Econometrics and Time Series Analysis

Project Title: How does implementation of Shall-Issue Law affect the Crime Rates in USA

With the guidance of Prof. Moran Blueshtein

Group Members:

- Arpit Chaukiyal – Wednesday 4 PM
- Arun Kumar – Monday 4 PM
- Foram Gosrani – Wednesday 4 PM
- Pranav Shil – Wednesday 4 PM

1. Abstract.

In our study we focus on the effect of shall-issue in the 51 states (50 states + District of Columbia) in USA for a period of 23 years. We have analyzed several models to find an appropriate fit for the data we have and want to see the variation in crime rates before and after the law was introduced. We consider the effect of variables such as population density, income and the ethnic mix of the population, namely percentage of black and white males in the population. From our study we have concluded that the shall-issue law has no significant effect on the crime rate.

2. Data Description.

The data set we have is a balanced panel data of 50 states of United States, plus the District of Columbia, from year 1977 to year 1999 by year. Hence there are 51 entities in the data set and each entity has 23 row corresponds to a year between 1977 to 1999. In this data set each row represents various crime-rates of one of the 51 entity at a given year of time.

- The different crime rate given in the data set are *Violence crime rate, robbery rate and murder rate* (***vio, rob and mur*** respectively). All of these three rates are in terms of incident occurs per 100,000 members of the population.
- The variable ***shall*** indicate whether that particular state have 'shall-carry' law in effect in that particular state or not. For example, if for a particular state the 'shall-carry' law is in effect in the year of 1980 then for this particular row the value of *shall* is 1 and if the 'shall-carry' law is not in effect in the year of 1980 then for this particular row the value of *shall* is 0. This is very important variable as its value divide our data set into groups to study the effect of crime rate before and after of the introduction of the crime-law.
- ***Incarc_rate*** variable contains the information of number of sentenced prisoners per 100,000 residences in the previous year. This is very interesting variable because if the crime rate increase, the increases because the law governing body will panelize the guilty persons but also with the increase of incarceration rate the crime rate is suspected to lowers down.
- ***density*** variable contains population per square mile of land divided by 1000 for that particular state in that year.
- Population of the state in millions of people in given by variable ***pop****.*
- The population percentage of the state population that is male and whose age ranges from 10 to 29 years is provided by ***pm1029****.*
- The population percentage of the state population that is black and whose age ranges from 10 to 64 years is provided by ***pw1064****.*

3. Exploratory data Analysis:

Before doing the actual regression and obtain the fitted models, we first do a descriptive analysis to understand the data and the trends in the data over the years. For our visualization, we have used Tableau and Python.
The variable vio, mur and rob are potential dependent variables as they constitute the crimes committed and we want to understand the impact of shall laws on crime rate. According to economic theory the shall laws should be inversely correlated with crime i.e. vio, mur and rob in this case.
The order to better understand the data to get more accurate insights we have performed some exploratory data analysis, descriptive statistics and visualizations.

3.1. Summary Statistics:

Below is the summary statistics of important variables n our data set.

	vio	mur	rob	incarc_rate	pb1064	pw1064	pm1029	pop	avginc	density
count	1173.000000	1173.000000	1173.000000	1173.000000	1173.000000	1173.000000	1173.000000	1173.000000	1173.000000	1173.000000
mean	503.074681	7.665132	161.820204	226.579710	5.336217	62.945432	16.081127	4.816341	13.724796	0.352038
std	334.277195	7.522710	170.509961	178.888094	4.885688	9.761527	1.732143	5.252115	2.554543	1.355472
min	47.000000	0.200000	6.400000	19.000000	0.248207	21.780430	12.213680	0.402753	8.554884	0.000707
50%	443.000000	6.400000	124.099998	187.000000	4.026213	65.061279	15.895169	3.271332	13.401551	0.081569
max	2921.800049	80.599998	1635.099976	1913.000000	26.979570	76.525749	22.352686	33.145123	23.646713	11.102116

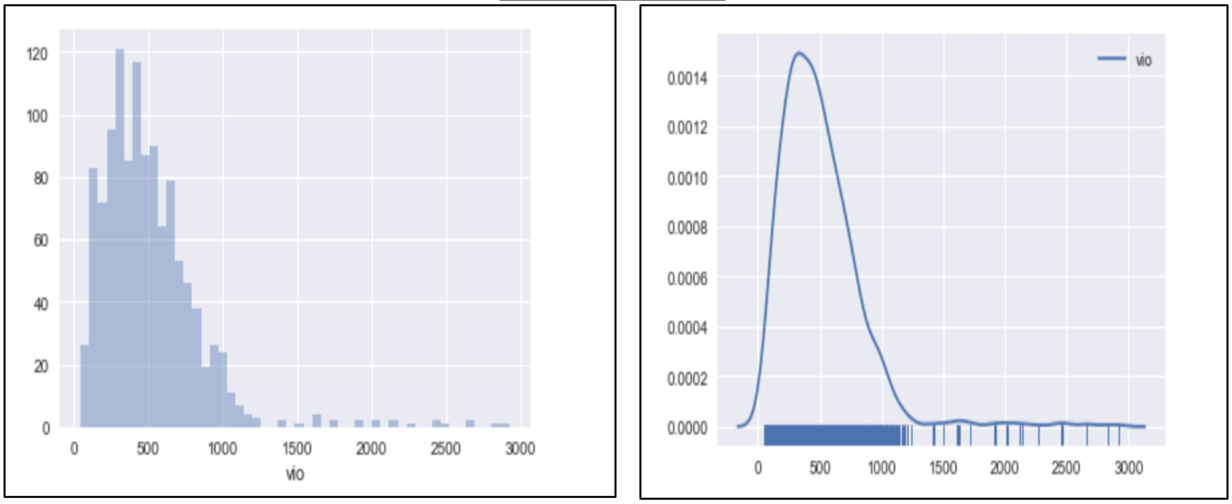
As form the above summary statistics we can see that all the variables have the same count. Hence it is inferred that we do not have any missing data issue in our data set. One interesting this which can be inferred from this summary statistic is as follows:

- **vio:** the minimum value of this variable is 47.0 and maximum value is 2921.8 but the 50% data lies on and below is 433.0. So, we suspect skewness in the data.
- **mur:** the minimum value of this variable is 0.20 and maximum value is 80.59 but the 50% data lies on and below is 6.4. So, we suspect skewness in the data.
- **rob:** the minimum value of this variable is 6.40 and maximum value is 1635.09 but the 50% data lies on and below is 124.09. So, we suspect skewness in the data.

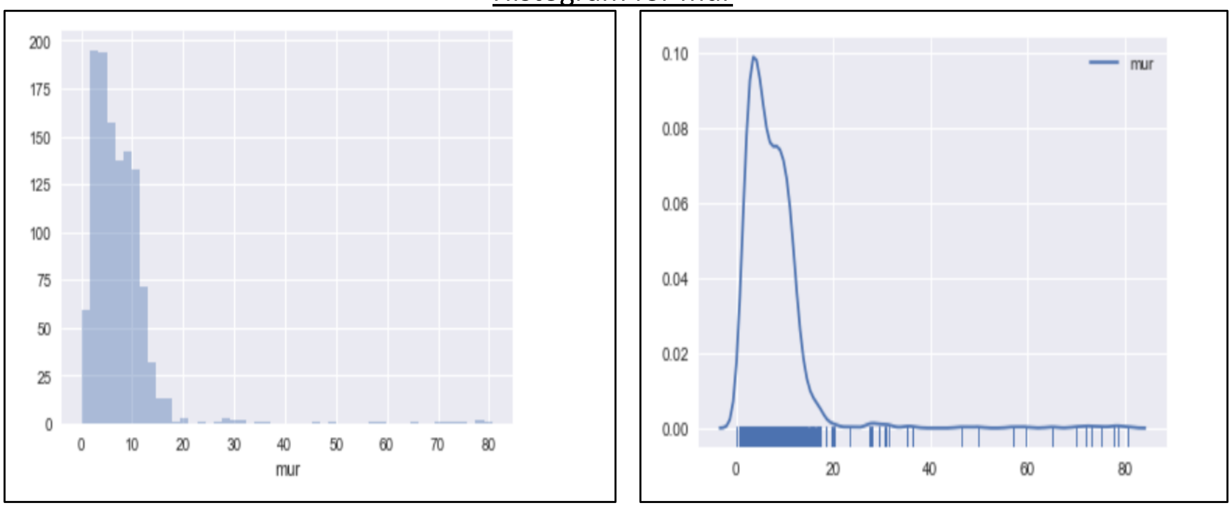
3.2. Histograms:

To confirm our suspicion from the summary statistics we plotted the histogram for all the three variables.

