BUAN 6312- APPLIED ECONOMETRICS AND TIME SERIES ANALYSIS

EFFECT OF SHALL-CARRY LAW ON VIOLENCE IN UNITED STATES

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INTRODUCTION

The answer to crime is not gun control, it is law enforcement and self-control.

-Alan Keyes

Of all the basic rights each human being possesses, the priority of self-defense cannot be questioned. After all, it is bluntly put up as “Survival of the fittest” by Charles Darwin in his book Principles of Biology (1864). The second amendment of the United States Constitution protects the right to keep and bear arms which is also known as shall carry law. The eligibility criteria to be issued the license is as follows:

1. The person should be mentally stable
2. Have no criminal history in the past
3. Successfully completion of a course in firearms training (as per the law)

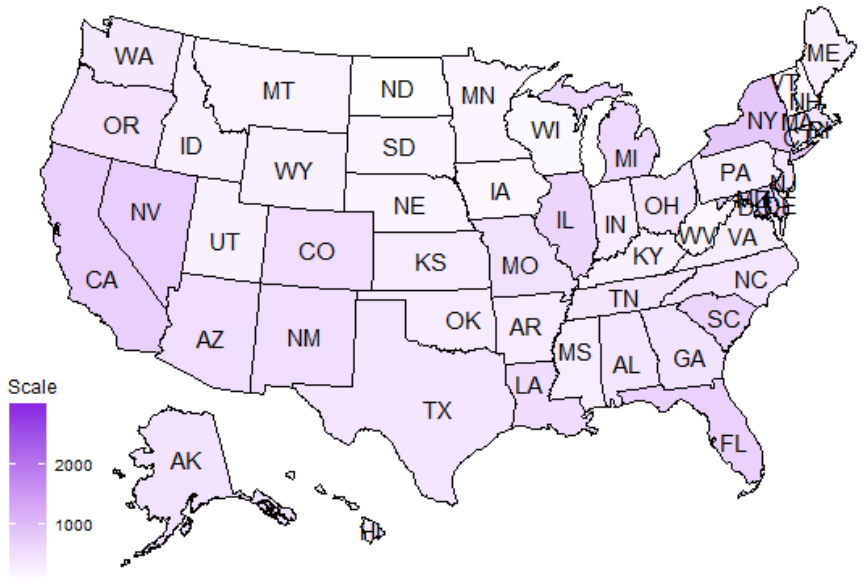
Whether a person has the necessity to carry arms or not, the above criteria makes an individual eligible for a license. The cultural attitude of the people is not pictured which has made shall-carry law one of the most debatable topics in the history of United States. The question is **“Has shall carry laws reduced or increased the violence rate in the United States”**?

This is a case study to measure the impact of shall carry law on violence rates. The data is a balanced panel dataset of 51 states in the United States observed over 23 years each from 1977-1999. We consider shall-carry law as an important dependent variable which is used along with other dependent variables to understand the impact on violence rate. The study first covers the descriptive analysis followed by predictive analysis. The inclusion or exclusion of the variables in the models is supported by the economic theory and the significance of the variable.

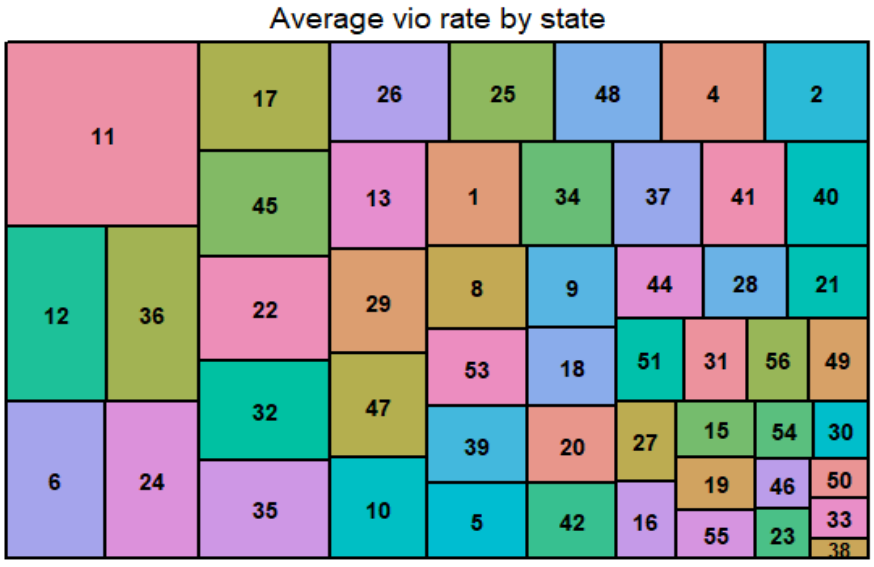
Following table explains the variables in the dataset:

1. Year : Yearly time effects (1977-1999)
2. Vio : Crime incidents per 100,000 members in the population
3. Rob : Robbery incidents per 100,000 members in the population
4. Mur : Murder incidents per 100,000 members in the population
5. Shall : Whether shall carry law is in effect (yes=1, No=0)
6. Incarc_rate : Number of prisoners sentenced per 100,000 residents in previous year
7. Density : Population per square mile of land area (divided by 1000)
8. Avginc : Real per capita personal income in thousands of dollars
9. Pop : Population in millions
10. Pm1029 : Percentage of male population, aged 10-29 in the state
11. Pw1064 : Percentage of whites aged 10-64 in the state
12. Pb1064 : Percentage of black aged 10-64 in the state
13. Stateid : ID number of every state

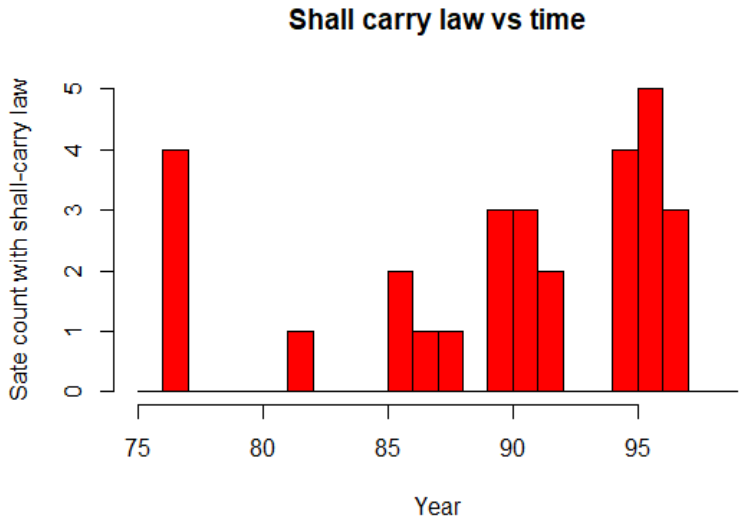
DESCRIPTIVE ANALYSIS



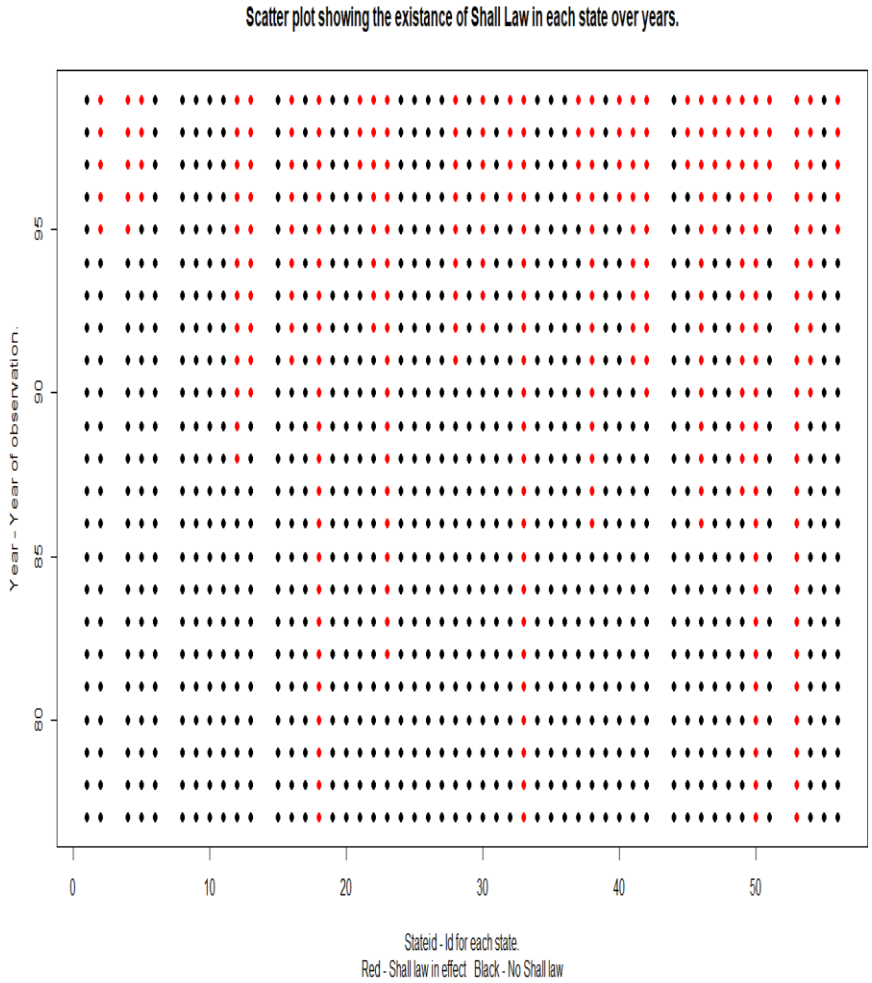
- The US map plot shows the average violence rates over the period of 23 years from 1977-1999
- We can infer that District of Columbia, Florida, New York and California have highest violence rate



