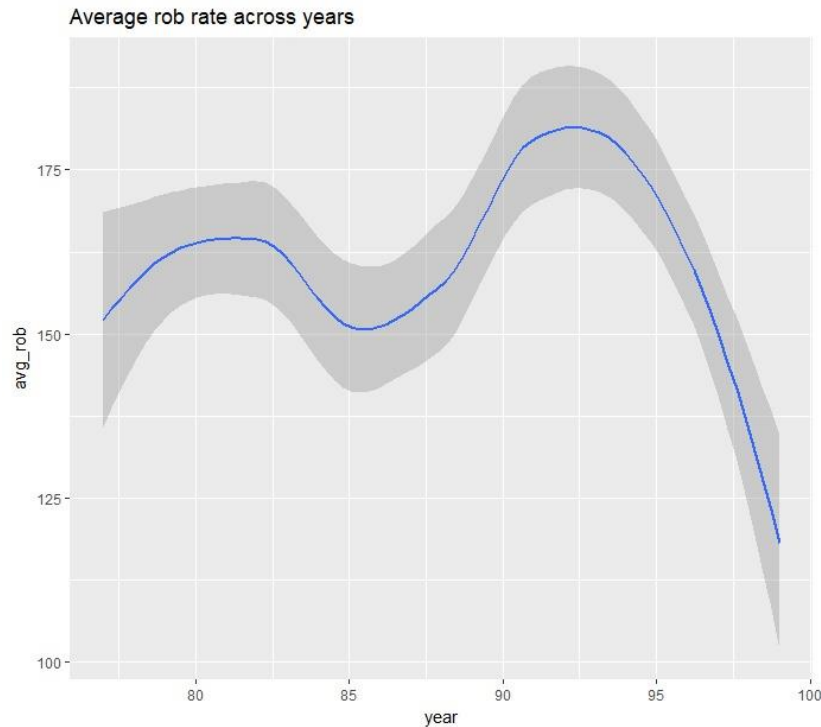
Average vio rate across years



Average rob rate across years



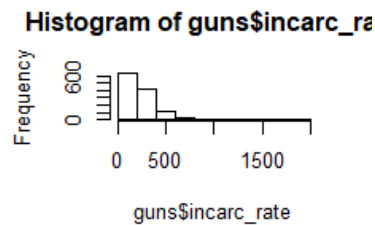
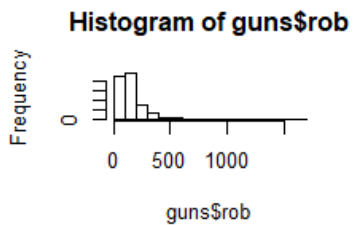
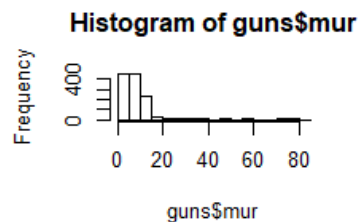
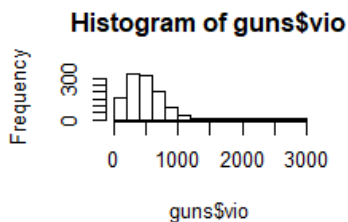