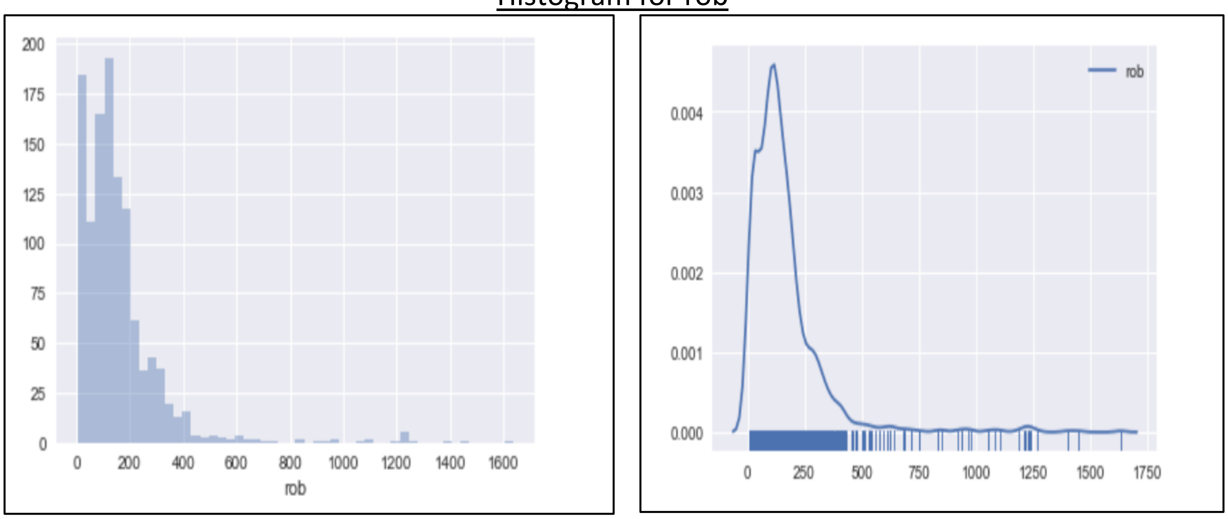
Histogram for vio



Histogram for mur

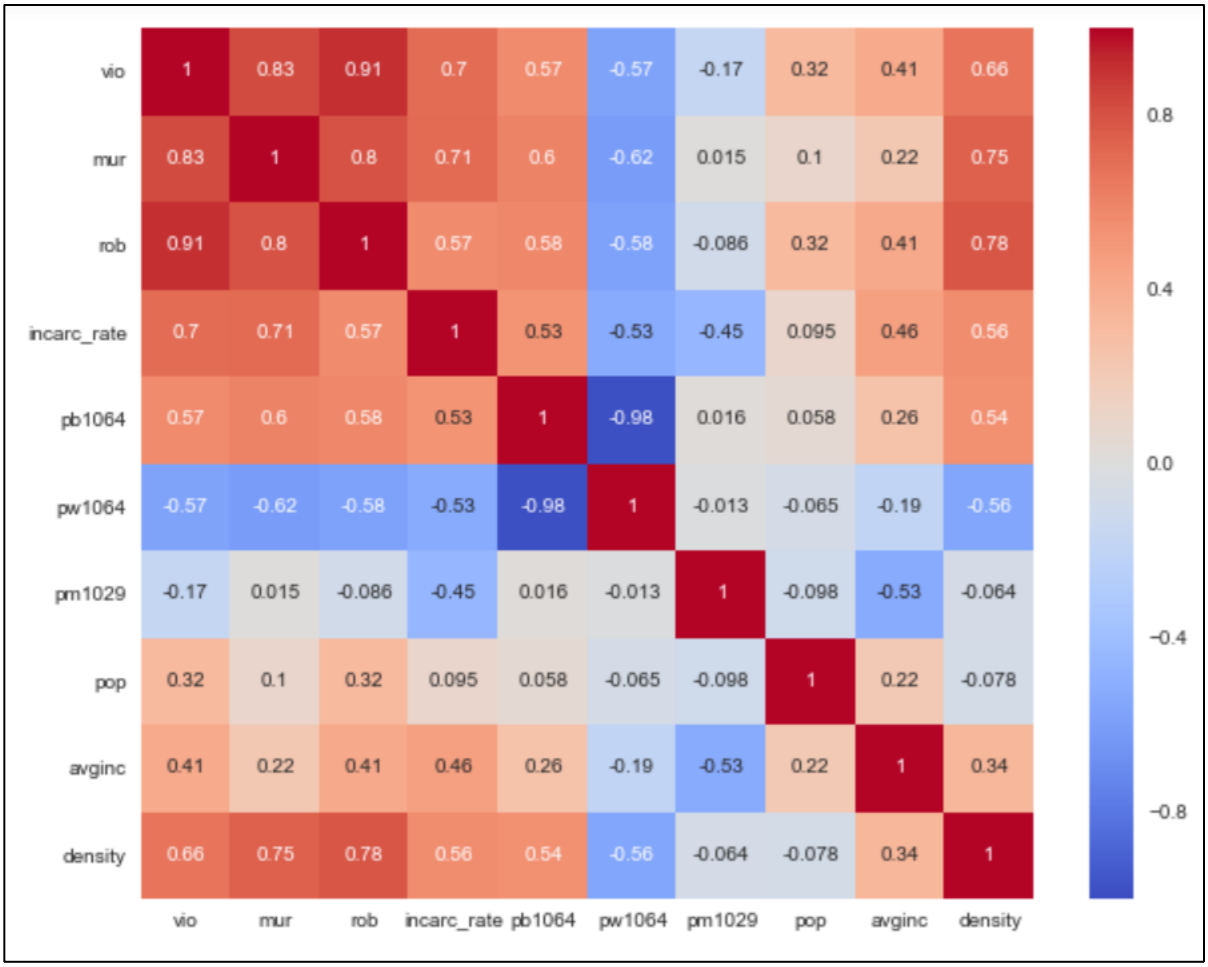


Histogram for rob



3.3. <u>Correlation Between the variables</u>

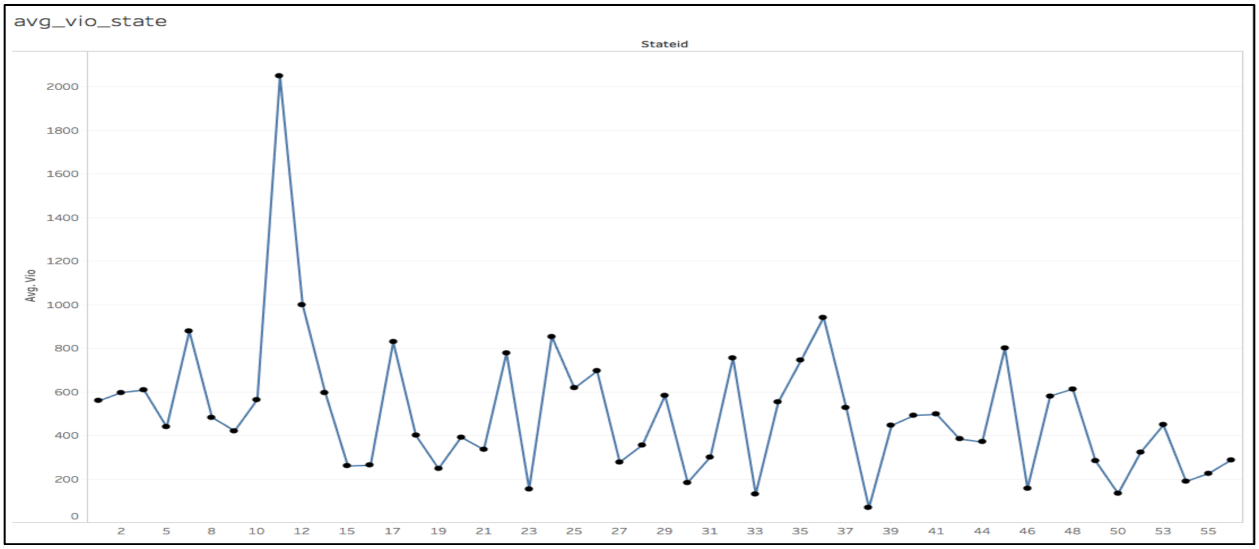
To analyse the correlation between the variables we made the correlation matrix of all the variables. From the matrix below it is clear thar variables *vio, mur and rob* are highly positivey correlated in our data set. This correlation ca be explained by the economic theory. Futhermore there a moderate correlation between *incarc_rate* and *vio, mur* & *rob* which is justified. There is a strong negative correlation exist in between balck and white polulation (*pw1064* & *pb1064*) this is due to the fact that in a give state and time there should be either of them.



Correlation matrix

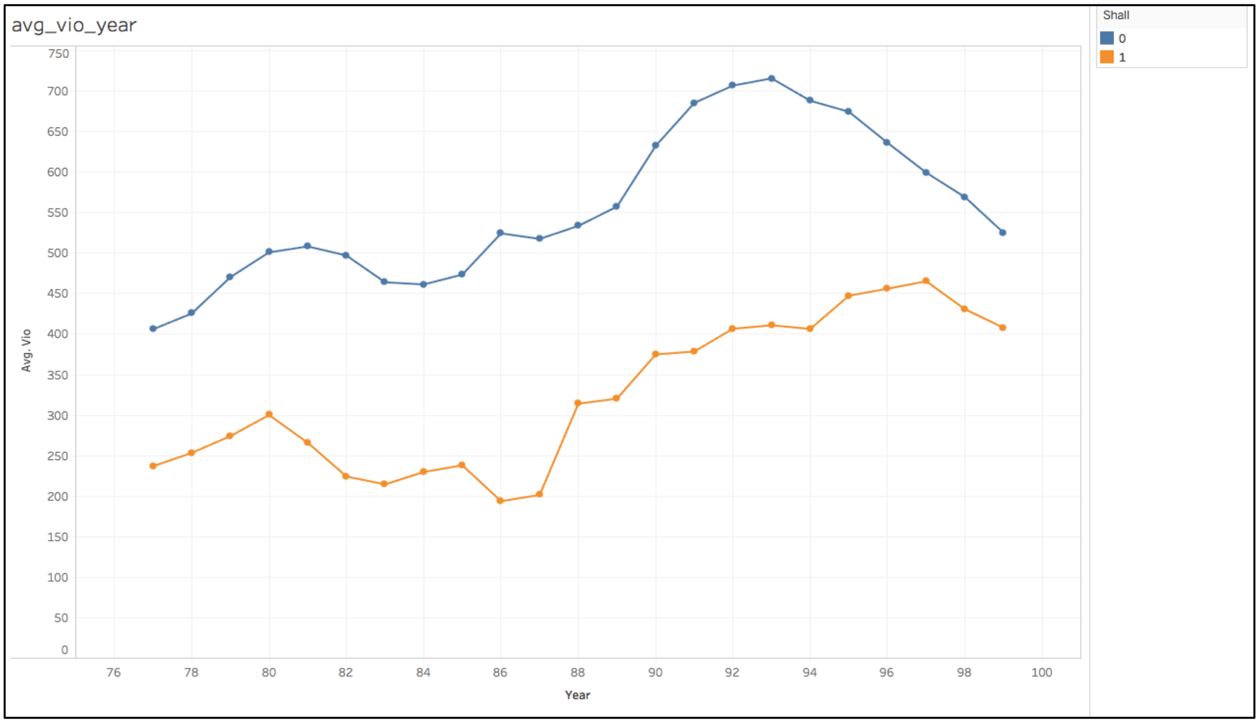
3.4. Violence (avg) rate

We plotted the trend of average violence rate over the years and for each state to get more better understanding of our data set.