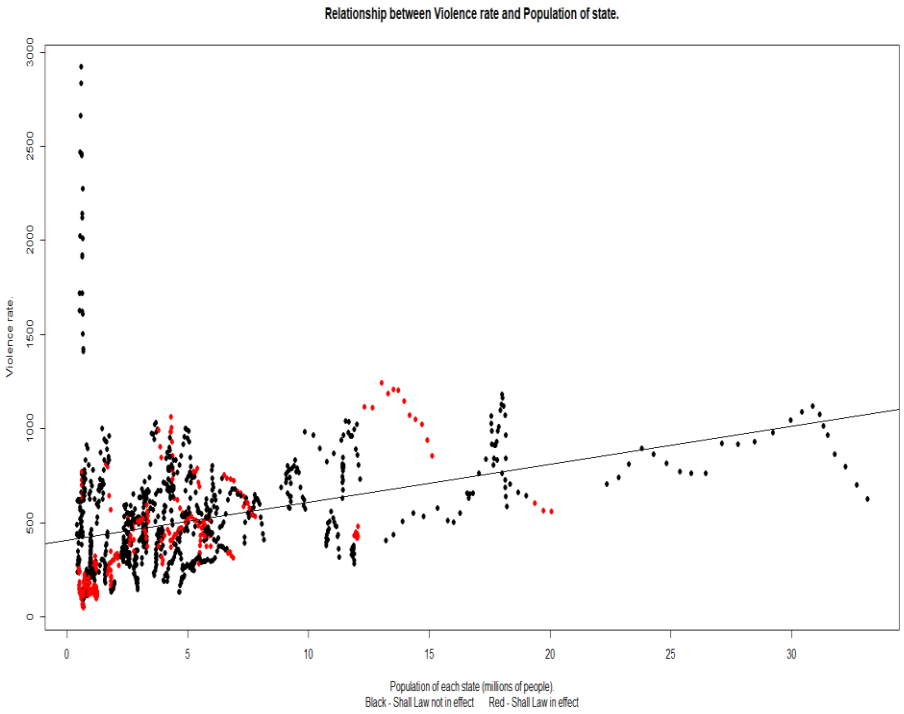
- The tree-map shows the avg violence rate with respect to state ID
- Here, 11, 12, 36, 6 belongs to District of Columbia, Florida, New York and California respectively



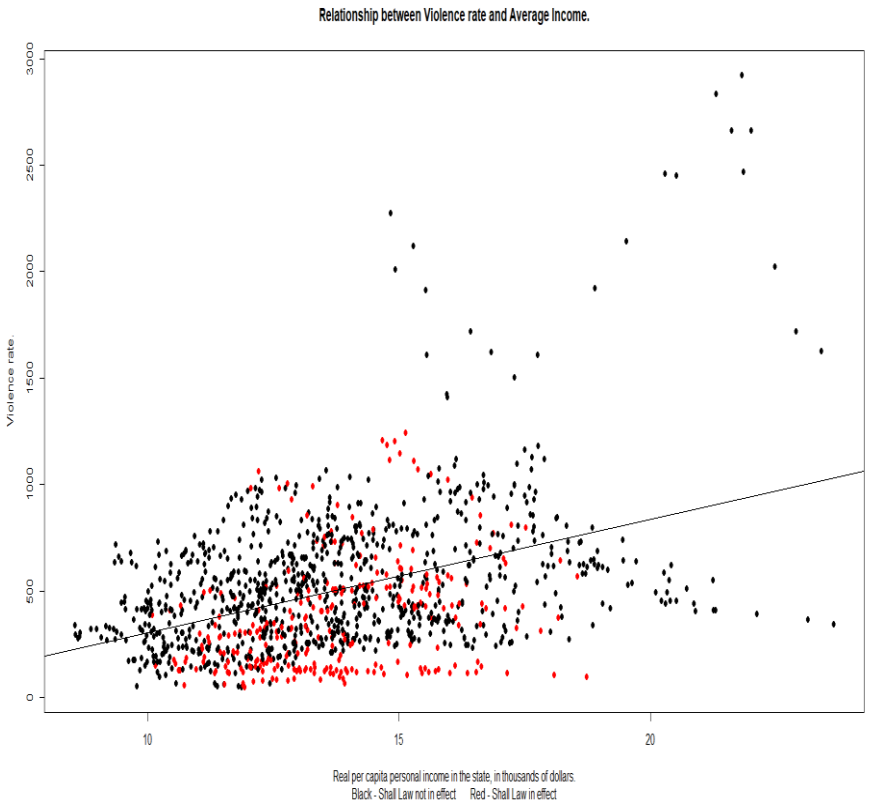
- The histogram on the left shows the number of states for which shall law was introduced in that particular year
- Only 29 states out of 51 had shall laws introduced from 1977-1999
- Out of 29 states, only 5 states had shall laws before 1985, which is almost 40% of the time period in the data



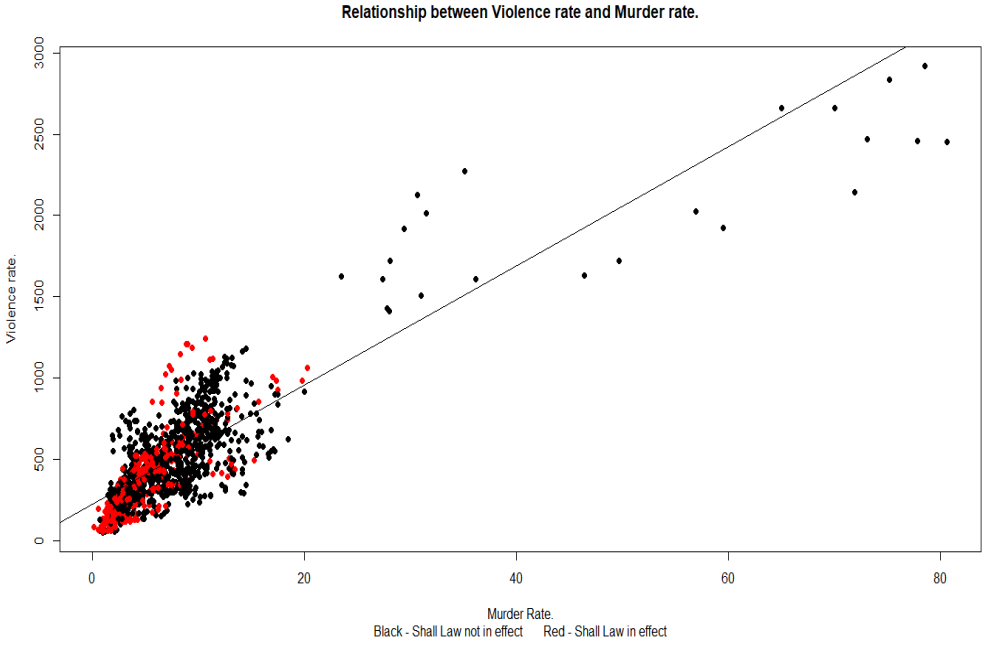
- The plot on the left explains the status of shall carry law in each state over years
- The red data points in the graph explain the year from which the Shall Carry Law was introduced and put into effect
- The black data points in the graph explain the states that did not have shall carry law in effect
- For example, for State ID 22, the Shall Carry Law was put into effect in the year 1992