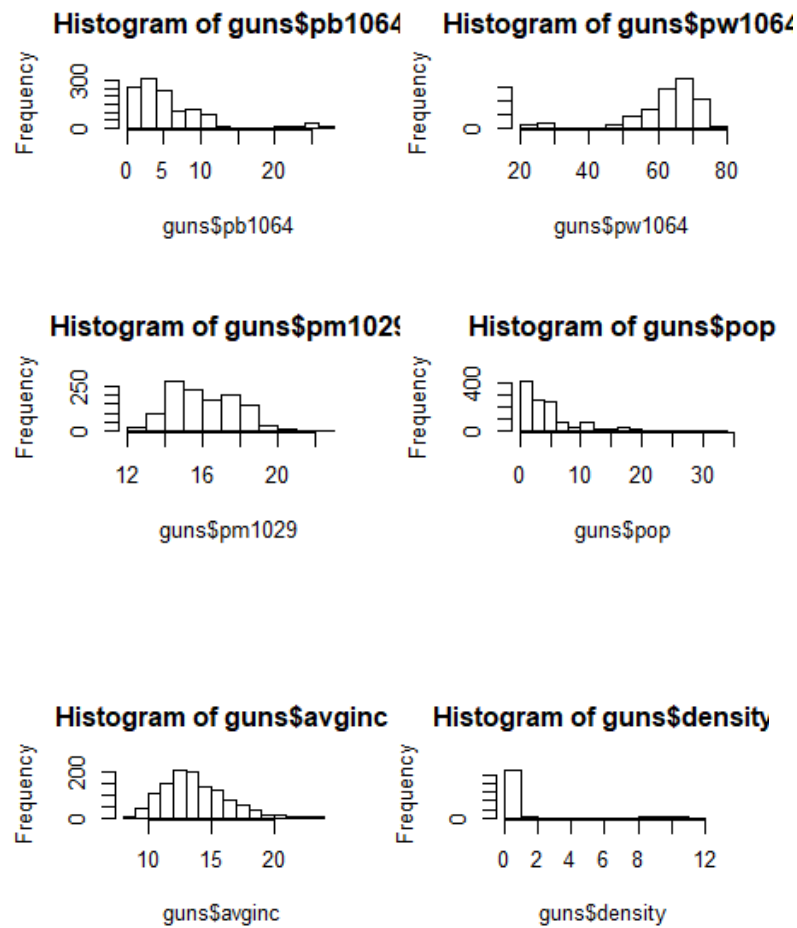


As we could see from the above plots, all the dependent variables (violent crime, murder and robbery rate) take a huge dip between the years 85 -87.

### Checking for skewness and transformation of the variables before regression:

Below are the histograms for the necessary variables used in regression and through these plots we have checked normality distribution and skewness of desired variables.





Violent crime rate, murder rate, robbery rate, incarceration rate, percent of state population that is black and density variables have been transformed using the logarithmic functions.

## REGRESSION MODELS

### Model 1: Simple Linear Regression

```
Call:
plm(formula = log(vio) ~ shall, data = guns, model = "pooling")

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

Residuals :
      Min.      1st Qu.      Median      3rd Qu.      Max.
-2.284771 -0.427476   0.046552   0.421717   1.845036

Coefficients :
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)   6.134919   0.020717  296.130 < 2.2e-16 ***
shall        -0.442965   0.042029 -10.539 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    488.63
Residual Sum of Squares: 446.3
R-Squared:              0.08664
Adj. R-Squared:         0.08586
F-statistic: 111.079 on 1 and 1171 DF, p-value: < 2.22e-16
```

In the following model above, we were simply trying to determine the relationship between  $\log(\text{vio})$  – violent crimes on a logarithmic scale – and shall-law, which is an issued law that requires that governments issue concealed carry handgun permits to any applicant who meets the necessary criteria. The data that the estimate for Shall is -0.443, which means that the presence of shall law will decrease violent crime by 44%. This estimate is also very highly significant.

## Model 2: Pooled Regression with Additional Variables; Dependent Variable = $\log(vio)$

```
Call:
plm(formula = log(vio) ~ shall + log(pb1064) + pw1064 + pm1029 +
    pop + avginc + log(density), data = guns, model = "pooling")

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

Residuals :
    Min.    1st Qu.    Median    3rd Qu.    Max.
-1.576456 -0.228143  0.024336  0.262894  1.115662

Coefficients :
              Estimate Std. Error t-value Pr(>|t|)
(Intercept)  4.0536260  0.2789434  14.5321 < 2.2e-16 ***
shall        -0.1641126  0.0316043  -5.1927 2.444e-07 ***
log(pb1064)   0.5522002  0.0283327  19.4898 < 2.2e-16 ***
pw1064        0.0183648  0.0025679   7.1518 1.510e-12 ***
pm1029       -0.0095629  0.0089141  -1.0728  0.2836
pop           0.0166243  0.0027336   6.0814 1.613e-09 ***
avginc        0.0269283  0.0060726   4.4344 1.011e-05 ***
log(density)  0.0651087  0.0098848   6.5867 6.791e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:  488.63
Residual Sum of Squares: 202.83
R-Squared: 0.58491
Adj. R-Squared: 0.58241
F-statistic: 234.514 on 7 and 1165 DF, p-value: < 2.22e-16
```

In this model, we were observing the effect of all the variables on the rate of  $\log(vio)$ . The results show that all the variables are significant except for *pm1029*, which are the percent of males between 10 and 29 years, in each state. We also note that the implementation of Shall-law shows that when shall-law is in place, there is a decrease in violent crime by 16.4%. It is also interesting to see that *avginc* leads to an increase in violent crime – we were assuming that with higher income, violent crime would go down.