Average violence across different states

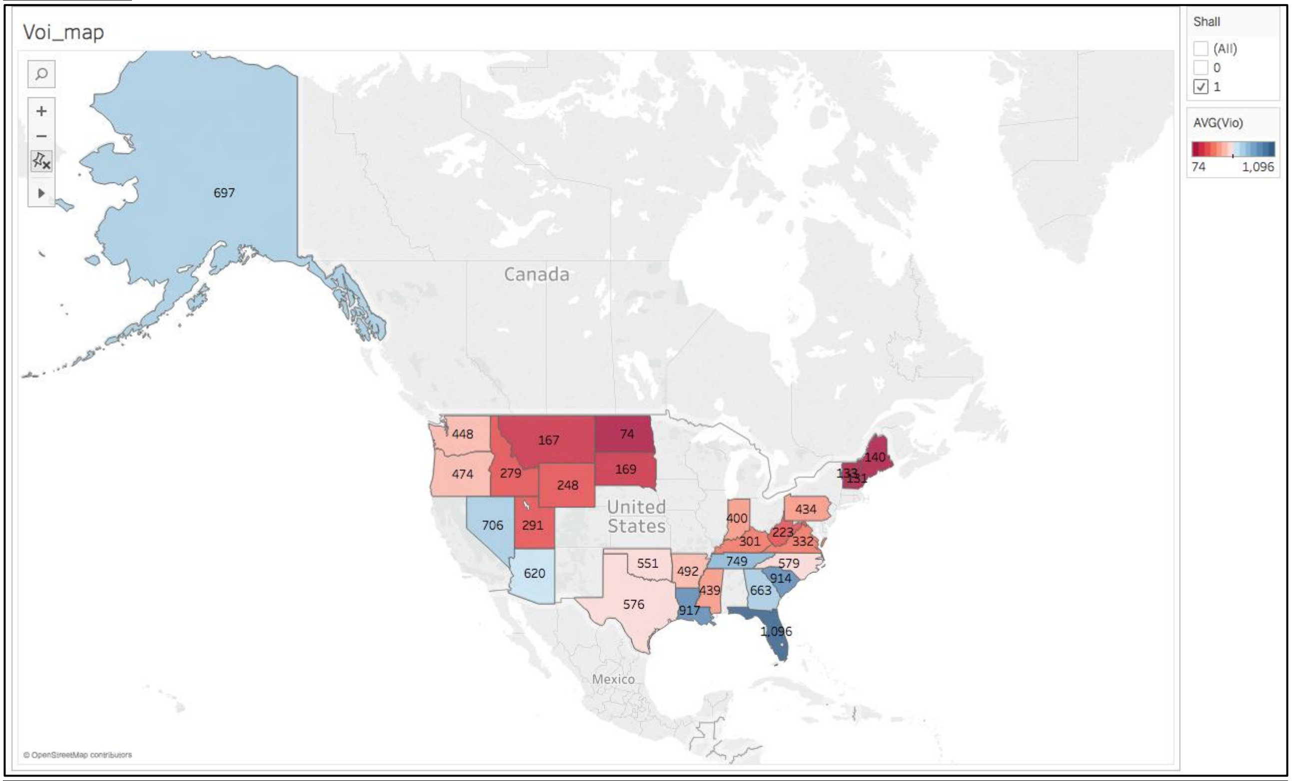
The above graph depicts the avgrage violence rate across different sates. As it is clear from the graph that *stateid* 11 (District of Columbia) there is an exceptional increase in the violence rate as compared to the other state of United States.



Average violence trends across the years

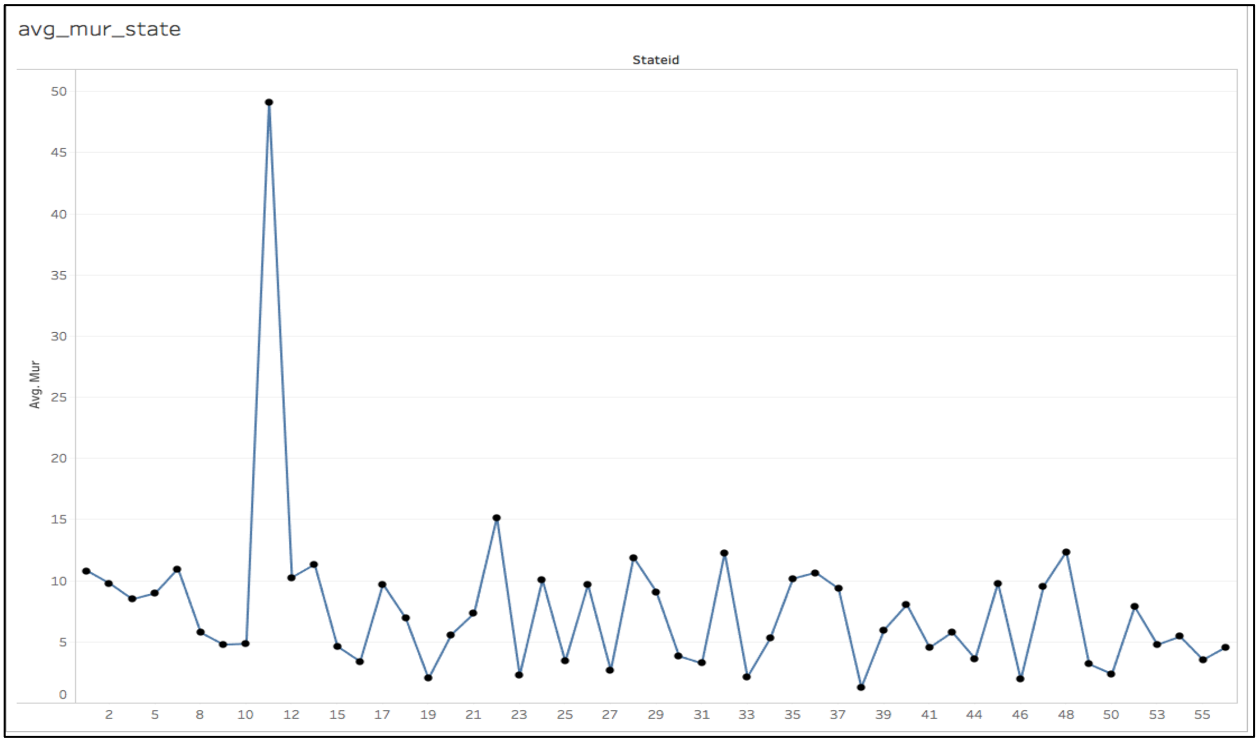
The above graph shows the average violence rate trends over the years from 1977 to 1999. The blue trend line dipicts the average violence rate for all those states where ‘shall-carry’ in not in effect and orange trend line dipicts the average violence rate for all those states where ‘shall-carry’ in in effect. As suspected the average violence rate is lower for the states where ‘shall-carry’ in in effect as compared to those where it is not in effect.

Heat Map



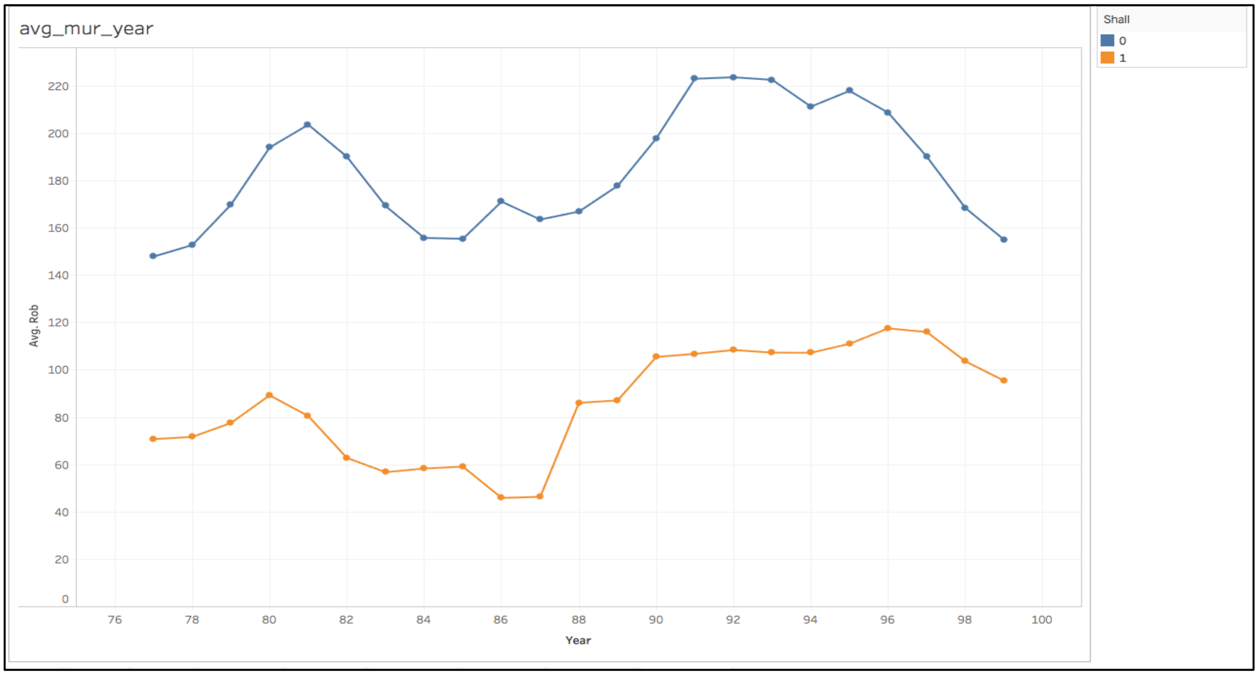
3.5. Mudder (avg) rate

Just like the violence rate, we plotted the trend of average murdder rate over the years and for each state to get more better understanding of our data set.