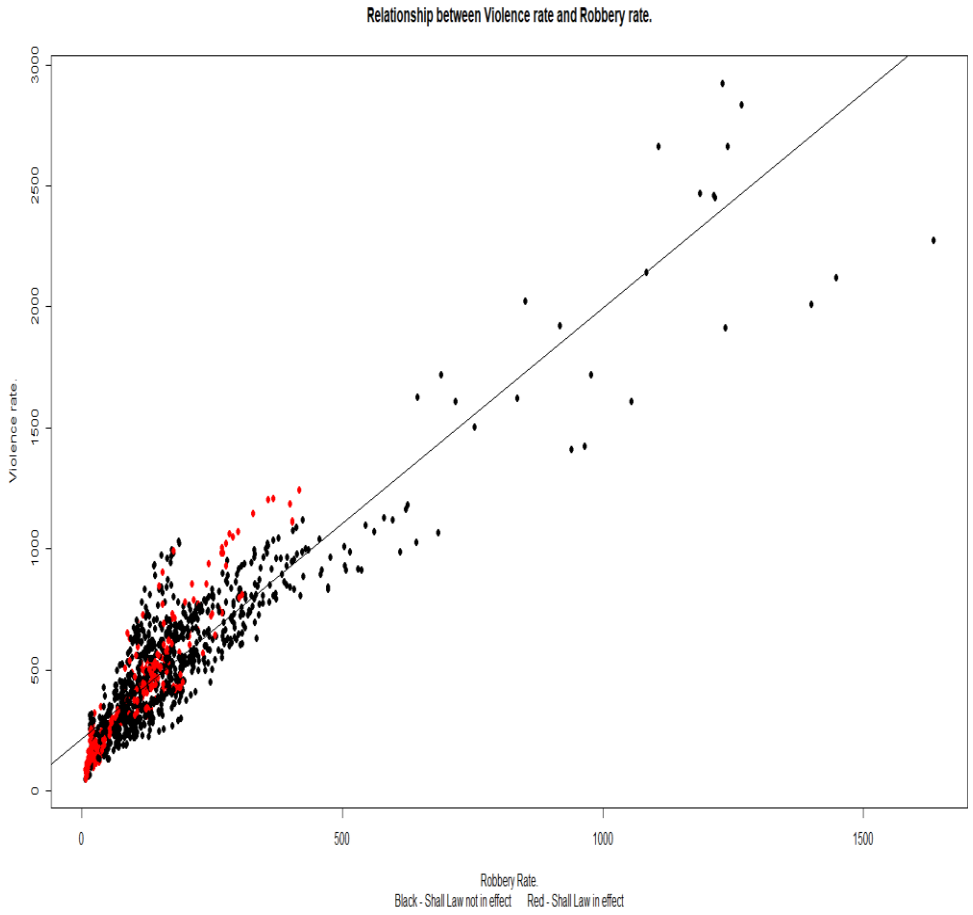
- The scatter plot shows a **positive linear** relationship between both variables Violence Rate (vio) & Population of each state (pop)
- The red data points in the graph represents the state where shall carry Law was passed and put into effect
- The black data points in the graph represents the state where shall carry Law was not passed



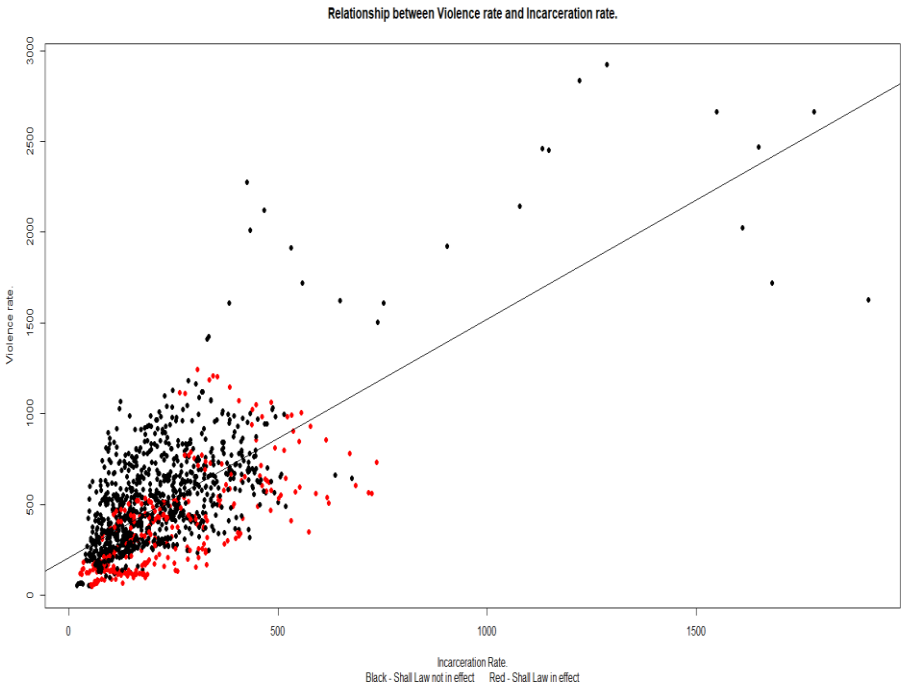
- shows a **positive linear** relationship between both variables Violence Rate (vio) and average per capita income (avginc)
- The red data points in the graph represents the state where shall carry Law was passed and put into effect
- The black data points in the graph represents the state where shall carry Law was not passed



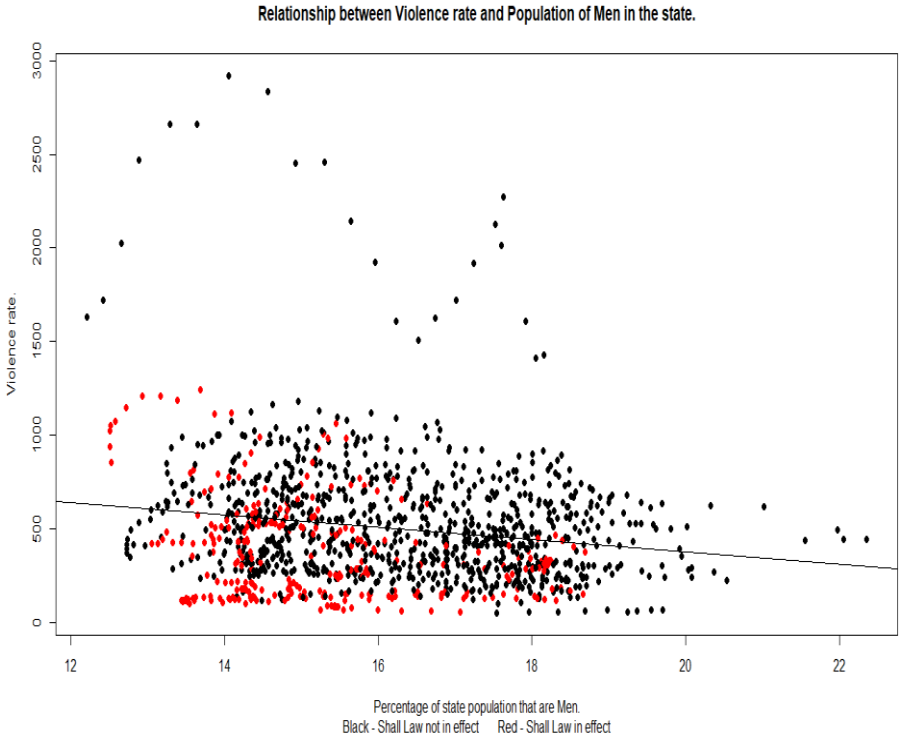
- This shows a **strong positive linear** relationship between both variables Violence Rate (vio) and Murder Rate (mur)



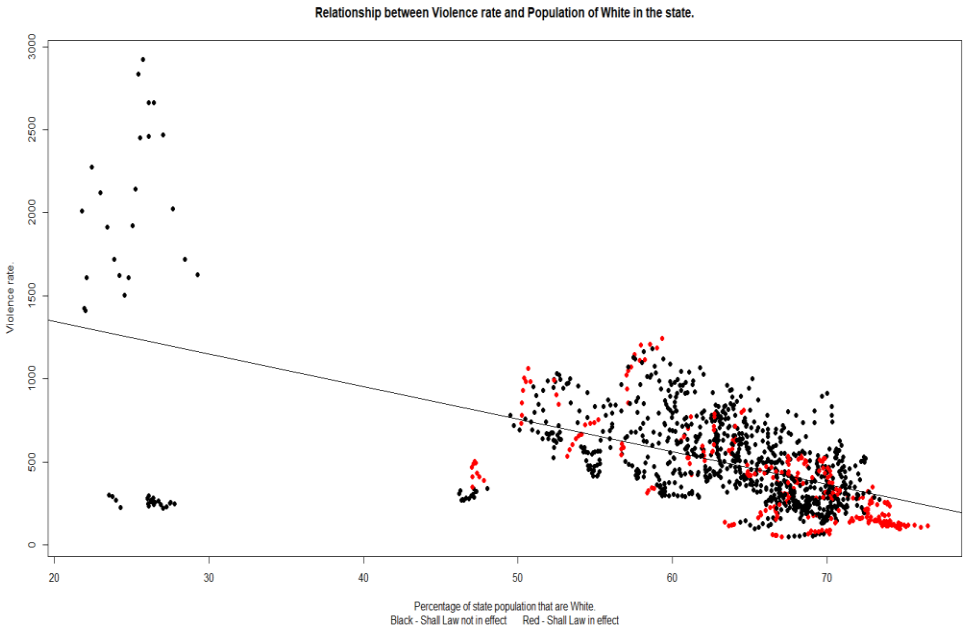
- This shows a **strong positive linear** relationship between both variables Violence Rate (vio) and Murder Rate (mur)