## White Corrected Standard Errors (Cluster Robust) for Model 2:

Note: Coefficient variance-covariance matrix supplied: `vcovHC(model1, method = "white1")`

Call:

```
plm(formula = log(vio) ~ shall + log(pb1064) + pw1064 + pm1029 +  
    pop + avginc + log(density), data = guns, model = "pooling")
```

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

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-1.576456	-0.228143	0.024336	0.262894	1.115662

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t )	
(Intercept)	4.0536260	0.3103842	13.0600	< 2.2e-16	***
shall	-0.1641126	0.0307466	-5.3376	1.131e-07	***
log(pb1064)	0.5522002	0.0321880	17.1555	< 2.2e-16	***
pw1064	0.0183648	0.0039032	4.7050	2.842e-06	***
pm1029	-0.0095629	0.0087812	-1.0890	0.2764	
pop	0.0166243	0.0019808	8.3928	< 2.2e-16	***
avginc	0.0269283	0.0059797	4.5033	7.362e-06	***
log(density)	0.0651087	0.0099446	6.5472	8.772e-11	***

---

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

Total Sum of Squares: 488.63

Residual Sum of Squares: 202.83

R-Squared: 0.58491

Adj. R-Squared: 0.58241

F-statistic: 255.39 on 7 and 22 DF, p-value: < 2.22e-16

### Model 3: Random Effects (Between) Regression; Dependent Variable = *log(vio)*

```
call:
plm(formula = log(vio) ~ shall + log(pb1064) + pw1064 + pm1029 +
    pop + avginc + log(density), data = guns, model = "between")
```

Balanced Panel: n=23, T=51, N=1173  
Observations used in estimation: 23

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.0850211	-0.0190088	-0.0046837	0.0201807	0.0832751

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t )
(Intercept)	-1.149418	24.056305	-0.0478	0.962522
shall	-0.358819	0.471043	-0.7618	0.458017
log(pb1064)	-0.362233	2.619270	-0.1383	0.891847
pw1064	0.081341	0.034206	2.3780	0.031135 *
pm1029	-0.223431	0.067993	-3.2861	0.004999 **
pop	0.390980	1.905974	0.2051	0.840225
avginc	-0.091104	0.055725	-1.6349	0.122880
log(density)	-2.191579	6.531183	-0.3356	0.741853

---

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

Total Sum of Squares: 0.27645

Residual Sum of Squares: 0.037882

R-Squared: 0.86297

Adj. R-Squared: 0.79902

F-statistic: 13.4951 on 7 and 15 DF, p-value: 1.8941e-05

In this random effects model, the shall-law variable is not significant. Random effects is not an efficient model as this is a full panel-data and not a randomly generated data. The below Hausman Test proves our conjecture. Because the shall-law is not significant, this leads us to question whether or not shall-law presence actually reduces crime. Finally, the presence of endogeneity invalidates the use of random effects model; this is because *incarc\_rate*, which is omitted in this mode, is endogenous with variables like *avginc*, *pop*, *density*, *pb1064*, *pm1029*.

#### Hausman Test

```
data: log(vio) ~ shall + log(pb1064) + pw1064 + pm1029 + pop + avginc + ...
chisq = 44.539, df = 7, p-value = 1.681e-07
alternative hypothesis: one model is inconsistent
```



#### Model 4: Pooled OLS Regression; Dependent Variable = *log(rob)*

Call:

```
plm(formula = log(rob) ~ shall + log(pb1064) + pw1064 + pm1029 +  
    pop + avginc + log(density), data = guns, model = "pooling")
```

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

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-1.817627	-0.280232	0.011559	0.305688	1.642292