Average mudder across different states

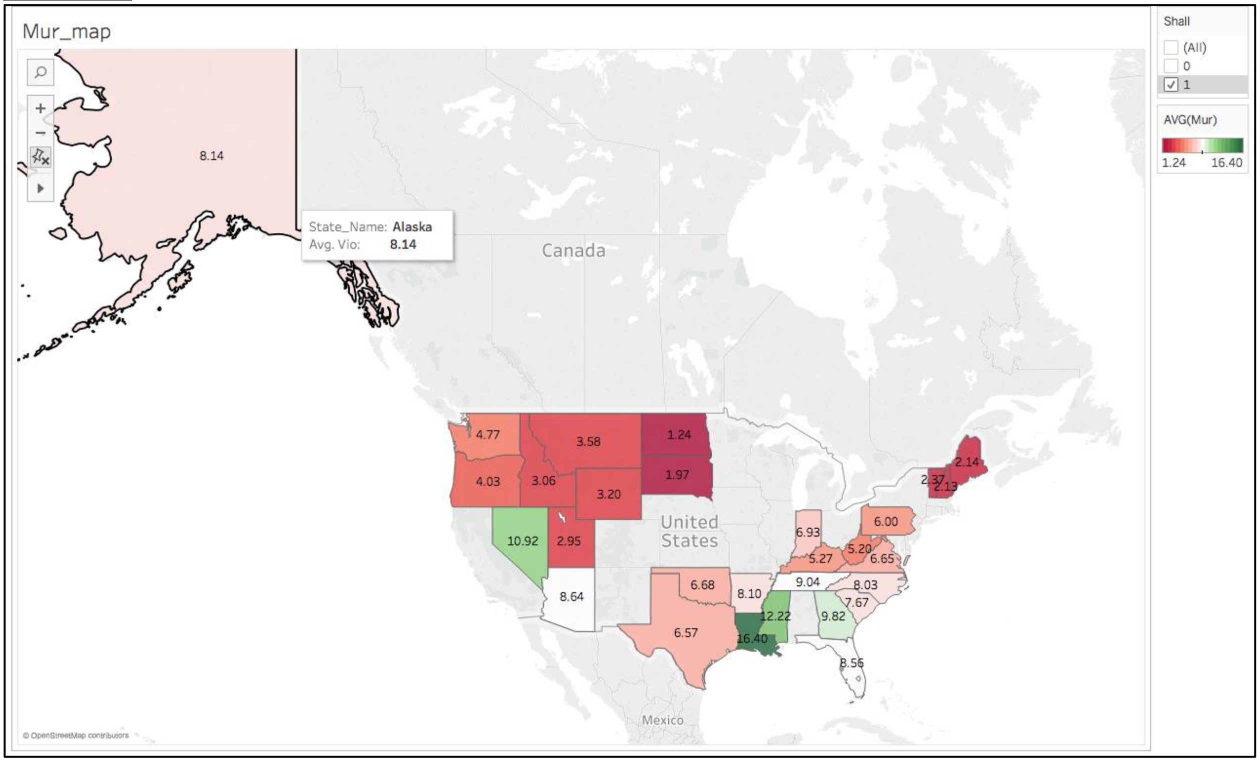
The above graph depicts the average murder rate across different sates. As it is clear from the graph that *stateid* 11 (District of Columbia) there is an exceptional increase in the murder rate as compared to the other state of United States the similar trend what we saw in average voilence graph above.



Average murder trends across the year

The above graph shows the average murder rate trends over the years from 1977 to 1999. The blue trend line dipicts the average violence rate for all those states where 'shall-carry' in not in effect and orange trend line dipicts the average violence rate for all those states where 'shall-carry' in in effect. As suspected the average murder rate is lower for the states where 'shall-carry' in in effect as compared to those where it is not in effect.

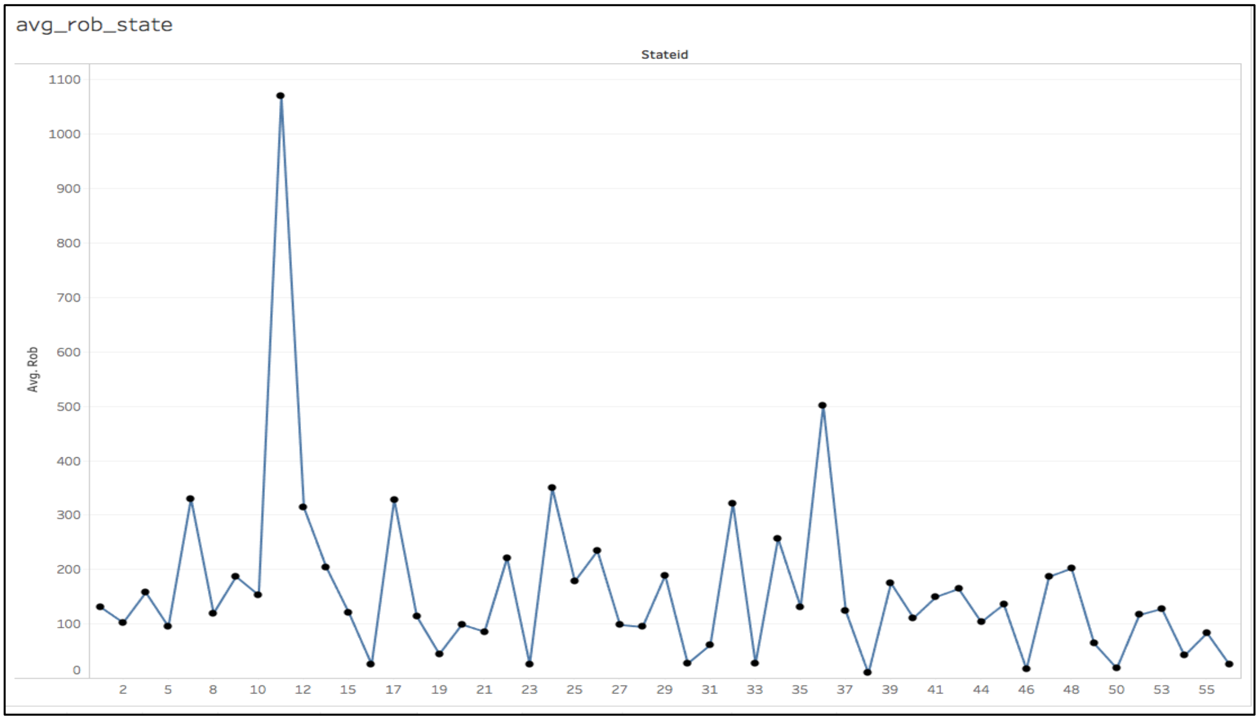
Heat Map



3.6. Robbery (avg) rate

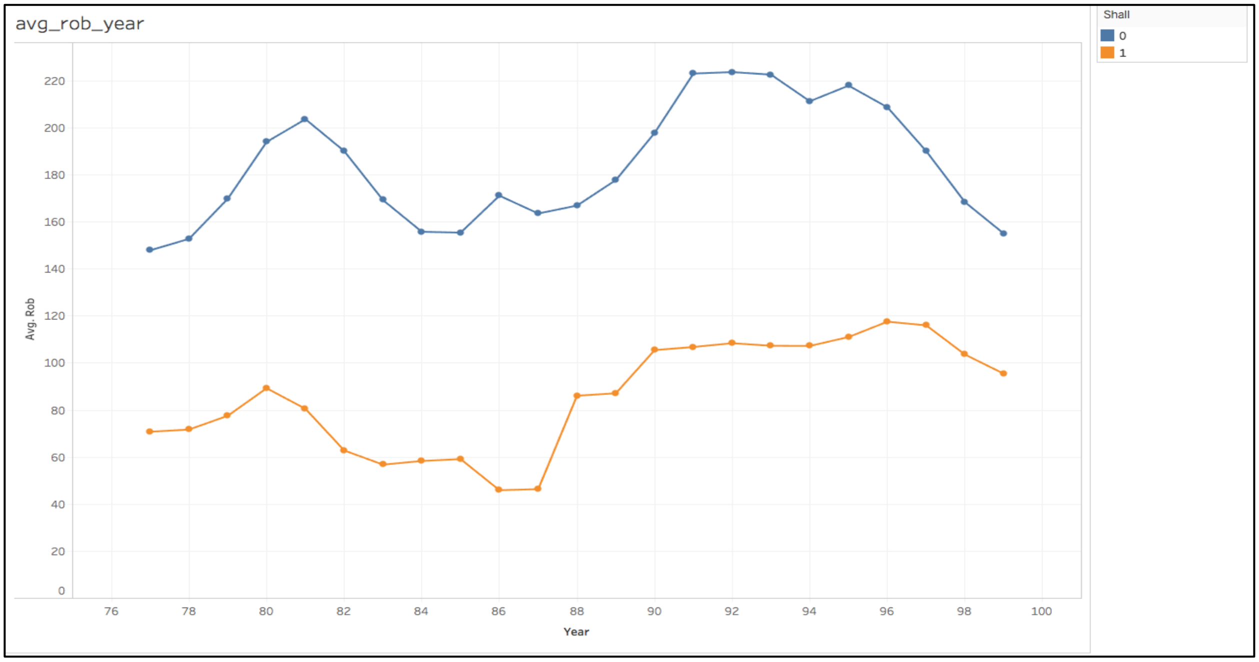
Just like the violence rate and the murder rate, we plotted the trend of average robbery rate over the years and for each state to get more better understanding of our data set.

The below graph depicts the avgrage robbery rate across different sates. As it is clear from the graph that *stateid* 11 (District of Columbia) there is an exceptional increase in the robbery rate as compared to the other state of United States, the similar trend what we saw in average voilence graph and average murder graphs above.



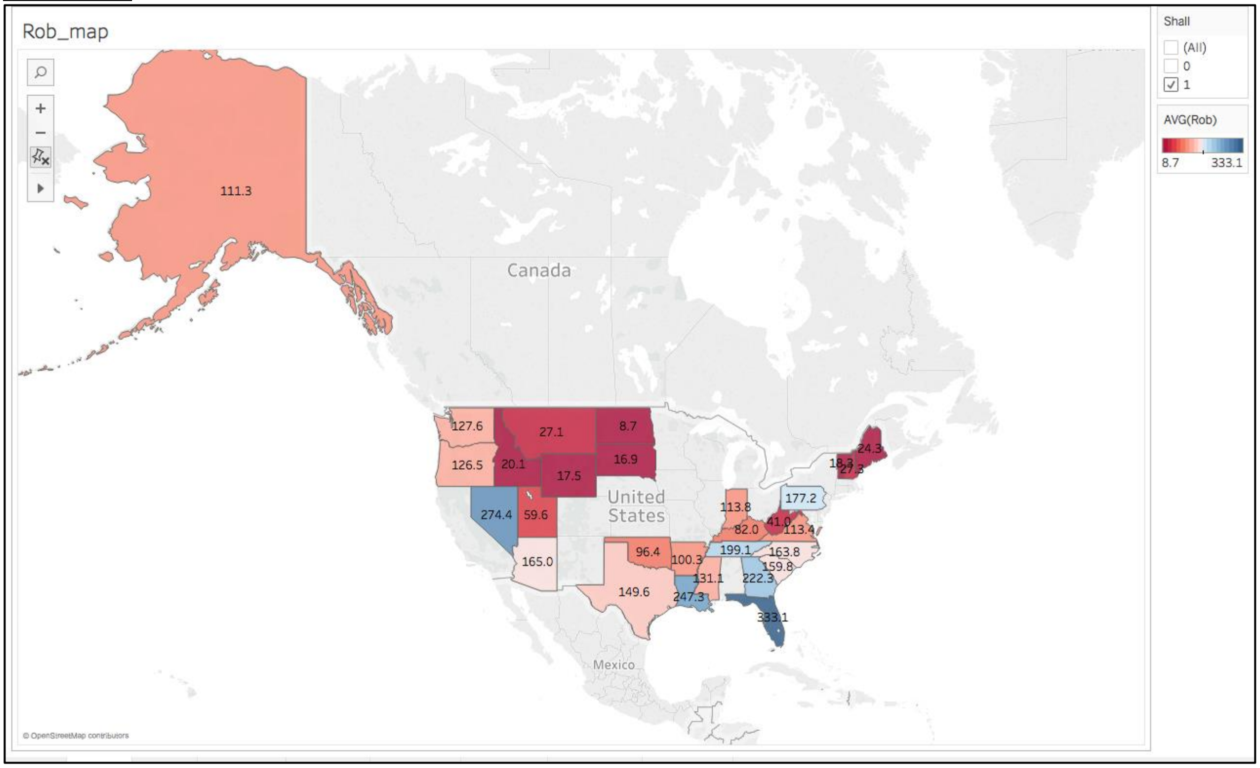
Average robbery across different states

The below graph shows the average robbery rate trends over the years from 1977 to 1999. The blue trend line dipicts the average violence rate for all those states where 'shall-carry' in not in effect and orange trend line dipicts the average violence rate for all those states where 'shall-carry' in in effect. As suspected the average robbery rate is lower for the states where 'shall-carry' in in effect as compared to those where it is not in effect.