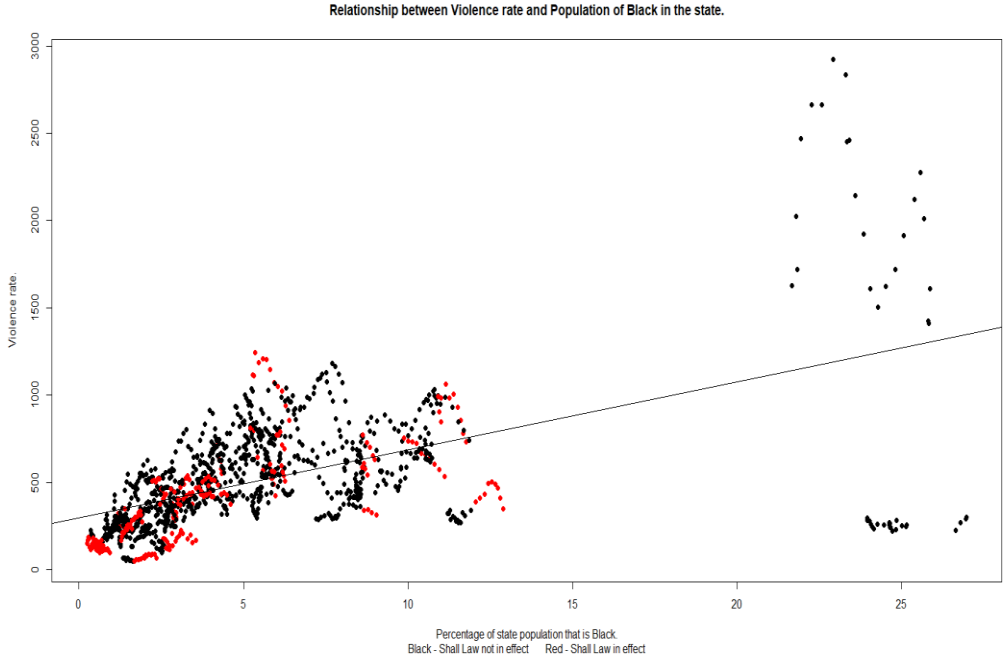
- This shows a **strong positive relationship** between both variables Violence Rate (vio) and Incarceration rate (incarc_rate)
- The result is weird as increase in incarceration rate should result in decrease of violence rate
- This is also known as **Prison Paradox**



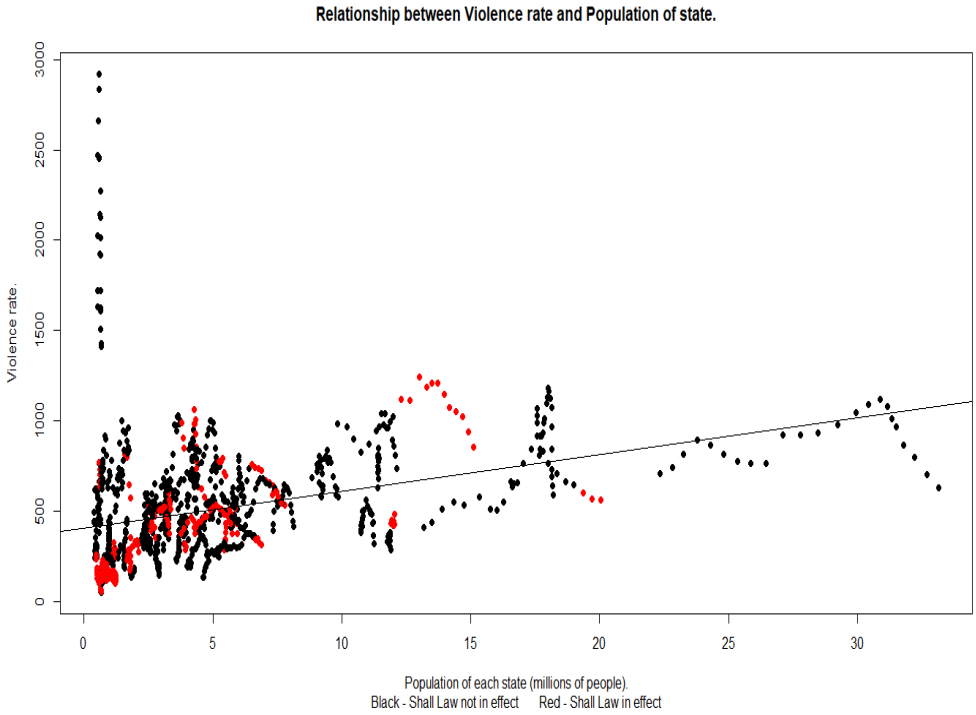
- It shows a **weak negative relationship** between Violence Rate and Percentage of state population that are men (pm1029)



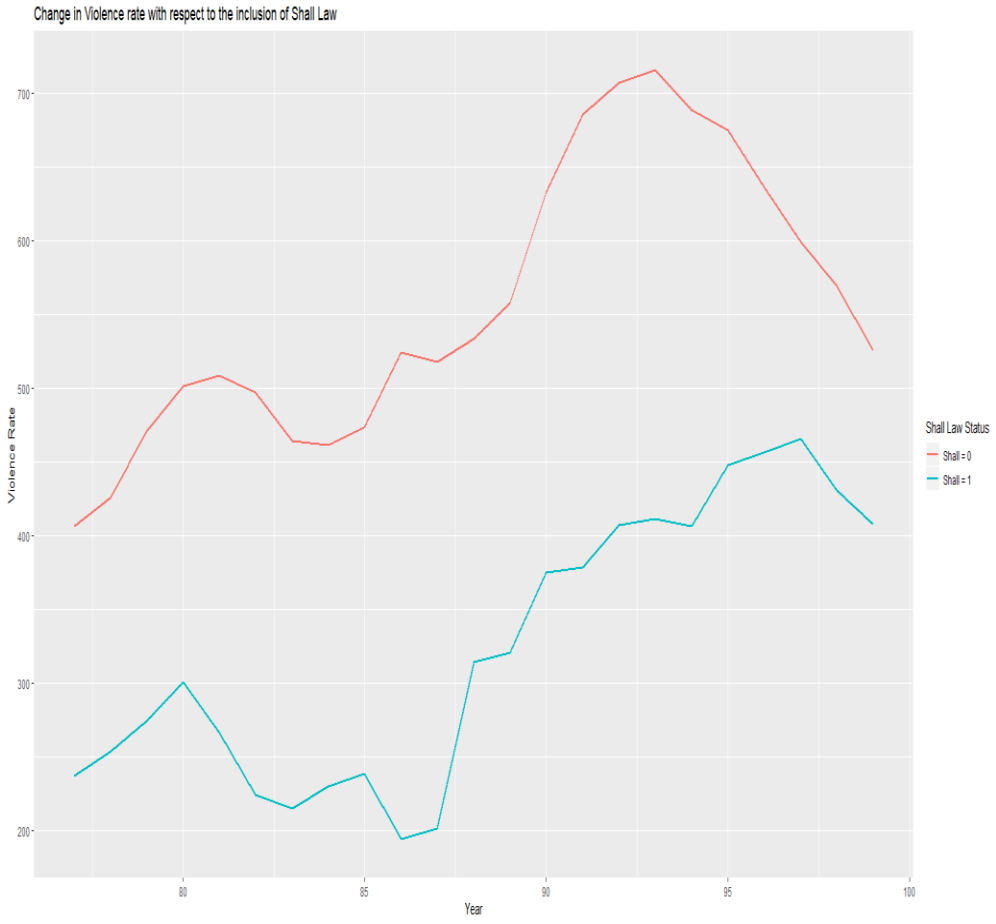
- It shows a **negative linear relationship** between both variables Violence Rate (vio) and Percentage of state population that are White (pw1064)



- It shows a **positive linear relationship** between both variables Violence Rate (vio) and the percentage of state population that are black (pb1069)