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t )	
(Intercept)	0.7900214	0.3438109	2.2978	0.02175	*
shall	-0.2442733	0.0389538	-6.2708	5.050e-10	***
log(pb1064)	0.7227407	0.0349214	20.6962	< 2.2e-16	***
pw1064	0.0265747	0.0031650	8.3964	< 2.2e-16	***
pm1029	0.0624947	0.0109870	5.6881	1.624e-08	***
pop	0.0312236	0.0033693	9.2670	< 2.2e-16	***
avginc	0.0534826	0.0074848	7.1455	1.577e-12	***
log(density)	0.2198346	0.0121835	18.0436	< 2.2e-16	***

---

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

Total Sum of Squares: 1068

Residual Sum of Squares: 308.13

R-Squared: 0.7115

Adj. R-Squared: 0.70976

F-statistic: 410.441 on 7 and 1165 DF, p-value: < 2.22e-16

In this Pooled OLS, the Shall-law (estimate = -0.244) is highly significant (p-value 5.05E-10), which reinforces, based on the last model, that Shall-law has a significant effect in the reduction of crime rate. In this model, we should really note that a 100% increase in density leads to a 22% increase in robbery rate.

## White Corrected Standard Error for Model 4:

Note: Coefficient variance-covariance matrix supplied: `vcovHC(model5, method = "white1")`

Call:

```
plm(formula = log(rob) ~ shall + log(pb1064) + pw1064 + pm1029 +  
      pop + avginc + log(density), data = guns, model = "pooling")
```

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

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-1.817627	-0.280232	0.011559	0.305688	1.642292

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t )	
(Intercept)	0.7900214	0.3359219	2.3518	0.01885	*
shall	-0.2442733	0.0389375	-6.2735	4.968e-10	***
log(pb1064)	0.7227407	0.0358930	20.1360	< 2.2e-16	***
pw1064	0.0265747	0.0035614	7.4618	1.664e-13	***
pm1029	0.0624947	0.0097486	6.4106	2.101e-10	***
pop	0.0312236	0.0032416	9.6321	< 2.2e-16	***
avginc	0.0534826	0.0067505	7.9228	5.393e-15	***
log(density)	0.2198346	0.0121512	18.0916	< 2.2e-16	***

---

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

Total Sum of Squares: 1068

Residual Sum of Squares: 308.13

R-Squared: 0.7115

Adj. R-Squared: 0.70976

F-statistic: 381.728 on 7 and 22 DF, p-value: < 2.22e-16



### Model 5: Fixed Effects (within) Regression; Dependent Variable = *log(rob)*

Oneway (individual) effect Within Model

Call:

```
plm(formula = log(rob) ~ shall + log(pb1064) + pw1064 + pm1029 +  
    pop + avginc + log(density), data = guns, model = "within")
```

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

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-1.644563	-0.271881	0.025831	0.298756	1.336477

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t )	
shall	-0.1125788	0.0406022	-2.7727	0.0056492	**
log(pb1064)	0.7741013	0.0344055	22.4994	< 2.2e-16	***
pw1064	0.0251656	0.0030616	8.2198	5.483e-16	***
pm1029	-0.0794469	0.0207173	-3.8348	0.0001325	***
pop	0.0319615	0.0032331	9.8858	< 2.2e-16	***
avginc	0.0795505	0.0076269	10.4303	< 2.2e-16	***
log(density)	0.1648016	0.0132680	12.4210	< 2.2e-16	***

---

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

Total Sum of Squares: 1057.5

Residual Sum of Squares: 277.68

R-Squared: 0.73742

Adj. R-Squared: 0.73076

F-statistic: 458.569 on 7 and 1143 DF, p-value: < 2.22e-16

~ |

In this model, we were observing the effect of all the variables on the rate of *log(rob)*. The results show that **all** the variables are significant. We also note that the implementation of Shall-law shows that when shall-law is in place, there is a decrease in violent crime by 11.25%. We should also note that an increase in the percentage of males in a state between the ages of 10-64 leads to an increase in robbery by 2.5%. This is not contradicted by percent males between the age of 10 and 29 (value of -0.079); rather, we can hypothesize that the amount of crimes – specifically robberies - occur at a greater rate outside of this age range.