Average robbery trends across the years

Heat Map



The graphs of violence rate, murder rate and robbery rate are pretty much similar. This can be explained by the high correlation which we found between these three variables in our correlation matrix.

4. Regression Models:

As now we had completed our EDA, and we are familiar with our data, we ran several models of our data set to find statistical relationships between shall law, violence rate, murder rate and robbery rate.

Since, in our exploratory data analysis we founded that violence rate, murder rate and robbery rate are highly skewed, hence we cannot take all these three variables directly. To make these variables normalized we have taken the log of these variable and used these normalized variables in our model.

4.1. Violence Rates.

LINEAR REGRESSION:

```
Call:
lm(formula = file_data$vio ~ file_data$shall)
```

Output

```
Residuals:
    Min      1Q  Median      3Q     Max
-495.24 -228.84  -63.64  134.06 2379.56

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)        542.24      10.98  49.386  < 2e-16 ***
file_data$shall1  -161.19      22.27  -7.236 8.32e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 327.2 on 1171 degrees of freedom
Multiple R-squared:  0.0428,    Adjusted R-squared:  0.04199
F-statistic: 52.36 on 1 and 1171 DF,  p-value: 8.319e-13
```

Output Analysis:

1. We run a regular regression on the model with Shall Law as the independent variable. We observe that for once Shall Law has been implemented, the violence rate comes down by 161%, which is extremely huge number.

POOLED OLS

```
Call:
plm(formula = log(vio) ~ shall + incarc_rate + pb1064 + pw1064 +
    pm1029 + pop + avginc + density, data = file_data, model = "pooling",
    index = c("stateid", "year"))
```

Output

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.723001 -0.266205  0.047669  0.304780  1.059977

Coefficients:
               Estimate  Std. Error  t-value  Pr(>|t|)
(Intercept)  2.98173825  0.54339379   5.4873 5.006e-08 ***
shall1      -0.36838695  0.03256743 -11.3115 < 2.2e-16 ***
incarc_rate  0.00161263  0.00010716  15.0495 < 2.2e-16 ***
pb1064       0.08085260  0.01665138   4.8556 1.364e-06 ***
pw1064       0.03120051  0.00837759   3.7243 0.0002053 ***
pm1029       0.00887088  0.01077367   0.8234 0.4104577
pop          0.04270983  0.00255883  16.6912 < 2.2e-16 ***
avginc       0.00120512  0.00778022   0.1549 0.8769305
density      0.02668847  0.01316805   2.0268 0.0429146 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    488.63
Residual Sum of Squares: 212.92
R-Squared:      0.56426
Adj. R-Squared: 0.56126
F-statistic: 188.411 on 8 and 1164 DF, p-value: < 2.22e-16
>
```

Output Analysis:

1. **Shall-Law**: The negative coefficient for the coefficient implies that the value has come down extremely from the linear regression model. Which further asserts that the value was overestimated in the previous output. According to pooled OLS, the violence rate comes down by 36.83% after the implementation of the law.
2. **Incarceration rate**: While this variable is significant, the percentage change after implementation of law is positive 0.16% which means that increase in implementation will increase the incarceration rate. Which is a case of simultaneous causality bias. When violence rate goes up, the police will put more people in prison which will bring down the crime rate.
3. **Population Density**: As the population density increases by 1%, the violence rate increases 2.6% which indicates, denser the state, more is the violence rate which is as expected in the real-world sense.
4. **Population of Blacks**: As the number of blacks increase by 1%, the violence rate will increase by 8.0%. Which is biased but significant results at 5% level of significance.

ENTITY FIXED-EFECT MOEL

```
> model_3<-plm(log(vio)~shall+log(incarc_rate)+pb1064+pw1064+avginc+I(avginc*avginc)
+             +pop+density+pm1029,index=c("stateid","year"),model="within",data=file_data)
> summary(model_3)
```

Output

```
Oneway (individual) effect Within Model

Call:
plm(formula = log(vio) ~ shall + log(incarc_rate) + pb1064 +
    pw1064 + avginc + I(avginc * avginc) + pop + density + pm1029,
    data = file_data, model = "within", index = c("stateid",
        "year"))

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.4887577 -0.0922696  0.0048568  0.0952031  0.5539989

Coefficients:
                      Estimate  Std. Error t-value  Pr(>|t|)
shall1              -0.07634139  0.01847384 -4.1324 3.859e-05 ***
log(incarc_rate)    -0.04611789  0.02760637 -1.6706   0.09509 .
pb1064               0.10335904  0.01755168  5.8888 5.145e-09 ***
pw1064               0.02588163  0.00551108  4.6963 2.980e-06 ***
avginc               0.20154294  0.02593146  7.7721 1.747e-14 ***
I(avginc * avginc) -0.00667070  0.00080903 -8.2453 4.603e-16 ***
pop                  0.00642304  0.00822049  0.7813   0.43477
density             -0.38525595  0.06813498 -5.6543 1.988e-08 ***
pm1029              -0.04015551  0.00811945 -4.9456 8.759e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 26.999
R-Squared:      0.26612
Adj. R-Squared: 0.22722
F-statistic: 44.8448 on 9 and 1113 DF, p-value: < 2.22e-16
```

Coefficients of this model:

```
> coeftest(model_3, vcovHC)

t test of coefficients:

                     Estimate Std. Error t value  Pr(>|t|)
shall1             -0.0763414  0.0410303 -1.8606 0.0630628 .
log(incarc_rate)   -0.0461179  0.0624597 -0.7384 0.4604498
pb1064              0.1033590  0.0359910  2.8718 0.0041588 **
pw1064              0.0258816  0.0134655  1.9221 0.0548525 .
avginc              0.2015429  0.0568173  3.5472 0.0004055 ***
I(avginc * avginc) -0.0066707  0.0018121 -3.6812 0.0002433 ***
pop                 0.0064230  0.0113586  0.5655 0.5718637
density            -0.3852560  0.1082564 -3.5587 0.0003883 ***
pm1029             -0.0401555  0.0225681 -1.7793 0.0754632 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>
```

Output Analysis:

1. **Shall Law**: As we move to fixed effects, we understand that pooled OLS overestimated Shall-Law by approximately 8 times. Upon output of Fixed Effects, as the implementation of law helps bring down the violence rate by about 7.6%, which was 36% in the previous output.
2. **Incarceration Rate**: The output here is somewhat as expected. As the implantation of law increases, the incarceration rate decreases by 4.6% which means: law is implemented, violence rate decreases, incarceration rate also decreases.
3. **Average Income**: Once the average income is increased quadratically, the violence rate drops by 0.67%. Which is means there could be many exogenous variables affecting the model.
4. **Population Density**: The value of coefficient has increased slightly which means, as population density increases by 1%, the violence rate comes down further by 38.52%
5. **Omitted Variable Bias**: We can possible consider other variables that have affected these results. For example, the education levels in the states, the attitudes of people towards weapons and usage, the cultural inclinations of the population. These variables also contribute towards the outcome of the model.

ENTITY AND TIME FIXED EFFECT MODEL

```
> fixed_time <- plm(log(vio)~factor(year)+shall+incarc_rate+pb1064+pw1064+pm1029+pop
+                   +avginc+density, data=file_data, index=c("stateid", "year"),     model="within")
> summary(fixed_time)
```

Output

```
Coefficients:
                  Estimate  Std. Error t-value  Pr(>|t|)
factor(year)78  5.8526e-02  2.8137e-02  2.0800   0.03776 *
factor(year)79  1.6395e-01  2.8595e-02  5.7335 1.272e-08 ***
factor(year)80  2.1708e-01  2.9089e-02  7.4626 1.728e-13 ***
factor(year)81  2.1726e-01  3.0107e-02  7.2161 9.990e-13 ***
factor(year)82  1.9463e-01  3.1705e-02  6.1388 1.162e-09 ***
factor(year)83  1.5864e-01  3.3962e-02  4.6712 3.367e-06 ***
factor(year)84  1.9299e-01  3.7489e-02  5.1479 3.122e-07 ***
factor(year)85  2.4448e-01  4.0979e-02  5.9659 3.283e-09 ***
factor(year)86  3.2409e-01  4.4955e-02  7.2092 1.049e-12 ***
factor(year)87  3.2437e-01  4.9068e-02  6.6105 5.978e-11 ***
factor(year)88  3.8674e-01  5.3661e-02  7.2071 1.064e-12 ***
factor(year)89  4.4221e-01  5.7918e-02  7.6352 4.906e-14 ***
factor(year)90  5.4305e-01  7.0971e-02  7.6517 4.343e-14 ***
factor(year)91  5.9595e-01  7.4423e-02  8.0076 2.978e-15 ***
factor(year)92  6.2752e-01  7.8597e-02  7.9840 3.568e-15 ***
factor(year)93  6.4974e-01  8.1660e-02  7.9566 4.399e-15 ***
factor(year)94  6.3542e-01  8.5452e-02  7.4360 2.093e-13 ***
factor(year)95  6.2768e-01  8.9120e-02  7.0431 3.320e-12 ***
factor(year)96  5.7134e-01  9.2561e-02  6.1726 9.453e-10 ***
factor(year)97  5.5012e-01  9.5891e-02  5.7369 1.248e-08 ***
factor(year)98  4.9329e-01  9.9779e-02  4.9439 8.860e-07 ***
factor(year)99  4.3288e-01  1.0333e-01  4.1892 3.026e-05 ***
shall1         -2.7994e-02  1.7158e-02 -1.6315   0.10307
incarc_rate     7.5995e-05  9.0284e-05  0.8417   0.40013
pb1064          2.9186e-02  2.2692e-02  1.2862   0.19865
pw1064          9.2501e-03  7.8617e-03  1.1766   0.23961
pm1029          7.3325e-02  1.5614e-02  4.6962 2.988e-06 ***
pop            -4.7544e-03  7.8675e-03 -0.6043   0.54576
avginc          9.5865e-04  6.4349e-03  0.1490   0.88160
density        -9.1555e-02  7.6282e-02 -1.2002   0.23032
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 21.411
R-Squared:      0.418
Adj. R-Squared: 0.37536
F-statistic: 26.1427 on 30 and 1092 DF, p-value: < 2.22e-16
```

Coefficients of this model:

```
> coeftest(fixed_time, vcovHC)  ##Test for heteroskedasticity

t test of coefficients:

                 Estimate  Std. Error t value  Pr(>|t|)    
factor(year)78  5.8526e-02  1.5790e-02  3.7065 0.0002207 ***
factor(year)79  1.6395e-01  2.3905e-02  6.8583 1.164e-11 ***
factor(year)80  2.1708e-01  3.2663e-02  6.6459 4.746e-11 ***
factor(year)81  2.1726e-01  3.8310e-02  5.6710 1.816e-08 ***
factor(year)82  1.9463e-01  4.5521e-02  4.2756 2.073e-05 ***
factor(year)83  1.5864e-01  5.8042e-02  2.7333 0.0063720 ** 
factor(year)84  1.9299e-01  7.5261e-02  2.5642 0.0104729 *  
factor(year)85  2.4448e-01  9.0137e-02  2.7123 0.0067871 ** 
factor(year)86  3.2409e-01  1.0646e-01  3.0444 0.0023876 ** 
factor(year)87  3.2437e-01  1.2216e-01  2.6552 0.0080417 ** 
factor(year)88  3.8674e-01  1.3655e-01  2.8323 0.0047071 ** 
factor(year)89  4.4221e-01  1.5006e-01  2.9468 0.0032788 ** 
factor(year)90  5.4305e-01  1.9165e-01  2.8335 0.0046890 ** 
factor(year)91  5.9595e-01  1.9946e-01  2.9879 0.0028721 ** 
factor(year)92  6.2752e-01  2.1212e-01  2.9583 0.0031605 ** 
factor(year)93  6.4974e-01  2.1954e-01  2.9596 0.0031473 ** 
factor(year)94  6.3542e-01  2.2797e-01  2.7873 0.0054074 ** 
factor(year)95  6.2768e-01  2.3688e-01  2.6498 0.0081709 ** 
factor(year)96  5.7134e-01  2.4768e-01  2.3068 0.0212527 *  
factor(year)97  5.5012e-01  2.5544e-01  2.1536 0.0314921 *  
factor(year)98  4.9329e-01  2.6845e-01  1.8376 0.0663957 .  
factor(year)99  4.3288e-01  2.7975e-01  1.5474 0.1220619    
shall1         -2.7994e-02  3.9796e-02 -0.7034 0.4819441    
incarc_rate     7.5995e-05  2.0319e-04  0.3740 0.7084685    
pb1064          2.9186e-02  4.8421e-02  0.6028 0.5467921    
pw1064          9.2501e-03  2.3219e-02  0.3984 0.6904275    
pm1029          7.3325e-02  5.1287e-02  1.4297 0.1530876    
pop            -4.7544e-03  1.4885e-02 -0.3194 0.7494775    
avginc          9.5865e-04  1.6120e-02  0.0595 0.9525898    
density        -9.1555e-02  1.2106e-01 -0.7563 0.4496538    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Output Analysis:

1. **Shall Law**: The value of the coefficient in Shall Law is now almost equal to zero. Which means the implementation of the law is now almost has no significant impact on the violence rate.
2. The output results using time effects are not much better and significant. This means that this model is better than all the previous models.

We now perform the F Test to check if the implementation of the law has same impact in all the states:

F test:

```
> pFtest(fixed_time, model_3) #Test of individual and/or time effects based on the

        F test for individual effects

data:  log(vio) ~ factor(year) + shall + incarc_rate + pb1064 + pw1064 +  ...
F = 13.57, df1 = 21, df2 = 1092, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Output Analysis:
H0: The implementation has the same impact in all the states for violence rate
H1: At least one state has a different rate upon implementation

F-value: 13.57 which is greater than 10 which means it is statistically significant
Therefore, we reject the null hypothesis.

This implies that at least one of states has a different violence rate.

4.2. Murder Rate:

POOLED OLS

1. First, we did the regression of the of the murder rate against the shall law alone.

```
> pooled_model<- plm(log(mur)~shall,data=file_data, model ="pooling",index=c("stateid","year"))
> summary(pooled_model)
```

Output:

```
Pooling Model

Call:
plm(formula = log(mur) ~ shall, data = file_data, model = "pooling",
    index = c("stateid", "year"))

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

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-3.03362 -0.48657  0.10187  0.46289  2.49194

Coefficients:
             Estimate Std. Error t-value  Pr(>|t|)
(Intercept)  1.897556   0.022609  83.928 < 2.2e-16 ***
shall1      -0.473372   0.045869 -10.320 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    579.9
Residual Sum of Squares: 531.56
R-Squared:      0.08337
Adj. R-Squared: 0.082587
F-statistic: 106.506 on 1 and 1171 DF, p-value: < 2.22e-16
```

Coefficients of this model:

```
> coeftest(pooled_model, vcovHC)

t test of coefficients:

             Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.897556   0.092184 20.5845  < 2e-16 ***
shall1      -0.473372   0.147338 -3.2128  0.00135 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

2. Our second model is the pooled OLS model with all the variables

```
> pooled_model1<-plm(log(mur)~shall+incarc_rate+pb1064+pm1029+pop
+                   +avginc,data=file_data,model ="pooling",index=c("stateid","year"))
> summary(pooled_model1)
```

Output:

```
Pooling Model

Call:
plm(formula = log(mur) ~ shall + incarc_rate + pb1064 + pm1029 +
    pop + avginc, data = file_data, model = "pooling", index = c("stateid",
    "year"))

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-2.547825 -0.242108  0.062302  0.313254  1.202410

Coefficients:
               Estimate  Std. Error t-value  Pr(>|t|)
(Intercept)  0.21196813  0.22479730  0.9429    0.3459
shall1      -0.26818289  0.03293639 -8.1424 9.873e-16 ***
incarc_rate  0.00215622  0.00010355 20.8236 < 2.2e-16 ***
pb1064       0.04037887  0.00344981 11.7047 < 2.2e-16 ***
pm1029       0.08979682  0.01033920  8.6851 < 2.2e-16 ***
pop          0.03824620  0.00257736 14.8393 < 2.2e-16 ***
avginc      -0.05074996  0.00658523 -7.7066 2.752e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    579.9
Residual Sum of Squares: 234.7
R-Squared:      0.59528
Adj. R-Squared: 0.5932
F-statistic: 285.838 on 6 and 1166 DF, p-value: < 2.22e-16
```

Coefficients of this model:

```
> coeftest(pooled_model1, vcovHC)

t test of coefficients:

              Estimate  Std. Error t value  Pr(>|t|)
(Intercept)  0.21196813  0.76701233  0.2764 0.7823240
shall1      -0.26818289  0.08875518 -3.0216 0.0025692 **
incarc_rate  0.00215622  0.00050884  4.2375 2.438e-05 ***
pb1064       0.04037887  0.02294123  1.7601 0.0786530 .
pm1029       0.08979682  0.03401190  2.6402 0.0083974 **
pop          0.03824620  0.01028409  3.7190 0.0002096 ***
avginc      -0.05074996  0.02136700 -2.3752 0.0177025 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Output Analysis:

1. **Shall Law:** Our first model estimates that on implementing the shall-law will reduce the murder rate by 47% while in our second model this estimate drops to 26.8%. The reason behind this is due to the fact that in our second model we have include other variables. Our first model have omitted variable bias.
2. **Variable pb1064:** From the above results this variable is not significant at 95% significance level.

ENTITY FIXED-EFFECT MODEL

```
> fe_model_mur <-plm(log(mur)~shall+log(incarc_rate)+pb1064+pw1064+pm1029
+                    +avginc+density+pop,data=file_data, model ="within", index=c("stateid","year"))
> summary(fe_model_mur)
```

Output:

```
Oneway (individual) effect Within Model

Call:
plm(formula = log(mur) ~ shall + log(incarc_rate) + pb1064 +
    pw1064 + pm1029 + avginc + density + pop, data = file_data,
    model = "within", index = c("stateid", "year"))

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.6910831 -0.1158345 -0.0010569  0.1238851  0.8894331

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
shall1           -0.0688337  0.0254212 -2.7077 0.0068783 **
log(incarc_rate) -0.1720664  0.0385247 -4.4664 8.765e-06 ***
pb1064            0.0465690  0.0245469  1.8971 0.0580676 .
pw1064            0.0168079  0.0071043  2.3659 0.0181583 *
pm1029            0.0167073  0.0108066  1.5460 0.1223831
avginc            0.0275250  0.0080371  3.4248 0.0006377 ***
density          -0.4928947  0.0863167 -5.7103 1.446e-08 ***
pop              -0.0292536  0.0114829 -2.5476 0.0109807 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    63.314
Residual Sum of Squares: 53.069
R-Squared:      0.16181
Adj. R-Squared: 0.11817
F-statistic: 26.8827 on 8 and 1114 DF, p-value: < 2.22e-16
```

Coefficients of this model:

```
> coeftest(fe_model_mur, vcovHC)

t test of coefficients:

                  Estimate Std. Error t value Pr(>|t|)
shall1           -0.068834   0.038547 -1.7857 0.074422 .
log(incarc_rate) -0.172066   0.060793 -2.8304 0.004733 **
pb1064            0.046569   0.065853  0.7072 0.479610
pw1064            0.016808   0.013178  1.2754 0.202425
pm1029            0.016707   0.019933  0.8381 0.402127
avginc            0.027525   0.016669  1.6513 0.098966 .
density          -0.492895   0.152529 -3.2315 0.001268 **
pop              -0.029254   0.023743 -1.2321 0.218170
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Output Analysis:

1. **Shall Law:** As we can see in this model, effect of shall-law constitutes on an average of 6.8% reduction of the murder rate. Entity-fixed models automatically caters the unobserved endogeneity; hence we see this huge drop of in the coefficient of shall.
2. In this model the shall variable become statistically insignificant at 95% significance.
3. All the other variables are insignificant in this model except log of incarc_rate and density.
4. One of the important characteristics of the FE models that made them more reasonable is that they control unobserved characteristics the vary between the states but constant over time.