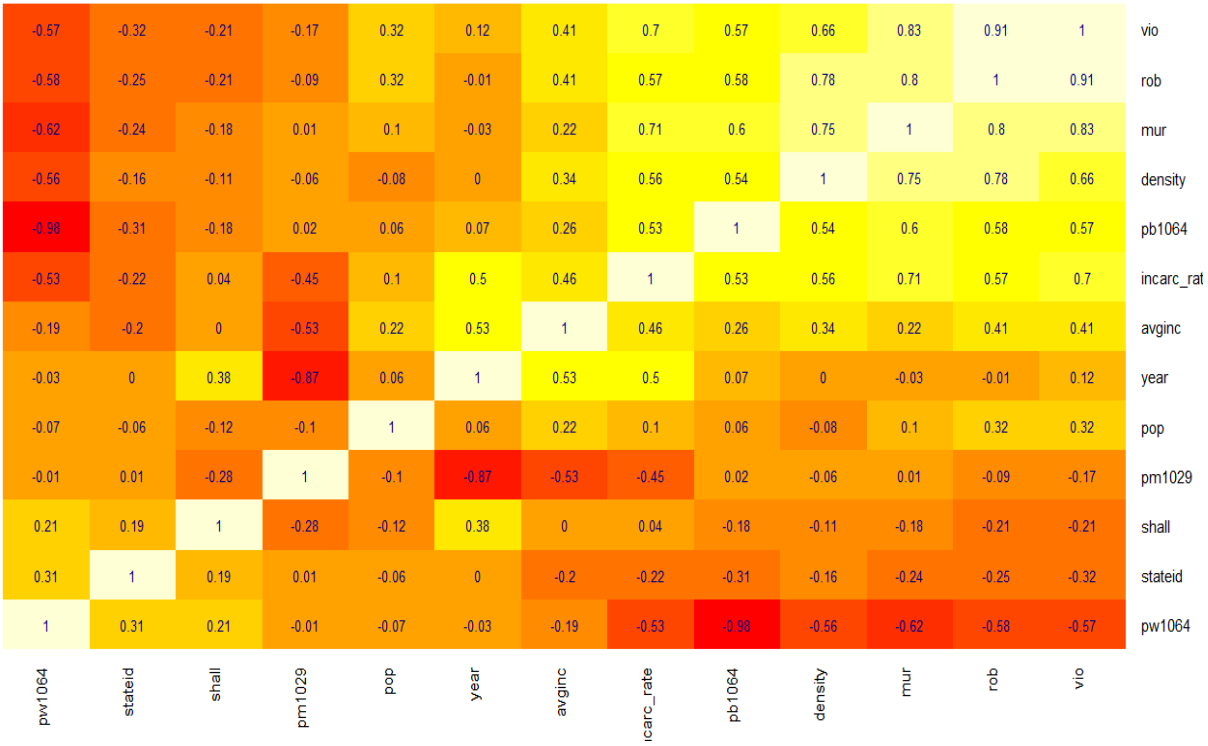


- It shows a **positive linear relationship** between both variables Violence Rate (vio) and state population (pop)



- The graph explains the trend in the average Violence Rate (vio) Vs Year based on the status of the Shall Carry Law
- The blue trend line shows average Violence Rate in states where shall law was not introduced
- The red trend line shows average Violence Rate in states where shall law was introduced at some point of time

CORRELATION MATRIX



The above heatmap explains the correlation among variables in the dataset. The key takeaways from the above correlation matrix are as follows:

- The dependent variable violence rate (vio) has a strong positive correlation of 0.91 and 0.83 with robbery (rob) and murder (mur) respectively
- The percentage of white in the state (pw1064) variable has a strong negative correlation -0.98 with the Percentage of Black in the state (pb1064)
- Robbery (rob) and murder (mur) have strong positive correlation of 0.8
- Murder (mur) and density have strong positive correlation of 0.75
- Inceration rate (incarc_rate) possesses a strong positive correlation of 0.7 with violence rate (vio)
- Inceration rate (incarc_rate) has a strong positive correlation of 0.71 with murder (mur)
- Inceration rate (incarc_rate) has a strong positive correlation of 0.57 with robbery (rob)
- The percentage of black (pb1064) has a positive correlation of 0.57 with violence (vio)
- The percentage of black (pb1064) has a positive correlation of 0.56 with murder (mur)
- The percentage of black (pb1064) has a positive correlation of 0.58 with robbery (rob)

REGRESSION ANALYSIS

MULTIPLE LINEAR REGRESSION WITH MUR AND ROB

To analyze the data, we started with a multiple regression model to see the effect of independent variables on the dependent variable i.e. violence rate.

```
Call:
lm(formula = log(vio) ~ mur + log(rob) + log(incarc_rate) + pm1029 +
    pb1064 + log(density) + shall, data = df)

Residuals:
     Min       1Q   Median       3Q      Max
-0.54281 -0.13175  0.00348  0.12557  0.65403

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     1.460343   0.137173  10.646  < 2e-16 ***
mur             0.007003   0.001141   6.138 1.14e-09 ***
log(rob)        0.552382   0.010246  53.914  < 2e-16 ***
log(incarc_rate) 0.305521   0.016359  18.676  < 2e-16 ***
pm1029          0.018617   0.005309   3.507 0.000471 ***
pb1064         -0.012814   0.001738  -7.374 3.13e-13 ***
log(density)   -0.045797   0.005520  -8.297 2.93e-16 ***
shall          -0.049019   0.015780  -3.106 0.001939 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2045 on 1165 degrees of freedom
Multiple R-squared:  0.9002,    Adjusted R-squared:  0.8996
F-statistic:  1502 on 7 and 1165 DF,  p-value: < 2.2e-16
```

INFERENCES:

- As compared to a state where Shall Carry Law has not been introduced (Shall = 0), the state where Shall Law has been introduced the violence rate (vio) will reduce by ~ 4.9%
- It is significant at 1% level of significance. The coefficient aligns with the economic theory as shall carry law should result in reducing violence
- With 1 percent increase in the Incarceration Rate, the Violence Rate goes up by 0.3%, which is weird. It is significant at any level of significance
- With 1 unit increase in the Murder Rate, the Violence Rate goes up by 0.7%. It is significant at any level of significance
- With 1 percent increase in Robbery Rate, the Violence Rate goes up by ~0.55%. It is significant at any level of significance
- With 1 % increase in male state population, aged between 10-29 (pm1029), the violence rate goes up by ~1.8%. It is significant at any level of significance. This aligns with the economic theory as most of the crime are committed by males aged between 10 to 29
- We have seen that murder and robbery have very high correlation. Also, there is **simultaneous causality bias with violence rate & robbery and violence rate & murder**

MULTIPLE LINEAR REGRESSION WITHOUT MUR AND ROB

```
Call:
lm(formula = log(vio) ~ log(incarc_rate) + pm1029 + pb1064 +
    log(density) + shall, data = df)

Residuals:
     Min       1Q   Median       3Q      Max
-1.24776 -0.26390 -0.01555  0.26529  1.07157

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.697481   0.245167   2.845  0.00452 **
log(incarc_rate) 0.764276   0.025869  29.544  < 2e-16 ***
pm1029           0.112914   0.009381  12.036  < 2e-16 ***
pb1064          -0.008920   0.003230  -2.762  0.00584 **
log(density)     0.132760   0.008619  15.404  < 2e-16 ***
shall           -0.315212   0.028865 -10.920  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3929 on 1167 degrees of freedom
Multiple R-squared:  0.6313,    Adjusted R-squared:  0.6297
F-statistic: 399.6 on 5 and 1167 DF,  p-value: < 2.2e-16
```

INFERENCES:

- We have omitted murder and robbery from our previous model as they are highly correlated
- As compared to a state where Shall Carry Law has not been introduced (Shall = 0), the state where Shall Law has been introduced will reduce violence rate (vio) by ~ 31.5%. It is significant at 1% level of significance. The coefficient aligns with the economic theory as shall carry should result in reducing violence, but the effect is **overstated**
- With 1 % increase in Incarceration Rate, the Violence Rate goes up by 0.76% which does not make sense. It is significant at any level of significance
- An increase in density of a state by 1% will increase the violence rate by 0.13%. This is highly significant at any level of significance. We cannot really support/condemn the sign as it depends on the **kind of society and the cultural attitude** of the people
- Hence, to capture the effect of individual entities we will move to Pooled model, Fixed effects and random models
- Therefore, the OLS estimates seem to be **biased and inconsistent**