## White Corrected Standard Error for Model 5

Oneway (individual) effect within Model

Note: Coefficient variance-covariance matrix supplied: `vcovHC(model9, method = "white1")`

Call:

```
plm(formula = log(rob) ~ shall + log(pb1064) + pw1064 + pm1029 +  
      pop + avginc + log(density), data = guns, model = "within")
```

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

Residuals :

	Min.	1st Qu.	Median	3rd Qu.	Max.
	-1.644563	-0.271881	0.025831	0.298756	1.336477

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t )	
shall	-0.1125788	0.0398588	-2.8244	0.004819	**
log(pb1064)	0.7741013	0.0356448	21.7171	< 2.2e-16	***
pw1064	0.0251656	0.0033467	7.5195	1.108e-13	***
pm1029	-0.0794469	0.0248932	-3.1915	0.001454	**
pop	0.0319615	0.0025053	12.7574	< 2.2e-16	***
avginc	0.0795505	0.0069261	11.4856	< 2.2e-16	***
log(density)	0.1648016	0.0146371	11.2592	< 2.2e-16	***

---

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

Total Sum of Squares: 1057.5

Residual Sum of Squares: 277.68

R-Squared: 0.73742

Adj. R-Squared: 0.73076

F-statistic: 448.559 on 7 and 22 DF, p-value: < 2.22e-16

### Model 6: Pooled OLS Regression; Dependent Variable = $\log(\text{mur})$

Pooling Model

Call:

```
plm(formula = log(mur) ~ shall + log(pb1064) + pw1064 + pm1029 +  
    pop + avginc + log(density), data = guns, model = "pooling")
```

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

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-2.874020	-0.240126	0.031565	0.266640	1.882769

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t )	
(Intercept)	0.5085763	0.3145327	1.6169	0.1061648	
shall	-0.0770425	0.0356366	-2.1619	0.0308293	*
log(pb1064)	0.5785314	0.0319476	18.1088	< 2.2e-16	***
pw1064	0.0052592	0.0028955	1.8163	0.0695768	.
pm1029	0.0395573	0.0100514	3.9355	8.793e-05	***
pop	0.0148344	0.0030824	4.8126	1.685e-06	***
avginc	-0.0291374	0.0068474	-4.2553	2.256e-05	***
log(density)	0.0424940	0.0111460	3.8125	0.0001448	***

---

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

Total Sum of Squares: 579.9

Residual Sum of Squares: 257.89

R-Squared: 0.55529

Adj. R-Squared: 0.55262

F-statistic: 207.816, Prob(F >= 207.816) = 7.111e-65, Likelihood ratio test = 207.816, p = 7.111e-65, Wald test = 207.816, p = 7.111e-65, Score test = 207.816, p = 7.111e-65

This Pooled Regression Model shows us that presence of shall-law decreases the rate of crime by 7.7%. Additionally, we should also notice that a 100% increase in pb1064 increases the rate of murder 58%. This does not seem consistent with our previous models, and also with economic theory.

## White Corrected Standard Error for Model 6

Note: Coefficient variance-covariance matrix supplied: `vcovHC(model8, method = "white1")`

Call:

```
plm(formula = log(mur) ~ shall + log(pb1064) + pw1064 + pm1029 +  
    pop + avginc + log(density), data = guns, model = "pooling")
```

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

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-2.874020	-0.240126	0.031565	0.266640	1.882769

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t )
(Intercept)	0.5085763	0.3931969	1.2934	0.1961156
shall	-0.0770425	0.0326498	-2.3597	0.0184558 *
log(pb1064)	0.5785314	0.0398924	14.5023	< 2.2e-16 ***
pw1064	0.0052592	0.0052052	1.0104	0.3125278
pm1029	0.0395573	0.0101885	3.8825	0.0001092 ***
pop	0.0148344	0.0025194	5.8881	5.104e-09 ***
avginc	-0.0291374	0.0082542	-3.5300	0.0004318 ***
log(density)	0.0424940	0.0122811	3.4601	0.0005595 ***

---

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

Total Sum of Squares: 579.9

Residual Sum of Squares: 257.89

R-Squared: 0.55529

Adj. R-Squared: 0.55262

F-statistic: 269.949 on 7 and 22 DF, p-value: < 2.22e-16



### Model 7: Fixed Effects (within) model; Dependent Variable = $\log(\text{mur})$

Oneway (individual) effect Within Model

Call:

```
plm(formula = log(mur) ~ shall + log(pb1064) + pw1064 + pm1029 +  
      pop + avginc + log(density), data = guns, model = "within")
```