ENTITY AND TIME FIXED EFFECT MODEL

```
> fe_time_mur<- plm(log(mur)~shall+incarc_rate+pb1064+pw1064+pm1029+pop
+                   +avginc+density+factor(year),data=file_data,
+                   model ="within", index=c("stateid","year"))
> summary(fe_time_mur)
```

Output:

```
Coefficients:
                  Estimate   Std. Error  t-value  Pr(>|t|)
shall1          -0.01495237  0.02485211 -0.6017  0.547529
incarc_rate     -0.00011640  0.00013077 -0.8901  0.373588
pb1064           0.02198327  0.03286808  0.6688  0.503743
pw1064          -0.00048933  0.01138722 -0.0430  0.965732
pm1029           0.06919411  0.02261584  3.0595  0.002271 **
pop             -0.03207693  0.01139563 -2.8148  0.004968 **
avginc           0.05664917  0.00932062  6.0778 1.681e-09 ***
density         -0.54426353  0.11049019 -4.9259 9.694e-07 ***
factor(year)78 -0.00071950  0.04075520 -0.0177  0.985918
factor(year)79  0.05924812  0.04141770  1.4305  0.152859
factor(year)80  0.09018140  0.04213308  2.1404  0.032544 *
factor(year)81  0.10215430  0.04360795  2.3426  0.019331 *
factor(year)82  0.02240978  0.04592349  0.4880  0.625661
factor(year)83 -0.03143848  0.04919258 -0.6391  0.522899
factor(year)84 -0.13591915  0.05430007 -2.5031  0.012456 *
factor(year)85 -0.08661433  0.05935551 -1.4592  0.144785
factor(year)86 -0.01227518  0.06511525 -0.1885  0.850508
factor(year)87 -0.02903376  0.07107209 -0.4085  0.682978
factor(year)88 -0.01745941  0.07772487 -0.2246  0.822308
factor(year)89 -0.01456168  0.08389087 -0.1736  0.862229
factor(year)90  0.05999806  0.10279726  0.5837  0.559573
factor(year)91  0.10530717  0.10779711  0.9769  0.328834
factor(year)92  0.06810019  0.11384264  0.5982  0.549833
factor(year)93  0.15442971  0.11828015  1.3056  0.191955
factor(year)94  0.04426479  0.12377161  0.3576  0.720687
factor(year)95  0.05566015  0.12908509  0.4312  0.666416
factor(year)96 -0.01570898  0.13406848 -0.1172  0.906746
factor(year)97 -0.12218236  0.13889265 -0.8797  0.379221
factor(year)98 -0.18633807  0.14452340 -1.2893  0.197557
factor(year)99 -0.25542854  0.14967118 -1.7066  0.088181 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    63.314
Residual Sum of Squares: 44.92
R-Squared:      0.29051
Adj. R-Squared: 0.23854
F-statistic: 14.9047 on 30 and 1092 DF, p-value: < 2.22e-16
```

Coefficients of this model:

```
> coeftest(fe_time_mur, vcovHC)

t test of coefficients:

                 Estimate  Std. Error t value  Pr(>|t|)    
shall1        -0.01495237  0.03737581 -0.4001 0.6891944    
incarc_rate   -0.00011640  0.00035487 -0.3280 0.7429608    
pb1064         0.02198327  0.07410114  0.2967 0.7667781    
pw1064        -0.00048933  0.01964987 -0.0249 0.9801373    
pm1029         0.06919411  0.04084962  1.6939 0.0905744 .  
pop           -0.03207693  0.02050751 -1.5642 0.1180710    
avginc         0.05664917  0.01618114  3.5009 0.0004823 ***
density       -0.54426353  0.31200365 -1.7444 0.0813683 .  
factor(year)78 -0.00071950  0.03154260 -0.0228 0.9818058    
factor(year)79  0.05924812  0.03041073  1.9483 0.0516393 .  
factor(year)80  0.09018140  0.04012984  2.2472 0.0248237 *  
factor(year)81  0.10215430  0.04990922  2.0468 0.0409165 *  
factor(year)82  0.02240978  0.05687064  0.3940 0.6936223    
factor(year)83 -0.03143848  0.06261388 -0.5021 0.6156978    
factor(year)84 -0.13591915  0.07004191 -1.9405 0.0525712 .  
factor(year)85 -0.08661433  0.08375918 -1.0341 0.3013242    
factor(year)86 -0.01227518  0.09063231 -0.1354 0.8922895    
factor(year)87 -0.02903376  0.09768139 -0.2972 0.7663481    
factor(year)88 -0.01745941  0.11698351 -0.1492 0.8813865    
factor(year)89 -0.01456168  0.12911696 -0.1128 0.9102265    
factor(year)90  0.05999806  0.16124231  0.3721 0.7098915    
factor(year)91  0.10530717  0.17152354  0.6140 0.5393751    
factor(year)92  0.06810019  0.17870184  0.3811 0.7032159    
factor(year)93  0.15442971  0.18552024  0.8324 0.4053571    
factor(year)94  0.04426479  0.19273292  0.2297 0.8183919    
factor(year)95  0.05566015  0.19441147  0.2863 0.7747021    
factor(year)96 -0.01570898  0.20773166 -0.0756 0.9397341    
factor(year)97 -0.12218236  0.21372710 -0.5717 0.5676601    
factor(year)98 -0.18633807  0.22802245 -0.8172 0.4139971    
factor(year)99 -0.25542854  0.23657145 -1.0797 0.2805098    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Output Analysis:

1. One of the advantage of using the above model is it takes into consideration of omitted variables that is discarded in Fixed Effects models. Hence, the above model is more efficient than FE models.
2. In this model, the coefficient of Shall Law is further reduced from 0.068 to 0.014 although this effect is not significant just as in FE model.
3. All the variable in this model is insignificant except average income variable.

4. The large estimated values of the coefficient of shall in pooled OLS models is reduced to in the FE and time & entity FE models. This is due to the unobserved endogeneity in pooled OLS models.

4.3. **Robbery Rate**.

POOLED OLS

1. First, we did the regression of the robbery rate keeping the Shall Law as the variable alone.

```
> pooled__model <- plm(log(rob)~shall, data=file_data, model = "pooling", index = c("stateid","year"))
> summary(pooled__model)
```

Output:

```
Pooling Model

Call:
plm(formula = log(rob) ~ shall, data = file_data, model = "pooling",
    index = c("stateid", "year"))

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-3.016753 -0.521484  0.054927  0.612161  2.526408

Coefficients:
             Estimate Std. Error t-value  Pr(>|t|)
(Intercept)  4.873051   0.030050 162.163 < 2.2e-16 ***
shall1      -0.773321   0.060964 -12.685 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1068
Residual Sum of Squares: 939.01
R-Squared:      0.12081
Adj. R-Squared: 0.12006
F-statistic: 160.904 on 1 and 1171 DF, p-value: < 2.22e-16
```

Coefficients of this model:

```
> coeftest(pooled__model, vcovHC)

t test of coefficients:

             Estimate Std. Error t value  Pr(>|t|)
(Intercept)  4.87305    0.11446 42.5756 < 2.2e-16 ***
shall1      -0.77332    0.22292 -3.4691 0.0005412 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Output Analysis:

1. **Shall Law:** From the output of the model, it can be estimated that making the shall-law in effect can will reduce the robbery rate by 77.33%.
2. Although this result is very significant, but we suspect that this is overstated because of the unobserved endogeneity in the model.
3. Further we will perform the pooled OLS regression with all the variables included to check our suspicion.

2. Our second model is the pooled OLS model with all the variables: We see that the variables are right skewed. Therefore, we use the log function for normal distribution.

```
> pooled__model1 <- plm(log(rob)~log(incarc_rate)+log(pb1064)+pw1064+pm1029+log(pop)
+                 +log(avginc)+log(density)+shall, data=file_data, model = "pooling",  index = c("stateid","year"))
> summary(pooled__model1)
```

Output:

```
Pooling Model

Call:
plm(formula = log(rob) ~ log(incarc_rate) + log(pb1064) + pw1064 +
    pm1029 + log(pop) + log(avginc) + log(density) + shall, data = file_data,
    model = "pooling", index = c("stateid", "year"))

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.478572 -0.277269 -0.011166  0.296851  1.614357

Coefficients:
                   Estimate Std. Error t-value  Pr(>|t|)
(Intercept)      -3.6283894  0.4756608 -7.6281 4.934e-14 ***
log(incarc_rate)  0.4010048  0.0365320 10.9768 < 2.2e-16 ***
log(pb1064)       0.3288989  0.0414020  7.9440 4.587e-15 ***
pw1064            0.0083744  0.0032740  2.5578   0.01066 *
pm1029            0.1605866  0.0122932 13.0630 < 2.2e-16 ***
log(pop)          0.2748983  0.0187784 14.6390 < 2.2e-16 ***
log(avginc)       1.1245734  0.0983859 11.4302 < 2.2e-16 ***
log(density)      0.1847102  0.0124336 14.8558 < 2.2e-16 ***
shall1           -0.2814399  0.0358072 -7.8599 8.708e-15 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1068
Residual Sum of Squares: 257.67
R-Squared:      0.75874
Adj. R-Squared: 0.75708
F-statistic: 457.589 on 8 and 1164 DF, p-value: < 2.22e-16
```

Coefficients of this model:

```
> coeftest(pooled__model1, vcovHC)

t test of coefficients:

                  Estimate Std. Error t value  Pr(>|t|)    
(Intercept)      -3.6283894  1.7831290 -2.0348 0.0420928 *  
log(incarc_rate)  0.4010048  0.1578236  2.5408 0.0111876 *  
log(pb1064)       0.3288989  0.1424906  2.3082 0.0211618 *  
pw1064            0.0083744  0.0112906  0.7417 0.4584092    
pm1029            0.1605866  0.0387436  4.1449 3.647e-05 ***
log(pop)          0.2748983  0.0673878  4.0793 4.824e-05 ***
log(avginc)       1.1245734  0.2800491  4.0156 6.308e-05 ***
log(density)      0.1847102  0.0375761  4.9156 1.012e-06 ***
shall1           -0.2814399  0.0783108 -3.5939 0.0003394 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

<u>**Output Analysis**:</u>

1. **Shall Law**: According to the output generated, we see that the coefficient of Shall Law is now reduced. Upon implementation of it, the robbery rate reduces by 28.14% which is far lesser value than the previous output. It indicates exaggerated output when we use single variable.
2. **Average Income**: As average income increases by 1%, robbery rate is also increasing by 1.12% which is an unexpected outcome.
3. However, this model also does not consider heterogeneity. We would want to consider certain attributes like education, attitudes of the population and also cultural inclinations.

ENTITY FIXED-EFFECT MODEL