POOLED MODEL

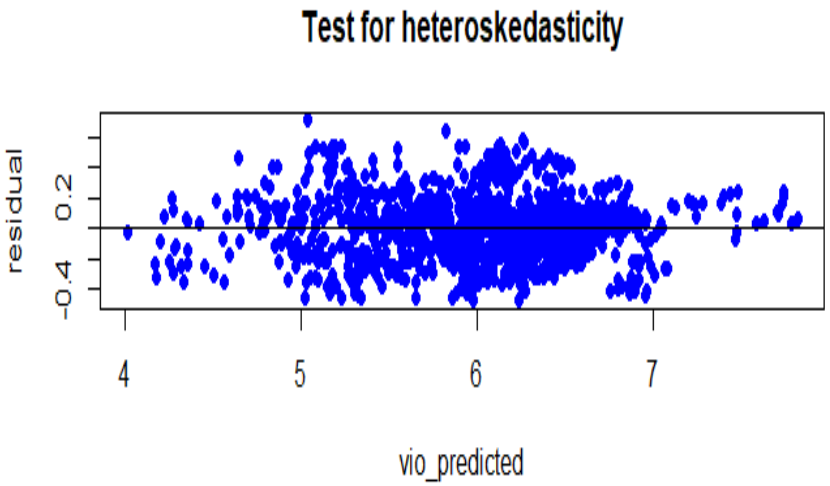
```
Pooling Model

Call:
plm(formula = log(vio) ~ log(incarc_rate) + pm1029 + pop + avginc +
    log(density) + shall, data = df_pool, model = "pooling")

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.257753 -0.236823  0.015087  0.261175  1.099112

Coefficients:
                  Estimate Std. Error  t-value  Pr(>|t|)
(Intercept)       0.5193308  0.2328941   2.2299   0.02594 *
log(incarc_rate)  0.6781482  0.0202026  33.5673 < 2.2e-16 ***
pm1029            0.1134168  0.0086277  13.1457 < 2.2e-16 ***
pop               0.0245819  0.0022304  11.0215 < 2.2e-16 ***
avginc            0.0239844  0.0053965   4.4445 9.651e-06 ***
log(density)      0.0880118  0.0079309  11.0973 < 2.2e-16 ***
shall            -0.2780539  0.0274432 -10.1320 < 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: 160.81
R-Squared:      0.67089
Adj. R-Squared: 0.6692
F-statistic: 396.152 on 6 and 1166 DF, p-value: < 2.22e-16
>
```

INFERENCES:

- With 1 % increase in Incarceration Rate, the Violence Rate goes up by 0.67%. It is not significant at any level of significance. The positive sign of the coefficient still does not align with the economic theory
- With 1 % increase in state population that is male, aged 10-29 (pm1029), the violence rate goes up by ~11.3 %. It is significant at any level of significance
- With 1 unit increase in the state population (pop), the violence rate goes up by ~2.45 %. It is significant at any level of significance. This makes sense as more population would lead to more crimes
- With 1 unit increase in average income (avginc), the Violence Rate increases by 2.39 %. This makes sense as when people have more money, it leads to more violence
- With 1 % increase in density of the state population, the Violence Rate goes up by 0.088%
- As compared to a state where Shall Carry Law has not been introduced (Shall = 0), the state where Shall Law has been introduced the violence rate (vio) will reduce by ~ 27.8%. It is significant at any level of significance. The effect of shall law is again overstated

The variables in the pooled model are highly significant but incarceration rate and shall do not align with the economic theory. This is also known as **Prison Paradox.** This could be due to **serial autocorrelation** among the states and **presence of heteroskedasticity**. Therefore, let us check for heteroskedasticity.

TEST FOR HETEROSKEDASTICITY



- The heteroskedasticity is not visible completely form the residual plot on the left- hand side
- Therefore, we do the hypothesis test for heteroskedasticity using Breusch-Pagan test

BREUSCH-PAGAN TEST

NULL HYPOTHESIS ➔ Ho: No heteroskedasticity

ALTERNATE HYPOTHESIS ➔ H1: Heteroskedasticity exists

```
> bptest(plm(log(vio)~log(incarc_rate)+pm1029+pop+avginc+log(density)+shall,
+            data=df_pool,model="pooling"))

        studentized Breusch-Pagan test

data:  plm(log(vio) ~ log(incarc_rate) + pm1029 + pop + avginc + log(density) +
   shall, data = df_pool, model = "pooling")
BP = 56.357, df = 6, p-value = 2.465e-10
```

INFERENCES:

As the P-value is almost zero, there is strong evidence of presence of heteroskedasticity in the pooled model

- The pooled model is still unbiased and consistent but no longer efficient. In fact, it is **not** the **BEST LINEAR UNBIASED ESTIMATOR (BLUE)**
- We use **cluster robust standard errors** to correct for Standard error to get right statistical inference of the coefficients

POOLED MODEL WITH CLUSTER ROBUST STANDARD ERRORS

```
t test of coefficients:

                 Estimate Std. Error t value  Pr(>|t|)
(Intercept)     0.5193308  0.7026614  0.7391 0.4600004
log(incarc_rate) 0.6781482  0.0666298 10.1779 < 2.2e-16 ***
pm1029          0.1134168  0.0227080  4.9946 6.796e-07 ***
pop             0.0245819  0.0074874  3.2831 0.0010571 **
avginc          0.0239844  0.0163878  1.4635 0.1435869
log(density)    0.0880118  0.0270546  3.2531 0.0011742 **
shall          -0.2780539  0.0779611 -3.5666 0.0003763 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

←=== CLUSTER ROBUST STANDARD ERRORS

```
Pooling Model

Call:
plm(formula = log(vio) ~ log(incarc_rate) + pm1029 + pop + avginc +
    log(density) + shall, data = df_pool, model = "pooling")

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.257753 -0.236823  0.015087  0.261175  1.099112

Coefficients:
                 Estimate Std. Error  t-value  Pr(>|t|)
(Intercept)     0.5193308  0.2328941   2.2299   0.02594 *
log(incarc_rate) 0.6781482  0.0202026  33.5673 < 2.2e-16 ***
pm1029          0.1134168  0.0086277  13.1457 < 2.2e-16 ***
pop             0.0245819  0.0022304  11.0215 < 2.2e-16 ***
avginc          0.0239844  0.0053965   4.4445 9.651e-06 ***
log(density)    0.0880118  0.0079309  11.0973 < 2.2e-16 ***
shall          -0.2780539  0.0274432 -10.1320 < 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: 160.81
R-Squared:      0.67089
Adj. R-Squared: 0.6692
F-statistic: 396.152 on 6 and 1166 DF, p-value: < 2.22e-16
>
```

←=== POOLED OLS STANDARD ERRORS

INFERENCES:

- We see the differences in the Cluster Robust standard errors and Pooled OLS Standard errors
- As we know, Robust standard errors allow you to arrive at meaningful statistical inference like confidence intervals, but do not change coefficients of the variable
- Hence, the estimator is still not BLUE but is **unbiased and consistent**
- Therefore, we will use Fixed Effects estimator which captures the heteroskedasticity in the intercept

FIXED EFFECTS MODEL WITH AVGINC

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

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|)
log(incarc_rate) -0.0672299  0.0282092 -2.3833  0.017327 *
pb1064            0.0952893  0.0150322  6.3390 3.352e-10 ***
pm1029           -0.0690675  0.0083143 -8.3071 2.821e-16 ***
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
log(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
```

INFERENCES:

- With 1 percent increase in the value of Incarceration Rate, the Violence Rate for the state goes down by 0.0672 %. It is significant at 5% level of significance. It makes sense now as the increase in incarceration rate decreases the violence rate
- As compared to a state where Shall Carry Law has not been introduced (Shall = 0), the state where Shall Law has been introduced will reduce violence rate (vio) by ~ 3.79 percent. It is significant at 5 % level of significance
- With one unit / one thousand dollars increase in real per capita personal income of state, the Violence rate goes down by ~ 0.41 percent. It is not at all significant as the p-value is 0.4691
- With increase in the state population by one million or one unit, the Violence Rate (vio) goes up by ~ 2.43 percent. It is significant at 1% level of significance
- With 1 % increase in the population density of the state, the violence rate goes down by ~ 0.25 percent. It is significant at 1% level of significance

FIXED EFFECTS MODEL WITHOUT AVGINC

This is the Fixed Effects model after omitting avginc from previous model.

```
Call:
plm(formula = log(vio) ~ log(incarc_rate) + pb1064 + pm1029 +
    pw1064 + pop + log(density) + shall, data = df_pool, model = "within")

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.569832 -0.098051  0.009509  0.101680  0.580039

Coefficients:
                  Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.0726069  0.0272087 -2.6685  0.007729 **
pb1064            0.0940313  0.0149283  6.2989 4.307e-10 ***
pm1029           -0.0672520  0.0079256 -8.4854 < 2.2e-16 ***
pw1064            0.0425889  0.0051975  8.1941 6.872e-16 ***
pop               0.0241646  0.0092753  2.6052  0.009303 **
log(density)     -0.2503523  0.0859108 -2.9141  0.003638 **
shall            -0.0380101  0.0189840 -2.0022  0.045503 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 28.576
R-Squared:      0.22326
Adj. R-Squared: 0.18355
F-statistic: 45.7826 on 7 and 1115 DF, p-value: < 2.22e-16
```