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

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-2.887258	-0.217619	0.016267	0.267832	1.801066

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t )
shall	0.0014325	0.0381511	0.0375	0.97005
log(pb1064)	0.6105366	0.0323285	18.8854	< 2.2e-16 ***
pw1064	0.0046600	0.0028768	1.6199	0.10554
pm1029	-0.0400614	0.0194666	-2.0580	0.03982 *
pop	0.0152359	0.0030379	5.0153	6.135e-07 ***
avginc	-0.0155677	0.0071665	-2.1723	0.03004 *
log(density)	0.0124800	0.0124670	1.0010	0.31702

---

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

Total Sum of Squares: 567.38

Residual Sum of Squares: 245.17

R-Squared: 0.5679

Adj. R-Squared: 0.55693

F-statistic: 214.599 on 7 and 1143 DF, p-value: < 2.22e-16

In this model, we can see that the effect of shall-law is not significant. As a result, we cannot conclude that shall law has no effect on crime rate (murder rate, specifically). We believe this model is not significant, and thus do not hold it to be as significant for analysis as other models.

## White Corrected Standard Error for Model 7

Note: Coefficient variance-covariance matrix supplied: `vcovHC(model9, method = "white1")`

Call:

```
plm(formula = log(mur) ~ shall + log(pb1064) + pw1064 + pm1029 +  
      pop + avginc + log(density), data = guns, model = "within")
```

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

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-2.887258	-0.217619	0.016267	0.267832	1.801066

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t )
shall	0.0014325	0.0358374	0.0400	0.96812
log(pb1064)	0.6105366	0.0400600	15.2406	< 2.2e-16 ***
pw1064	0.0046600	0.0051750	0.9005	0.36806
pm1029	-0.0400614	0.0173053	-2.3150	0.02079 *
pop	0.0152359	0.0022155	6.8769	1.005e-11 ***
avginc	-0.0155677	0.0084555	-1.8411	0.06586 .
log(density)	0.0124800	0.0131762	0.9472	0.34375

---

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

Total Sum of Squares: 567.38

Residual Sum of Squares: 245.17

R-Squared: 0.5679

Adj. R-Squared: 0.55693

F-statistic: 286.621 on 7 and 22 DF, p-value: < 2.22e-16

**Model 8: Time-Fixed Effects; Dependent Variable =  $\log(vio)$**

```
. xtreg l(vio) avginc l(pb1064) pw1064 pm1029 pop l(density) shall i.year
```

Random-effects GLS regression

```
Number of obs      =      1,122
```

```
Group variable: stateid
```

Number of groups = 51

R-sq:

Obs per group:

```
within = 0.3832
```

```
min = 22
```

between = 0.3379

```
avg = 22.0
```

```
overall = 0.3034
```

```
max = 22
```

Wald chi2 (28) = 647.44

$$\text{corr}(u_i, X) = 0 \text{ (assumed)}$$

```
Prob > chi2      = 0.0000
```

L.vio	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
avginc	23.74642	3.949927	6.01	0.000	16.0047 31.48813
pb1064 L1.	-23.36912	10.82551	-2.16	0.031	-44.58672 -2.151518
pw1064	-13.21648	4.475623	-2.95	0.003	-21.98854 -4.444425
pm1029	18.92872	9.653024	1.96	0.050	.0091418 37.8483
pop	10.88897	3.765967	2.89	0.004	3.507809 18.27013
density L1.	-.8065723	20.76043	-0.04	0.969	-41.49626 39.88312
shall	7.277708	11.02444	0.66	0.509	-14.3298 28.88521