```
> fe_model_rob <- plm(log(rob)~log(incarc_rate)+log(pb1064)+pw1064+pm1029+log(pop)
+                     +log(avginc)+log(density)+shall, data=file_data, model = "within",index =c("stateid","year"))
> summary(fe_model_rob)
```

Output:

```
Oneway (individual) effect Within Model

Call:
plm(formula = log(rob) ~ log(incarc_rate) + log(pb1064) + pw1064 +
    pm1029 + log(pop) + log(avginc) + log(density) + shall, data = file_data,
    model = "within", index = c("stateid", "year"))

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.6373291 -0.1404385  0.0013793  0.1406179  0.7272359

Coefficients:
                  Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.1309037  0.0360648 -3.6297 0.0002967 ***
log(pb1064)      -0.4517934  0.0721415 -6.2626 5.397e-10 ***
pw1064            0.0107922  0.0054786  1.9699 0.0490976 *
pm1029           -0.0146667  0.0109826 -1.3354 0.1820029
log(pop)         -4.5355223  1.9238903 -2.3575 0.0185719 *
log(avginc)       0.4018976  0.1139404  3.5273 0.0004370 ***
log(density)      4.8757127  1.9467986  2.5045 0.0124053 *
shall1            0.0083804  0.0244126  0.3433 0.7314511
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    53.526
Residual Sum of Squares: 49.393
R-Squared:      0.077223
Adj. R-Squared: 0.029179
F-statistic: 11.6532 on 8 and 1114 DF, p-value: 5.1801e-16
```

Coefficients of this model:

```
> coeftest(fe_model_rob, vcovHC)

t test of coefficients:

                  Estimate Std. Error t value Pr(>|t|)
log(incarc_rate) -0.1309037  0.0896032 -1.4609  0.14432
log(pb1064)      -0.4517934  0.2514141 -1.7970  0.07261 .
pw1064            0.0107922  0.0145132  0.7436  0.45727
pm1029           -0.0146667  0.0317735 -0.4616  0.64446
log(pop)         -4.5355223  4.7318070 -0.9585  0.33801
log(avginc)       0.4018976  0.3077423  1.3060  0.19184
log(density)      4.8757127  4.7346585  1.0298  0.30333
shall1            0.0083804  0.0531299  0.1577  0.87469
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

>
```

<u>Output Analysis</u>:

1. Looking at the magnitude and sign of Shall Law, as well as the p value, we can see that it is become almost insignificant. It has no impact on the robbery rate.
2. This model still does not have a greater control over omitted variables. So, we check the impact by using Entity and Time Fixed Effects model

ENTITY AND TIME FIXED EFFECT MODEL

```
> fe_time_rob <- plm(log(rob)~incarc_rate+pb1064+pw1064+pm1029+pop+avginc+density+shall
+                  +factor(year), data=file_data, model = "within", index = c("stateid","year"))
> summary(fe_time_rob)
```

Output

```
Coefficients:
                  Estimate  Std. Error t-value  Pr(>|t|)
incarc_rate     3.1370e-05  1.2478e-04  0.2514 0.8015503
pb1064          1.4108e-02  3.1362e-02  0.4498 0.6529193
pw1064         -1.2832e-02  1.0865e-02 -1.1810 0.2378570
pm1029          1.0460e-01  2.1580e-02  4.8474 1.432e-06 ***
pop             1.6388e-05  1.0874e-02  0.0015 0.9987977
avginc          1.4357e-02  8.8936e-03  1.6143 0.1067522
density        -4.4745e-02  1.0543e-01 -0.4244 0.6713489
shall1          2.6830e-02  2.3713e-02  1.1314 0.2581289
factor(year)78  3.2850e-02  3.8888e-02  0.8447 0.3984482
factor(year)79  1.3759e-01  3.9520e-02  3.4816 0.0005182 ***
factor(year)80  2.4341e-01  4.0203e-02  6.0545 1.934e-09 ***
factor(year)81  2.7371e-01  4.1610e-02  6.5780 7.382e-11 ***
factor(year)82  2.1599e-01  4.3819e-02  4.9291 9.541e-07 ***
factor(year)83  1.2082e-01  4.6939e-02  2.5739 0.0101867 *
factor(year)84  7.8831e-02  5.1812e-02  1.5215 0.1284302
factor(year)85  1.1315e-01  5.6636e-02  1.9978 0.0459822 *
factor(year)86  1.8957e-01  6.2132e-02  3.0511 0.0023354 **
factor(year)87  1.5722e-01  6.7816e-02  2.3183 0.0206189 *
factor(year)88  1.9276e-01  7.4164e-02  2.5991 0.0094727 **
factor(year)89  2.4873e-01  8.0047e-02  3.1073 0.0019368 **
factor(year)90  3.5098e-01  9.8087e-02  3.5782 0.0003611 ***
factor(year)91  4.6685e-01  1.0286e-01  4.5388 6.284e-06 ***
factor(year)92  4.6332e-01  1.0863e-01  4.2653 2.170e-05 ***
factor(year)93  4.7970e-01  1.1286e-01  4.2503 2.317e-05 ***
factor(year)94  4.9438e-01  1.1810e-01  4.1860 3.067e-05 ***
factor(year)95  4.9402e-01  1.2317e-01  4.0108 6.462e-05 ***
factor(year)96  4.3416e-01  1.2793e-01  3.3939 0.0007139 ***
factor(year)97  3.6524e-01  1.3253e-01  2.7559 0.0059502 **
factor(year)98  2.6771e-01  1.3790e-01  1.9413 0.0524740 .
factor(year)99  1.8947e-01  1.4281e-01  1.3267 0.1848915
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    53.526
Residual Sum of Squares: 40.899
R-Squared:      0.23591
Adj. R-Squared: 0.17994
F-statistic: 11.2385 on 30 and 1092 DF, p-value: < 2.22e-16
```

Coefficients of this model:

```
t test of coefficients:

                 Estimate  Std. Error t value  Pr(>|t|)
incarc_rate     3.1370e-05  3.3981e-04  0.0923 0.9264649
pb1064          1.4108e-02  8.2161e-02  0.1717 0.8636974
pw1064         -1.2832e-02  3.2022e-02 -0.4007 0.6886955
pm1029          1.0460e-01  7.1347e-02  1.4661 0.1428956
pop             1.6388e-05  2.5351e-02  0.0006 0.9994843
avginc          1.4357e-02  2.4208e-02  0.5931 0.5532558
density        -4.4745e-02  1.9373e-01 -0.2310 0.8173874
shall1          2.6830e-02  5.0996e-02  0.5261 0.5989129
factor(year)78  3.2850e-02  2.1199e-02  1.5496 0.1215371
factor(year)79  1.3759e-01  3.1391e-02  4.3832 1.282e-05 ***
factor(year)80  2.4341e-01  4.4436e-02  5.4777 5.347e-08 ***
factor(year)81  2.7371e-01  4.9729e-02  5.5040 4.625e-08 ***
factor(year)82  2.1599e-01  6.2955e-02  3.4309 0.0006241 ***
factor(year)83  1.2082e-01  8.4746e-02  1.4256 0.1542649
factor(year)84  7.8831e-02  1.0402e-01  0.7578 0.4487280
factor(year)85  1.1315e-01  1.2439e-01  0.9097 0.3631997
factor(year)86  1.8957e-01  1.4871e-01  1.2748 0.2026554
factor(year)87  1.5722e-01  1.6507e-01  0.9524 0.3410950
factor(year)88  1.9276e-01  1.8364e-01  1.0497 0.2940997
factor(year)89  2.4873e-01  2.0922e-01  1.1889 0.2347525
factor(year)90  3.5098e-01  2.6083e-01  1.3456 0.1786992
factor(year)91  4.6685e-01  2.7287e-01  1.7109 0.0873778 .
factor(year)92  4.6332e-01  2.8845e-01  1.6062 0.1085137
factor(year)93  4.7970e-01  3.0127e-01  1.5923 0.1116122
factor(year)94  4.9438e-01  3.1610e-01  1.5640 0.1181121
factor(year)95  4.9402e-01  3.2630e-01  1.5140 0.1303147
factor(year)96  4.3416e-01  3.4251e-01  1.2676 0.2052180
factor(year)97  3.6524e-01  3.5008e-01  1.0433 0.2970350
factor(year)98  2.6771e-01  3.6070e-01  0.7422 0.4581152
factor(year)99  1.8947e-01  3.7585e-01  0.5041 0.6142866
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Output Analysis:

1. Even with this output, the coefficients of Shall Law and its p-value show that implementation of it, will have negligible impact on the robbery rate.
2. In fact, all the variables look insignificant according to this model output.

5. Comparison between different models:

- Pooled OLS model does not account for qualities that vary over entities or time
- Coefficients of 'shall' in Pooled OLS model are very biased and seem to be an overestimation of true parameters. This could be caused by omitted variable bias.
- We know that there is unobserved heterogeneity being introduced due to variables like cultural attitude, drug/alcohol abuse, state enforced crime prevention programs, etc. so Time and Entity Fixed model is the most appropriate model for our data

6. Limitations of Entity and Time fixed effect model:

- Omitted Variables
  - Several important variables that vary across states and over time might be omitted. For example, the reasons and strategies behind why the shall-issue law was introduced in the first place, or the attitude of people towards guns.

- Simultaneous causality bias
  - This happens when x affects y and also y affects x. In our case, inclusion of incarceration rate as one of the explanatory variables could cause a major simultaneous causality bias.
  - Increased incarceration rate will instill fear in people and reduces the crime rate.
  - Also, if the crime rate were to increase, due to some unknown factors, this will force the hands of government to enforce stricter laws that could lead to an increased incarceration rate.

7. Conclusion

- Based on our results, the most appropriate model would be entity and time fixed estimator as it accounts for unobserved heterogeneity and time effects.
- We note that introduction of shall-issue law has not had a major impact on the crime rate, be it robbery or homicides.
- States should probably look into alternative methods to reduce the crime rate.
- Another way to model the data would be using Instrumental Variables that can better account for endogeneity. But finding the right variables would be a huge challenge.