INFERENCES:

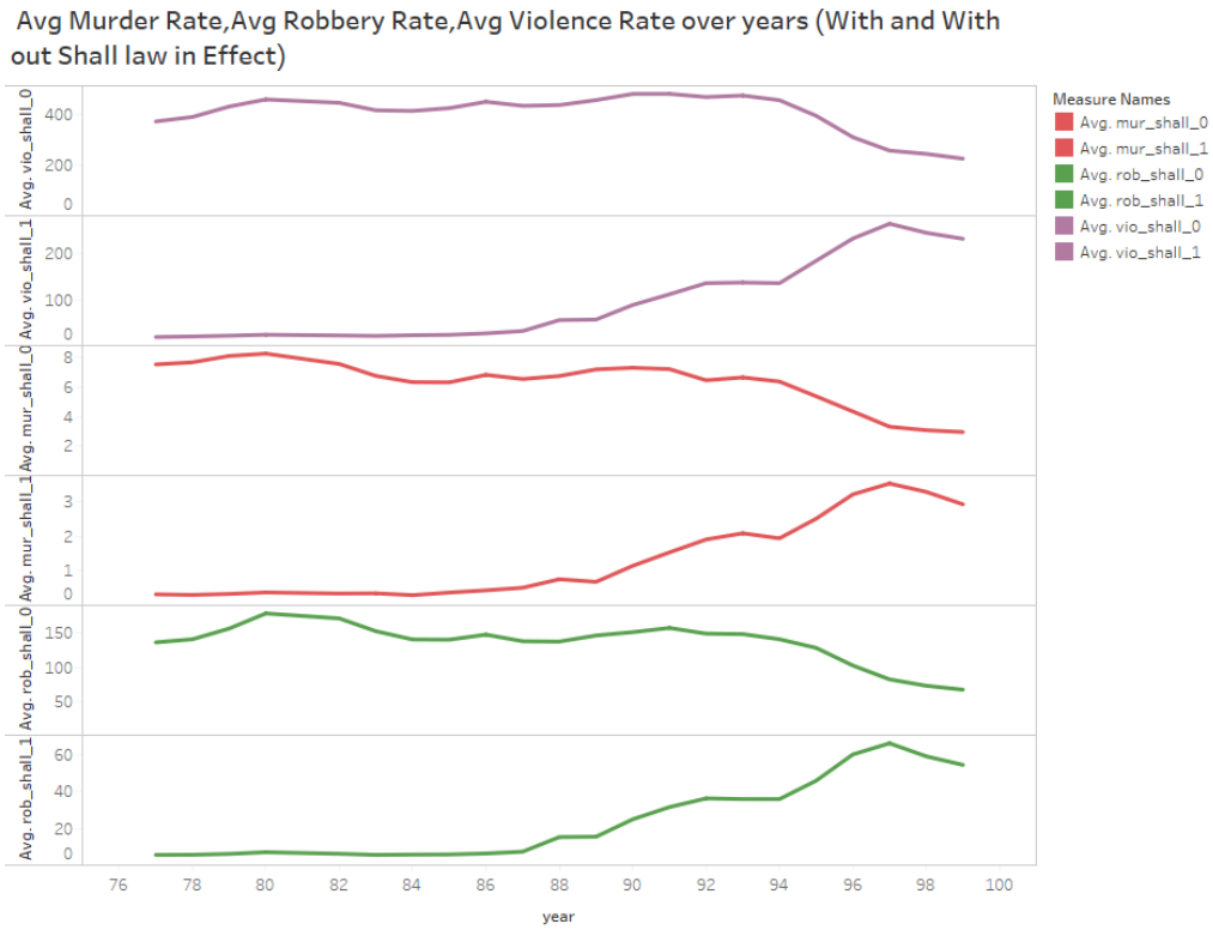
- With 1 percent increase in the value of Incarceration Rate, the Violence Rate for the state goes down by 0.072 %. It is significant at any level of significance
- As compared to a state where Shall Carry Law has not been introduced (Shall = 0), the state where Shall Law has been introduced will reduce violence rate (vio) by ~ 3.8 %. It is significant at 5 % level of significance
- With increase in the state population by one million / One unit, the Violence Rate (vio) goes up by ~ 2.41 %. It is significant at 1% level of significance
- With 1 % increase in the population density of the state, the violence rate goes down by ~ 0.25 %. It is significant at 1% level of significance

TOTAL VIOLENCE AS A FUNCTION

FIXED EFFECTS MODEL ON MURDER

As stated by disastercenter.com,

Violence= Murder + robbery + rape + assault + burglary + larceny



INFERENCES:

- The above line graph shows the trend of average violence rate, average murder, average robbery over years to compare between states which had shall laws and states where shall law was not introduced
- Hence, we see a very high correlation of violence with murder and robbery from the correlation matrix as well as the graph

We regress on the murder and robbery to see the effect of incarceration rate and shall-carry law.

```
Call:
plm(formula = log(mur) ~ log(incarc_rate) + pb1064 + pw1064 +
    pm1029 + pop + log(density) + shall, data = df_pool, model = "within")

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-1.7274899 -0.1202039 -0.0015879  0.1221164  0.8517610

Coefficients:
                 Estimate Std. Error t-value Pr(>|t|)
log(incarc_rate) -0.1101118  0.0378395 -2.9100 0.003686 **
pb1064           -0.0119793  0.0207610 -0.5770 0.564050
pw1064            0.0163906  0.0072283  2.2676 0.023547 *
pm1029           -0.0127102  0.0110223 -1.1531 0.249101
pop              -0.0068012  0.0128994 -0.5272 0.598125
log(density)     -0.3842213  0.1194775 -3.2158 0.001338 **
shall            -0.0554868  0.0264014 -2.1017 0.035807 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    63.314
Residual Sum of Squares: 55.268
R-Squared:      0.12708
Adj. R-Squared: 0.082458
F-statistic: 23.1895 on 7 and 1115 DF, p-value: < 2.22e-16
```

INFERENCES:

- With 1 percent increase in Incarceration Rate, the Violence Rate goes down by 0.11%. It is significant at 1 % level of significance
- As compared to a state where Shall Carry Law has not been introduced (Shall = 0), the state where Shall Law has been introduced violence rate (vio) will reduce by ~ 5.54 %. It is significant at 5% level of significance
- With 1 % increase in density of the state population, the Violence Rate goes down by 0.38 percent. It is significant at 1% significance level

Therefore, the findings of total violence go along with the results for murders in the data.

FIXED EFFECTS MODEL ON ROBBERY

```
Call:
plm(formula = log(rob) ~ log(incarc_rate) + pb1064 + pw1064 +
    pm1029 + pop + log(density) + shall, data = df_pool, model = "within")

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

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.6985118 -0.1353001  0.0012956  0.1378696  0.8375971

Coefficients:
                  Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate) -0.2042487  0.0361317 -5.6529 2.003e-08 ***
pb1064            0.1085814  0.0198240  5.4773 5.336e-08 ***
pw1064            0.0359243  0.0069021  5.2049 2.310e-07 ***
pm1029           -0.0240192  0.0105248 -2.2822   0.02267 *
pop               0.0187632  0.0123172  1.5233   0.12796
log(density)      0.0754582  0.1140851  0.6614   0.50848
shall            -0.0128524  0.0252098 -0.5098   0.61028
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    53.526
Residual Sum of Squares: 50.392
R-Squared:      0.058559
Adj. R-Squared: 0.010432
F-statistic: 9.90787 on 7 and 1115 DF, p-value: 4.8691e-12
```

INFERENCES:

- With 1 % increase in Incarceration Rate, the Violence Rate goes down by 0.204%. It is significant at 1 % level of significance
- As compared to a state where Shall Carry Law has not been introduced (Shall = 0), the state where Shall Law has been introduced, violence rate (vio) will reduce by ~ 1.2%. It is not at all significant
- With 1 % increase in density of the state population, the Violence Rate goes down by 0.075 %. It is not at all significant

We can see that the variables shall, density and pop turn insignificant for robbery. Hence, we do not the same effect of total violence and murder when it comes to robbery.