year						
79	22.70301	17.75766	1.28	0.201	-12.10135	57.50738
80	75.5693	17.96731	4.21	0.000	40.35401	110.7846
81	108.4018	18.39394	5.89	0.000	72.35037	144.4533
82	115.8597	19.03111	6.09	0.000	78.55938	153.16
83	94.06965	19.99422	4.70	0.000	54.8817	133.2576
84	51.34506	21.51877	2.39	0.017	9.169048	93.52107
85	45.74026	23.26491	1.97	0.049	.1418655	91.33865
86	52.03873	25.32626	2.05	0.040	2.400171	101.6773
87	77.52609	27.48105	2.82	0.005	23.66422	131.388
88	62.38316	29.89142	2.09	0.037	3.797049	120.9693
89	85.03632	32.12902	2.65	0.008	22.06461	148.008
90	131.4953	38.54087	3.41	0.001	55.95661	207.0341
91	194.9212	40.63651	4.80	0.000	115.2751	274.5672
92	213.0732	42.71659	4.99	0.000	129.3503	296.7962
93	226.1102	44.39807	5.09	0.000	139.0916	313.1288
94	230.7076	46.3441	4.98	0.000	139.8748	321.5404
95	208.7062	48.04881	4.34	0.000	114.5322	302.8801
96	191.1261	49.69597	3.85	0.000	93.72375	288.5284
97	147.1893	51.27875	2.87	0.004	46.6848	247.6938
98	113.6424	52.98939	2.14	0.032	9.785072	217.4997
99	75.51916	54.54674	1.38	0.166	-31.39047	182.4288
_cons	661.3172	264.5255	2.50	0.012	142.8568	1179.778
sigma_u	183.42242					
sigma_e	81.693351					
rho	.83446918	(fraction of variance due to u_i)				

As we can see from the following, Shall-Law is not statistically significant.



**Model 9: Time-Fixed Effects; Dependent Variable =  $\log(\text{rob})$**

```
. xtreg l(rob) avginc l(pb1064) pw1064 pm1029 pop l(density) shall i.year
```

Random-effects GLS regression

```
Group variable: stateid
```

```
Number of obs      =      1,122
```

Number of groups = 51

R-sq:

within = 0.1363

between = 0.8481

```
overall = 0.7948
```

Obs per group:

```
min = 22
```

```
avg = 22.0
```

max = 22

Wald chi2 (28) = 426.77

$$\text{corr}(u_i, X) = 0 \text{ (assumed)}$$

```
Prob > chi2      =      0.0000
```

L.rob	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avginc	3.613547	1.882773	1.92	0.055	-.0766201	7.303714
pb1064						
L1.	14.14093	4.782507	2.96	0.003	4.767384	23.51447
pw1064	3.604421	2.112938	1.71	0.088	-.5368626	7.745704
pm1029	-5.084302	4.595202	-1.11	0.269	-14.09073	3.922129
pop	8.190532	1.465071	5.59	0.000	5.319045	11.06202
density						
L1.	71.76251	7.489684	9.58	0.000	57.083	86.44202
shall	14.04603	5.509842	2.55	0.011	3.246939	24.84513

year						
79	3.506768	8.953656	0.39	0.695	-14.04208	21.05561
80	20.19741	9.051805	2.23	0.026	2.4562	37.93862
81	41.32776	9.234112	4.48	0.000	23.22923	59.42628
82	48.25439	9.525111	5.07	0.000	29.58551	66.92326
83	29.58245	9.952638	2.97	0.003	10.07564	49.08926
84	6.426879	10.61498	0.61	0.545	-14.3781	27.23186
85	-8.256485	11.39625	-0.72	0.469	-30.59272	14.07975
86	-11.75151	12.32911	-0.95	0.341	-35.91613	12.41311
87	-6.65991	13.31052	-0.50	0.617	-32.74806	19.42824
88	-18.68841	14.40299	-1.30	0.194	-46.91775	9.54093
89	-13.88655	15.41821	-0.90	0.368	-44.10569	16.33259
90	-14.09849	18.23822	-0.77	0.440	-49.84474	21.64776
91	-2.280938	19.22075	-0.12	0.906	-39.95291	35.39104
92	7.344133	20.15864	0.36	0.716	-32.16608	46.85435
93	1.901086	20.92541	0.09	0.928	-39.11197	42.91414
94	-1.704793	21.79974	-0.08	0.938	-44.4315	41.02191
95	-12.36414	22.5727	-0.55	0.584	-56.60582	31.87753
96	-18.55938	23.31341	-0.80	0.426	-64.25283	27.13406
97	-33.63889	24.00781	-1.40	0.161	-80.69334	13.41556
98	-51.38572	24.73659	-2.08	0.038	-99.86855	-2.90289
99	-70.66452	25.40956	-2.78	0.005	-120.4663	-20.8627
_cons	-170.4937	125.5578	-1.36	0.174	-416.5825	75.59508
sigma_u	63.386608					
sigma_e	43.995019					
rho	.67488259	(fraction of variance due to u_i)				