ENTITY FIXED TIME EFFECTS

Let us see if there is any time effect which exists on the violence rate. We should be able to see the time effect as the shall laws were introduced at different periods for different states.

```
Call:
plm(formula = log(vio) ~ log(incarc_rate) + pb1064 + pw1064 +
    pm1029 + pop + log(density) + shall + as.factor(year), data = df_pool,
    model = "within")

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

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.443809 -0.077342  0.004785  0.079136  0.678052

Coefficients:
                    Estimate Std. Error t-value  Pr(>|t|)
log(incarc_rate)  -0.1043341  0.0281554 -3.7056 0.0002214 ***
pb1064            -0.0130955  0.0190270 -0.6883 0.4914357
pw1064            -0.0019243  0.0072882 -0.2640 0.7918060
pm1029             0.0801748  0.0149116  5.3767 9.275e-08 ***
pop                0.0058570  0.0082851  0.7069 0.4797652
log(density)      -0.2563098  0.0763925 -3.3552 0.0008204 ***
shall             -0.0288042  0.0170906 -1.6854 0.0921999 .
as.factor(year)78  0.0688136  0.0277243  2.4821 0.0132116 *
as.factor(year)79  0.1877998  0.0283456  6.6254 5.426e-11 ***
as.factor(year)80  0.2493540  0.0290952  8.5703 < 2.2e-16 ***
as.factor(year)81  0.2580909  0.0302212  8.5401 < 2.2e-16 ***
```

```
as.factor(year)79  0.1877998  0.0283456  6.6254 5.426e-11 ***
as.factor(year)80  0.2493540  0.0290952  8.5703 < 2.2e-16 ***
as.factor(year)81  0.2580909  0.0302212  8.5401 < 2.2e-16 ***
as.factor(year)82  0.2518348  0.0324587  7.7586 1.962e-14 ***
as.factor(year)83  0.2312016  0.0352156  6.5653 8.008e-11 ***
as.factor(year)84  0.2749803  0.0380284  7.2309 9.000e-13 ***
as.factor(year)85  0.3344810  0.0410000  8.1581 9.282e-16 ***
as.factor(year)86  0.4235679  0.0444672  9.5254 < 2.2e-16 ***
as.factor(year)87  0.4333483  0.0481226  9.0051 < 2.2e-16 ***
as.factor(year)88  0.5060538  0.0519771  9.7361 < 2.2e-16 ***
as.factor(year)89  0.5721197  0.0555931 10.2912 < 2.2e-16 ***
as.factor(year)90  0.7103155  0.0673886 10.5406 < 2.2e-16 ***
as.factor(year)91  0.7749214  0.0713680 10.8581 < 2.2e-16 ***
as.factor(year)92  0.8186854  0.0748359 10.9397 < 2.2e-16 ***
as.factor(year)93  0.8511992  0.0778462 10.9344 < 2.2e-16 ***
as.factor(year)94  0.8481079  0.0809506 10.4769 < 2.2e-16 ***
as.factor(year)95  0.8546609  0.0841930 10.1512 < 2.2e-16 ***
as.factor(year)96  0.8111688  0.0871196  9.3110 < 2.2e-16 ***
as.factor(year)97  0.8013465  0.0895338  8.9502 < 2.2e-16 ***
as.factor(year)98  0.7574311  0.0918091  8.2501 4.513e-16 ***
as.factor(year)99  0.7087833  0.0942369  7.5213 1.128e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    36.789
Residual Sum of Squares: 21.134
R-Squared:      0.42555
Adj. R-Squared: 0.38402
F-statistic: 27.9198 on 29 and 1093 DF, p-value: < 2.22e-16
```

INFERENCES:

- With 1 percent increase in Incarceration Rate, the Violence Rate goes down by 0.104 percent. It is significant at any level of significance
- As compared to a state where Shall Carry Law has not been introduced (Shall = 0), the state where Shall Law has been introduced will increase violence rate (vio) by ~ 2.88 percent. It is significant at 10% level of significance
- With 1% increase in state population that are men, ages 10 to 29 (pm1029), the violence rate goes up by ~8.01 %. It is significant at any level of significance
- As compared to year 77, for the year 79, the value of violence rate goes up by 18.77%. It is significant at any level of significance

F-TEST TO CONFIRM TIME EFFECTS

We perform a F-test to confirm the time effects in the above model. The hypothesis is as follows:

Null Hypothesis➔

Ho: beta(as.factor(year))78= beta(as.factor(year))79= beta(as.factor(year))80= beta(as.factor(year))81……. beta(as.factor(year))99=0 **All year coefficients are zero**

Alternative Hypothesis➔

H1: **At least any one of the above coefficients is not equal to zero**

```
        F test for individual effects

data:  log(vio) ~ log(incarc_rate) + pb1064 + pm1029 + pw1064 + pop +  ...
F = 13.199, df1 = -22, df2 = 1115, p-value = NA
alternative hypothesis: significant effects
```

INFERENCES:

- The high value of F-statistics conclude that we can reject the null hypothesis
- Therefore, time effect exists

As we know Fixed Effects accounts for the within entity and not across entities, let us move to random effects model which would take care of within entity effects as well as across entities effect. The random effects model doesn't seem to be the best model for two reasons

1. The data is not random as it has 51 states for 23 years (51*23= 1173 observations)
2. The problem of endogeneity could exist

Let us find out.

RANDOM EFFECTS MODEL

```
plm(formula = log(rob) ~ log(incarc_rate) + pop + log(density) +
    shall, data = df_pool, model = "random")

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

Effects:
                 var std.dev share
idiosyncratic 0.0466  0.2159 0.183
individual    0.2083  0.4564 0.817
theta: 0.9019

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.7922288 -0.1486153  0.0030577  0.1488714  0.6499415

Coefficients:
                  Estimate Std. Error z-value  Pr(>|z|)
(Intercept)       5.8431194  0.1734843 33.6810 < 2.2e-16 ***
log(incarc_rate) -0.1048549  0.0174779 -5.9993 1.982e-09 ***
pop               0.0285479  0.0088852  3.2130  0.001314 **
log(density)      0.2948729  0.0416255  7.0840 1.401e-12 ***
shall             0.0042993  0.0237641  0.1809  0.856435
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    63.298
Residual Sum of Squares: 58.47
R-Squared:      0.076277
Adj. R-Squared: 0.073113
Chisq: 96.448 on 4 DF, p-value: < 2.22e-16
```

INFERENCES:

- With 1 % increase in Incarceration Rate, the Violence Rate goes down by 0.10%. It is significant at any level of significance
- With 1 unit increase in the state population (pop), the violence rate goes up by ~2.85 %. It is significant at any level of significance
- With 1 % increase in density of the state population, the Violence Rate goes up by 0.29%. It is significant at any level of significance
- As compared to a state where Shall Carry Law has not been introduced (Shall = 0), the state where Shall Law has been introduced, will increase violence rate (vio) by ~ 0.42 %. It is not significant at all with p-value of 0.85

Let us check for endogeneity.

HAUSMAN-TEST

Endogeneity exists when the dependent variable is correlated with the error term of the model. We do Hausman-test to check for endogeneity. The hypothesis is as follow:

Null Hypothesis ➔ Ho: No Endogeneity

Alternative Hypothesis➔ H1: Endogeneity exists

```
> phtest(plm(log(rob)~log(incarc_rate)+pop+log(density)+shall,data=df_pool,
+            model="random"),
+        plm(log(vio)~log(incarc_rate)+pb1064+pw1064+pm1029+pop+log(density)+
+              shall,data=df_pool, model="within"))

        Hausman Test

data:  log(rob) ~ log(incarc_rate) + pop + log(density) + shall
chisq = 1331.7, df = 4, p-value < 2.2e-16
alternative hypothesis: one model is inconsistent
```

INFERENCES:

With the p-value of almost zero we can reject the null hypothesis

- Hence, we can conclude that endogeneity exists, and we cannot use random effects model

We can use murder or robbery as an Instrumental variable (z) to replace the endogenous variable if all the following three conditions satisfy:

1. Z is not related to dependent variable (violent rate in this case) X
2. Z is exogenous and is not correlated with the error term cov (z, e) = 0
3. Z has strong correlation with the endogenous variable X

Hence, we do not have any Instrumental variable right now.

CONCLUSION

1. Of all the models we ran i.e. Multiple Linear regression, Pooled effects, Time Fixed Effects and random effects model, our best model is Entity Time Fixed Effects Model
2. With reference to our Entity Time Fixed Effects Model, we saw that the crime or violence has reduced by 2.88% for the states that have shall carry laws introduced as compared to states who do not have shall carry law
3. With 1% increase in incarceration rate, violence increases by 0.10%
4. 1% increase in male population between the age of 10-29 leads to an increase of violent crime rate by 8.1%
5. An increase of 1% in density of population, violence rate increases by 0.25%
6. Therefore, we have conclusive evidence that shall-carry laws have managed to reduce violence to some extent

LIMITATIONS

1. An instrumental variable which could satisfy the conditions of an ideal IV on previous page could result in a better model
2. The IV estimator is biased and consistent. But with larger dataset we could have converged to the true parameter
3. Hence, we would have stronger evidence to support/reject the claim of shall-carry law reducing violence in the United States

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