In this model, we can see that the effect of shall-law is significant, but it is not in line with our earlier conclusions from pooled and within-fixed effects model. This could be because across the years, the effect of shall-law might vary.

# Model 10: Time-Fixed Effects Model; Dependent Variable = *log(mur)*

. xtreg l(mur) avginc l(pb1064) pw1064 pm1029 pop l(density) shall i.year						
Random-effects GLS regression			Number of obs		= 1,122	
Group variable: stateid			Number of groups		= 51	
R-sq:			Obs per group:			
within = 0.1611			min =		22	
between = 0.2728			avg =		22.0	
overall = 0.2523			max =		22	
			Wald chi2(28)		= 233.00	
corr(u_i, X) = 0 (assumed)			Prob > chi2		= 0.0000	
L.mur	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
avginc	1.489501	.1278545	11.65	0.000	1.23891	1.740091
pb1064						
L1.	-.9185752	.3139253	-2.93	0.003	-1.533858	-.3032928
pw1064	-.4901172	.1427739	-3.43	0.001	-.7699489	-.2102854
pm1029	.3445237	.31176	1.11	0.269	-.2665147	.9555621
pop	-.2067578	.087819	-2.35	0.019	-.3788798	-.0346358
density						
L1.	.7173516	.4370262	1.64	0.101	-.139204	1.573907
shall	.1047491	.3864837	0.27	0.786	-.652745	.8622431

year						
79	.2719028	.6333923	0.43	0.668	-.9695233	1.513329
80	1.312694	.6400185	2.05	0.040	.0582807	2.567107
81	1.548049	.6516892	2.38	0.018	.270762	2.825337
82	1.461284	.6709244	2.18	0.029	.1462968	2.776272
83	.6028768	.6986434	0.86	0.388	-.7664391	1.972193
84	-1.111648	.7408111	-1.50	0.133	-2.563611	.3403153
85	-2.038956	.79161	-2.58	0.010	-3.590483	-.4874286
86	-2.4606	.852717	-2.89	0.004	-4.131894	-.7893052
87	-2.23416	.9173151	-2.44	0.015	-4.032065	-.4362555
88	-2.863877	.9889787	-2.90	0.004	-4.80224	-.9255147
89	-2.816036	1.055664	-2.67	0.008	-4.885098	-.746973
90	-1.555129	1.236335	-1.26	0.208	-3.978302	.868043
91	-.6583341	1.302507	-0.51	0.613	-3.2112	1.894532
92	-.7658881	1.363813	-0.56	0.574	-3.438913	1.907136
93	-1.152169	1.414497	-0.81	0.415	-3.924532	1.620194
94	-1.05208	1.471547	-0.71	0.475	-3.93626	1.8321
95	-1.653041	1.522301	-1.09	0.278	-4.636696	1.330614
96	-2.370571	1.570636	-1.51	0.131	-5.448961	.7078186
97	-3.157629	1.615131	-1.96	0.051	-6.323228	.0079692
98	-4.67281	1.660683	-2.81	0.005	-7.927688	-1.417931
99	-5.541956	1.703323	-3.25	0.001	-8.880409	-2.203504
_cons	19.50553	8.536715	2.28	0.022	2.773872	36.23718
sigma_u	2.8355229					
sigma_e	2.4897734					
rho	.56465335	(fraction of variance due to u_i)				

In this model, we can see that the effect of Shall-Law is not significant. This, as previously stated, could be because the effect of shall-law varies throughout the years.

## **CONCLUSION**

Based on initial analysis and regression models that were run, Within Fixed Effects is the best fit model for the given panel data. It is our opinion that Shall-Law is decreasing the crime rate (violence, murder, and robbery rates). The exact magnitude of impact of Shall-Law cannot be correctly gauged from this data.

